

# Reference-Dependent Return Chasing

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## Abstract

How mutual fund investors chase alpha (abnormal performance) with their money is strongly mediated by the nominal price gain or loss that they hold the fund at. For high alpha funds, the investment response to alpha is reduced by as much as 37% if the fund is held at a loss as opposed to a gain considering the average dollar invested. This distinct interaction of alpha and losses attenuates the performance-flow relation and eliminates convexity for high alpha but loss funds. The empirical evidence supports ambiguity aversion and the social transmission of investment opportunities as mechanisms.

*Keywords:* Performance-Flow Relation, Mutual Funds, Trading Decisions, Ambiguity Aversion, Social Transmission

*JEL Codes:* G11, G23, G41

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# 1. Introduction

That mutual fund investors chase past abnormal performance (“alpha”) is one of the strongest empirical regularities in research on fund investment. High alpha funds incur high net inflows.<sup>1</sup> Although there is weak evidence of the persistence of abnormal performance,<sup>2</sup> [Berk and Green \(2004\)](#) provide a model to rationalize the observed performance chasing behavior of funds investors based on Bayesian’ learning about the fund manager’s skill and decreasing returns to scale in the fund manager’s investment strategy. A separate but closely related stream of literature is concerned with the reaction to the nominal value changes of individual investor’s investments and associated trading decisions. More specifically for mutual funds, [Chang, Solomon, and Westerfield \(2016\)](#) document a reverse disposition effect: fund investors are more likely to sell funds that they hold at a loss compared to a gain and provide a cognitive dissonance theory as explanation.

Both streams of literature thus find a positive relation between a signal that is ultimately related to past fund returns and the investment in mutual funds. This is the first paper to provide a comprehensive perspective on the relation of fund investment and both alpha and gains and losses. Besides confirming the parallel existence of alpha chasing and gain and loss related trading in a common setting based on fund level data, I discover a new and economically large interaction effect between alpha and losses: The investment flow response to high alpha funds is reduced by about 37% if the average dollar invested in the fund is held at a loss. Moreover, the commonly known convexity in the performance-flow relation is eradicated for the 36% of funds held at a loss on average. This finding highlights the importance of the joint consideration of both alpha and gains and losses in the determination of mutual fund investment decisions.

Why should we study whether and how fund investors react to signals beyond abnormal performance, especially whether they are holding the fund at a gain or loss? After all, alpha is the central measure for evaluating mutual funds in the academic literature. This measure properly

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<sup>1</sup>[Sirri and Tufano \(1998\)](#) and [Chevalier and Ellison \(1997\)](#) show a positive and convex relation between abnormal performance and net fund flows. [Barber, Huang, and Odean \(2016\)](#) and [Berk and van Binsbergen \(2016\)](#) show that it is especially the alpha estimated with respect to the CAPM that drives the allocation of money by investors.

<sup>2</sup>[Bollen and Busse \(2001\)](#), [Bollen and Busse \(2005\)](#) and [Mamaysky, Spiegel, and Zhang \(2008\)](#) find small persistence effects in fund alpha at short horizons. [Carhart \(1997\)](#) does not find persistent abnormal performance at longer horizons.

adjusts returns for risk and abstracts from the timing of the individual trading decisions of investors. At short horizons, it can help to infer the skill of a fund manager. Gains and losses do not share most of these good properties. Nevertheless, gains and losses likely influence investors for two reasons. First, information about gains and losses is frequently and saliently displayed, e.g. in financial statements or online brokerage accounts. Research in cognitive psychology suggests that decision-makers are influenced by information that is salient and quickly comes to mind (e.g., [Kahneman, 2011](#)). Second, the gain or loss made with an investment reflects the personal experience that an investor associates with the investment as it is a consequence of the actual timing of the buy and sell decisions of the investor with her real money. Previous research (e.g., [Malmendier and Nagel, 2011](#) and [Strahilevitz, Odean, and Barber, 2011](#)) shows that these individual experiences considerably affect financial decisions.

Gathering a precise understanding of fund investors' trading decisions is relevant because of the large size of the mutual fund market and its importance for households as retirement savings vehicle. According to recent estimates of the Investment Company Institute ([Investment Company Institute, 2018](#)), US mutual funds manage about \$19 trillion and 44% of US households participate in the market, accounting for 90% of the invested assets. Conditional on owning funds, the median household holds funds worth \$120'000. From an academic perspective, several theoretical papers assume that investors learn about the quality of their investment as a function of past returns signals (e.g., [Berk and Green, 2004](#) and [Huang, Wei, and Yan, 2007](#)) and I provide insights on how investors use and interpret different return related signals and which considerations are important.

I find a strong empirical pattern in how mutual fund investors react to alpha and gains and losses: The flow sensitivity with respect to alpha is significantly attenuated if the fund is held at a loss by the average investor. I demonstrate that this effect is different from the established alpha chasing behavior and the base effect of holding the fund at a loss (reverse disposition effect). The attenuation effect is economically significant: The reaction in net flows to a one standard deviation change in alpha is reduced from 124 basis points in the gain region to 78 basis points in the loss region. For the mean fund in the sample this translates to a reduction in net flow of \$8.8 million in the next month. The findings imply that investors not only consider both alpha and gains and losses, but that they are reacting to the two signals jointly and interdependently when making mutual fund investment decisions. To my knowledge, this is the first paper to show

an impact of reference-dependent trading on fund level flows and to document an interaction effect between alpha and nominal gains and losses in determining flows.

To arrive at these findings, I rely on mutual fund data as well as flow data from SEC form N-SAR, which allow me to cleanly separate inflows from outflows. Fund flows are particularly useful to study investors' decisions as they are a direct measure of the purchasing and selling volumes of all fund investors and available for a large sample of funds for many years. Using these fund level in- and outflows as well as returns, I am able to develop a new reference price measure for each fund-month. The approach resembles the work of [Grinblatt and Han \(2005\)](#) and [Frazzini \(2006\)](#) that use asset-level data to calculate reference prices for stocks. With the help of the reference price variable, I can determine whether the average dollar invested in the fund is currently held at a gain or at a loss and document the diminishing flow sensitivity with respect to alpha if the average dollar is invested at a loss. Taking advantage of the separate in- and outflow data, I show that this interaction effect only operates via buy decisions.

Next, I investigate the functional form of the conditional alpha-flow relation in greater detail. Does the attenuation affect all levels of alpha? It is an established empirical fact that the response to alpha is generally convex (e.g. [Chevalier and Ellison, 1997](#)). I show that the average attenuation effect does not operate equally strong for all levels of alpha. Instead, the alpha sensitivity of flows is especially reduced if the level of alpha is relatively high but the fund is nevertheless held at a loss. Actually, the convexity in the relation of performance and fund flows disappears when focusing on funds held at a loss.

Together, these findings show that investors not only react to both alpha and gain and losses, but that these signals are jointly considered. Beyond its individual effect, the gain/loss signal results in a different reaction to alpha: Investors are more hesitant to buy mutual funds if the high alpha is at conflict with the information that they are currently holding the fund at a loss. By exploiting cross-sectional variation, I show that the interaction effect is stronger for funds targeted at retail investors and that the interaction effect is stronger if the conflict is more severe, as indicated by a higher alpha or a greater loss.

I provide two mechanisms that are consistent with the empirical result that investors are hesitant to invest when facing the conflict of high alpha and losses. The first mechanism is based on ambiguity aversion and focuses on current investors of a fund. I interpret the conflict between alpha and losses as an increase in the perceived ambiguity (Knightian uncertainty)

about the quality of a fund investment. Especially literature in psychology theoretically (Einhorn and Hogarth, 1985) and experimentally (Smithson, 1999) argues that conflicting information is affecting choice by the means of increasing ambiguity. The model of Epstein and Schneider (2008) provides a very similar mechanism. Consistent with ambiguity aversion, flows show a reduced sensitivity to alpha for the high alpha but loss scenario.

The second potential mechanism is based on the social transmission of investment ideas between investors. Social interactions between people have an impact on the investment decisions of investors.<sup>3</sup> The model of Han, Hirshleifer, and Walden (2018) provides a formalization of the idea the social transmission depends on the gains and losses investors make with their investments. In the model, investors are more likely to share information about their investment if this investment has been successful. Combining this idea with confirmatory external information, the addressed potential investors will be more likely to invest if alpha, the external information that investors can look up in addition, is also positive. This mechanism can explain a stronger relation of alpha and inflows for funds held at a gain, as social transmission in this case is more effective to attract new investors to the fund. Moreover, it is able to rationalize why the interaction effect only occurs for buy but not for sell decisions.

Besides the literature cited above dealing with the performance-flow relation in mutual funds, I contribute to the literature that examines how the gains and losses of existing investments matter for the trading decisions of individual investors at the micro-level. Most prominently, Odean (1998) empirically shows that investors are more likely to realize gains than losses in their stock portfolio, which is a finding that was replicated in different contexts and named disposition effect.<sup>4</sup> In the context of mutual funds, Ivković and Weisbenner (2009) and Chang, Solomon, and Westerfield (2016) document a reverse disposition effect: investors are more likely to realize a loss than a gain.

Taking a broader perspective, my paper is related to a recent effort to investigate which information market participants use and how they understand and interpret this information. For example, Hartzmark and Solomon (2017b) show that investors seem to look at dividends

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<sup>3</sup>Empirical evidence includes Ivković and Weisbenner (2007) and Hong, Kubik, and Stein (2005).

<sup>4</sup>The term disposition effect was originally termed by Shefrin and Statman (1985). The effect is experimentally shown by Weber and Camerer (1998). Grinblatt and Keloharju (2001) confirm the disposition effect in a large panel of retail investors. Ben-David and Hirshleifer (2012) find that the disposition effect is inverted when considering additional purchases instead of sales. Consider Barber and Odean (2013) for a comprehensive literature review on empirical and experimental papers on the disposition effect.

and price changes as separate properties of an investment, and extend this idea in [Hartzmark and Solomon \(2017a\)](#) by showing that investors act upon price change measures instead of total returns.

I proceed as follows. Section 2 describes what data are used and how the reference price and other return measures are estimated. Section 3 presents the results and addresses concerns regarding omitted residual return information. Section 4 discusses ambiguity aversion and social transmission as channels of the findings. Finally, section 5 concludes. In the appendix to this paper, I explain in detail the calculation of variables and provide additional results and robustness checks.

## 2. Data

In this section, I explain how the sample of funds is constructed and how variables are calculated. Most importantly, I describe how I arrive at an estimate of the reference price of a fund for the average dollar invested. Finally, summary statistics are also presented.

### 2.1. Sample Construction

I obtain data on all mutual funds registered in the United States from Morningstar. Morningstar is used as data provider, as the database includes data on the monthly volume of new sales and redemptions of funds in addition to standard variables such as fund returns and TNA. The sales and redemptions volumes are extracted from SEC form N-SAR by Morningstar. All registered investment companies in the US are required to file form N-SAR under the Investment Company Act of 1940.<sup>5</sup> Using the sales and redemptions volumes allows to study the buying and selling decisions of fund investors separately, as opposed to plain net flows which net buying and selling activity. In addition, I obtain standard fund data points, i.e. returns, total net assets (TNA), net asset value (NAV), fund and family affiliation, expense ratio, turnover, inception date, Morningstar category, Morningstar rating and supplemental characteristics (e.g. whether a fund is classified as index fund).

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<sup>5</sup>While it would be possible to collect the N-SAR filings directly from the SEC, matching the N-SAR reports with standard fund databases is very challenging, as frequently there are no identifiers included in the N-SAR filings, companies report many funds in a single form and the exact layout of the form varies strongly between companies and over time. The only study I am aware of that uses a similarly large sample of N-SAR flows is [Cashman et al. \(2012\)](#).

Data at the fund level allow me to look at mutual fund investor behavior through a comprehensive perspective. While they do not allow me to study the behavior of individual investors at the same granularity as brokerage datasets, using aggregate fund data provides other advantages. The data include the investments of essentially all investors for a very broad sample of funds and for a long time span. Many investors are not acquiring their funds through a discount brokerage. According to a survey of the [Investment Company Institute \(2018\)](#), only 24% of mutual fund owners purchase their mutual funds at least partly through a discount brokerage. The years covered here (2000-2017) are characterized by the availability of low-cost information via the internet and expanded knowledge concerning the factor-structure of the cross-section of stock returns.

I obtain data from Morningstar via the Morningstar Direct platform for the years 1990 to 2017. The data are survivorship bias free, in the sense of [Carhart \(1997\)](#), as data of dead funds are included. Before the early 1990s monthly data items are hardly available in Morningstar and coverage of fund objectives is sparse. For this reason, I obtain data from 1990 on. I need several years of data to calculate both alpha and reference prices and the regressions rely on the inflow and outflow data which is broadly available only from 2000 on. Therefore, the observations included in the regressions cover the years 2000 to 2017. I include actively managed US equity funds as identified by the union of Morningstar categories along the market capitalization (“Small-Cap”, “Mid-Cap”, “Large-Cap”) and value-growth dimension (“Value”, “Blend”, “Growth”). Morningstar provides the data at the share class level, while N-SAR data are available at the fund level only. Therefore, share classes are aggregated on the fund level. Funds are identified using the Morningstar identifier “fundid”. For numerical variables (such as returns or expense ratios), I calculate a TNA-weighted average at the fund level. For variables where a value-weighted average is not meaningful (such as categorical variables like the institutional share class identifier), I keep the value that is associated with the largest total share of TNA across the different share classes of a fund.

To be included in the sample, I require that a fund has at least 80% of its TNA invested in equity and I exclude funds with short positions exceeding 10% of TNA or that are identified as index funds or funds of funds by Morningstar in order to obtain a sample of standard equity funds comparable to previous studies. Fund-month observations covering the first three years since the inception of a fund are excluded to avoid the incubation bias documented by [Evans](#)

(2010). As funds with less than \$15 mio. TNA are subject to reduced reporting requirements those observations are excluded, following [Elton, Gruber, and Blake \(2001\)](#). In addition to these standard data requirements, I employ a filter to ensure a proper matching of N-SAR data with the remaining fund data to minimize the impact of mismatches made by Morningstar. I calculate gross dollar flows using standard fund data (TNA difference in excess of the return implied value change) and N-SAR data only (new sales in excess of redemptions). To be included in the sample, I require at least 12 overlapping months of gross flows (such that at least two semi-annual N-SAR forms are matched to the fund) and for the whole overlapping time-period, the correlation between the two measures of gross flows needs to be at least 0.85. I discuss and compare the sample before and after imposing this filter in [Appendix IA3](#). I conclude that the N-SAR matched sample is a broad and representative sample for the largest part of the domestic equity mutual fund market in the US. For any month in the time period used for later analysis, my sample includes between \$0.5 and \$2.5 trillion in assets under management.

I construct the following flow variables from the fund and N-SAR data. Subscripts  $i$  and  $t$  index fund and month, respectively.

$$\text{Flow}_{i,t} = \frac{\text{New Sales}_{i,t} - \text{Redemptions}_{i,t}}{\text{TNA}_{i,t-1}}$$

$$\text{Inflow}_{i,t} = \frac{\text{New Sales}_{i,t}}{\text{TNA}_{i,t-1}}$$

$$\text{Outflow}_{i,t} = \frac{\text{Redemptions}_{i,t}}{\text{TNA}_{i,t-1}}$$

Flow measures the percentage net flow of money into or out of a mutual fund. Inflow and Outflow measure separately the fractional in- and outflows of the fund. I exclude net flows that are smaller than -90% or larger than 1000% from the sample, and inflows and outflows that exceed 10000%. The results of this study however do not depend on their exclusion.<sup>6</sup>

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<sup>6</sup>In the internet appendix, I repeat the baseline regressions using flows winsorized at the 1st and 99th percentile, which is the practice most frequently observed in papers on mutual fund flows but manipulates much more data points. The results are very similar and can be found in [Table IA3](#).



## 2.2. Calculation of Reference Prices and Performance Measures

To study the effect of reference prices<sup>7</sup> on flows, I need to construct a proper measure of a reference price on the fund level. In this sense my objective is similar to [Grinblatt and Han \(2005\)](#) and [Frazzini \(2006\)](#). Both of these studies construct aggregate reference prices to study how market outcomes are influenced by the reference points of individual investors. Overall, I aim to construct a measure that is as close as possible to what existing investors of the fund observe in their financial accounts.

As compared to the stock market set-up of these earlier studies, examining the mutual fund market provides two advantages. First, the gross dollar flows in and out of mutual funds are directly observable and a direct measure of the purchasing and selling activity of market participants. This should result in a more precise estimation of reference prices as compared to the use of simple aggregate trading volume as in [Grinblatt and Han \(2005\)](#), which is not directional. Second, those flows are covering the decisions of all participating investors. Again, this should result in a more precise estimate of the reference price as compared to the stock market set-up of [Frazzini \(2006\)](#), where only a subset of market participants is considered (mutual fund managers via their holdings).

In essence, the reference price  $\phi_{i,t}$  is an average of past prices  $p_{i,s}$  since the inception of the fund, weighted by the amount of money  $m_{i,t,s}$  that was invested in fund  $i$  in month  $s$  and is still invested as of month  $t$ .

$$\phi_{i,t} = \frac{\sum_{s=0}^t m_{i,t,s} \cdot p_{i,s}}{\sum_{s=0}^t m_{i,t,s}} \quad (1)$$

Intuitively, I find the answer to the question: for each dollar of the current value of the fund, what was the relevant purchasing price? This is equivalent to the answer to the question: for each fund share existing, what was the relevant purchasing price?<sup>8</sup> As a price of the fund, I use the NAV which is easily observed and does not include any adjustment for distributions made by the fund. The findings of [Hartzmark and Solomon \(2017a\)](#) strongly suggest that this is the price

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<sup>7</sup>In a mutual fund context, the relevant price of a fund share is the NAV. Throughout this study, I use the terms price and NAV interchangeably.

<sup>8</sup>Let  $n_{i,s}$  be the number of fund shares bought in month  $s$  and assume without loss of generality that no shares are sold between  $s$  and  $t$ . In this case  $m_{i,t,s} = n_{i,s} \cdot p_{i,t}$ . Using this equation, simple algebra shows that finding the relevant purchase price for each dollar still invested or for each share still held is equivalent.

$$\phi_{i,t} = \frac{\sum_{s=0}^t m_{i,t,s} \cdot p_{i,s}}{\sum_{s=0}^t m_{i,t,s}} = \frac{\sum_{s=0}^t n_{i,s} \cdot p_{i,t} \cdot p_{i,s}}{\sum_{s=0}^t n_{i,s} \cdot p_{i,t}} = \frac{\sum_{s=0}^t n_{i,s} \cdot p_{i,s}}{\sum_{s=0}^t n_{i,s}}$$

investors typically observe through their financial accounts and the benchmark against which gains and losses are calculated. Calculating reference prices based on this definition requires specifying  $m_{i,t,s}$ , the amount of money that was invested in month  $s$  in the fund and still is invested in the fund at time  $t$ . For this calculation, I make use of the TNA and flow data that are available for mutual funds. The intuition of the procedure is simple. Basically, I treat each dollar invested in the fund as a separate investor. This way, I can observe investors investing in and leaving the fund over time via the fund’s in- and outflows and calculate the aggregate reference price as a weighted average of past transaction prices.<sup>9</sup>

For outflows, which represent investors that leave the fund, I need to make an assumption about which investors leave first. I assume that money which is invested in the fund for a longer time, is more likely to be withdrawn (“First-in, first-out”). I consider this a reasonable assumption as mutual funds are typically long-term investment products, which is underlined by their importance in retirement savings, e.g. as an option in 401(k) plans. According to the [Investment Company Institute \(2018\)](#), 75% of mutual fund owning households view retirement as their primary financial goal, highlighting the long-term nature of fund investments. In addition, the fee structure of those products often involves significant front and rear loads and other charges that render short-term trading on high-frequencies unprofitable. Very similar assumptions are made in the previous literature that examines the effects of reference points in an aggregate setting ([Grinblatt and Han, 2005](#) and [Frazzini, 2006](#)).

This way, I arrive at an estimate for the reference price for each fund in every month. The technical details of the implementation of the reference price calculation are explained in [Appendix A](#). For later investigations in the regression analyses I am mainly interested in whether the average investor is holding the fund at a loss. Therefore, I create the indicator variable  $I[\text{Loss}]$ .

$$I[\text{Loss}]_{i,t} = \mathbb{1}(\phi_{i,t} > p_{i,t}) \tag{2}$$

To disentangle the effects of alpha and gains and losses from other information about the time-series of fund returns, I calculate additional return related variables that could have an impact on fund flows. All the measures are characterizations of certain aspects of the time-series of fund returns, that could be appealing to investors for different reasons, such as signaling

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<sup>9</sup>Alternatively, you may think about the construction as if only a single investor were investing in a fund, such that her buying and selling decisions are captured by the flows.

managerial skill, preferences for certain return characteristics or visibility arguments.

In order to account for risk considerations in a CAPM context or in the context of modern portfolio theory under  $\mu - \sigma$  preferences, I include the market beta and return volatility (“Beta” and “Vola”, respectively). Furthermore, I include several variables that might describe properties of returns that are relevant under lottery- or skewness preferences or visibility/search costs and attention considerations.<sup>10</sup> Papers such as [Kumar \(2009\)](#), [Bali, Cakici, and Whitelaw \(2011\)](#) and [Barberis and Huang \(2008\)](#) argue both theoretically and empirically that parts of the investor population might exhibit skewness or lottery preferences. Hence, I include variables that proxy for the relevant features of lotteries and were used in the cited papers. These variables are the skewness of returns (“Skew”), the kurtosis of returns (“Kurt”), as well as the minimum and maximum return of the fund in the rolling-window (“MIN” and “MAX”). Following the extension of the previous argument by [Boyer, Mitton, and Vorkink \(2010\)](#), I furthermore include idiosyncratic skewness (“ISkew”). As an additional predictor in relation to lottery preferences, I include idiosyncratic volatility (“IVola”) ([Ang et al., 2006](#) and [Hou and Loh, 2016](#)).

[Del Guercio and Tkac \(2008\)](#) show that Morningstar star ratings, which are based on past cross-sectional performance, have an effect on fund flows. I therefore include an indicator variable for each level of the discrete rating. Finally, [Hartzmark and Solomon \(2017a\)](#) show that investors reward funds whose NAV change exceeds the change in the S&P500 price index. Consequently, I include a dummy variable (“Beat SP500”) when the price change of the fund exceeds the relative change in the S&P500 in a given month.

Appendix [B](#) explains in detail the construction of the variables used in this study.

### *2.3. Descriptive Statistics*

Table [1](#) presents summary statistics for the constructed sample. In my sample period, net flows were on average very close to zero. The net flows calculated from standard fund data as well as from N-SAR data display very similar properties when inspecting the displayed quantiles. As an additional verification of the N-SAR based flows, I calculate the correlation between N-SAR based and standard net flows. The correlation is 0.96.<sup>11</sup> Generally, net flows hide much larger variation in inflows and outflows. At the mean, inflows and outflows are close to 280 basis

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<sup>10</sup>Variables like MAX, MIN or Skew might well proxy for both lottery characteristics and extreme return induced attention in the sense of [Kaniel and Parham \(2017\)](#) or [Kumar, Ruenzi, and Ungeheuer \(2017\)](#).

<sup>11</sup>The correlation table for flows is provided in the internet appendix [IA1](#).

points each, consistent with close to zero net flows. For the return measures, CAPM alpha is slightly positive at 10 basis points per month (pre-expenses) and the market beta is close to one, as expected for these diversified mutual funds. Considering the constructed reference price variable, the average investor is holding the fund at a loss for about 36% of fund-months in the sample and the correlation between alpha and the gain/loss indicator is almost zero.<sup>12</sup>

[Insert Table 1 about here.]

### 3. Results

In this section, I document the main finding of this paper: Investors' chasing of past returns in mutual funds is strongly weakened if the average investor is holding the fund at a loss. In the following, I show the robustness of the results with respect to variation in return information and non-linearity.

#### 3.1. Main Result

I rely on portfolio sorts as the first step of the analysis. In each month, I sort all funds based on their cross-sectional alpha into ten decile portfolios. I then look at the average net flow of the funds in a given portfolio in the following month. In a second step, I split each alpha decile portfolio into two sub-portfolios, according to whether the fund is held at a gain or loss by the average investor. The results of these dependent double sorts are presented graphically in figure 1.

[Insert Figure 1 about here.]

Panel A contains the results for the sorting on alpha without sorting on the loss variable. The figure shows strong performance chasing behavior in mutual funds. Funds ranked in the 1st alpha decile exhibit negative net flows at -1.9 percentage points on average. Net flows monotonically increase across the alpha deciles and funds ranked in the 10th alpha decile receive net flows of 2.8 percentage points in the following month. Hence, the spread in flows between high and low alpha funds is as large as 4.7 percentage points. Note the convexity in the relation, especially for the high alpha portfolios, as the incremental net flow into funds increases across the deciles.

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<sup>12</sup>See internet appendix [IA1](#).

In addition to sorting on alpha, funds are sorted according to whether the average investor is holding the fund at a gain (green bars) or loss (red bars) in panel B. Visual inspection shows that flows are considerably lower within any given alpha decile if the average investor holds the fund at a loss. This is consistent with the reverse disposition effect finding of [Chang, Solomon, and Westerfield \(2016\)](#) who show that investors are more likely to sell losing funds. I confirm this finding using fund level data while controlling for the impact of alpha. This analysis shows that alpha chasing and reference dependent trading are two distinct effects that coexist.

The additional new observation is that the total strength of the alpha chasing effect varies strongly according to whether the fund is held at a gain or loss. When comparing the height of the bars across different alpha deciles, the sensitivity of net flows with respect to alpha is much stronger if the fund is held at gain. Here, the difference between the top and bottom alpha deciles in flows amounts to 5.1 percentage points. In contrast, this difference only amounts to 3 percentage points if the fund is held at a loss on average, considerably undercutting also unconditional difference. The difference in flows between funds held at a gain and held at a loss is not constant across deciles. In the bottom alpha decile, the difference amounts to 98 basis points, increases to 106 basis points in the sixth alpha decile, and increases further to 328 basis points in the top decile. Thus, the difference between funds held at a gain or loss is not simply a level effect, that could be a manifestation of reverse disposition effect induced selling pressure. Rather, the graph suggests that the two performance measures are considered jointly and that investors react differently to a given alpha depending upon whether they currently hold the fund at a gain or loss. A similar level of alpha is much less rewarded with additional net flow if the fund is held at a loss, and this reduction is increasing in the level of alpha. Looking at the red bars across alpha deciles, convexity in the performance-flow relation is not present if the fund is held at a loss but is present for funds held at a gain.

To investigate this observation more carefully by controlling for covariates, I turn to panel regressions. I estimate the effects on fund flows by variations of the following OLS regression.

$$\text{Flow}_{i,t+1} = \lambda_1 \text{Alpha}_{i,t} + \lambda_2 \text{I[Loss]}_{i,t} + \lambda_3 \text{Alpha}_{i,t} \text{I[Loss]}_{i,t} + \lambda_X X_{i,t} + \delta_{t,c} + \gamma_i + \epsilon_{i,t}$$

The flows of fund  $i$  in month  $t+1$  are regressed on alpha,  $\text{Alpha}_{i,t}$ , the loss variable,  $\text{I[Loss]}_{i,t}$ , their interaction term as well as a vector of control variables,  $X_{i,t}$ , and category by time and

fund fixed effects,  $\delta_{t,c}$  and  $\gamma_i$ . Control variables include both fund and fund family characteristics and variables that characterize additional properties of the time-series of fund returns. I choose a deliberately investor centric approach by using only lagged independent variables, such that the variables reflect information an investor could obtain by the time she decides to invest or dis-invest in the fund. I include fund and category by month fixed effects to capture effects of time-invariant unobserved fund level variables or general time-series developments that affect all funds in a category or as a whole in a given month. Throughout the paper, all standard errors are conservatively two-way clustered by fund and month.<sup>13</sup>

Table 2 presents the results of the regressions of fund flows on alpha, the loss indicator variable, their interaction term as well as control variables.

[Insert Table 2 about here.]

Columns 1 and 2 confirm the insights derived from the sorting analysis after the inclusion of control variables and fixed effects. First, the classical result of the performance-flow relation holds: lagged alpha is a strong predictor of net fund flows as the coefficient on alpha is positive and statistically highly significant with a coefficient of 2.7 in column 2. Funds with higher cross-sectional alpha performance receive higher net flows in the following month. Second, funds that are held at a loss on average exhibit significantly smaller net flows (a level effect of the loss variable independent of the level of alpha). The coefficient of -0.007 on the loss variable suggests that a fund held at a loss on average attracts about 70 basis points smaller net flows than a comparable fund held at a gain. This is in line with the reverse disposition effect documented by [Chang, Solomon, and Westerfield \(2016\)](#). The effect exists after controlling for the impact of alpha. Third, I find a significantly negative interaction term of alpha and the loss variable. The sensitivity of net flows with respect to alpha is attenuated for funds held at a loss as indicated by the negative coefficient on the interaction term of -1.0. The effect is statistically significant at the 1%-level. This pattern suggests that investors not only incorporate both alpha and gains and losses when trading mutual funds, but that they react to the signals inter-dependently. The inclusion of fixed effects in column 2 does not alter the qualitative insights of column 1. Hence, fund specific clientele or visibility arguments or time-varying preferences for certain fund categories do not drive the findings. The attenuation effect is economically large. The slope

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<sup>13</sup>This specification allows for heteroskedasticity and arbitrary dependence structures in residuals within the time-series of a single fund or in the cross-section of all funds in a given month.

on alpha is reduced by 37% from 2.7 to 1.7 if the fund is held at a loss compared to a gain. Consider the change in flows for a one standard deviation increase in alpha (46 basis points). If the fund is held at a gain, net flows increase by about 124 basis points next month. If the fund is held at a loss instead, the increase only amounts to 78 basis points.<sup>14</sup>

Considering the other independent variables, I obtain results in line with previous literature, such as [Sirri and Tufano \(1998\)](#) or [Chevalier and Ellison \(1997\)](#). Net flows are smaller for larger and older funds, while flows are typically larger for funds that are part of larger fund families. Consistent with the recent work of [Hartzmark and Solomon \(2017a\)](#), I find that funds obtain significantly higher net flows if they are beating the S&P500 index in terms of price changes. The effects of other covariates are small or not robust to the inclusion of fixed effects. For the remainder of this paper, I continue with the specification including all fixed effects as the more conservative approach.

In the remaining columns of table 2, I split net flows into buying and selling activity. Columns 3 and 4 reveal that both inflows and outflows are sensitive to alpha performance. Investors both buy more fund shares and redeem less fund shares following good alpha performance as indicated by the positive and significant alpha coefficient of 2.0 for inflows in column 3 and the negative and significant alpha coefficient of -0.6 for outflows in column 4. The larger part of the effect is driven by buy decisions as the absolute value of the alpha coefficient is more than three times as large for inflows as compared to outflows. Consistent with the reverse disposition effect, I find a positive and significant coefficient of 0.003 on the loss variable for outflows. Outflows increase by about 30 basis points if the fund is held at a loss. Additionally, I also find an impact of the loss variable on inflows. Inflows decrease by about 40 basis points if the fund is held at a loss. This finding is consistent with the inversion of the disposition effect if repeated purchases are considered instead of sales as shown by [Ben-David and Hirshleifer \(2012\)](#).

Focusing on the newly documented attenuation effect, I find that the effect is driven by buy decisions. On the one hand, the coefficient on alpha is reduced by the interaction term of -1.1 from 2.0 to 0.9 if the fund is held at a loss instead of a gain for inflows in column 3. On the other hand, the coefficient on the interaction term is insignificant in column 4, where outflows are considered.

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<sup>14</sup>This calculation does not include the level effect of holding the fund at a loss. Considering this effect, the net flow would decrease further to 8 basis points for funds held at a loss in the example.

Overall, I document that reference prices have an effect on the performance-flow relation of mutual funds. Investors dislike funds held at a loss, as both inflows are significantly lower and outflows significantly higher if the fund is held at a loss on average. Besides this level-effect, I show that the reaction to a marginal unit of alpha performance is attenuated if the fund is held at a loss. This slope effect works via inflows. Hence, either current fund investors drive the slope effect with their additional purchase decisions or new investors learn in some way about the gains and losses of current investors through an external channel, such as social interaction.

### *3.2. Omitted Information*

A concern with these results may be that the loss variable incorporates information not included in the calculation of alpha. In this case, the effect of the loss variable on flows may only be obtained due to this residual information not reflected. While the baseline regressions already contain a large number of variables to control for the impact of other properties of the time-series of fund returns, I present evidence against this concern for two additional dimensions: the time span of the return information used and the treatment of risk in the return related measures.

While alpha is based on a fixed number of months (36 in the baseline specification), the loss variable is not constrained in the number of months used in its construction. This number is endogenously determined by the flows and returns that the fund is incurring. The predictive ability of the loss variable might thus be spurious due to a different number of months used for the estimation. As an additional complication different investors of a fund might be looking at different measures of performance at the same point in time. To address this concern, I estimate regressions including alpha calculated among different time horizons (12, 36, 60 and 120 months) simultaneously and also include the average raw return for the corresponding time periods. The results of this analysis<sup>15</sup> are presented in table 3.

[Insert Table 3 about here.]

The negative and statistically highly significant interaction effect of alpha and losses persists after controlling simultaneously for alpha and raw returns calculated for different time horizons. This is the case both in column 1, where the horizons between 1 and 10 years are included, and

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<sup>15</sup>A simpler analysis of time horizons with just the variation of the time horizon can be found in the internet appendix Table IA5.



column 2, where I also add the measures calculated on the fund-month specific time-horizon of the average dollar invested. Hence, investors usage of different performance measures that might be correlated with gains and losses are very unlikely to drive of the interaction effect. In line with results from previous literature (e.g. [Barber, Huang, and Odean, 2016](#)), I find positive and significant coefficients for several alpha and return variables, with a larger impact of short- to medium-term measures.

A different concern with respect to omitted residual information could be the specific model used for the generation of alpha. The loss variable could in this case proxy for other risk related considerations concerning fund returns. In the baseline results, I employ the CAPM as the model for performance measurement. While the findings of [Barber, Huang, and Odean \(2016\)](#) and [Berk and van Binsbergen \(2016\)](#) suggest that the CAPM is the most frequently used model, they also present evidence consistent with the idea that some investors use more or less complicated models. Therefore, I repeat the analysis using different factor models for the calculation of alpha. I consider the three factor model of [Fama and French \(1993\)](#), the four factor model of [Carhart \(1997\)](#), the five factor model of [Fama and French \(2015\)](#) as well as the four factor model of [Hou, Xue, and Zhang \(2015\)](#).<sup>16</sup> I also analyze simple excess returns over the market. Table 4 presents the results of these tests.

[Insert Table 4 about here.]

As we can see in columns 1 through 7, the interaction effect of alpha and the loss variable is negative and statistically significant on at least the 1%-level across all model specifications. Also the economic significance is hardly affected by the specific choice of a performance evaluation model and ranges between 37% and 55% of the alpha coefficient for funds held at a gain. Hence, a more complex or simpler treatment of risk is not the reason for the predictability of the loss variable or the attenuation effect in fund flows. Moreover, the interaction effect in column 3 is still significant, when NAV changes instead of returns are considered for fund performance in a CAPM-style model. This implies that loss effects are not just an artifact of using price changes instead of total returns in the calculation of whether the fund is held at a loss. In the last column, I include all additional alphas in one specification to allow for the possibility that different investors might be looking at different alpha specifications. Both the interaction

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<sup>16</sup>I would like to thank Kenneth French and Lu Zhang for making the factor data available.

and the level loss effect remain unaffected also in this specification. As expected, the base effect of alpha is decreased, as some of the other alpha specifications also exhibit positive and significant coefficients. Overall, the evidence suggests that omitted information in terms of the risk-adjustment or the use of price changes for the loss variable are not drivers of the reference-dependent alpha chasing behavior.

Finally, I ensure that the reference-dependent reaction with respect to abnormal performance is not driven by a reference-dependent reaction to other return variables. For example, research in finance and economics has shown that decision makers exhibit risk-seeking behavior when facing losses (e.g. [Tversky and Kahneman, 1992](#)). Hence, a reference-dependent reaction to other return related variables, such as volatility, could potentially drive the interaction effect of alpha and the loss variable. I test this idea by including interaction effects of the loss variable and all control variables. The results are shown in table 5. The table shows a negative and statistically significant interaction effect between alpha and the loss dummy for both net flows (column 1) and inflows (column 2) after controlling for the additional interaction terms between the loss dummy and covariates. Thus, reference-dependent reactions with respect to other return related variables do not explain the heterogeneous reaction to alpha.

[Insert Table 5 about here.]

I provide additional robustness test in the internet appendix of the paper. In this appendix, I confirm the results for the inclusion of lagged flows, lagged returns, the use of flow data not based on form N-SAR and for winsorized flows.

### *3.3. Non-linearity*

Starting with [Chevalier and Ellison \(1997\)](#), several papers argue that the performance-flow relation is convex. Higher levels of alpha attract increasingly higher flows. Substantial literature in the following discusses the risk-shifting incentives of fund managers induced by the convex relation of fund flows and performance. It is therefore relevant to examine the conditional functional form of the alpha chasing to understand in what scenarios the reaction to alpha is most strongly influenced by the fact that the average investor is holding the fund at a loss. Furthermore, this analysis addresses potential concerns regarding omitted convexity driving the effects regarding the loss variable.

Adapting the approach of [Sirri and Tufano \(1998\)](#), I estimate linear spline regressions of the conditional alpha flow relation. I define three linear spline segments, based on the 20th and 80th cross-sectional alpha percentile. The cross-sectional alpha percentiles are recalculated each month. I then introduce these alpha splines ("Alpha Low", "Alpha Mid" and "Alpha High") to the fixed effects panel regressions and interact them with the loss indicator. The results of this estimation are presented in [table 6](#).

[Insert [Table 6](#) about here.]

Focusing on the response in net flows in [column 1](#) first, I find considerable convexity in the performance-flow relation for funds held at a gain. Even for the low alpha segment, we observe a responsiveness of net flows with respect to alpha as indicated by the positive and significant coefficient of 1.7. The magnitude of the alpha coefficients increases considerably to 2.6 and further to 3.5 for mid and high alpha funds, respectively. Hence, the reaction in flows more than doubles for a marginal increase of alpha in the 80th through 100th percentile relative to the 1st through 20th cross-sectional percentile, such that the relation between alpha and flows is convex for funds held at a gain.

The picture looks very different for funds held at a loss. The interaction term of 1.0 of the loss variable and alpha is positive and significantly different from zero for the low alpha interval, while it is negative and significant at the 1%-level for the mid and high alpha range at -1.2 and -2.4, respectively. Hence, the average attenuation effect shown previously does not operate equally strong across different levels of alpha performance. The attenuation is highest for the high alpha interval (amounting to about 76% of the slope for funds held at a gain), considerably larger than for the mid alpha interval (about 41%). The slopes obtained by adding up the alpha spline terms with the respective interaction terms results in slopes of 2.6, 1.5 and 0.8 for the low, mid and high alpha interval for funds held at a loss. If the total response to alpha for funds held at a loss is considered, the attenuation basically wipes out any convexity in the relation of alpha and net flows: Investors do not become increasingly performance sensitive to a marginal unit of alpha if they hold the fund at a loss. Rather, the reaction turns slightly concave. This implies an extensive interplay in the evaluation of performance information for relatively high levels of alpha and funds that are held at a loss on average by mutual fund investors. These high alpha funds incur strongly weaker flow sensitivity with respect to alpha than a comparable

fund that is held at a gain.

In columns 2 and 3, I repeat the analysis separately for the buying and selling volume of the funds. Consistent with previous results, the total alpha sensitivity of net flows is driven by responses of both inflows and outflows to performance, as indicated by the positive alpha coefficients in column 2 and the negative alpha coefficients in column 3. The performance sensitivity of inflows (column 2) mainly operates through mid and high levels of alpha, as the coefficients on alpha mid and high (1.7 and 3.5) are positive and significantly different from zero at the 1%-level. Hence, investors especially create buying pressure for funds with medium to high levels of performance. The performance sensitivity of outflows (column 3) with respect to alpha is driven by low and mid alpha levels, as the coefficients for alpha low and mid (-1.1 and -0.9) are negative and significantly different from zero. Thus, investors redeem fund shares especially following medium to low levels of performance. Overall, the reaction of inflows with respect to performance is stronger as compared to outflows, as the absolute magnitude of the significant alpha coefficients is larger.

The attenuation effect in the performance-flow relation for funds held at a loss is driven via the inflow channel. We can observe a negative and significant interaction term of alpha and the loss dummy for the mid and high alpha interval for inflows in column 2. When holding the fund at a loss, investors do not increase their buying volume for a marginal unit of alpha in increasing proportion for high cross-sectional levels of performance, as they would when holding the fund at a gain. For the low alpha interval, the interaction term is positive and marginally significant. The magnitude of the attenuation amounts to 67% and 70% relative to the slope on the respective alpha segment for funds held at a gain. Considering outflows, the coefficients on the interaction terms are much smaller in absolute magnitude and not significantly different from zero, suggesting that the reference-dependence feature of the performance-flow relation is mainly relevant for buy decisions.

### *3.4. Performance Prediction*

To rule out that investors act upon the gain/loss information to identify funds with positive abnormal performance in the future, I test whether performance prediction is possible using the loss variable and the interaction term with alpha. Therefore, I regress the alpha realizations next month on lagged alpha, the loss variable, the interaction term as well as control variables.

I repeat the analysis for the following three months of alpha realizations. Table 7 presents the results of this analysis.

[Insert Table 7 about here.]

As we can see, neither the loss variable nor the interaction term with alpha provides significant predictive ability for the out-of-sample alpha realizations at the 10%-level. Hence, investors seem not to consider the loss variable because the variable provides additional predictive ability for the abnormal performance of funds. Additionally, the alpha coefficients provide weak evidence in favor of short-term persistence of alpha, in line with the findings of [Bollen and Busse \(2005\)](#).

Throughout this section, I establish a new and robust empirical fact about mutual fund flows: the chasing of past alpha is considerably attenuated if the fund is held at a loss considering the average dollar invested. This average attenuation effect does not work equally across the whole cross-sectional range of alpha performance. The effect stronger for buy decisions and for high levels of alpha if the fund is held at a loss.

## 4. Mechanism

What can explain the reference-dependent nature of investors' return chasing in mutual funds? As we are dealing with an interaction effect, it is not sufficient to present a mechanism that describes how both return measures matter individually. This already rules out several additional explanations. First, exclusive clienteles, such as a sub-group of more sophisticated investors only looking at alpha, while another sub-group is considering the price change they observe in their brokerage account, does not explain the interaction effect of alpha and losses. Second, the gain/loss variable could be relevant for tax considerations, as capital gains taxes are based on the gains and losses of the investment. However, tax considerations are not relevant for the interaction effect, as alpha, that is part of the interaction, has no tax consequences. Hence, tax considerations should be captured by the loss variable. Furthermore, buy decisions are the driver of the interaction effect and buy decisions do not have direct tax consequences.

I document a weaker flow sensitivity to alpha information if the fund is held at a loss and the level of alpha is relatively high. The key characteristic of this set-up is that the two signals

disagree with each other. While a high alpha is a positive signal about the fund's performance, the existing experience of the investor with the fund investment is opposing this information. Furthermore, the largest part of this effect is driven by buy decisions. To learn more about the potential mechanisms driving the reference-dependent nature of the alpha flow relation, I explore additional variation in the data with regard to investor characteristics and the strength of the effect in table 8.

[Insert Table 8 about here.]

First, I analyze the difference of the attenuation effect between funds targeted at more or less sophisticated investors in column 1. Therefore, I interact the variables of interest with an indicator that takes on a value of one if the fund is designed to be an investment for institutional investors. Morningstar provides an identifier for those funds.<sup>17</sup> According to their definition, a fund is classified as targeted at institutional investors if it meets at least one of the following three criteria: the fund's name includes the word "institutional", the fund has a minimum initial purchase amount of at least \$100'000 or the fund's prospectus states that it is specifically designed for institutional investors.

The coefficients presented in column 1 show that the negative interaction effect of alpha and losses is larger in magnitude for fund targeted at less sophisticated retail investors. Considering retail funds, the interaction term of alpha and losses is negative and significant at -1.1. The triple interaction of alpha, the loss variable and the indicator whether the fund is targeted at institutional investors is positive at 0.5 and statistically significant at the 10%-level.<sup>18</sup> This implies that the weakening of the alpha flow relation with respect to losses is less pronounced considering more sophisticated investors, with a combined interaction term of -0.6. The effect is economically meaningful. The strength of the attenuation effect is almost cut in half for institutional funds. The coefficients on alpha and the loss variable confirm the baseline effects shown above.

Second, I analyze how the strength of the interaction term varies with the severity of the loss that the average dollar is invested in a fund. I implement this test by breaking the loss

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<sup>17</sup>The identifier is available at the share class level, but as the flow variables used are available at the fund level only, I implement this test on the fund level.

<sup>18</sup>Note that this is a test with very high data requirements. It considers the difference in the alpha-flow sensitivity for funds held at a loss versus funds at a gain and the difference of this difference for institutional versus non-institutional funds, limiting the statistical power with regressions at this sample size.

dummy variable further down into two variables. One for small losses ("I[Small Loss]"), that takes on a value of one if the the current price of the fund is less than the reference price, but the difference is smaller than 15%. The second indicator is for larger losses ("I[Large Loss]") and takes on a value of one if the current price of the fund is less than the reference price and the difference is at least 15%. I choose the value of 15% as cut-off as this is the median relative loss in the sample. I introduce the two indicator variables to the regression and interact both indicators with alpha. The results of this analysis are presented in column 2 of table 8.

The coefficients show that the attenuation effect in the alpha sensitivity of fund flows with respect to losses is larger for larger losses. For funds held at a small loss, the attenuation effect, measured by the interaction term of the small loss variable and alpha, is -0.9 and significant at the 1%-level. For funds held at a larger loss, the attenuation increases by more than 50% to -1.4 and is also significantly different from zero at the 1%-level. An F-test of the two coefficients on the interaction terms rejects the null hypothesis that the coefficients are equal at the 5%-level (p-value of 0.013). Hence, the reference-dependent feature of the performance-flow relation is significantly stronger if the conflict between alpha and the loss information is higher due to a larger loss. This results nicely complements the findings from above that the interaction effect gets stronger for higher levels of alpha. Both set of results imply that the interaction effect gets stronger if the conflict or disagreement between the two return related signals alpha and losses increases.

In the following, I provide two possible mechanisms for these reference-dependent alpha chasing behavior of fund investors: ambiguity aversion and the social transmission of information.

#### *4.1. Ambiguity Aversion*

Under ambiguity aversion, introduced by [Ellsberg \(1961\)](#), decision makers are averse to uncertainty about the potential outcomes of a decision problem. This idea is increasingly used in theories of financial markets (consider [Epstein and Schneider, 2010](#), for a review of this literature) and ambiguity aversion is used to rationalize several irregularities about portfolio choice, such as the home bias (see [Dimmock et al., 2016](#)).

I interpret the conflicting signal content of alpha and gains and losses as increasing the ambiguity about the performance of a fund investment. This interpretation is rooted in literature on psychology. [Einhorn and Hogarth \(1985\)](#) develop a model that shows increasing aversion to

choices if the amount of ambiguity increases and [Smithson \(1999\)](#) provides explicit experimental evidence that decision-makers are averse to options characterized by conflicting information. In the finance domain, [Epstein and Schneider \(2008\)](#) suggest a representative agent model in which conflicting information plays a similar role and predict that ambiguity averse investors dislike assets with poor information quality.

In the high alpha but loss scenario the two signals are at conflict regarding the quality of the fund investment and thus induce additional ambiguity to the specific fund. Consistent with ambiguity induced by conflicting information, I find that these funds receive comparatively smaller inflows for a similar level of alpha performance. Investors are ambiguity averse and may prefer to invest into a different fund without conflicting information. Consistent with retail investors exhibiting stronger ambiguity aversion, I find that the attenuation in flows due to the conflicting signals is stronger for retail investors. Also consistent with this mechanism, the attenuation increases with the strength of the conflict between the signals: for a higher alpha or a larger loss.

It is however not clear, why the effects of ambiguity should only affect the buy decisions in mutual funds, which is a strong and persistent result throughout the different analyses.

#### *4.2. Social Transmission*

A second potential mechanism that can produce the patterns described in this paper is the social transmission of investment opportunities between investors. [Ivković and Weisbenner \(2007\)](#) and [Hong, Kubik, and Stein \(2005\)](#) show that investors from geographically close locations exhibit correlated buying and selling behavior and attribute this effect to the communication between investors. [Han, Hirshleifer, and Walden \(2018\)](#) formalize the idea that the social transmission of investments depends on the returns of current investors. In their model, investors transmit more information about their investment if they have experienced higher returns. Other people addressed by this information do not fully account for this effect, such that the number of new investors increases in the return of existing investors. In the context of this study, fund investors are more likely to talk about their investment if they are holding the fund at a gain. This effect of gains and losses is likely to be mediated by alpha information: If a new investor hears about the gains an existing investor made with his fund investment, she will likely react stronger to this information if she can confirm the recommendation with external information, i.e. a positive



alpha. Hence, the reaction to alpha will be especially strong if the fund is held at a gain by current investors. In this case, more new investors become convinced to invest in the fund.

This explanation produces the patterns observed in the empirical tests. Flows react strongly to alpha if existing investors hold the fund at a gain. When they hold the fund at a loss, the negative interaction effect of alpha and the loss variable shows that flows react much less to the same level of alpha, consistent with less new investors attracted by social interaction and finding consistent alpha information. The attenuation gets stronger for retail investors, as social transmission is more relevant for retail as opposed to institutional investors. The attenuation gets stronger for larger losses, as the rate of social transmission decreases with losses. Flows react stronger to for higher levels of alpha in gain funds, as the rate of social transmission is high and investor can find confirmatory external information.

In distinction to the ambiguity aversion channel, it is clear that the social transmission mechanism will work stronger for buy decisions. To have an affect on sell decisions, social transmission needs to take place between two investors already owning the same fund. For buy decision, the mechanism can potentially work on every investor addressed irrespective of whether they are already holding the fund.

## 5. Conclusion

In this study, I show that mutual fund investors react to the combination of alpha and gains and losses when making investment decisions. More specifically, the sensitivity of flows with respect to alpha is significantly reduced if the average investor is holding the fund at a loss, suggesting that investors judge and interpret these signals jointly. This effect is distinct from the base reaction to the individual signals and is economically large. I arrive at these findings by using fund-level data and investment flows from SEC form N-SAR and develop a new measure for whether the average dollar invested in a fund is held at a gain or loss. Panel regressions reveal a robust interaction effect between alpha and the loss variable. The strength of this effect increases in the conflict between the signals, is stronger for funds targeted at retail investors and only affects buy decisions.

I propose two mechanism for the interaction effect of alpha and losses. The effect is consistent with fund investors being ambiguity averse decision-makers and increased ambiguity being

induced by conflicting information. If the two pieces of performance information disagree, investors invest less in a fund for the same level of objective performance. Similarly, the social transmission of investment outcomes can produce the observed interaction effect. Current investors are more likely to promote their investment to others if they are holding the fund at a gain. The addressed potential new investors are more likely to invest if this is in line with external information such as alpha. While both mechanisms are consistent with most of the empirical patterns observed, only the social transmission channel provides a direct rationalization for why the interaction is not observed considering sell decisions. For funds held at loss considering the average dollar invested, there is no convexity in the performance-flow relation.

Overall, I show that different signals available to agents trigger an extensive interplay in determining choice. For the mutual fund market, the joint consideration of abnormal performance and gains and losses uncovers a previously undocumented aspect in how investors react to the combination of both signals, which also creates a considerable impact at the fund level. In general, the results emphasize the relevance of recent efforts to understand the actual use, presentation and joint interpretation of different signals for financial decisions and related market outcomes.

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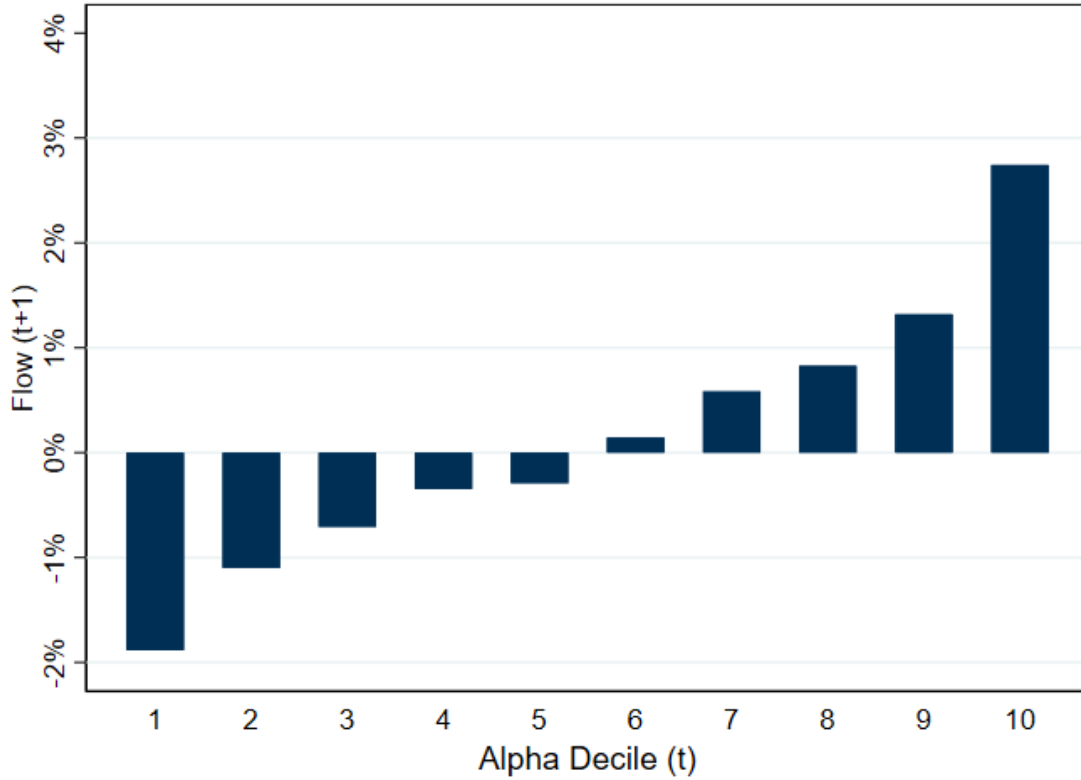
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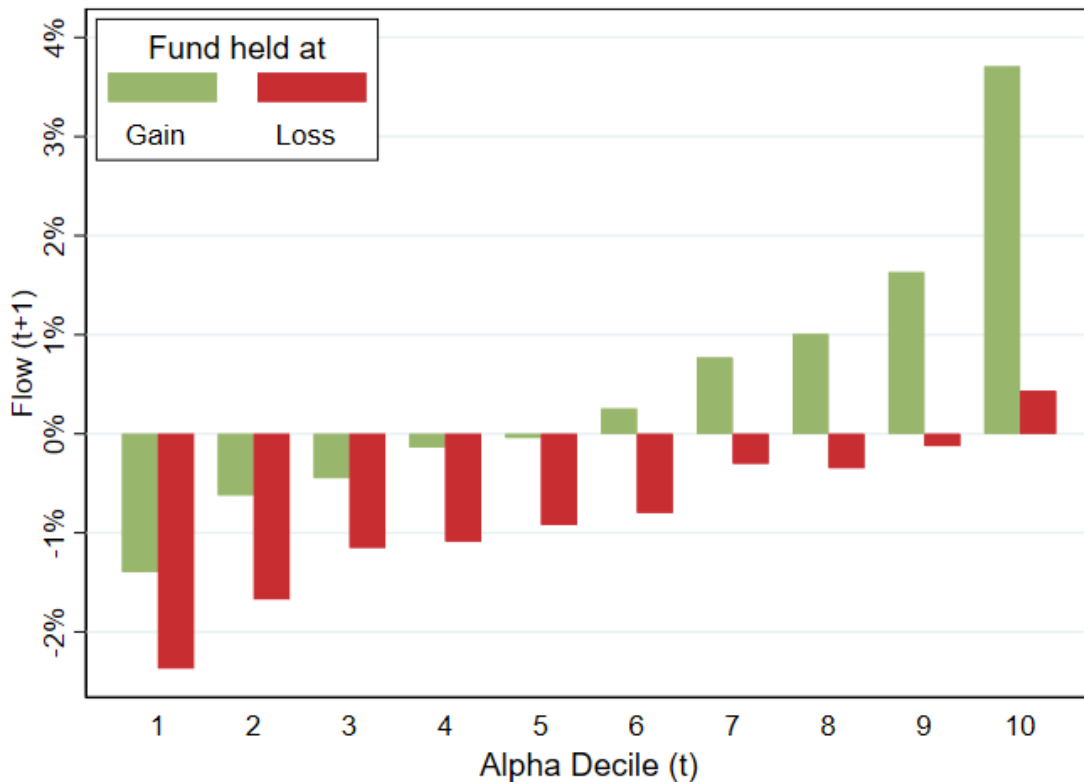
**Figure 1:** Fund Flows, Alpha and Gains and Losses

This figure illustrates the reference-dependent return chasing behavior in mutual fund flows. In panel A, funds are sorted into ten decile portfolios according to their alpha as of month  $t$ , and the height of the bars depicts the average net flow of the funds in the portfolio in month  $t+1$ . Panel B repeats this exercise, but additionally splits the portfolios according to whether the fund is held at a gain or at a loss by the average investor. The height of the green bars depicts the average net flow if the fund is held at a gain, the height of the red bars depicts the average net flow if the fund is held at a loss. Refer to section 2 and appendix B for the construction of variables.

Panel A: Unconditional Alpha Chasing



Panel B: Reference-Dependent Alpha Chasing



**Table 1:** Summary Statistics

This table provides summary statistics on the sample of actively managed mutual funds, i.e. flows, characteristics and return related measures on the fund-month level. I[Loss] is an indicator variable that takes on a value of 1 if the current NAV of the fund is below the reference price. Details on the construction of the variables can be found in appendix B.

	count	mean	sd	p1	p25	p50	p75	p99
Flow (standard)	167249	-4.8e-05	.0837	-.131	-.0147	-.00453	.0073	.172
Flow	167457	.00037	.0841	-.126	-.0141	-.00409	.00729	.169
Inflow	167457	.0285	.0848	0	.00704	.0146	.029	.224
Outflow	167457	.0281	.0418	0	.0128	.0197	.0304	.178
I[Loss]	167457	.359	.48	0	0	0	1	1
Holding Time	167457	27.2	17.3	4.66	15.9	23.3	33.7	90.2
LN(Holding Time)	167457	3.13	.601	1.54	2.77	3.15	3.52	4.5
Alpha	167457	.00107	.00463	-.00886	-.00146	.0005	.00288	.0176
Beta	167457	1.05	.233	.446	.932	1.04	1.17	1.72
TNA	167457	1923	7060	17	104	364	1304	29378
LN(TNA)	167457	5.96	1.72	2.83	4.64	5.9	7.17	10.3
Age	167457	15.1	12	3.17	7.33	12.1	18.4	68.7
LN(Age)	167457	2.57	.619	1.43	2.12	2.57	2.97	4.24
Family TNA	167457	60950	1.6e+05	23.5	1307	11442	35681	7.1e+05
LN(Family TNA)	167457	8.87	2.44	3.15	7.18	9.35	10.5	13.5
Turnover	167457	.766	.725	.03	.31	.59	.98	3.3
Expense Ratio	167457	.0116	.00374	.0029	.00932	.0113	.0137	.022
MS Stars	167457	3.13	1.05	1	2	3	4	5
Beat SP500	167457	.514	.5	0	0	1	1	1
Amihud R2	167457	.827	.144	.305	.767	.871	.928	.989
IVola	167457	.0186	.0118	.0043	.0108	.0161	.0229	.0662
ISkew	167457	.0494	.517	-1.15	-.267	.0348	.339	1.52
Vola	167457	.0492	.0184	.0205	.0354	.0467	.0602	.106
Skew	167457	-.306	.433	-1.62	-.554	-.25	-.0373	.655
Kurtosis	167457	3.18	.959	1.95	2.53	2.94	3.6	6.56
MAX	167457	.107	.0454	.0403	.076	.0978	.128	.277
MIN	167457	-.113	.057	-.254	-.157	-.0974	-.069	-.0299



**Table 2:** Reference-Dependent Return Chasing: Baseline Results

This table provides regression estimates from OLS panel regressions of different fund flow variables on lagged return measures and controls as well as fund and category $\times$ time fixed effects. Flow is New Sales minus Redemptions from SEC form NSAR standardized by last month TNA. Inflow and Outflow is New Sales and Redemptions only standardized by last month TNA respectively. Alpha is the intercept from a 36 month rolling-window regression of the fund's excess return on the market excess return. I[Loss] is an indicator variable that takes on a value of 1 if the current NAV of the fund is below the aggregate reference price. Refer to section 2 for how the reference price is calculated. Details on the construction of the other variables can be found in appendix B. Standard errors are two-way clustered by fund and month. \*\*\*, \*\* and \* represent significance at the 1%-, 5%- and 10%-level, respectively.

	(1) Flow (t+1)	(2) Flow (t+1)	(3) Inflow (t+1)	(4) Outflow (t+1)
Alpha	1.852*** (11.35)	2.693*** (14.58)	2.048*** (10.87)	-0.645*** (-5.64)
I[Loss]	-0.007*** (-7.77)	-0.007*** (-7.39)	-0.004*** (-4.75)	0.003*** (4.91)
Alpha $\times$ I[Loss]	-0.897*** (-5.15)	-1.008*** (-5.38)	-1.169*** (-6.56)	-0.161 (-1.61)
LN(Holding Time)	-0.009*** (-10.90)	-0.012*** (-9.92)	-0.023*** (-13.68)	-0.010*** (-8.72)
LN(TNA)	-0.003*** (-9.96)	-0.014*** (-12.63)	-0.013*** (-11.59)	0.000 (0.62)
LN(Age)	-0.000 (-0.25)	-0.011*** (-4.08)	-0.001 (-0.32)	0.010*** (4.90)
LN(Family TNA)	0.001*** (7.16)	0.003*** (3.34)	0.003*** (3.32)	0.000 (0.05)
Turnover	-0.000 (-0.09)	0.001 (1.37)	0.002*** (2.61)	0.001 (1.60)
Expense Ratio	0.070 (0.63)	0.190 (0.78)	0.272 (1.04)	0.082 (0.49)
Amihud R2	-0.007 (-1.17)	-0.006 (-0.76)	-0.004 (-0.50)	0.003 (0.57)
Beta	-0.003 (-1.48)	0.006 (1.06)	0.007 (1.22)	0.000 (0.06)
Vola	-0.068 (-0.62)	-0.137 (-0.85)	-0.033 (-0.24)	0.103 (0.90)
Skew	0.003 (1.53)	0.002 (0.65)	0.003 (1.02)	0.001 (0.76)
IVola	-0.278*** (-2.69)	-0.256* (-1.69)	-0.118 (-0.81)	0.138 (1.50)
ISkew	0.001 (0.79)	-0.000 (-0.63)	-0.001* (-1.95)	-0.001** (-2.35)
Kurtosis	0.001* (1.77)	0.001 (1.39)	0.001 (1.46)	-0.000 (-0.05)
MAX	0.008 (0.34)	-0.010 (-0.30)	-0.004 (-0.14)	0.006 (0.28)
MIN	-0.043 (-1.51)	-0.038 (-1.04)	-0.025 (-0.73)	0.013 (0.60)
Beat SP500	0.003*** (5.53)	0.003*** (4.94)	0.002*** (2.83)	-0.001*** (-3.75)
MS Stars FE	Yes	Yes	Yes	Yes
Fund FE	No	Yes	Yes	Yes
Category $\times$ Time FE	No	Yes	Yes	Yes
Observations	167457	167440	167440	167440
Months	210	210	210	210
Funds	1977	1960	1960	1960
Adjusted R2	0.040	0.070	0.080	0.121

**Table 3:** Omitted Information: Multiple Return Horizons

This table provides regression estimates from OLS panel regressions of Flow on lagged return measures and controls as well as fund and category×time fixed effects. The specifications include both alpha and monthly average return calculated from four time-periods (12, 36, 60 and 120 months) and the custom time period implied the average dollar is invested in the fund. Flow is New Sales minus Redemptions from SEC form NSAR standardized by last month TNA. Alpha is the intercept from a rolling-window regression of the fund’s excess return on the market excess return. I[Loss] is an indicator variable that takes on a value of 1 if the current NAV of the fund is below the reference price. Control variables are the remaining variables included in table 2. Details on the construction of the other variables can be found in appendix B. Standard errors are two-way clustered by fund and month. \*\*\*, \*\* and \* represent significance at the 1%-, 5%- and 10%-level, respectively.

	(1)	(2)
	Flow (t+1)	Flow (t+1)
Alpha36	1.547*** (5.87)	1.177*** (4.83)
Alpha36 × I[Loss]	-0.848*** (-4.65)	
AlphaCustom		0.987 (1.47)
AlphaCustom × I[Loss]		-1.249*** (-5.17)
I[Loss]	-0.005*** (-5.73)	-0.004*** (-3.31)
Alpha12	0.568*** (4.30)	0.535*** (4.09)
Alpha60	0.621* (1.84)	0.675** (2.00)
Alpha120	-0.057 (-0.19)	-0.158 (-0.38)
Return12	0.590*** (4.86)	0.616*** (5.06)
Return36	0.139 (0.56)	0.036 (0.15)
Return60	0.123 (0.48)	-0.044 (-0.17)
Return120	-0.192 (-0.81)	-0.535 (-1.35)
ReturnCustom		0.640 (1.38)
Controls	Yes	Yes
MS Stars FE	Yes	Yes
Fund FE	Yes	Yes
Category × Time FE	Yes	Yes
Observations	167415	167415
Months	210	210
Funds	1960	1960
Adjusted R2	0.073	0.073

**Table 4: Omitted Information: Factor Models**

This table provides regression estimates from OLS panel regressions of Flow on lagged return measures and controls as well as fund and category×time fixed effects. Across the different specification in columns the factor model for the estimation of the fund’s alpha is varied. Flow is New Sales minus Redemptions from SEC form NSAR standardized by last month TNA. Alpha is the intercept from a rolling-window regression of the fund’s excess return on different factors depending on the specific model. I[Loss] is an indicator variable that takes on a value of 1 if the current NAV of the fund is below the reference price. Control variables are the remaining variables included in table 2. Details on the construction of the other variables can be found in appendix B. Standard errors are two-way clustered by fund and month. \*\*\*, \*\* and \* represent significance at the 1%-, 5%- and 10%-level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	CAPM	Market	NAV	FF3	FF4	FF5	HXZ	CAPM
Dependent: Flow (t+1)								
Alpha	2.693*** (14.58)	2.478*** (11.82)	1.594*** (12.76)	2.632*** (14.06)	2.657*** (13.66)	2.252*** (11.58)	2.396*** (11.96)	1.463*** (4.24)
I[Loss]	-0.007*** (-7.39)	-0.007*** (-7.10)	-0.010*** (-8.02)	-0.008*** (-8.11)	-0.008*** (-8.25)	-0.008*** (-8.25)	-0.008*** (-8.67)	-0.007*** (-6.73)
Alpha × I[Loss]	-1.008*** (-5.38)	-1.032*** (-5.77)	-0.778*** (-5.59)	-1.260*** (-6.01)	-1.388*** (-6.27)	-1.229*** (-5.95)	-1.304*** (-6.34)	-1.053*** (-5.66)
All other Alphas	No	No	No	No	No	No	No	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
MS Stars FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Category × Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	167440	167440	167440	167440	167440	167440	167440	167440
Months	210	210	210	210	210	210	210	210
Funds	1960	1960	1960	1960	1960	1960	1960	1960
Adjusted R2	0.070	0.069	0.068	0.070	0.069	0.069	0.069	0.069

**Table 5: Fully Interacted Model**

This table provides regression estimates from OLS panel regressions of different fund flow variables on lagged return measures and controls as well as fund and category×time fixed effects. All variables are interacted with I[Loss]. Flow is New Sales minus Redemptions from SEC form NSAR standardized by last month TNA. Inflow and Outflow is New Sales and Redemptions only standardized by last month TNA respectively. Alpha is the intercept from a rolling-window regression of the fund’s excess return on different factors depending on the specific model. I[Loss] is an indicator variable that takes on a value of 1 if the current NAV of the fund is below the reference price. Control variables are the remaining variables included in table 2. Details on the construction of the other variables can be found in appendix B. Standard errors are two-way clustered by fund and month. \*\*\*, \*\* and \* represent significance at the 1%-, 5%- and 10%-level, respectively.

	(1) Flow (t+1)	(2) Inflow (t+1)	(3) Outflow (t+1)
Alpha	2.745*** (14.07)	2.072*** (10.63)	-0.673*** (-5.87)
I[Loss]	-0.031** (-2.56)	-0.016 (-1.40)	0.015** (2.39)
Alpha × I[Loss]	-1.061*** (-4.97)	-1.224*** (-5.94)	-0.162 (-1.33)
Controls × I[Loss]	Yes	Yes	Yes
MS Stars × I[Loss] FE	Yes	Yes	Yes
Controls	Yes	Yes	Yes
MS Stars FE	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes
Category × Time FE	Yes	Yes	Yes
Observations	167440	167440	167440
Months	210	210	210
Funds	1960	1960	1960
Adjusted R2	0.071	0.080	0.122

**Table 6:** Non-linearity: Spline Regressions

This table provides regression estimates from linear spline panel regressions of different fund flow variables on lagged return measures and controls as well as fund and category×time fixed effects. Alpha Low, Mid and High are the slope coefficients for the respective alpha interval. Spline breakpoints are defined as the 20th and 80th cross-sectional percentile of alpha in each month. Flow is New Sales minus Redemptions from SEC form NSAR standardized by last month TNA. Inflow and Outflow is New Sales and Redemptions only standardized by last month TNA respectively. Alpha is the intercept from a rolling-window regression of the fund’s excess return on the market’s excess return. I[Loss] is an indicator variable that takes on a value of 1 if the current NAV of the fund is below the reference price. Control variables are the remaining variables included in table 2. Details on the construction of the other variables can be found in appendix B. Standard errors are two-way clustered by fund and month. \*\*\*, \*\* and \* represent significance at the 1%-, 5%- and 10%-level, respectively.

	(1) Flow (t+1)	(2) Inflow (t+1)	(3) Outflow (t+1)
I[Loss]	-0.002 (-1.07)	0.000 (0.06)	0.002** (2.20)
Alpha Low	1.654*** (4.38)	0.565* (1.72)	-1.089*** (-3.64)
Alpha Mid	2.560*** (9.71)	1.676*** (6.46)	-0.884*** (-5.29)
Alpha High	3.516*** (7.36)	3.477*** (6.85)	-0.038 (-0.24)
I[Loss] × Alpha Low	0.956** (2.16)	0.618* (1.68)	-0.337 (-1.21)
I[Loss] × Alpha Mid	-1.056*** (-3.55)	-1.181*** (-4.21)	-0.125 (-0.88)
I[Loss] × Alpha High	-2.669*** (-5.02)	-2.383*** (-4.08)	0.286 (1.10)
Controls	Yes	Yes	Yes
MS Stars FE	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes
Category × Time FE	Yes	Yes	Yes
Observations	167440	167440	167440
Months	210	210	210
Funds	1960	1960	1960
Adjusted R2	0.070	0.080	0.121

**Table 7: Predicting Alpha**

This table provides regression estimates from OLS panel regressions of realized alpha on lagged return measures and controls as well as category×time fixed effects. In the columns I vary the point in time of the alpha prediction from one through four months ahead. Alpha is the intercept from a rolling-window regression of the fund’s excess return on the market excess return. The dependent variable Alpha is the fund’s return in excess of the market return multiplied with lagged market beta. I[Loss] is an indicator variable that takes on a value of 1 if the current NAV of the fund is below the reference price. Control variables are the remaining variables included in table 2. Details on the construction of the other variables can be found in appendix B. Standard errors are two-way clustered by fund and month. \*\*\*, \*\* and \* represent significance at the 1%-, 5%- and 10%-level, respectively.

	(1) Alpha (t+1)	(2) Alpha (t+2)	(3) Alpha (t+3)	(4) Alpha (t+4)
Alpha	0.225** (2.16)	0.154* (1.66)	0.181** (2.07)	0.167** (1.99)
I[Loss]	-0.000 (-0.72)	-0.000 (-1.32)	-0.000 (-0.48)	0.000 (0.10)
Alpha × I[Loss]	-0.096 (-1.22)	0.058 (0.82)	0.049 (0.74)	0.063 (0.90)
Controls	Yes	Yes	Yes	Yes
MS Stars FE	Yes	Yes	Yes	Yes
Category × Time FE	Yes	Yes	Yes	Yes
Observations	167253	166810	166365	165888
Months	210	210	210	210
Funds	1976	1973	1967	1962
Adjusted R2	0.503	0.485	0.481	0.480

**Table 8:** Variation in Effect Strength

This table provides regression estimates from OLS panel regressions of different fund flow variables on lagged return measures and controls as well as fund and category×time fixed effects. In column 1, the variables of interest are interacted with a dummy for funds that are targeted at institutional investors. In column 2, the overall loss variable is split into small and large losses (exceeding -15%). Flow is New Sales minus Redemptions from SEC form NSAR standardized by last month TNA. Alpha is the intercept from a rolling-window regression of the fund’s excess return on the market excess return. I[Loss] is an indicator variable that takes on a value of 1 if the current NAV of the fund is below the reference price. Control variables are the remaining variables included in table 2. Details on the construction of the other variables can be found in appendix B. Standard errors are two-way clustered by fund and month. \*\*\*, \*\* and \* represent significance at the 1%-, 5%- and 10%-level, respectively.

	(1) Flow (t+1)	(2) Flow (t+1)
Alpha	2.658*** (14.03)	2.866*** (14.69)
I[Loss]	-0.007*** (-7.41)	
Alpha × I[Loss]	-1.100*** (-5.81)	
Institutional	-0.006*** (-2.88)	
Alpha × Institutional	0.140 (0.62)	
I[Loss] × Institutional	0.001 (0.47)	
Alpha × I[Loss] × Institutional	0.493* (1.74)	
I[Small Loss]		-0.006*** (-6.94)
I[Large Loss]		-0.011*** (-7.13)
Alpha × I[Small Loss]		-0.927*** (-4.93)
Alpha × I[Large Loss]		-1.409*** (-6.41)
Controls	Yes	Yes
MS Stars FE	Yes	Yes
Fund FE	Yes	Yes
Category × Time FE	Yes	Yes
Observations	167440	167440
Months	210	210
Funds	1960	1960
Adjusted R2	0.070	0.068

## Appendix A. Calculation of Reference Prices

The reference price  $\phi_{i,t}$  is a weighted average of past prices  $p_{i,s}$  since the inception of the fund, weighted by the amount of money  $m_{i,t,s}$  that was invested in fund  $i$  in month  $s$  and is still invested as of month  $t$ .

$$\phi_{i,t} = \frac{\sum_{s=0}^t m_{i,t,s} \cdot p_{i,s}}{\sum_{s=0}^t m_{i,t,s}}$$

The challenge for the calculation of reference prices according to this definition are the amounts of money that were invested in the fund at some point in time in the past and are still invested in the fund  $m_{i,t,s}$ . For notation purposes, I summarize all the elements  $m_{i,t,s}$  that are relevant for fund-month  $i,t$  in the vector  $\mathbf{M}_{i,t}$ . To calculate  $\mathbf{M}_{i,t}$ , I make use of the TNA and flow data that are available for mutual funds.

Whenever a fund is incepted or observed in the database for the first time ( $t = s = 1$ ), I set the amount of money invested in this month to the TNA of the fund in that month. At this point, the vector  $\mathbf{M}_{i,1}$  is a singleton.

$$\mathbf{M}_{i,1} = m_{i,1,1} = \text{TNA}_{i,1}$$

I then proceed in a recursive algorithm across the months for which the fund is available in the database. The structure of  $\mathbf{M}_{i,t}$  starts as a plain copy of  $\mathbf{M}_{i,t-1}$ , hence containing only  $t - 1$  elements when a new iteration of the algorithm starts. Within this iteration, I need to consider new inflows and outflows as well as any value changes. In a first step, I incorporate any changes in the money still invested in the fund due to the returns  $r_{i,t}$  earned by the fund.

$$m_{i,t,s} = m_{i,t-1,s} \cdot (1 + r_{i,t}) \quad \forall s \leq t - 1$$

I next consider the new investments made in that period, hence adding a new element  $m_{i,t,t}$  to the vector  $\mathbf{M}_{i,t}$ . This element captures all inflows that occurred during that month and increase the length of the vector from  $t - 1$  to  $t$ .

$$m_{i,t,t} = \text{New Sales}_{i,t}$$

In a final step, I have to distribute all outflows occurring in month  $t$  across the money that



is invested in the fund. As discussed in the main text, I operate on a first-in, first-out basis. Let  $s'$  be the month as far back in the past (as close to zero) as possible such that  $m_{i,t,s'} > 0$ .

$$\hat{m}_{i,t,s'} = m_{i,t,s'} - \text{Redemptions}_{i,t}$$

In this case, element  $m_{i,t,s'}$  of the vector  $\mathbf{M}_{i,t}$  is replaced by  $\hat{m}_{i,t,s'}$ . Should the redemption volume exceed the remaining money still invested  $m_{i,t,s'}$ , I carry the remaining part of redemptions over to the next month with positive remaining money ( $m_{i,t,s''} > 0$  with  $s'' > s'$ ) and repeat, if necessary, until all outflows are distributed. As a byproduct of these calculations, I also arrive at an estimate for how long the average investor is holding the fund by calculating the dollar-weighted average of the dates with positive  $m_{i,t,s}$  elements.

A remaining issue with this procedure are gaps in the mutual fund data. In order to minimize the impact of gaps on the estimation of the reference prices, I use standard net flows extracted from fund TNA and returns in case N-SAR data are not available and assume that either sales or redemptions are zero, depending on whether the net flow is positive or negative. For any remaining gaps, I treat the fund as if it was newly created after a gap. It should be noted that for very young funds, the development of the reference price can be volatile as those funds frequently encounter large absolute returns and flows. However, observations from the first three years since the inception of the fund are excluded from the regression sample as described in the main text.

## Appendix B. Variable Descriptions

In the following, the variables used in the empirical analysis are defined and the relevant paper (if applicable) is named. Relevant data source are:

- Morningstar Direct Mutual Fund database
- Ken French’s website
- CRSP stock database
- Factor Data provided by Lu Zhang

The variables are described in alphabetical order.

Most return related measures require the estimation of a factor-based model using the time-series of fund returns. I use a rolling-window regression of (gross) funds excess return on  $k$  factors  $f$  to estimate the different measures. Unless explicitly stated otherwise, the regressions or other rolling-window estimations are based on the CAPM and using a window of 36 months.

$$r_{i,t} - r_{f,t} = \text{Alpha}_i + \sum_{j=1}^k \beta_{i,j,t} f_{j,t} + \epsilon_{i,t}$$

Variable Name	Description	Relevant Paper
Age	Time passed since the inception date of the fund in years.	
Alpha	Intercept from a rolling window regression of excess fund returns on the excess return of the CRSP value-weighted market index.	
Alpha (FF3)	Intercept from a rolling window regression of excess fund returns on the three factor model of the relevant paper.	<a href="#">Fama and French (1993)</a>
Alpha (FF4)	Intercept from a rolling window regression of excess fund returns on the four factor model of the relevant paper.	<a href="#">Carhart (1997)</a>
Alpha (FF5)	Intercept from a rolling window regression of excess fund returns on the five factor model of the relevant paper.	<a href="#">Fama and French (2015)</a>
Alpha (HXZ)	Intercept from a rolling window regression of excess fund returns on the four factor model of the relevant paper.	<a href="#">Hou, Xue, and Zhang (2015)</a>
Alpha (Market)	Average fund return in excess of the return of the CRSP value-weighted market index in a rolling window.	
Alpha (NAV)	Intercept from a rolling window regression of relative NAV changes of the fund on the excess return of the CRSP value-weighted market index.	
Alpha (t+1)	One month out-of-sample alpha realization based on the most recently available factor loading and the contemporary realization of the factors.	

*Continued on next page*

Variable Name	Description	Relevant Paper
Amihud R2	R-Squared from a rolling window regression of excess fund returns on the excess return of the CRSP value-weighted market index.	<a href="#">Amihud and Goyenko (2013)</a>
Beat SP500	Indicator whether the fund's NAV change exceed the price change of the SP500 index.	<a href="#">Hartzmark and Solomon (2017a)</a>
Beta	Coefficient on the market return from a rolling window regression of excess fund returns on the excess return of the CRSP value-weighted market index.	
Expense Ratio	Net Expense Ration of the fund.	
Family TNA	Sum of Total Net Assets of all Funds of a fund family as identified by Morningstar variable firmname in \$ million.	
Flow	(New Sales - Redemptions) / TNA(t-1). Sales and Redemptions data are taken from SEC form N-SAR.	
Holding Time	Dollar-weighted average of the dates with positive $m_{i,t,s}$ elements according to reference price calculation. See appendix A.	This paper
I[Loss]	Indicator variable where the NAV is below the reference price.	
I[Large Loss]	Indicator variable where the NAV is below the reference price and the loss is at least 15%.	
I[Small Loss]	Indicator variable where the NAV is below the reference price but the loss is smaller than 15%.	
Inflow	New Sales / TNA(t-1). Sales data are taken from SEC form N-SAR.	
Institutional	Indicator for funds that are classified by Morningstar as institutional fund.	
ISkew	Idiosyncratic Skewness calculated as the skewness of residuals of a rolling window regression of excess fund returns on the excess return of the CRSP value-weighted market index.	<a href="#">Boyer, Mitton, and Vorkink (2010)</a>
IVola	Idiosyncratic Volatility calculated as the standard deviation of residuals of a rolling window regression of excess fund returns on the excess return of the CRSP value-weighted market index.	<a href="#">Ang et al. (2006)</a>
Kurtosis	Kurtosis of fund returns in a rolling-window.	
LN(Age)	Natural Logarithm of the Age Variable.	
LN(Family TNA)	Natural Logarithm of the Family TNA Variable.	
LN(Holding Time)	Natural Logarithm of the Holding Time Variable.	
LN(TNA)	Natural Logarithm of the TNA Variable.	
MAX	Maximum return of a fund in a rolling-window	<a href="#">Bali, Cakici, and Whitelaw (2011)</a>
MIN	Minimum return of a fund in a rolling-window	<a href="#">Bali, Cakici, and Whitelaw (2011)</a>
MS Stars	Morningstar Star Rating of the fund.	
Outflow	Redemptions / TNA(t-1). Redemptions data are taken from SEC form N-SAR.	

*Continued on next page*

Variable Name	Description	Relevant Paper
Reference Price $\phi_{i,t}$	Refer to section 2 and appendix A for details of the construction.	This paper
Skew	Skewness of fund returns in a rolling-window.	
TNA	Total Net Assets in \$ million.	
Turnover	Decimal turnover rate of the fund.	
Vola	Volatility of fund returns in a rolling-window.	

## Internet Appendix to “Reference-Dependent Return Chasing”

This appendix presents and discusses additional statistics, results and robustness checks.

### *IA1. Additional Descriptive Statistics and Correlations*

For comparison with N-SAR based flows, I also construct the net flow measure usually employed in the literature following the definition of [Sirri and Tufano \(1998\)](#), assuming that all flows occur at the end of the month.

$$\text{Flow (standard)}_{i,t} = \frac{\text{TNA}_{i,t} - \text{TNA}_{i,t-1} \cdot (1 + r_{i,t})}{\text{TNA}_{i,t-1}}$$

Table [IA1](#) shows the correlation between the different flow variables. The correlation between the usual net flows and my definition based on N-SAR data is 0.96.

Table [IA2](#) shows the correlations between the loss indicator and different alpha measures.

### *IA2. Winsorized Flows*

I rerun the base-line regressions of the paper but use winsorized flows (1st and 99th percentile) instead of flows treated for outliers as discussed in the main text. Table [IA3](#) presents the results of this analysis. The results line up strongly with the results presented in the main text. The only mentionable difference is an increase in r-squared.

### *IA3. Base vs. N-SAR Sample*

I rely on N-SAR extracted flows provided by Morningstar for the empirical analyses in this paper. N-SAR data are not available for all mutual funds otherwise available in the Morningstar database due to the limited matching of N-SAR forms. Therefore, I compare the sample of all available equity mutual funds in the sample with the sub-sample where N-SAR data could be matched and passes the filter criteria. This comparison is presented in table [IA4](#). The mean and median value across variables is displayed. As we can infer, both samples exhibit very similar properties along most variables. Most importantly, net flow, alpha and whether the fund is held at a loss on average do not differ by an economically relevant magnitude. Matched funds tend to be slightly larger and belong to larger families. Overall, I conclude that the N-SAR matched

sample is a broad and representative sample for the largest part of the domestic equity mutual fund market in the US. For any month in the time period used for later analysis, my sample includes between 0.5 and 2.5 \$ trillion in assets under management.

#### *IA4. Lagged Flows and Returns*

In this robustness test, I examine whether a different weighting scheme along the time-series of past returns is confounding the results. Potentially, investors place more weight on recent returns than returns further back in the past. Therefore, I estimate an additional model where I include 36 lags of fund returns in addition to the return measures. This specification can accommodate any time-series weighting scheme of past returns, such as a higher weighting of recent returns, with minimal ex-ante assumptions about the weights. The results of this tests are presented in table [IA6](#).

Column 1 shows that the reference-dependent return chasing behavior is unaffected by the inclusion of lagged returns. The interaction effect of alpha and the loss variable is negative with a coefficient of -0.8, significant at the 1%-level and the attenuation amounts to an economically meaningful 35% measured relative to the strength of alpha chasing for funds held at a gain. Results in column 2 show that the same finding is obtained when I include 36 lags of NAV changes (instead of returns). To raise the bar in the empirical model further, I estimate a model using 36 lags of net flows in column 3. This specification can incorporate autocorrelation in the dependent variable, that could be induced by inertia in investors' decisions that might be correlated with the variables of interest.<sup>19</sup> Column 3 shows that including 36 lags of the dependent variable hardly affects the results concerning the main variables of interest. In the final column of table [IA6](#), I include all of the lags mentioned before. The negative and highly significant interaction effect of alpha and the loss indicator persists. I conclude that the introduction of lags does not weaken the reference-dependence feature of the performance chasing in mutual funds.

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<sup>19</sup>While the inclusion of lagged dependent variables in a panel model with unit fixed effects creates the bias described in [Nickell \(1981\)](#), he shows that this bias is of order  $1/T$ . Given that I observe the funds in my sample for more than 87 months on average, this bias is a minor concern.

**Table IA1:** Correlations: Flow Variables

This table displays Pearson correlations for different fund flow variables. Flow (standard) is calculated using fund returns and TNA following the definition of [Sirri and Tufano \(1998\)](#). Flow is calculated as New Sales-Redemptions from SEC Form NSAR divided by previous month TNA. Inflow and Outflow are calculated accordingly.

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	Flow (standard)	Flow	Inflow	Outflow
Flow (standard)	1			
Flow	0.959	1		
Inflow	0.836	0.878	1	
Outflow	-0.237	-0.231	0.263	1

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**Table IA2:** Correlations: I[Loss] and Alpha

This table displays Pearson correlations for the gain/loss dummy and different alpha measures. Refer to appendix B for the definition of those variables.

	I[Loss]	Alpha (Market)	Alpha (NAV)	Alpha (FF3)	Alpha (FF4)	Alpha (FF5)	Alpha (HXZ)
I[Loss]	1						
Alpha	-0.00589	1					
Alpha (Market)	-0.0594	0.892	1				
Alpha (NAV)	-0.246	0.758	0.693	1			
Alpha (FF3)	-0.0255	0.781	0.722	0.565	1		
Alpha (FF4)	-0.0458	0.741	0.687	0.539	0.951	1	
Alpha (FF5)	-0.0489	0.681	0.613	0.894	0.858	0.858	1
Alpha (HXZ)	-0.108	0.699	0.675	0.816	0.807	0.810	0.810



**Table IA3: Winsorized Flows**

This table repeats the exact analysis of table 2, but relies on flows that are winsorized at the 1st and 99th percentile. Net Flow (NSAR) is calculated as New Sales minus Redemptions from SEC Form NSAR divided by previous month TNA. Inflow (NSAR) and Outflow (NSAR) are calculated accordingly. Details on the construction of the other variables can be found in appendix B. Standard errors are two-way clustered by fund and month. \*\*\*, \*\* and \* represent significance at the 1%-, 5%- and 10%-level, respectively.

	(1) F.Net Flow (NSAR)	(2) F.Inflow (NSAR)	(3) F.Outflow (NSAR)
Alpha	2.625*** (15.53)	2.061*** (11.68)	-0.634*** (-5.86)
I[Loss]	-0.007*** (-9.03)	-0.004*** (-5.54)	0.003*** (5.52)
Alpha $\times$ I[Loss]	-0.980*** (-6.02)	-1.166*** (-7.37)	-0.150 (-1.59)
Controls	Yes	Yes	Yes
MS Stars FE	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes
Category $\times$ Time FE	Yes	Yes	Yes
Observations	167440	167440	167440
Months	210	210	210
Funds	1960	1960	1960
Adjusted R2	0.196	0.194	0.148

**Table IA4: Sample Comparison**

This table compares mean and median fund variables on the fund-month level for the entire Morningstar actively managed US equity fund universe as well as the sub-sample with matching NSAR data that meet the data requirements detailed in section 2 of the text.

	Base Sample		NSAR Sample	
	mean	p50	mean	p50
Flow (standard)	0.00095	-0.0050	0.0012	-0.0044
I[Loss]	0.36	0	0.36	0
Holding Time	29.6	24.8	27.2	23.3
LN(Holding Time)	3.19	3.21	3.13	3.15
Alpha	0.00092	0.00038	0.0011	0.00050
Beta	1.05	1.04	1.05	1.04
TNA	1703.2	345.2	1925.1	364.1
LN(TNA)	5.91	5.84	5.96	5.90
Age	16.1	12.7	15.1	12.1
LN(Age)	2.62	2.61	2.57	2.57
Family TNA	49749.0	11473.1	61007.2	11459.3
LN(Family TNA)	8.83	9.35	8.87	9.35
Turnover	0.77	0.60	0.77	0.59
Expense Ratio	0.012	0.011	0.012	0.011
MS Stars	3.10	3	3.14	3
Beat SP500	0.51	1	0.51	1
Amihud R2	0.83	0.87	0.83	0.87
IVola	0.019	0.016	0.019	0.016
ISkew	0.044	0.029	0.049	0.035
Vola	0.049	0.046	0.049	0.047
Skew	-0.31	-0.25	-0.31	-0.25
Kurtosis	3.17	2.93	3.18	2.94
MAX	0.11	0.096	0.11	0.098
MIN	-0.11	-0.096	-0.11	-0.097
Observations	276058		167246	

**Table IA5: Omitted Information: Return Horizons**

This table provides regression estimates from OLS panel regressions of Flow on lagged return measures and controls as well as fund and category×time fixed effects. Across the different specification in columns the number of months for the estimation of alpha is varied from 12 to 120 months. Flow is New Sales minus Redemptions from SEC form NSAR standardized by last month TNA. Alpha is the intercept from a rolling-window regression of the fund's excess return on the market excess return. I[Loss] is an indicator variable that takes on a value of 1 if the current NAV of the fund is below the reference price. Control variables are the remaining variables included in table 2. Details on the construction of the other variables can be found in appendix B. Standard errors are two-way clustered by fund and month. \*\*\*, \*\* and \* represent significance at the 1%-, 5%- and 10%-level, respectively.

	(1)	(2)	(3)	(4)	(5)
	12 Months	36 Months	60 Months	120 Months	Custom
Dependent: Flow (t+1)					
Alpha	1.498*** (12.81)	2.693*** (14.58)	2.063*** (8.32)	1.438*** (5.48)	3.536*** (7.68)
I[Loss]	-0.007*** (-7.38)	-0.007*** (-7.39)	-0.008*** (-7.77)	-0.008*** (-7.35)	-0.007*** (-5.81)
Alpha × I[Loss]	-0.367*** (-3.05)	-1.008*** (-5.38)	-0.888*** (-3.83)	-0.983*** (-4.42)	-1.291*** (-5.24)
Controls	Yes	Yes	Yes	Yes	Yes
MS Stars FE	Yes	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes	Yes
Category × Time FE	Yes	Yes	Yes	Yes	Yes
Observations	167432	167440	167440	167440	167440
Months	210	210	210	210	210
Funds	1960	1960	1960	1960	1960
Adjusted R2	0.071	0.070	0.068	0.067	0.068

**Table IA6: Omitted Information: Lagged Variables**

This table provides regression estimates from OLS panel regressions of Flow on lagged return measures and controls as well as fund and category×time fixed effects. Additionally, the regressions contain 36 lags of flows, returns or NAV changes as indicated in the table. Flow is New Sales minus Redemptions from SEC form NSAR standardized by last month TNA. Alpha is the intercept from a rolling-window regression of the fund's excess return on different factors depending on the specific model. I[Loss] is an indicator variable that takes on a value of 1 if the current NAV of the fund is below the reference price. Control variables are the remaining variables included in table 2. Details on the construction of the other variables can be found in appendix B. Standard errors are two-way clustered by fund and month. \*\*\*, \*\* and \* represent significance at the 1%-, 5%- and 10%-level, respectively.

	(1) Flow (t+1)	(2) Flow (t+1)	(3) Flow (t+1)	(4) Flow (t+1)
Alpha	2.254*** (7.73)	2.618*** (11.94)	2.587*** (10.21)	2.188*** (5.70)
I[Loss]	-0.006*** (-5.86)	-0.005*** (-4.68)	-0.006*** (-5.33)	-0.005*** (-3.80)
Alpha × I[Loss]	-0.782*** (-4.16)	-0.884*** (-4.78)	-0.861*** (-3.67)	-1.047*** (-4.68)
36 Lags of Returns	Yes	No	No	Yes
36 Lags of NAV Changes	No	Yes	No	Yes
36 Lags of Flows	No	No	Yes	Yes
Controls	Yes	Yes	Yes	Yes
MS Stars FE	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes
Category × Time FE	Yes	Yes	Yes	Yes
Observations	162569	162631	103463	103383
Months	210	210	184	184
Funds	1860	1865	1640	1637
Adjusted R2	0.073	0.073	0.068	0.071