Reference-Dependent Return Chasing

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Abstract

The performance-flow relation in mutual funds is mediated by the gains and losses investors hold a fund at. The chasing of past abnormal performance gets strongly attenuated and convexity is eliminated if the average investor holds the fund at a loss. Thus, fund investors distinctly react to an interaction between abnormal performance and gains and losses after controlling for the respective base effects. This interaction is not an artifact of omitted residual information or non-linearity. The empirical patterns support ambiguity induced by conflicting information and the social transmission of investment opportunities as explanations.

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 performance is one of the strongest empirical regularities in research on fund investment. Investors follow performance, although there is weak evidence for persistence of abnormal performance in mutual funds.[1] The model of Berk and Green (2004) provides an explanation of this seemingly anomalous behavior: Investors are rational Bayesian' learners and correctly follow past performance as an indication of managerial skill, but the fund managers' are facing decreasing returns to scale in their investment strategies. Hence, investors' flows are a positive and convex function of past performance, but in equilibrium performance does not persist.

[Insert Figure 1 about here.]

In figure 1, I plot the relation between mutual fund flows and their past abnormal performance ("Alpha") both unconditionally (panel A), and separately for funds held on average at a loss and at a gain (panel B). There is striking heterogeneity in the response of flows to alpha between the two groups. This response is attenuated and the commonly known performance-flow convexity is eradicated for (the 36% of) funds held at a loss on average. In this paper, I empirically document this phenomenon and discuss explanations and implications. Most importantly, the documented difference in the response to past performance cannot be reconciled with plain Bayesian' learning from fund returns. In particular, models that link investors actions to past returns, such as Berk and Green (2004), abstract from important aspects of how investors respond to signals about mutual fund performance and leave important variation in market outcomes unexplained.

Why should we study whether and how 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 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

[1] Research on the performance-flow relation in mutual funds goes back at least to Sirri and Tufano (1998) and Chevalier and Ellison (1997). Both papers show that investors chase past abnormal performance in convex fashion. Bollen and Busse (2001), Bollen and Busse (2005) and Mamaysky, Spiegel, and Zhang (2008) find small persistence effects in fund alpha at short horizons, contrasting work on persistence at longer horizons, such as Carhart (1997), that does not find performance persistence.

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 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, gain/loss information reflects the experience that an investor associates with an investment and individual experiences affect financial decisions (e.g., Malmendier and Nagel, 2011 and Strahilevitz, Odean, and Barber, 2011). The gains and losses are a consequence of the actual timing of the buy and sell decisions of the investor with her real money and therefore better describe the personal experience with the investment. The rich literature on the disposition effect and more specifically for mutual funds, the reverse disposition effect of Chang, Solomon, and Westerfield (2016), empirically and experimentally shows the relevance of gains and losses for investors. The main contribution of this paper is to jointly study the effects and especially the interaction of performance-chasing and gain/loss-related trading in mutual funds in a unified setting.

I find a strong and so far undocumented empirical pattern in how investors react to return-related signals about mutual funds: 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 usual alpha chasing behavior and the base effect of holding the fund at a loss (reverse disposition effect). The attenuation effect is economically significant: regression analysis suggests that the response of flows to a marginal unit of alpha decreases by more than 37% in the loss domain. 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. Looking at inflows and outflows separately, I find that this interaction effect operates via buy decisions. The findings imply that investors not only consider both signals, 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 gain/loss information 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 measure whether the average dollar invested in the fund is currently invested 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.

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 fund is held at a loss but the level of alpha is relatively high. 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 use different signals of fund performance, but that these signals are jointly considered. In addition to alpha, investors also rely on the gains or losses of their investment. Moreover, their decisions are not only driven by the gain or loss in itself, but the gain/loss signal results in a different reaction to alpha information: 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. This type of multiplicative interaction effect is inconsistent with standard models relying on Bayesian' learning with two signals.

I provide two explanations that are consistent with the empirical results. The first potential explanation is based on ambiguity aversion and focuses on existing investors of a fund. I interpret the conflict between alpha and gains and losses as an increase in the perceived ambiguity about the quality of a fund investment. Especially literature in psychology has theoretically (Einhorn and Hogarth, 1985) and experimentally (Smithson, 1999) argued that conflicting information is affecting choice by the means of increasing ambiguity. The model of Epstein and Schneider (2008) provides a very similar mechanism. Conflict occurs when the objective measure of performance, alpha, is high, but the fund is nevertheless held at a loss and increases ambiguity. Consistent with ambiguity aversion, flows show a reduced sensitivity to alpha performance in those scenarios. In line with this interpretation, I show that the attenuation effect is stronger if the conflict is more severe, as indicated by a higher alpha or greater loss. Retail investors are likely to display stronger ambiguity aversion. In line with this conjecture, I show that the interaction effect is stronger for retail as opposed to institutional funds.

The second potential explanation is based on the social transmission of investment ideas between investors. Social interactions between people have an impact on the investment decisions of investors.[2] The model of Han, Hirshleifer, and Walden (2018) provides a formalization of this idea: in the model, investors are more likely to share information about their investment if this investment has been successful. This effect will likely be stronger if alpha, the external information that new investors can look up in addition, is also positive. Together, 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.

A general objection against the findings that gains and losses carry predictability for flows and interact with alpha information, is that gains and losses only measure omitted residual alpha information sucht that the relation with individual investment gains and losses may be spurious. I show that this residual information is not driving the empirical pattern in a variety of tests. The effect is neither driven by the number of months used for the calculation of alpha or returns, nor the specific risk-adjustment, nor by the fact alone that the gain/loss measure captures only price changes and not total returns.

Besides the literature discussed above, I contribute to two strands of the finance literature that have implicitly dealt with how investors process return related signals in the market for mutual funds. First, at an aggregate level, researchers have examined the relation of fund-level flows and performance. Refining early work on the performance-flow relation, 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 rather than alpha estimated with respect to more complicated factor models or simpler market-adjusted returns. The authors conclude that most investors use the CAPM to risk-adjust fund returns. This work is conceptually similar in the sense that mutual fund flows, which are direct measures of the buying and selling volume of investors, are used to study the actual choice of market participants.

Second, in a distinct stream of literature, researchers show that the gains and losses of

[2] Empirical evidence includes Ivković and Weisbenner (2007) and Hong, Kubik, and Stein (2005).

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.[3] 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.

Considering the ideas put forth in these two streams of literature together is relevant for at least two reasons. First, return chasing and reverse disposition effect induced trading predict very similar patterns, namely higher flows following a good signal and vice versa. I study and separate both effects in a unified setting at the fund level. In this context, I confirm the parallel existence of the effects and demonstrate the new interaction effect. Second, we can learn how investors use and interpret different return related signals when making their investment decisions. This is by itself a relevant mechanism, as a number of theoretical papers assume that investors learn about the quality of their investment as a function of past returns (e.g., Berk and Green, 2004 and Huang, Wei, and Yan, 2007). This study examines these mechanism in detail and documents which considerations are important to investors.

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 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 explanations 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.

[3] 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.

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 investor. 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.[4] 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).

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. Moreover, the data allow me to study a relatively recent time-period as compared to discount brokerage datasets typically available for the US market. The years covered here (2000-2017) are characterized by the availability of low-cost information via the internet and

[4] 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 off that uses a similarly large sample of N-SAR flows is Cashman et al. (2012).

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 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.[5]

2.2. Calculation of Reference Prices and Performance Measures

To study the effect of reference prices[6] 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

[5] In the 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 appendix ?? Table IA3.

[6] 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.

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.

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

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?[7] 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 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.[8]

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 assump-

[7]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.

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

[8]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.

tion 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[Loss].

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

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 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.[9] 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

[9]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).

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 indicator variables for 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.[10] Generally, net flows hide much larger variation in inflows and outflows. At the mean, inflows and outflows are close to 280 basis 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.[11]

[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

[10]The correlation table for flows is provided in Appendix IA1.
[11]See Appendix IA1.

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 the decile portfolios into two sub-portfolios, according to whether the fund is held at a gain or loss by the average investor. The results of these portfolio sorts are presented graphically in figure 1.

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.

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.

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. As the correlation between alpha and gains and losses is very close to zero, 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.

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

The flows of fund i in month $t+1$ are regressed on alpha, $\mathrm{Alpha}_{i,t}$, the loss variable, $\mathrm{I[Loss]}_{i,t}$, 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 γ_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.[12]

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

[12] 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.

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 use both alpha and gain/loss information 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 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.[13]

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.

[13]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.

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 of Chang, Solomon, and Westerfield (2016), 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.

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 existing fund investors (investors that currently hold the fund) drive the slope effect with their additional purchase decisions or new investors learn in some way about the gains and losses of existing 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 or other return measures. In this case, the effect of the loss variable on flows may only be obtained due to this residual information not reflected. I present evidence against this concern for two dimensions: the return information used and the treatment of risk in the return related measures.

While alpha and the other returns measures are 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. In table 3, I present evidence against this argument. I repeat the baseline regressions as before, but vary the number of months used for the estimation of return measures between 12 to 120 months.

[Insert Table 3 about here.]

The previously shown effects are highly robust across the different columns. The interaction term of alpha and the loss dummy is negative and statistically highly significant in all columns, no matter how many months are used for the estimation of return measures. The attenuation in the reaction of flows to alpha for funds held at a loss ranges between 24% (for 12 months) and 68% (for 96 months) of the alpha coefficient for funds held at a gain. In column 5, I estimate alpha using the fund-month specific time horizon that the average dollar is currently invested in the fund. Also for this specification, the negative attenuation effect persists.[14] The robustness of the interaction effect suggests that results concerning the loss variable are no artifact of residual information from months not used for the estimation of other return measures.

While this test rules out the concern that all investors use a different abnormal performance specification than the one I consider, it does not rule out the possibility that different investors of a fund are looking at different measures of performance at the same point in time. To address this concern, I estimate regressions including alpha calculated among the different time horizons simultaneously and also include the average raw return for the corresponding time periods. The results of this analysis are presented in table 4.

[Insert Table 4 about here.]

Table 4 indeed presents positive and significant coefficients for several alpha and return variables. However, the negative attenuation effect between alpha and gains and losses persists.

[14] The results are very similar if I include alpha estimated over the maximum time period a dollar is invested in the fund according to the reference price calculation.

This is the case both in column 1, where the horizons between 1 and 10 years are included, and column 2, where I 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.

Another 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).[15] I also analyze simple excess returns over the market. Table 5 presents the results of these tests.

[Insert Table 5 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 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

[15] I would like to thank Kenneth French and Lu Zhang for making the factor data available.

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 people 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 6. 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 6 about here.]

I provide additional robustness test in appendix of the paper. In the 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. Therefore, I examine whether omitted convexity is driving the observed interaction effect and check whether the effect operates equally across all levels of alpha. Examining the conditional functional form of the alpha chasing helps 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.

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 7.

[Insert Table 7 about here.]

The specification results in several insights. 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 the loss variable and alpha is positive and significantly different from zero at 1.0 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, investor 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 8 presents the results of this analysis.

[Insert Table 8 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 5%-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 have established 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 findings imply that the reference-dependent attenuation effect in the flow sensitivity to alpha is especially strong for buy decisions for high levels of alpha if the fund is held at a loss.

4. Discussion

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. In the following, I provide two possible explanations for these patterns: 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 and in the low alpha but gain 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. For the buy decision, this is easily possible, as there is a whole universe of funds available. If investors have to sell a fund, e.g. due to a liquidity shock, they have to choose among the investments in place. This might explain why I do not find a significant interaction effect for sell decisions.

With this potential explanation, I should expect variation in the strength of the attenuation effect along the following two dimensions: investor sophistication and the strength of the conflict. Alpha is a more objective and complete measure of the true performance of a fund investment, as it is measured incorporating total returns and does adjust for returns just earned as a compensation for bearing market risk. However, understanding these properties and properly judging alpha requires more financial sophistication. Just looking at the gain or loss an investment has obtained since purchase is easy, but is an objectively worse measure of fund performance. Therefore, I should expect the reference-dependency of the alpha chasing to be weaker for more sophisticated investors. In addition, these investors might generally have a higher tolerance for ambiguity. I test this argument by analyzing the difference of the attenuation effect between funds targeted at more or less sophisticated investors. 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.[16] 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 results of this analysis are presented in column 1 of table 9.

[Insert Table 9 about here.]

The coefficients presented in column 1 show the expected pattern regarding investor sophistication. 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.[17] This implies that the weakening of the alpha flow relation with respect to losses is less pronounced considering more sophisticated investors. The coefficient on the triple interaction is offsetting the negative and significant interaction term of -1.1 of alpha and the loss variable for retail funds. 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.

Another implication of ambiguity aversion is that the documented attenuation effect should be stronger if the conflict between the two signals is stronger. We have already seen a corresponding pattern for increasing the level of alpha above. As high levels of alpha increase the conflict with the loss information, this is consistent with ambiguity aversion. Furthermore, I

[16]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.

[17]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.

test whether the attenuation effect increases if the conflict between alpha and the loss variable increases due to a higher loss. I implement this test by breaking the loss 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 NAV 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 NAV 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 columns 2 of table 9.

The coefficients show that the mediating effect in the alpha sensitivity of fund flows with respect to losses is larger if the conflict between the two signals is stronger. 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. Moreover, we can observe that the negative base effect of the loss indicators gets stronger for larger losses, consistent with Ben-David and Hirshleifer (2012). The negative reaction in net flows increases from 60 to 110 basis points for large losses compared to small losses.

4.2. Social Transmission

A second potential explanation 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 retail and institutional 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 existing 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 confirmatory information, i.e. a positive alpha. Hence, the reaction to alpha will be especially strong when the fund will be held at a gain by existing 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. As sell decisions only involve existing investors of the fund, social transmission can directly rationalize why no interaction effect between alpha and gains and losses is observed for outflows. While it is difficult to derive a clear prior for the relative importance of social transmission for retail versus institutional investors, this explanation is also in line with a stronger attenuation effect for increasingly disagreeing signals (tables 7 and 9). A key difference of the social transmission based explanation is the prediction that the attenuation effect works strongly on the extensive margin by not attracting as many new investors when signals disagree.

5. Conclusion

In this study, I show that mutual fund investors react to both alpha and salient and experienced 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. I show this – I would consider – stylized fact 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. High-dimensional fixed effects panel regressions reveal a robust interaction effect between alpha and the new loss variable. I check that the results are not driven by omitted return information or non-linearity.

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. Also consistent with this argument, I find that the reference-dependent feature of the performance-flow relation is stronger for high levels of alpha and high levels of losses, when the conflict is especially strong. In addition, I find that the effect is weaker for institutional funds and thus more sophisticated investors that rely more on the objective alpha information even if they hold the fund at a loss.

Similarly, the social transmission of investment outcomes can produce the patterns observed in the data. Existing 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 they observe a positive alpha as confirmatory external signal. This mechanism suggests a higher sensitivity of flows with respect to alpha information for funds held at a gain.

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. Given the size of more than $16 trillion of assets under management of the US mutual fund industry and the pronounced importance for retirement savings in the US (Investment Company Institute, 2018), it is important to study the decisions of fund investors, both from a consumer perspective to provide guidance and recommendation for improved decisions and to help fund companies understand the drivers of monetary flows into their products. 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 connected market outcomes.

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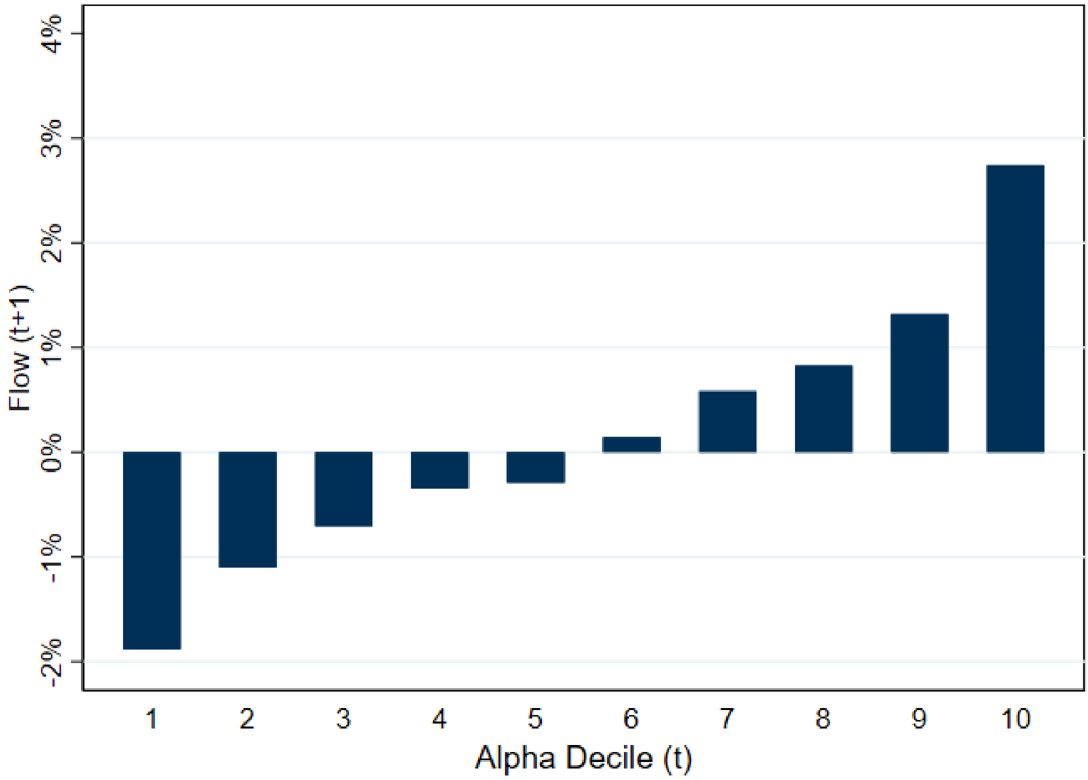
Figure 1: Fund Flows, Alpha and Gains and Losses

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

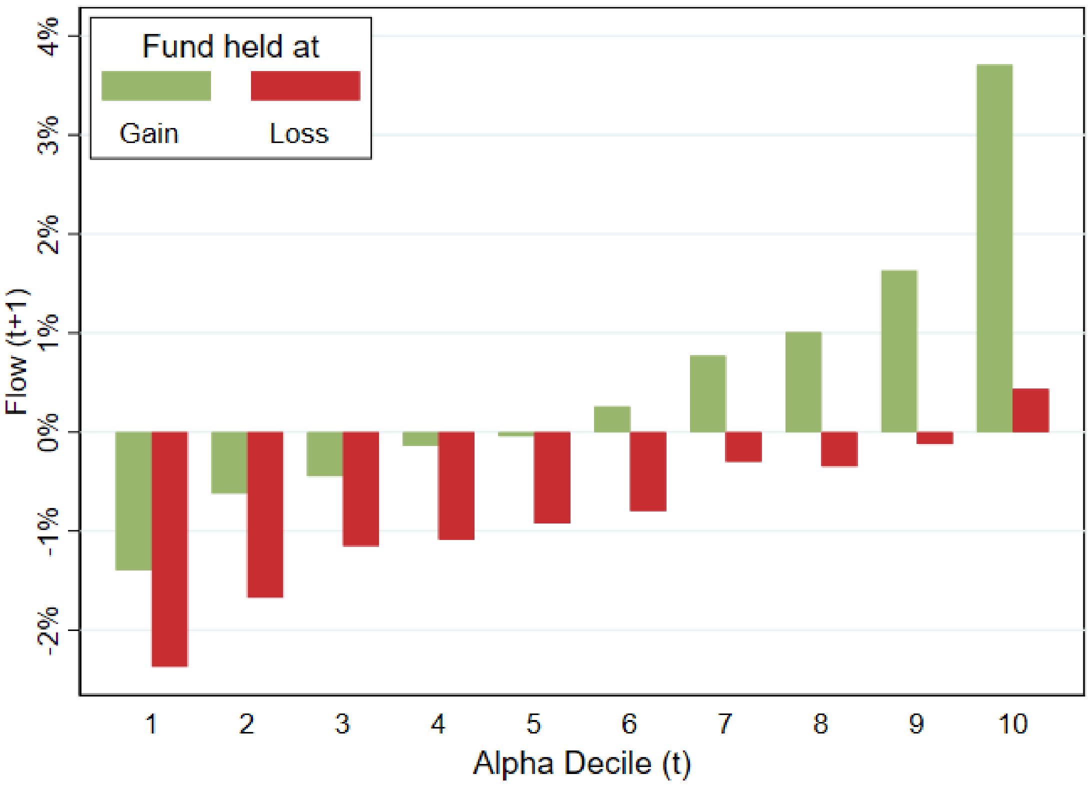


Table 1: Summary Statistics

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×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***	2.693***	2.048***	-0.645***
	(11.35)	(14.58)	(10.87)	(-5.64)
I[Loss]	-0.007***	-0.007***	-0.004***	0.003***
	(-7.77)	(-7.39)	(-4.75)	(4.91)
Alpha × I[Loss]	-0.897***	-1.008***	-1.169***	-0.161
	(-5.15)	(-5.38)	(-6.56)	(-1.61)
LN(Holding Time)	-0.009***	-0.012***	-0.023***	-0.010***
	(-10.90)	(-9.92)	(-13.68)	(-8.72)
LN(TNA)	-0.003***	-0.014***	-0.013***	0.000
	(-9.96)	(-12.63)	(-11.59)	(0.62)
LN(Age)	-0.000	-0.011***	-0.001	0.010***
	(-0.25)	(-4.08)	(-0.32)	(4.90)
LN(Family TNA)	0.001***	0.003***	0.003***	0.000
	(7.16)	(3.34)	(3.32)	(0.05)
Turnover	-0.000	0.001	0.002***	0.001
	(-0.09)	(1.37)	(2.61)	(1.60)
Expense Ratio	0.070	0.190	0.272	0.082
	(0.63)	(0.78)	(1.04)	(0.49)
Amihud R2	-0.007	-0.006	-0.004	0.003
	(-1.17)	(-0.76)	(-0.50)	(0.57)
Beta	-0.003	0.006	0.007	0.000
	(-1.48)	(1.06)	(1.22)	(0.06)
Vola	-0.068	-0.137	-0.033	0.103
	(-0.62)	(-0.85)	(-0.24)	(0.90)
Skew	0.003	0.002	0.003	0.001
	(1.53)	(0.65)	(1.02)	(0.76)
IVola	-0.278***	-0.256*	-0.118	0.138
	(-2.69)	(-1.69)	(-0.81)	(1.50)
ISkew	0.001	-0.000	-0.001*	-0.001**
	(0.79)	(-0.63)	(-1.95)	(-2.35)
Kurtosis	0.001*	0.001	0.001	-0.000
	(1.77)	(1.39)	(1.46)	(-0.05)
MAX	0.008	-0.010	-0.004	0.006
	(0.34)	(-0.30)	(-0.14)	(0.28)
MIN	-0.043	-0.038	-0.025	0.013
	(-1.51)	(-1.04)	(-0.73)	(0.60)
Beat SP500	0.003***	0.003***	0.002***	-0.001***
	(5.53)	(4.94)	(2.83)	(-3.75)
MS Stars FE	Yes	Yes	Yes	Yes
Fund FE	No	Yes	Yes	Yes
Category × 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: 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) 12 Months	(2) 36 Months	(3) 60 Months	(4) 120 Months	(5) Custom
Dependent: Flow (t+1)					
Alpha	1.498***	2.693***	2.063***	1.438***	3.536***
	(12.81)	(14.58)	(8.32)	(5.48)	(7.68)
I[Loss]	-0.007***	-0.007***	-0.008***	-0.008***	-0.007***
	(-7.38)	(-7.39)	(-7.77)	(-7.35)	(-5.81)
Alpha × I[Loss]	-0.367***	-1.008***	-0.888***	-0.983***	-1.291***
	(-3.05)	(-5.38)	(-3.83)	(-4.42)	(-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 4: 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) Flow (t+1)	(2) 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 5: 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 depeding 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) CAPM	(2) Market	(3) NAV	(4) FF3	(5) FF4	(6) FF5	(7) HXZ	(8) CAPM
Dependent: Flow (t+1)								
Alpha	2.693***	2.478***	1.594***	2.632***	2.657***	2.252***	2.396***	1.463***
	(14.58)	(11.82)	(12.76)	(14.06)	(13.66)	(11.58)	(11.96)	(4.24)
I[Loss]	-0.007***	-0.007***	-0.010***	-0.008***	-0.008***	-0.008***	-0.008***	-0.007***
	(-7.39)	(-7.10)	(-8.02)	(-8.11)	(-8.25)	(-8.25)	(-8.67)	(-6.73)
Alpha × I[Loss]	-1.008***	-1.032***	-0.778***	-1.260***	-1.388***	-1.229***	-1.304***	-1.053***
	(-5.38)	(-5.77)	(-5.59)	(-6.01)	(-6.27)	(-5.95)	(-6.34)	(-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 6: 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 depeding 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***	2.072***	-0.673***
	(14.07)	(10.63)	(-5.87)
I[Loss]	-0.031**	-0.016	0.015**
	(-2.56)	(-1.40)	(2.39)
Alpha × I[Loss]	-1.061***	-1.224***	-0.162
	(-4.97)	(-5.94)	(-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 7: 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	0.000	0.002**
	(-1.07)	(0.06)	(2.20)
Alpha Low	1.654***	0.565*	-1.089***
	(4.38)	(1.72)	(-3.64)
Alpha Mid	2.560***	1.676***	-0.884***
	(9.71)	(6.46)	(-5.29)
Alpha High	3.516***	3.477***	-0.038
	(7.36)	(6.85)	(-0.24)
I[Loss] × Alpha Low	0.956**	0.618*	-0.337
	(2.16)	(1.68)	(-1.21)
I[Loss] × Alpha Mid	-1.056***	-1.181***	-0.125
	(-3.55)	(-4.21)	(-0.88)
I[Loss] × Alpha High	-2.669***	-2.383***	0.286
	(-5.02)	(-4.08)	(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 8: 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**	0.154*	0.181**	0.167**
	(2.16)	(1.66)	(2.07)	(1.99)
I[Loss]	-0.000	-0.000	-0.000	0.000
	(-0.72)	(-1.32)	(-0.48)	(0.10)
Alpha × I[Loss]	-0.096	0.058	0.049	0.063
	(-1.22)	(0.82)	(0.74)	(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 9: 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.	Fama and French (1993)
Alpha (FF4)	Intercept from a rolling window regression of excess fund returns on the four factor model of the relevant paper.	Carhart (1997)
Alpha (FF5)	Intercept from a rolling window regression of excess fund returns on the five factor model of the relevant paper.	Fama and French (2015)
Alpha (HXZ)	Intercept from a rolling window regression of excess fund returns on the four factor model of the relevant paper.	Hou, Xue, and Zhang (2015)
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.	

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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.	Amihud and Goyenko (2013)
Beat SP500	Indicator whether the fund's NAV change exceed the price change of the SP500 index.	Hartzmark and Solomon (2017a)
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 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.	Boyer, Mitton, and Vorkink (2010)
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.	Ang et al. (2006)
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	Bali, Cakici, and Whitelaw (2011)
MIN	Minimum return of a fund in a rolling-window	Bali, Cakici, and Whitelaw (2011)
MS Stars	Morningstar Star Rating of the fund.	
Outflow	Redemptions / TNA(t-1). Redemptions data are taken from SEC form N-SAR.	

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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 Decriptive 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 IA5.

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 be inertia in investors' decisions that might be correlated with the variables of interest.[18] 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 IA5, 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.

[18] 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 tables displays Pearson correlations for different fund flow variables. Flow (standard) is calculated using fund returns and TNA following the defintion 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.

	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

Table IA2: Correlations: I[Loss] and Alpha

This tables 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	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	0.517	0.894	0.858	1	
Alpha (HXZ)	-0.108	0.699	0.675	0.513	0.816	0.807	0.810	1

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***	2.061***	-0.634***
	(15.53)	(11.68)	(-5.86)
I[Loss]	-0.007***	-0.004***	0.003***
	(-9.03)	(-5.54)	(5.52)
Alpha $\times$ I[Loss]	-0.980***	-1.166***	-0.150
	(-6.02)	(-7.37)	(-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: 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 depeding 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***	2.618***	2.587***	2.188***
	(7.73)	(11.94)	(10.21)	(5.70)
I[Loss]	-0.006***	-0.005***	-0.006***	-0.005***
	(-5.86)	(-4.68)	(-5.33)	(-3.80)
Alpha × I[Loss]	-0.782***	-0.884***	-0.861***	-1.047***
	(-4.16)	(-4.78)	(-3.67)	(-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