A Tale of Bad Days: Flow-Performance Sensitivity and Portfolio Manager Skill[☆]

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Abstract

We show that weekly mutual fund flows are highly responsive to single-day performance, revealing a flow-performance sensitivity at a much higher frequency than previously studied. Notably, this sensitivity is primarily driven by days with unusually low market returns. On these bad days, investors reward funds that outperform and penalize those that underperform. Performance on bad days is persistent and plays a significant role in overall fund performance, supporting the smart-money hypothesis. Our results further highlight a specific bad-day skill distinct from the general managerial skill previously discussed in the literature. Overall, this paper emphasizes the importance of studying the interaction between fund and market returns at high frequency to better understand incentives and skills in the mutual fund industry.

Keywords: Mutual funds, daily flows, and performance, flow-performance sensitivity, bad days, smart money hypothesis, investor attention

JEL Classification:G11; G23; G41

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1. Introduction

Given the key role the mutual fund industry plays in channeling household savings into the economy, understanding the behavior of flows to this industry is of primary importance. Previous literature focuses on understanding whether investors are sensitive to funds' relative past performance at *low frequency*, that is, whether annual or monthly flows respond to past year's performance in the cross section (see Christoffersen et al., 2014, for a review). In contrast, we study the *higher frequency* sensitivity of next week's flows to current daily performance and, in particular, examine when this sensitivity is strongest. Our high-frequency approach not only sheds new light on the behavior of investors but also on the incentives and skills of fund managers. Indeed, one would expect skilled managers to outperform when it matters most to investors.

Our main hypothesis is that investors' sensitivity to relative fund performance is stronger when the level of performance is generally lower, that is, on days the market is doing poorly or "bad days." We expect investors to be more sensitive on bad days for at least three reasons. First, a large body of previous work supports (i) preference specifications in which investors care more about losses than gains and (ii) narrow framing.[1,2] The implication is that investors tend to focus on short-term performance, and short-term losses in particular, rather than considering how a fund fits with their long-term investment goals. Consequently, the hypothetical utility of having invested in another fund or asset class varies relatively more on bad days, and this variation may be reflected in fund flows. Second, existing work argues that bad macroeconomic news disproportionately raises investor attention, which may also be reflected in increased attention to fund performance.[3] Third, demand for (out-of-the-money)

[1]Examples of such preference specifications include loss aversion (Kahneman and Tversky, 1979), disappointment aversion (Gul, 1991), and salience (Bordalo et al., 2012, 2013, 2022).

[2]See, e.g., Tversky and Kahneman (1981); Barberis and Huang (2006) and a recent column written by Schlomo Benartzi.

[3]As discussed in Fisher et al. (2022), attention should rise more following bad news than following good news of the same magnitude. The reason is that in models of endogenous attention (see, e.g., Bansal and

index puts reveals that the average investor is "crashophobic" and desires to outperform the market specifically on bad days (Rubinstein, 1994; Garleanu et al., 2008). Gao et al. (2018) argue that some hedge fund managers have the skill to exploit such disaster concerns. We leverage a new dataset of traffic to major financial websites (including brokerage firms, investment advisors, and other financial services firms) to further motivate this hypothesis. We find that website visits are strictly decreasing in market returns, suggesting that attention to financial market outcomes is higher on bad days.[4]

Does this increase in attention translate to more fund flows? If it does, several follow-up questions are of primary interest for the broader literature on delegated asset management: Do flows react to both out- and underperformance on bad days or is the higher frequency flow-performance relation convex (like it is at lower frequencies)?[5] Is the time-variation in flow-performance sensitivity reflecting "dumb" or "smart" money? Does outperforming on bad days require specific bad day skill or is general skill driving performance on all days?[6] If skill is specific to bad days, how much do these days contribute to overall unconditional fund performance? Do fund managers with bad day skill charge higher management fees because they cater to investors' revealed preference?

We study these questions using a sample of 1,967 active US equity mutual funds over the

Shaliastovich, 2011; Kacperczyk et al., 2016), attention reflects the value of information. This value is driven by both uncertainty about fundamentals and the price of risk, which is countercyclical.

[4]This finding is interesting in and of itself because it challenges the idea that attention is mostly impacted by extremely positive returns or news, as assumed in Yuan (2015). Sicherman et al. (2016) find that positive returns increase attention measured as defined contribution retirement accounts logins in a large sample of individual investors in the years 2007 and 2008. However, more consistent with us, these authors find that conditional on login, trading is decreasing in market returns. Further, Barber and Odean (2008) and Da et al. (2011) assume a symmetric impact of stock-level attention-grabbing events on trading behavior.

[5]Existing work offers both rational (Sirri and Tufano, 1998; Lynch and Musto, 2003; Huang et al., 2007) and behavioral (Goetzmann and Peles, 1997) explanations for a convex flow-performance relation.

[6]Suppose a manager outperforms unconditionally. If this outperformance is due to general skill, it means that – in expectation – all days contribute equally to outperformance. If this outperformance is due to specific skill, it means that some days contribute relatively more than others. For instance, a manager with specific bad day skill generates unconditional outperformance, because he/she outperforms specifically on bad days. He/she has the skill to choose appropriate investment or trading strategies on bad days, but does not necessarily have to outperform also on other days.

period from August 2008 to June 2022. Our daily sample combines returns from the CRSP mutual fund database with Total Net Assets (TNA) from Morningstar. We focus on the response of weekly flows to one day of fund performance and specifically examine whether this response strengthens on bad days. A reasonable null is that flows are not sensitive to daily performance at all. The reason is that, at high frequency, relative fund performance is noisy, market returns are hard to predict for fund managers, and – most importantly – there is little advertising of performance. Most news about top funds is based on annual rankings or even longer evaluation periods, as seen with Morningstar Ratings. Previous literature (see, e.g., Sirri and Tufano, 1998) argues that such advertising is a key driver of the convex flow-performance relationship at low frequency. That said, modern digitalized financial markets enable investors to check fund performance at high frequency and we consider the possibility that they actually do. If investors are more attentive to fund performance on bad days than on good days, distinguishing investors' flows between these days provides a more powerful test of the null hypothesis.

Our results strongly reject the null. On an average day, flows significantly respond to both out- and underperformance. Beyond the absence of convexity, the higher frequency flow-performance relation is noteworthy because it varies significantly over time. Consistent with our main hypothesis, bad days have an outsized effect on flows. We estimate that a one standard deviation decrease in market return leads to a large and significant increase in flow-performance sensitivity of about 25%. This finding is robust across various measures of fund performance, under different sets of fixed effects, and for both retail and institutional investors' flows; all while controlling for a range of fund characteristics. We further quantify the importance of bad days by estimating their contribution to the variance of weekly flows. We show that the 20% of days with the lowest market returns contribute orders of magnitude more to this variance than the 20% of days with the highest market returns. Moreover, these bad days contribute about as much as the remaining 60% of normal days. Consequently, a fund manager who underperforms on a single bad day can cause as much outflow as another manager who underperforms on several other days.

Overall, the time-variation in flow-performance sensitivity reveals a preference for fund performance on bad days, which is when most funds generate negative returns. On such days, attentive investors act on relative fund performance because the hypothetical change in utility from having invested in another fund or a less risky asset class is larger. When decomposing the aggregate flow out of active US equity mutual funds on bad days, we find that funds in the bottom quintile of fund performance contribute disproportionately more.[7] Conversely, the aggregate outflow among the top quintile of performers is small and insignificant, consistent with the idea that investors are happy with these funds' relative performance.

The economic importance of these results is limited if relative performance on bad days is completely random. If not, these findings are crucial for understanding the incentives of fund managers (whose compensation is generally tied to assets under management) as well as fund management companies (which aim to maximize revenue through their hiring and capital reallocation decisions (Berk et al., 2017)). Indeed, even if investors' reactions to performance on bad days explain a large fraction of the variation in flows, only funds managed by skilled individuals who consistently outperform on such days will be significantly affected. Our second set of results serves to differentiate skill and luck in bad day performance. These results will also help to determine whether bad day flows represent "smart" money (Gruber, 1996; Zheng, 1999) or "dumb" money (Frazzini and Lamont, 2008). In our setting, a "smart money hypothesis" consists of two testable predictions. First, performance on bad days must be persistent. In this case, the higher flow-performance sensitivity on bad days reflects money flowing into (out of) funds that perform better (worse) when marginal utility is higher on future bad days. Second, outperformance on bad days must not come at the expense of

[7] Our results suggest that a large share of this aggregate outflow ends up in money market funds.

performance on other days, at least not to the extent that it leads to significant unconditional underperformance.

Consistent with the first prediction, we find strong evidence that performance on bad days is persistent. To this end, we define a bad day as any day d in month t with a market return below the 5th percentile of market returns over the last year (from $t-12$ to $t-1$). We thus study persistence in performance on approximately the worst day every month. We regress the fund performance ranking on a bad day on the average performance ranking on all bad days over the previous year. In our most conservative specification, using CAPM abnormal returns and controlling for a range of fund characteristics as well as day×style and fund fixed effects, we find that a one standard deviation increase in the performance ranking on past bad days increases the fund's ranking on the next bad day by a large and significant 1.5 ($t = 3.2$) percentage points.

One might be inclined to conclude that managers who outperform on past bad days are generally more skilled. In fact, the stronger response of flows to performance on bad days could even suggest that this performance provides a better signal of general skill than performance on other days. Both of these interpretations are unlikely to be correct. First, bad days account for only 5% of the sample, so past performance on other days is likely a more reliable signal of general skill. In fact, Franzoni and Schmalz (2017) argue that fund performance during periods with larger factor returns provides a less informative signal about general skill.[8] Second, we find that (i) the across-fund correlation between past performance on bad days and past performance on other days is negative at -0.19, and (ii) past performance on other days does not positively predict performance on the next bad day. We conclude that past performance on bad and other days are unlikely to be noisy proxies of the same, unobservable, general managerial skill. Rather, our evidence suggests that bad

[8]The idea is that to learn about a fund's alpha, Bayesian investors also need to learn about its beta. The higher the factor return (in absolute value), the larger the noise that pollutes the signal about alpha, making investors less confident in updating their inference about skill based on a given observation of fund returns.

days are special. Some managers have the specific skill to outperform on bad days, while others lack it. Investors rely on this specific performance when deciding where to invest their money. The flows of these investors are smart in the sense that performance on bad days is persistent. Are these flows also smart in terms of unconditional performance?

Ex ante, it is not obvious that managers with bad day skill will outperform unconditionally. First, there are relatively few bad days. Second, investors competing to invest in funds that outperform on bad days may be willing to pay higher fees and thus accept lower unconditional after-fee performance (see Berk and Green, 2004; Berk and van Binsbergen, 2017). Finally, theories of downside risk (see, e.g., Ang et al., 2006) generally imply that an investment with a lower beta in down markets generates a negative unconditional CAPM alpha, because it is attractive as a hedge.[9] To study how much unconditional abnormal return managers with bad day skill generate compared to other (skilled) managers, we sort all funds into TNA-weighted decile portfolios based on their performance on all bad days in the year from month $t-12$ to $t-1$ and analyze the unconditional performance of these portfolios in month t.

In short, we find large differences in unconditional performance across active funds. Funds in the highest decile of past bad day performance generate a net CAPM alpha that is 2.3% ($t = 1.83$) higher than funds in the lowest decile. This high-minus-low difference remains large in the FF4M at 1.45% ($t = 2.11$) and translates to an economically large improvement in information ratio of about 0.75. In contrast to net performance, differences in fees between the high and low decile portfolios are economically small. Thus, our evidence rejects the idea that investors ex ante pay a higher price for funds that outperform on bad days, either through higher fees or a downside risk premium.

Even though there is little overlap between the sets of funds that generate past outperfor-

[9]Given that volatility tends to be higher in down markets, such an investment is also likely to have high coskewness. Absent manager skill, theory suggests that alpha and coskewness should be negatively correlated across mutual funds (see Kraus and Litzenberger, 1976; Back et al., 2018).

mance on bad versus other days, we find that sorting on past other day performance leads to similar high-minus-low differences in alphas as sorting on past bad day performance. We thus conclude that the response of flows to bad day performance is smart: bad day performance is persistent, and it provides a signal as useful as performance on other days for choosing between active managers. Further, in both sorts, it is only the high decile of outperforming funds that generates a positive value added, which is the measure of skill proposed in Berk and Van Binsbergen (2015). We thus conclude that a manager's specific skill to outperform on bad days is valuable for both fund investors and fund management companies, just like the skill to outperform on other days.

The key difference between these two sets of skilled managers lies in when they earn their abnormal return. Past outperformers on bad days (up to month $t-1$) continue to outperform in month t only because they outperform on bad days. Their outperformance on (approximately) the worst day of each month explains their entire monthly abnormal return. In contrast, past outperformers on other days generate monthly outperformance by continuing to outperform on other days, but they strictly underperform on bad days.[10] The performance of managers with other day skill may simply reflect a strategy of selling insurance, for instance, by overweighting stocks with high downside risk (e.g., stocks with high market beta, volatility, or illiquidity, and stocks with negative co-skewness with the market) or writing index puts. However, the performance of managers with bad day skill must be more sophisticated than simply buying this insurance, because that would be expensive and thus lower unconditional performance.

This paper contributes to our understanding of the important link between flows and performance in active US equity mutual funds. Recent literature uses the response of fund flows to annual performance to infer investor preferences. Barber et al. (2016); Berk and

[10]Thus, the response of flows to performance on other days, albeit smaller than on bad days, is also quite smart: performance on other days is persistent and contributes to unconditional outperformance.

Van Binsbergen (2016); Evans and Sun (2021); Ben-David et al. (2022) study *what* measure of performance investors value the most. Harvey and Liu (2019), Jiang et al. (2016), Franzoni and Schmalz (2017) study *when* investors value performance the most, focusing, respectively, on periods with high versus low fund return dispersion, economic policy uncertainty, and factor volatility (see also Ben-David et al., 2022). Instead, we study the high frequency.[11] We argue that high-frequency flow-performance sensitivity is relatively strong on bad days, which we demonstrate to be days with unusually high attention to financial market outcomes. While flows are sensitive to both out- and underperformance on bad days, they are not sensitive to either on good days. We rule out several alternative explanations for investors' revealed preference for performance on bad days, such as dumb performance chasing or learning about general managerial skill. Moreover, given that we control for fund performance over longer periods in the past in all of our tests, our findings are not driven by investors learning about long-term past performance on days when the market return captures their attention. More generally, our findings emphasize that investors respond to performance at a much higher frequency than what is typically considered in the literature.

The fact that some managers have specific bad day skill contributes to a large previous literature on managerial skill that primarily highlights general skill. For instance, Kacperczyk et al. (2014) (see also Kacperczyk et al., 2016) argue that generally skilled managers time the market during recessions and successfully pick stocks during expansions.[12] Similarly, skill is considered general (or one-dimensional) in the structural model of mutual fund marketing

[11] Busse et al. (2023) study conditional fund betas measured using daily returns. They argue that some fund managers have timing ability and that this is correlated to fund performance. Our paper is different in that we highlight the distinct importance of bad days, that is, days with market returns in the far left tail of the distribution. We also differ from them in that we study high- rather than low-frequency flow-performance sensitivity. Finally, they do not study whether timing ability contributes to across-fund variation in future abnormal returns nor when this contribution is realized. Consequently, they do not discuss implications for important hypotheses, such as dumb versus smart money and general versus specific skill.

[12] Zambrana and Zapatero (2021) argue, like us, that fund families can add value for their investors by efficiently allocating funds to managers with different skills. In contrast to us, they study timing versus picking skill.

with costly investor search of Roussanov et al. (2021). If skill is day-specific, this will only increase informational frictions relative to such a model. Consequently, it is perhaps unsurprising that we find that the flows due to funds' relative performance on bad days are not large enough to offset this variation in skill through diseconomies of scale. That said, the fact that even those active US equity mutual fund managers with bad day skill do not outperform passive benchmarks is consistent with the implications of an overall money management industry in equilibrium (Berk and Green, 2004; Berk and van Binsbergen, 2017).

The remainder of the paper proceeds as follows. We present a motivating exercise using website traffic data in Section 2. We describe the data and provide details on the key variable constructions in Section 3. Section 4 studies high-frequency flow-performance sensitivity and, in particular, how this sensitivity varies with the market return. Section 5 analyzes the persistence of fund performance on bad days. Section 6 analyzes what bad days have to say about managerial skill. Section 7 concludes.

2. Investor Attention and Market Returns

In this section, we use a novel dataset provided by SimilarWeb, Ltd. to show that investors' attention increases on days with unusually low market returns. SimilarWeb is a digital intelligence provider that offers web analytics services. They report a wide range of statistics to assess website traffic and user engagement, aggregated at the domain level.[13] SimilarWeb provides us with five years (from February 2019 to February 2024) of daily web traffic data for fifteen financial websites, including six brokerage firms mostly catering to retail investors (E*TRADE, Fidelity Investments, Firstrade Securities, Robinhood, Charles Schwab Corpo-

[13]SimilarWeb collects web traffic data through a multi-source approach that includes data partnerships, direct measurement from websites and apps via SDKs (Software Development Kits), anonymized clickstream data from ISPs (Internet Service Providers), and web crawling technologies. Then, they process this aggregated data through proprietary algorithms to provide estimates of website traffic. Some of the key daily metrics include total visits, unique visitors, average time spent, and the number of pages visited.

ration, and TD Ameritrade), two financial institutions mostly catering to high-net-worth clients (JPMorgan Chase & Co. and Vanguard Group), one brokerage firm mostly dedicated to professional traders (Interactive Brokers), and six research websites mostly used by retail investors (Morningstar, Inc., The Motley Fool, Zacks Investment Research, Benzinga, and The Wall Street Journal). Although other websites may be of interest to specific groups of investors, we believe that general attention to financial market outcomes is highly correlated to what we study here.

We ask a simple question: How does attention relate to aggregate market returns? To answer this question, we run the following regressions:

$$\begin{aligned} Visits_{j,d+H} &= \gamma_1 MKT_d + \gamma_2 MKT_d^2 + \\ &\quad \lambda Visits_{j,d} + \text{Fixed effects} + \epsilon_{j,d+H} \text{ and} \end{aligned} \tag{1}$$

$$\begin{aligned} Visits_{j,d+H} &= \gamma_{Low} D_{MKT,d,Low} + \gamma_{High} D_{MKT,d,High} \\ &\quad + \lambda Visits_{j,d} + \text{Fixed effects} + \epsilon_{j,d+H}. \end{aligned} \tag{2}$$

The dependent variable in these regressions is the $H = 1, 3, 5$ days ahead log of total visits to website j, denoted $Visits_{j,d+H}$. The main independent variable is the CRSP value-weighted excess stock market return on day d, MKT_d.[14] Further, $D_{MKT,d(t),Low}$ ($D_{MKT,d(t),High}$) is a dummy equal to one when the market return on day d is below its 20th percentile (above its 80th percentile) based on all days in the previous year. We include lag visits and year×day-of-the-week×website fixed effects. The standard errors are clustered at the day level. The results are reported in Table II.

Overall, we see that attention is decreasing in market returns. In the continuous specification of Eq. (1), our estimates imply that a 1 percentage point lower market return is associated with an increase in visits of 0.24% the day after and about 0.6% in the week

[14]This return, as well as other factor returns used in this study, are taken from Kenneth French's website.

after. There is weak evidence of non-linearity, with the coefficient on the squared market return being positive and significant only at the 3-day horizon. In the dummy specification, visits increase (decrease) by about 2% (1.5%) in the week after a market return in the lowest (highest) quintile.

This evidence suggests that attention to financial market outcomes is higher after days with low market returns, consistent with the idea that investors care more about days with losses than gains. Attention takes a few days to build up, consistent with the idea that investors do not react immediately. These results challenge the idea that attention to extreme market events is symmetric or that attention is mostly impacted by extremely positive returns or good news. For instance, Yuan (2015) argues that historically high Dow Jones index levels capture investors' attention and translate to significant aggregate flows out of mutual funds. In the next section, we similarly ask whether increases in website visits after bad days translate to financial market actions. Although we will also present results for aggregate flows as in Yuan (2015), our main focus is on the across-fund relation between flows and performance.

3. Mutual Fund Data

In this section, we describe the mutual fund data used in our study, provide details on the key variable constructions, and present summary statistics of our final sample.

3.1 Data collection

Our analyses rely on two primary datasets: daily flow data of active US equity mutual funds from Morningstar and fund returns and characteristics from the CRSP Survivor-Bias-Free US Mutual Fund database. We combine these datasets following Pastor et al. (2015) and Choi et al. (2022). To start, we merge the Morningstar and CRSP datasets using the procedure outlined in Pastor et al. (2015). Specifically, to match FundId (from Morningstar) with WFICN (from CRSP), we first match by CUSIP, followed by Ticker, and then by name using a fuzzy matching technique. To ensure the accuracy of our matches, we discard month-fund observations where the daily TNA flow from the last day of the month from Morningstar does not align with the monthly TNA in CRSP. Morningstar's daily Total Net Assets (TNA) data is only available from July 2007 for a limited number of funds, and it is not until mid-July 2008 that the coverage extends to at least 1000 funds per day. Hence, our sample period starts in August 2008 and ends in June 2022. We exclude funds outside the 3×3 Morningstar style categories (i.e., Large, Mid, Small interacted with Growth, Blend, Value), funds with less than $20 million assets under management, funds that are younger than three years, and funds with an expense ratio lower than 20%. Our final sample covers a total of 1967 unique funds.

3.2 Variable construction and summary statistics

As discussed in Choi et al. (2022), the daily TNA data suffers from some inconsistencies because it is self-reported. For instance, because funds do not necessarily learn of purchase and redemption orders in real-time, some funds report TNA including same-day flows, whereas others exclude it. To alleviate measurement error concerns, we follow Choi et al. (2022) and aggregate flows to the weekly frequency. By studying weekly flows, we also give investors more time to act on the performance of their funds.

To be precise, we define log daily flows as in Berk and Tonks (2007):

$$Flow_{d+1} = \ln\left(\frac{TNA_{d+1}}{TNA_d \times (1 + R_{d+1})}\right), \tag{3}$$

where TNA_d is the TNA of the fund as reported in Morningstar at the end of day d and R_d is the daily return of the fund as reported in CRSP. This definition ensures that the sum of five daily flows is exactly equal to the log weekly flow:

$$\sum_{s=1}^{5} Flow_{d+s} = \ln\left(\frac{TNA_{d+5}}{TNA_d \times (1 + R_{d+1:d+5})}\right) = Flow_{d+1:d+5} = Flow_{d+1w}, \tag{4}$$

which accommodates interpretation.[15]

We use two different measures of fund performance that are common in the mutual fund literature: simple returns (net of all management expenses and 12b-fees) and CAPM abnormal (net) returns. For a day d in month t, market beta is estimated using one year of past daily excess returns from month $t-12$ to $t-1$. We transform each fund performance measure to a $[0,1]$-ranking to accommodate interpretation and reduce the effect of outliers. Similar to fund returns, we define the market return on day d of month t as a $[0,1]$-ranking based on that day's CRSP value-weighted excess market return relative to all daily returns in the previous year (from month $t-12$ to $t-1$). In this way, we use no forward-looking information and again accommodate interpretation. Our conclusions on the relative importance of bad days are identical if we use the raw performance measures instead.[16]

Table I reports summary statistics for the main variables used in our analyses. On an average day in our sample, we observe flows and returns of 999 funds with an average of 1.2 billion USD in TNA. Consistent with the usual sample studied in the mutual fund literature, we find that expense ratios are typically close to 1% per year, Turnover is about

[15] We exclude funds with more than 5 days of flows missing in a given month t. If daily flows are missing for fewer than five days, we interpolate daily flows as follows. Suppose day d' to d'' are missing. We then define the total flow from day d' to $d''+1$ as:

$$Flow_{d':d''+1} = \ln\left(\frac{TNA_{d''+1}}{TNA_{d'-1} \times \prod_{s=d'}^{d''+1}(1 + R_s)}\right). \tag{5}$$

We allocate this flow equally to all days that are missing, such that $(Flow_s = Flow_{d':d''+1}/(d''+1-d')$ for $s = d', d'+1, ..., d''+1$.

[16] This robustness check is reported in Table D.1. The intuition is that the cross-sectional variation in (abnormal) fund returns is similar on days with extremely high versus low market returns. For instance, on days with a market return above and below its 95th and 5th percentile, respectively, the cross-sectional standard deviation of CAPM abnormal fund returns is roughly equal at about 48 bps (and this number is only slightly larger than what it is unconditionally: 39 bps).

65% on average, and the typical fund age is about 18 years. Log flows are negative on average, volatile, and left-skewed. Log weekly flows average -0.08%, which, combined with a standard deviation of 0.54%, gives an average weekly inflow of about $e^{-0.0008+\frac{1}{2}\times 0.0054} - 1 = 0.2\%$. Perhaps unsurprisingly, net returns and CAPM abnormal returns are volatile as well.

4. High-Frequency Flow-Performance Sensitivity

In this section, we study the high-frequency flow-performance relation. While previous literature mostly studies this relation at low frequency and focuses on non-linearity due to out- versus under-performing funds, we study this relation at higher frequency and focus on non-linearity due to the interaction of fund performance with the return of the aggregate market. Towards the end of this section, we study both non-linearities.

Let us start by introducing the basic flow-performance regression that we estimate:

$$Flow_{i,d(t)+1w} = \delta Rank_{i,d(t)} + \text{Controls} + \text{Fixed effects} + \epsilon_{i,d(t)+1w}. \tag{6}$$

Here, the left-hand side is the cumulative log flow in the five days after fund performance is realized on day d of month t. The right-hand side variables are defined as follows. $Rank_{i,d(t)}$ is the $[0,1]$-ranking of the fund based on either the simple return or CAPM abnormal return. The control variables include fund age, size, expense ratio, turnover, and the volatility of daily performance over the previous year, as well as lagged performance and flows. These lags are measured over the last week and year before the day we measure performance $d(t)$ (e.g., from $d(t)-5$ to $d(t)-1$ for the weekly lag), because that is the frequency of interest in our paper and in most previous work on flow-performance sensitivity, respectively.[17] We run

[17] We show in Table D.1 of the Online Appendix that our conclusions are robust to controlling for additional lags of flows and performance. In this table, we also show similar results from a two-stage Fama-MacBeth procedure. In the first cross-sectional stage, we regress flows on performance on each sample day. In the second time-series stage, we regress the estimated flow-performance sensitivities on the market return.

these regressions without and with style×time and fund fixed effects. The regression without fixed effects is interesting because investors may not be fully aware (at high frequency) of (i) the performance of other funds in the same style category and (ii) the unconditional performance of their fund. If they are fully aware, we should be interested in the net effect that partials out these fixed effects. Standard errors are two-way clustered at the fund and time level. Table III presents the coefficient estimates. We see that the coefficient estimates for the control variables are broadly consistent with previous work. For instance, larger and more expensive funds, as well as funds that underperform in the week and year before the day of interest d, receive smaller flows. Moreover, flows are quite persistent.

Our primary interest is in the response of flows to a single day of performance, which is significantly positive in all four specifications. For both performance measures and both without and with fixed effects, the coefficient on $Rank_{i,d(t)}$ equals about 1.5 bps and is strongly significant ($t > 6$). Given that the standard deviation of weekly flows equals 54 bps and the controls and fixed effects together explain about 40% of this variation, we have that a coefficient of 1.5 bps represents about 4% of the residual standard deviation of weekly flows ($= \frac{1.5}{\sqrt{54^2 \times (1-0.4)}}$). Although this effect may seem small economically, recall that no effect at all is a reasonable null: high-frequency flows and performance are considerably more noisy than the annual measures used in previous work. Moreover, funds generally do not advertise their (relative) performance at such high frequency (nor do financial services firms like Morningstar). We confidently reject this null in favor of positive sensitivity in weekly flows to daily performance. Comparing the t-statistics on past performance measured over different horizons, we further note that the contribution of daily past performance is statistically about as strong as the contribution of performance over the full week before, but weaker than the contribution of performance over the full year before.

4.1 Flow-performance sensitivity and market returns

As mentioned before, our main interest is in understanding whether this high-frequency sensitivity varies with the market return. To analyze such time variation, we estimate a conditional specification that interacts daily fund performance with the market return:

$$
\begin{aligned}
Flow_{i,d(t)+1w} &= \delta Rank_{i,d(t)} + \lambda(Rank_{i,d(t)} \times Rank_{MKT,d(t)}) + \beta Rank_{MKT,d(t)} \\
&\quad \text{Controls} + \text{Fixed effects} + \epsilon_{i,d(t)+1w} \text{ and} \qquad (7) \\
Flow_{i,d(t)+1w} &= \delta Rank_{i,d(t)} + \lambda_{Low}(Rank_{i,d(t)} \times D_{MKT,d(t),Low}) \\
&\quad + \lambda_{High}(Rank_{i,d(t)} \times D_{MKT,d(t),High}) + \text{Controls} + \text{Fixed effects} + \epsilon_{i,d(t)+1w}. \qquad (8)
\end{aligned}
$$

In the first equation, $Rank_{MKT,d(t)}$ is the $[0,1]$-ranking of the daily CRSP value-weighted market return (based on past daily returns from month $t-12$ to $t-1$) and in the second equation $D_{MKT,d(t),Low}$ is a dummy equal to one when the market return is below the 20th (above the 80th) percentile, based on the same historical comparison. Thus, the coefficients on the dummies measure the change in flow-performance sensitivity on bad and good days relative to a normal day with market return between the 20th and 80th percentile.

Table IV presents the coefficient estimates from these regressions. Because the coefficient estimates for the control variables are largely unchanged from Table III, we leave these out for brevity. We see that the estimated interaction effect (λ in Eq. (7)) is significantly negative in all specifications. This means that flows are significantly more sensitive to relative performance on days when the market return is lower. It is easy to see that this interaction effect is economically large because its coefficient estimate (λ) is similar in absolute magnitude to that of fund performance (δ). Thus, our estimates imply that for a one standard deviation decrease in $Rank_{MKT,d(t)}$, flow-performance sensitivity increases by about 20 to 30% across specifications. In fact, flows hardly respond to performance on days when the market return is unusually high. Consider the case of CAPM abnormal returns and fixed effects; the coefficient on fund performance ranking equals 2.9 bps ($t > 8$), and the coefficient on the interaction equals -2.9 bps ($t = -4.8$). Combining these coefficients, we see that when the market return is larger than all daily market returns over the last year ($Rank_{MKT,d(t)} = 1$), flows are not sensitive to relative performance at all. In contrast, when the market return is historically low ($Rank_{MKT,d(t)} = 0$), the high-frequency sensitivity of flows to performance is nearly double its unconditional level (compare to Table III above). We conclude that investors hardly react to relative fund performance when the market return is high, consistent with the idea that investors are generally not concerned with the performance of their fund on such days. In contrast, on bad days, when most funds generate a negative return, investors react strongly to relative performance. In Online Appendix A, we discuss additional evidence that shows that both retail and institutional investors' flows are significantly more sensitive to performance on bad days. This finding suggests that our results are not driven by investor characteristics, such as sophistication or investment horizon.

The regression with dummies (Eq. (8)) reported in Panel A of Table V provides additional insight. We see that λ_{High} is negative and significant in all specifications, and its magnitude almost completely offsets the estimated δ. Thus, flows are not sensitive to relative performance when the market return is above the 80th percentile. Instead, λ_{Low} is positive and significant in three out of four specifications and insignificant in the other. To understand the economics behind the estimated coefficients, let us consider the most conservative specification that measures performance using CAPM abnormal returns and includes all controls and fixed effects. In this specification, the sensitivity of flows to performance when the market return is in the lowest quintile is about 65% larger than when the market return falls in quintiles two to four and more than 100 times larger than when the market return falls in its highest quintile.

Another way to see the relatively strong flow-performance sensitivity on days that the market does poorly is by comparing the relative contribution of different days to the variation in weekly flows. Because the performance measure is rank-normalized, we have that $Var(Rank_{i,d(t)} \times D_{MKT,d(t),Low}) \approx Var(Rank_{i,d(t)} \times D_{MKT,d(t),High}) \approx \frac{1}{5} Var(Rank_{i,d(t)})$. Thus, the relative variance contribution of bad versus good days approximately equals $(\delta + \lambda_{Low})^2/(\delta + \lambda_{High})^2$ and that of bad versus normal days approximately equals $(\delta + \lambda_{Low})^2/(\delta^2 \times 3)$. We report these relative variance contributions in Panel B of Table V. These relative variance contributions equal 23,000 and 0.9 in the most conservative specification (with CAPM abnormal returns and all fixed effects), which means that bad days have an outsized impact on fund flows. One bad day contributes orders of magnitude more to flow variation than one good day and about as much as three normal days. Thus, relative to the average fund, a manager who outperforms (underperforms) on one bad day generates more inflow (outflow) than a manager who outperforms (underperforms) on multiple other days. This conclusion is robust in all other specifications except the one using simple returns and all fixed effects. In this specification, a bad day still contributes much more to flow variation than a good day (the relative contribution is 35), but about as much as a normal day.

One may be inclined to conclude that fund management companies should take the distinction between good and bad days into account in their hiring decisions. Indeed, a skilled manager who consistently outperforms on bad days is relatively valuable. However, it may also be that the performance ranking on bad days is mostly random, for instance, because fund managers cannot predict when a bad day will occur or because fund performance is relatively noisy on bad days. To understand which of these two cases is relevant empirically, we test in the next section whether relative performance on bad days is persistent. In the remainder of this section, we follow the large literature on flow-performance sensitivity (see the seminal work of Chevalier and Ellison, 1997; Sirri and Tufano, 1998) and ask whether sensitivity varies in the cross-section, that is, between out- and underperforming funds. We also analyze the implications of our findings for aggregate flows.

4.2 Flow-performance sensitivity in the cross-section

We expand Eqs. (7) and (8) as follows:

$$\begin{aligned}
Flow_{i,d(t)+1w} = {} & \delta_{0,L} D_{i,d(t),Low} + \delta_{0,H} D_{i,d(t),High} \\
& \delta_{1,L} Rank_{i,d(t),Low} + \delta_{1,M} Rank_{i,d(t),Mid} + \delta_{1,H} Rank_{i,d(t),High} + \\
& \text{Controls} + \text{Fixed effects} + \epsilon_{i,d(t)+1w} \text{ and} \qquad (9) \\
Flow_{i,d(t)+1w} = {} & \delta_{0,L} D_{i,d(t),Low} + \delta_{0,H} D_{i,d(t),High} + \\
& \delta_{1,L} Rank_{i,d(t),Low} + \delta_{1,M} Rank_{i,d(t),Mid} + \delta_{1,H} Rank_{i,d(t),High} + \beta Rank_{MKT,d(t)} + \\
& \lambda_{0,L}(D_{i,d(t),Low} \times Rank_{MKT,d(t)}) + \lambda_{0,H}(D_{i,d(t),High} \times Rank_{MKT,d(t)}) \\
& \lambda_{1,L}(Rank_{i,d(t),Low} \times Rank_{MKT,d(t)}) + \lambda_{1,M}(Rank_{i,d(t),Mid} \times Rank_{MKT,d(t)}) \\
& + \lambda_{1,H}(Rank_{i,d(t),High} \times Rank_{MKT,d(t)}) + \text{Controls} + \text{Fixed effects} + \epsilon_{i,d(t)+1w}. \qquad (10)
\end{aligned}$$

Starting with the first specification, $D_{i,d(t),Low}$ and $D_{i,d(t),High}$ are dummy variables that equal one when fund i's performance ranking on day $d(t)$ is in the lowest and highest quintile, respectively (i.e., $Rank_{i,d(t)} \leq 0.2$ and $Rank_{i,d(t)} \geq 0.8$); $Rank_{i,d(t),Low}$ is defined as $Rank_{i,d(t)} - 0.1$ for all funds with $Rank_{i,d(t)} \leq 0.2$; $Rank_{i,d(t),High}$ is defined as $Rank_{i,d(t)} - 0.9$ for all funds with $Rank_{i,d(t)} \geq 0.8$; and, $Rank_{i,d(t),Mid}$ is defined as $Rank_{i,d(t)} - 0.5$ for all remaining funds. With these definitions, the coefficients on the dummies $\delta_{0,L}$ and $\delta_{0,H}$ capture the marginal flow-performance sensitivity across performance ranking categories and the coefficients on the continuous variables $\delta_{1,L}$, $\delta_{1,M}$, and $\delta_{1,H}$ capture the flow-performance sensitivity within each performance ranking category. This specification is similar to, but more general than, the piecewise linear specification often studied in the literature.

The second specification is straightforward to interpret, noting that $Rank_{MKT,d(t)}$ is equal to zero (one) on days with the lowest (highest) market return relative to all days in the previous year. For $Rank_{MKT,d(t)} = 0$, the coefficients on the not-interacted dummies (e.g., $\delta_{0,L}$) and continuous variables (e.g., $\lambda_{1,L}$) capture the same effects as in Eq. (9). For $Rank_{MKT,d(t)} = 1$, these effects are captured by the sum of two coefficients. For instance, $\delta_{0,L} + \lambda_{0,L}$ capture the average flow to funds in the lowest performance ranking category (relative to funds in the mid category) on days when the market return is higher than all days in the previous year. On these days, $\delta_{1,L} + \lambda_{1,L}$ similarly captures the flow-performance sensitivity within funds in the lowest performance ranking category.

We present coefficient estimates for these regressions in Table VI. The evidence for the unconditional specification (Eq. (9)) indicates that the average flow to funds in the lowest (highest) quintile of performance is significantly lower (higher) than the average flow to funds in the mid quintiles. These differences are similar in absolute magnitude and range across specifications from -0.87 to -0.50 bps for the lowest quintile and from 0.19 to 0.70 bps for the highest quintile. Thus, flows are, on average, increasing across performance ranking categories. What about the flow-performance sensitivity within ranking categories? We see that the coefficient on the continuous ranking variables is positive in all three performance ranking categories. That said, across all four specifications, the coefficients are about 5 to 15 times larger for the Low and High ranking categories when compared to the Mid ranking category. For instance, when measuring performance using CAPM abnormal returns and including all fixed effects, flow-performance sensitivity equals 5.0 and 7.6 bps ($t > 4$) in the Low and High ranking categories but only 0.8 bps in the Mid ranking category. We thus conclude that flows are sensitive to performance also within ranking categories and significantly more so in the tails of the performance distribution.

To summarize these insights, we plot in Panel A of Figure 1 the predicted flow (with 95% confidence interval) from the unconditional model of Eq. (9) for funds with performance ranking ranging from 0 to 1. We normalize these flows such that the flow for the median fund (with $Rank_{i,d(t)} = 0.5$) equals 0. Looking from left to right, we broadly see that flows are increasing in performance, and this is due to both across- and within-ranking category effects. The within-ranking category effects are perhaps most surprising: While the line is rather flat for funds ranked between the 20th and 80th percentile (meaning that flows are not increasing in performance), the line is steeply upward sloping for both the High and Low quintile of funds (i.e., flows are significantly increasing in performance in the tails of the performance distribution). This result differs markedly from what is typically found in low-frequency data: a convex flow-performance relation that is due to monthly and annual flows responding only to past annual outperformance.

Let us turn to the conditional evidence from Eq. (10). Broadly, the coefficient estimates confirm the previous insight that flows are exceptionally sensitive to performance on days with relatively low market returns. In both the High and Low-performance ranking categories and in all four specifications, a one standard deviation decrease in the market return generates a significant increase in flow-performance sensitivity of about 18 to 36%. In the most conservative specification (last column), we have an increase in flow-performance sensitivity within the bottom quintile of underperforming funds of 25% (=−7.38 × −0.29/8.73). In turn, in the top quintile of outperforming funds, the regression estimates an increase in flow-performance sensitivity of 18% (=−7.07 × −0.29/11.14).

To accommodate further interpretation, we show what these coefficients jointly imply for flow-performance sensitivity conditional on market returns in Figure 1. In Panels B and C, we consider the case that the market return is either lower or higher than all market returns in the previous year ($Rank_{MKT,d(t)} = 0$ and $Rank_{MKT,d(t)} = 1$, respectively). In short, we see that the unconditional flow-performance relation documented in Panel A of Figure 1 is exacerbated on days with low market returns (Panel B). On these bad days, both the across and within effects for the High- and Low-performance ranking categories are about double what they are unconditionally. In contrast, these effects are small on days when the market return is exceptionally high (Panel C). Consider the across-performance ranking category effect first. For the average fund in the lowest (highest) quintile of performance, the average flow on the worst of days with $Rank_{MKT,d(t)}$ = 0 is -1.5 bps lower (0.9 bps higher) than for the average fund in the Mid ranking category. On the best of days with $Rank_{MKT,d(t)}$ = 1, both these differences are positive but small at less than 0.25 bps. The within effects are similar. On the worst of days, flows strongly increase in performance among funds in the Low- and High-performance ranking categories: from -2.3 bps for the worst-ranked fund to -0.6 bps for a fund ranked at the 20th percentile and from -0.2 bps for the fund ranked at the 80th percentile to 2.0 bps for the best-ranked fund. Again, these increases are much smaller on the best of days. The figure also shows that flows are relatively insensitive to performance among funds ranked in the middle quintiles, regardless of whether the market return is high or low. We conclude that flows respond to both out- and under-performance at high frequency and, in particular, on bad days.

4.3 Implications for aggregate flows

So far, we have identified how flows respond to relative performance in the cross-section. This response combines (i) reallocation of flows from underperforming to outperforming active US equity mutual funds and (ii) aggregate flows into or out of active US equity mutual funds. While it is hard to precisely quantify reallocations due to the lack of access to investors' portfolios, we can precisely quantify aggregate flows. To this end, we sum for each day d in the sample five-day dollar flows over all funds i and divide that by the sum of lagged TNA: $\frac{\sum_i (e^{Flow_{i,d(t)+1w}} - 1) TNA_{i,d(t)-1}}{\sum_i TNA_{i,d(t)-1}}$. We also study how each of the three performance groups contributes to this aggregate flow. To this end, we sum the dollar flows for those funds in the bottom quintile of performance (Low), the funds in the top quintile (High), or all other funds (Mid). To determine which funds belong in each group, we orthogonalize in the cross-section the two performance measures (i.e., both simple returns and CAPM abnormal returns) on bad days from the same set of style dummies and control variables used in the previous regressions. Then, we rank funds on residual bad day performance.

To quantify the response of each of these aggregate flow measures on bad days, we run the following time-series regression:

$$\sum_{X} \$Flow_{d(t)+1w} / \sum_{All} TNA_{d(t)} = \lambda_X \times D_{MKT,d(t),Low} + \text{Controls} + \epsilon_{X,d(t)+1w}, \tag{11}$$

where $X = \{All, Low, Mid, High\}$, $D_{MKT,d(t),Low}$ is a dummy equal to one when the market return on day d of month t is below the 20th percentile (relative to all market returns from month $t-12$ to $t-1$), and the standard errors are Newey-West with five daily lags. We control for lagged flows of All funds (over the last week and year) such that the coefficients for the Low, Mid, and High groups sum up to the coefficients for All funds. Note that the total TNA allocated to the High and Low groups is roughly equal over time. So, if flows are insensitive to relative performance and respond only to the performance of the market, we should find that the contribution of the High and Low groups to the total outflow is similar. This is not what we find in Table VII, which reports the coefficient estimates.

In the week after a day with a market return below its 20th percentile, 2.64 and 1.53 bps flow out of the active US equity mutual fund market (in the case of simple returns and CAPM abnormal returns, respectively).[18] Both these estimates are statistically significant and – given the size of the active US equity mutual fund market – economically large. For both performance measures, we see that the contribution to this aggregate flow from the subset of outperforming funds is small and insignificant. In contrast, both underperforming and funds in the middle-performance ranking group contribute significantly. In the case of simple returns (CAPM abnormal returns), the contribution of the Low group is about 10 times (3 times) as large as the contribution of the High group (both in absolute magnitude

[18]The difference between these numbers is due to the fact that the CAPM abnormal returns require pre-estimation of the fund's beta so that the sample ends up being one year shorter and slightly more funds drop out because of insufficient data to calculate beta.

and relative to the standard deviation of weekly flows). Further, taking into account that the Mid group contains three times as many funds as the other groups, we see that the contribution to the aggregate flow is monotonic from Low to High. In conclusion, funds experience outflows on bad days independent of their performance ranking. While relatively little money flows out of the best performers, consistent with the idea that their investors are generally happy and see little reason to act, a lot more money flows out of the worst performers.

In Online Appendix B, we study where the bad day flows out of active US equity mutual funds go. To this end, we use aggregate flow data across asset classes from Morningstar. Key findings include: (1) active US equity funds experience significant outflows averaging 438 million USD in the week after a bad day; (2) significant outflows also occur in other active equity fund categories as well as active corporate bond funds, reflecting broader market declines; (3) outflows from passive US equity funds are small and insignificant; and (4) there is a substantial and significant inflow of about 2.8 billion USD into money market funds. In particular, finding (3) is consistent with the idea that passive US equity funds are matched with passive investors that do not respond strongly to performance, even on bad days. Findings (1), (2) and (4) together suggest that outflows from risky active mutual funds largely shift into the least risky category —- money market funds -— following days with poor market returns.

To conclude this section, we have seen that flows are sensitive to performance at high frequency, and this sensitivity varies significantly in the time series. Sensitivity is larger on bad days with relatively low market returns and this ultimately leads to large outflows from especially underperforming active US equity mutual funds. An important question is whether these bad day flows represent dumb or smart money. To answer this question, we ask in the next sections whether performance on bad days is persistent and analyze how much bad days contribute to unconditional fund outperformance.

5. Skill versus luck: Persistence of bad day performance

In this section, we analyze the persistence of performance on bad days. Given that both market and fund returns are hard to predict at high frequency due to a low signal-to-noise ratio, a reasonable null hypothesis is that relative fund performance on bad days is mostly random. Under this null hypothesis, past performance on bad days does not predict future performance on bad days. Past performance is simply due to luck, and the response of flows to this performance represents "dumb money." If we can reject this null hypothesis and find that some managers are able to consistently outperform on bad days, this would support our "smart money" hypothesis. We would further like to assess if persistent outperformance is a sign of general skill that aligns with outperformance on other days or if it is a sign of specific bad day skill (recall the discussion in footnote 6).

To study these alternative hypotheses, we test whether fund performance on bad days is predictable by past performance on either bad or other days by running the regression:

$$\begin{aligned} Rank_{i,d(t),Bad} = \delta_B Rank_{i,t-1y,Bad} + \delta_O Rank_{i,t-1y,Other} + \\ \gamma \text{Controls} + \text{Fixed effects} + \epsilon_{i,d(t)}. \end{aligned} \tag{12}$$

A bad day is a day d in month t with a market return that is below the 5th percentile of market returns over the last year ($Rank_{MKT,d(t)} < 0.05$). $Rank_{i,d(t),Bad}$ is the $[0,1]$ performance ranking of funds on these bad days. Other days are all remaining days (with $Rank_{MKT,d(t)} \geq 0.05$). With these definitions, we focus on the relative fund performance on approximately the worst daily market return each month. Although the median distance between two bad days in our sample is 21 days, it is possible to have multiple bad days in month t, and each of these is included as a separate observation in the regression. To address autocorrelation, we double-cluster the standard errors at both the fund and day levels.[19]

On the right-hand side, $Rank_{i,t-1y,Bad}$ is the $[0,1]$-ranking of the fund based on its average performance (either simple fund return or CAPM abnormal return) on all bad days in the previous year from month $t-12$ to $t-1$. If we estimate $\delta_B > 0$, this would mean that performance on bad days is persistent, consistent with a story of skill. We also include past performance on other days, $Rank_{i,t-1y,Other}$, which is defined as the $[0,1]$-ranking of the fund based on its average performance on all other days over the previous year. Comparing the coefficient estimates on past bad and other day performance informs us about the relative importance of general and specific skill.

The general skill hypothesis means that all days are created equal, such that past performance on any day is informative about future performance. Under this hypothesis, we should find that $\delta_O > \delta_B > 0$, because $Rank_{i,t-1y,Other}$ ought to be a better proxy for general skill than $Rank_{i,t-1y,Bad}$. The reason is that there are relatively few bad days in a year and days with extreme factor returns are generally less informative about skill (see Franzoni and Schmalz, 2017). In contrast, the specific skill hypothesis predicts that $\delta_B > 0$ and $\delta_B > \delta_O$. The idea is that bad days are unique, such that they require a different set of skills to outperform than outperformance on the average day. As a result, performance on bad days is both persistent and significantly more informative than past performance on other days. In fact, depending on the specificity of the skills or portfolio positions needed to outperform on bad days, past performance on other days may be uninformative or even negatively correlated with future performance on bad days. The latter scenario applies, for instance, when a sufficient number of funds "pick up pennies in front of a steamroller:" they invest in strategies that do well on average, but strongly underperform on bad days, such as overweighting high beta, volatile or illiquid stocks.

[19]As in the previous section, these regressions control for a variety of fund characteristics, and we consider specifications with and without fixed effects (fund and style×day).

We further test whether persistence is driven by outperformance or underperformance. To do this, we convert the performance rankings on past bad days and other days into three performance ranking categories, as in the previous section, and run the following regression:

$$\begin{aligned} Rank_{i,d(t),Bad} = \delta_{B,L} D_{i,t-1y,Bad,Low} + \delta_{B,H} D_{i,t-1y,Bad,High} + \\ \delta_{O,L} D_{i,t-1y,Other,Low} + \delta_{O,H} D_{i,t-1y,Other,High} + \\ \text{Controls} + \text{Fixed effects} + \epsilon_{i,d(t)}, \end{aligned} \tag{13}$$

where $D_{i,t-1y,Bad,Low}$ ($D_{i,t-1y,Bad,High}$) is equal to one when $Rank_{i,t-1y,Bad} < 0.2$ ($Rank_{i,t-1y,Bad} > 0.8$) and analogously for other days. The constant in the regression absorbs the Mid-ranking category. If we estimate $\delta_{B,H} > 0$, this would indicate that outperformance on bad days is persistent, consistent with the idea that the funds in the highest quintile of past bad day performance are skilled. If this skill is specific to bad days, we should find that $\delta_{B,H} > \delta_{O,H}$. In turn, if this skill is general, we should find that $\delta_{B,H} < \delta_{O,H}$. Analogously, $\delta_{B,L} < 0$ indicates that underperformance on bad days is persistent, consistent with the idea that the funds in the lowest quintile of past bad day performance lack skill. If this is a lack of specific skill, we should find $\delta_{B,L} < \delta_{O,L}$; if this is a lack of general skill, we should find that $\delta_{B,L} > \delta_{O,L}$.

Comparing the coefficients for out- and underperformance also sheds light on a "learning hypothesis." If flows are unusually sensitive to performance on bad days, we should expect fund managers to be incentivized (by the fund management company) to learn from past underperformance to avoid such an event happening again. As a result, bad day underperformance should be less persistent than bad day outperformance, so $\delta_{B,H} + \delta_{B,L} > 0$. This learning hypothesis also interacts with the skill hypotheses. If bad days are special, learning would imply that $\delta_{B,L} > \delta_{O,L}$, because managers would learn more from their past performance on bad days. If all days are created equal, we should find that $\delta_{B,L} < \delta_{O,L}$, because managers would learn more from their past performance on all other days.

Table VIII presents the evidence from Eq. (12).[20] For both performance measures (net returns and CAPM abnormal returns), we see that δ_B is significantly positive in all four specifications (columns (1), (2), (5) and (6)) indicating that past performance on bad days ($Rank_{i,t-1y,Bad}$) predicts future performance. In the specification with CAPM abnormal returns and without fixed effects, the coefficient estimate implies that moving a fund from the 10th to the 90th percentile of historical performance on bad days increases the ranking of the fund on the next bad day by $0.8 \times 11\%$. The effect is halved when controlling for style×time and fund fixed effects ($0.8 \times 5\%$), which suggests that there is considerable persistence in bad day performance across styles and within funds. Similarly, the fact that the coefficient estimates are about 3 times larger when the performance ranking is based on simple net returns suggests that there is considerable persistence in performance due to variation in unconditional market exposure. In all cases, however, we confidently reject the null in favor of the alternative hypothesis that performance on bad days is predictable based on past bad day performance. Thus, the evidence supports the first prediction derived from our "smart money" hypothesis: The stronger response of flows to performance on bad days is smart, at least from the point of view of investors with high marginal utility on bad days. In the next section, we analyze the second prediction and ask whether these flows are also smart from the point of view of unconditional performance.

If some fund managers have the skill to outperform on bad days while others lack it, what else can we infer about the nature of this skill? To answer this question, we compare the coefficients on past performance on bad days versus other days. First, we observe that past performance on bad days provides more information for future bad day performance than past performance on other days. In all four specifications, the coefficient estimate for past bad

[20] For consistency, we study in this table the same set of funds and sample period as in Section 4.1. Table D.4 of the Online Appendix shows similar results when we extend our sample either in the time dimension (by adding daily fund return data back to January 2000 from CRSP) or the fund dimension (by including all funds, even those without daily TNA data in Morningstar).

day performance is economically and statistically much larger than that for past performance on other days ($\delta_B > \delta_O$). In fact, the estimated coefficient δ_O is significantly negative, indicating that funds that outperformed on other days in the past – arguably a better proxy for unconditional skill than past performance on bad days – tend to underperform on bad days in the future. This evidence is inconsistent with the general skill hypothesis. Rather, it suggests that outperforming on bad days requires specific (bad day) skill. This confirms one of the main takeaways from our paper: bad days are special. As discussed before, if outperforming on bad days relies on distinct investment and/or trading strategies, it may well be that a position that improves performance on other days ends up being detrimental to performance on bad days. In the next section, we quantify exactly how performance on bad versus other days contributes to the unconditional performance of funds.

Before doing so, let us discuss the remaining evidence in columns (3), (4), (7), and (8), which speaks to the learning hypotheses laid out above (see Eq. (13)). First, we see that the coefficients on the high and low past bad day performance dummies ($\delta_{B,H}$ and $\delta_{B,L}$) are statistically significant, have opposite signs, and are similar to each other in absolute magnitude in all specifications. Our most conservative estimates (using CAPM abnormal return and including fixed effects) indicate that the average fund in the highest (lowest) quintile of past performance on bad days is ranked higher (lower) than the average fund by a significant 1.4 (-2.0) percentage points. Thus, we reject the learning hypothesis that underperformance is less persistent than outperformance.

Furthermore, we find that the coefficient estimates for the high and low past other day performance dummies have the opposite sign to those for past bad day performance, such that we have $\delta_{B,H} > \delta_{O,H}$ and $\delta_{B,L} < \delta_{O,L}$, respectively. This evidence is again inconsistent with the general skill hypothesis. These results also reject a second feature of the learning hypothesis: if bad days are special, managers should learn more from their past underperformance on those special days than from past underperformance on other days. This is not what we find.

We conclude that performance on bad days is persistent, consistent with our "smart money" hypothesis. We reject two major hypotheses related to this persistence. First, there is little evidence of learning. Second, variation in general skill is not a likely explanation for variation in performance on bad days. Instead, our evidence supports the specific skill hypothesis, which asserts that bad days are unique and some fund managers possess the specific skill to outperform on these days, while others do not. In Online Appendix C we analyze data on the usage of derivatives reported in funds' NSAR filings. In short, we find that the specific bad day skill uncovered in this paper is not strongly correlated with reported usage of any derivatives. We therefore leave a more detailed analysis of the strategies employed by these skilled managers for future research. To highlight the economic importance of our findings, we now turn to a monthly sorting exercise that clearly separates fund managers with different skill sets.

6. Unconditional fund performance and (bad day) skill

In this section, we compare the monthly performance of portfolios of funds sorted on past performance on bad versus other days. To be precise, past bad day performance is measured as the average ranking of the fund based on its CAPM abnormal return on all bad days in the previous year (from $t-12$ to $t-1$). Past other day performance is measured as the average ranking on all other days in the previous year.

We start by sorting funds in decile portfolios on past other day performance, which we orthogonalize from style dummies to ensure our results are not driven by the unconditional outperformance of a particular style over the relatively short sample period we study. Each portfolio contains, on average, about 100 funds, and we value-weight the portfolios using fund TNA to ensure that our results are not driven by the smallest of funds. Recall that other day performance should be a relatively good proxy for general managerial skill. So, if unconditional performance is at all predictable from past performance, we should be able to pick it up with this sort. We next sort on past bad day performance. This sort is interesting because it is an open question how much unconditional (abnormal) return is generated by the skill to outperform on this small set of special days. We also orthogonalize past bad day performance from style dummies as well as from past other day performance. Because the correlation between the two types of skill is low (at -0.19), the latter has little impact on our results. The fact that past bad and other day performance are negatively correlated is another indication that these two are not likely proxies for general skill (i.e., a single, unobservable, one-dimensional measure of skill).

To start, Table D.2 in the Appendix shows that the two past performance measures have similar persistence. For instance, the probability that a fund currently ranked above the 90th percentile still ranks above the 90th percentile (above the median) one year later equals about 20% (75%), regardless of whether we sort on past bad or other day performance. Since performance is noisy, it is perhaps unsurprising that these measures are not more persistent. What is more surprising is that past bad day performance measured over about 5% of all days is about as persistent as past other day performance. The important question is then whether performance on bad days contains a strong enough signal that can be filtered through all the noise and how this performance signal compares to past other day performance.

We report average post-ranking monthly (abnormal) returns and various other statistics for the decile portfolios from both sorts in Table IX, respectively. Returns are net (after subtracting fees) and annualized (×12). Consistent with prior literature (e.g., Carhart, 1997), we see in both panels that all decile portfolios generate negative net CAPM (and FF4M) alphas.[21,22] Our main interest is in the variation in performance across active US equity mutual funds, and, in fact, we find large and significant variation.

In Panel A, we see that the decile of funds that performed best on other days generates an average return that is about 1.3% higher than the decile of funds that performed worst. Although this difference is economically large, it is not significant in our short 13-year sample. When we control for market exposure, the difference almost doubles to 2.4% and turns significant (t = 2.0). The difference is due to the fact that the Low portfolio underperforms relatively much more than the high portfolio: a significant -3.1% versus an insignificant -0.8%. We further see that CAPM alphas are roughly monotonically increasing from the low to the high portfolio. The high-minus-low difference is not due to different loadings on factor risk. The Fama-French-Carhart four-factor model (FF4M) alpha equals -2.3% for the Low portfolio versus -1.1% for the high portfolio, which translates to a difference of 1.2% that is marginally significant (t = 1.85). We thus conclude that past performance on other days provides a valuable signal about relative future fund performance. How does this signal compare to past bad day performance?

The evidence for past bad day performance is reported in Panel B and is surprisingly similar to what we saw in Panel A. The high decile, containing funds that outperformed the most on bad days in the past, outperforms the low decile by a marginally significant 2.0% (t = 1.69) in average return. The high-minus-low difference in CAPM and FF4M alphas is similarly large and significant at 2.3% (t = 1.83) and 1.5% (t = 2.11). The fact that average returns and alphas are similar in magnitude is consistent with skill: Past bad day

[21] Following Boguth et al. (2011) and Cederburg et al. (2018), we define the alpha as the time-series average of within-portfolio TNA-weighted abnormal fund returns $R_{i,t} - \beta_{i,t-1} R_{MKT,t}$, where $\beta_{i,t-1}$ is measured using all days in the year from month $t-12$ to $t-1$. This approach accommodates time variation in portfolio-level betas, which is important because (i) funds with different unconditional betas may end up in a given portfolio at different times and (ii) unconditional portfolio-level alphas are biased when betas correlate with the market risk premium or volatility. The four-factor alpha is defined analogously.

[22] Even mutual fund portfolios sorted on performance predicted using state-of-the-art machine learning methods underperform the four-factor benchmark over the recent sample period that we study (see Panel B of Figure 6 in Kaniel et al., 2023).

outperformers generate higher average returns without taking more market or factor risk.[23,24] As in Panel A, we further see that CAPM alphas are roughly monotonically increasing from the low to the high portfolio. Funds that did well on past bad days generate an economically small and statistically insignificant net CAPM alpha of about -0.3%. Funds that did poorly on past bad days do underperform significantly relative to the CAPM at a net alpha that is almost an order of magnitude larger: -2.6% ($t = -2.95$). Given the relatively short sample that we study, the fact that these alphas are significant at conventional levels is a testament to the strength of the return predictability that we find. Indeed, consider that the standard deviation of CAPM residual returns for both the high and low portfolio roughly equal 3% in both sorts. Thus, the differences in alphas we estimate translate to an improvement in the information ratio (from investing in the high rather than the low portfolio) of about 0.75; surely a large number economically. Overall, these results support the second prediction derived from our smart money hypothesis. The increased sensitivity of flows to performance on bad days represents "smart money," because these flows are correlated to unconditional fund performance. In fact, past bad day outperformers perform about as well unconditionally as active funds run by skilled managers that outperform on other days.

In the last rows of each panel, we also report the average fees and flows of the funds in each decile portfolio as well as the share of the active US equity mutual fund market TNA in each portfolio.[25] Because the high-minus-low difference in fees is economically small for both sorts, the difference in gross alpha is similar to what it is in net alpha. Next, we see that fund size is quite evenly distributed across the deciles in both sorts. If anything,

[23]Table D.5 of the Online Appendix shows that this evidence is robust when we extend our sample either in the time dimension (by adding daily fund return data back to January 2000 from CRSP) or the fund dimension (by including all funds, even those without daily TNA data in Morningstar).

[24]In Table D.6 of the Online Appendix, we show that the high-minus-low portfolio sorted on bad day performance generates a similarly large alpha of 1.9% ($t = 1.72$) in a regression on the market and the Frazzini and Pedersen (2014) betting against beta (BAB) factor. This result indicates that outperforming on bad days requires more sophistication than simply overweighting low beta stocks.

[25]Fees are per year, while flows are annualized (×12). Further, flows are from month t, while market shares are from $t-1$, thus excluding the impact of flows.

the outperforming decile contains slightly larger funds than the underperforming decile. Combining, our evidence implies that portfolio-level value-added, which measure of skill we define as (net CAPM α + Fees)×Market Share following Berk and Van Binsbergen (2015), is also increasing from the low to the high portfolio. In fact, value added is positive only for one decile portfolio in each sort, that is the high portfolio, and it is largest for the high portfolio sorted on past bad day performance. For this portfolio, value added equals approximately \$5.5 million per year ($=0.087\% \times \$1 trillion \times (-0.32\% + 0.94\%)$).

Finally, flows are monotonically increasing from low to high for both sorts. For the sort on past other day performance, the high-minus-low difference in flows is 31.4% (annualized). For the sort of past bad day performance, the difference in flows is smaller, though economically still meaningful at 9.7%. Given the aforementioned distribution of fund size across portfolios, these percentage flows represent large dollar values.

Overall, these results are consistent with the idea that skilled fund managers are compensated for relative outperformance through flows, not through higher fees. These results also provide important insights for our understanding of the low-frequency relation between performance and flows. Recall from the high-frequency evidence in Section 4 that weekly flows respond more strongly to relative performance on bad days than on other days. Instead, here we are studying the lower frequency relation between a full year of past performance on bad versus other days and future monthly flows. Yet, the evidence suggests once again that the relative contribution of bad days is large: even though other days contribute about 95% of the total annual performance of a fund, other day performance contributes only about three times more future monthly flow than bad day performance.

While both sets of days provide an equally valuable signal of future performance, we argue that these two signals measure different types of skill. To see some intuition for this conclusion, first recall that past bad and other day performance are weakly negatively correlated. As a result, the high portfolio contains completely different funds in the two sorts.[26] Second, we show in Table D.7 of the Online Appendix that sorting on the average of the two performance measures does not predict returns better than either individual measure. If past bad and other day performance are noisy proxies of the same underlying general skill and it is such general skill that leads to outperformance on all days, we should have found that the average predicts returns better. We also conclude that the signal derived from past bad day performance has a relatively high signal-to-noise ratio. Although bad days only account for about 5% of the days in our sample, performance on these days predicts future monthly fund returns about as well as the remaining 95% days.

To conclude this section, we return to the daily frequency and ask which type of days drive the relative outperformance of managers with bad and other day skill. To this end, we regress daily CAPM abnormal portfolio returns on a bad day indicator that is equal to one on a day d in month t with a market return below the 5th percentile of market returns over the last year:[27]

$$AR_{p,d(t)} = \alpha_{p,0} + \alpha_{p,B} I_{Rank_{MKT,d(t)}<0.05} + \epsilon_{p,d(t)}. \tag{14}$$

We report the coefficient estimates for this regression for all portfolios sorted on past bad and other day performance in Table X. We multiply each daily return by 12 for the sake of comparison to Table IX. t-statistics are based on Newey-West standard errors with five daily lags.

First, we see that sorting on past bad day performance leads to large variation across portfolios in future performance on bad days. In contrast, there is little variation in future

[26] Only about 12.5% of the funds in the high portfolio sorted on past other day performance overlap with the funds in the high portfolio sorted on past bad day performance. The same result holds for the low portfolio.

[27] For all days d in month t, the daily abnormal return of a fund equals $R_{i,d(t)} - \beta_{i,t-1} R_{MKT,d(t)}$, where $\beta_{i,t-1}$ is measured using all days in the year from month $t-12$ to $t-1$. In this way, we account for the fact that portfolio-level betas vary significantly over time (see footnote 21). For instance, the standard deviation of the monthly beta for the high-minus-low portfolio sorted on bad day skill is economically large at 0.125. If we would instead regress daily portfolio (abnormal) returns on the daily market return and its interaction with the bad day dummy, we would be ignoring this variation. Moreover, as already shown in Pfleiderer and Bhattacharya (1983), such a regression can be severely biased if funds change their betas at higher-than-daily frequency.

performance on other days. To be precise, average abnormal returns on bad days are almost monotonically increasing from the low to high portfolio, from a significantly negative -1% to a significantly positive 0.7%. The difference is large and significant at 1.7%. In contrast, average abnormal returns on other days are mostly flat, and the high-minus-low difference is small and insignificant at 0.01%. Combined with the fact that there is on average one bad day per month, these results suggest that virtually all of the difference in monthly CAPM abnormal return we saw in Panel B of Table IX is earned on that single bad day. Surely, these managers are skilled, and, in fact, this skill is specific.[28]

To see this, consider also the sorting exercise on past performance on other days. In this case, we find large variation across portfolios in future performance on both types of days. On bad days, the high portfolio significantly underperforms the low portfolio by about -1.3%. In turn, the high portfolio significantly outperforms on other days by about 0.19%. Thus, managers with the skill to outperform on other days actually earn more than 100% of their total abnormal return on these other days, because they underperform on bad days.

We conclude that fund managers who outperform on bad days have specific bad day skill. Fund managers that outperform on other days are unable to cushion infrequent, large drops in the market, but these fund managers outperform by a small amount on all the remaining days that are not so bad. While the performance of managers with other day skill is consistent with a simple strategy of selling insurance for downside risk, the performance of managers with bad day skill suggests their strategies are much more sophisticated than simply buying such insurance. Indeed, such strategies would underperform on other days. We thus uncover a different and novel distinction between the skills of active managers.

[28]A related hypothesis is that outperformance on bad days avoids outflows and therefore the need to sell stocks in a down market. This hypothesis implies that underperforming on a bad day leads to outflows that cause somewhat persistent underperformance. We test this hypothesis in Table D.3. We show that the high-minus-low difference drops quickly from a significant 1.67% on bad days, to an insignificant 40 bps ($t = 1.29$) the day after, and virtually zero in days two to five after a bad day. Thus, bad day outperformers realize most of their unconditional monthly outperformance on bad days or quickly after, inconsistent with the idea that it is the lack of outflows that drives their outperformance.

Consider, for instance, Kacperczyk et al. (2014), who argue that the same generally skilled fund managers switch between market timing and selection over the business cycle. We instead argue that relative outperformance on bad days requires specific skill, and there is no evidence to suggest that there are many generally skilled fund managers that outperform on both bad and other days.

7. Conclusion

We study when investors care about fund performance using high-frequency data on fund flows and market returns. We find that weekly flows strongly respond to daily performance, especially on days with unusually low market returns (bad days). The stronger flow-performance sensitivity on bad days aligns with asymmetric attention from investors who act on relative fund performance when the average fund performs poorly. Unlike existing low-frequency evidence showing that investors mostly respond to outperformance ("convexity"), we find that flows significantly respond to both out- and underperformance on bad days.

Consistent with a "smart money" hypothesis, we find that outperformance on bad days is persistent and significantly contributes to unconditional fund outperformance. Fund managers who outperform on the 5% of worst market days generate as much future outperformance as those who outperform on the other 95% of days. Since there is little overlap between these two sets of fund managers, we conclude that outperformance on bad days requires specific skill that is distinct from general skill. We find no evidence to suggest that there are many generally skilled fund managers that outperform on both bad and other days.

Our study uses relatively high-frequency data to reveal a new set of facts about investor behavior in the mutual fund industry and the distinct skills fund managers possess. We argue that distinguishing days with unusually low market returns from other days is important for management companies, portfolio managers, and investors alike. Our study opens many avenues for future research. For instance, how do fund managers with bad day skills consistently outperform without compromising their overall performance? Is it a particular form of market timing, where skilled managers see bad days coming? Is it an ingenious form of stock-picking, where skilled managers select stocks with low downside betas that still have high returns? Are skilled managers able to use derivatives at relatively low cost? Or, do skilled managers respond faster to bad shocks due to smart stop-loss strategies and/or better trading facilities and broker connections? Since (i) extreme market returns are hard-to-predict at high frequency, (ii) the decile portfolio containing the most skilled managers only barely outperforms the unconditional CAPM in gross terms, and (iii) derivative usage is largely uncorrelated to performance on bad days, we believe the last of these explanations is most plausible. Future versions of this paper will analyze the fast-response hypothesis in more detail.

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Figure 1: **Flow-Performance Sensitivity and Market Returns**
This figure presents the additional flow (relative to the median fund) a fund receives as a function of its performance ranking between 0 and 1. We report these flows for our unconditional specification of Equation (6) (Panel A) as well as for the conditional specification of Equation (7) (Panels B and C). For the conditional specification, we distinguish between a day where the market return is historically low versus high ($Rank_{MKT,d(t)} = 0$ versus $Rank_{MKT,d(t)} = 1$). We report results for the most conservative setup using CAPM abnormal returns and including a range of controls and fixed effects (for which the coefficient estimates are reported in columns (7) and (8) of Table VI). We also plot the 95% confidence intervals.

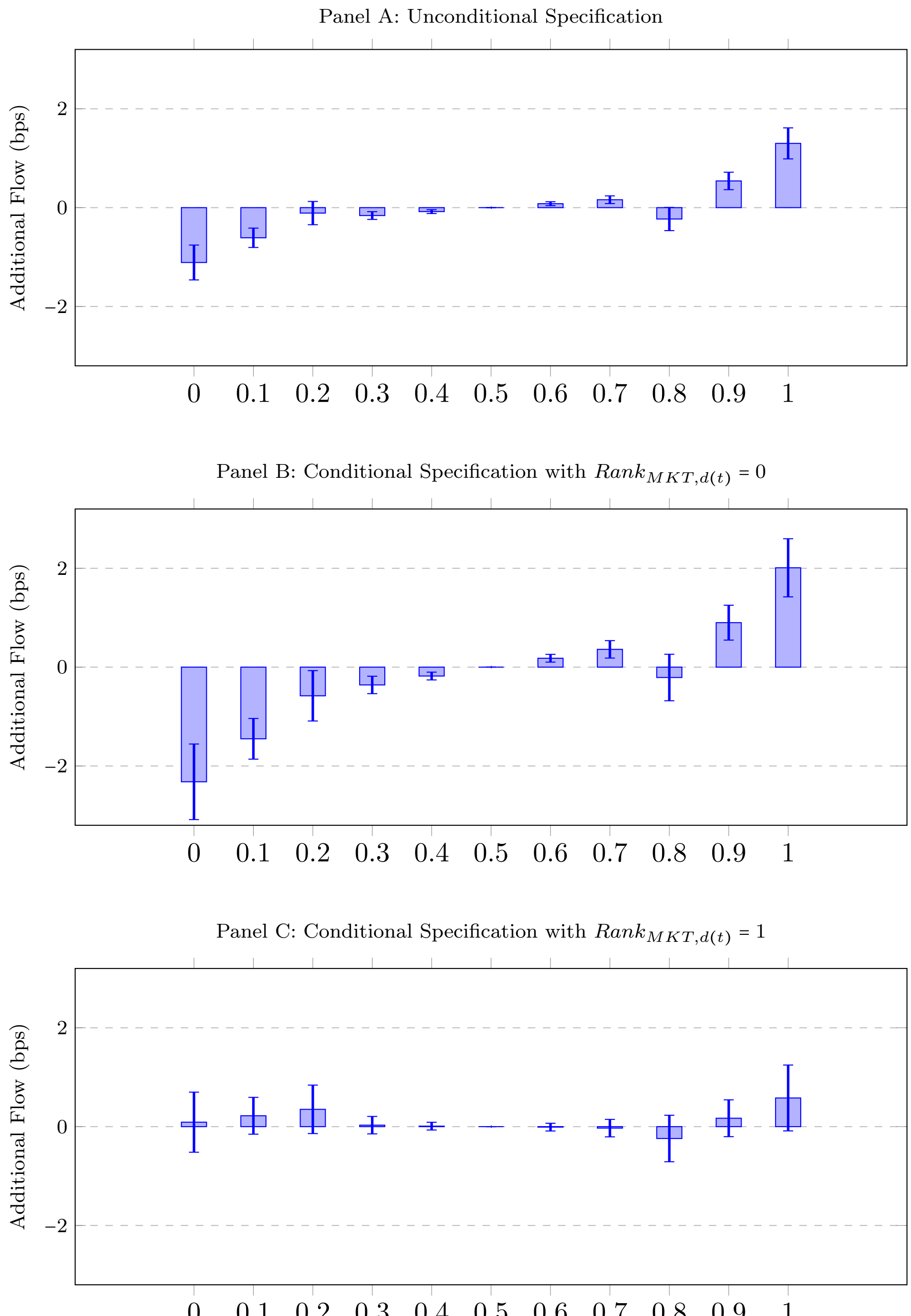

Table I: **Summary Statistics**

This table reports summary statistics for the main variables used in our analysis. Panel A presents (log) flows (see Eq. (3)) and performance variables aggregated at the daily, weekly, and yearly frequency. Net return is fund gross return minus fees (divided by 252 at the daily frequency, for instance). CAPM abnormal return is the net return in excess of the risk-free rate minus the fund's market beta (estimated using a one-year historical window of daily returns) times the excess market return. Panel B reports the control variables. These include the volatility of net (abnormal) returns over the past year, total net assets (TNA) and fund age (observed daily), and fund expense ratio and turnover (observed monthly). We also report the average number of funds per day and the unique number of funds over the whole sample. The sample period in all of our tests runs from August 2008 to June 2022.

Variable	Mean	SD	p(25)	p(50)	p(75)	N
Panel A: Flows and Performance						
Flow (% day)	-0.01	0.16	-0.06	-0.01	0.03	3,500,271
Flow (% week)	-0.08	0.54	-0.31	-0.10	0.11	3,500,271
Flow (% year)	-3.62	16.09	-12.48	-5.20	2.62	3,500,271
Net Return (% day)	0.04	1.41	-0.53	0.09	0.69	3,500,271
Net Return (% week)	0.17	2.68	-1.06	0.39	1.67	3,500,271
Net Return (% year)	8.41	18.61	0.00	10.42	19.47	3,500,271
CAPM Abnormal Return (% day)	-0.01	0.39	-0.20	-0.01	0.19	3,081,213
CAPM Abnormal Return (% week)	-0.03	0.75	-0.38	0.00	0.33	3,500,271
CAPM Abnormal Return (% year)	-1.42	5.89	-3.94	-0.38	1.39	3,500,271
Panel B: Control Variables						
Vol Net Return (% year)	1.30	0.70	0.84	1.06	1.49	3,495,926
Vol Abnormal Return (% year)	0.34	0.17	0.22	0.31	0.42	3,095,857
TNA ($M)	1241.18	2601.99	104.10	338.38	1148.88	3,500,271
Expense Ratio (% year)	1.09	0.30	0.91	1.08	1.26	167,297
Turnover (% year)	64.36	50.96	28.00	51.00	85.57	167,297
Fund Age (Years)	18.06	12.66	9.42	15.58	22.83	167,297
Number of Funds per Day	999					
Number of Unique Funds	1,967					

Table II: **Financial Website Visits and Market Returns**

This table reports the coefficient estimates from Equations (1) and (2). We regress the log of total visits $H = 1, 3, 5$ days ahead ($Visits_{j,d(t)+H}$) to fifteen financial websites ($j = 1 : 15$) from SimilarWeb, Ltd. over the period February 2019 to February 2024 on the stock market return and squared stock market return on day $d(t)$. $D_{MKT,d,low}$ ($D_{MKT,d,High}$) is a dummy that equals one when the market return on day $d(t)$ is below the 20th (above the 80th) percentile of returns over the past year (from months $t - 12$ to $t - 1$). The regressions control for lagged visits $Visits_{j,d(t)}$ as well year×day-of-the-week×website fixed effects.

	1 Day		3 Days		5 Days	
	(1)	(2)	(3)	(4)	(5)	(6)
MKT_d	-0.241		-0.593		-0.555	
	(-1.847)		(-2.659)		(-2.419)	
MKT_d^2	0.951		6.765		4.387	
	(0.396)		(1.915)		(1.219)	
$D_{MKT,d,Low}$		0.007		0.023		0.019
		(1.291)		(2.517)		(2.290)
$D_{MKT,d,High}$		-0.008		-0.016		-0.014
		(-1.475)		(-1.562)		(-1.514)
Lag		0.859		0.762		0.720
		(87.497)		(51.448)		(47.535)
R^2	0.993	0.993	0.986	0.986	0.986	0.986
N	18,490	18,490	18,490	18,490	18,490	18,490
Year×Day-of-the-Week×Website	✓	✓	✓	✓	✓	✓

TABLE III: **High-Frequency Flow-Performance Sensitivity**

This table reports the unconditional flow-performance sensitivity as estimated using Equation (6). We regress weekly flows (from $d(t)+1$ to $d(t)+5$) on rank-normalized performance ($Rank_{i,d(t)}$ ranges from $[0,1]$ on each sample day $d(t)$) over the period from July 2008 to June 2022. We consider both net returns and abnormal returns to measure performance. We control for fund size, age, expense ratio, turnover, volatility of past performance, and flows and performance measured over the past week and year. All controls are lagged and observable as of day $d(t)-1$. Columns (2) and (4) also control for style×day and fund fixed effects. We present t-statistics based on fund and day clustered standard errors in parentheses.

	Net Return		CAPM Abnormal Return	
	(1)	(2)	(3)	(4)
$Rank_{i,d(t)}$	1.86	1.38	1.27	1.43
	(8.49)	(6.76)	(6.27)	(7.77)
TNA	-0.89	-5.93	-0.78	-5.24
	(-14.86)	(-22.66)	(-12.36)	(-19.36)
Age	-0.99	-6.19	-0.01	0.39
	(-6.91)	(-7.51)	(-0.09)	(0.49)
Expense Ratio	-1.67	-1.66	-1.41	-1.54
	(-4.54)	(-1.26)	(-3.55)	(-1.26)
Turnover	-0.01	0	-0.01	0
	(-4.71)	(0.63)	(-4.56)	(0.28)
Vol. Perf	1.52	-4.83	5.49	1.91
	(4.95)	(-4.48)	(7.65)	(0.92)
Flows -1Y	0.01	0.01	0.01	0.01
	(67.66)	(60.01)	(63.04)	(56.44)
Perf -1Y	0.15	0.64	0.64	1.33
	(14.34)	(24.49)	(28.75)	(33.31)
Flows -1W	0.36	0.32	0.33	0.29
	(51.89)	(49.34)	(46.16)	(42.29)
Perf -1W	0.96	0.9	1.16	0.56
	(10.09)	(7.11)	(8.08)	(3.78)
Constant	-8.73	-8.49	-8.3	-7.91
	(-43.24)	(-85.03)	(-46.06)	(-78.81)
N	3,495,925	3,495,925	3,495,925	3,495,925
R^2	0.37	0.41	0.38	0.41
Style×Day		✓		✓
Fund		✓		✓

TABLE IV: **Flow-Performance Sensitivity and Daily Market Returns**

This table is analogous to Table III above, but now we report the conditional flow-performance relation as estimated using Equation (7). We regress weekly flows (from $d(t)+1$ to $d(t)+5$) on rank-normalized performance ($Rank_{i,d(t)}$ ranges from $[0,1]$ on each sample day $d(t)$). Still, now we interact fund performance with the market return ($Rank_{MKT,d(t)}$ ranges from $[0,1]$, and this ranking is based on a comparison to all daily returns over the past year). The last row reports the marginal effect of a one standard deviation increase in the market return on the flow-performance sensitivity (see Section 4.1 for more detail).

	Net Return		CAPM Abnormal Return	
	(1)	(2)	(3)	(4)
$Rank_{i,d(t)}$	3.96	2.07	2.6	2.87
	(9.41)	(5.32)	(6.66)	(8.03)
$Rank_{MKT,d(t)}$	7.35		4.53	
	(10.5)		(8.03)	
$Rank_{i,d(t)} \times Rank_{MKT,d(t)}$	-4.39	-1.37	-2.67	-2.87
	(-6.3)	(-2.07)	(-4.3)	(-4.78)
N	3,495,926	3,495,926	3,495,926	3,495,926
R^2	0.37	0.41	0.38	0.41
Controls	✓	✓	✓	✓
Style×Day		✓		✓
Fund		✓		✓
Marginal effect	-32%	-19%	-30%	-29%

Table V: **Flow-Performance Sensitivity and Low vs High Market Returns**
This table is analogous to Table III above, but now we report the conditional flow-performance relation as estimated using Equation (8). In Panel A, we report coefficient estimates from regressing weekly flows (from $d(t)+1$ to $d(t)+5$) on rank-normalized performance ($Rank_{i,d(t)}$ ranges from $[0,1]$ on each sample day $d(t)$). Still, now we interact fund performance with a dummy $D_{MKT,d(t),Low}$ ($D_{MKT,d(t),High}$) that is equal to one when the market return on day $d(t)$ is below the 20th (above the 80th) percentile of returns over the past year. Panel B reports the contribution of bad days to the variation in weekly flows relative to normal and good days (see Section 4.1 for more detail).

	Net Return		CAPM Abnormal Return	
	(1)	(2)	(3)	(4)
	Panel A: Coefficient Estimates			
$Rank_{i,d(t)}$	1.74	1.69	1.35	1.53
	(7.81)	(7.69)	(6.05)	(7.39)
$D_{MKT,d(t),Low}$	-3.04		-2.47	
	(-5.68)		(-5.82)	
$D_{MKT,d(t),High}$	2.95		1.14	
	(7.09)		(3.13)	
$Rank_{i,d(t)} \times D_{MKT,d(t),Low}$	1.95	-0.07	0.84	1.0
	(4.3)	(-0.15)	(1.84)	(2.45)
$Rank_{i,d(t)} \times D_{MKT,d(t),High}$	-1.8	-1.42	-1.29	-1.51
	(-4.18)	(-3.33)	(-3.24)	(-3.81)
N	3,495,926	3,495,925	3,077,229	3,077,229
R^2	0.37	0.41	0.38	0.41
Controls	✓	✓	✓	✓
Style×Day		✓		✓
Fund		✓		✓
	Panel B: Relative Variance Contribution			
Low vs. Normal	1.5	0.3	0.9	0.9
Low vs. High	3841.3	35.1	1451.8	22992.5

Table VI: **Flow-Performance Sensitivity in the Cross-section**

This table is analogous to Table III above, but now we allow the flow-performance relation to vary with both market returns as well as across fund performance quintiles. We estimate a flexible model that is more general than a standard piecewise linear specification. We report estimates from two different regressions. First, columns (1), (3), (5), and (7) report the coefficient estimates from Equation (9), obtained by regressing weekly flows on dummy variables $D_{i,d(t),Low}$ and $D_{i,d(t),High}$ that equal one if fund i's performance ranking on day $d(t)$ is in the lowest and highest quintile, respectively; on $Rank_{i,d(t),Low}$ (defined as $Rank_{i,d(t)} - 0.1$ for all funds with $Rank_{i,d(t)} \leq 0.2$); on $Rank_{i,d(t),High}$ (defined as $Rank_{i,d(t)} - 0.9$ for all funds with $Rank_{i,d(t)} \geq 0.8$); and on $Rank_{i,d(t),Mid}$ (defined as $Rank_{i,d(t)} - 0.5$ for all for all remaining funds). Second, columns (2), (4), (6), and (8) report coefficient estimates from Equation 10, which interacts these dummies and these continuous ranking variables with the market ranking variable $Rank_{MKT,d(t)}$. We refer the interested reader to Figure 1 to accommodate the interpretation of these estimates.

	Net Return				CAPM Abnormal Return			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$D_{i,d(t),Low}$	-0.82	-2.44	-0.5	-1.2	-0.87	-1.8	-0.61	-1.45
	(-6.59)	(-8.91)	(-4.55)	(-5.31)	(-7.55)	(-7.86)	(-6.12)	(-6.9)
$D_{i,d(t),High}$	0.7	1.27	0.61	0.72	0.19	0.4	0.54	0.9
	(6.12)	(6.14)	(5.82)	(3.7)	(1.8)	(2.04)	(5.82)	(5)
$Rank_{i,d(t),Low}$	3.86	16.09	5.07	14.22	8.89	12.9	5.02	8.73
	(2.14)	(3.45)	(3.94)	(4.96)	(6.69)	(4.76)	(4.3)	(3.4)
$Rank_{i,d(t),Mid}$	0.74	1.61	0.6	0.42	0.58	1.43	0.82	1.78
	(2.94)	(2.56)	(2.76)	(0.92)	(2.53)	(2.98)	(3.93)	(4.1)
$Rank_{i,d(t),High}$	12.9	15.62	9.07	15.94	5.22	8.47	7.64	11.14
	(6.98)	(5.33)	(7.56)	(6.93)	(4.17)	(3.47)	(7)	(5.5)
$Rank_{MKT,d(t)}$		4.72				2.91		
		(7.86)				(6.05)		
$D_{i,d(t),Low} \times Rank_{MKT,d(t)}$		3.25		1.35		1.86		1.67
		(7.59)		(3.63)		(5.24)		(4.86)
$D_{i,d(t),High} \times Rank_{MKT,d(t)}$		-1.2		-0.18		-0.43		-0.73
		(-3.44)		(-0.53)		(-1.27)		(-2.26)
$Rank_{i,d(t),Low} \times Rank_{MKT,d(t)}$		-19.27		-17.63		-7.94		-7.38
		(-2.65)		(-3.74)		(-1.91)		(-1.81)
$Rank_{i,d(t),Mid} \times Rank_{MKT,d(t)}$		-1.76		0.37		-1.71		-1.91
		(-1.71)		(0.45)		(-2.08)		(-2.47)
$Rank_{i,d(t),High} \times Rank_{MKT,d(t)}$		-9.6		-12.46		-6.56		-7.07
		(-1.56)		(-3.37)		(-1.56)		(-1.92)
N	3,495,926	3,495,926	3,495,925	3,495,925	3,077,229	3,077,229	3,077,229	3,077,229
R^2	0.37	0.37	0.41	0.41	0.38	0.38	0.41	0.41
Controls	✓	✓	✓	✓	✓	✓	✓	✓
Style×Day			✓	✓			✓	✓
Fund			✓	✓			✓	✓

Table VII: **Aggregate Fund Flows and Market Returns**

This table reports coefficient estimates from Equation (11). We regress aggregate weekly flows (from $d(t)+1$ to $d(t)+5$) for four groups of funds (all funds, funds in the bottom quintile of performance on day $d(t)$, funds in the mid quintiles, and funds in the top quintile) on a dummy that equals one when the market return on day d of month t is below the 20th percentile relative to all daily market returns from month $t-12$ to $t-1$. We control for lagged weekly and yearly flows for all funds, such that the coefficients across the three other groups sum up to those of all funds. We present t-statistics based on Newey-West standard errors with five lags in parentheses. The last two rows report the mean and standard deviation of aggregate weekly flows.

	Net Return				CAPM Abnormal Return			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	All funds	Low	Mid	High	All funds	Low	Mid	High
Constant	-2.66	-0.53	-1.59	-0.54	-2.51	-0.59	-1.45	-0.47
	(-6.73)	(-6.33)	(-6.57)	(-6.34)	(-8.73)	(-9.66)	(-7.94)	(-7.28)
$D_{MKT,d(t),Low}$	-2.64	-0.93	-1.63	-0.08	-1.53	-0.49	-0.88	-0.16
	(-4.25)	(-6.44)	(-4.37)	(-0.52)	(-4.04)	(-5.15)	(-3.65)	(-1.58)
Lagged Flow (Year)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	(3.43)	(3.02)	(3.33)	(3.36)	(4.05)	(2.73)	(4.30)	(3.56)
Lagged Flow (Week)	0.52	0.10	0.31	0.10	0.57	0.11	0.34	0.11
	(6.70)	(6.66)	(6.73)	(6.36)	(11.53)	(12.07)	(10.95)	(10.76)
R^2	0.33	0.24	0.30	0.24	0.40	0.27	0.36	0.26
N	3,500	3,500	3,500	3,500	3,311	3,311	3,311	3,311
Mean	-6.99	-1.47	-4.20	-1.32	-6.74	-1.44	-4.04	-1.26
Standard Deviation	11.38	2.69	7.12	2.64	9.53	2.24	6.16	2.26

TABLE VIII: **Persistence of Bad vs Other Days Performance**

In this table, we report coefficient estimates for the models that test if performance on bad days is persistent. We report estimates from two different regressions. First, columns (1), (2), (5), and (6) report results from Equation (12), which regresses performance on bad days on past performance on bad days ($Rank_{i,t-,Bad}$) and on other days ($Rank_{i,t-,Other}$). A bad day is a day $d(t)$ with a market return that is below the 5th percentile of market returns over the past year (from months $t-12$ to $t-1$). $Rank_{i,t-,Bad}$ ($Rank_{i,t-,Other}$) is the average performance ranking of the fund on bad days (non-bad days) in this past year. Second, columns (3), (4), (7), and (8) report results from Equation 13, which regresses performance on bad days on a set of Low- and High-performance dummies that equal one when the average performance ranking of fund i overall bad or other days over the past year is below the 20th and above the 80th percentile, respectively. In all specifications, we use the same controls as in Table III. Columns (2), (4), (6), and (8) also control for style×day and fund fixed effects. We present t-statistics based on fund and day clustered standard errors in parentheses.

	Net Return				CAPM Abnormal Return			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$Rank_{i,t-1y,Bad}$	38.28	14.20			10.87	4.98		
	(16.84)	(7.26)			(4.2)	(3.24)		
$Rank_{i,t-1y,Other}$	-12.11	-4.74			-2.76	-2.98		
	(-4.09)	(-3.53)			(-0.98)	(-2.25)		
$D_{i,t-1y,Bad,Low}$			-12.78	-2.54			-3.85	-2.04
			(-13.42)	(-5.13)			(-4.02)	(-3.98)
$D_{i,t-1y,Bad,High}$			17.66	4.45			4.92	1.39
			(22.31)	(7.58)			(3.93)	(2.13)
$D_{i,t-1y,Other,Low}$			6.93	1.90			1.96	0.99
			(7.33)	(4.41)			(1.7)	(2.06)
$D_{i,t-1y,Other,High}$			-5.56	-1.14			-0.83	-1.27
			(-4.27)	(-2.66)			(-0.69)	(-2.69)
TNA	-0.26	-1.34	-0.36	-1.45	-0.07	-0.67	-0.07	-0.65
	(-2.88)	(-5.46)	(-3.48)	(-5.63)	(-0.76)	(-2.38)	(-0.68)	(-2.31)
Age	0.34	-0.24	0.32	-0.37	-0.27	0.35	-0.34	0.27
	(1.65)	(-0.39)	(1.33)	(-0.55)	(-1.14)	(0.56)	(-1.36)	(0.42)
Exp. Ratio	-0.95	-0.93	-1.74	-1.00	-0.05	-1.12	0.04	-1.03
	(-1.19)	(-1)	(-2.02)	(-0.99)	(-0.06)	(-1.12)	(0.04)	(-1.01)
Turn.	-0.01	-0.01	-0.02	-0.01	0.02	0.01	0.02	0.01
	(-1.59)	(-2.22)	(-3.64)	(-2.81)	(3.02)	(2.27)	(3.09)	(2.27)
Vol. Perf	-2.93	-43.21	-4.83	-52.94	11.91	18.84	12.57	19.28
	(-3.83)	(-7.44)	(-4.83)	(-9.41)	(3.13)	(3.1)	(3.29)	(3.14)
Flows -1Y	0.01	0.01	0.02	0.01	-0.01	-0.03	-0.01	-0.03
	(1.04)	(1.12)	(1.31)	(1.28)	(-1.02)	(-2.05)	(-0.92)	(-2.06)
Flows -1M	0.24	-0.01	0.23	-0.04	0.07	0.00	0.08	0.00
	(1.81)	(-0.09)	(1.67)	(-0.43)	(0.48)	(0.03)	(0.59)	(-0.01)
Flows -1W	0.62	0.94	0.67	0.92	0.48	1.09	0.46	1.08
	(2.05)	(5.26)	(2.18)	(5.16)	(1.32)	(5.41)	(1.29)	(5.36)
Constant	36.08	34.79	47.42	36.64	46.75	49.75	50.38	50.95
	(15.29)	(20.5)	(116.75)	(26.77)	(21.19)	(42.42)	(174.37)	(310.09)
N	164,808	164,796	164,808	164,796	153,846	153,837	153,846	153,837
R^2	0.23	0.55	0.20	0.54	0.02	0.41	0.02	0.41
Style×Day		✓		✓		✓		✓
Fund		✓		✓		✓		✓

TABLE IX: **Unconditional Fund Performance Predictability**

This table reports results for decile portfolios of funds sorted at the end of each month on past CAPM abnormal return performance on other days (Other day skill, Panel A) and bad days (Bad day skill, Panel B). In each month, past performance is orthogonalized from style dummies. We report TNA-weighted average returns as well as CAPM and Fama-French-Carhart four-factor model abnormal returns (see footnote 21). These performance measures are annualized (×12), and t-statistics are based on Newey-West standard errors with 1 monthly lag. We further report average fees and flows (also annualized) as well as the fraction of total active US equity mutual fund TNA allocated to each portfolio.

	Low	2	3	4	5	6	7	8	9	High	High-Low
					Panel A: Past performance on Other days						
Avg. Ret.	11.87	12.14	12.80	12.49	12.90	12.36	13.17	12.97	13.19	13.16	1.29
	(2.64)	(2.81)	(3.02)	(2.89)	(3.11)	(3.00)	(3.19)	(3.20)	(3.36)	(3.31)	(1.05)
CAPM α	-3.14	-2.67	-1.90	-2.04	-1.63	-2.01	-1.35	-1.42	-1.13	-0.77	2.37
	(-3.20)	(-3.23)	(-2.59)	(-2.76)	(-3.03)	(-4.61)	(-2.64)	(-2.72)	(-1.96)	(-0.97)	(2.09)
FF4M α	-2.26	-1.71	-1.60	-1.77	-1.18	-1.59	-1.10	-1.04	-0.96	-1.10	1.15
	(-3.88)	(-4.01)	(-3.99)	(-4.19)	(-3.17)	(-3.87)	(-2.68)	(-2.50)	(-2.14)	(-2.06)	(1.82)
Fees	0.99	0.93	0.91	0.90	0.89	0.88	0.90	0.90	0.92	0.93	-0.06
	(80.04)	(54.31)	(61.44)	(68.82)	(69.34)	(66.36)	(71.62)	(67.37)	(88.77)	(69.57)	(-5.62)
Flows	-21.29	-13.00	-10.23	-8.84	-6.22	-4.48	-2.03	0.20	3.34	10.12	31.41
	(-18.71)	(-14.79)	(-15.31)	(-12.86)	(-11.57)	(-6.72)	(-2.83)	(0.29)	(3.73)	(9.83)	(19.81)
Market Share	7.53	8.55	9.44	9.74	10.10	10.51	10.56	11.03	11.35	11.19	3.66
	(30.94)	(44.05)	(48.09)	(50.86)	(53.51)	(50.74)	(46.57)	(58.90)	(51.44)	(38.99)	(8.33)
					Panel B: Past performance on Bad days						
Avg. Ret.	11.96	12.04	12.71	12.99	12.40	13.12	12.90	12.93	13.77	13.92	1.96
	(2.80)	(2.96)	(3.06)	(3.17)	(2.99)	(3.16)	(3.08)	(3.07)	(3.18)	(3.23)	(1.69)
CAPM α	-2.57	-2.67	-2.02	-1.79	-2.35	-1.80	-1.77	-1.86	-0.77	-0.32	2.25
	(-2.97)	(-3.71)	(-2.86)	(-2.67)	(-4.33)	(-3.38)	(-3.14)	(-3.19)	(-1.01)	(-0.40)	(1.83)
FF4M α	-2.00	-1.79	-1.80	-1.20	-1.46	-1.42	-1.38	-1.65	-0.89	-0.54	1.46
	(-3.03)	(-4.02)	(-3.53)	(-2.94)	(-3.52)	(-3.57)	(-3.38)	(-4.04)	(-1.85)	(-0.98)	(2.11)
Fees	0.99	0.93	0.91	0.90	0.89	0.88	0.89	0.89	0.90	0.94	-0.05
	(72.58)	(68.14)	(72.59)	(67.91)	(69.91)	(71.56)	(68.11)	(73.93)	(73.67)	(68.93)	(-5.31)
Flows	-9.19	-8.28	-6.04	-5.19	-3.79	-3.37	-2.72	-3.00	-1.55	0.48	9.67
	(-9.88)	(-10.24)	(-8.25)	(-7.34)	(-5.82)	(-4.71)	(-3.97)	(-4.74)	(-2.14)	(0.50)	(7.89)
Market Share	8.38	9.73	9.88	10.56	11.02	10.65	10.43	10.40	10.29	8.67	0.29
	(29.47)	(45.49)	(49.60)	(53.59)	(59.09)	(57.16)	(55.96)	(47.85)	(48.35)	(53.50)	(0.91)

Table X: **Bad vs Other Days Performance Predictability**

This table reports coefficient estimates from Equation (14). We regress daily CAPM abnormal returns (of the TNA-weighted fund portfolios presented in Table IX above) on a bad day dummy that is equal to one on a day d in month t with a market return below the 5th percentile of market returns over the last year (see Footnote 27 for more detail). We report results for portfolios sorted by bad and other day skill. Each coefficient estimate is multiplied by 12 to accommodate comparison to Table IX. t-statistics are based on Newey-West standard errors with 5 lags.

	Panel A: Past performance on Other days					Panel B: Past performance on Bad days				
	α_0		α_B		R^2	α_0		α_B		R^2
Low	-0.19	(-3.75)	0.27	(0.95)	0.01%	-0.09	(-2.25)	-0.98	(-2.44)	0.92%
2	-0.17	(-3.63)	0.31	(1.07)	0.03%	-0.13	(-3.56)	-0.43	(-1.27)	0.19%
3	-0.15	(-3.90)	0.57	(2.44)	0.33%	-0.10	(-2.93)	-0.33	(-1.01)	0.13%
4	-0.13	(-3.57)	0.07	(0.26)	-0.03%	-0.09	(-3.12)	-0.25	(-0.76)	0.08%
5	-0.10	(-3.68)	-0.08	(-0.41)	-0.02%	-0.12	(-4.52)	-0.33	(-1.64)	0.27%
6	-0.12	(-5.20)	0.14	(0.97)	0.02%	-0.09	(-3.32)	-0.24	(-1.33)	0.09%
7	-0.08	(-3.03)	-0.11	(-0.50)	-0.01%	-0.10	(-3.83)	-0.07	(-0.39)	-0.02%
8	-0.06	(-2.52)	-0.47	(-2.39)	0.56%	-0.13	(-4.27)	0.37	(1.65)	0.20%
9	-0.04	(-1.22)	-0.61	(-2.05)	0.58%	-0.07	(-2.01)	0.30	(1.36)	0.08%
High	0.00	(0.07)	-1.02	(-3.23)	0.71%	-0.08	(-1.89)	0.70	(2.01)	0.44%
High - Low	0.19	(2.62)	-1.29	(-3.31)	0.44%	0.01	(0.24)	1.68	(2.74)	1.23%

Online Appendix

A. Retail versus institutional investors

To estimate whether the increased sensitivity of flows to performance on bad days is driven by retail or institutional investors, we extend Eq (7) as follows:

$$\begin{aligned} Flow_{i,d(t)+1w} = \delta Rank_{i,d(t)} + \lambda(Rank_{i,d(t)} \times Rank_{MKT,d(t)}) + \beta Rank_{MKT,d(t)} + \\ \delta_I(Rank_{i,d(t)} \times D_{Inst,i,t-1}) + \beta_I(Rank_{MKT,d(t)} \times D_{Inst,i,t-1}) + \\ \lambda_I(Rank_{i,d(t)} \times Rank_{MKT,d(t)} \times D_{Inst,i,t-1}) + d_I D_{Inst,i,t-1} + \\ \text{Controls} + \text{Fixed effects} + \epsilon_{i,d(t)+1w}. \end{aligned} \quad (15)$$

Here, $D_{Inst,i,t-1}$ is a dummy that equals one when fund i has at least one institutional share class (following the definition in Evans, 2010) or when fund i has a larger share of its TNA coming from institutional share classes than the median fund (in the same style and on the same day). Our main interest is in the triple interaction, which asks whether institutional investors' sensitivity to performance varies more with the market return than retail investors' sensitivity. A priori, the effect can go both ways. The horizon of institutional investors is more long-term, and as a result, their capital is often considered more "patient." This means that we should expect institutional investors to respond less to performance on an average day and thus $\delta_I < 0$. Institutional investors are also often argued to be more sophisticated. If institutional investors believe that bad day performance provides a particularly useful signal about long-term manager skill, we would expect them to be relatively more sensitive to performance on bad days and thus $\lambda_I < 0$. If institutional investors believe that bad days contain particularly little information about manager skill, for instance, because there is a lot of noise in fund returns, we would instead expect $\lambda_I > 0$. If institutional investors' attention increases on bad days just like retail investors' attention, we would expect $\lambda_I = 0$.

Table A.1 reports the coefficient estimates. In most specifications, flows to institutional funds are less sensitive to performance. This conclusion holds for both fund performance and market performance and is consistent with the idea that institutions represent patient capital. For instance, in Panel A we use the more restrictive definition of the institutional dummy (institutional TNA share > median) and find that the coefficient estimates for both interactions ($Rank_{i,d(t)} \times D_{Inst,i,t-1}$) and ($Rank_{MKT,d(t)} \times D_{Inst,i,t-1}$) are negative and significant in all four specifications. Most of these coefficients remain negative in Panel B (using the less restrictive definition: institutional TNA share > 0), although these estimates tend to be smaller and less significant.

Looking at the triple interaction, our main interest, we see that it is positive in most specifications. Combining the estimates for the triple interaction with those for the interaction $Rank_{i,d(t)} \times Rank_{MKT,d(t)}$, we see that the increase in flow-performance sensitivity on bad days is lower by about one-third for institutional relative to retail funds. That said, the triple interaction is never significant, and it switches sign-in specifications (7) and (8). These specifications use CAPM abnormal returns to measure fund performance and the less restrictive definition of the institutional dummy. Overall, there is little evidence to suggest that institutional investors' flows are very different from those of retail investors: both retail and institutional investors' flows respond relatively strongly to fund performance on bad days.

Table A.1: **Flow-Performance Sensitivity and Daily Market Returns: Retail vs Institutional Investors**

This table is analogous to Table IV, but now we allow the flow-performance relation to vary with both market returns as well as an institutional investor dummy as estimated using Equation (15). We regress weekly flows (from $d(t)+1$ to $d(t)+5$) on rank-normalized performance ($Rank_{i,d(t)}$ ranges from $[0,1]$ on each sample day $d(t)$), measured using net returns (specifications (1), (2), (5) and (6)) or CAPM abnormal returns (specifications (3), (4), (7) and (8)). We interact fund performance with the market return ($Rank_{MKT,d(t)}$ ranges from $[0,1]$, and this ranking is based on a comparison to all daily returns over the past year) and a dummy ($D_{Inst,i,t-1}$) indicating funds with higher than median (within each style × day) TNA from institutional investors (Panel A) or funds with at least one institutional share class (Panel B).

	Panel A: Above median institutional TNA share				Panel B: Institutional share> 0			
	Net Return		CAPM Abnormal Return		Net Return		CAPM Abnormal Return	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$Rank_{i,d(t)}$	5.18	3.15	3.71	3.90	5.02	3.06	2.95	3.35
	(10.89)	(7.12)	(8.74)	(9.75)	(7.64)	(5.19)	(5.50)	(6.54)
$Rank_{MKT,d(t)}$	8.27		5.11		8.15		4.03	
	(10.94)		(8.59)		(8.52)		(5.62)	
$D_{Inst,i,t-1}$	1.44	1.45	1.32	1.22	1.24	-0.14	0.77	0.14
	(3.30)	(2.74)	(3.22)	(2.48)	(2.50)	(-0.18)	(1.70)	(0.19)
$Rank_{i,d(t)} \times Rank_{MKT,d(t)}$	-5.08	-1.83	-3.07	-3.23	-5.36	-2.14	-1.98	-2.37
	(-6.35)	(-2.41)	(-4.46)	(-4.79)	(-4.75)	(-2.08)	(-2.21)	(-2.73)
$Rank_{i,d(t)} \times D_{Inst,i,t-1}$	-2.55	-2.27	-2.29	-2.22	-1.33	-1.33	-0.45	-0.64
	(-3.93)	(-3.76)	(-4.22)	(-4.32)	(-1.81)	(-2.01)	(-0.75)	(-1.15)
$Rank_{MKT,d(t)} \times D_{Inst,i,t-1}$	-1.88	-1.58	-1.17	-1.15	-0.98	-0.42	0.64	0.69
	(-2.85)	(-2.56)	(-2.15)	(-2.21)	(-1.19)	(-0.56)	(0.96)	(1.13)
$Rank_{i,d(t)} \times Rank_{MKT,d(t)} \times D_{Inst,i,t-1}$	1.54	1.02	0.83	0.80	1.19	1.04	-0.88	-0.65
	(1.53)	(1.08)	(1.03)	(1.04)	(0.96)	(0.92)	(-0.90)	(-0.72)
N	3,495,926	3,495,925	3,077,229	3,077,229	3,495,926	3,495,925	3,077,229	3,077,229
R^2	37%	41%	38%	41%	37%	41%	38%	41%
Controls	✓	✓	✓	✓	✓	✓	✓	✓
Style × Day		✓		✓		✓	✓	✓
Fund		✓		✓		✓		✓

B. Aggregate flows across asset classes

To understand where the aggregate flow of money out of active US equity mutual funds ends up, we use Morningstar flow data. Specifically, we focus on the fund-level daily dollar flow variable, "estimated fund level net flow (comprehensive) (daily)," for the sample of active, passive and money market funds. We combine active and passive funds into 5 major groups: (1) International Equity, (2) Sector Equity, (3) Taxable Bond, (4) U.S. Equity, and (5) Other (combining Allocation, Alternative, Commodities, Miscellaneous, Nontraditional Equity funds, and Municipal Bonds). Because we are interested in market-wide flows, we aggregate the fund-level flow data on a daily basis for each type of funds z. We then run:

$$\$Flow_{z,d(t)+1w} = \lambda_z \times D_{MKT,d(t),Low} + \text{Controls} + \epsilon_{z,d(t)+1w}, \tag{16}$$

where we control for lagged flow measured over the previous week and year, as in Table III. we convert the flows to real values using the end of sample CPI level as the base year. We also winsorize the flows to remove outliers, but this has little impact on our conclusions. The sample period runs from July 2008 to April 2023. We present results in Table B.1 below.

Several interesting facts stand out from this table. First, we see that the total flow out of active US equity funds after a bad day is, on average, 438 million USD and significant. Second, we also see large outflows for the other active equity fund categories as well as corporate bond and other funds. This finding is perhaps unsurprising, noting that bad days in the US stock market tend to roughly coincide with bad days in international equities, equity sectors, and the corporate bond market.[29] Third, the average flow in passive funds after bad days is small compared to those in active funds, consistent with the idea that

[29] Although the ICE Bank of America US Corporate Index return is on average positive (at 11 bps) on days that the US stock market return is below its 5th percentile, the bond index average return is negative in the five days following (at values ranging from -18 bps the day after to -8 bps three days after, and -3 bps five days after.

passive (active) investors invest with passive (active) funds. Fourth, there is a large and significant flow into money market funds of about 2.8 billion USD in the first week after a bad day. Since this inflow roughly matches the total outflow from the active fund categories, we conclude that the bad day outflows from risky mutual funds end up, to a large extent, in this least risky fund category.

We leave for future work the interesting question of what the cross-sectional flow-performance relation looks like on bad days in these other fund categories. Given that the unconditional flow-performance relation can differ across asset classes (Goldstein et al., 2017), studying such conditional variation has the potential to shed new light on the behavior of fund investors as well as the skills of fund managers across different asset classes.

Table B.1: **Aggregate Flows across Asset Classes**

This table reports coefficient estimates from Equation (16). Panels A and B, respectively, report the results for five categories of active and passive mutual funds: International Equity, Sector Equity, Taxable Bond, US Equity, and Other (combining Allocation, Alternative, Commodities, Miscellaneous, Nontraditional Equity, and Municipal Bond). Panel C reports the coefficient estimates for Money Market funds. We present t-statistics in parentheses based on Newey-West standard errors with lag length equal to 20 days. The last two rows in each panel report the mean and standard deviation of aggregate weekly flows. The sample period runs from July 2008 to April 2023.

	International Equity	Sector Equity	Taxable Bond	U.S. Equity	Other
	(1)	(2)	(3)	(4)	(5)
			Panel A: Active Funds		
Intercept	68.16	20.90	251.97	-29.79	164.00
	(2.15)	(2.50)	(3.28)	(-0.43)	(2.61)
Bad day	-268.79	-120.09	-815.01	-437.64	-486.09
	(-5.01)	(-7.55)	(-5.90)	(-4.82)	(-4.41)
Flow -1W	0.73	0.60	0.67	0.53	0.69
	(12.04)	(10.14)	(9.34)	(8.01)	(9.46)
Flow -1Y	0.00	0.01	0.00	0.01	0.00
	(2.40)	(6.13)	(2.51)	(5.70)	(2.6)
R^2	0.61	0.57	0.53	0.46	0.55
N	3602	3602	3602	3602	3602
Mean	64.80	-19.17	567.34	-1,260.38	463.88
Standard Deviation	1,276.16	351.48	2,556.01	1,918.64	1,928.86
			Panel B: Passive Funds		
Intercept	44.50	56.51	52.99	161.70	50.27
	(2.73)	(2.93)	(3.81)	(2.90)	(4.50)
Bad day	-38.58	-110.06	-66.76	-51.87	-16.20
	(-3.15)	(-4.26)	(-2.46)	(-0.95)	(-2.42)
Flow -1W	0.43	0.19	0.58	-0.16	0.00
	(8.05)	(3.55)	(11.85)	(-3.17)	(0.04)
Flow -1Y	0.01	0.01	0.01	0.02	0.01
	(5.79)	(4.46)	(6.14)	(10.63)	(5.32)
R^2	0.38	0.11	0.64	0.11	0.04
N	3602	3602	3602	3602	3602
Mean	253.24	153.69	497.60	689.97	103.92
Standard Deviation	295.53	289.70	583.84	1,177.01	117.80
			Panel C: Money Market Funds		
Intercept	94.11				
	(0.15)				
Bad day	2,803.95				
	(2.31)				
Flow -1W	0.28				
	(2.51)				
Flow -1Y	0.01				
	(2.69)				
R^2	0.11				
N	3853				
Mean	1,760.88				
Standard Deviation	23,422.07				

C. Can derivative usage explain bad day skill?

Following Back et al. (2018), we collect NSAR filings for the funds in our sample from the SEC Web site. Funds are required to disclose whether they are allowed to invest in certain derivative products as well as whether they engaged in such activity over the six-month reporting period. Given our focus on bad days with low aggregate stock market returns, we are particularly interested in activity related to five derivative types: options on equities, options on stock indices, stock index futures, options on stock index futures, and short selling. To understand whether it is derivative usage that is driving outperformance on bad versus other days, we run the following regressions:

$$Rank_{i,t-6:t-1,Bad} = \beta_{A,B} Allowed_{i,t-6:t-1} + \beta_{E,B} Engaged_{i,t-6:t-1} + X_i + \mathrm{FE} + \epsilon_{i,t-6:t-1} \tag{17}$$

$$Rank_{i,t-6:t-1,Other} = \beta_{A,O} Allowed_{i,t-6:t-1} + \beta_{E,O} Engaged_{i,t-6:t-1} + X_i + \mathrm{FE} + \epsilon_{i,t-6:t-1}. \tag{18}$$

Thus, we ask whether the skill to outperform on bad days (or other days) is correlated with derivative activity. We rescale the left-hand side performance measures to range from 0 to 1 to accommodate interpretation. We run these regressions separately for each of the five derivative types but also consider a joint specification. The controls (X_i) are the same fund characteristics as in the rest of the paper (i.e., TNA, expense ratio, turnover, age, and the volatility of returns). We omit these coefficient estimates from the table below because we discuss in detail the economic implications of any correlation between these types of fund characteristics and fund performance on bad versus other days in Section 6. We finally include style × time fixed effects.

Table C.1 reports coefficient estimates on the derivative activity variables. Looking across the various specifications, we see in Panel A that engaging in derivatives is positively correlated to performance on other days. This finding is consistent with the idea that the mandate of skilled managers provides them with more freedom to pick appropriate investment strategies. In contrast, Panel B shows that derivatives activity is largely uncorrelated to performance on bad days. For instance, in the joint specification (specification (1)), engaging in at least one type of derivatives is associated with a marginally significant 2% increase in the average performance ranking of the fund on other days. For bad days, the same coefficient estimate is negative but small and insignificant. Similarly, when we consider trading in each separate type of derivative (specifications (2) to (6)), we find positive and typically significant coefficient estimates ranging from 1% (stock index futures) to 8% (options on stock indices) for other day performance in Panel A. In contrast, these coefficient estimates are relatively small and vary in sign from -3% (options on stock indices) to 2% (stock index futures) for bad day performance in Panel B. Overall, funds that use derivatives are less likely to outperform on bad days than they are to outperform on other days.

Given that we do not have access to precise high-frequency data about the size and sign of funds' derivative positions, we cannot directly study the particular derivatives strategies that are used by managers that outperform on bad versus other days. That said, our goal in Section 6 is to study the end result of funds' strategies, that is, to study how funds that outperform on bad days perform on other days and vice versa. Here we also ask how outperformance on bad versus other days translates to unconditional performance. If funds use derivatives to amplify exposure to stock returns as argued in Kaniel and Wang (2022), we expect this practice to hurt performance on bad days, and it should be costly unconditionally.[30] If funds use derivatives to buy or sell insurance for downside risk or volatility, this practice will also have a distinct impact on performance on bad days and the funds' unconditional alpha.

[30] Kaniel and Wang (2022) use a new dataset extracted from SEC's Form N-PORT, which became available only in September 2019, to infer the performance of fund derivative positions at a relatively low monthly or quarterly frequency.

Table C.1: **Fund Performance and Derivative Usage**

In this table, we report coefficient estimates for the models that test whether derivative usage is correlated to fund performance on bad days versus other days. Panel A (Panel B) reports results from Equation 17, which regresses average performance, measured using ranked CAPM abnormal return, on other days (bad days) on a dummy that equals one when a fund is allowed ($Allowed_{t-6:t-1}$) to trade in one type (specifications (2) to (6)) or all six types (specification (1)) of derivatives. The regressions also include an indicator, $Engaged_{i,t-6:t-1}$, that is equal to one when the fund actually traded the corresponding derivative (specifications (2) to (6)) or at least one of them (while being allowed to trade all, specification (1)). In all specifications, we control for fund characteristics at the start of the six-month period (TNA, age, expense ratio, turnover ratio, and the volatility of performance) as well as style×day fixed effects.

	Joint Specification	Options on Equities	Options on Stock Indices	Stock Index Futures	Options on Stock Index Futures	Short Selling
	(1)	(2)	(3)	(4)	(5)	(6)
			Panel A: Other Day Performance			
$Allowed_{i,t-6:t-1}$	0.00	0.01	0.01	0.01	0.00	0.00
	(-0.41)	(0.91)	(1.00)	(0.64)	(0.27)	(-0.49)
$Engaged_{i,t-6:t-1}$	0.02	0.05	0.08	0.01	0.06	0.05
	(1.68)	(3.33)	(2.15)	(0.97)	(1.06)	(2.24)
N	8,903	8,918	8,918	8,918	8,918	8,918
R^2	33.42%	33.59%	33.43%	33.41%	33.40%	33.44%
Controls	✓	✓	✓	✓	✓	✓
Time × style	✓	✓	✓	✓	✓	✓
			Panel B: Bad Day Performance			
$Allowed_{i,t-6:t-1}$	-0.01	0.00	-0.01	0.00	0.00	-0.01
	(-0.81)	(0.18)	(-0.93)	(-0.32)	(-0.10)	(-1.04)
$Engaged_{i,t-6:t-1}$	0.00	-0.02	-0.03	0.02	0.00	0.01
	(-0.30)	(-1.54)	(-0.60)	(1.96)	(0.13)	(0.31)
N	8,580	8,583	8,583	8,583	8,583	8,583
R^2	36.52%	36.44%	36.43%	36.47%	36.42%	36.43%
Controls	✓	✓	✓	✓	✓	✓
Time × style	✓	✓	✓	✓	✓	✓

D. Supplementary Tables and Figures

Table D.1: **Alternative Estimation Methods**

This table is similar to Table IV, but reports coefficient estimates from alternative specifications. Column 1 repeats the main result of the paper. In column 2, we redefine the first weekly lag of flows to include the day $d(t)$ on which we measure fund performance $(d(t)-4:d(t)))$. In column 3, we control for three additional weekly lags of flows and performance (from $d(t)-10:d(t)-6$, $d(t)-15:d(t)-11$ and $d(t)-20:d(t)-16$). In column 4, we use the exact same specification as in the paper but use raw (rather than rank-normalized) fund performance $(A)R_{i,d(t)}$ and market returns $R_{MKT,d(t)}$. In column 5, we report results from a Fama-MacBeth estimation. In the first stage, we regress weekly flows on daily performance on each day of our sample and include all the same controls as in Table IV. In the second stage, we regress in the time series the estimated flow-performance sensitivities on the market return.

	Paper	Lagged weekly flow includes $t(d)$	Four lags of flow and performance		Raw returns		Fama-MacBeth
$Rank_{i,t(d)}$	2.87	3.04	2.24	$(A)R_{i,t(d)}$	1.75	Intercept	2.26
	(8.03)	(8.44)	(7.09)		(8.32)		(7.42)
$Rank_{MKT,t(d)}$							
$Rank_{i,t(d)} \times Rank_{MKT,t(d)}$	-2.87	-2.61	-1.50	$(A)R_{i,t(d)}$	-46.21	$Rank_{MKT,t(d)}$	-2.22
	(-4.78)	(-4.31)	(-2.90)	$\times R_{MKT,t(d)}$	(-3.89)		(-4.31)
R^2 (Pooled)	0.41	0.40	0.44		0.41	R^2 (Time-series)	0.01
Controls	✓	✓	✓		✓	Controls	✓
Style×Day	✓	✓	✓		✓		
Fund	✓	✓	✓		✓		
Marginal effect (%)	-29	-25	-19		-34		-28

Table D.2: **Markov Transition Matrix for Fund Performance**
This table reports the Markov transition matrix for the dynamics of bad and other day skill. We sort all funds into ten deciles based on these skill measures and estimate the monthly transition probabilities (from $t-1$ to t) across deciles.

	Low	2	3	4	5	6	7	8	9	High
					Panel A: Sorting on Other Day Skill					
Low	0.77	0.19	0.03	0.01	0.00	0.00	0.00	0.00	0.00	0.00
2	0.19	0.48	0.23	0.07	0.02	0.00	0.00	0.00	0.00	0.00
3	0.03	0.23	0.38	0.23	0.09	0.03	0.01	0.00	0.00	0.00
4	0.01	0.07	0.23	0.33	0.22	0.10	0.03	0.01	0.00	0.00
5	0.00	0.02	0.09	0.23	0.31	0.22	0.10	0.03	0.00	0.00
6	0.00	0.00	0.03	0.10	0.22	0.31	0.23	0.09	0.02	0.00
7	0.00	0.00	0.01	0.03	0.09	0.23	0.33	0.23	0.07	0.00
8	0.00	0.00	0.00	0.01	0.03	0.09	0.23	0.38	0.23	0.03
9	0.00	0.00	0.00	0.00	0.01	0.02	0.07	0.23	0.49	0.18
High	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.03	0.18	0.78
					Panel B: Sorting on Bad Day Skill					
Low	0.77	0.16	0.04	0.02	0.01	0.00	0.00	0.00	0.00	0.00
2	0.16	0.54	0.19	0.06	0.03	0.02	0.01	0.00	0.00	0.00
3	0.04	0.19	0.44	0.19	0.07	0.03	0.02	0.01	0.00	0.00
4	0.02	0.06	0.20	0.41	0.18	0.08	0.04	0.02	0.01	0.00
5	0.01	0.03	0.07	0.18	0.39	0.19	0.08	0.03	0.01	0.00
6	0.00	0.01	0.03	0.08	0.19	0.40	0.19	0.07	0.02	0.01
7	0.00	0.01	0.02	0.03	0.08	0.19	0.41	0.19	0.06	0.01
8	0.00	0.00	0.01	0.02	0.03	0.07	0.19	0.45	0.19	0.03
9	0.00	0.00	0.00	0.01	0.01	0.03	0.06	0.19	0.54	0.16
High	0.00	0.00	0.00	0.00	0.00	0.01	0.01	0.04	0.16	0.78

Table D.3: **Performance Predictability on Bad Days and Subsequent Days**

This table reports coefficient estimates similar to table X, where now we also control for indicator variables for one to five days after a bad day:

$$AR_{p,d(t)} = \alpha_{p,0} + \alpha_{p,B} I_{Rank_{MKT,d(t)}<0.05} + \alpha_{p,B_1} I_{Rank_{MKT,d(t)-1}<0.05} + \alpha_{p,B_2} I_{Rank_{MKT,d(t)-2}<0.05}$$
$$+\alpha_{p,B_3} I_{Rank_{MKT,d(t)-3}<0.05} + \alpha_{p,B_4} I_{Rank_{MKT,d(t)-4}<0.05} + \alpha_{p,B_5} I_{Rank_{MKT,d(t)-5}<0.05} + \epsilon_{p,d(t)}.$$

We report results for portfolios sorted by bad day skill. Each coefficient estimate is multiplied by 12 to accommodate comparison to Table IX. t-statistics are based on Newey-West standard errors with 5 lags.

	α_0		α_B		α_{B_1}		α_{B_2}		α_{B_3}		α_{B_4}		α_{B_5}		R^2
Low	-0.06	(-1.13)	-0.90	(-2.42)	-0.60	(-2.98)	0.20	(0.65)	0.15	(0.71)	-0.24	(-0.95)	-0.30	(-1.08)	1.31%
2	-0.11	(-2.46)	-0.39	(-1.27)	-0.25	(-1.56)	0.17	(0.69)	0.01	(0.05)	0.06	(0.31)	-0.37	(-1.47)	0.30%
3	-0.07	(-1.63)	-0.26	(-0.90)	-0.26	(-1.55)	0.09	(0.33)	0.00	(-0.02)	-0.11	(-0.49)	-0.37	(-1.73)	0.33%
4	-0.07	(-1.68)	-0.19	(-0.63)	-0.28	(-1.21)	0.06	(0.19)	0.12	(0.55)	-0.23	(-0.89)	-0.28	(-1.25)	0.33%
5	-0.10	(-3.35)	-0.29	(-1.56)	-0.27	(-1.85)	0.09	(0.55)	-0.05	(-0.41)	-0.04	(-0.28)	-0.12	(-0.83)	0.39%
6	-0.07	(-2.31)	-0.20	(-1.16)	-0.39	(-2.32)	0.22	(1.22)	0.01	(0.10)	-0.07	(-0.38)	-0.17	(-1.03)	0.41%
7	-0.07	(-2.38)	0.00	(0.01)	-0.42	(-2.60)	0.05	(0.26)	0.20	(1.40)	-0.15	(-0.83)	-0.30	(-2.14)	0.58%
8	-0.11	(-3.42)	0.42	(1.81)	-0.46	(-2.35)	0.22	(1.17)	0.19	(0.86)	-0.17	(-0.75)	-0.17	(-0.82)	0.58%
9	-0.03	(-0.80)	0.39	(1.75)	-0.42	(-1.66)	0.10	(0.35)	0.15	(0.59)	-0.28	(-0.90)	-0.40	(-1.67)	0.51%
High	-0.05	(-1.09)	0.77	(2.16)	-0.20	(-0.70)	0.04	(0.16)	0.28	(0.88)	-0.36	(-1.17)	-0.38	(-1.26)	0.65%
High - Low	0.01	(0.10)	1.67	(2.74)	0.40	(1.29)	-0.15	(-0.46)	0.13	(0.38)	-0.12	(-0.36)	-0.09	(-0.21)	1.16%

Table D.4: **Persistence of Bad vs Other Days Performance: External Validity**
This table reports results similar to specifications (5) to (8) of table VIII, but extends our sample either in (i) the time dimension (by adding daily fund return data back to January 2000 from CRSP) or (ii) the fund dimension (by including all funds, even those without daily TNA data in Morningstar).

	(i) Sample starting in January 2000				(ii) All funds			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$Rank_{i,t-1y,Bad}$	12.25	7.22			10.15	6.28		
	(6.04)	(6.01)			(4.22)	(4.21)		
$Rank_{i,t-1y,Other}$	-6.89	-3.78			-3.12	-2.74		
	(-3.28)	(-3.51)			(-1.22)	(-2.30)		
$D_{i,t-1y,Bad,Low}$			-5.15	-2.87			-3.67	-2.33
			(-6.40)	(-6.60)			(-4.07)	(-4.53)
$D_{i,t-1y,Bad,High}$			4.88	2.07			4.44	1.82
			(5.21)	(4.40)			(3.74)	(2.94)
$D_{i,t-1y,Other,Low}$			3.49	1.58			2.16	0.99
			(4.11)	(4.06)			(2.06)	(2.25)
$D_{i,t-1y,Other,High}$			-2.49	-1.50			-0.77	-1.26
			(-2.74)	(-3.66)			(-0.68)	(-2.81)
TNA	0.02	-0.35	0.02	-0.35	-0.13	-0.65	-0.13	-0.66
	(0.19)	(-2.22)	(0.25)	(-2.16)	(-1.26)	(-2.64)	(-1.23)	(-2.67)
Age	0.06	0.31	0.00	0.24	0.20	0.56	0.15	0.53
	(0.34)	(0.88)	(-0.01)	(0.66)	(0.96)	(1.10)	(0.71)	(1.02)
Exp. Ratio	0.03	0.06	0.16	0.09	-1.05	-1.25	-1.02	-1.25
	(0.06)	(0.10)	(0.29)	(0.16)	(-1.45)	(-1.60)	(-1.42)	(-1.56)
Turn.	0.02	0.01	0.02	0.01	0.01	0.01	0.02	0.01
	(3.91)	(1.84)	(4.01)	(1.84)	(2.91)	(2.03)	(2.97)	(2.03)
Vol. Perf	7.23	12.65	8.19	12.58	6.17	8.80	6.61	8.63
	(2.44)	(3.35)	(2.76)	(3.27)	(1.85)	(1.76)	(1.98)	(1.69)
Flows -1Y	-3.17	-2.21	-3.46	-2.39	-1.12	-1.61	-1.08	-1.64
	(-4.26)	(-4.10)	(-4.63)	(-4.38)	(-1.35)	(-2.10)	(-1.30)	(-2.15)
Flows -1M	21.77	9.72	21.99	9.65	11.14	6.02	11.49	6.06
	(4.04)	(3.33)	(4.18)	(3.23)	(2.01)	(1.78)	(2.15)	(1.76)
Constant	48.13	49.14	50.68	51.01	47.18	48.95	50.27	50.88
	(28.45)	(54.68)	(199.64)	(390.44)	(23.42)	(45.86)	(184.28)	(336.49)
N	279,234	279,225	279,234	279,225	210,057	210,047	210,057	210,047
R^2	0.03	0.39	0.02	0.39	0.02	0.40	0.01	0.40
Style×Day		✓		✓		✓		✓
Fund		✓		✓		✓		✓

Table D.5: **Unconditional Fund Performance Predictability: External Validity**
This table reports CAPM abnormal returns similar to Panel B of Table IX, but but extends our sample either in (i) the time dimension (by adding daily fund return data back to January 2000 from CRSP) or (ii) the fund dimension (by including all funds, even those without daily TNA data in Morningstar).

	Low	2	3	4	5	6	7	8	9	High	High-Low
	(i) Sample starting in January 2000										
CAPM α	-1.75	-1.76	-1.56	-1.39	-1.32	-1.35	-1.26	-0.91	-1.09	0.09	1.84
	(-2.73)	(-3.07)	(-2.95)	(-2.45)	(-3.24)	(-2.72)	(-2.78)	(-1.86)	(-1.98)	(0.15)	(2.25)
	(ii) All funds										
CAPM α	-2.12	-2.59	-1.60	-1.42	-1.45	-1.53	-1.58	-0.92	-0.79	-0.17	1.94
	(-2.68)	(-3.89)	(-2.51)	(-2.36)	(-3.28)	(-3.28)	(-3.31)	(-1.63)	(-1.17)	(-0.23)	(1.82)

Table D.6: **Unconditional Fund Performance Predictability: Betting Against Beta**
This table is constructed similar to Table IX, and reports alphas from the regression on the market and the Frazzini and Pedersen (2014) betting against beta (BAB) factor.

	Low	2	3	4	5	6	7	8	9	High	High-Low
					Panel A: Past performance on Other days						
α_{BAB}	-1.79	-1.38	-0.98	-1.19	-0.79	-1.40	-0.73	-1.11	-0.76	-0.32	1.47
	(-1.56)	(-1.52)	(-1.31)	(-1.53)	(-1.57)	(-3.10)	(-1.44)	(-2.16)	(-1.38)	(-0.44)	(1.15)
					Panel B: Past Performance on Bad days						
α_{BAB}	-1.63	-1.88	-1.35	-1.10	-1.65	-1.21	-1.20	-1.16	-0.09	0.27	1.90
	(-1.94)	(-2.78)	(-2.02)	(-1.62)	(-3.19)	(-2.27)	(-2.06)	(-1.97)	(-0.11)	(0.36)	(1.72)

Table D.7: **Unconditional Fund Performance Predictability: Sorting on the Average of Past Performance on Other and Bad Days**

This table reports results similar to table IX, but sorting on the average of past CAPM abnormal return performance on other days and bad days. In each month, average past performance is orthogonalized from style dummies. We report TNA-weighted average returns as well as CAPM and Fama-French-Carhart four-factor model abnormal returns (see footnote 21). These performance measures are annualized (×12), and t-statistics are based on Newey-West standard errors with 1 monthly lag. We further report average fees and flows (also annualized) as well as the fraction of total active US equity mutual fund TNA allocated to each portfolio.

	Low	2	3	4	5	6	7	8	9	High	High-Low
Avg. Ret.	12.19	11.90	13.34	13.28	12.62	12.78	12.81	13.28	13.38	13.79	1.61
	(2.71)	(2.76)	(3.08)	(3.02)	(2.91)	(2.91)	(2.95)	(3.06)	(2.98)	(3.15)	(1.35)
CAPM α	-2.44	-2.66	-1.53	-1.44	-2.20	-2.15	-2.06	-1.38	-1.12	-0.36	2.08
	(-2.79)	(-3.89)	(-2.14)	(-2.22)	(-4.10)	(-3.64)	(-3.61)	(-2.19)	(-1.60)	(-0.45)	(1.75)
FF4M α	-1.91	-1.83	-1.30	-1.17	-1.73	-1.25	-1.72	-1.20	-1.11	-0.50	1.41
	(-2.83)	(-3.81)	(-2.68)	(-2.70)	(-3.97)	(-3.18)	(-3.58)	(-2.48)	(-2.27)	(-0.83)	(1.89)
Fees	0.99	0.93	0.91	0.90	0.89	0.88	0.90	0.89	0.89	0.94	-0.05
	(103.46)	(91.81)	(92.56)	(96.05)	(89.99)	(86.10)	(93.94)	(109.84)	(99.34)	(96.08)	(-6.84)
Flows	-9.65	-9.09	-7.10	-6.25	-3.99	-2.79	-2.87	-2.11	-0.85	1.31	10.96
	(-11.07)	(-12.09)	(-9.93)	(-10.63)	(-6.26)	(-4.31)	(-4.81)	(-3.45)	(-1.33)	(1.61)	(8.96)
Market Share	8.24	9.67	9.97	10.36	10.86	10.54	10.34	10.59	10.14	9.29	1.04
	(40.51)	(56.58)	(56.98)	(63.29)	(56.37)	(59.33)	(63.31)	(63.07)	(55.62)	(56.87)	(3.99)