Saliency Bias in Mutual Fund Portfolios and its Implications for Stock Price Efficiency: Evidence from a Natural Experiment

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Abstract

We examine whether professional money managers overreact to the salient events using hurricane strikes as a natural experiment. Specifically, we analyze the trading response of mutual fund managers to the hurricane strikes with respect to the firms located in the disaster zone. We report two major findings. First, we find that managers close to the disaster zone underweight diaster zone firms more than that underweighted by the distant managers. Second, the underweighting of disaster zone firms is not driven by information asymmetry between the close and distant managers, rather this underweighting is driven by saliency bias. This saliency bias driven underweighting decreases with both time and distance. Finally, the managerial overreaction to the salient event is costly to the fund investors. A long-short strategy exploiting the extent of overreaction by close fund managers generates economically and statistically significant risk-adjusted returns. Overall, our paper provides causal evidence supporting the idea that the supposedly rational portfolio managers act in a behaviorally biased way by overreacting to the salient events.

1 Introduction

Institutional funds hold more than 60% of domestic equity and account for around 70% of trading volume (Gompers and Metrick (2001), Bennett, Sias, and Starks (2003), Boehmer and Kelley (2009)). According to the *Investment Company Fact Book 2015*, the total net assets of investment companies is close to \$18 trillion, of which \$16 trillion is held in open-ended mutual funds. The shares held by mutual funds represent 30% of outstanding shares in the U.S. market.

Given their large holdings and trading volume, the underlying rationale of portfolio decisions of fund managers is a question of key economic importance because their portfolio trades impact stock prices (Wermers (1999), Nofsinger and Sias (1999), Dasgupta, Prat, and Verado (2011)). If supposedly rational money managers trade in a behaviorally biased way, it may adversely affect the informational efficiency of stock prices. This is important because stock price distortions can affect the real economy through inefficient allocation of capital (Subrahmanyam and Titman (2001), Wurgler (2000)). However, thus far large sample evidence on the impact of biases on portfolio decisions of mutual fund managers and its implications for stock price efficiency has been lacking. In this paper, we use a natural experiment to show that the professional money managers trade in a behaviorally biased way. The stocks associated with such trades exhibit large subsequent return reversals.

The main empirical challenge is to isolate the behaviorally biased decisions of portfolio managers. This is because we cannot observe whether a particular portfolio choice is rational that may be driven by access to superior information or whether the portfolio choice is driven by some bias. We focus on one particular bias that is relatively easier to isolate: *saliency bias*. Saliency bias is the tendency to overweight probabilities based on the ease with which the events can be recalled. According to Taylor and Thompson (1982), "Salience refers to the phenomenon that when one's attention is differentially directed to one portion of the environment rather than to others, the information contained in that portion will receive disproportionate weighing in subsequent judgments". This is also referred to as "availability heuristic". In the presence of such a bias, subjects overestimate the risk of salient events based on vividness, proximity or emotional impact ("saliency bias", Tversky and Kahneman (1973)).[1] Hurricane disasters are vivid traumatic events and it is thus likely that proximity to such a disaster can affect peoples attitude towards risk in the short or long-term (Castillo and Carter (2011), Cameron and Shah (2013), Bernile, Bhagwat, and Rau (2014)). In this study, we use hurricane disasters as our experimental setting to examine whether saliency bias affects the portfolio decisions of money managers. This saliency can arise because managers may overestimate the losses and risk of firms located in the disaster zone.

More specifically, we ask the following empirical questions. First, are mutual fund managers more likely to underweight firms located in the disaster zone, if the managers themselves are closer to the disaster zone? Second, whether such an under-weighting is due to the saliency bias (*saliency hypothesis*) or informational advantage (*information hypothesis*, see Coval and Moskowitz (2001))? Finally, we assess whether such an under-weighting is associated with return reversals in the subsequent quarters. If underweighting is driven by the information channel, then we do not expect return reversal in the post-disaster quarters. However, if the underweighting is driven by the saliency bias, we expect prices to reverse in the post-disaster quarters.

The empirical identification of our research questions poses two important challenges. First, we require a salient event which is exogenous to the portfolio decisions of fund managers and whose occurrence does not convey any new information regarding its true probability distribution, i.e. it should not mandate a rational updating of ones priors. Hurricanes are especially suited for our research question as hurricanes are exogenous events whose frequency is stationary over time (Elsner, Kara, and Owens (1999), Elsner and Bossak (2001)). So, the occurrence of a hurricane does not convey any new information regarding the probability of a similar event occurring in future. We are not the first to employ natural disasters as an identification strategy. Kortez (2014) uses natural disasters as an exogenous shock to the local economy to understand whether areas with more local banks are more resilient

[1]...overweighting of salient values is likely to be the mechanism that explains why low-probability events sometimes loom large in decision making. *Daniel Kahneman, Nobel Prize Lecture - December 8, 2002.*

to such shocks. Our identification strategy is similar to the experimental setup of Dessaint and Matray (2014) who also employ hurricane strikes to answer a different question. We highlight and discuss the important differences between our papers in Section 2.

The second econometric challenge is the lack of counterfactual mutual fund portfolios in the absence of saliency bias. Our empirical design addresses this issue by exploiting the distance of mutual funds from the disaster zone as a source of exogenous variation in saliency of the hurricane strike for fund managers. Specifically, we employ a difference-in-differences strategy and compare the portfolio decisions of mutual fund managers within 100 miles of the disaster zone *(treatment group funds)* to those located far away *(control group funds)* with regard to the disaster zone stocks. Figure 2 highlights our empirical strategy. Our empirical design relies on comparing the change in weights on disaster zone stocks (such as, Firms A and B) around hurricane strikes in the portfolio of close funds (Fund 1) relative to the distant funds (Fund 2). The identifying assumption is that the hurricane strikes will be more salient for mutual funds located closer to the disaster zone and consequently such funds will underweight stocks of firms headquartered in the disaster zone around the time of hurricane strikes. Our analysis controls for both fund and year effects. Fund fixed effects ensure that our regressions are identified through within-fund variation that absorb all time-invariant differences across mutual funds. The year fixed effects further control for aggregate macroeconomic shocks.

We now turn to our main findings. We begin by examining the change in portfolio weights of stocks of firms headquartered in the disaster zone following hurricane strikes. To the extent that the saliency of hurricanes declines with distance from the disaster zone, we expect to observe an overreaction by our treatment group funds relative to the control group funds with respect to these stocks. Consistent with this idea, we find that while on average there is a post-hurricane decrease in portfolio weights of disaster zone stocks for all mutual funds, the decrease is significantly greater for close (treatment group) mutual funds. The result is robust to controlling for a host of firm and fund characteristics.

When we examine the dynamic effects of hurricane strikes on portfolio weights of disaster zone stocks, we find that underweighting is sharpest three quarters after the disaster and gradually diminishes over the subsequent quarters. Importantly, portfolio weights of disaster zone stocks for control group and treatment groups funds do not have any differential pre-trends. We also conduct a placebo test, where we compare the portfolio decisions of close and far funds with respect to the firms located in the neighboring counties (near-disaster zone) of the disaster zone counties. The underlying assumption is that the adverse changes in local economic conditions are likely to affect firms located in the disaster zone and near-disaster zone alike. We do not find that the firms located in the near-disaster zone are underweighted more by the close funds relative to the distant funds. These results further strengthen the causal interpretation of our findings and show that underweighting of disaster zone stocks decreases with time and distance.

In additional robustness tests, we address various alternatives that might bias our findings. First, we investigate if close funds underweight disaster zone stocks because they experience outflows from their investors. The idea is that the fund managers may reduce their portfolio investments in the disaster zone stocks not because they are themselves biased, but because they may be catering to the preferences of their investors. The retail investors may exhibit saliency bias and overreact to the hurricane disasters by liquidating their investments in funds with greater investments in the disaster zone stocks. We do not find evidence of such a possibility.

Second, we address the potential concern that the observed underweighting may be mechanically driven by an overall drop in stock price of disaster zone stocks. Such a drop in prices will automatically lead to a drop in portfolio weights of these stocks even in the absence of any actual trading by close funds. We test this explanation in two ways. One, we explicitly control for quarterly stock returns and find our results to be robust. In other words, our results persist even after holding stock prices constant. Second, we change our LHS variable from weight to the number of shares held by funds. We still find similar results. We conclude from our analysis that the greater underweighting of disaster zone firms by close funds relative to the distant funds is not driven by flow-driven trading pressure created by biased investors or due to the drop in stock price of disaster zone firms.

Next, we conduct two tests to distinguish between the *saliency hypothesis* and the *information hypothesis*. These tests are based on the idea that if the underweighting of disaster zone stocks is driven by access to superior information regarding the future performance of such stocks, then we expect to observe a drop in performance of disaster zone stocks in the periods after the hurricane strikes.

In the first test, we perform a difference-in-differences test and compare pre- and post-hurricane profitability of disaster zone firms relative to the firms located in the near-disaster zone. Importantly, because (a) funds closer to the near-disaster zone do not underweight near-disaster zone stocks in their portfolio, and (b) funds closer to the disaster zone underweight disaster zone stocks, information hypothesis would suggest that firms in near-disaster zone should outperform firms in the disaster zone around hurricane strikes. We use two proxies for firm performance: *ROA* and *Sales Growth*.

We find that post-hurricane change in the performance of firms in the disaster zone relative to those in the near-disaster zone is statistically indistinguishable from zero. This suggests that the temporary underweighting of the disaster zone stocks by close funds is more likely to be consistent with the saliency bias hypothesis than with the information hypothesis.

Our second set of tests that further supports the saliency bias hypothesis is based on the abnormal return performance of stocks in the disaster zone. Specifically, we evaluate the subsequent performance of stocks that are underweighted by funds just after the hurricane disasters. If underweighting of disaster zone firms by close funds is consistent with the saliency bias hypothesis, then we would expect the underweighted firms to perform well in the post-event quarters. While future outperformance by such firms will be consistent with the information hypothesis. We test this hypothesis using both portfolio and regression analysis. We find that the the stocks underweighted by the funds close to the disaster zone subsequently outperform the stocks that are overweighted by such funds, based on both raw returns and risk-adjusted returns. That is, the long-short (underweighted minus overweighted) portfolio exhibits sharp return reversal in the post-hurricane quarters.

The return reversal is clearly evident in Figure 3. It shows the cumulative average returns (as in, Coval and Stafford (2007)) of long-short portfolio of stocks held by funds that are close and far from the disaster zone. Figure 3a shows returns around all hurricane-quarters in our sample, while Figure 3b shows returns for the five most damaging hurricanes. These five hurricane disasters are expected to be more salient for close mutual funds. In both the figures, we find that the stocks underweighted by the close funds during the event-quarter (when a hurricane strikes) exhibit return reversal subsequently. In contrast, the counterfactual long-short portfolio of stocks held by the funds that are far away from the disaster zone do not exhibit any significant reversal. We conclude that the statistically and economically large return reversal in the underweighted portfolio of disaster zone firms by the proximate funds is consistent with the *saliency bias hypothesis*.

In summary, our findings show that portfolio managers overreact to the salient events by under-weighting fundamentally sound stocks. This bias in their portfolio decisions due to saliency decreases both with time and distance from the disaster zone. We also show that saliency motivated portfolio decisions adversely affect informational efficiency by pushing prices temporarily away from the fundamentals. To the best of our knowledge, ours is the first paper to provide large sample causal evidence of the impact of salient events on the portfolio decisions of "supposedly rational" mutual fund managers.

The remainder of the paper is organized as follows. Section 2 describes the related literature and develops the hypotheses. In Section 3, we describe our empirical design and discuss the endogeneity concerns. Section 4 describes the data, key variables and provides the summary statistics. In Section 5, we show that the funds close to the disaster zone underweight disaster zone stocks. In Section 6, we disentangle the saliency and informational channel. We conclude in Section 7.

2 Related Literature and Hypotheses

In this section, we first briefly review the related literature and then develop the hypotheses.

2.1 Related literature

Our paper is related to the finance literature that studies the role of behavioral biases and personal experiences of CEOs, investment managers, and retail investors on financial choice variables, such as capital structure, cash holdings and investment in the financial markets. We briefly go over the papers that study the behavior of (a) corporate managers and (b) investors.

2.1.1 Corporate Managerial Behavior

Malmendier, Tate, and Yan (2011) find that CEOs who grew up during the great depression are conservative in their capital structure choices and are less likely to seek external financing. Relatedly, Bernile, Bhagwat, and Rau (2014), find that early life exposure to natural disasters can cause a CEO to be more less risk averse depending on the extent of fatalities caused by the disaster. Malmendier and Tate (2005, 2008) find that overconfident CEOs overestimate their ability to generate returns leading to suboptimal investment decisions. Our study adds to the above literature by showing that exposure to the natural disasters can also impact the portfolio allocation decisions of money managers. These portfolio decisions can induce localized and short-lived time-varying inefficiencies in stock prices of firms in the disaster zone.

In terms of identification strategy, two recent papers employ natural disasters to study cash holdings of firms. Ramirez and Altay (2011) examine the impact of natural disaster on corporate cash holdings in a cross-country setting and find that firms tend to rationally increase their cash hoardings following disasters. Dessaint and Matray (2014) analyze whether firms located in neighboring counties of the disaster counties hoard excess liquidity following hurricanes strikes. Consistent with Ramirez and Altay (2011), they also find that firms hold more cash following hurricane strikes. However, in contrast to Ramirez and Altay (2011), they conclude that such cash hoarding is irrational and consistent with the use of "availability heuristic".

In contrast to Ramirez and Altay (2011) and Dessaint and Matray (2014), we seek to understand whether the marginal price setting investors in the market, such as the institutional fund managers, exhibit irrationality. We only use hurricanes as an experimental set up to answer the above question. In particular, we try to understand whether relative to mutual funds located far away, those located closer to the disaster counties underweight stocks of firms located in these counties following hurricane strikes (see Section 3 for more details). More importantly, we want to analyze whether such an underweighting is a result of an over-reaction by "supposedly rational" money managers and leads to temporary mispricing in stock prices. Our answers to both these questions is a resounding yes. Our findings have implications for stock-price informativeness of firms located in disaster counties in particular and market efficiency in general.[2]

2.1.2 Investor Behavior

Our paper is also related to the growing body of literature that studies the implications of personal experiences and behavioral biases on investor behavior and consequently stock market efficiency (Hirshleifer (2001)). Greenwood and Nagel (2009) find that young mutual fund managers engage in trend-chasing. They are also more heavily invested in technology shocks and are partly to blame for fueling the technology bubble of late 1990s. Malmendier and Nagel (2011) find that individuals with adverse stock market experiences tend to be

[2]There are other subtle but important differences in our identification strategy as well. Dessaint and Matray (2014) compare the cash hoarding behavior of *neighboring area* firms with respect to the firms located in the rest of the US in the aftermath of a hurricane strike. While we compare the portfolio trades of mutual funds located close to and distant from the disaster area with regard to the firms headquartered in the disaster area. If anything, we do not find any over-reaction by close mutual fund managers with respect to firms located in the neighboring areas (near-disaster zone) of disaster hit counties. In contrast, most of the findings of Dessiant and Matray pertains to firms located in neighboring areas. In other words, firms located in the neighboring area serve as a *treatment group* for Dessiant and Matray and a *placebo* group for us.

risk-averse in their investment choices. Kaustia and Knüpfer (2008) find a strong positive link between past IPO returns and future IPO subscriptions which suggests that investors overweight personal experiences. Anagol, Balasubramaniam, and Ramadorai (2015) analyze IPO lotteries in India and find that endowment effect can explain an individual's propensity to hold on to a stock. We add to this literature by using a large sample data on the actual trading behavior of price setting investors, such as the mutual fund managers, and show that exposure to hurricane disasters induces bias in the portfolio decisions of fund managers. This induced bias has a real impact on stock prices in a manner that is not consistent with rational expectations.

Kaplanski and Levy (2010) also examine the behavior of investors in response to a large disaster. They show that aviation disasters negatively impact investor sentiments and are associated with temporary decline in stock markets. Although related, there are important differences between our papers. First, Kaplanski and Levy (2010) analyze the broader overreaction of all market participants to aviation disasters, while our setup allows us to causally identify the decisions of mutual fund managers who are in close proximity to the disaster for whom the event is more salient. This is important because Kaplanski and Levy (2010) argue that price reversal occurs because sophisticated investors arbitrage away inefficient prices. While we show that even "sophisticated" mutual fund managers (also see Levitt and List (2007)) are not immune to behavioral biases when exposed to disasters. Second, we find that the overreaction is confined to the managers closer to the disaster and vanishes with time and with distance from the disaster zone. In this respect, our study complements their findings and shows that there exists heterogeneity in asset allocation decisions in response to exposure to large disasters based on differences in how salient the event is for different investors. So the price reversal after a disaster possibly happens because the event becomes less salient as time passes.

2.2 Hypotheses

Theoretical work on saliency by Thakor (2015), and in particular by Bordalo, Gennaioli, and Shleifer (2012) provide foundations for our hypotheses. Thakor (2015) proposes a model of financial crisis based on availability heuristic. Specifically, in his setting banks, investors and regulators overestimate the skill of bankers following long periods of banking profitability (as recent history is salient) resulting in a risky lending boom and eventually a crisis. More directly related to our idea, Bordalo, Gennaioli, and Shleifer (2012) model choice under salient risks and argue that people may overweight the downside of a risky event when it is salient and may act in a risk-averse manner. In our setting, this implies that the mutual fund managers may overestimate either the adverse impact of salient hurricane disasters on the impacted firms or the probability of such hurricane strikes in future and consequently underweight such firms in their portfolio. We call this the *saliency hypothesis*.

Alternately, Coval and Moskowitz (2001) find that mutual fund managers possess significant informational advantage with respect to the firms located in their proximity. Specifically, mutual fund managers that overweight nearby firms earn substantial abnormal returns in their local holdings. We call this the *information hypothesis*. This implies that mutual fund managers may possess superior information regarding proximate firms and consequently may underweight local disaster firms, if they expect such firms to underperform in near future as a result of hurricane strike. The above discussion leads to the following hypotheses:

H1: Mutual funds located close to the firms in the disaster zone subsequently underweight such firms more than that by the funds located far away from the disaster zone.

H2A (Information Hypothesis): If mutual fund managers underweight disaster zone stocks because of superior information, then such stocks underperform in near future.

H2B (Saliency Hypothesis): If mutual fund managers underweight disaster zone stocks because of saliency bias, then such stocks do not underperform in near future.

3 Empirical Methodology

The main econometric challenge in evaluating whether portfolio decisions of mutual fund managers are susceptible to saliency bias is obtaining the counterfactual portfolio in the absence of such a bias. In other words, it is difficult to empirically distinguish biased portfolio decisions from rational decisions that may be driven by access to superior information or the unobserved risk-preferences of the managers. Our research design is able to circumvent these issues by focusing on the changes in the portfolios of fund managers around hurricane disasters.

As mentioned earlier, our reliance on hurricane strikes for identification draws upon the experimental setup of Dessaint and Matray (2014). As discussed in Dessaint and Matray (2014), three features of hurricanes make them especially suitable for our research question. First, hurricanes are exogenous events whose frequency is stationary over time. So, the occurrence of a hurricane does not convey any new information regarding the probability of a similar event occurring in future. Second, hurricanes are large events that are likely to draw the attention of all people, including portfolio managers. Third, and most importantly hurricanes are localized events that affect a specific geographical area and consequently its saliency is likely to decrease with distance from the disaster area. In particular, hurricanes will be most salient for mutual funds located close to the disaster zone and may have no bearing on funds located far away.

Our empirical design exploits this idea and relies on a difference-in-differences strategy that compares the portfolio decisions of funds located close to the disaster zone (*treatment group funds*) to those located farther away (*control group funds*), with respect to the firms headquartered in the disaster zone. The identifying assumption is that hurricane strikes will be more salient for funds located closer to the disaster zone. Consequently, such funds may underweight stocks of firms located in the disaster zone more than that by the distant funds around the time of hurricane strikes.

To implement our difference-in-differences test, we use the county location of fund companies and firm headquarters to calculate distance in miles between fund-firm pairs and classify the funds into two groups. If the distance between fund and firm headquarters is less than 100 miles, we classify the fund-firm pair as $CLOSE$, else we classify the pair as FAR.[3] Formally, our baseline specification is as follows:

$$\begin{aligned} WEIGHT_{mst} = \beta_0 + \beta_1 CLOSE_{ms} + \beta_2 POST_{st} + \beta_3 CLOSE_{ms} \times POST_{st} + \\ X_{s,t-1} + X_{m,t-1} + \mu_m + \delta_{year} + \epsilon_{mst} \end{aligned} \tag{1}$$

where $WEIGHT_{mst}$ is the weight of stock s in the portfolio of mutual fund m at the end of quarter t. In these baseline tests, we focus on two quarters before to two quarters after the disaster. That is, if the hurricane strikes in quarter $t = Q$, we focus on quarters $Q - 2$ to $Q + 2$.[4] $POST$ take the value 1 for the disaster quarter Q and the two quarters following the disaster, $Q + 1$ and $Q + 2$, and 0 for the two quarters before the disaster quarter, $Q - 2$ and $Q - 1$. Note that $POST = 1$ for the disaster quarter Q because $WEIGHT_{mst}$ is measured at the end of the quarter $t = Q$. For instance, if the hurricane strikes on February 15, 2005, and because the weight is measured at the end of March 31, 2005, thus $POST = 1$ for the disaster quarter $Q = 2005 : Q1$.

$CLOSE$ takes the value 1 if the headquarter of mutual fund m is located within 100 miles of the headquarter of firm s, else $CLOSE$ takes the value 0. $X_{m,t-1}$ is a vector of lagged firm-level covariates such as expense ratio, turnover ratio, fund size, net fund flows and past fund returns. $X_{s,t-1}$ is a vector of lagged firm-level covariates, such as, size, book-to-market ratio, momentum and profitability. These covariates are measured at the end of the quarter $t-1$. μ_m is a vector of fund fixed effects that absorb all time-invariant differences across funds. This implies that the regressions are identified through within-fund variation in portfolio decisions around a hurricane disaster. Finally, δ_{year} are year fixed effects that control for aggregate macroeconomic shocks. The coefficient of interest is β_3 which measures

[3] For robustness, we also use alternate cutoff distances of 75 miles, 150 miles and 200 miles.

[4] Focussing on two quarters before and two quarters after the disaster ensures that our results are not driven by idiosyncratic small or large weights in any given quarter. In unreported results, for robustness, we also work with $Q - 2$ to $Q + 1$, $Q - 2$ to Q, $Q - 1$ to $Q + 2$, $Q - 1$ to $Q + 1$, $Q - 1$ to Q and find similar results.

the extent of underweighting of disaster zone stocks by close mutual funds relative to the distant funds. Specifically, underweighting by $CLOSE$ funds is given by

$$\beta_2+\beta_3 = E(WEIGHT|POST = 1, CLOSE = 1) - E(WEIGHT|POST = 0, CLOSE = 1)$$

Similarly, the underweighting by FAR funds is given by

$$\beta_2 = E(WEIGHT|POST = 1, CLOSE = 0) - E(WEIGHT|POST = 0, CLOSE = 0)$$

Thus, the relative underweighting by close funds relative to the distant funds is given by β_3. A negative β_3 coefficient indicates that the mutual funds close to the disaster zone decrease their portfolio investments in the disaster zone stocks more than the distant funds do. The key identifying assumption for consistency of β_3 is the presence of pre-event parallel trends in portfolio weights of disaster zone stocks in the portfolios of both the *treatment* ($CLOSE$) and *control* (FAR) funds.

4 Data and Descriptive Statistics

4.1 Hurricanes

We obtain data on hurricanes from the SHELDUS (Spatial Hazard and Loss Database for the United States) database at the University of South Carolina. Among other things SHELDUS provides information on names, dates and county locations of the main hurricane landfalls in the US. We collect additional information on number of fatalities and total damages from National Oceanic and Atmospheric Administration (NOAA) Technical Memorandum dated August 11. We restrict our sample to "major hurricanes" defined as category 3,4 and 5 on the Saffir-Simpson hurricane wind scale.[5] This leaves us with 12 hurricanes during our sample period. Table 1 lists these 12 major hurricanes.

[5] These are hurricanes with sustained wind speed over 50-58 m/s and the ability to impose maximum damage.

We obtain data on firm financials and headquarter county locations from Compustat Quarterly files. We eliminate all firms in the financial services industry (SIC codes 6000-6999) and those firms for which county location of headquarter is missing. Further, we restrict our sample to the period 1995-2010 because there are not many funds in the disaster zone before 1995. This is expected because the growth in the mutual fund industry started from mid-1990s. The last major hurricane in our sample occurred in 2008.

4.2 Mutual Funds

We obtain data on actively managed, open-ended diversified U.S. equity mutual funds from CRSP Survivor-Bias Free US Mutual Fund database. Our sample starts from January 1995. We eliminate index funds by using the CRSP-defined index fund flags and by screening the names of funds for words such as "Index" or "S&P." We further remove funds whose names have words such as "ETF." The net (after-expense) monthly return comes from CRSP. To avoid multiple counting of funds that have more than one class, we value-weight fund-class returns using prior month total net assets to obtain fund level net returns. Similarly, we also value-weight expense and turnover ratios. Fund size is the sum of total net assets of all fund classes. Fund age is in years, and is computed as of the month end relative to the fund's earliest first offer-date. We exclude funds with negative age. We also obtain zipcodes of fund company location from CRSP, which are converted to county level.

We obtain snapshots of quarterly holdings of funds from the Thomson Reuters mutual fund holdings database. Since our focus is on U.S. equity mutual funds, we exclude all funds whose objective code is one of the following: International, Municipal Bonds, Bond & Preferred. For funds that do not report quarterly, we extrapolate the previous quarter holdings to the current quarter. This is done for at most one quarter to avoid excessively stale data. Holdings disclosures before a quarter end are carried forward to the quarter end. From the fund-quarter portfolios identified through the holdings data, we remove all funds whose total net assets (TNA) are less than $5 million. We do not necessarily eliminate fund-quarters with missing TNA because these observations are sometimes for funds that have large previously disclosed TNA. Because our focus is on diversified funds, we eliminate funds with less than 10 stocks in their portfolio. These funds are unlikely to be diversified. By design, we have to restrict ourselves to the calendar quarters that correspond to the hurricanes listed in Table 1. We then combine the CRSP sample with the Thomson Reuters holdings sample using the MFLINKS dataset developed by Wermers (2000). Our combined sample consists of 3131 unique funds over 12,341 fund-quarters.

4.3 Descriptive Statistics

Table 2 presents summary statistics for our dataset. Panel A reports summary statistics over all fund-quarters in the sample, while Panel B reports summary statistics over fund-quarters that are close to the disaster zone. The average fund size in the full sample is $1194 million, while median size is about $200 million, which suggests the sample is skewed towards smaller sized funds. The average age of a typical fund is about 13 years. The annual expense ratio is 1.30% and turnover is about 94%. This just reflects that our sample consists of actively managed funds.

Comparing the sample of funds that are close to the disaster zone, we find very similar statistics. For instance, the average size in Panel B is about $1254 million, which is $60 million more than the average size of a typical fund in the full sample. The median size in Panel B is about $216 million, which is roughly the same as in Panel A. Similarly, the other statistics of funds close to the disaster zone are similar that of a typical fund in the full sample. Thus our sample of close funds is fairly representative of the mutual fund industry.

5 Do Managers Overreact to Salient Risks?

We begin our empirical analysis with tests of hypothesis *H1*. In these tests, we seek to understand whether the mutual funds close to the disaster zone underweight disaster zone stocks more than the funds that are far away from the disaster zone. This relatively greater underweighting by close funds can be either due to *saliency bias* or because they possess superior information. Our tests are based on the specification 1 in Section 3.

We present the results from these tests in Table 3. Focusing on column 1, the positive and significant coefficient on $CLOSE$ indicates that on an average mutual fund managers exhibit preference for close stocks (home bias from now), i.e. stocks of firms close to the mutual funds receive greater weights in their portfolios. This is consistent with Coval and Moskowitz (1999). The coefficient on $POST$ shows that on an average, even the distant mutual funds sell stocks located in the disaster zone after the hurricane strike. This is consistent with the idea that these stocks may be adversely impacted by the disaster. The coefficient of interest is the interaction term $CLOSE \times POST$ which measures the differential portfolio response of close and distant mutual funds to the stocks in the disaster zone around the hurricane strike.

The coefficient on the interaction term is negative and statistically significant with a p-value of 0.01. Consistent with the hypothesis *H1*, the coefficient on the interaction term demonstrates that the funds close to the disaster zone reduce the portfolio weights on the disaster zone stocks by approximately 0.06% as compared to the reduction in weight by the funds that are far away from the disaster zone. For a typical fund in our sample, this translates into a sizeable 10.5% drop in dollar value of each disaster stock held by close mutual funds.[6]

In column 2, we repeat our tests after controlling for fund and year fixed effects and obtain qualitatively similar results. The fixed effects ensure that the results are not driven by time-varying macroeconomic shocks or time-invariant characteristics of mutual funds that may explain the differential response of close and distant funds to the disaster zone stocks.

In column 3, we follow Kang and Stulz (1997) and repeat the results after controlling for log of firm size ($LSIZE$), log of 1+BM ratio (LBM), price momentum (MOM), profitability (ROA), sales growth ($SALESGROWTH$), and leverage ($DEBT/ASSETS$) in addition to

[6]The median size of mutual fund portfolio in our sample is \$216 millions. The dollar value invested in the median stock is \$1.23 millions (unreported in tables). So a reduction in overall portfolio weight of 0.06% translates into $\frac{0.06*\$216millions}{\$1.23millions} \approx 10.5\%$ reduction in dollar value of stock holding.

the year and fund fixed effects. All firm level covariates are measured at the beginning of the quarter. We find that our results are robust to controlling for these firm level characteristics.

One concern with our tests is that the funds closer to the disaster zone could be catering to the local investors. To the extent, that local investors themselves may be impacted by the disaster and may need to liquidate their investments, funds close to the disaster zone may experience withdrawals from such investors. Consequently, funds may respond by reducing their stock holdings. However, note that this does not explain why mutual funds would specifically choose to reduce their holdings of the disaster zone stocks relative to the other stocks in their portfolio. Nonetheless, in column 4, we repeat our tests after controlling for net flows and other fund characteristics and obtain similar results. Finally, in column 5, we repeat our tests after simultaneously controlling for fund and firm characteristics and obtain similar results. We conclude from our analysis so far that the funds close to the disaster zone indeed underweight disaster zone stocks more than that by the funds located far away from the disaster zone.

5.1 Robustness Tests

We begin this section by discussing our robustness tests to validate the identifying assumptions for our difference-in-differences research design.

5.1.1 Placebo Test with Near-Disaster Firms

We repeat our analysis in the previous section and analyze the portfolio response of close and far funds with respect to firms located in the near-miss counties that are not directly impacted by the disaster. Specifically, each disaster zone is matched with five closest neighboring counties that are not directly affected by the hurricanes. To perform the matching, we first compute the geographical distance between the centers of disaster counties and all non-affected counties. The distance is computed using Haversine formula from the latitude and longitude coordinates of the centers of counties. We then match each disaster county to five nearest neighbors with replacement.[7] For ease of reference, we call the set of such counties as near-disaster zone from now.

The *saliency hypothesis* suggests that fund managers close to the disaster zone firms rely on availability heuristic and thus over-estimate either the adverse impact of the hurricane strike on these firms or overweight the probability that a hurricane strike will occur again in future. To the extent that hurricane strikes do not directly impact firms located in the near-disaster zone, we expect weaker or no differential response between close and far funds with respect to the firms located in the near-disaster zone.

We repeat specification 1 test for near-disaster zone firms. The dependent variable now, $WEIGHT_{mst}$, is the weight in the portfolio of mutual fund m on stock s located in *near-disaster zone* at the end of quarter t.[8] Again, $CLOSE$ takes the value 1 if the headquarter of mutual fund m is located within 100 miles of the headquarter of near-disaster zone firm s, else $CLOSE$ takes the value 0. Rest of the RHS variables are defined similarly as in specification 1.

Table 4 presents the results from these tests. Focusing on column 1, we find that consistent with our conjecture, the coefficient on the interaction term, $CLOSE \times POST$ is statistically indistinguishable from zero. We find that this result is robust to including firm and fund level covariates, as well as fund and year fixed effects in our regressions (columns 2-5). This insignificant coefficient on the interaction term suggests that there is no differential response between close and distant funds with respect to the near-disaster zone firms.

5.1.2 Temporal Dynamics of Portfolio Response to Hurricane strikes

We now perform additional robustness tests. These tests are collected in the Appendix A. We start by examining the temporal dynamics of portfolio changes in response to hurricane strikes. Specifically, we are interested in two questions. First, when does the differential

[7] A hurricane impacts multiple counties in the disaster zone. Thus, one neighboring county can be matched to more than one county in the disaster zone.

[8] Note that the close and far funds are defined with respect to an area. Thus, the close (far) funds with respect to the near-disaster zone can be different from the close (far) funds with respect to disaster zone.

response of close funds relative to the distant funds start, and second, for how long this differential response lasts? Note that the absence of pre-trends (differential response *before* the hurricane strike) in the outcome variable is a necessary condition for the validity of our difference-in-differences setting. Formally, we run the following regression specification:

$$
\begin{aligned}
WEIGHT_{mst} = \beta_0 + \beta_1 CLOSE \times PRE_{[\leq -2]} + \sum_{0}^{6} \delta_s \times CLOSE \times POST[s] + \\
\beta_2 CLOSE + \beta_3 PRE_{[\leq -2]} + \sum_{0}^{6} \theta_s POST[s] + X_{s,t-1} + X_{m,t-1} + \mu_m + \delta_{year} + \epsilon_{mst}
\end{aligned} \tag{2}
$$

where m refers to a fund, s refers to a firm and t refers to a quarter. We focus on eight quarters before to eight quarters after the disaster. That is, if the hurricane strikes in quarter $t = Q$, we focus on quarters $Q - 8$ to $Q + 8$. $POST[0]$ is a dummy variable that takes the value 1 for the disaster quarter. $POST[1]$ is a dummy variable that takes the value 1 for first quarter after the disaster quarter (quarter $Q+1$). Likewise $POST[s]$ ($\forall s \in (2,5)$) takes the value 1 for quarter $Q+s$ and 0 otherwise. $POST[6]$ takes the value 1 for quarters $Q+6$ to $Q+8$. *PRE[*$\leq$ *-2]* takes the value 1 for all quarters from $Q - 8$ to $Q - 2$. The omitted category in these tests is quarter $Q - 1$. Therefore, the coefficients on the interaction terms *CLOSE X POST[s]* ($s \in (1,6)$) compares the difference in portfolio weights of the disaster zone stocks between close and far funds in quarters $Q + s$ relative to quarter $Q - 1$. Rest of the control variables as same as in specification 1.

We report the results in Table A1. First, focusing on column 1, consistent with the absence of pre-trends, we find that there is no differential response between the close and distant funds with respect to the disaster zone firms before the hurricane. The coefficient on *CLOSE X PRE*$_{[} \leq -2]$ is statistically indistinguishable from zero (p-value of 0.75).

Second, focusing on the effect of hurricane in the period after the disaster (coefficients *CLOSE X POST[s]*, $s \in (1,6)$), we find that the greater underweighting by the close funds relative to the distant funds in the disaster zone stocks start from the quarter $t = Q$, and lasts up to 3 quarters after the disaster. Thus, the saliency of hurricane strikes decreases as time passes and so does its impact on fund managers' decisions.

5.1.3 Are the Fund Managers Catering to the Withdrawal Requests of Retail Investors?

As discussed in Section 5, fund managers may reduce their portfolio investments in the disaster zone stocks not because they are themselves biased, but because they may be catering to the preferences of their investors. The retail investors may exhibit saliency bias and overreact to the hurricane disasters by liquidating their investments in funds with greater investments in the disaster zone stocks. Alternatively, local bias of individual investors (preference for stocks located in close proximity; see Ivković and Weisbenner (2005)) may induce a preference for local mutual funds (Bailey, Kumar, and Ng (2011)) and to the extent that such local investors themselves may be impacted by disaster, they may simply want to reduce their exposure to the local firms. Thus, close funds may experience outflows driven by the behavioral bias of their investors and consequently managers may reduce their holdings in the disaster zone firms to assuage such investors and curb outflows. This may be interesting in itself as it suggests that even though fund managers may themselves be rational, flow-driven trading pressures created by behavioral biases of their investors can still cause them to trade in a biased way.[9]

We perform two tests that examine whether our results can be explained by outflows from close funds. First, note from Table 3, column 4 that our results are robust to controlling for net fund flows. So fund flows alone cannot account for the underweighting of disaster zone stocks by close funds.

Second, if our results were indeed driven by capital outflows from close funds, then we should expect greater outflows from close funds following hurricane strikes relative to the outflows from the distant funds. In Table A2 we explicitly examine whether close funds experience greater outflows relative to the outflows from the distant funds. Again, in these tests we focus two quarters before to two quarters after the disaster. Each observation represents a unique fund-quarter. The dependent variable in these tests is the natural log of

[9] Coval and Stafford (2007) show that flow-driven mutual fund trading pressure can cause temporary mispricing in stock prices.

(1 + normalized net flows).[10] Focusing, on the coefficient on the interaction term *CLOSE* $\times$ *POST* in column 1, we do not find a differential change in net fund flows into close funds as compared to the net flows into distant funds. The result is robust to including fund and year fixed effects, as well as fund level covariates (columns 2 and 3).

5.1.4 Other Robustness Tests

Finally, one potential concern regarding our empirical tests is that our results may be mechanically driven by a temporary drop in stock price of disaster zone firms around the hurricane strikes. This would automatically lead to a drop in portfolio weights of these stocks even in the absence of any actual trading by close funds. This is an interesting puzzle in itself as it implies that other investors may be selling the disaster zone stocks in response to the hurricanes driving the prices downward. To ensure that our results are driven by a deliberate reduction in weights on these stocks by close funds, first, we repeat our baseline tests after controlling for quarterly stock returns in Table A3 and find our results to be robust. In other words, our results persist even after holding stock prices constant.[11]

Second, in Table A4, we repeat our baseline test (equation 1) with an alternate dependent variable capturing the number of shares of a disaster zone stock held by a fund. Specifically, the LHS variable in these tests is defined as

$$SHARES_{mst} = \frac{\#SHARES_{mst}}{\sum_{k=1}^{N} \#SHARES_{ks,Q-2}} \tag{3}$$

where $\#SHARES_{mst}$ is the number of shares of stock s held by fund m in quarter t, $\#SHARES_{ks,Q-2}$ is the number of shares of stock s held by fund k in quarter $Q-2$ and N is the total number of funds that hold stock s in quarter $Q-2$.[12] Again, consistent with

[10] We first normalize fund flows by adding the absolute value the minimum net fund flow (across all funds) in a quarter and then take log of 1 + normalized fund flows. This is done so that we do not lose observations with negative fund flows while performing log transformation.

[11] In unreported tests, we also find that all other results are robust to controlling for stock returns.

[12] Our results are unchanged if we scale by total number of shares outstanding for stock s rather than the total number of shares of stock s held by all mutual funds at the beginning of quarter Q-2.

the hypothesis *H1* and our results from Table 3, the statistically significant coefficient on the interaction term shows that the funds close to the disaster zone reduce their holdings of disaster zone stocks more than that by the funds that are far away from the disaster zone. The result holds across all our specifications in columns 1 through 5.

Overall, the results in this section provide compelling evidence in favor of the identifying assumptions underlying our research design and further strengthen the causal interpretation of our findings. We conclude that the differential response of funds close to the disaster zone relative to the funds far from the disaster zone *decreases* with both distance and time. The result is not driven just by flow-driven trading pressure created by biased investors or due to drop in stock price of disaster zone stocks.

6 Is Underweighting Rational or Driven by Saliency?

We now seek to distinguish whether the portfolio changes of funds close to the disaster zone are consistent with the *information hypothesis* or with the *saliency hypothesis*. We perform two tests. These tests are based on the post-hurricane profitability and return performance of the disaster zone firms.

6.1 Impact on Profitability

Our results from Tables 3 and 4 and further from the robustness tests in Tables A1 to A4 show that close mutual funds reduce the portfolio weights on firms located in disaster zone, while we do not observe such an effect for firms located in the near-disaster zone. If the underweighting of disaster zone stocks is driven by access to superior information regarding the future performance of such stocks, then we expect to observe a drop in performance of disaster zone stocks in the periods after the hurricane strikes. Importantly, because (a) funds closer to the near-disaster zone do not underweight near-disaster zone stocks in their portfolio, and (b) funds closer to the disaster zone do underweight disaster zone stocks, *information hypothesis* would suggest that firms in near-disaster zone should outperform the firms in the disaster zone around hurricane strikes.

To test this idea we begin with the univariate tests on financial characteristics of disaster and near-disaster zone firms. In Table 5, we split our sample in two time periods: pre-disaster (quarters $Q-2$ and $Q-1$) and post-disaster (quarters Q to $Q+2$). We then compare the financial characteristics of firms in the disaster zone and with those in the near-disaster zone across the two time periods. We report estimates from the two-sample univariate t-test for equality of means across the two time periods. Columns 1-4 report the results for the disaster zone firms, while columns 5-8 report the results for the near-disaster zone firms. We do not find any statistically significant effect of the disaster on most financial characteristics of the firms.

Columns 9 and 10 of Table 5 report the difference-in-differences estimates and p-values, respectively. We find that except for sales growth, the change in financial characteristics of the disaster zone firms around the hurricane strikes as compared to those of the near-disaster zone firms is statistically indistinguishable from zero. This is consistent with the *saliency hypothesis*. While our univariate tests show that there is a drop in sales growth of the disaster zone firms relative to the firms in the near-disaster zone, in our multivariate tests (discussed below), we find that this result is not robust to controlling for other firm characteristics.

Next, we employ a multivariate difference-in-differences strategy to evaluate whether hurricanes have an adverse incremental impact on the performance of disaster zone firms relative to the firms in the near-disaster zone. We report estimates from the following regression specification:

$$\begin{aligned} PERFORMANCE_{st} = \beta_0 + \beta_1 POST_t + \beta_2 DISASTER_{st} + \\ \beta_3 POST \times DISASTER + X_{s,t-1} + \mu_s + \delta_{year} + \epsilon_{st} \end{aligned} \tag{4}$$

where s refers to a stock, t refers to a quarter. The dependent variable *PERFORMANCE* is *ROA* in columns 1 and 2 and *Sales Growth* in columns 3 and 4. *POST* takes the value 1 for the disaster quarter $t = Q$ and the two following quarters $Q+1$ and $Q+2$ and 0 for quarters

$Q-1$ and $Q-2$. $DISASTER$ is a dummy variable that identifies firms in the disaster zone when the hurricane strikes. It takes the value 1 for all firms in the disaster zone and 0 for all firms in the near-disaster zone for all quarters from $Q-2$ to $Q+2$. The coefficient of interest is β_3 which measures the difference in performance of firms in the disaster zone as compared to firms in the near-disaster zone.

Table 6 reports coefficient estimates from the above regression. Focusing on the coefficient on the interaction term $POST\times$ $DISASTER$ in column 1, we do not observe any differential impact of hurricanes on the profitability of disaster zone firms. This finding is consistent with the *saliency hypothesis* and inconsistent with *information hypothesis*. In column 2, we repeat the test after controlling for firm fixed effects and year fixed effects and obtain similar results. In columns 3 and 4, we repeat these tests using sales growth as a measure of firm performance and obtain qualitatively similar results. Overall, the evidence from analyzing the post-hurricane profitability of disaster and near-disaster zone firms is consistent with the *saliency hypothesis*.

6.2 Disaster Proximity, Portfolio Change and Stock Returns

In this section, we perform the second test to understand the channel that drives the underweighting of the disaster zone stocks by funds close to the disaster zone. The idea is to evaluate the subsequent return performance of the disaster zone stocks. If the underweighting of the disaster zone firms by close funds is consistent with the *saliency bias hypothesis*, then we would expect the underweighted firms to perform well in the post-event quarters. On the other hand, the future underperformance by underweighted firms will be consistent with the *information hypothesis*. The underlying motivation (saliency or information) of trades of active fund managers is of fundamental importance because they are likely the price setting marginal investors in the market. Several studies show the impact of mutual fund trading on stock prices (Wermers (1999), Nofsinger and Sias (1999), Sias (2004), Dasgupta, Prat, and Verado (2011). Behaviorally biased portfolio decisions of managers may push stock prices away from their fundamental values and affect informational efficiency of prices. We employ both portfolio and regression analysis to evaluate the subsequent performance of underweighted firms.

6.2.1 Portfolio Analysis

We start with the portfolio analysis and follow the standard calendar-time portfolio methodology. We first identify the firms located in the disaster zone. We then identify the funds that hold the disaster zone firms and are within 100 miles of firm's headquarters. As before, we call such fund-firm pairs as $CLOSE$. Then for each stock i held by close funds, we obtain the average change in portfolio weight across all close funds that hold the stock around the event-quarter (Q) as follows:

$$\Delta W_{Q,i} = \frac{\sum_{k=1}^{N} (W_{Q,k(i)} - (W_{Q-1,k(i)} + W_{Q-2,k(i)})/2)}{N} \tag{5}$$

where $W_{Q,k(i)}$ is the weight on stock i in the k^{th} fund's portfolio at the end of Q, while $W_{Q-1,k(i)}$ and $W_{Q-2,k(i)}$ are the pre-event weights on stock i in the k^{th} fund's portfolio at the end of quarters Q-1 and Q-2.[13] N is the total number of close funds that hold the stock i.[14]

At the end of each event-quarter, Q, we sort stocks into equal-weighted tercile portfolios by $\Delta W_{Q,i}$ and track the performance of tercile portfolios over nine quarters, Q-2 to Q+6. We calculate raw returns as well as the risk-adjusted returns. We use DGTW benchmarks for risk-adjusted returns (Daniel, Grinblatt, Titman, and Wermers (1997) and Wermers (2004)).[15] Finally, we obtain average quarterly DGTW-adjusted returns by taking average over the entire time-series for all quarters before the hurricane disaster (Q-2 and Q-1), during the hurricane disaster (Q), and also for all quarters after the hurricane disaster (Q+1

[13]Note that we treat each disaster-quarter as a separate quarter even if there are multiple disasters in the same calendar quarter. This is important because underweighting of a disaster zone stock by a nearby fund depends on the saliency of the particular disaster. For nearby fund X, hurricane A may be salient, but a far away hurricane in the same quarter is not salient. Thus, underweighting has to be measured with respect to a disaster. We control for time-effects in the next section in regression analysis.

[14]Some stocks in the disaster zone are held by both close and distant funds. These stocks add noise in the tests. For clean inference, we remove such common stocks from each group. Our results are qualitatively similar if we include common stocks.

[15]Data are from http://www.smith.umd.edu/faculty/rwermers/ftpsite/Dgtw/coverpage.htm

to Q+6).

Tables 7 reports raw return portfolio returns in Panel A and DGTW-adjusted returns in Panel B. Tercile portfolio 1 is the most underweighted portfolio, while the tercile portfolio 3 is the most overweighted portfolio. 1-3 represents the zero-investment long-short portfolio that is long on tercile 1 and short on tercile 3. p-values are reported in parentheses.

In Panel A, we find that the pre-event returns of 1-3 portfolio are negative and statistically significant for Q-1 (-6.81%, p-value=0.05). As expected, the trading quarter returns during are large and negative (-17.60%, p-value=0.00). This is in line with the earlier studies, such as Wermers (1999), where trading quarter returns increase in direction of the trade. It is the post-hurricane returns that we are most interested in. We find statistically insignificant returns from Q+1 to Q+3, but thereafter from Q+4 to Q+6, we find returns that are both statistically and economically significant in magnitude. For instance, for Q+4 quarter the 1-3 portfolio return is 9.08% with a p-value=0.00. Similarly for Q+5 and Q+6 quarters, the returns are 5.17% (p-value=0.16) and 5.38% (p-value=0.02).[16] We further note that the return reversal is driven mainly by the returns on portfolio 1. That is, the portfolio that is most underweighted (or traded-out), exhibits statistically and economically positive returns over subsequent quarters. For instance, the Q+4 quarter return is 14.14% with a p-value=0.01. Similarly, the returns for Q+5 and Q+6 quarter, the returns are 11.60% (p-value=0.04) and 9.97% (p-value=0.00). Portfolio 3, the most overweighted (or traded-in) portfolio does not exhibit return reversal. In all post-event quarters, the returns are positive and large in magnitude, except in quarter Q+2. Thus, our raw return analysis suggests that the disaster zone stocks that are most heavily underweighted by the funds in proximity of the disaster zone exhibit return reversal.

In Panel B, we repeat our analysis with the risk-adjusted returns using DGTW benchmarks. We again find that the 1-3 portfolio exhibits return reversal in the post-event quarters. The Q+4 quarter return is 7.78% (p-value=0.01) and the Q+6 quarter return is 4.60% (p-value=0.04). The Q+5 quarter return is also large and positive (6.59%), but it is statisti-

[16]The sometimes large p-values are due to conservative approach of our portfolio analysis. We only have twelve event-quarters, yet we find economically large return reversals.

cally insignificant. We also find that the return reversal is primarily due the reversal in the underweighed portfolio 1.

We can graphically see the return reversal in Figure 3. It shows the cumulative returns of long-short portfolio for stocks held by the close and distant funds. Figure 3a shows returns for all twelve quarters, while Figure 3b shows returns for the five most damaging quarters (see Section 6.3 for more details). Five most damaging quarters capture the intensity of saliency. We find that the stocks underweighted by the close funds during the event-quarter exhibit return reversal subsequently. The return reversal is most stark post more damaging quarters. That is, when the event is more salient for proximate funds. In contrast, the counterfactual portfolio of stocks underweighted by the distant funds does not exhibit any significant reversal. We conclude that the statistically and economically large return reversal in the underweighted portfolio of the disaster zone firms by the proximate funds is consistent with the *saliency bias hypothesis.*

6.2.2 Regression Analysis

We now perform the post-disaster abnormal return analysis using regression tests with firm level control variables and time fixed effects. Using time fixed effects is important because some of our disasters are in the same quarter (for instance, 2004:Q3). Table 8 revisits the hypothesis that the disaster zone underweighted stocks by nearby funds is due to the saliency bias. We report the coefficient estimates from the following regression model:

$$RET_{st} = \beta_0 + \beta_1 DRANK1 + \beta_2 DRANK2 + \beta_3 CLOSE + \beta_4 DRANK1 \times CLOSE + \beta_5 DRANK2 \times CLOSE + CONTROLS_{s,t_0} + \delta_{t_0} + \epsilon_{st}$$

where s refers to a firm and t refers to a subsequent quarter (Q+1, Q+2,..,Q+6) and t_0 refers to the disaster quarter Q. The dependent variable is the quarterly raw return during subsequent quarters of a stock after the event-quarter. $DRANK1$ is a dummy variable that takes the value 1 if the stock is in tercile 1 in the portfolio analysis, else it takes the value 0. Similarly, we define $DRANK2$ and $DRANK3$. Dummy variable $CLOSE$ and stock level control variables are same as defined earlier in specification 1. All control variables are measured at the start of the event quarter $t_0 = Q$. All regressions include time fixed effects and standard errors are clustered by firm. p-values are reported in parentheses.

The above analysis essentially mimics the portfolio analysis but additionally allows us to control for covariates that may influence future returns, such firm as size, book-to-market ratio, momentum, and profitability. We omit $DRANK3$ from the regression, so that the coefficient on $DRANK1$ corresponds to the hedge portfolio return (1-3) in the portfolio analysis, when $CLOSE = 1$. That is, 1-3 hedge portfolio return is given by $E(RET|DRANK1 = 1, CLOSE = 1) - E(RET|DRANK3 = 1, CLOSE = 1) = \beta_1 + \beta_4$. The above regression also gives us the 1-3 hedge portfolio return on disaster zone stocks held by the counterfactual group of far away funds from the disaster zone. This is given by $E(RET|DRANK1 = 1, CLOSE = 0) - E(RET|DRANK3 = 1, CLOSE = 0) = \beta_1$. Thus, the incremental return on 1-3 portfolio is given by the coefficient on $DRANK1 \times CLOSE$, β_4.

We find that the coefficient on $DRANK1 \times CLOSE$ is 5.23% with p-value of 0.04 in quarter Q+4. Thus, there is a 5.23% greater return reversal on the underweighted minus overweighted portfolio of disaster zone stocks held for close funds relative to the distant funds. We also find that there is a significant incremental return reversal in quarter Q+6 as well (4.99%, p-value=0.03). These findings are consistent with our earlier portfolio analysis in Table 7, where we also find significant return reversal in quarters Q+4 and Q+6.[17]

6.3 Intensity of Saliency

Some events are more salient than others, and therefore it is possible that managers may overreact more to such events. Further, analyzing our results for more salient events provides a robustness check on our hypothesis. For instance, if we do not find similar results for more

[17]The exact return reversal on 1-3 portfolio for disaster zone stocks held by close funds is given by $\beta_1 + \beta_4$. This is equal to 7.18% in Q+4 and 3.50% in Q+6. The corresponding return in Table 7, Panel A are 9.08% and 5.38%, respectively. Thus, after controlling for other variables and time fixed effects, the magnitude of return reversal decreases slightly.

salient events, then it would suggest that our findings are probably driven by some other factors. We repeat our portfolio and regression by restricting the sample to the five most damaging quarters where saliency is expected to be most intense for nearby funds. Table 9 and 10 present results from portfolio and regression analysis, respectively.

We now find that there is even greater return reversal in 1-3 portfolio during the post-hurricane quarters. For instance, the Q+4 return is 14.41% (p-value=0.04) and the Q+6 return is 9.95% (p-value=0.06). We also note that this reversal is driven by the reversal in the underweighted portfolio of disaster zone firms (tercile 1). The tercile 1 portfolio return in Q+4, Q+5 and Q+6 is 16.75%, 10.65% and 13.38%, respectively. Panel B of Table 9 shows risk-adjusted returns. We find that the results are qualitatively similar. Finally, Table 10 reports regression analysis results for the five most damaging quarters. Here again as in the full sample results in Table 8, we find that there is a large incremental return reversal in 1-3 hedge portfolio returns of stocks held by close funds relative to the distant funds in quarters Q+3 and Q+4 after controlling for firm characteristics and time fixed effects. These findings further provide evidence in favor of the *saliency bias hypothesis*.

7 Conclusion

Prior studies evaluating the role of behavioral biases on investment decisions have primarily focused on retail investors (Barber and Odean (2001), Barber and Odean (2007), Bailey, Kumar, and Ng (2011)). In this paper, we use hurricane strikes as our experimental setting, and provide first large sample evidence of *saliency bias* in the portfolio decisions of mutual fund managers.

Using a difference-in-differences strategy, we first show that relative to the distant funds, mutual fund managers closer to the disaster zone reduce their portfolio holdings of firms located in the disaster area. We do not observe such a differential underweighting by close funds relative to the distant funds with respect to the firms located in the neighboring counties.

Consistent with the fund managers overestimating the adverse impact of hurricanes on stocks located in the disaster zone, we find that the bias in their trading response is transitory and vanishes with time and distance. Moreover, the response of close mutual funds is not driven by any information advantage they may possess over the distant mutual funds as we do not find any difference in the post-disaster profitability across firms in the disaster area and those in the neighboring counties. The greater underweighting of the disaster zone firms by the close funds relative to the distant funds is not driven by flow-driven trading pressure created by the biased investors or due to the drop in stock price of the disaster zone firms.

Finally, we find that such a bias is costly to the fund investors as it adversely affects portfolio returns. Specifically, a portfolio that goes long on the disaster zone stocks that experience the sharpest reduction in weights in portfolios of close funds and goes short on the stocks that experience the least reduction generates statistically and economically significant positive risk-adjusted returns after the disaster.

Overall, our analysis provides causal evidence of over-reaction in the response of mutual fund managers to the salient events.

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Figure 1: **This graph reports the frequency of hurricanes in US by decade starting in 1850.**

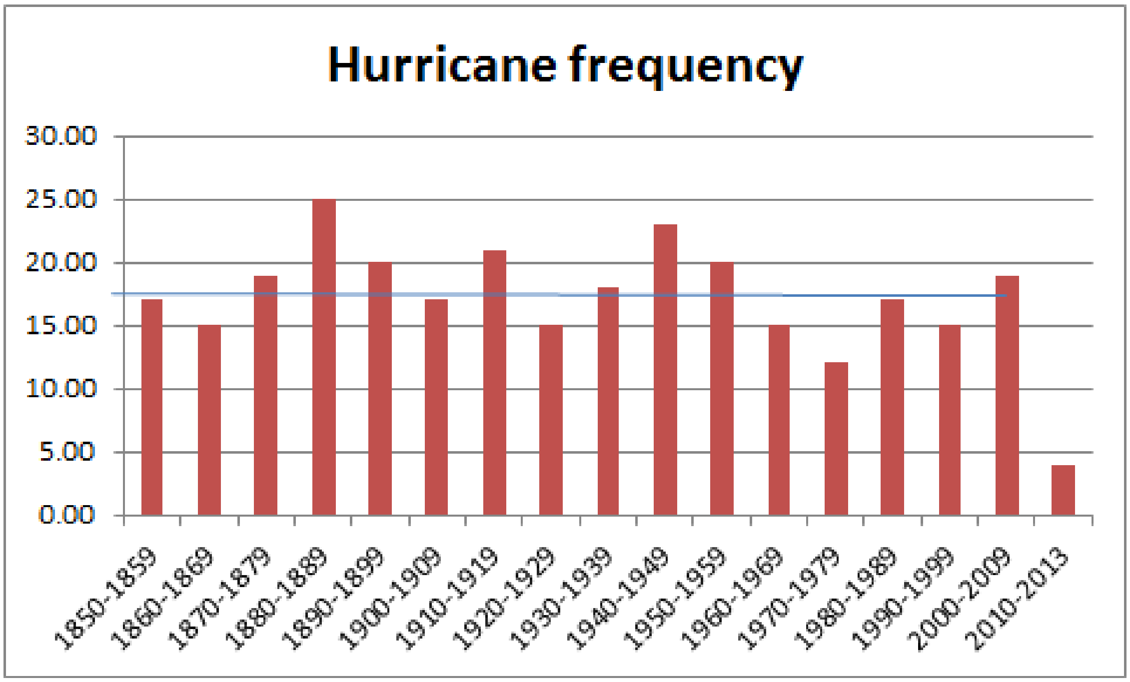


Figure 2: **This graph presents our empirical design.**

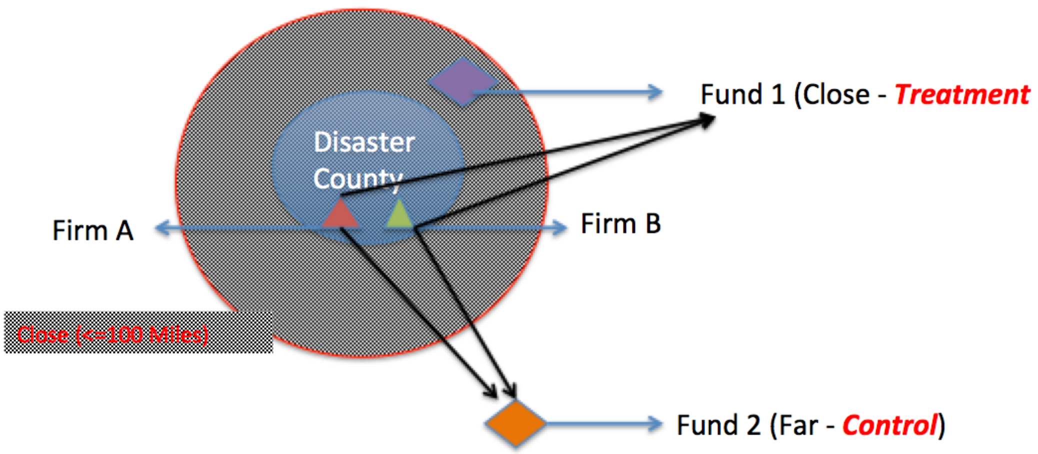
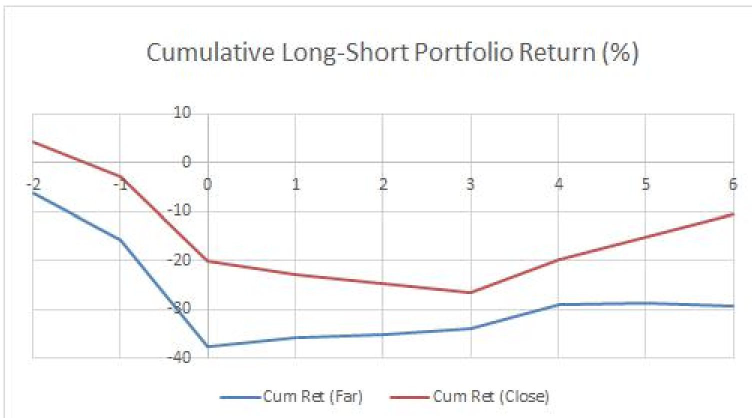
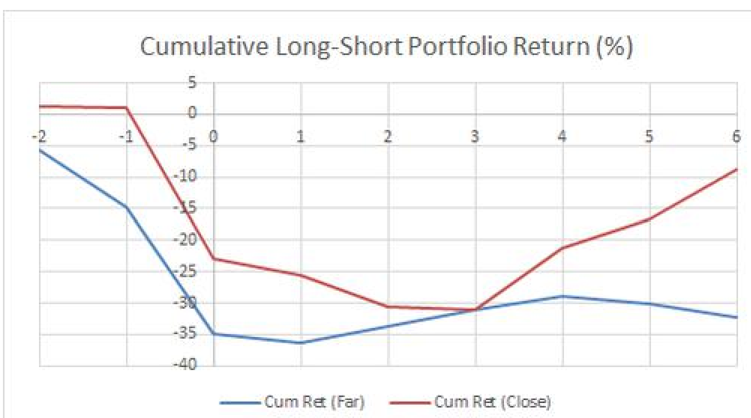


Figure 3: **Cumulative Return of Firms Located in the Disaster Zone**
This figure shows cumulative return over seven quarters (-2 to 4) on a long-short portfolio of firms based on the overreaction (see text) of funds located close to the disaster zone. The figure also shows returns on a similar long-short portfolio of firms based on the overreaction of funds located far from the disaster zone.



(a) Return Reversal (Full Sample)



(b) Return Reversal (5 Most Damaging Hurricanes)

TABLE 1: **Major Hurricanes**

This table reports information on the major hurricanes strikes in US during our sample period (1995-2010). Data on hurricanes is obtained from National Oceanic and Atmospheric Administration Technical Memorandum, August 2011.

Date	Hurricane Name	Total Damages ($ Billions)
08/23/96	FRAN	4.16
09/07/99	FLOYD	6.9
09/06/03	ISABEL	5.37
09/30/04	IVAN	18.82
08/09/04	CHARLIE	15.11
08/25/04	FRANCES	9.51
09/13/04	JEANNE	7.66
07/04/05	DENNIS	2.55
08/23/05	KATRINA	108
09/18/05	RITA	12.03
08/25/08	GUSTAV	4.618
09/01/08	IKE	29.52

TABLE 2: **Summary Statistics**
This table reports summary statistics over the full sample of fund-quarters in Panel A, and over the fund-quarters that are close to the disaster zone in Panel B.

Panel A: Fund-Quarters (Full Sample)						
Variable	NOBS	Mean	STD	P25	Med	P75
FundSize($M)	12301	1193.577	5010.452	57.600	199.600	721.832
FundAge(Yrs)	12326	13.126	13.255	4.797	9.197	15.756
ExpRatio	12133	0.013	0.005	0.010	0.013	0.016
TurnRatio	11978	0.936	1.283	0.352	0.660	1.140
FundQtrs	12341					

Panel B: Fund-Quarters (Close Funds)						
Variable	NOBS	Mean	STD	P25	Med	P75
FundSize($M)	9338	1254.657	5074.363	60.100	216.333	784.700
FundAge(Yrs)	9357	13.204	13.216	4.926	9.356	15.756
ExpRatio	9209	0.013	0.005	0.010	0.013	0.015
TurnRatio	9089	0.954	1.322	0.360	0.680	1.160
FundQtrs	9366					

TABLE 3: **Portfolio Response to Hurricane Disasters**
This table reports the coefficient estimates from the following regression model:

$$WEIGHT_{mst} = \beta_0 + \beta_1 CLOSE_{ms} + \beta_2 POST_{st} + \beta_3 CLOSE \times POST + X_{s,t-1} + X_{m,t-1} + \mu_m + \delta_{year} + \epsilon_{mst}$$

where m refers to fund, s refers to firm and t refers to a quarter. We focus on two quarters before to two quarters after the disaster. $CLOSE$ takes the value 1 for fund-firm pairs that are less than 100 miles away from each other. $POST$ takes the value 1 for the disaster quarter and the two following quarters. All variables are defined in Appendix B. The data spans the period 1995-2010. Standard errors are robust to heteroscedasticity and clustered at the fund level. p-values are reported in parentheses.

	(1)	(2)	(3)	(4)	(5)
CLOSE	0.403	0.131	0.091	0.134	0.097
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
POST	-0.047	-0.020	-0.028	-0.017	-0.025
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
CLOSE X POST	-0.058	-0.028	-0.038	-0.029	-0.041
	(0.010)	(0.035)	(0.003)	(0.039)	(0.002)
DEBT/ASSETS$_{s,t-1}$			0.020		0.017
			(0.097)		(0.159)
LBM$_{s,t-1}$			0.018		0.014
			(0.190)		(0.331)
LSIZE$_{s,t-1}$			0.228		0.232
			(0.000)		(0.000)
ROA$_{s,t-1}$			0.248		0.167
			(0.018)		(0.117)
SALES GROWTH$_{s,t-1}$			0.040		0.048
			(0.000)		(0.000)
MOMENTUM$_{s,t-1}$			0.060		0.065
			(0.000)		(0.000)
EXPENSE RATIO$_{m,t-1}$				-6.502	-3.766
				(0.048)	(0.226)
TURN RATIO$_{m,t-1}$				-0.034	-0.029
				(0.012)	(0.025)
LFUNDSIZE$_{m,t-1}$				-0.042	-0.066
				(0.000)	(0.000)
FUND RETURNS$_{m,t-1}$				-0.005	-0.351
				(0.948)	(0.000)
NET FLOW$_{m,t-1}$				-0.001	-0.001
				(0.192)	(0.078)
CONSTANT	1.045	1.063	-2.114	1.356	-1.788
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
YEAR FE	No	Yes	Yes	Yes	Yes
FUND FE	No	Yes	Yes	Yes	Yes
N	453231	453231	433712	434299	415578
ADJRSQ	0.005	0.521	0.586	0.518	0.584

TABLE 4: **Placebo Tests with Near-Disaster Firms**

This table reports the coefficient estimates from the following regression model:

$$WEIGHT_{mst} = \beta_0 + \beta_1 CLOSE_{ms} + \beta_2 POST_{st} + \beta_3 CLOSE \times POST + X_{s,t-1} + X_{m,t-1} + \mu_m + \delta_{year} + \epsilon_{mst}$$

where m refers to fund, s refers to firm and t refers to a quarter. We focus on two quarters before to two quarters after the disaster. $CLOSE$ takes the value 1 for fund-firm pairs that are less than 100 miles away from each other. $POST$ takes the value 1 for the disaster quarter and the two following quarters. All variables are defined in Appendix B. The data spans the period 1995-2010. Standard errors are robust to heteroscedasticity and clustered at the fund level. p-values are reported in parentheses.

	(1)	(2)	(3)	(4)	(5)
CLOSE	0.113	0.005	0.016	0.005	0.015
	(0.004)	(0.741)	(0.251)	(0.737)	(0.293)
POST	-0.034	-0.033	-0.022	-0.033	-0.022
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
CLOSE X POST	-0.015	-0.005	-0.010	-0.004	-0.007
	(0.365)	(0.628)	(0.272)	(0.670)	(0.446)
DEBT/ASSETS$_{s,t-1}$			-0.102		-0.103
			(0.000)		(0.000)
LBM$_{s,t-1}$			0.039		0.031
			(0.000)		(0.002)
LSIZE$_{s,t-1}$			0.233		0.237
			(0.000)		(0.000)
ROA$_{s,t-1}$			0.599		0.549
			(0.000)		(0.000)
SALES GROWTH$_{s,t-1}$			0.011		0.021
			(0.098)		(0.003)
MOMENTUM$_{s,t-1}$			0.056		0.064
			(0.000)		(0.000)
EXPENSE RATIO$_{m,t-1}$				-10.210	-8.356
				(0.002)	(0.008)
TURN RATIO$_{m,t-1}$				-0.031	-0.024
				(0.030)	(0.069)
LFUNDSIZE$_{m,t-1}$				-0.058	-0.080
				(0.000)	(0.000)
FUND RETURNS$_{m,t-1}$				-0.527	-0.596
				(0.000)	(0.000)
NET FLOW$_{m,t-1}$				-0.001	-0.001
				(0.365)	(0.015)
CONSTANT	1.005	0.889	-2.210	1.307	-1.753
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
YEAR FE	No	Yes	Yes	Yes	Yes
FUND FE	No	Yes	Yes	Yes	Yes
N	417371	417371	395852	396015	375712
ADJRSQ	0.001	0.502	0.572	0.493	0.566

TABLE 5: **Univariate Tests on the Impact of Hurricanes on Firm Financials**

This table reports univariate test on financial characteristics of firms around the hurricane strikes. We split our sample in two time periods: pre-disaster (Q-2, Q-1) and post-disaster (Q, Q+1 and Q+2) and compare the financial characteristics of firms in the *disaster zone* and those in the *near-disaster zone* across the two time periods. Columns 1-4 report the results for the disaster zone stocks, while columns 5-8 represent the results for the near-disaster zone stocks. The reported estimates in columns 3 and 7 are from two-sample univariate t-tests for equality of means across the two time-periods. Column 9 reports difference-in-differences estimates. p-values are reported in columns 4, 8 and 10. All variables are defined in Appendix B.

	Disaster				Near-Disaster				DID	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Variable	Pre	Post	Diff	P-Value	Pre	Post	Diff	P-Value	DID	P-Value
LSIZE	13.132	13.154	0.021	0.505	12.995	13.000	0.005	0.897	0.017	0.731
LBM	0.411	0.420	0.009	0.075	0.419	0.428	0.009	0.194	0.001	0.947
DEBT/ASSET	0.570	0.570	0.000	0.972	0.572	0.568	-0.004	0.421	0.004	0.520
ROA	0.017	0.016	-0.001	0.174	0.015	0.014	-0.001	0.255	0.000	0.973
SALES GROWTH	0.051	0.061	0.010	0.024	0.050	0.072	0.023	0.000	-0.013	0.054

TABLE 6: Impact of Hurricane Disaster on Profitability
This table reports the coefficient estimates for the following regression model:

$$PERFORMANCE_{st} = \beta_0 + \beta_1 POST_t + \beta_2 DISASTER_{st} + \beta_3 POST \times DISASTER + X_{s,t-1} + \mu_s + \delta_{year} + \epsilon_{st}$$

where the dependent variable *performance* is ROA in columns 1 and 2 and *Sales Growth* in columns 3 and 4. $POST$ takes the value 1 for the disaster quarter and the two following quarters. $DISASTER$ is a dummy variable that identifies stocks that are in the disaster zone. It takes the value 1 for all stocks that are in the disaster zone and 0 for the stocks in the near-disaster zone for two quarters before and after the disaster. All variables are defined in Appendix B. The data spans the period 1995-2010. Standard errors are robust to heteroscedasticity and clustered at the fund level. p-values are reported in parentheses.

	$\text{ROA}_{s,t}$		$\text{Sales Growth}_{s,t}$	
	(1)	(2)	(3)	(4)
POST	0.000	0.001	0.016	0.007
	(0.969)	(0.107)	(0.003)	(0.283)
DISASTER	0.001	-0.000	0.000	-0.005
	(0.229)	(0.582)	(0.924)	(0.429)
POST X DISASTER	-0.000	-0.001	-0.008	-0.005
	(0.806)	(0.249)	(0.231)	(0.452)
$\text{DEBT/ASSETS}_{s,t-1}$	-0.015	-0.010	-0.021	0.162
	(0.000)	(0.009)	(0.001)	(0.000)
$\text{LBM}_{s,t-1}$	-0.001	-0.001	-0.025	0.031
	(0.455)	(0.452)	(0.000)	(0.014)
$\text{LSIZE}_{s,t-1}$	0.005	0.008	-0.001	0.020
	(0.000)	(0.000)	(0.122)	(0.001)
$\text{MOMENTUM}_{s,t-1}$	0.004	0.003	0.032	0.010
	(0.000)	(0.000)	(0.000)	(0.066)
CONSTANT	-0.038	-0.074	0.082	-0.279
	(0.000)	(0.000)	(0.000)	(0.002)
YEAR FE	No	Yes	No	Yes
FIRM FE	No	Yes	No	Yes
N	22884	22884	22916	22916
ADJRSQ	0.101	0.713	0.009	0.022

TABLE 7: **Disaster Proximity, Portfolio Change and Stock Returns: Portfolio Analysis**

This table reports quarterly equal-weighted portfolio raw returns in Panel A and DGTW-adjusted returns in Panel B. At the end of each disaster quarter (Q), we sort firms into tercile portfolios on the basis of average change in firm weight ($\sum_{k=1}^{N}(weight_{Q,i} - (weight_{Q-1,i} + weight_{Q-2,i})/2)$) across N funds that are close to the disaster zone and hold the stock i. We then obtain equal-weighted returns on portfolios from Q-2 to Q+6 quarter. Finally, we obtain average quarterly returns by taking average over the entire time-series for each quarter. Portfolio one is the most underweighted portfolio, while portfolio three is the most overweighted portfolio. 1-3 represents zero-investment long-short portfolio that is long on tercile one and short on tercile three. p-values are reported in parentheses.

Panel A: Raw Returns

Tercile	Q-2	Q-1	Q (Event Qtr)	Q+1	Q+2	Q+3	Q+4	Q+5	Q+6
1	2.207	1.419	-10.361	4.441	-2.754	2.584	14.147	11.603	9.972
	(0.266)	(0.660)	(0.002)	(0.243)	(0.401)	(0.635)	(0.013)	(0.047)	(0.000)
2	-2.860	1.596	-1.352	3.538	-1.434	2.726	6.866	3.800	4.354
	(0.097)	(0.750)	(0.619)	(0.425)	(0.681)	(0.471)	(0.086)	(0.175)	(0.018)
3	-1.985	8.230	7.246	7.862	-0.378	4.974	5.063	5.838	4.587
	(0.483)	(0.043)	(0.002)	(0.030)	(0.915)	(0.224)	(0.187)	(0.037)	(0.012)
1-3	4.193	-6.811	-17.607	-3.421	-2.376	-2.391	9.084	5.765	5.385
	(0.139)	(0.058)	(0.000)	(0.123)	(0.119)	(0.480)	(0.007)	(0.168)	(0.029)

Panel B: Risk-adjusted Returns

Tercile	Q-2	Q-1	Q (Event Qtr)	Q+1	Q+2	Q+3	Q+4	Q+5	Q+6
1	3.202	-2.605	-9.187	-1.943	-1.930	0.519	6.879	7.264	3.620
	(0.062)	(0.210)	(0.000)	(0.219)	(0.207)	(0.870)	(0.037)	(0.153)	(0.042)
2	-1.848	-2.719	-2.332	-2.440	1.215	0.553	-2.035	-1.691	-2.283
	(0.146)	(0.315)	(0.264)	(0.416)	(0.470)	(0.781)	(0.438)	(0.164)	(0.295)
3	-1.454	4.230	7.486	1.469	-0.382	2.926	-0.910	0.675	-0.988
	(0.374)	(0.006)	(0.001)	(0.269)	(0.757)	(0.216)	(0.647)	(0.703)	(0.202)
1-3	4.656	-6.835	-16.673	-3.412	-1.548	-2.408	7.789	6.590	4.608
	(0.076)	(0.044)	(0.000)	(0.112)	(0.269)	(0.480)	(0.010)	(0.190)	(0.042)

TABLE 8: **Disaster Proximity, Portfolio Change and Stock Returns: Regression Analysis**

This table reports the coefficient estimates from the following regression model:

$$RET_{st} = \beta_0 + \beta_1 DRANK1 + \beta_2 DRANK2 + \beta_3 CLOSE + \beta_4 DRANK1 \times CLOSE + \beta_5 DRANK2 \times CLOSE + CONTROLS_{s,t_0} + \delta_{t_0} + \epsilon_{st}$$

where s refers to a firm and t refers to a subsequent quarter (Q+1, Q+2,..,Q+6) and t_0 refers to the disaster quarter Q. The dependent variable is the quarterly raw return during subsequent quarters of a stock after the event-quarter. $DRANK1$ is a dummy variable that takes the value 1 if the stock is in tercile one in the portfolio analysis, else it takes the value 0. Similarly, we define $DRANK2$. $CLOSE$ takes the value 1 for fund-firm pairs that are less than 100 miles away from each other. The control variables are log of firm size ($LSIZE$), log of 1+BM ratio (LBM), price momentum (MOM), profitability (ROA), sales growth ($SALESGROWTH$), and leverage ($DEBT/ASEETS$). All control variable are measured at the start of the disaster quarter (Q). N is the number of observation in a regression and $ADJRSQ$ is adj-Rsquared. All regressions include time fixed effects and standard errors are clustered by firm. p-values are reported in parentheses.

	(1)	(2)	(3)	(4)	(5)	(6)
	Q+1	Q+2	Q+3	Q+4	Q+5	Q+6
DRANK1	1.645	0.281	-0.362	1.948	0.124	-1.439
	(0.327)	(0.857)	(0.828)	(0.188)	(0.930)	(0.320)
DRANK2	-2.312	1.289	1.344	-1.135	-0.699	-1.467
	(0.156)	(0.404)	(0.407)	(0.425)	(0.603)	(0.327)
CLOSE	1.098	0.189	-0.048	-2.108	1.293	-2.883
	(0.582)	(0.921)	(0.981)	(0.265)	(0.424)	(0.071)
DRANK1 X CLOSE	-4.223	-0.669	4.057	5.237	-0.708	4.991
	(0.108)	(0.793)	(0.158)	(0.045)	(0.762)	(0.031)
DRANK2 X CLOSE	2.189	-0.646	-1.303	3.327	-0.638	2.015
	(0.412)	(0.811)	(0.640)	(0.206)	(0.772)	(0.379)
LSIZE	-0.348	-1.532	0.778	0.712	1.481	-1.144
	(0.329)	(0.000)	(0.035)	(0.030)	(0.000)	(0.000)
LBM	-12.400	-8.475	2.065	8.927	5.950	8.364
	(0.000)	(0.004)	(0.551)	(0.004)	(0.024)	(0.006)
MOMENTUM	6.263	2.765	-2.509	-3.361	-2.219	-5.785
	(0.000)	(0.073)	(0.062)	(0.006)	(0.071)	(0.000)
ROA	-51.814	-75.929	7.012	-5.602	72.801	3.190
	(0.029)	(0.002)	(0.724)	(0.737)	(0.000)	(0.877)
SALESGROWTH	3.197	6.689	-4.030	-5.717	-3.287	0.987
	(0.381)	(0.026)	(0.176)	(0.019)	(0.196)	(0.710)
DEBT/ASSETS	-7.919	-10.036	-0.388	2.360	1.325	4.169
	(0.002)	(0.000)	(0.870)	(0.289)	(0.514)	(0.050)
CONSTANT	15.218	29.978	-5.249	-6.917	-21.087	18.548
	(0.009)	(0.000)	(0.363)	(0.185)	(0.000)	(0.000)
TIME FE	YES	YES	YES	YES	YES	YES
N	2510	2491	2452	2404	2350	2291
ADJRSQ	0.300	0.170	0.194	0.170	0.121	0.082

TABLE 9: **Disaster Proximity, Portfolio Change and Stock Returns: Portfolio Analysis (Five Most Damaging Hurricanes)**

This table reports quarterly equal-weighted portfolio raw returns in Panel A and DGTW-adjusted returns in Panel B. At the end of each disaster quarter (Q), we sort firms into tercile portfolios on the basis of average change in firm weight ($\sum_{k=1}^{N}$ $(weight_{Q,i} - (weight_{Q-1,i} + weight_{Q-2,i})/2)$) across N funds that are close to the disaster zone and hold the stock i. We then obtain equal-weighted returns on portfolios from Q-2 to Q+6 quarter. Finally, we obtain average quarterly returns by taking average over the entire time-series for each quarter. Portfolio one is the most underweighted portfolio, while portfolio three is the most overweighted portfolio. 1-3 represents zero-investment long-short portfolio that is long on tercile one and short on tercile three. p-values are reported in parentheses.

Panel A: Raw Returns

Tercile	Q-2	Q-1	Q (Event Qtr)	Q+1	Q+2	Q+3	Q+4	Q+5	Q+6
1	1.395	2.579	-14.552	1.474	-3.359	7.876	16.755	10.658	13.887
	(0.617)	(0.291)	(0.019)	(0.875)	(0.553)	(0.513)	(0.077)	(0.028)	(0.003)
2	-0.861	-3.801	2.379	2.666	-1.484	11.065	7.222	2.119	2.871
	(0.780)	(0.362)	(0.660)	(0.761)	(0.790)	(0.110)	(0.360)	(0.310)	(0.370)
3	0.160	2.864	9.148	4.886	3.307	8.783	2.336	4.887	4.329
	(0.974)	(0.108)	(0.014)	(0.529)	(0.539)	(0.168)	(0.621)	(0.280)	(0.095)
1-3	1.235	-0.285	-23.700	-3.412	-6.665	-0.907	14.419	5.771	9.558
	(0.745)	(0.929)	(0.001)	(0.443)	(0.009)	(0.908)	(0.046)	(0.232)	(0.069)

Panel B: Risk-adjusted Returns

Tercile	Q-2	Q-1	Q (Event Qtr)	Q+1	Q+2	Q+3	Q+4	Q+5	Q+6
1	2.721	1.292	-12.489	0.551	-2.993	3.531	9.685	5.336	5.093
	(0.105)	(0.614)	(0.007)	(0.800)	(0.379)	(0.638)	(0.134)	(0.176)	(0.224)
2	-0.955	-5.068	1.095	2.366	0.353	4.355	-3.220	-2.805	-6.247
	(0.271)	(0.309)	(0.785)	(0.340)	(0.861)	(0.248)	(0.628)	(0.189)	(0.206)
3	-0.209	1.437	9.381	3.658	1.965	5.532	-3.436	-0.030	-1.496
	(0.937)	(0.131)	(0.001)	(0.191)	(0.137)	(0.112)	(0.127)	(0.994)	(0.294)
1-3	2.930	-0.144	-21.870	-3.107	-4.958	-2.001	13.121	5.366	6.589
	(0.387)	(0.959)	(0.000)	(0.463)	(0.081)	(0.802)	(0.049)	(0.190)	(0.232)

TABLE 10: **Disaster Proximity, Portfolio Change and Stock Returns: Regression Analysis (Five Most Damaging Hurricanes)**

This table reports the coefficient estimates from the following regression model for the five most damaging hurricanes:

$$RET_{st} = \beta_0 + \beta_1 DRANK1 + \beta_2 DRANK2 + \beta_3 CLOSE + \beta_4 DRANK1 \times CLOSE + \beta_5 DRANK2 \times CLOSE + CONTROLS_{s,t_0} + \delta_{t_0} + \epsilon_{st}$$

where s refers to a firm and t refers to a subsequent quarter (Q+1, Q+2,..,Q+6) and t_0 refers to the disaster quarter Q. The dependent variable is the quarterly raw return during subsequent quarters of a stock after the event-quarter. $DRANK1$ is a dummy variable that takes the value 1 if the stock is in tercile one in the portfolio analysis, else it takes the value 0. Similarly, we define $DRANK2$. $CLOSE$ takes the value 1 for fund-firm pairs that are less than 100 miles away from each other. The control variables are log of firm size ($LSIZE$), log of 1+BM ratio (LBM), price momentum (MOM), profitability (ROA), sales growth ($SALESGROWTH$), and leverage ($DEBT/ASSETS$). All control variable are measured at the start of the disaster quarter (Q). N is the number of observation in a regression and $ADJRSQ$ is adj-Rsquared. All regressions include time fixed effects and standard errors are clustered by firm. p-values are reported in parentheses.

	(1)	(2)	(3)	(4)	(5)	(6)
	Q+1	Q+2	Q+3	Q+4	Q+5	Q+6
DRANK1	-5.036	-0.772	-0.159	2.794	-0.271	-0.585
	(0.008)	(0.726)	(0.956)	(0.204)	(0.874)	(0.768)
DRANK2	-5.126	0.386	-0.928	-1.987	-2.041	-2.038
	(0.005)	(0.853)	(0.721)	(0.353)	(0.216)	(0.290)
CLOSE	3.884	1.208	-4.287	-4.249	0.651	-2.022
	(0.112)	(0.659)	(0.230)	(0.134)	(0.761)	(0.354)
DRANK1 X CLOSE	-1.167	-5.821	13.620	11.219	2.231	3.631
	(0.727)	(0.143)	(0.016)	(0.013)	(0.453)	(0.208)
DRANK2 X CLOSE	3.691	-6.540	4.298	8.197	-0.022	3.411
	(0.295)	(0.080)	(0.369)	(0.049)	(0.994)	(0.283)
LSIZE	-0.106	-2.068	1.100	0.933	0.943	-0.256
	(0.804)	(0.000)	(0.089)	(0.068)	(0.016)	(0.547)
LBM	-7.703	-10.720	2.742	11.113	-2.767	11.140
	(0.034)	(0.015)	(0.671)	(0.032)	(0.455)	(0.006)
MOMENTUM	0.073	-0.874	-6.081	-4.954	0.252	-1.858
	(0.972)	(0.656)	(0.041)	(0.012)	(0.878)	(0.419)
ROA	33.069	11.913	-44.731	-67.495	-10.322	-50.489
	(0.177)	(0.691)	(0.230)	(0.011)	(0.717)	(0.111)
SALES GROWTH	-2.011	4.569	-2.422	2.412	5.125	0.432
	(0.541)	(0.304)	(0.573)	(0.556)	(0.235)	(0.913)
DEBT/ASSETS	-3.333	-10.374	-0.247	5.513	-2.876	-0.026
	(0.288)	(0.001)	(0.955)	(0.122)	(0.312)	(0.993)
CONSTANT	-2.594	36.992	0.178	-8.552	-4.831	9.936
	(0.692)	(0.000)	(0.986)	(0.285)	(0.391)	(0.143)
TIME FE	YES	YES	YES	YES	YES	YES
N	1035	1028	1014	998	986	968
ADJRSQ	0.472	0.228	0.230	0.244	0.046	0.052

Appendix A

This Appendix reports results of robustness tests that are briefly described in the text. Additional details are available from the authors upon request.

TABLE A1: Dynamics of Portfolio Response to Hurricane Disasters

This table reports the coefficient estimates from the following regression model:

$$WEIGHT_{mst} = \beta_0 + \beta_1 CLOSE \times PRE[\leq -2] + \sum_{0}^{6} \delta_s \times CLOSE \times POST[s] +$$

$$\beta_2 CLOSE + \beta_3 PRE[\leq -2] + \sum_{0}^{6} \theta_s POST[s] + X_{s,t-1} + X_{m,t-1} + \mu_m + \delta_{year} + \epsilon_{mst}$$

where m refers to a fund, s refers to a firm and t refers to a quarter. We focus on eight quarters before and eight quarters after the disaster. That is, if the hurricane strikes in quarter $t = Q$, we focus on quarters $Q-8$ to $Q+8$. $POST[0]$ is a dummy variable that takes the value 1 for the disaster quarter. $POST[1]$ is a dummy variable that takes the value 1 for first quarter after the disaster quarter (quarter $Q+1$). Likewise $POST[s]$ ($\forall s \in (2,5)$) takes the value 1 for quarter $Q+s$ and zero otherwise. $POST[6]$ takes the value 1 for quarters $Q+6$ to $Q+8$. *PRE[$\leq$ -2]* takes the value 1 for all quarters from $Q-8$ to $Q-2$. The omitted category in these tests is quarter $Q-1$. All variables are defined in detail in Appendix B. The data spans the period 1995-2010. Standard errors are robust to heteroscedasticity and clustered at the fund level. p-values are reported in parentheses.

	(1)	(2)
CLOSE X POST[0]	-0.029	-0.045
	(0.013)	(0.000)
CLOSE X POST[1]	-0.026	-0.036
	(0.092)	(0.018)
CLOSE X POST[2]	-0.038	-0.053
	(0.048)	(0.005)
CLOSE X POST[3]	-0.050	-0.083
	(0.014)	(0.000)
CLOSE X POST[4]	-0.023	-0.040
	(0.301)	(0.059)
CLOSE X POST[5]	-0.040	-0.055
	(0.107)	(0.023)
CLOSE X POST[6]	-0.032	-0.032
	(0.225)	(0.216)
CLOSE	0.146	0.115
	(0.000)	(0.000)
CLOSE X PRE[-2]	-0.004	0.001
	(0.754)	(0.957)
CONSTANT	1.044	-2.430
	(0.000)	(0.000)
CONTROLS	No	Yes
YEAR	Yes	Yes
FUND FE	Yes	Yes
N	885208	847087
ADJRSQ	0.506	0.570

TABLE A2: **Net Fund Flows around Hurricane Disasters**

This table reports the coefficient estimates from the following regression model:

$$LOG(FLOW)_{mt} = \beta_0 + \beta_1 CLOSE_{ms} + \beta_2 POST_{st} + \beta_3 CLOSE \times POST + X_{m,t-1} + \mu_m + \delta_{year} + \epsilon_{mst}$$

where m refers to a fund, s refers to a firm and t refers to a quarter. The dependent variable in these tests is $LOG(FLOW)$, which is defined as the natural log of (1 + normalized net flow). We normalize net fund flow to positive values by adding the absolute value of minimum flow in a quarter across all funds. We focus on two quarters before to two quarters after the disaster. $CLOSE$ takes the value 1 for fund-firm pairs that are less than 100 miles away from each other. $POST$ takes the value 1 for the disaster quarter and the two following quarters. All variables are defined in Appendix B. The data spans the period 1995-2010. Standard errors are robust to heteroscedasticity and clustered at the fund level. p-alues are reported in parentheses.

	(1)	(2)	(3)
CLOSE	-0.0212	-0.0131	-0.0188
	(0.179)	(0.493)	(0.304)
POST	0.0370	0.0524	0.0601
	(0.000)	(0.000)	(0.000)
CLOSE X POST	0.0100	0.0246	0.0197
	(0.568)	(0.193)	(0.290)
EXPENSE RATIO$_{m,t-1}$			3.349
			(0.213)
TURN RATIO$_{m,t-1}$			0.00287
			(0.760)
LFUNDSIZE$_{m,t-1}$			0.0389
			(0.000)
FUND RETURNS$_{m,t-1}$			1.537
			(0.000)
CONSTANT	2.584	2.679	2.380
	(0.000)	(0.000)	(0.000)
YEAR FE	No	Yes	Yes
FUND FE	No	Yes	Yes
N	31165	31165	29802
ADJRSQ	0.002	0.123	0.128

TABLE A3: Portfolio Response to Hurricane Disasters after Controlling for Stock Returns

This table reports the coefficient estimates from the following regression model:

$$WEIGHT_{mst} = \beta_0 + \beta_1 CLOSE_{ms} + \beta_2 POST_{st} + \beta_3 CLOSE \times POST + X_{s,t-1} + X_{m,t-1} + \mu_m + \delta_{year} + \epsilon_{mst}$$

where m refers to a fund, s refers to a firm and t refers to a quarter. We focus on two quarters before to two quarters after the disaster. $CLOSE$ takes the value 1 for fund-firm pairs that are less than 100 miles away from each other. $POST$ takes the value 1 for the disaster quarter and the two following quarters. All variables are defined in Appendix B. The data spans the period 1995-2010. Standard errors are robust to heteroscedasticity and clustered at the fund level. p-values are reported in parentheses.

	(1)	(2)	(3)	(4)	(5)
CLOSE	0.403	0.131	0.090	0.134	0.095
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
POST	-0.044	-0.017	-0.026	-0.014	-0.022
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
CLOSE X POST	-0.056	-0.024	-0.031	-0.025	-0.033
	(0.013)	(0.066)	(0.016)	(0.075)	(0.013)
STOCK RETURN$_{s,t}$	0.249	0.236	0.316	0.240	0.318
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
DEBT/ASSETS$_{s,t-1}$			0.035		0.033
			(0.004)		(0.007)
LBM$_{s,t-1}$			0.026		0.024
			(0.059)		(0.090)
LSIZE$_{s,t-1}$			0.231		0.235
			(0.000)		(0.000)
ROA$_{s,t-1}$			0.324		0.266
			(0.002)		(0.014)
SALES GROWTH$_{s,t-1}$			0.024		0.029
			(0.001)		(0.000)
MOMENTUM$_{s,t-1}$			0.047		0.050
			(0.000)		(0.000)
EXPENSE RATIO$_{m,t-1}$				-6.448	-3.569
				(0.051)	(0.249)
TURN RATIO$_{m,t-1}$				-0.036	-0.031
				(0.007)	(0.016)
LFUNDSIZE$_{m,t-1}$				-0.043	-0.066
				(0.000)	(0.000)
FUND RETURNS$_{m,t-1}$				0.225	0.017
				(0.004)	(0.822)
NET FLOW$_{m,t-1}$				-0.001	-0.001
				(0.108)	(0.034)
CONSTANT	1.038	1.047	-2.183	1.338	-1.866
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
YEAR FE	No	Yes	Yes	Yes	Yes
FUND FE	No	Yes	Yes	Yes	Yes
N	451775	451775	433623	432897	415495
ADJRSQ	0.008	0.525	0.589	0.521	0.587

TABLE A4: **Portfolio Response to Hurricane Disasters (#Shares Held)**
This table reports the coefficient estimates from the following regression model:

$$SHARES_{mst} = \beta_0 + \beta_1 CLOSE_{ms} + \beta_2 POST_{st} + \beta_3 CLOSE \times POST + X_{s,t-1} + \mu_m + \delta_{year} + \epsilon_{mst}$$

where m refers to a fund, s refers to a firm and t refers to a quarter. The dependent variable is *# Shares Held*, which is defined as the ratio of total number of shares of stock s held by fund m in quarter t to the total number of shares of stock s held by all mutual funds at the beginning of quarter Q-2 (where Q denotes the disaster quarter). We focus on two quarters before to two quarters after the disaster. $CLOSE$ takes the value 1 for fund-firm pairs that are less than 100 miles away from each other. $POST$ takes the value 1 for the disaster quarter and the two following quarters. All variables are defined in Appendix B. The data spans the period 1995-2010. Standard errors are robust to heteroscedasticity and clustered at the fund level. p-values are reported in parentheses.

	(1)	(2)	(3)	(4)	(5)
CLOSE	0.005	0.001	0.002	0.001	0.003
	(0.015)	(0.527)	(0.027)	(0.400)	(0.014)
POST	0.002	0.002	0.002	0.001	0.002
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
CLOSE X POST	-0.002	-0.002	-0.002	-0.002	-0.002
	(0.032)	(0.003)	(0.000)	(0.001)	(0.000)
DEBT/ASSETS$_{s,t-1}$			-0.002		-0.002
			(0.097)		(0.078)
BOOK TO MARKET$_{s,t-1}$			-0.008		-0.007
			(0.000)		(0.000)
LSIZE$_{s,t-1}$			-0.009		-0.009
			(0.000)		(0.000)
ROA$_{s,t-1}$			-0.106		-0.101
			(0.000)		(0.000)
SALES GROWTH$_{s,t-1}$			0.003		0.003
			(0.000)		(0.000)
MOMENTUM$_{s,t-1}$			0.003		0.003
			(0.000)		(0.000)
EXPENSE RATIO$_{m,t-1}$				0.656	0.539
				(0.000)	(0.000)
TURN RATIO$_{m,t-1}$				-0.001	-0.001
				(0.178)	(0.018)
LFUNDSIZE$_{m,t-1}$				0.008	0.008
				(0.000)	(0.000)
FUND RETURNS$_{m,t-1}$				0.025	0.025
				(0.000)	(0.000)
NET FLOW$_{m,t-1}$				0.000	0.000
				(0.217)	(0.539)
CONSTANT	0.016	0.042	0.166	-0.003	0.126
	(0.000)	(0.000)	(0.000)	(0.512)	(0.000)
YEAR FE	No	Yes	Yes	Yes	Yes
FUND FE	No	Yes	Yes	Yes	Yes
N	450707	450707	433436	431884	415327
ADJRSQ	0.001	0.360	0.419	0.368	0.429

Appendix B: Variable Definitions

Fund level Variables

- *EXPENSE RATIO*: Annual expense ratio of a fund.
- *TURN RATIO*: Turnover ratio of a fund.
- *LFUNDSIZE*: Natural log of total assets under management in $Millions.
- *FUND RETURNS*: Three month average return. For instance, for the quarter ending $t-1$, this variable is defined as the average monthly net return over the three months in quarter $t-1$.
- *NET FLOW*: Monthly net flows in to a fund. Flows during the month j are defined as $\frac{TNA_{m,j}-TNA_{m,j-1}(1+r_{m,j})}{TNA_{m,j-1}}$, where $TNA_{m,j}$ represents the total net assets of fund m at the end of month j and $r_{m,j}$ is the CRSP reported net return of the fund m in month j.

Firm Level Variables

- *DEBT/ASSETS*: The ratio of the book value of total debt to the book value of book value of total assets.
- *LBM*: Natural log of the ratio of the book value of total assets to the sum of the market value of equity and the book value of debt.
- *LSIZE*: Natural log of the book value of total assets.
- *MOM*: Cumulative 12 month return of a stock, excluding the immediate past month.
- *ROA*: The ratio of earnings before interest, depreciation, and taxes to the book value of total assets.
- *SALES GROWTH*: Percentage annual change in division sales.

Fund-Firm level Variables

- *SHARES*: Ratio of total number of shares of stock s held by fund m in quarter t to the total number of shares of stock s held by all mutual funds at the beginning of quarter Q-2 (where Q denotes the disaster quarter).

- *WEIGHT*: Weight of stock s in the portfolio of mutual fund m at the end of a quarter t.

Difference-in-Differences Dummy Variables

- *CLOSE*: A dummy variable that takes the value 1 if the headquarters of mutual fund m is located within 100 miles of the headquarters of firm s (located in disaster zone), else takes the value 0.

- *DISASTER*: A dummy variable that takes the value 1 for counties in which there was a hurricane strike during our sample period.

- *POST*: A dummy variable that takes the value 1 for the disaster quarter Q and the two quarters following the disaster, Q+1 and Q+2, and 0 for the two quarters before the disaster quarter, Q-2 and Q-1.