ESSAYS IN FINANCIAL ECONOMICS

By

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A DISSERTATION

Submitted to
Michigan State University
in partial fulfillment of the requirements
for the degree of

Business Administration - Finance – Doctor of Philosophy

2019

ABSTRACT

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Stress negatively affects decision-making processes and limits individuals' ability to concentrate or learn new information. Therefore, investors affected by stress experience an increase in their marginal costs of processing economic information and, consequently, face greater difficulty in making investment allocation decisions. Medical and epidemiology literature document increased levels of Post-Traumatic Stress Disorder within the general population in the aftermath of widely reported disaster events. Accordingly, I construct a time-series sample of nationally significant traumatic events such as school shootings to identify periods of elevated stress in the United States in the period from 1995 to 2017 and study the effects of stress on investors' financial decision-making abilities.

In this dissertation, I exploit geographic variation in the level of stress exposure across mutual-fund managers and find that managers in close proximity to traumatic events underperform their geographically distant peers over the quarter following a nearby traumatic event by approximately 50 basis points. I also find that, following traumatic events, investors experience increased sensitivity to search costs, lower sensitivity to financial information, and decreased ability to pick mutual funds that generate positive risk-adjusted returns. These findings are especially pronounced for retail investors, who likely face greater information-processing constraints than financially sophisticated institutional investors do.

This thesis is dedicated to my wife, Qingqiu Li.

ACKNOWLEDGEMENTS

I would like to thank my dissertation advisor, Zoran Ivković, for the many helpful comments. I also received numerous very helpful comments from Andrei Simonov, Charles Hadlock, and Xing Huang. I would also like to thank the participants of the workshop at Michigan State University. All remaining errors are my own.

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CHAPTER 1

INTRODUCTION

The study of behavioral finance has led to many insights into the biases that govern how individuals make financial decisions.Thaler and Sunstein (2008) suggest that these biases regularly lead individuals to make sub-optimal economic decisions with incomplete information. Recent literature has examined how investment decisions vary with investor psychology and emotion (Goetzmann et al. (2015) and Lo et al. (2005)). Stress is a widely experienced psychological mechanism that negatively impairs decision-making processes. According to the American Psychological Association's *2015 Stress in America* Survey, 24% of adults experienced 'extreme' levels of stress during the past year, 27% of adults reported an inability to concentrate due to stress in the past month, and 1/3 of respondents reported feelings of anxiety, worry, and a lack of patience(American Psychological Association, 2016). Investor stress has implications for financial markets because investors experiencing stress will have greater difficulty in making investment allocation decisions. Furthermore, environmental shocks that affect individual levels of stress may have economic consequences.

In this study, I explore how post-traumatic stress disorder affects investor decision-making within the mutual-fund sector. Medical and psychological research has shown that post-traumatic stress directly impairs the cognitive abilities related to decision-making by reducing concentration and analytical abilities (Vasterling, Brailey, Constans, and Sutker (1998) and Vasterling, Duke, Brailey, Constans, Allain, and Sutker (2002)). Slone (2000) and Ahern, Galea, Resnick, and Kilpatrick (2002) find evidence of high levels of PTSD symptoms within the general public following traumatic events, with individuals who consume television coverage of these events being particularly affected. Based on this evidence, I conjecture that stress and post-traumatic stress symptoms increase investor information-processing costs by reducing the investors' ability to concentrate and acquire new financial information. Financial decision-makers suffering from post-traumatic stress face increased difficulty in analyzing and utilizing financial information, resulting in impaired investment decision abilities. Subsequently, investment decisions made during high-stress periods are likely to be less informed.

I construct a data set of national traumatic events, such as school shootings, to identify periods of elevated post-traumatic stress symptoms within the general public. I find that, in periods associated with high PTSD, investors suffer from impaired decision-making ability. Mutual-fund managers located near the sites of traumatic events underperform compared to their distant peers. I also find that investors have increased sensitivity to search costs and are less sensitive to financial information. These findings are especially pronounced for retail investors, who likely face greater information processing constraints than more financially sophisticated institutional investors do. Furthermore, I find evidence of a reduction in investors' mutual-fund selection, with the fund's investors choose earning lower alphas.

The traumatic events I use in this study are based on the Vanderbilt Television News Archive. This archive contains a listing of nightly evening news broadcasts from major national networks such as CNN, Fox, ABC, NBC, and CBS. The events in my set are highly tragic, sensational, and dominate the evening news coverage when they occur. They include school shootings, plane crashes, celebrity deaths, and bombings. Importantly, these events occur randomly and are largely independent of aggregate market information.

1.1 Fund Managers

In my first study, I investigate how post-traumatic stress affects the decision-making of financially sophisticated mutual-fund managers. I exploit geographic variation in the exposure of fund managers to the stress shocks to identify the effects of PTSD on financial decision-making abilities. Psychology research has documented that geographic proximity to traumatic events is related to an increased exposure to acute post-traumatic stress. (Gabriel et al. (2007), Rubin et al. (2005)). When a traumatic event exogenously shocks a geographic region, local mutual-fund managers will experience a higher incidence of post-traumatic stress than distant mutual-fund managers do.

I find evidence of reduced portfolio performance within the subsample of managers local to the traumatic event. This underperformance amounts to 56 basis points over the 3 months following the event for domestic equity mutual-fund managers when benchmarked against a matched sample of funds located more than 1,000 miles away from the event. To rule out the possibility of local information effects (Shive (2011)) or any potential home bias (Pool et al. (2012)), I restrict this sample to include only international equity funds located in the United States and find a similar 40-basis point underperformance over the following quarter. In simulations of randomized event days, I find that my results are robust at the 5% level.

Managers may respond to this shock to their marginal information processing costs by either delaying investment decisions (lowering decision frequency) or by making relatively 'easier' decisions (changing investment strategy). To test this first channel, I proxy investment decision frequency with mutual-fund turnover. If psychological stress is a limiting factor on managers ability to make decisions, managers may reduce their decision volume and shift new investments into a future period, resulting a lower fund turnover. I find that, following traumatic events, local fund managers reduce fund turnover relative to distant managers. On an annual basis, this reduction in turnover amounts to 20% of fund assets for the local managers, while distant managers experience no observable decrease in annual turnover.

Next, I explore whether the managers' investment strategy changes in the aftermath of traumatic events. When making investment decisions, managers strike a trade-off between the extent to which they will replicate their benchmark index and the extent to which they will actively deviate from the index (Cremers and Petajisto (2009)). Replicating the benchmark index is a relatively easier task because the portfolio positions and weights are known in advance. On the other hand, deviating from the index requires considerable effort to identify promising investment opportunities. I calculate tracking errors between each fund and their respective benchmark and find that managers who were more inclined to track their benchmark prior to traumatic events further increase their indexing behavior and have lower tracking errors in the post-event period.

The finance literature has proposed two alternative hypothesis for a shift in manager behavior following traumatic events. The first is that the events may change fund managers' risk aversion. This risk-aversion hypothesis has been at the core of research into the market reactions to terrorist activities in studies such as Antoniou et al. (2018), Wang, Albert and Young, Michael (2018), and Wang and Young (2018). To rule out that post-event performance is affected by shifts in risk aversion, I measure the changes to Fama-French 3-Factor exposures between the pre-event and post-event quarters. I find no evidence of a shift in mutual funds' risk-factor exposures, suggesting that changes in risk aversion do not play a role in this context. The second alternative hypothesis I consider is that managers may be distracted by the traumatic events. Managers have limited attention capabilities and may reallocate their attention from financial information to following the traumatic events. Similarly, in an effort to boost their coverage of the traumatic events and thereby increase viewership, news programs may disregard market-relevant information events. If the results were driven by the distraction while the event was in the news-cycle, the bulk of the measured effects would occur contemporaneously. However, I find that PTSD impairment affects trading behavior up to 60 trading days following the initial event.

1.2 Fund Managers

In a parallel set of results, I study mutual-fund flows—the observable outcomes of investor wealth-allocation decisions, to investigate how these events affect mutual-fund investors' financial decisions. I test for cross-sectional differences in of fund flows between normal periods and high-stress periods. Changes in how investors allocate their wealth across different types of mutual funds indicate a shift in how financial decisions are made in the aftermath of traumatic events. In other tests, I examine how stress affects more financially sophisticated market participants, the mutual-fund managers. The availability of daily mutual-fund returns allows for repeated observations of individual managers' performance over time.

I first examine whether stress impairs the investors' ability to identify investment opportunities. In a high-stress environment, in which investors' ability to concentrate is impaired, managing mutual-fund search costs likely plays a more pronounced role in determining fund allocation decisions. Low-visibility funds require more costly effort to identify and are less likely to enter the choice set of individual investors than large more prominent funds are. I find that high-visibility funds receive a greater portion of fund flows during high stress periods. The expected net flows to the largest funds are approximately 1% greater after traumatic periods.

I next study whether post-traumatic stress limits the amount of information investors incorporate into their mutual-fund investment decisions. A large body of literature has found that investors chase past returns in mutual funds by investing disproportionately in the funds that outperformed in the prior period (Chevalier and Ellison (1997), Sirri and Tufano (1998), Lynch and Musto (2003),Jonathan B. Berk and Richard C. Green (2004)). To implement the strategy of chasing past winners, individuals must first exert effort to gather, analyze, and compare financial information. The effort required to learn and process such information is greater in the aftermath of traumatic events because of increased levels of stress. I estimate the sensitivity of mutual-fund flows to past returns and find that the flow-performance sensitivity is reduced in periods following traumatic events. The expected flows to the highest-performing funds is almost halved, with the top-performing funds receiving only 2.5% higher flows compared to 4% for the normal period. This evidence suggests that investors weigh past return information less heavily during high stress periods.

Prior familiarity with financial information may mitigate the effects of stress on financial decision-making. Unlike institutional investors, retail investors often face barriers in accessing mutual-fund return information and may lack prior experience in analyzing mutual funds. These investors need to compare prospectus statements or access premium subscriptions to online tools such as Morningstar. On the other hand, sophisticated institutional investors face virtually no barriers in accessing this type of financial information. Stress may have a greater effect on retail investors who face larger marginal increases in information processing costs following traumatic events. To test this hypothesis, I split my sample of mutual funds and separately estimate flow-performance sensitivities within retail and institutional fund share classes. I only find evidence of a flatter flow-performance sensitivity within the retail share-class group, confirming my hypothesis.

My next hypothesis addresses whether the quality of investment decisions is reduced by stress. If investors efficiently use financial information to allocate their wealth, an increase in information costs during high stress periods will lead to worse investment decisions and reduced portfolio alphas. In the spirit of Zheng (1999), I construct a monthly portfolio representing the aggregate decision-making ability of investors. This portfolio weighs the returns of mutual funds that investors purchased (large inflows) less the returns of funds that experienced share redemptions (large outflows). I test the difference in portfolio alphas between funds purchased and funds sold for normal and stress periods and perform a series of simulations using randomized event days. For retail investors, I find no evidence of decision-making impairment during high stress periods. However, for institutional investors, I find a decrease in expected alpha of 17 basis points. One interpretation of this evidence is that institutional investors efficiently use financial information and an increase in stress limits their ability to optimally allocate portfolio capital.

Changes in the pattern of net fund flows could be driven by distortions in either purchases of fund shares (inflows) or share redemptions (outflows). Investors may respond to the shock of a traumatic event by delaying their investment decisions. However, investors may have limited ability to delay share redemptions because these decisions are more likely to be motivated by liquidity reasons (Barber and Odean, 2000) making share purchases more sensitive to the cognitive effects of stress. I test this hypothesis using EDGAR Form N-SAR filings, which separately report fund inflows and outflows. I only find evidence of a reduction of share purchases following traumatic events and no effect for share redemptions.

1.3 Combined

My paper explores the role investor psychology has in financial decision-making and investment allocations. I identify environmental shocks to stress as a separate dynamic channel for investor psychology to affect financial markets. My work is related to the study of how environmental factors affect investor behavior. Kamstra, Kramer, and Levi (2003) and Kamstra, Kramer, Levi, and Wermers (2017) analyze the effects of Seasonal Affective Disorder on market prices and fund flows. Investor emotions have been widely studied within the finance literature in studies such as Hirshleifer and Shumway (2003), Edmans, García, and Norli (2007), and Goetzmann, Kim, Kumar, and Wang (2015).

The connection between traumatic events and financial markets is a growing area of financial research. Antoniou, Maligkris, and Kumar (2018) studies the forecasts of financial analysts in the quarter after domestic terrorist attacks and finds evidence of increased forecast pessimism. Ahern (2018) studies terrorist attacks at the institutional and macroeconomic level. Wang and Young (2018) uses household-level financial data and documents reduced participation in equity markets following terrorist attacks. My dissertation builds upon this literature by connecting the changes in investor behavior to post-traumatic stress related symptoms and documenting how stress effects different types of investor groups.

Fund flows have been widely studied within the literature in papers such as Elton, Gruber, and Busse (2004), Cooper, Gulen, and Rau (2005), Cronqvist (2006), Sensoy (2009), and Barber, Huang, and Odean (2016). My dissertation is also related to the cross-section of mutual-fund flows. I contribute to this literature by showing how fund allocations are sensitive to changes in investor psychology.

1.4 Background

Post-traumatic Stress Disorder is the most common type of mental disorder experienced after large traumatic events Neria, DiGrande, and Adams (2011). PTSD is defined by the DSM-IV (American Psychiatric Association, 2000) criteria as mental disorder which develops after exposure to a catastrophic event involving death or injury or perceived threat to one's physical integrity. Importantly, individuals can develop symptoms of PTSD without physically being present at a traumatic event. PTSD only necessitates that individuals perceive a threat to their well-being. Individuals suffering PTSD symptoms commonly experience: substantial functional impairment; depression and generalized anxiety disorder; feelings of helplessness, avoidance or numbing; and hyper-arousal (lack of focus). These symptoms can persist for more than four weeks. Silver, Holman, McIntosh, Poulin, and Gil-Rivas (2002) finds that individuals often cope with PTSD symptoms by 'giving up.'

Post-Traumatic Stress Disorder symptoms are directly related to individual decision-making processes. Vasterling et al. (1998) and Vasterling et al. (2002) study the learning abilities of Vietnam veterans suffering from PTSD and find that PTSD reduces learning abilities by impairing sustained attention, working memory, and initial acquisition of information. Shaw, Applegate, and Schorr (1996) examine the performance of children in classrooms 21 months following Hurricane Andrew and find evidence of increased attention problems and signs of moderate to severe stress-related symptoms. Furthermore, PTSD symptoms are psychologically related to those of ADHD because both disorders share similar symptoms of hyper-arousal (lack of focus). A few papers in this area of literature, including Szymanski, Sapanski, and Conway (2011), have studied whether childhood ADHD may be misdiagnosed PTSD.

A growing body of literature has emerged studying the incidence of PTSD symptoms within the general population following widely reported traumatic events. There is strong evidence of high levels of PTSD symptoms within the general U.S. population outside of New York City following the September 11th attacks (Galea, Vlahov, Resnick, Ahern, Susser, Gold, Bucuvalas, and Kilpatrick (2003), Silver, Holman, McIntosh, Poulin, and Gil-Rivas (2002), Silver et al. (2004), and Schuster et al. (2001)). These studies find that approximately 44% of the U.S. population reported substantial stress reactions in the first week following the attacks. 17% of the population outside of New York City reported post-traumatic stress symptoms two months after the attacks. Television news coverage is an important channel for the transmission of these psychological effects. Notably, Schuster et al. (2001), Ahern et al. (2002), Schlenger, Caddell, Ebert, Jordan, Rourke, Wilson, Thalji, Dennis, Fairbank, and Kulka (2002), and Slone (2000) find that post-traumatic stress symptoms following the September 11th attacks are increasing with the number of hours of TV news viewed. In an economic setting, Melnick and Eldor (2010) finds larger economic effects to terrorism following increased media coverage of the event.

The emergence of PTSD symptoms within the general population has been studied for traumatic events other than the September 11th terrorist attacks. Terr, Bloch, Michel, Shi, and al (1999) studies the effects of PTSD in school age children following the 1989 Challenger Space Shuttle explosion and finds that East Coast children who watched the explosion exhibited PTSD symptoms in greater frequency than West Coast children who heard about the event afterwards. The authors also find no difference in symptoms after 5-7 weeks between students who watched the event on television and students who were present at Cape Canaveral. Similar patterns emerge for the Oklahoma City bombing (Pfefferbaum, Doughty, Reddy, Patel, Gurwitch, Nixon, and Tivis, 2002), the 2005 London Subway Bombings (Gabriel, Ferrando, Cortón, Mingote, García-Camba, Liria, and Galea, 2007), and the 2004 Madrid Train Bombings (Rubin et al., 2005).

This line of medical and psychological research suggests a long-lived lingering psychological impairment following the televised reporting of traumatic events. Based upon these past findings, I conjecture that individual information-processing costs are increased during periods of elevated post-traumatic stress. A reduced ability to concentrate and acquire new information prompts individuals to have limited ability to process financial information before feeling overwhelmed. The affected individuals must exert more effort to process the same amount of information. As a result, investment decisions made during high-stress periods are likely to reflect less information, leading to distortions of the cross-section of fund flows and reduced investment performance. These mutual-fund allocations may be long-lived because individuals infrequently revisit retirement portfolio allocation decisions (Sialm, Starks, and Zhang, 2015).

1.5 Related Work: Investor Psychology and Attention

The connection between psychological symptoms and financial decision-making has been well established in the financial literature. The underlying psychological mechanisms of emotions and mood have been studied more generally in Lo and Repin (2002) and Kuhnen and Knutson (2011), who find that physiological emotional responses affect financial decisions. A large literature has emerged studying how financial markets are affected by environment-induced changes in investor psychology and moods. Kamstra, Kramer, and Levi (2003) and Kamstra, Kramer, Levi, and Wermers (2017) analyze the effects of Seasonal Affective Disorder on market prices and fund flows. The authors use changes in seasons to identify aggregate levels of depression-related symptoms within the investor population and measure subsequent effects on market prices and decisions. Hirshleifer and Shumway (2003) and Goetzmann, Kim, Kumar, and Wang (2015) explore daily variation in weather and the resulting effects of changes in investor mood. Edmans, García, and Norli (2007) finds similar results using the changes in investor mood following national sporting events. I build upon this literature by providing evidence that exogenous environmental shocks in the national media can spill over into financial markets. This is a potentially cleaner setting to study environmental shocks to investor psychology because weather and seasonal trends are fairly predictable within geographic regions.

My paper is also related to the growing literature studying the economic effects of terrorist activities. Similar to prior literature on investor moods, Drakos (2010) and Arin, Ciferri, and Spagnolo (2008) document negative returns attributable to a negative sentiment and mood in investors following terrorist activity. Melnick and Eldor (2010) find that these economic effects are greater when there is more media coverage of the event. Antoniou, Maligkris, and Kumar (2018) report that financial analysts are more pessimistic in their earnings forecasts following terrorist activity. Terrorism may also lead to an increased risk aversion among household investors. Building on Guiso, Sapienza, and Zingales (2018), Wang and Young (2018) finds reduced participation in equity markets following terrorist activities and Wang, Albert and Young, Michael (2018) report evidence that investors shift investment preferences towards less risky mutual funds. Ahern (2018) studies how psychological stress is connected to economic activity; the paper explores the link between psychology and the macro-level economy and finds an overall increase in income following terrorist activity. This dissertation identifies a separate channel for terrorist activities and traumatic events to affect investor psychology through PTSD and stress. Whereas other studies focus on investor risk aversion following terrorist attacks, this PTSD channel affects financial markets through an increase in marginal information costs, reducing the market participants' investment ability.

My dissertation is also related to investor attention, a topic widely studied in the financial literature. Peng (2005), DellaVigna and Pollet (2009), Hirshleifer, Lim, and Teoh (2009), Kempf, Manconi, and Spalt (2017) look at the immediate effects of investor attention at the daily level. Lu, Ray, and Teo (2016) study the performance of hedge-fund managers during marital events. In these papers, there are constraints on investors' information-processing capacity. My dissertation is related to this strand of research because stress directly affects investor's concentration and information consumption. Israeli, Kasznik, and Sridharan (2017) and Peress and Schmidt (2016) use news media reporting as an attention grabbing event and study the subsequent effects on trading volume and liquidity. Rather than study the contemporaneous market effects of attention during the reporting period, this dissertation examines how stress generated by news media events can lead to longer-term effects. PTSD can affect individuals over a period of one to two months (Silver, Holman, McIntosh, Poulin, and Gil-Rivas, 2002), which can lead to stress symptoms and information inattention long after the initial event seizes to be reported in the news media.

I also contribute to the literature exploring investor financial sophistication and differences in investment decisions between retail and institutional investors, building upon the literature studying individual investors (Barber and Odean (2000) and Barber and Odean (2008)). Recent papers by Foerster, Linnainmaa, Melzer, and Previtero (2017) and Linnainmaa, Melzer, and Previtero (2017) examine how sophisticated financial advice affects investment decisions by unsophisticated retail investors. Other work by Barber, Huang, and Odean (2016) finds that sophisticated and unsophisticated investors exhibit different preferences for investment risk when choosing between mutual funds.

1.6 Sample Construction and Methodology

The data for my analysis comes from two primary sources. Data on mutual funds characteristics, fund flows, and returns is from the Center for Research in Security Prices (CRSP). Data on media events comes from the Vanderbilt Television News Archive, an online database containing program descriptions for nightly news broadcasts by nationally broadcast news stations since 1968. This data set contains program descriptions for the ABC, CBS, NBC, CNN, MSNBC, and Fox News networks. Additional data on mutual fund share purchases and redemptions is from SEC From

N-SAR, available from EDGAR.

1.6.1 Mutual Fund Variables and Data

Using the CRSP mutual fund database, I construct a sample of mutual funds for the period from 1995 to 2016. I first use a mapping file provided by CRSP to link CRSP fund identifiers into EDGAR contract, series, and company CIK identifiers. This allows me to aggregate the CRSP share classes into EDGAR fund series (a single fund may have separate share classes for retail, institutional, and broker sales). My first set of tests is conducted at the aggregated fund-series level. I proportionally weigh CRSP fund characteristics based on monthly total net assets of each share class within the mutual fund. I apply a standard set of filters to construct my final sample used in my tests. I require funds to be at least 2 years old, have at least 10 million in monthly total net assets, have monthly flows of less than 10,000% and flows greater than -97%, and at least 24 monthly-return observations in my data. I further restrict the sample to remove both VAU funds and ETFs. To reduce the effect of outliers, monthly return data is winsorized at the 1% level. Furthermore, the fund share classes in CRSP must have existing mappings into the EDGAR data to identify the fund series and the fund family to which they belong. My fund manager tests use this sample with the inclusion of the daily mutual fund returns data from CRSP. However, daily mutual fund returns are only available post-2001. Furthermore, I restrict the mutual-fund manager sample to only include domestic or international equity funds. This step ensures that I am able to compare funds along measures of risk exposures and risk adjusted performance. To construct this sample, I require that the first letter of the CRSP objective identifier begins with E.

Panel A of Table 2.1 reports the summary statistics for the daily return sample of mutual fund managers. This entire sample includes 4,185 mutual funds from 2001 to 2016. The sample of mutual funds used for my fund flows results are reported in 3.1. This second sample contains 7,928 unique fund series from 1,030 different fund companies from 1995 to 2016.

I also run tests directly at the CRSP share-class level. I use individual share-classes to proxy for differences in investor sophistication based on the separated retail and institutional sales channels.

All of the same data filters are applied to this second subsample. This sample is reported in Panel B of Table 3.1.

For fund inflow and outflow data I use SEC filing Form N-SAR from EDGAR. Since 2004, mutual funds have been filing Form NSAR semiannually with the SEC. Monthly inflows and outflows are reported at the fund-series level in item 28. To ensure a consistent sample and eliminate data reporting errors, I merge this data with my CRSP fund-series sample and require a 90% correlation for computed net flows for the N-SAR filings and CRSP. This step retains a set of 2,320 unique fund series from 2004 to 2016.

1.6.2 Key Variables: Choice of Events

I construct a time series of national traumatic events and high-stress periods based on the daily news programming listings from the Vanderbilt Television News Archive. Traumatic event days are identified using a calculated measure based on the number of news outlets covering a story along with the proportion of the nightly news coverage dedicated to the story. I assume that stories covered by the majority of news outlets for most of the broadcast period report to be highly significant events. I use keyword filters to eliminate events containing market-relevant information such as politics and wars. This approach allows the aggregate news media to determine which events are attention-grabbing and traumatic.

The Vanderbilt Television News Archive reports news broadcasts using a separate subject heading for each segment of the evening broadcast. For example, the first 5 topics for the January 17, 2003 broadcast of the NBC Nightly News is listed as: 1. *Preview/Introduction Tom Brokaw (New York)*; 2. *Iraq-US Relations / War Talk / Weapons Inspections*; 3. *Affirmative Action / University of Michigan / Rice*; 4. *Afghanistan / Accidental Bombing / Hearing*; and 5. *Stock Market Report (Studio: Tom Brokaw)*. Data for other days and networks is presented similarly. Networks have the discretion to devote as many of the evening broadcast segments to the same topic as they desire. For instance, on April 16, 2007 the day of the tragic Virginia Tech shootings, the NBC news broadcasts are listed as: 1. *Virginia Tech / Massacre / Interviews*; 2. *Virginia Tech / Massacre*;

3. *Iraq War / Casualties*; 4. *Spring Weather / East Storm*; and 5. *Virginia Tech / Massacre / Steger Interview*. On the same day, CBS is listed as broadcasting the following: 1. *Virginia Tech / Massacre / O'Dell Interview*; 2. *Virginia Tech / Massacre / Steger Interview*; 3. *Spring Weather / East Storm*; and 4. *Virginia Tech / Massacre*.

I calculate the proportion of the daily news broadcast devoted to a single story for each day in the period from 1995 to 2016 across each network. To implement this step, I use the text prior to the '/' symbols in the segment description fields to categorize news topics as belonging to the same story and calculate the proportion of the daily broadcast devoted to the same news story. I form an initial list of news events from the pool of the top 10% most heavily covered news stories in the sample period.

As a second step, I implement a word filter to eliminate news stories likely to contain market-relevant information. Subject words relating to politics, wars, business, natural disasters (such as Hurricane Katrina), and September 11th terrorist attacks are removed. This process retains a list of 63 unique major traumatic events between 1995 and 2016, by construction heavily reported across the entire country. Figure 1.1 depicts the distribution of events over the sample period. The first portion of the sample period has a relatively uniform distribution of events, while the final 3 years of the sample experience a sharp rise in event frequency.

The list of events in my sample includes mass shootings and other attacks such as Columbine Highschool, DC Sniper, Virginia Tech, Orlando Nightclub shootings, Boston Marathon Bombing, Fort Hood Shootings, Aurora Colorado Movie Theater Shootings, and the Paris newspaper attacks. Other events that received national attention, such as the Columbia space shuttle explosion, Princess Diana's death, and Michael Jackson's death are also included.

As a final step, to match the monthly frequency of my fund-flow observations, I map the series of daily events onto individual months. The intuition is that an event that occurs at the end of a month would have minimal effect on that month's aggregate net flows. For instance, if an event occurred on the 28th of a given month, only the investment decisions made in the final 2 days would be affected, whereas the investment decisions made during the previous 28 days of the same month would be untreated. Furthermore, the stress effects would carry over into the following month.

I designate event months using a simple rule. For each event, I create a four- week ‘event window’ and proceed to sum for each month the number of ‘event days’ during that month. Months with at least 20 ‘event days’ are considered as ‘event months.’ In other words, if the event occurred at the beginning of the month, that month is counted as a treatment month. If an event occurred at the end of the month, I count the following month as a treatment month. If the event happened during the middle of the month, I do not count that month unless there is an additional nearby event. Figure 1.2 illustrates these rules.

CHAPTER 2

FUND MANAGERS

2.1 Motivation and Methodology

In this study, I examine how stress affects the decision-making abilities of presumably sophisticated mutual-fund managers. This setting has two key advantages. First, I can observe the daily return performance of individual managers. Although I cannot directly observe the fund managers' actual decision-making process, daily returns are a direct outcome of the unobserved decision-making process. Second, fund managers have a known geographic location. This allows me to exploit exogenous variation in the geographic exposure of managers to each traumatic event and thereby identify with reasonable precision the effects of stress on managerial performance.

Fund managers have a pre-existing geographic distribution across population centers in the United States (Pool et al. (2012)). Similarly, the locations of the traumatic events in my sample are highly correlated with population centers across the country, with few events occurring in rural areas. Figure 1.3 depicts the locations of traumatic events over a map of the United States. The majority of events are located in coastal areas with high density populations. For each of these events, managers in close geographic proximity to the event are more likely to have experienced greater stress exposure (Gabriel, Ferrando, Cortón, Mingote, García-Camba, Liria, and Galea (2007), Rubin, Brewin, Greenberg, Simpson, and Wessely (2005)).

The emergence of PTSD symptoms is related to a perceived threat to one's personal integrity (Neria, Nandi, and Galea (2008)). Importantly, the threat to the individual need not be actual. Geographic proximity to an event is positively related to increased knowledge and salience of the traumatic event. Individuals are more likely to have visited the location or have personal familiarity with it, creating pathways toward vividly imagining the event. Local media is also more likely to cover heavily the event taking place within its coverage area, increasing media exposure to images and videos of the event.

Therefore, fund managers in close proximity to an event are more likely to be affected by stress and post-traumatic stress symptoms than distant fund managers are. I treat my series of traumatic events as a series of exogenous shocks to a geographic location. Fund managers local to an event will be exposed to a relatively high level of post-traumatic stress compared to distant managers. As a result, these local managers will face an increase to their marginal cost of information processing and have greater difficulty in making investment decisions. For each event, I treat this local group of managers as an exogenously defined treatment group, while managers distant to the event are a natural control group.

Using the manager office locations in CRSP, I measure the distance between each mutual fund and event. I manually identify zip codes for each event, map the set of fund and event zip codes onto latitude and longitude coordinates, and calculate the pairwise distances between events and funds using the Haversine method. Managers whose offices are within 100 miles of an event are defined to be the sample of 'near' managers, while those 1,000 miles from the event are designated as the 'far' control group subsample.

I then separately examine 'Foreign Equity' and 'Domestic Equity' mutual funds. 'Foreign Equity' funds are managed within the United States, but have overseas portfolio holdings. This empirical design avoids any potential home bias (Pool et al. (2012)) or local information effects (Shive (2011)) that managers may have about firms in the local region surrounding their offices. Neither the 'near' nor the 'far' group of managers have a geographically-based information advantage when investing in international firms. This feature helps isolate the information about the traumatic event itself from the information about the cash flows of portfolio companies. For example, information about a US school shooting is almost entirely irrelevant for a mutual fund investing in the Middle East. Any additional market-wide effect of the traumatic event will affect both the treatment and control group managers. The cash flows of foreign firms are unlikely to be affected by local US shocks, and changes to market sentiment will affect near and distant funds equally.

Table 2.1 reports summary statistics for my sample of mutual fund managers. Panels B and C display data separately for the Domestic and International equity mutual funds. International funds tend to be smaller and younger than their domestic counterparts, and to have higher expense ratios. International equity funds also typically have less turnover than domestic equity funds do.

To further control for potential geographic differences between the treatment and control manager groups, I use propensity score matching to identify a set of treatment and control group funds. The matching criteria I include are investment objective, past returns, fund size, fund age, and portfolio turnover. I separately perform this matching step on both the domestic equity and international equity group of funds. This process ensures that the treatment and control group funds will have similar distributions along these observable dimensions.

Table 2.2 reports subsample summary statistics for the near and far matched samples. Panel (A) reports summary stats for the sample of 361 'near' international equity funds with the corresponding 632 'far' funds are shown in Panel B. As expected, the two subsamples are fairly consistent. Panels C and D similarly show summary statistics for the 'near' and 'far' domestic equity manager samples, for a total of 1,031 unique 'near' managers and 1,804 'far' managers. Once again, these two subsamples, by design, have highly similar observable fund characteristics.

I begin by defining a one-quarter event window (63 trading days) before and after each traumatic event in the sample. Taking advantage of the localized shocks to stress following traumatic events, I employ a Difference-in-Differences approach to testing the effects of stress on manager investment abilities. The general specification used to test hypotheses is:

$$Y_{i_t} = \beta_1 Post\_Event_{i,t} + \beta_2 Near_{i,t} + \beta_3 Post\_Event_{i,t} x Near_{i,t} \\ + Controls_{i,t} + Event_t + Objective_i + \epsilon_{i,t} \quad (2.1)$$

In this model, Y represents various fund characteristics such as risk factor weightings, turnover, or benchmark tracking errors estimated over the pre-event and post-event window. The primary variable of interest is the interaction between $Post\_Event_{i,t}$ and the near fund indicator $Near_{i,t}$. This variable estimates whether the average change in fund characteristics between the pre- and post-event periods is conditional upon proximity to the event itself.

The above specification includes controls for various fund characteristics, including fund size, fund age, and turnover. Additionally, the specification also includes event (time) effects and investment objective effects.

As a final step, to control for potential omitted time-series or geographic effects, I perform a series of simulations selecting 1,500 randomized event days and locations to create test statistics for the purpose of testing against the observed pre- and post-event changes in fund characteristics. Based on Figure 1.1, I draw treatment days from two separate uniform distributions for the 2001 to 2013 and 2014 to 2016 periods to capture the actual observed event frequency distribution. As a second step, I randomly assign the actual traumatic events to each of the simulated treatment dates. This randomizes the order in which events occur, but maintains the existing geographic distribution of the events. This process generates the entire distribution of differences in fund characteristics between 'near' and 'far' fund manager groups.

2.2 Fund Manager Results

2.2.1 Primary Results: Fund Returns

The mutual-fund industry is a competitive market and managers optimize information usage to pursue profitable investment opportunities. If there is a shock to the marginal cost of information processing, managers will tend to use less information (and interpret whatever information they do us with a greater error rate) in shaping investment decisions. To the extent that information is beneficial to managers, an increase in information costs will reduce investment performance, resulting in lower realized returns for high stress managers.

Therefore, my first hypothesis is: *Hypothesis 1: Fund managers located in close proximity to stressful events will underperform compared to geographically distant peers.*

To test this hypothesis I implement an event study approach. First, I construct an event window (t_{-21} to t_{+63} surrounding each traumatic event in my sample) and calculate event period returns for both the 'near' and the 'far' fund manager groups. My first set of results directly benchmarks the 'near' group of manager returns against the 'far' group. I then repeat the same procedure, but instead compare Fama-French 3 Factor returns between the geographic groups.

Figure 2.1 reports the initial results. The green line depicts the cumulative difference in the matched sample of 'near' and 'far' international equity mutual funds. The cumulative pre-event difference in returns is relatively small and is statistically insignificant. In the course of the first month of trading, day 0 to day 21, there is a gradual decline in returns from -10 basis points to -25 basis points. During the second month of trading, the underperformances intensifies to -60 basis points. By the third month, there is no additional underperformance, with the two sets of funds having similar performance.

The observed delay in effect, with minor underperformance over the initial trading month is not consistent with a distraction-based interpretation. While managers may be distracted for a short period of time surrounding the very occurrence of an event, it is unlikely that this would significantly affect returns 4-8 weeks after the initial period of distraction.

To assess whether this underperformance is an artifact of the particular event days chosen, I perform a series of simulations to create test statistics for the stress effect.[1]. Figure 2.2 plots the median and bottom 5th percentile of simulated returns along with the actual observed return difference for the event period window. Results for international equity and domestic equity funds are separately reported in Panels A and B. As expected, there is a negligible performance difference at the median between the matched groups of mutual-fund managers. The cumulative difference in returns 8 weeks after the traumatic event is significant for both manager subsamples. The pattern of underperformance for domestic equity managers closely reflects that of the international group. The performance of local managers gradually declines over the course of the first month following the event, and the underperformance increases between 4 and 8 weeks.

In Figure 2.3 I repeat the above analysis using abnormal returns calculated with the Fama French 3 Factor Model. I use the 90 days prior to each event window to estimate factor loadings and calculate abnormal returns over the subsequent period. This approach further controls for any

[1] I also calculate cumulative abnormal returns variances over the 60 day event window using the event study methodology from MacKinlay (1997). Results from this approach are qualitatively similar and provide consistent statistical inference.

additional potential difference in expected returns between the 'near' and 'far' groups not captured by the previous matching process. Results are qualitatively similar; the results, depicted in Figure 2.2, show small declines over the first month following the event with rapid declines 4-8 weeks post-event.

Table 2.3 reports the actual cumulative abnormal returns along with the left tail of the simulated return distribution. Panel A shows the results for the group of international equity fund managers. The second column displays the actual event returns in basis points for each week of the event window. Columns (3) to (5) list the left tail of the simulated returns from randomized event days. The simulated median return is in the final, 6th column. The underperformance for domestic equity managers over the first 30 days is insignificant. Whereas some attention or distraction effects could be related to the traumatic events, these effects do not appear to have a materially stronger on local managers. After the first 30 days, there is a mostly monotonic decrease in cumulative abnormal returns for domestic equity managers up to one quarter following the event. This performance gap is significant at the 5% level. Panel (B) of Table 3.7 reports a similar pattern of results for domestic equity funds.

Simulated results using abnormal returns are shown in Table 2.4. The international equity results in Panel (A) are consistent with those reported in Table 2.3. Over the first month post-event, the difference in cumulative abnormal returns is approximately zero. Over the next two months, local funds underperform their distant counterparts by 80 basis points. This result is significant at the 5% simulated level. Results are slightly different with abnormal domestic equity returns, with a gradual decline of 20 basis points over the initial month.

2.2.2 Additional Results

2.2.2.1 Risk Exposure

Besides stress, one alternative explanation for the underperformance of local fund managers is a change in post-event expected returns. Wang, Albert and Young, Michael (2018) find that after terrorist attacks mutual-fund investors increase their allocations toward less risky asset classes; they interpret this finding as a relative increase in risk aversion following terrorist activity. If mutual-fund managers become more fearful after traumatic events, potentially through changing perceptions about the likelihood of disaster events, their portfolio allocations may become less risky and the observed underperformance may be driven by an intentional reduction in risk-factor loadings rather than impaired decision-making abilities. Antoniou et al. (2018) similarly use geographic distance between financial analysts and terrorist attacks to measure the relative effect of the terrorist attack on analyst risk aversion.

My second hypothesis is: *Hypothesis 2: Traumatic events are a greater shock to risk aversion for fund managers in close proximity to the event.*

I test this hypothesis by estimating the Fama French 3 factor and momentum factor weightings for each fund over the 63 trading days prior to each traumatic event and, again, for the 63 trading days following each event. I use a difference-in-differences specification while controlling for turnover and pre-event risk factor weightings to test whether there is an overall change in risk-factor exposures following traumatic events.

The results of this test are reported in Table 2.5. Column (1) of Panel A shows the change in market betas after traumatic events. I find a decline in market betas across the entire sample of domestic-equity funds. However, because the interaction term $Post\_EventxNear$ is insignificant, I find no evidence that funds in close proximity to traumatic events experience an additional decline in betas. Columns 2-4 report results for changes in Small-Minus-Big, High-minus-Low and the Momentum factors. I find no evidence of a change in any of these additional risk factors for domestic equity funds.

Panel B of Table 2.5 shows the same results for my sample of International Equity funds. These results are largely consistent with those of the domestic equity funds, with little evidence of changes in risk exposures between near and far funds following traumatic events.

Panel C displays the simulation results for the change in market-risk exposure following traumatic events. The observed actual differences in market betas are approximately equal to the overall simulated median from selecting random event days from the sample. There is little evidence that mutual-fund managers adjust their portfolio holdings in a manner consistent with an increase in risk aversion following traumatic events. A change in expected returns prompted by shifting portfolio weights is unlikely to explain the observed underperformance by local funds.

2.2.2.2 Fund Turnover

The symptoms of post-traumatic stress disorder offer two potential explanations for the observed underperformance of local mutual funds in the aftermath of traumatic events. In an environment in which with increased marginal information processing costs could prompt the managers to respond by either applying mental efforts toward fewer investment decisions or by reducing the investment opportunity set that they will consider. Either of these options would reduce the cognitive burden of the investment decision-making process and, conceivably, reduce relative portfolio performance.

In considering the first explanation, if managers reduce their intensity of trading activity, on average, fewer profitable investments will be made and the remaining portfolio positions may grow stale, reducing the daily fund returns observed in the aftermath of traumatic events. Managers self-select whether to pursue a high or low investment turnover strategy. Within the subset of managers pursuing a high turnover strategy, a shock to marginal information processing costs is more likely to be a binding constraint on the number of trades made, resulting, at the same time, in a larger reduction in fund turnover. Similarly, low-turnover funds will likely see a lesser shift in turnover between the pre- and post-event period because managers had previously self-selected into investment strategies where information processing costs were not a binding constraint on the number of trades being made.

My third hypothesis is *High stress managers in close proximity to traumatic events will reduce their investment turnover compared to distant managers. This effect will be more pronounced for managers pursuing a high-turnover strategy prior to the event.*

Empirically, the quantity of fund-trading activity is observable through portfolio turnover, provided on a quarterly basis in the CRSP database. This variable is calculated as the dollar value of the prior 12 month purchases and sales divided by the average total assets of the fund over the prior 12 months. For each fund in my sample, I classify funds in the bottom quartile of turnover as 'low turnover' and funds in the upper quartile of turnover as 'high turnover'. Because turnover is reported at the quarterly frequency, I use the nearest observation before and after each endogenously occurring event. This introduces some noise into my turnover measurements because turnover may be reported between one and three months following each event. However, this measurement error noise is unlikely to bias my results in favor of finding results.

Turnover results are reported in Table 2.6. Columns 1 and 2 display results separately for the low- and high-turnover groups. Column 3 shows results for the difference between the low and high turnover subsamples. For this test, a joint model is estimated with the full set of interactions. The difference between coefficients will have a χ^2 distribution. Panel A reports the results for the set of domestic-equity managers. The variable of interest, $Post\_EventxNear$, is negative and significant for both the low- and high-turnover funds. The point estimate for high turnover funds is -0.88. This constitutes a 24% annual reduction in asset turnover for funds in close proximity to traumatic events.

Panel B of Table 2.6 shows results for the international fund sub-sample. In that subsample, high-turnover managers near traumatic events once again decrease their turnover relative to distant funds. The difference between low- and high-turnover funds is statistically significant. For high-turnover international funds, the estimated decrease in turnover for $Near$ funds is $-.21$, a 15% reduction in annual turnover.

Panel C displays simulated results for the near and far funds. For international funds, managers in close proximity to traumatic events have 20% lower turnover post-event. This difference is significant at the 95th simulated percentile. Distant managers have no decrease in turnover. Similarly, for domestic equity managers, 'near' managers have a 40% decline in turnover following events, also significant at the 95th percentile. Distant managers have 4.5% decline in turnover, but this decline is not significant.

2.2.2.3 Fund Indexing Strategies

For the second explanation, I consider whether the manager's investment strategy changes in the aftermath of traumatic events. Within a given investment objective, managers must strike a trade-off between the extent to which they will replicate their benchmark index ('closet indexing') and the extent to which they will actively deviate from the index ('active management') (Cremers and Petajisto (2009)). From this perspective, replicating the underlying index is the default position for a manager because the requisite portfolio weights are known in advance and require minimal effort to determine. In contrast, active management is a more cognitively intense strategy because the portfolio positions are determined through a process of financial research and analysis. If managers local to a venue of a traumatic event have skill in selecting securities, forgoing profitable active-management opportunities to pursue an increased indexing strategy will lead to their observed underperformance. This is intuitive because the only way to outperform a given benchmark is intentionally to deviate from the benchmark security weights.

For managers who have chosen to follow a strategy of closely tracking their benchmark, when making a investment allocation decision the 'default' option is to invest in the benchmark itself. When faced with a shock to their level of stress, these managers are more likely to maintain the status quo and invest in the benchmark. However, for the set of managers pursuing an active strategy who have made large deviations from their benchmark, it is less clear what these managers would consider to be their 'default' option as they have explicitly chosen not to track their benchmark closely. For managers who have chosen to follow a strategy of closely tracking their benchmark, the 'default' investment-allocation decision s to invest in the benchmark itself. When faced with a shock to their stress level, these managers are more likely to maintain the status quo and continue investing in the benchmark. However, the 'default' option for the set of managers pursuing an active strategy, involving large deviations from their benchmark, is less clear.

My fourth hypothesis is *Managers pursuing a 'closet indexing' strategy will increase their weights in their respective index in the aftermath of traumatic events. This effect will be greater for mangers with exposure to stressful events.*

Empirically, this can be observed by measuring tracking errors between managers and their self-selected benchmark. Following Cremers and Petajisto (2009)), for each event I identify the benchmark index whose returns most closely align with the actively-managed fund by using the following test:

$$r_{i,t} = \alpha + \beta r_{index,t} + \epsilon_t \tag{2.2}$$

At the start of each calendar year, I estimate this equation using the full set of U.S. equity benchmark returns from the St. Louis Fed data website (FRED). [2] For each fund, I select the index whose estimated model has the highest R^2 as the benchmark index for that calendar year.

After the benchmark indices are identified, I proceed to measure event-time tracking errors for the 'near' and 'far' subsamples. Tracking errors are defined as the standard deviation of the difference in returns between the fund and underlying benchmark. I categorize funds in the bottom quartile of tracking errors as 'closet index' funds and funds in the upper quartile as 'active' funds. To remove potential noise from the event itself, I drop the initial 21 days before and after each event and calculate tracking errors over the remaining 42 days pre- and post-event.

Table 2.7 reports the results of this test. The variable of interest is the interaction between post-event and the indicator for near funds. Column 1 displays results for the set of closet-indexing funds. The interaction term has an estimated coefficient of -0.08, a 12% reduction in post-event tracking errors for the group of managers near events. On the other hand, active fund managers increase their tracking errors by 32%. This increase in tracking errors could either be due to an intentional increase in active positions or a result of stale portfolio positions.

2.3 Alternative Hypotheses

The effects I document could be driven by a pure investor attention or distraction effect (Hirshleifer, Lim, and Teoh, 2009). This would suggest that investors neglect financial information while

[2] The major U.S. indices considered are: Russell 1000, Russell 1000 Value, Russell 2000, Russell 2000 Growth, Russell 2000 Value, Russell 3000, Russell 3000 Value, Russell Midcap, Russell Midcap Growth, Russell Midcap Value, S&P 500, Wilshire 4500, Wilshire 5000.

traumatic events are occurring because they choose to pay attention to the event instead. Under this hypothesis, all of the effect should occur during a short window after the event, while the event is heavily covered by the news media, and with negligible lingering effects over the next several weeks. The time series of daily returns facilitates the measurement of when performance shifts happen. Information shocks should affect trades and decisions made immediately following the event, rather than affect medium to long term performance. Although I cannot directly observe trades and decisions from the daily return data, delays in performance shifts after the event are consistent with a stress hypothesis.

Based upon the timeline of event returns in Table 2.3 and Table 2.4, this distraction hypothesis is unlikely to explain my results. The cumulative underperformance by local funds is negligible over the first 10-21 days post-event. If managers are temporarily distracted by the event, they would quickly revert to prior abilities and subsequent trades would be unaffected. However, a shock to stress will impair abilities over the following 8-12 weeks, consistent with the observed effect.

Additionally, the effects may be driven by a change in investor sentiment. Traumatic events may change expectations of future returns and cash flows and alter incentives to invest in mutual funds (Ben-Rephael, Kandel, and Wohl, 2010). By restricting my sample to international equity funds for my tests, I am able to rule out this hypothesis. These are funds headquartered in the United Sates investing in overseas companies. This controls for home bias and any local information effects for the managers. Furthermore, any information about the traumatic event is especially irrelevant to foreign equity portfolio returns. If traumatic events affect the market as a whole and shift investor sentiment, both the ‘near’ and ‘far’ groups of funds will be affected and any changes will be netted out in the differences between the two groups and event effects.

CHAPTER 3

MUTUAL FUND CLIENTS

3.0.1 Methodology

In my next set of results, I examine how stress affects the clients of mutual funds in their decisions to allocate wealth across the mutual-fund sector. Mutual-fund flows represent the outcomes of investment decision-making processes by individual investors. While I am unable to observe daily fund flows, I can estimate changes to the cross-section of fund allocations across time. This enables the measurement off the sensitivity of net flows to information about observable fund characteristics.

This setting complements that of the mutual-fund managers and fosters a deeper examination into the choices made by individual investors. If stress increases the marginal cost of information, investors will demand less information. A study of post-event mutual-fund flows allows for a more precise examination of how information is used to inform investment decisions and how these decisions are affected by a shock to relative information costs.

To test my hypothesis, I first calculate fund flows using the standard approach in the literature. Following Sensoy (2009), for each fund I back out net fund flows from the proportional difference in monthly total net assets less the returns earned on fund assets.

$$Flow_{i,t,t+1} = \frac{TNA_{i,t+1}}{TNA_{i,t}} - (1 + R_{i,t+1}) \tag{3.1}$$

Next, I specify a baseline empirical model to estimate expected fund flows to fund i for time i for time t to $t + 1$. I include in this specification a set of indicator variables specifying the past return quintile of fund i. Each month, I rank funds by their past year and quarter return within their investment style group and assign each fund to a past return quintile. This set of past return indicators is intended to capture the convexity of the flow-performance sensitivity (Chevalier and Ellison (1997), Sirri and Tufano (1998), Lynch and Musto (2003),Jonathan B. Berk and Richard C. Green (2004)). I also include various fund characteristic controls (such as fund age, fund size, and expense ratio), time effects, and investment style effects based on CRSP objective codes.

$$Flow_{t+1,i} = \alpha + \beta Return\_Quintile_{t,i} + \beta Search\_Costs + Controls_{t,i} + Year_t + Fund\_style_i + \epsilon_{t,i} \quad (3.2)$$

I estimate this model separately for both normal and high stress periods. Standard errors are clustered at the fund level. I employ a methodology similar to a Chow Test to compare coefficients between the normal and high stress periods. First, I estimate a combined model incorporating a full set of interaction terms for both periods. For each coefficient, I then estimate the model under the restriction of no difference between normal and stress periods. Differences in residuals between the restricted and unrestricted model follow a χ^2 distribution with n degrees of freedom.

3.1 Mutual Fund Client Results

3.1.1 Fund Visibility

My fifth hypothesis examines how stress affects the formation of investor choice sets. Odean (1999) suggests that, when making an asset-allocation decision, investors first form a set of securities to consider and then decide within this reduced set of investment opportunities. Relatively small and unknown funds are more difficult for investors to consider because learning about them requires more effort. During periods of high stress, the cognitive effort required to seek out additional funds will be more costly to investors. As a result, cognitively-constrained investors will be less willing to exert the effort required to find smaller, less known funds and will be more likely to limit their choice set to highly visible large funds.

This leads to my fifth hypothesis: *Hypothesis 5: In periods of high post-traumatic stress and reduced investor concentration, funds with lower search costs and greater marketing expenditures will receive a greater portion of fund flows relative to normal periods*

Following Sirri and Tufano (1998), I proxy for search costs using fund size and 12b1 fees. Under this hypothesis, the proportion of funds allocated to both larger finds (more monthly assets under management) and funds with increased marketing and sales commission costs (12b1 fees) should be greater under stress periods than under normal periods. Table 3.2reports these results for the universe of CRSP fund series from 1995 to 2016. Panel A displays results using rolling 12-month past returns to assign return quintiles while Panel B uses past quarter returns.

Column (1) shows results under normal (non-stress) time periods. The coefficient associated with $log(Monthly\_Total\_Net\_Assets)$ in Panel A is -0.0093. The negative estimate is consistent with the literature because larger funds, simply by virtue of their asset size, generally have decreasing fund growth rates. During periods of high stress, reported in Column (2), this coefficient is less negative, with an estimate of -0.0063. This increase between time periods of $-.003$ is highly statistically significant. At the 90th percentile of fund size, this difference between normal and stress periods is equivalent to a 1% increase in expected fund flows. The proportion of fund flows allocated to large funds increases following traumatic events, consistent with the interpretation of an increase in investors' marginal search costs. Results are consistent across Panels (A) and (B) regardless of how past return groups are defined.

Results for 12b1 fees follow a similar pattern. When using past year returns (Panel A), the coefficient estimate for actual 12b1 fees is -1.5599; this increases to 0.6949 during the stress periods. Once again, the difference between the two periods is highly statistically significant and is equivalent to a .2% i increase in expected fund flows at the mean 12b1 fee level.

When information costs are low, investors are sensitive to mutual-fund fees, resulting in a negative coefficient estimate for the normal periods. However, this sensitivity is reduced during high-stress periods. 12b1 fees are predominately associated with broker-sold funds (Yang, 2016). This increase suggests an increase in flow towards broker-sold funds during high-stress periods. [1]

These estimated results are consistent with Hypothesis 5. When stress-related search costs are high, the distribution of fund flows shifts towards funds with low search costs, that is, large funds with high marketing-related fees.

[1] Two explanations could be that investors are more willing to pay for broker advice during these periods or brokers are able to exploit less sensitive investors and sell more expensive funds.

3.1.2 Flow-Performance Sensitivity

In normal environments, investors chase past performance and allocate wealth towards mutual funds that have outperformed in the prior period (Chevalier and Ellison (1997), Sirri and Tufano (1998), Lynch and Musto (2003),Jonathan B. Berk and Richard C. Green (2004)). The cognitive impairments to concentration and learning ability that stem from shocks to stress limit the amount of information, including information concerning past returns, that can be processed before the investor feels overwhelmed. Investors may still weigh past returns heavily in their decisions, but the ability to identify funds with their preferred financial characteristics is reduced. Empirically, this can be estimated by separately measuring the flow-performance convexity for normal and stress-related periods.

Therefore, my sixth hypothesis can be stated as: *Hypothesis 6: Following traumatic event shocks, the sensitivity of fund-flow response to fund information is reduced relative to normal time periods*

Figure 3.1 depicts these results using return deciles. This figure was estimated using past 12 month return rankings. The red line represents the familiar flow-performance sensitivity under normal circumstances. The top-performing funds receive approximately 4% expected monthly net flows. This quickly drops off, with the 9th decile earning 2.1% in expected net flows. Subsequent deciles decline approximately linearly, with the bottom decile receiving only about .5% expected net flows. The flow-performance sensitivity materially changes during periods of high post-traumatic stress; it becomes flatter. The expected flows to the highest-performing funds are almost halved, with the top-performing funds only receiving 2.5% higher net flows following traumatic events compared to 4% for the normal period. The lower deciles also display less sensitivity with a flattened slope. Both the 9th decile and the bottom decile both have the same 1.75% estimated expected net flows. This evidence suggests that investors weigh past return information less heavily during high stress periods.

Table 3.3 reports the estimates for the flow-sensitivity tests. Panel (A) reports results using the prior 12 month returns to construct return quintiles. There is a monotonic increase in net flows during the normal period between the bottom quintile and the top quintile. The flow-performance relation is highly convex. The top-performing funds receive 2.26% more expected net flows than the 3rd quintile funds do. This increase, directed toward the top past performers, is four times greater than the range between the first and 4th quintiles (.5%). Column (2) shows that this convexity decreases following traumatic events. Flows directed to the top quintile during stress periods are almost halved, with the top quintile only receiving 1.3% higher expected net flows. The difference between normal and stress periods, reported in Column (3), is highly statistically significant. Furthermore, these results carry over to Panel (B), characterized by the use of past quarter returns. Once again, during high-stress periods, the proportion of flows allocated to the highest-performing funds is almost halved compared to the normal periods.

The pattern of reduced sensitivity to financial characteristics carries over to other aspects of mutual funds. The coefficients on both expense ratios and return risk (volatility) are smaller in magnitude, indicating a reduced sensitivity of flows to fund fees and fund risk. These results are consistent across Panels (A) and (B). However, interpreting coefficients is less clear in this setting because the size of a fund family may be related to search costs or fund spillover effects Massa (2003).

These results are consistent with Hypothesis 6. This evidence suggests a flatter slope for the flow-performance relation during high-stress periods. When stress is high and individuals have less ability to concentrate and acquire new information, financial decision outcomes are less sensitive to relevant financial information.

3.1.3 Retail and Institutional Share-Classes

Expertise with analyzing financial information may mitigate the effects of stress on financial decision-making processes. Retail investors with low financial sophistication face significant barriers in accessing financial information. This group of low sophistication investors accesses mutual fund information through channels such as brokers, mutual fund prospectus statements, or premium subscriptions to online websites such as Morningstar. Post-Traumatic Stress also reduces individuals' ability to learn new information. For retail investors, who already have high marginal costs of gathering financial information, the increases in information processing costs from post-traumatic stress will likely severely limit the amount of information incorporated into their investment decisions. On the other hand, sophisticated institutional investors have specialized tools and processes to handle this type of information and likely have more robust decision-making structures in place. The information-gathering processes for high sophistication investors is less likely to be directly affected by the psychological effects of stress.

My seventh hypothesis is then: *Hypothesis 7: The effects of stress on decision-making will be more pronounced among less sophisticated investors than among sophisticated investors with high information-processing ability*

To test this hypothesis, I perform the same flow-sensitivity tests using separate subsamples of retail and institutional share classes to proxy for investor sophistication. My results are reported in Table 3.4 where Panel (A) reports results for the retail subsample, and Panel (B) reports results for institutional subsample. The same set of controls, effects, and standard errors are used as in Table 3.3.

For retail investors, the results show a similar pattern as in Table 3.3. The normal period results depict the familiar convex flow-performance sensitivity, with the top-performing funds receiving 1.66% higher net flows than the 3rd quintile of funds. During high-stress periods, the proportion of flows to the highest-performing funds drops to .91%. The share of flows going to the 4th quintile of funds also decreases significantly. Similar to Panel (B) of Table 3.3, the worst-performing funds have a small increase in expected flows, further suggesting that investors may pay less attention to return performance.

Among institutional investors, there is no difference in the flow-performance sensitivity between normal and high stress periods for the top two quintiles of past returns. During normal periods, the top quintile of funds receives 1.32% higher flows. During high stress periods, this is reduced to 1.17%. The difference between the two is not statistically significant. Bottom-performing funds receive slightly smaller flows, but this is of marginal significance.

Overall, these results are consistent with an interpretation of the shift in flow-performance sensitivity being driven by retail investors, who face barriers in accessing past return information. Institutions with few barriers in researching mutual funds' past returns display no change in behavior that could be tied to their usage of return information.

3.1.4 Decision Making Ability

My next hypothesis addresses whether the investment decision-making ability is reduced by stress. If information is beneficial towards optimal asset allocation, increased information costs will lead to a lower quality of observed decisions and investment alphas. While the literature has reported mixed evidence as to whether the expected alpha of investor mutual funds decisions is positive (Zheng (1999), Frazzini and Lamont (2008), and Akbas, Armstrong, Sorescu, and Subrahmanyam (2015)), under stress and with increased information costs, there likely is a decrease in expected alphas compared to normal periods.

My eighth hypothesis is then: *Hypothesis 8: The portfolio of mutual funds chosen by investors during high-stress periods underperforms relative to the portfolio of funds chosen by investors during normal periods*

To test this hypothesis, I construct a time series of flow-weighted portfolios pursuing a methodology similar to Zheng (1999). I create a series of mutual-fund portfolios weighted by the proportion of net flows each fund received in a given month. For each month, I identify funds with net flows greater than (and less than) 1.5 standard deviations above (below) their mean fund flow. Investors as a whole are taking an implicit long position in funds receiving a large portion of inflows, and short position in funds with large outflows. I hold this monthly portfolio of net mutual-fund investment decisions for 24 months and calculate its 4-factor alpha (Carhart, 1997). This alpha is representative of the investors' mutual-fund selection ability as it increases when either the funds that received large inflows outperformed on a risk-adjusted basis, or the funds that experienced large outflows underperform. This can be interpreted as investors' ability to improve their portfolio allocations by shifting capital from underperforming funds to better mutual funds.

Panel A in Table 3.5 reports means and t-tests on the set of calculated net fund flow portfolio alphas. Both retail and institutional investors have an observed aggregate ability to improve their portfolios by shifting capital into better-performing mutual funds. I find that, during normal periods, the funds that have received large inflows outperform the funds that had large outflows by 12 basis points per month. Similarly, funds chosen by institutional investors outperform the sold funds by 8 basis points per month. Following stress events, the ability of investors to shift capital into higher-performing funds is impaired. Neither group of investors is able to earn a significantly positive alpha from their net fund flow investment decisions. The aggregate portfolio of funds purchased does not outperform the aggregate portfolio of funds sold.

The third column of Panel A reports the differences in alphas between normal and stress periods and the joint hypothesis test that normal and stress period portfolio alphas are equal. For retail investors, the decision-making impairment of 10 basis points is nearing conventional levels of statistical significance, with a t-statistic of 1.5. This is not surprising because a common investment strategy, as evidenced by Table 3.4, is to chase past returns. A pure strategy of chasing past returns is not likely to generate a large alpha or make efficient use of financial information.

Panel B reports the simulated distribution of net portfolio alphas using 3,000 draws of randomized event days. For each draw of the simulation, I draw random event days from two separate uniform distributions, for the period from 1995 to 2013 and the period from 2013 to 2016, to mimic the observed actual frequency of events during this period from Figure 1.1. I then calculate the net high and low fund flow portfolios and resulting alphas using the same process, and compare the generated alphas using the actual stress event dates to the distribution of net alphas.[2]. Again, I find no evidence of an impairment to expected returns for the group of retail investors. While retail investors may have less ability to pursue a strategy of chasing past mutual-fund performance it is not clear that the expected return on their investments is significantly decreased.

However, for institutional investors, likely efficient users of financial information, I do find evidence of a diminished investment ability during periods of high stress. In Panel A, the 17

[2]This simulation approach is designed to alleviate concerns of my results being driven by sampling bias. Standard time series regression methodology produces qualitatively similar results

basis-point drop in expected net alphas is highly significant with a t-statistic of 2.13. Furthermore, the decrease in portfolio alpha is at the far right tail of the simulated distribution (95% level), suggesting that this observed decrease is unlikely to engender sample bias in the event days. When information costs are high during stressful periods, institutions are unable to allocate as efficiently, reducing their expected alpha by 17 basis points. While there is no evidence in Table 3.4 that institutions use past return information differently between normal and high stress periods, the increase in information costs from stress is likely affecting the more sophisticated information analysis processes that occur when determining institutional asset allocations.

3.1.5 Share Purchases and Redemptions

Finally, I examine whether mutual-fund share purchases or redemptions are more sensitive to the cognitive effects of stress. Purchasing new mutual fund shares is a cognitively difficult task that requires investors to identify investment opportunities from the entire universe of mutual funds. Common PTSD coping mechanisms include ‘giving up’ or ‘avoidance.’ This increases the likelihood that investors may choose to delay cognitively difficult investment decisions. However, redeeming shares is an easier decision to make because it only requires investors to consider the smaller set of funds or assets in their personal portfolio. Furthermore, investors may not have the ability to delay share redemption decisions if the decision is motivated by liquidity constraints or tax-loss selling (Barber and Odean, 2000).

For these reasons, my ninth hypothesis is: *Mutual fund share purchases will display greater sensitivity to stress than share redemptions.*

Results using separated inflows and outflows for my mutual fund sample are reported in Table 3.6. After controlling for past returns and fund characteristics, during normal periods the conditional expected fund inflow reported in Column (1) is 8.2% of monthly total net assets. The expected outflow during this sample period, reported in Column (2), is 5.2%. The Stress Ind coefficient reports the shift in expected inflows and outflows. Inflows are reduced by .3%, while there is no expected change in fund redemptions. This suggests that the change in net-flow behaviors is primarily driven through a reduction in mutual-fund purchases, rather than individuals pulling their wealth out of the mutual-fund sector.

As a robustness check on the Form N-SAR sample, Column (3) repeats the same tests for net $inflows - outflows$. Estimated coefficients here are consistent with those reported in previous tables.

3.2 Robustness Checks

I perform two out-of-sample robustness tests. In the first test, I use my original set of mutual-fund flows, but change the event sample and only consider the out-of-sample September 11th terrorist attacks and natural disasters. In the second test, I separately test the early and late time periods of my sample to ensure the results are not driven by changes in investment patterns over time.

In the first test, I examine initially discarded traumatic events with my original sample of fund flows. In this test, I use the following 6 traumatic events: the September 11th terrorist attacks, Hurricanes Rita, Katrina, and Sandy, and the Haiti and Tokyo earthquakes. These events were initially discarded during my initial filtering process because of the concerns for changes in expected market cash flows. While there might be some cash-flow implications, these events are also highly traumatic and directly associated with high levels of stress, anxiety, and PTSD-related symptoms.

Table 3.8 reports the flow-performance sensitivity results for the out-of-sample events test, using the same methodology and data as in Table 3.3. Within this separate set of events and time periods, the highest-performing funds receive a reduced proportion of fund inflows during periods of elevated stress symptoms. These results are highly consistent with the previously reported results.

Table 3.9 reports the second robustness test. I separately estimate the fund-flow sensitivities for the early and late sample periods using a set of interaction terms to identify high stress periods. Column (1) limits the sample to 1995-2008, while column (2) uses 2009-2016. Consistent with the original tests from Table 3.3, both periods estimate a similar reduction in flow-performance sensitivity for the highest quintile of fund returns.

APPENDICES

APPENDIX A

INTRODUCTION

Figure 1.1: The frequency distribution of events by year

This figure reports the number of unique traumatic events include in my sample set for each year between 1995 and 2016. Events are chosen in a two part process. The first step identifies the top 10% of days with abnormally high news coverage of a single topic from the Vanderbilt Television News Archive. The second step filters out these high coverage news days to discard events relating to wars, politics, economics, business, natural disasters, and September 11th to limit the set of events to identify events with limited market information.

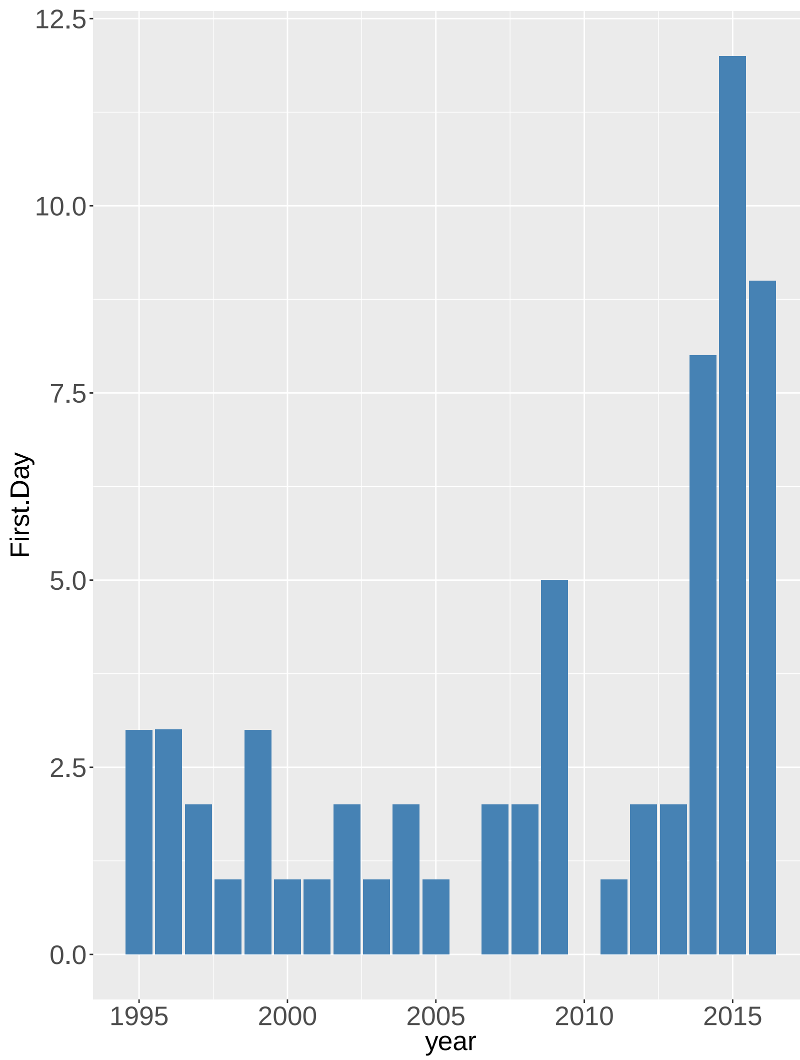
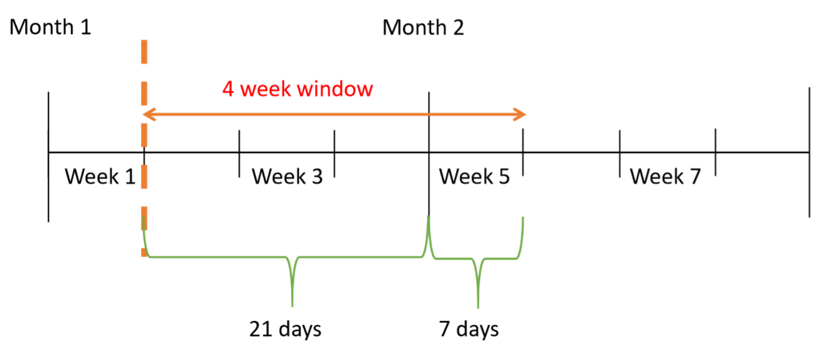


Figure 1.2: Event Month Formation Rules

Panel A: Beginning of Month

For each event, create 4 week window of treatment days and count months where two-thirds of the month contain treatment days



Panel B: End of Month

Events at end of month are counted the following month. Overlapping windows are just counted as single treatment days

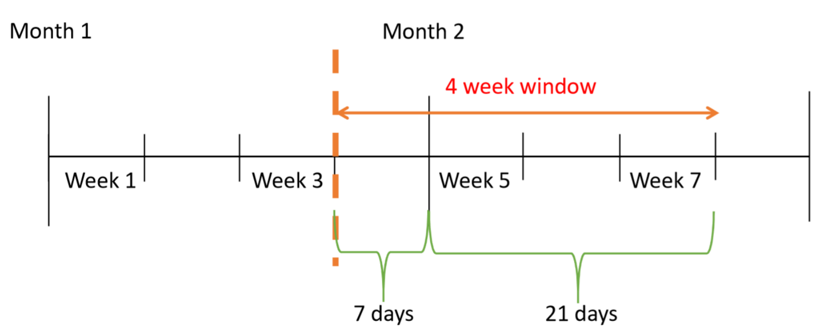
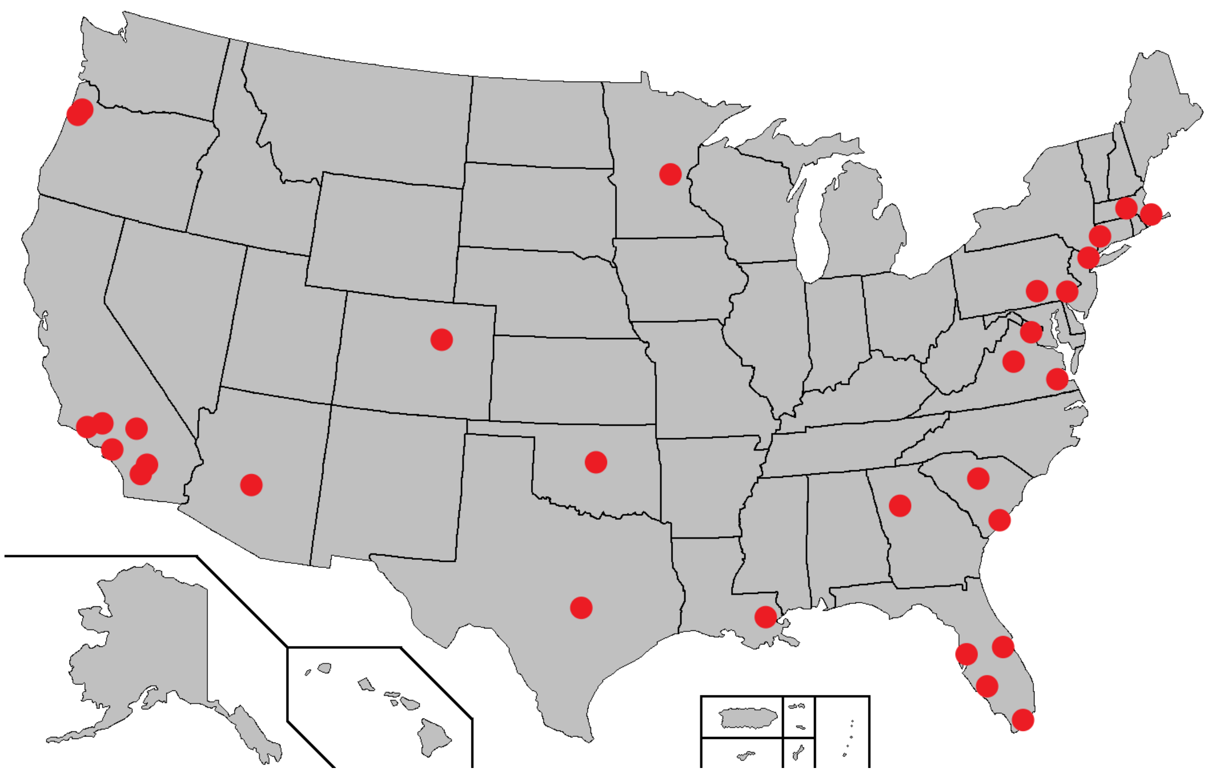


Figure 1.3: US Event Locations



APPENDIX B

FUND MANAGERS

Figure 2.1: Cumulative Event Time Returns for International Equity Funds

This figure reports the event time cumulative returns for 'near' and 'distant' group of international equity mutual fund managers across the sample of traumatic events from 2001 to 2016. The grey line depicts the cumulative returns of the 'near' group of funds from 1 month(21 trading days) prior to the event and the dashed orange line shows cumulative returns for the group of 'far' funds. The triangle dotted blue line shows the cumulative difference in returns between the two sets of managers from 1 month prior to the event up to 3 months(63 trading days) after the event.

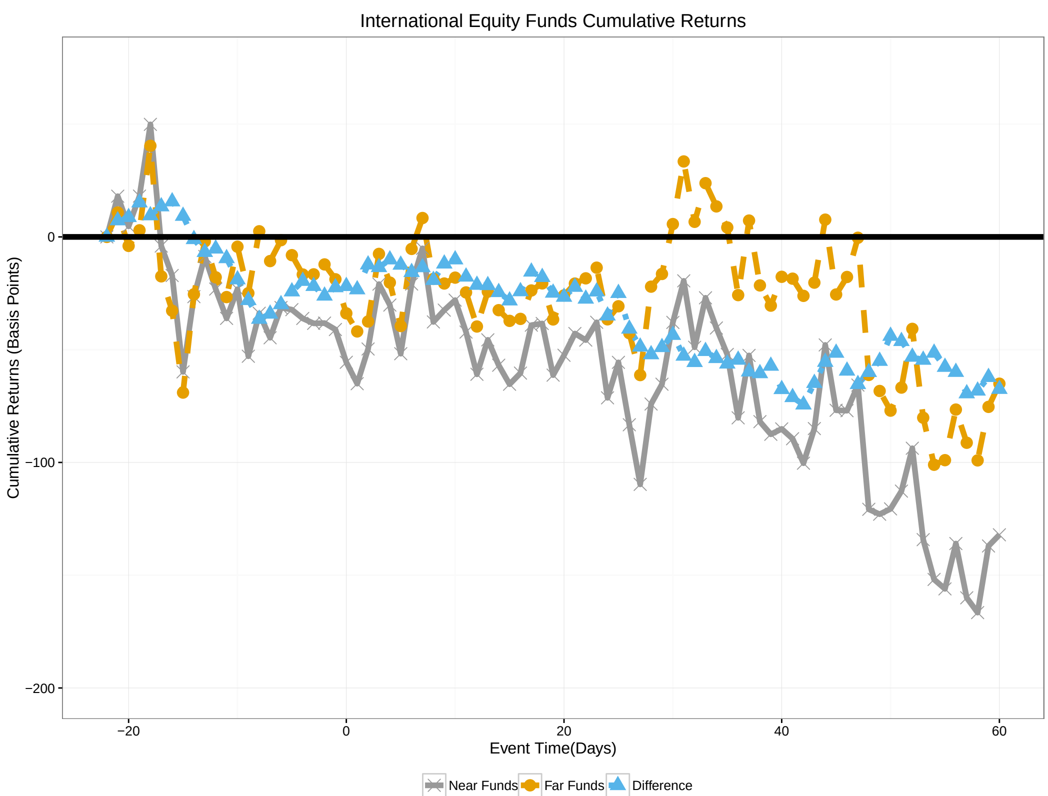


Figure 2.2: Cumulative Near vs Distant Simulated Mutual Fund Performance

The following figures depict the cumulative difference in returns for the ‘near’ and ‘distant’ group of managers across the sample of traumatic events from 2001 to 2016. The grey line depicts the actual observed difference in returns between the matched sample of ‘near’ and ’far mutual fund managers. Funds dare matched using a propensity score technique along observable characteristics of investment objective, past returns, fund size, fund age, and portfolio turnover. 1,500 simulations were conducted choosing randomized event days and locations. The orange line reports the median cumulative difference in returns between the ‘near’ and ‘distant’ mutual fund groups. The blue line reports the 95% percentile difference in simulated returns. Cumulative returns over the 1 month prior to the event up to 3 months after the event are depicted. Panel A plots returns for the sample of international equity fund managers and panel B plots the same returns for the sample of domestic equity fund managers.

Panel A: Daily International Equity Mutual Fund Managers

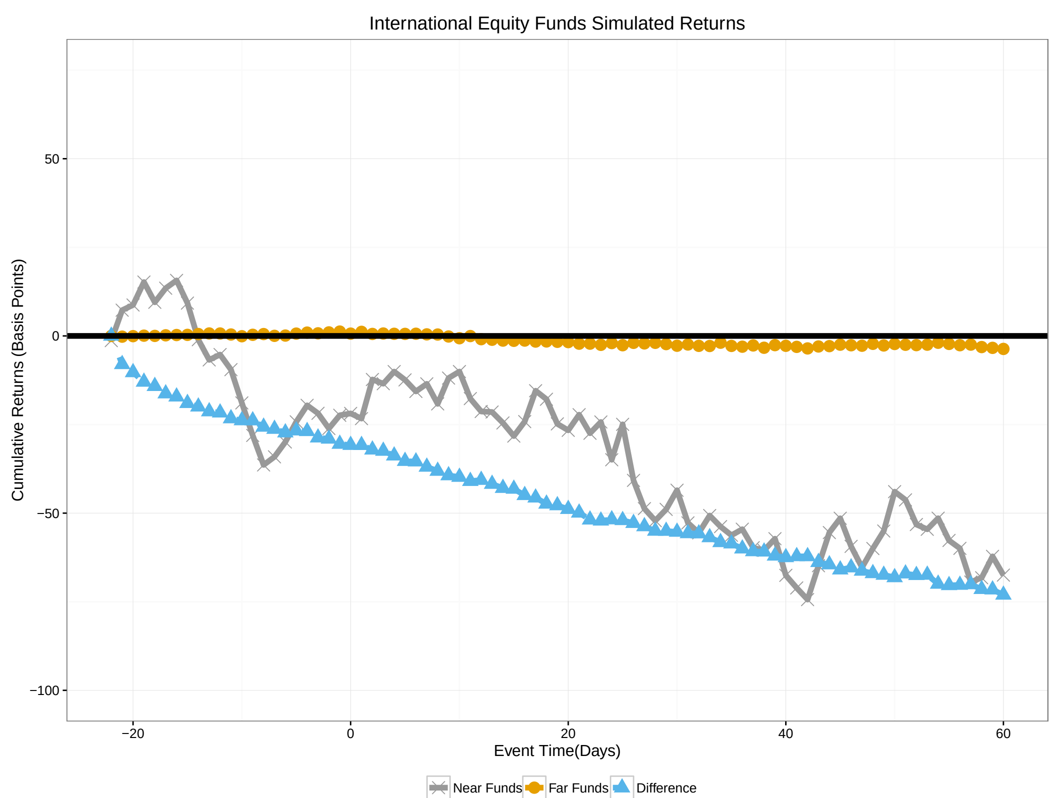


Figure 2.2 (cont'd): Cumulative Near vs Distant Simulated Mutual Fund Performance

Panel B: Daily Domestic Equity Mutual Fund Managers

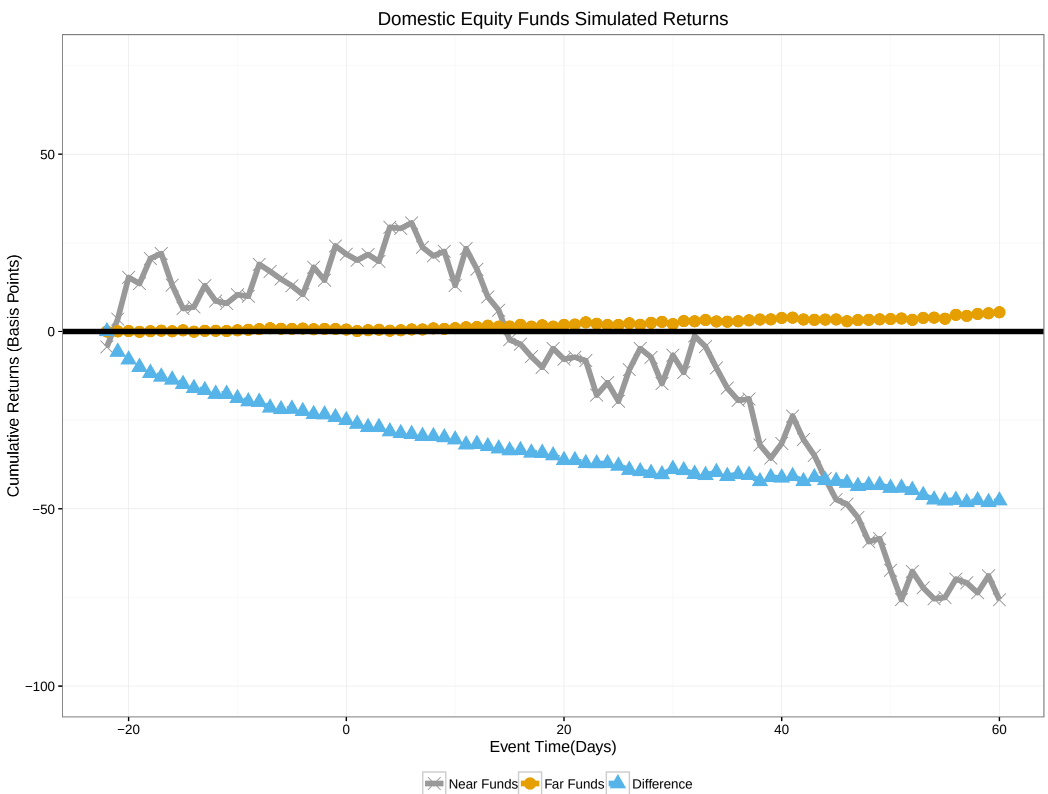


Figure 2.3: Cumulative Near vs Distant Simulated Abnormal Mutual Fund Performance

The following figures depict the cumulative difference in abnormal returns for the ‘near’ and ‘distant’ group of managers across the sample of traumatic events from 2001 to 2016. Abnormal returns are calculated as the daily residual return from the estimation of the Fama-French 3 factors and an additional momentum factor over the quarter preceding the event window. The grey line depicts the actual observed difference in returns between the matched sample of ‘near’ and ’far mutual fund managers. Funds dare matched using a propensity score technique along observable characteristics of investment objective, past returns, fund size, fund age, and portfolio turnover. 1,500 simulations were conducted choosing randomized event days and locations. The orange line reports the median cumulative difference in returns between the ‘near’ and ‘distant’ mutual fund groups. The blue line reports the 95% percentile difference in simulated returns. Cumulative returns over the 1 month prior to the event up to 3 months after the event are depicted. Panel A plots returns for the sample of international equity fund managers and panel B plots the same returns for the sample of domestic equity fund managers.

Panel A: Daily International Equity Mutual Fund Managers

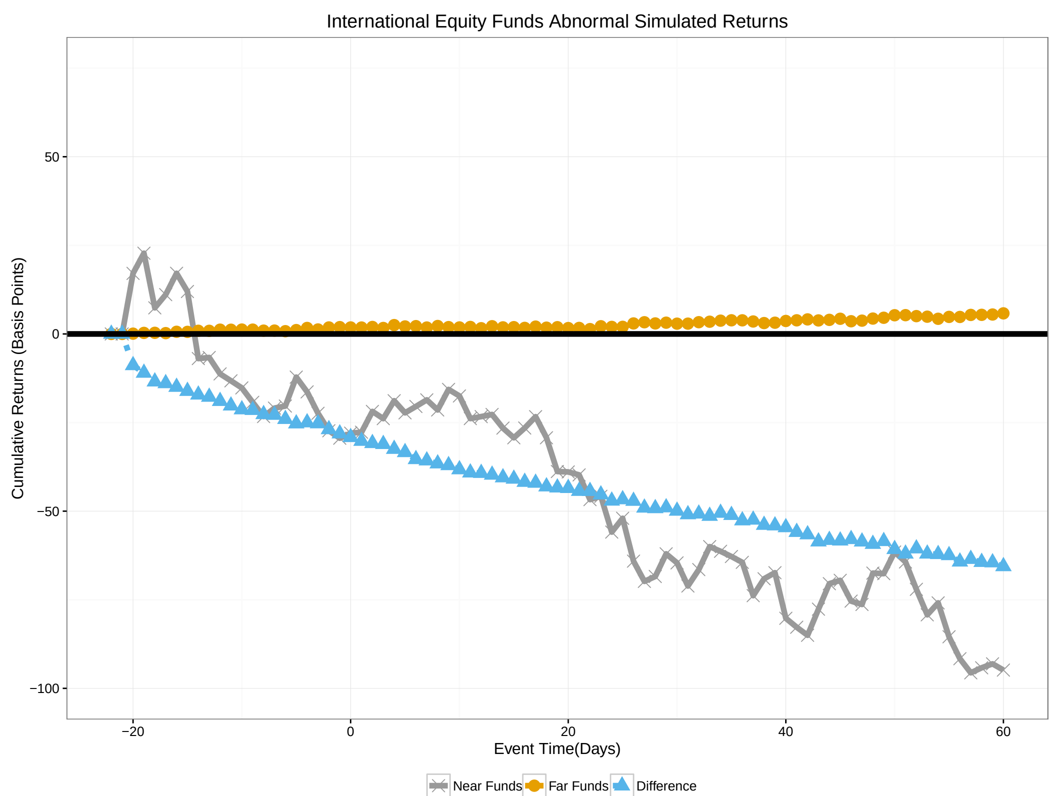


Figure 2.3 (cont'd): Cumulative Near vs Distant Simulated Abnormal Mutual Fund Performance

Panel B: Daily Domestic Equity Mutual Fund Managers

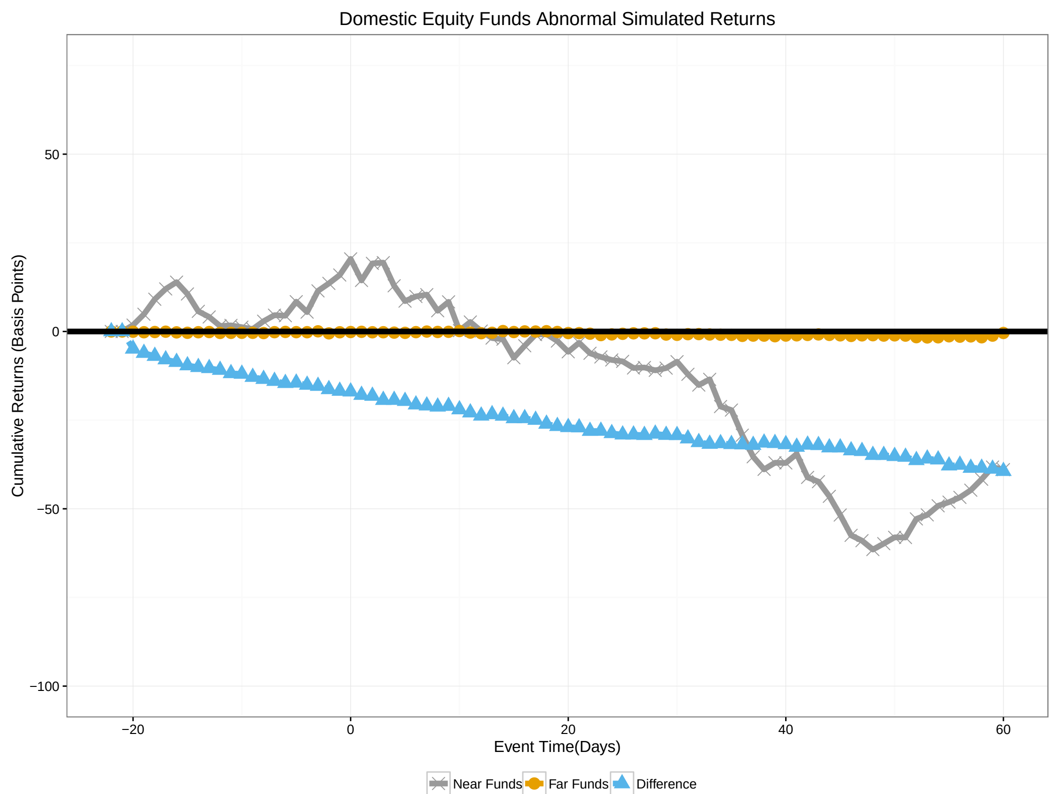


Table 2.1: Summary Statistics

The following tables report summary statistics for the sample of mutual fund managers. Panel A reports data for the entire sample of mutual funds from the CRSP universe aggregated to the fund series level using a mapping of CRSP fundnos to EDGAR Series CIKs. This is the same mapping as used for the accompanying fund-flow tests. This data is for the 2001 to 2016 period when daily data in CRSP becomes available. This data encompasses 4,185 distinct funds. Panel B reports the subsample of Domestic Equity mutual funds. This includes 1,860 unique funds from 492 separate fund companies. Panel C reports the subsample of International Equity funds in the CRSP dataset which includes 646 funds from 252 fund companies.

Panel A: CRSP Universe Mutual Funds

	mean	median	sd	P10	P90
Daily Return	0.000	0.000	0.010	-0.009	0.009
Fund Size	2392.211	432.900	9400.794	55.600	4702.700
Expense Ratio	0.009	0.009	0.010	0.002	0.015
12b1 Fees	0.001	0.000	0.009	0.000	0.004
Management Fees	0.006	0.006	0.004	0.002	0.010
Turnover	0.897	0.440	28.008	0.030	1.680
Fund Age(months)	168.385	140.000	132.119	45.000	307.000

Panel B: Domestic Mutual Funds

	mean	median	sd	P10	P90
Daily Return	0.000	0.001	0.014	-0.014	0.014
Fund Size	2350.272	448.500	10060.029	48.700	4574.100
Expense Ratio	0.010	0.011	0.005	0.003	0.016
12b1 Fees	0.001	0.000	0.002	0.000	0.004
Management Fees	0.007	0.007	0.003	0.002	0.010
Turnover	0.865	0.530	2.448	0.110	1.580
Fund Age(months)	169.648	133.000	147.532	45.000	312.000

Panel C: International Mutual Funds

	mean	median	sd	P10	P90
Daily Return	0.000	0.001	0.013	-0.013	0.013
Fund Size	2132.455	404.200	7995.388	52.700	3838.200
Expense Ratio	0.012	0.012	0.005	0.006	0.019
12b1 Fees	0.001	0.000	0.002	0.000	0.004
Management Fees	0.008	0.008	0.009	0.004	0.012
Turnover	0.683	0.500	0.832	0.110	1.330
Fund Age(months)	139.157	118.000	95.611	42.000	254.000

Table 2.2: Summary Statistics: Matched Sample

The following tables report summary statistics for the sample of matched mutual fund managers. Funds dare matched using a propensity score technique along observable characteristics of investment objective, past returns, fund size, fund age, and portfolio turnover. Near funds are defined as those with a headquarters zip code within 100 miles of a traumatic event. Far funds are those with a headquarters zipcode greater than 1,000 miles from a traumatic event. Panel A reports results for 361 near international equity fund managers. Panel B reports data for the 632 far international equity fund managers. Panel C reports data on the 1,031 near domestic fund managers. Finally in panel D, I show summary stats on the 1,804 far domestic fund managers.

Panel A: Near International Managers

	mean	median	sd	P10	P90
Daily Return	-0.004	0.001	0.011	-0.020	0.007
Fund Size	2563.602	377.550	11266.673	45.100	4226.300
Expense Ratio	0.012	0.012	0.005	0.006	0.018
12b1 Fees	0.001	0.000	0.002	0.000	0.003
Management Fees	0.008	0.008	0.003	0.004	0.011
Turnover	0.716	0.500	0.854	0.130	1.390
Fund Age(months)	144.331	116.000	98.708	44.000	264.000

Panel B: Far International Managers

	mean	median	sd	P10	P90
Daily Return	-0.002	0.000	0.010	-0.015	0.010
Fund Size	2337.357	395.500	9235.853	49.000	4110.900
Expense Ratio	0.012	0.012	0.005	0.006	0.018
12b1 Fees	0.001	0.000	0.002	0.000	0.003
Management Fees	0.008	0.008	0.003	0.004	0.012
Turnover	0.646	0.440	0.778	0.100	1.290
Fund Age(months)	147.043	117.000	103.815	43.000	272.000

Table 2.2 (cont'd): Summary Statistics: Matched Sample

Panel C: Near Domestic Managers

	mean	median	sd	P10	P90
Daily Return	-0.003	-0.000	0.013	-0.024	0.010
Fund Size	2776.801	456.200	14648.014	46.880	4573.900
Expense Ratio	0.010	0.010	0.005	0.003	0.015
12b1 Fees	0.001	0.001	0.002	0.000	0.003
Management Fees	0.007	0.007	0.003	0.002	0.010
Turnover	0.937	0.550	2.866	0.120	1.630
Fund Age(months)	175.487	146.000	148.416	44.000	325.400

Panel D: Far Domestic Managers

	mean	median	sd	P10	P90
Daily Return	-0.000	0.001	0.013	-0.013	0.014
Fund Size	2604.336	483.450	11573.472	47.200	5232.450
Expense Ratio	0.010	0.010	0.005	0.003	0.015
12b1 Fees	0.001	0.000	0.002	0.000	0.003
Management Fees	0.007	0.007	0.003	0.002	0.010
Turnover	0.874	0.490	2.718	0.100	1.520
Fund Age(months)	176.722	146.000	147.110	47.000	324.000

Table 2.3: Relative Daily Performance of Local and Distant Mutual Funds Following Stress Events

The following tables report estimated cumulative returns and simulated returns for U.S. based equity mutual fund managers following stressful events. Panel A reports results using a sample of 361 U.S. based foreign equity mutual funds located within 100 miles of stressful events bench-marked against a matched sample of funds headquartered 1,000 miles from the event. Panel B reports results for 1,031 domestic equity mutual fund managers located with 100 miles of the traumatic events. Daily returns for both groups are benchmarked against a matched sample of distant mutual funds. The matching criteria used is: CRSP 3 digit objective code, Monthly Total Net Assets, Quarterly Returns, Fund Turnover, and Fund Age. For each event day within the event window, the abnormal return is calculated as the mean abnormal return across each of the 20 events in the sample. Cumulative Abnormal Return (CAR) is calculated as the cumulative product of event days from t_0 to time t and reported in basis points. Columns (3) to (6) report simulated cumulative abnormal returns based on 1,500 random draws with randomized event days and randomized event order taken to match the original distribution of events across the sample period.

Panel A: International Equity Funds (Near less Far bps)

Event_Time (days)	Actual (bps)	Simulated_03	Simulated_05	Simulated_10	Simulated_50
1	-0.937	-9.166	-8.088	-6.077	-0.325
5	9.785	-21.596	-17.095	-13.248	-0.742
10	11.913	-28.931	-26.513	-20.075	-1.052
21	-0.748	-41.064	-36.420	-28.794	-3.212
31	-31.769	-51.831	-45.492	-36.041	-3.913
42	-53.927	-61.528	-53.213	-41.900	-4.381
63	-56.038	-73.538	-65.770	-54.387	-6.676

Panel B: Domestic Equity Funds (Near less Far bps)

Event_Time (days)	Actual (bps)	Simulated_03	Simulated_05	Simulated_10	Simulated_50
1	14.389	-4.818	-4.365	-3.266	0.053
5	8.566	-10.988	-9.592	-7.418	-0.075
10	0.247	-14.920	-12.704	-10.044	-0.016
21	-3.186	-24.342	-20.188	-15.682	-0.411
31	-12.074	-28.905	-25.378	-18.636	-0.339
42	-41.153	-36.143	-29.242	-22.326	-0.965
63	-49.052	-41.938	-37.050	-28.839	-1.500

Table 2.4: Relative Abnormal Performance of Local and Distant Mutual Funds Following Stress Events

The following tables report estimated cumulative abnormal returns and simulated returns for U.S. based equity mutual fund managers following stressful events. Panel A reports results using a sample of 361 U.S. based foreign equity mutual funds located within 100 miles of stressful events bench-marked against a matched sample of funds headquartered 1,000 miles from the event. Panel B reports results for 1,081 domestic equity mutual fund managers located with 100 miles of the traumatic events. Cumulative abnormal returns for the 'near' and 'distant' group of managers were calculated using the Fama French 3 Factors calculated over the quarter preceding each traumatic event. Abnormal returns for both groups are benchmarked against a matched sample of distant mutual funds. The matching criteria used is: CRSP 3 digit objective code, Monthly Total Net Assets, Quarterly Returns, Fund Turnover, and Fund Age. For each event day within the event window, the abnormal return is calculated as the mean abnormal return across each of the 20 events in the sample. Cumulative Abnormal Return (CAR) is calculated as the cumulative product of event days from t_0 to time t and reported in basis points. Columns (3) to (6) report simulated cumulative abnormal returns based on 1,500 random draws with randomized event days and randomized event order taken to match the original distribution of events across the sample period.

Panel A: International Equity Funds (Near less Far bps)

Event_Time (days)	Actual (bps)	Simulated_03	Simulated_05	Simulated_10	Simulated_50
1	0.365	-11.021	-9.448	-7.222	0.015
5	13.930	-24.760	-21.182	-15.929	0.534
10	15.856	-35.129	-30.298	-23.336	0.405
21	-0.724	-47.058	-42.269	-32.470	1.534
31	-47.030	-58.645	-52.155	-40.572	3.297
42	-70.204	-69.978	-61.069	-44.833	4.493
63	-80.936	-91.805	-72.628	-55.835	8.374

Panel B: Domestic Equity Funds (Near less Far bps)

Event_Time (days)	Actual (bps)	Simulated_03	Simulated_05	Simulated_10	Simulated_50
1	-6.069	-4.818	-4.365	-3.266	0.053
5	-11.880	-10.988	-9.592	-7.418	-0.075
10	-20.181	-14.920	-12.704	-10.044	-0.016
21	-23.608	-24.342	-20.188	-15.682	-0.411
31	-32.478	-28.905	-25.378	-18.636	-0.339
42	-61.497	-36.143	-29.242	-22.326	-0.965
63	-69.380	-41.938	-37.050	-28.839	-1.500

Table 2.5: Mutual Funds Change in Risk Exposure Following Traumatic Events

The following tables report regressions on the change in 3 Factor betas before and after traumatic events. Fama French 3 Factor coefficients are calculated over the quarter preceding each traumatic event and post-event factors use the quarter following each event. The three columns report the Market beta coefficients, SMB coefficients, and HML coefficients respectively. The regressions are estimated as a Difference-in-Difference Model between 'near' funds located 100 miles from the traumatic event and 'distant' funds located 1,000 miles from the event. The variable of interest is the interaction between Post Event and Near funds which captures whether funds located in close proximity to traumatic events change their risk exposure to a greater extent than distant funds. Control variables included are fund size, fund age, 12 month turnover and exposure to the other two risk factors. Event effects and 3 digit CRSP objective codes are included in each specification. Robust standard errors are reported in parentheses below the coefficient estimates. Statistical significance (two-sided) at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively. Panel (A) reports results for Domestic Equity funds and Panel (B) reports results for International Equity funds. Panel (C) reports simulated results for changes in market betas using 1,500 random draws for event dates and locations.

Panel A: Domestic Equity Funds

	Mkt Beta	SMB Beta	HML Beta	Mom Beta
Post_Event	-0.2155^{*}	0.0499	-0.0317	0.0995
	(-1.7250)	(0.6667)	(-0.7285)	(0.4232)
Near	0.0001	0.0001	0.0000	0.0001
	(0.5231)	(0.4723)	(0.3677)	(0.5220)
Post_Event x Near	-0.0942	-0.1207	-0.0590	-0.0850
	(-0.6067)	(-1.2919)	(-0.9777)	(-0.3127)
Turnover	0.0032	0.0014	0.0008	0.0032
	(1.1701)	(0.5848)	(0.4306)	(1.4138)
Pre_SMB	0.0307		-0.0033	-0.0063
	(0.2230)		(-0.0990)	(-0.0630)
Pre_HML	-0.2746^{*}	0.0115		-0.1503
	(-1.8264)	(0.1454)		(-1.1174)
Pre_Mom	-0.3702^{*}	-0.0259	-0.0979	
	(-1.8271)	(-0.2147)	(-1.1899)	
Pre_MKT		0.0360	-0.0854^{*}	-0.1838^{**}
		(0.3589)	(-1.8877)	(-2.4437)
Event Effects	Yes	Yes	Yes	Yes
Investment Style Effects	Yes	Yes	Yes	Yes
R^2	0.1373	0.1182	0.1664	0.1196
Adj. R^2	0.1295	0.1102	0.1588	0.1115
Num. obs.	3215	3215	3215	3215
RMSE	0.0059	0.0052	0.0033	0.0042

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table 2.5 (cont'd): Mutual Funds Change in Risk Exposure Following Traumatic Events

Panel B: International Equity Funds

	Mkt Beta	SMB Beta	HML Beta	Mom Beta
Post_Event	−0.0599	0.1314	0.0298	0.3896***
	(−0.9975)	(1.0835)	(0.5518)	(3.9105)
Near	0.0002	−0.0005	−0.0004	0.0005
	(0.7211)	(−1.2067)	(−1.4099)	(0.1074)
Post_Event x Near	−0.0678	−0.1460	0.0326	−0.2268
	(−0.9929)	(−1.0711)	(0.6898)	(−1.6202)
Turnover	−0.0229	−0.0012	−0.0276	−0.0115
	(−0.8719)	(−0.0340)	(−1.0403)	(−0.3665)
Pre_SMB	−0.1449**		−0.0235	−0.0034
	(−2.5113)		(−0.3614)	(−0.0222)
Pre_HML	−0.3115***	−0.0337		−0.1619*
	(−2.6108)	(−0.2502)		(−1.5760)
Pre_Mom	−0.1325**	−0.0266	−0.0913**	
	(−2.1208)	(−0.2532)	(−2.3654)	
Pre_MKT		−0.1980*	−0.1999***	−0.1936*
		(−1.7278)	(−4.2988)	(−1.8537)
Event Effects	Yes	Yes	Yes	Yes
Investment Style Effects	Yes	Yes	Yes	Yes
R^2	0.4823	0.2922	0.3154	0.5346
Adj. R^2	0.4709	0.2766	0.3003	0.5244
Num. obs.	1115	1115	1115	1115
RMSE	0.0058	0.0067	0.0045	0.0066

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Panel C: Actual and Simulated Change in Market Beta Following Traumatic Events

	Actual	3%	5%	10%	50%	90%	95%	97%
Near International	0.003	-0.372	-0.320	-0.249	-0.006	0.240	0.331	0.389
Far International	0.003	-0.371	-0.316	-0.243	-0.004	0.242	0.328	0.383
Near Domestic	-0.003	-0.268	-0.208	-0.134	-0.002	0.132	0.217	0.299
Far Domestic	-0.01	-0.250	-0.198	-0.131	-0.002	0.129	0.205	0.278

Table 2.6: Mutual Fund Change in Turnover Following Traumatic Events

The following tables report the change in fund asset turnover following traumatic events. Fund Turnover is taken from the CRSP database and reported on a quarterly basis. It is calculated within CRSP as the prior 12 month asset purchases divided by total net assets. For each event I identify the most recently reported turnover figure before and after each event and test for changes in manager purchasing activity in the months following traumatic events. I use a Difference-in-Differences approach using 'near' funds located 100 miles from the traumatic event and 'distant' funds located 1,000 miles from the event. The variable of interest is the interaction between Post Event and Near funds which captures whether funds located in close proximity to traumatic events change their purchasing activity following traumatic events. The sample of mutual fund managers is split between high and low turnover funds. Funds in the bottom quartile of turnover within the sample are considered low-turnover funds, and funds in the highest quartile are high-turnover funds. Columns (1) and (2) report results on the high and low turnover subsamples. Column (3) reports the combined results using an indicator for the low-turnover group. Control variables included are fund size and fund age. Event effects and 3 digit CRSP objective codes are included in each specification. Robust standard errors are reported in parentheses below the coefficient estimates. Statistical significance (two-sided) at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively. Panel (A) reports results for Domestic Equity funds and Panel (B) reports results for International Equity funds. Panel (C) reports simulated results for changes in turnover using 1,500 random draws for event dates and locations.

Panel A: Domestic Mutual Fund Turnover

	Low Turnover	High Turnover	Diff (χ^2)
Post_Event	0.5070***	1.1083***	−0.601
	(5.5932)	(4.8824)	(0.160)
Near	0.0574**	2.5564***	−2.499***
	(2.5977)	(3.3440)	(66.061)
Post_Event x Near	−0.4256***	−0.8880***	0.462
	(−4.0650)	(−3.6766)	(.267)
log(Fund Size)	−0.0010**	0.1597**	−0.161***
	(−2.1972)	(1.9809)	(8.843)
Fund Age	0.0017	0.0234	−0.022
	(1.3544)	(0.8703)	(2.362)
Event Effects	Yes	Yes	Yes
Investment Style Effects	Yes	Yes	Yes
R^2	0.3142	0.8159	0.7316
Adj. R^2	-1.0752	0.3803	0.2020
Num. obs.	582	617	1199

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table 2.6 (cont'd): Mutual Fund Change in Turnover Following Traumatic Events

Panel B: International Mutual Fund Turnover

	Low Turnover	High Turnover	Diff (χ^2)
Post_Event	0.7616^{***}	1.0507^{***}	-0.289^{*}
	(10.5929)	(10.9762)	(2.619)
Near	0.0390	0.3389^{**}	−0.300
	(1.4393)	(2.4514)	(0.302)
Post_Event x Near	−0.2700	-0.2147^{*}	-0.055^{**}
	(−1.3607)	(−1.8811)	(3.549)
log(Fund Size)	0.0003	0.0100	−0.010
	(1.3253)	(0.0948)	(.368)
Fund Age	0.0006	0.0072	−0.051
	(0.2376)	(0.6461)	(1.170)
Event Effects	Yes	Yes	Yes
Investment Style Effects	Yes	Yes	Yes
R^2	0.6745	0.8458	0.8543
Adj. R^2	-0.0185	0.4168	0.5586
Num. obs.	195	209	404

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Panel C: Combined Simulated Sample

	Actual	3%	5%	10%	50%	90%	95%	97%
Near International	0.194	-0.240	-0.150	-0.067	0.000	0.087	0.190	0.289
Far International	-0.002	-0.240	-0.150	-0.068	0.000	0.080	0.170	0.267
Near Domestic	0.407	-0.300	-0.190	-0.080	0.000	0.100	0.220	0.340
Far Domestic	0.0458	-0.287	-0.170	-0.073	0.000	0.090	0.202	0.320

Table 2.7: Mutual Fund Tracking Errors

The following tables report results on mutual fund benchmark tracking errors. Fund benchmarks are identified as the index with the highest R^2 to the fund when regression daily returns onto a set of indices from the St. Louis Federal Reserve. Tracking errors are calculated as the standard deviation of the difference in returns between the mutual fund and its benchmark index. Tracking errors are calculated the period $t + 21$ to $t + 63$ and $t - 21$ to $t - 63$ to control for any contemporaneous effects from the initial event itself. Funds are split along the dimension of pre-event tracking errors. Funds in the lowest quartile are considered 'closet-index' funds(Column 1) and funds in the highest quartile are considered 'Active' funds(Column 2). I use a Difference-in-Differences approach using 'near' funds located 100 miles from the traumatic event and 'distant' funds located 1,000 miles from the event. The variable of interest is the interaction between Post Event and Near funds which captures whether funds located in close proximity to traumatic events change their indexing strategy following traumatic events. Column (3) reports the combined sample with a triple interaction to capture differences in behavior between 'closet-index' and 'active' funds. Control variables included are fund size and fund turnover. Event effects and 3 digit CRSP objective codes are included in each specification. Robust standard errors are reported in parentheses below the coefficient estimates. Statistical significance (two-sided) at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively.

	Indexing	Active	Diff (χ^2)
Post_Event	0.6226^{***}	0.6566^{***}	-0.034
	(18.1494)	(22.1085)	(0.052)
Near	0.0134^{**}	-0.1104^{***}	0.124^{***}
	(2.2165)	(−2.6051)	(20.332)
Post_Event x Near	-0.0803^{*}	0.1761^{**}	-0.256^{*}
	(−1.7418)	(2.5464)	(2.698)
log(Fund Size)	−0.0007	−0.0069	0.006
	(−1.1665)	(−1.4769)	(1.699)
Turnover	0.0023^{**}	0.0120	-0.010^{**}
	(2.1298)	(1.5072)	(3.311)
Event Effects	Yes	Yes	Yes
Investment Style Effects	Yes	Yes	Yes
R^2	0.7309	0.8689	0.9198
Adj. R^2	0.7242	0.8650	0.9185
Num. obs.	662	621	1283

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

APPENDIX C

MUTUAL FUND CLIENTS

Figure 3.1: Flow-Performance Sensitivity: Normal vs Stress

This figure reports the flow performance sensitivity for mutual funds separately for the normal and high stress periods. Flow performance sensitivity is estimated for each past performance decile using past year returns. The grey line depicts fund flows for the normal periods and the dashed orange line reports the high stress periods.

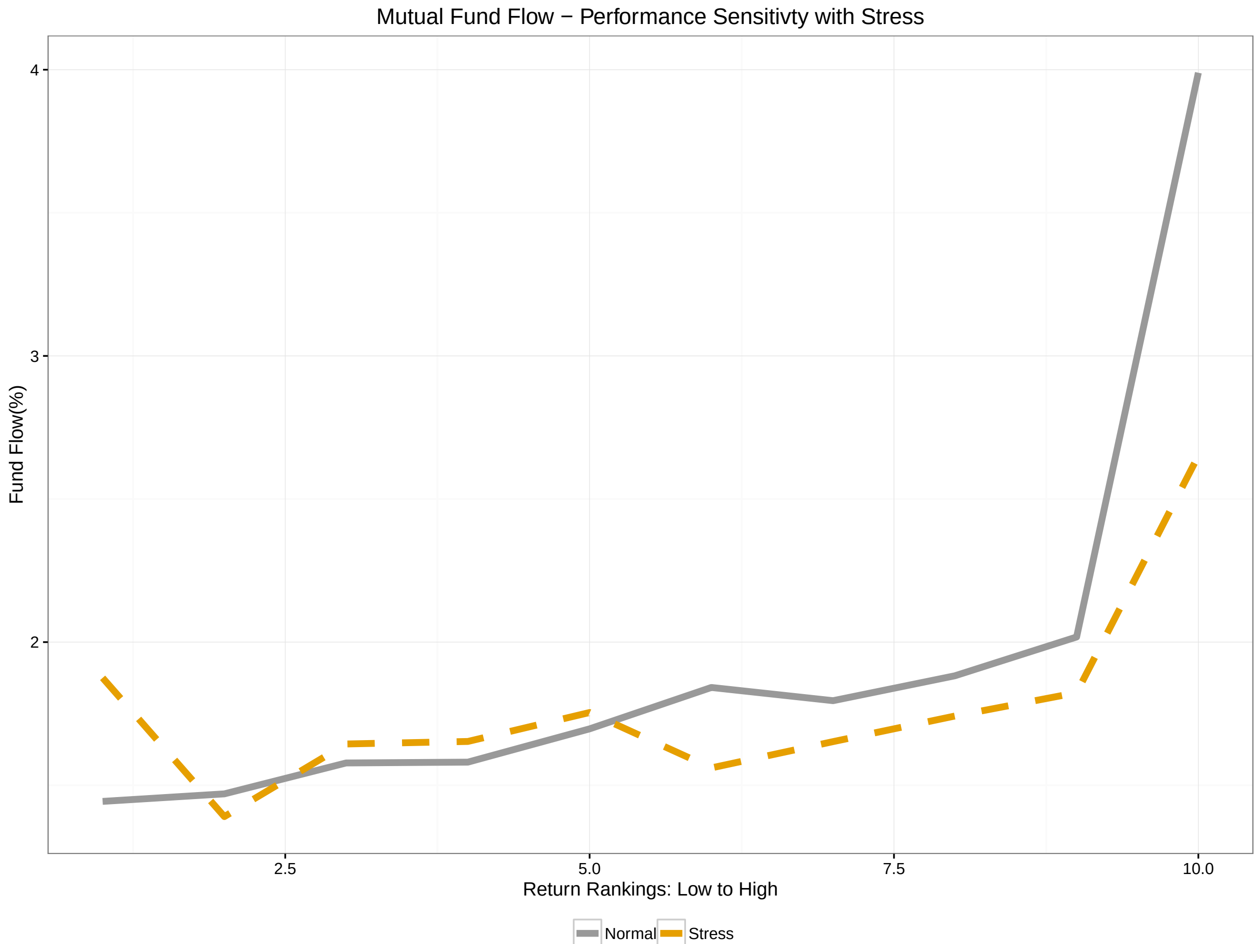


Table 3.1: Summary Stats

The following reports summary statistics for my two primary sample data sets. Panel A reports a constructed sample of mutual funds from the CRSP universe aggregated to the fund series level using a mapping of CRSP fundnos to EDGAR Series CIKs. This sample contains 7,928 unique fund series from 1,030 different fund companies. Panel B reports a second sample of funds dis-aggregated at the share-calss level which covers the same set of CRSP fund series in Panel A.

Panel A: Fund Series

	Mean	Median	Std. Deviation	P10	P90
Flow_t	0.020	0.007	0.169	-0.059	0.087
Monthly Return	0.000	0.000	0.000	-0.000	0.000
Monthly Total Net Assets	1683.846	309.800	6987.329	33.631	3177.000
Expense Ratio	0.008	0.007	0.011	0.002	0.014
12b1 Fees	0.001	0.000	0.002	0.000	0.002
Management Fee	0.005	0.004	0.007	0.001	0.009
Fund Age (Months)	157.845	126.000	131.804	43.000	292.000

Panel B: Share Class Level Data

	Mean	Median	Std. Deviation	P10	P90
Flow_t	0.007	-0.003	0.155	-0.040	0.050
Monthly Return	0.005	0.004	0.041	-0.035	0.049
Monthly Total Net Assets	761.233	123.900	3258.440	18.700	1387.000
Expense Ratio	0.011	0.010	0.006	0.003	0.019
12b1 Fees	0.003	0.000	0.004	0.000	0.010
Management Fee	0.006	0.006	0.003	0.001	0.010
Fund Age (Months)	131.964	107.000	102.521	40.000	244.000

Table 3.2: Mutual Fund Flow Sensitivity to Search Costs During Normal and Stress Periods

The following table reports the OLS estimated coefficients and t-statistics for fund flows for separate regressions between normal and high stress periods following nationally reported traumatic events. The variables of interest here are $log(MonthlyTotalNetAssets)$ and $12b1Fees$ which are proxies for mutual fund search costs. Panel (A) reports results using past year returns to assign funds into quintiles. Panel (B) repeats the same tests using past quarter returns. Column (1) displays results for normal periods. Column(2) shows results using only months identified as high stress periods. Column (3) reports the difference in coefficient estimates and the χ^2 test under the null of no difference between the group coefficients. Year effects and 3 digit CRSP objective code effects are included in each specification. Standard errors are reported in parentheses below the coefficient estimate and are clustered at the fund-series level in every specification. Statistical significance (two-sided) at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively.

Panel A: Past Year Returns

	(1) Past Year Ret. Rankings Normal Period	(2) Past Year Ret. Rankings Stress Events	(3) Diff χ^2
(Intercept)	0.0500^{***}	0.0444^{***}	
	(4.3229)	(3.9314)	
Return Quintile 1	-0.0051^{***}	-0.0087^{***}	0.004^{***}
	(−7.6603)	(−7.4135)	(7.489)
Return Quintile 2	-0.0022^{***}	-0.0038^{***}	0.002
	(−4.9125)	(−4.2411)	(1.468)
Return Quintile 4	−0.0002	0.0030^{***}	-0.003^{**}
	(−0.4497)	(3.1598)	(6.029)
Return Quintile 5	0.0225^{***}	0.0131^{***}	0.009^{***}
	(26.0246)	(9.9391)	(49.461)
log(Monthly Total Net Assets)	-0.0093^{***}	-0.0063^{***}	-0.003^{***}
	(−27.7274)	(−15.0288)	(116.771)
log(Fund Age)	-0.0026^{***}	-0.0032^{***}	0.002
	(−5.7654)	(−5.2426)	(1.012)
Return Risk	13.3324^{***}	6.3487^{***}	6.032^{***}
	(6.3821)	(2.6901)	(39.348)
Actual 12b1 fees	-1.5599^{***}	0.6949^{***}	-2.175^{***}
	(−7.2158)	(2.7861)	(82.555)
Management Fee	-0.2374^{*}	-0.3727^{***}	0.110
	(−1.6994)	(−3.6544)	(2.119)
log(fund family size)	0.0034^{***}	0.0019^{***}	0.001^{***}
	(17.0505)	(8.2693)	(35.165)
Return Quintile 1 - Return Quintile 5	-0.0276^{***}	-0.0218^{***}	-0.005^{***}
	(695.76)	(208.18)	(19.343)
Year Effects	Yes	Yes	
Investment Style Effects	Yes	Yes	
Fund Series Clustered Errors	Yes	Yes	
Adj. R^2	0.0213	0.0141	
Num. obs.	851948	211225	

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table 3.2 (cont'd): Mutual Fund Flow Sensitivity to Search Costs During Normal and Stress Periods

Panel B: Past Quarter Returns

	(1) Past Qtr Ret. Rankings Normal Period	(2) Past Qtr Ret. Rankings Stress Events	(3) Diff χ^2
(Intercept)	0.0507^{***}	0.0424^{***}	
	(4.3394)	(3.7239)	
Return Quintile 1	0.0014^{**}	0.0006	-0.003^{**}
	(1.9715)	(0.4391)	(4.457)
Return Quintile 2	0.0033^{***}	0.0005	−0.002
	(4.8921)	(0.4424)	(2.372)
Return Quintile 4	0.0041^{***}	0.0009	0.000
	(6.1405)	(0.8205)	(.111)
Return Quintile 5	0.0155^{***}	0.0059^{***}	0.007^{***}
	(18.0686)	(4.2655)	(26.607)
log(Monthly Total Net Assets)	-0.0097^{***}	-0.0061^{***}	-0.004^{***}
	(−28.3482)	(−14.7083)	(169.651)
log(Fund Age)	-0.0036^{***}	-0.0042^{***}	0.001
	(−7.7775)	(−6.7898)	(1.029)
Return Risk	16.2793^{***}	7.3001^{***}	8.979^{***}
	(5.9781)	(2.8333)	(65.089)
Actual 12b1 fees	-1.7611^{***}	0.6153^{**}	-2.376^{***}
	(−7.7508)	(2.4308)	(91.579)
Management Fee	-0.2509^{*}	-0.3473^{***}	0.096
	(−1.7101)	(−3.3520)	(1.075)
log(fund family size)	0.0034^{***}	0.0020^{***}	0.001^{***}
	(16.7654)	(8.3499)	(33.760)
Return Quintile 1 - Return Quintile 5	-0.0141^{***}	$.0001^{***}$	-0.004^{***}
	(326.47)	(18.194)	(53.488)
Year Effects	Yes	Yes	
Investment Style Effects	Yes	Yes	
Fund Series Clustered Errors	Yes	Yes	
Adj. R^2	0.0191	0.0123	
Num. obs.	851948	211225	

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table 3.3: Mutual Fund Flow Sensitivity to Past Performance During Normal and Stress Periods

The following table reports the OLS estimated coefficients and t-statistics for fund flows for separate regressions between normal and high stress periods following nationally reported traumatic events. This table estimates differences in fund flow - performance sensitivity between normal and high stress periods. Panel (A) reports results using past year returns to assign funds into quintiles. Panel (B) repeats the same tests using past quarter returns. Column (1) displays results for normal periods. Column(2) shows results using only months identified as high stress periods. Column (3) reports the difference in coefficient estimates and the χ^2 test under the null of no difference between the group coefficients. Return quintile 1 groups the lowest performing funds in each period and Quintile 5 groups the highest performing funds. Funds are ranked and assigned quintiles separately for each CRSP fund obejctive identifier. Year effects and 3 digit CRSP objective code effects are included in each specification. Standard errors are reported in parentheses below the coefficient estimate and are clustered at the fund-series level in every specification. Statistical significance (two-sided) at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively.

Panel A: Past Year Returns

	(1) Past Year Ret. Rankings Normal Period	(2) Past Year Ret. Rankings Stress Events	(3) Diff χ^2
Return Quintile 1	-0.0051^{***}	-0.0088^{***}	0.004^{***}
	(-7.7722)	(-7.4884)	(7.586)
Return Quintile 2	-0.0023^{***}	-0.0038^{***}	0.002
	(-4.9861)	(-4.2279)	(1.379)
Return Quintile 4	-0.0002	0.0029^{***}	-0.003^{**}
	(-0.4065)	(3.1117)	(5.783)
Return Quintile 5	0.0226^{***}	0.0130^{***}	0.010^{***}
	(26.0650)	(9.8112)	(52.202)
Expense Ratio	-0.2268^{**}	-0.0320^{***}	-0.003^{***}
	(-2.0524)	(-3.2446)	(41.330)
log(Monthly Total Net Assets)	-0.0093^{***}	-0.0063^{***}	0.004^{***}
	(-27.6638)	(-15.0158)	(122.212)
log(Fund Age)	-0.0026^{***}	-0.0032^{***}	0.002
	(-5.7607)	(-5.2125)	(0.838)
Return Risk	13.4865^{***}	6.1638^{***}	7.3337^{***}
	(6.3691)	(2.6450)	4(3.338)
log(fund family size)	0.0035^{***}	0.0020^{***}	0.010^{***}
	(17.0969)	(8.6053)	(36.963)
Return Quintile 1 - Return Quintile 5	-0.0277^{***}	-0.0218^{***}	-0.006^{***}
	(700.55)	(207.3)	(20.914)
Year Effects	Yes	Yes	
Investment Style Effects	Yes	Yes	
Adj. R^2	0.0211	0.0140	
Num. obs.	852030	211237	

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table 3.3 (cont'd): Mutual Fund Flow Sensitivity to Past Performance During Normal and Stress Periods

Panel B: Past Quarter Returns

	(1) Past Qtr Ret. Rankings Normal Period	(2) Past Qtr Ret. Rankings Stress Events	(3) Diff χ^2
Return Quintile 1	-0.0033^{***}	-0.0006	-0.003^{**}
	(-4.9096)	(-0.5216)	(4.198)
Return Quintile 2	-0.0020^{***}	0.0000	-0.002
	(-4.0491)	(0.0476)	(2.437)
Return Quintile 4	0.0009^{*}	0.0004	0.000
	(1.7902)	(0.4373)	(0.139)
Return Quintile 5	0.0123^{***}	0.0053^{***}	0.007^{***}
	(16.2215)	(4.2693)	(27.978)
Expense Ratio	-0.2559^{**}	-0.0348^{***}	0.000^{***}
	(-2.0627)	(-3.0048)	(53.162)
log(Monthly Total Net Assets)	-0.0097^{***}	-0.0061^{***}	-0.003^{***}
	(-28.2118)	(-14.6989)	(176.947)
log(Fund Age)	-0.0036^{***}	-0.0042^{***}	-0.002
	(-7.7323)	(-6.7699)	(0.835)
Return Risk	16.4805^{***}	7.1280^{***}	9.3525^{***}
	(5.9641)	(2.7999)	(70.752)
log(fund family size)	0.0035^{***}	0.0020^{***}	0.007^{***}
	(16.6361)	(8.6633)	(36.105)
Return Quintile 1 - Return Quintile 5	-0.0156^{***}	-0.0059^{***}	-0.01^{***}
	(329.33)	(18.273)	(54.487)
Year Effects	Yes	Yes	
Investment Style Effects	Yes	Yes	
Fund Series Clustered Errors	Yes	Yes	
Adj. R^2	0.0211	0.0140	
Num. obs.	852030	211237	

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table 3.4: Retail Share-Class Sensitivity to Past Performance During Normal and Stress Periods

The following table reports the OLS estimated coefficients and t-statistics for retail mutual fund share-class fund flows for separate regressions between normal and high stress periods following nationally reported traumatic events. This table estimates differences in fund flow - performance sensitivity between normal and high stress periods. Panel (A) reports results using past year returns to assign funds into quintiles. Panel (B) repeats the same tests using past quarter returns. Column (1) displays results for normal periods. Column(2) shows results using only months identified as high stress periods. Column (3) reports the difference in coefficient estimates and the χ^2 test under the null of no difference between the group coefficients. The variables of interest here are the reported past return quintile indicators which estimate the convexity of the flow-performance sensitivity. Return Quintile 3 is used as a baseline for the return ranking indicators. Return quintile 1 groups the lowest performing funds in each period and Quintile 5 groups the highest performing funds. Funds are ranked and assigned quintiles separately for each CRSP fund objective identifier. Year effects and 3 digit CRSP objective code effects are included in each specification. Standard errors are reported in parentheses below the coefficient estimate and are clustered at the fund-series level in every specification. Statistical significance (two-sided) at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively.

Panel A: Retail Past Quarter Returns

	(1) Past Qtr Ret. Rankings Normal Period	(2) Past Qtr Ret. Rankings Stress Events	(3) Diff χ^2
Return Quintile 1	-0.0041^{***}	-0.0019^{*}	-0.002^{**}
	(-8.9057)	(-1.9444)	(5.442)
Return Quintile 2	-0.0025^{***}	-0.0028^{***}	0.000
	(-7.0551)	(-3.4563)	(0.097)
Return Quintile 4	0.0034^{***}	-0.0000	0.003^{***}
	(9.4580)	(-0.0004)	(12.691)
Return Quintile 5	0.0166^{***}	0.0091^{***}	0.007^{***}
	(31.2768)	(9.7421)	(59.535)
Expense Ratio	-0.9383^{***}	-0.8245^{***}	0.003^{*}
	(-18.4022)	(-9.5077)	(2.964)
log(Monthly Total Net Assets)	-0.0031^{***}	-0.0032^{***}	-0.002
	(-15.2625)	(-9.7028)	(0.223)
log(Fund Age)	-0.0102^{***}	-0.0083^{***}	0.000^{***}
	(-32.6384)	(-15.6979)	(14.521)
Return Risk	0.0739^{**}	0.3228^{***}	$-.2489$
	(1.9732)	(3.7725)	(82.319)
log(fund family size)	-0.0003^{**}	-0.0002	0.007
	(-2.3666)	(-1.0483)	(0.269)
Return Quintile 1 - Return Quintile 5	-0.0207^{***}	-0.011^{***}	-0.009^{*}
	(2002)	(426.16)	(3.6997)
Year Effects	Yes	Yes	
Investment Style Effects	Yes	Yes	
Adj. R^2	0.0105	0.0075	
Num. obs.	1302261	258288	

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table 3.4 (cont'd): Retail Share-Class Sensitivity to Past Performance During Normal and Stress Periods

Panel B: Institutions Past Quarter Returns

	(1) Past Qtr Ret. Rankings Normal Period	(2) Past Qtr Ret. Rankings Stress Events	(3) Diff χ^2
Return Quintile 1	-0.0048^{***}	-0.0071^{***}	0.002^{*}
	(−6.6678)	(−6.0590)	(2.740)
Return Quintile 2	-0.0027^{***}	−0.0003	-0.002^{*}
	(−4.5505)	(−0.2307)	(2.970)
Return Quintile 4	0.0032^{***}	0.0030^{***}	0.000
	(5.2088)	(2.6326)	(0.025)
Return Quintile 5	0.0132^{***}	0.0117^{***}	0.001
	(17.9568)	(9.5196)	(1.093)
Expense Ratio	-1.2204^{***}	-1.2289^{***}	0.000
	(−14.8117)	(−10.3924)	(0.025)
log(Monthly Total Net Assets)	-0.0062^{***}	-0.0045^{***}	0.002^{***}
	(−23.8693)	(−14.4932)	(31.347)
log(Fund Age)	-0.0139^{***}	-0.0131^{***}	−0.002
	(−29.6529)	(−17.9946)	(1.324)
Return Risk	0.0668^{*}	0.1615^{***}	
	(1.8890)	(3.8845)	(10.42)
log(fund family size)	0.0013^{***}	0.0009^{***}	0.001
	(6.9611)	(3.5824)	(1.093)
Return Quintile 1 - Return Quintile 5	-0.018^{***}	-0.0188^{***}	0.001^{***}
	(1334.5)	(112.86)	(102.78)
Year Effects	Yes	Yes	
Investment Style Effects	Yes	Yes	
Adj. R^2	0.0095	0.0080	
Num. obs.	754396	195646	

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table 3.5: Smart Money: 24 month Fund Flow Weighted Alphas after Traumatic Events

In each month I construct high and low flow portfolios based on fund flows to retail and institutional share classes for actively managed equity mutual funds. I identify if the current periods fund flows are abnormally high or low(greater/less than 1.5 standard deviations above the rolling 36 month mean) and from this construct value weighted portfolios separately for retail and institutional share-classes which are then held for 24 months. I compute the 4 factor alpha for the portfolio constructed in each month to generate a time series of alphas representing the aggregate decisions made by investors. In Panel A, I report portfolio alpha means, differences, and t-tests between normal and stress periods. T-statistics are reported in parentheses. Panel B reports simulated differences in alphas between normal and randomized event days using a series of 3,000 simulated draws. The first 3 rows report mean normal period and stress period alphas along with the difference in alphas for retail and institutional share classes. The next group of rows report the simulated distribution for differences in normal and randomized stress event alphas.

Panel A: Summary Tests for Normal and Stress Period Alphas

	Normal Alpha	Stress Alpha	Diff
Retail	.0012	0.0002	.0010
	(3.1830)	(0.2493)	(1.500)
Institutional	0.0008	-0.0009	.0017
	(2.471)	(−1.204)	(2.132)
Diff	.0004	.0011	
	(0.70083)	(1.0951)	

Panel B: Simulated Differences between Normal and Stress Portfolio Alpha

	Actual_Diff	Simulated_97	Simulated_95	Simulated_90	Simulated_50	Simulated_10
Retail	0.0010	0.0019	0.0017	0.0015	0.0005	−0.0006
Institutional	0.0017**	0.0019	0.0017	0.0015	0.0006	−0.0006

Table 3.6: NSAR: Stress Effects on Mutual Fund Inflow and Outflows

The following table shows the breakdown of net mutual fund flows into their inflow (Column 1) and outflow (Column 2) components. The data for this table is taken from the NSAR filings from EDGAR with date back to 2006. Only funds whose NSAR flows have a correlation of .9 with CRSP are included in the sample used to construct the following table. This sample includes 2,320 unique fund series. The model regresses flows in month t onto an indicator to identify if month t is a high stress month or not. All other variables are lagged including past net flows. Year effects and 3 digit CRSP objective code effects are included in each specification. Standard errors are reported in parentheses below the coefficient estimate and are clustered at the fund-series level in every specification. Statistical significance (two-sided) at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively.

	(1) Inflow	(2) Outflow	(3) Net flow
Stress_Ind	-0.0030^{***}	0.0006	-0.0021^{***}
	(−3.9654)	(1.1743)	(−4.7816)
Return Quintile 1	-0.0059^{***}	0.0018	-0.0068^{***}
	(−2.6051)	(1.0256)	(−7.4745)
Return Quintile 2	−0.0024	−0.0007	-0.0018^{***}
	(−1.4613)	(−0.6097)	(−2.6937)
Return Quintile 4	0.0036^{**}	0.0030^{**}	0.0010
	(2.0163)	(2.1254)	(1.3781)
Return Quintile 5	0.0022	−0.0003	0.0027^{***}
	(0.9627)	(−0.1457)	(2.7920)
Expense Ratio	-0.6476^{*}	-0.5288^{**}	-0.2320^{**}
	(−1.7711)	(−2.0851)	(−1.9768)
log(Monthly Total Net Assets)	-0.0226^{***}	-0.0181^{***}	-0.0028^{***}
	(−16.2701)	(−17.4269)	(−6.3678)
log(Fund Age)	−0.0019	0.0046^{***}	-0.0056^{***}
	(−1.0553)	(3.0877)	(−8.7968)
Return Risk	−15.2956	−10.0676	-6.3713^{**}
	(−1.6099)	(−1.3713)	(−2.4202)
log(Fund Family Size)	0.0074^{***}	0.0062^{***}	0.0007^{*}
	(7.8074)	(8.1288)	(1.9435)
Year Effects	Yes	Yes	Yes
Investment Style Effects	Yes	Yes	Yes
Fund Share Class Clustered Errors	Yes	Yes	Yes
R^2	0.1021	0.1158	0.0244
Adj. R^2	0.1016	0.1153	0.0239
Num. obs.	91702	91817	89902

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table 3.7: Relative Daily Performance of Local and Distant Mutual Funds Following Stress Events

The following tables report estimated cumulative abnormal returns and simulated returns for U.S. based equity mutual fund managers following stressful events. Panel A reports results using a sample of 743 U.S. based foreign equity mutual funds located within 100 miles of stressful events bench-marked against a matched sample of funds headquartered 1,000 miles from the event. Panel B reports results for 1,825 domestic equity mutual fund managers located with 100 miles of the traumatic events. Daily returns for both groups are benchmarked against a matched sample of distant mutual funds. The matching criteria used is: CRSP 3 digit objective code, Monthly Total Net Assets, Quarterly Returns, Fund Turnover, and Fund Age. For each event day within the event window, the abnormal return is calculated as the mean abnormal return across each of the 20 events in the sample. Cumulative Abnormal Return (CAR) is calculated as the cumulative product of event days from t_0 to time t and reported in basis points. Columns (3) to (5) report simulated cumulative abnormal returns based on 3,000 random draws with randomized event days and randomized event order taken to match the original distribution of events across the sample period.

Panel A: Domestic Equity Funds

Event_Time	CAR(Near less Far)	Simulated_03	Simulated_05	Simulated_10	Simulated_50
1	4.6	-11.1	-9.3	-7.2	-0.1
7	10.1	-25.6	-21.9	-16.9	-0.8
14	-22.0	-35.6	-31.1	-24.7	-1.5
21	-19.0	-45.0	-39.2	-30.3	-1.5
28	-24.0	-52.1	-43.7	-35.2	-3.2
35	-33.2	-58.0	-51.3	-39.7	-3.9
42	-55.1	-64.5	-55.3	-44.1	-3.7
49	-52.0	-68.9	-60.3	-47.4	-4.1
56	-68.4	-74.1	-65.7	-51.5	-3.9
63	-74.0	-78.1	-67.8	-54.5	-4.4
70	-78.6	-81.9	-72.3	-58.1	-4.5
77	-80.0	-87.3	-76.4	-60.5	-4.5
84	-93.7	-90.7	-78.9	-62.0	-4.4
91	-90.8	-92.5	-81.1	-63.2	-4.1

Table 3.7 (cont'd): Relative Daily Performance of Local and Distant Mutual Funds Following Stress Events

Panel B: Foreign Equity Funds

Event_Time	CAR(Near less Far)	Simulated_03	Simulated_05	Simulated_10	Simulated_50
1	-6.3	-14.6	-12.8	-9.6	-0.1
7	2.2	-31.8	-26.8	-20.3	-0.6
14	-14.5	-42.1	-37.1	-28.7	-0.3
21	-27.2	-51.7	-44.4	-35.0	-0.1
28	-47.2	-57.3	-52.1	-39.4	-0.4
35	-62.7	-65.8	-55.1	-44.0	0.0
42	-84.9	-72.8	-61.0	-48.4	0.6
49	-90.8	-76.3	-66.6	-51.5	1.1
56	-96.9	-81.2	-70.8	-54.7	2.0
63	-104.2	-90.7	-78.3	-57.8	1.7
70	-101.1	-92.5	-79.3	-61.3	2.2
77	-98.6	-95.8	-82.8	-64.6	3.5
84	-102.5	-103.5	-89.9	-65.8	5.0
91	-90.2	-107.1	-92.0	-70.0	4.4

Table 3.8: Robustness Check: Out of Sample Events

The following table reports the OLS estimated coefficients and t-statistics for fund flows for out of sample events using interaction terms to capture differences fund flow sensitivity to fund characteristics between normal and high stress periods following nationally reported traumatic events. This table estimates differences in fund flow - performance sensitivity between normal and high stress periods. Panel (A) reports results using past year returns to assign funds into quintiles. Panel (B) repeats the same tests using past quarter returns. Column (1) displays results for normal periods. Column(2) shows results using only months identified as high stress periods. Column (3) reports the difference in coefficient estimates and the χ^2 test under the null of no difference between the group coefficients. The variables of interest here are the reported past return quintile indicators which estimate the convexity of the flow-performance sensitivity. Return Quintile 3 is used as a baseline for the return ranking indicatorss. Return quintile 1 groups the lowest performing funds in each period and Quintile 5 groups the highest performing funds. Funds are ranked and assigned quintiles separately for each CRSP fund objective identifier. Year effects and 3 digit CRSP objective code effects are included in each specification. Standard errors are reported in parentheses below the coefficient estimate and are clustered at the fund-series level in every specification. Statistical significance (two-sided) at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively.

Panel A: Regression Tests

	(1) Past Year Ret. Rankings Normal Period	(2) Past Year Ret. Rankings Stress Events	(3) Diff χ^2
Return Quintile 1	-0.0059^{***}	-0.0009	-0.005
	(-9.6136)	(-0.2561)	(2.022)
Return Quintile 2	-0.0026^{***}	-0.0015	-0.001
	(-6.3206)	(-0.5444)	(0.093)
Return Quintile 4	0.0006	-0.0079^{***}	0.009^{**}
	(1.5103)	(-2.7314)	(5.922)
Return Quintile 5	0.0211^{***}	0.0125^{***}	0.009^{**}
	(26.6526)	(3.3525)	(5.596)
Expense Ratio	-0.1069^{*}	-0.0954	0.009
	(-1.9136)	(-1.3241)	(0.024)
log(Monthly Total Net Assets)	-0.0087^{***}	-0.0091^{***}	-0.005
	(-27.3428)	(-8.5187)	(0.256)
log(Fund Age)	-0.0027^{***}	-0.0052^{***}	-0.001
	(-6.5463)	(-3.5937)	(2.084)
Return Risk	10.5537^{***}	20.1090^{**}	-9.5553
	(5.6477)	(2.4365)	(2.0835)
log(fund family size)	0.0032^{***}	0.0043^{***}	0.009
	(18.2576)	(6.5102)	(2.370)
Return Quintile 1 - Return Quintile 5	-0.027^{***}	-0.0134^{***}	-0.014^{***}
	(815.6)	(11.615)	(14.3)
Year Effects	Yes	Yes	
Investment Style Effects	Yes	Yes	
Adj. R^2	0.0186	0.0343	
Num. obs.	1039392	23875	

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table 3.9: Fund Flows - Early vs late period

The following table reports the OLS estimated coefficients and t-statistics for mutual fund flows in separate models for early and late sample sub-periods. Interaction terms are used to capture the difference in fund-flow performance convexity between normal and high stress periods. Column (1) displays results for the 1995-2008 sub-period. Column(2) shows results for the post-2009 sub-period. The variables of interest here are the reported interaction term coefficients on the return quintile indicators. Return Quintile 3 is used as a baseline for the return ranking indicators. Return quintile 1 groups the lowest performing funds in each period and Quintile 5 groups the highest performing funds. Funds are ranked and assigned quintiles separately for each CRSP fund objective identifier. Year effects and 3 digit CRSP objective code effects are included in each specification. Standard errors are reported in parentheses below the coefficient estimate and are clustered at the fund-series level in every specification. Statistical significance (two-sided) at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively.

Panel A: Regression Tests - Past Quarter Returns

	(1) Early Period 1995-2008	(2) Late Period 2009-2016
Return Quintile 1	-0.0019^{**}	-0.0044^{***}
	(-1.9825)	(-4.6341)
Return Quintile 2	-0.0017^{**}	-0.0021^{***}
	(-2.2196)	(-3.1406)
Return Quintile 4	0.0015^{**}	0.0004
	(2.2671)	(0.6352)
Return Quintile 5	0.0167^{***}	0.0089^{***}
	(13.6898)	(9.6644)
Stress_Ind	0.0036^{**}	-0.0087^{***}
	(1.9772)	(-9.4508)
Return Quintile 1:Stress_Ind	0.0063^{**}	0.0013
	(2.2672)	(0.8464)
Return Quintile 2:Stress_Ind	0.0037	0.0017
	(1.2616)	(1.2809)
Return Quintile 4:Stress_Ind	-0.0035	0.0001
	(-1.2967)	(0.0697)
Return Quintile 5:Stress_Ind	-0.0063^{*}	-0.0066^{***}
	(-1.6863)	(-4.5966)
Controls	Yes	Yes
Year Effects	Yes	Yes
Investment Style Effects	Yes	Yes
Fund Series Clustered Errors	Yes	Yes
Adj. R^2	0.0228	0.0149
Num. obs.	429814	633453

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

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