Do Catastrophic Experiences Affect Risk Attitudes? Evidence from U.S.-Based Managers of Non-U.S. Mutual Funds

GENNARO BERNILE, VINEET BHAGWAT,
AMBRUS KECSKÉS, and PHUONG-ANH NGUYEN*

Abstract

We use a novel empirical approach to show that personal catastrophic experiences affect the risk attitudes of professional money managers. Specifically, we examine changes in portfolio risk of U.S.-based mutual funds invested outside the U.S around the occurrence of severe natural disasters that the fund managers experience directly. Our identification relies on a difference-in-difference comparison between managers in disaster versus non-disaster counties before and after a disaster. We find that the monthly volatility of fund returns decreases by roughly 50 bps during the year after a disaster and this effect gradually dissipates by the fourth year after the event. This decrease is primarily due to lower systematic risk. Additional results rule out explanations based on wealth effects and managerial agency, skill, or catering. Overall, the evidence indicates that extreme events can cause large albeit transient changes in attitudes toward financial risk, even for professionals who deal with such risk for a living.

November 1, 2016

JEL classification: D01, D81, G02, G11, G23
Keywords: Mutual funds; Risk taking; Catastrophes; Natural disasters; Psychology; Behavioral

---

* Bernile is at the Lee Kong Chian School of Business, Singapore Management University; Bhagwat is at the Lundquist School of Business, University of Oregon; and Kecskés and Nguyen are at the Schulich School of Business, York University. We greatly appreciate the comments of Ran Duchin, Wayne Ferson, Dasol Kim, Shimon Kogan, Evgeny Lyandres, Ron Masulis, Adrien Matray, Dino Palazzo, and Johan Sulaeman, and seminar participants at Singapore Management University.

1. Introduction

Extreme negative experiences can affect investors' risk taking for a variety of reasons. Standard utility theory allows such events to affect risk taking due to their effect on background risk (Heaton and Lucas (2000) and Guiso and Paiella (2008)) or their perceived likelihood and salience (Caballero and Krishnamurthy (2009) and Bordalo, Gennaioli, and Shleifer (2013)). Models of habit persistence (Campbell and Cochrane (1999)) or prospect theory models (Barberis, Huang, and Santos (2001)) posit instead that large negative shocks affect investor risk tolerance. Finally, the psychology literature suggests that traumatic events can cause emotional responses that result in more conservative behavior even for events that have no direct economic consequences (Loewenstein (2000) and Loewenstein, Hsee, Weber, and Welch (2001)).

A growing number of studies in economics and finance show that experiencing extreme negative events does indeed affect financial decisions. Guiso, Sapienza, and Zingales (2016) conclude that negative emotions associated with the recent financial crisis reduce financial risk taking by individuals. Non-economic experiences appear have similar effects. For instance, natural disaster experiences lead both unsophisticated investors and firms to take less financial risk (Cameron and Shah (2013) and Dessaint and Matray (2016)).[1] Negative personal experiences such as bereavement seem to have similar consequences (Shu, Sulaeman, and Yeung (2016)).

Overall, previous studies suggest that salient shocks of various origins and natures affect risk taking via changes in individuals' wealth, preferences, or beliefs. However, it is not obvious whether similar inferences extend to professionals who work with financial risk for a living. It is this question that we aim to address. The answer matters greatly for investors who delegate their

[1] In a related but different vein, other studies find that exposure to extremely negative economic or natural events have long lasting effects on financial risk taking by households and firms (Malmendier and Nagel (2011), Bucciol and Zarri (2015), Bharath and Cho (2015), and Bernile, Bhagwat, and Rau (2016)).

investment decisions to professionals since managerial risk attitudes are known to influence investors' choice of managers, whether explicitly or implicitly, e.g., through style selection (Kumar (2009), Bailey, Kumar, and Ng (2011), and Barber, Huang, and Odean (2016)). If managers take more or less risk than investors anticipate, especially when it cannot be diversified away across investors' other holdings, this risk mismatch will leave investors worse off.

In this paper, we examine whether natural disasters that occur in the U.S. affect the risk taking of mutual fund managers who are based in the U.S. but invest exclusively outside the U.S. by mandate. Given our setting, our baseline prediction is that mutual fund managers acting in their investors' interests should not change their portfolio risk after experiencing a disaster that does not affect their portfolio stocks or investors. By contrast, we conjecture that if a disaster causes emotional responses by fund managers who directly experience it, then their risk taking would change even absent other effects suggested by neoclassical economic theory.

Our experimental design has numerous advantages. First, mutual fund managers are an ideal group of economic agents for studying risk taking. An important element of their job is to make optimal risk-return tradeoffs, including with respect to extreme events. As such, they are professional risk takers, in contrast to individuals in the population at large or even executives, few of whom are trained and experienced experts in financial risk taking. Furthermore, we are able to measure risk taking by mutual fund managers (ex post) as the realized volatility of their portfolio returns. This contrasts with other coarser proxies used in the literature, such as allocation of a household's assets to cash versus debt versus equity, risk attitudes inferred from survey responses, or the volatility of a firm's stock returns, which may be affected by other forces aside from these individuals' attitudes toward risk.

Another important advantage of our approach is that we focus on U.S.-based managers of international equity funds (as distinct from global equity funds). Hence, the managers themselves directly experience the disasters in our sample, when a disaster occurs in the county in which the manager is located. However, the individual stocks in the managers' portfolios should not be affected by these same disasters because none of the portfolio firms is located in the U.S. (as we carefully verify).[2] Therefore, the changes in the volatility of the fund portfolios around the disaster events should result from stock picking by fund managers rather than the performance of individual stocks.

Finally, the occurrence of natural disasters provides a unique opportunity to examine the effect of extreme negative exogenous shocks on risk attitudes. In particular, we focus on the most severe disasters (worst 1%) as captured by damages and fatalities, so our events are rare and extreme by construction. Moreover, there is a long tradition in economics of using events in nature as exogenous shocks (Wright (1928)). Natural disasters in particular are exogenous to risk attitudes (Roll (1992) and Hirshleifer and Shumway (2003)) and have pronounced psychological effects, as noted above. Importantly, in our empirical tests, we carefully match the treatment and control funds on the prior probability of a disaster given the fund's location. Therefore, by design, whether a fund experiences a disaster or not is conditionally random.

In our empirical analysis, we merge a dataset of all natural disaster that occur in the U.S., in which disasters are measured at the county-month level, with a dataset of all international equity mutual funds that are based in the U.S. The treatment sample, which corresponds to mutual funds located in counties that experience severe natural disasters, comprises over 1,700

[2] It is possible that some portfolio firms are directly affected by disasters because they have above average operations in the county of the fund, or they are indirectly affected by disasters because there are above average spillovers between domestic and foreign firms. These effects would have to be greater than average because we compare funds affected by disasters to those funds that are not. Moreover, we can test for these effects by comparing disasters driven by fatalities to those driven by damages. Our results indicate that these effects are not significant.

fund-years corresponding to over 700 different funds spanning 23 years. The "treatment" fund-years are matched to an equal number of "control" fund-years that do not experience a disaster. Using a difference-in-differences approach, we test whether treatment funds change their portfolio risk around disaster events relative to changes in the portfolio risk of control funds. Our approach allows us to hold fixed heterogeneity in risk taking across funds and over time. We are also able to control for determinants of risk taking that vary across treatment funds as well as between treatment funds and controls funds, including target foreign region, fund size, turnover, age, performance, flows, and the prior probability of a disaster. In this setting, as long as the treatment and control funds are comparable, changes in risk taking between treatment and control funds around disaster events must be caused by these events.

Consistent with a decrease in risk taking, we find that there is a significant albeit temporary decrease in portfolio volatility when a fund manager experiences a severe disaster. Compared to the year before the event, on average, the difference in portfolio volatility of the treatment and control funds is roughly 50 basis points lower in year +1 and 35 bps lower in year +2. These differences-in-differences are economically and statistically significant, corresponding to a roughly 10% decrease in volatility. Portfolio volatility is still lower in year +3 (by 17 bps) but no longer statistically significant, and the effect disappears by year +4.

Additional results show that the changes in portfolio risk are similar across disasters with high fatalities (and minimal property damage) or with high property damages (and low fatalities). This evidence is important because it indicates that wealth effects of disasters, whether on managers or investors, cannot explain our baseline results. When we decompose total portfolio risk using the global four-factor model, we find that both the systematic and idiosyncratic components decrease after a disaster. However, our estimates indicate that the change in the systematic component of the portfolio risk accounts for most of the decrease in total risk.

In the spirit of Loewenstein (2000), a natural interpretation of our results is that exposure to severe disasters induces emotional responses by fund managers that lead to more conservative investment choices. However, there are other potential explanations, which we examine in turn. It is worth stressing that our results must be driven by differences between county-years with disasters and matched county-years without disasters. In particular, differences across treatment funds located in different counties experiencing disasters at different times are eliminated by corresponding differences across the matched control funds. Therefore, any interpretation of our results must revolve around the occurrence of a disaster in a given county-year.

One alternative explanation is that the decrease in risk taking stems from agency conflicts between the manager and the investors of the fund that change as a result of the disaster. Since management fees depend on assets under management, managers have an incentive to increase assets to maximize fees. Moreover, it is well known that better fund performance leads to greater fund inflows (Chevalier and Ellison (1997)). Managers can therefore take more risk to improve raw performance and thus attract inflows. In our setting, disasters in the U.S. would not directly affect the performance of international funds. However, they could lower the performance of domestic funds located in the same county as the international funds – for example, because the disasters have a negative impact on U.S. firms owned by domestic funds. If investors substitute between domestic and international funds located in the same county based on their relative performance, managers of international funds in disaster county-years may take less risk due to lower incentives to attract flows with higher performance. The central prediction of this agency explanation is that international funds that experience disasters should subsequently receive greater inflows. The evidence refutes this explanation, as we find no significant effect of a disaster on the difference in fund flows between treatment and control funds.

A second alternative explanation is that the decrease in risk taking is a mere reflection of improved managerial skill resulting from disasters. In particular, fund managers that experience a disaster may become endowed with an information advantage relative those that do not experience a disaster. For instance, a disaster may improve managers' assessment of the impact of extreme events on the universe of stocks in which they invest, whether or not these stocks are affected by the disaster in question. As a specific case, managers in the U.S. may become better at valuing non-U.S. stocks taking into account their disaster exposure. Managers can combine this information advantage with their stock selection or timing abilities to generate superior performance relative to the risk that they take (Huang, Sialm, and Zhang (2011)). The central prediction of this skill explanation is that funds that experience disasters should subsequently perform better. The evidence refutes this explanation as well, as we find no significant effect of a disaster on risk-adjusted returns – neither using Sharpe ratios nor alphas – or fund survival during the next five years. The latter finding, which is also consistent with systematic risk accounting for most of the decrease in total risk, is important because it suggests that the decrease in fund risk is attributable to effect of disasters on managerial risk preferences rather than biased managerial beliefs.

A third alternative explanation for our main results is that managers cater to investors' demand for lower risk taking. It is possible that disasters do not affect the risk attitudes of managers, but they do increase the risk aversion of investors, to which managers respond by taking less risk. This catering explanation requires that most of the investors in the fund cluster within the county of the fund itself, which is possible but improbable. Nevertheless, we examine this possibility empirically using proxies for clustering of investors within the county of the fund: fund size and investor type. We find no difference in risk taking between the smallest funds or institutional funds, with investors plausibly concentrated within the county, and the largest funds or retail funds, with their investors spread across the country. The evidence suggests that it is not investor's risk preferences that are affected by disasters but rather managers'.

Additional evidence provides support for the psychological interpretation of our results. Specifically, we find that the effect of disasters on risk taking is significantly greater for managers with few prior disaster experiences. We also find that effect of disasters on risk taking is of similar magnitude over time, across all funds as well as individual funds, suggesting an evolutionary response by fund managers rather than a mistaken initial response that is subsequently corrected. Finally, in robustness tests, we find similar results for a few of our funds that have some domestic stock holdings as well as for funds located in major financial centers.

In summary, our main results show that natural disaster experiences lead mutual fund managers to lower the risk of their portfolios. Together with the results of additional tests, it appears this change in behavior stems from an increase in managerial risk aversion. In particular, the decrease in risk taking is primarily due to the systematic rather than idiosyncratic component of fund risk, and in fact risk adjusted returns are not affected. Nevertheless, investors typically make asset allocation and fund selection decisions with specific risk objectives in mind (Kumar (2009), Bailey, Kumar, and Ng (2011), and Barber, Huang, and Odean (2016)). Therefore, changes in risk taking resulting from disasters can plausibly lead to a mismatch between the risk anticipated by fund investors and the risk delivered by fund managers.

Our study makes several important contributions to the literature. First, we contribute to the developing literature on the effect of exogenous natural shocks on risk attitudes. Several studies find that the weather affects risk taking by investors (Saunders (1993), Hirshleifer and Shumway (2003), and Bassi, Colacito, and Fulghieri (2013)). A number of recent studies find that natural disasters affect risk taking of households (Cameron and Shah (2013)) and firms (Dessaint and Matray (2016)). Our study shows that natural disasters even affect the risk attitude of money managers, one of the most prominent groups of professional risk takers in financial markets.

Second, we contribute to the emerging literature on the forces that affect risk taking by mutual fund managers. Job related factors that affect the risk taking of investment professionals include agency problems and managerial skill (Huang, Sialm, and Zhang (2011), employment risk (Kempf, Ruenzi, and Thiele (2009)), and managerial tournaments (Kempf and Ruenzi (2008)). Moreover, investment decisions are also affected by factors related to managers' personal lives, including wealth shocks (Pool, Stoffman, Yonker, and Zhang (2014)), religious beliefs (Shu, Sulaeman, and Yeung (2012)), and even divorce (Lu, Ray, and Teo (2016)) and bereavement (Shu, Sulaeman, and Yeung (2016)). Our study shows that natural disasters affect risk taking by fund managers. Oftentimes, distraction or stress at home leads to lower performance at work for managers and losses to investors. In the case of natural disasters, the fund's risk adjusted returns are unaffected, which suggests the resulting changes in risk taking are plausibly due to emotional responses that affect the fund manager's risk aversion.

Finally, we contribute to the nascent literature on international mutual funds. Economic shocks in one part of the world can spread globally depending on the location of investors relative to the affected assets (Jotikasthira, Lundblad, and Ramadorai (2012) and Ferreira, Massa, and Matos (2016)). Our study shows that even non-economic domestic shocks such as natural disasters can have a spillover effect on risk taking in foreign financial markets. This is particularly important given that U.S.-based international equity funds account for approximately $2 trillion of assets as of 2015, or roughly a third of the assets of domestic equity funds, according to the Investment Company Institute's Fact Books. However, they receive modest scholarly attention compared to U.S. equity mutual funds, in spite of their growing importance in investors' portfolios.[3]

The rest of this paper is organized as follows. Section 2 presents the sample, data, and methodology. Section 3 presents the main results, and Section 4 presents alternative explanations. Section 5 presents cross-sectional contrasts and robustness tests. Section 6 concludes.

2. Sample, Data, and Methodology

2.1. Selection of Disasters

We obtain data on natural disasters from the Spatial Hazard Events and Losses Database for the United States. SHELDUS contains data for 18 different types of events including but not limited to thunderstorms, hurricanes, floods, wildfires, and tornados.[4] Our data include the number of fatalities and the amount of property damage for each county-month with an event. This is important because it allows us to distinguish between natural disasters involving fatalities alone (and hence with no effect on local wealth) and those involving property damage alone (and with an effect on local wealth).

SHELDUS is extremely comprehensive, whereas we need to focus on events that are severe and therefore can plausibly affect local risk taking. For this reason, we set thresholds for

[3] Notable exceptions of studies of international equity funds that invest in countries around the world include Cumby and Glen (1990), Didier, Rigobon, and Schmukler (2011), Busse, Goyal, and Wahal (2014), and Cremers, Ferreira, Matos, and Starks (2016).

[4] The full list of disaster types is as follows: avalanche, coastal, drought, earthquake, flooding, fog, hail, heat, hurricane/tropical storm, landslide, lightning, severe storm/thunder storm, tornado, tsunami/seiche, volcano, wildfire, wind, and winter weather.

what constitutes a natural disaster in our setting based on fatalities and/or damages. Since there is variation in population and income across counties and over time, we scale fatalities and damages by population and income.[5] We obtain county-year level data to this end from the Bureau of Economic Analysis.

A disaster in our sample must have a minimum of 2.5 fatalities per million population and/or a minimum of $500 of damages per million dollars of income. These thresholds are chosen to correspond to the 99th percentile of their respective distribution of events at the county-month level. It turns out that there is little overlap between disasters driven by fatalities as opposed to damages. Consequently, roughly 2% of county-months have a disaster driven either by fatalities or by damages or both. By definition, our disasters are the most severe events in SHELDUS.

It is worth noting that counties in which mutual funds are located tend to have higher population and income compared to the typical county. Fortunately, this makes no difference to our definition of natural disasters. For comparison purposes, we create four groups of counties: counties in which a mutual fund is located in any year (less than 100 counties); counties in which a mutual fund is located in a particular year; counties with both population and income per capita of at least the 1st percentile of counties in which a mutual fund is located in any year (about 1,300 counties); and all counties (roughly 3,100 counties). For all four groups of counties, our thresholds for fatalities and damages each produced a similar and roughly 1% rate of disasters at the county-month level. Consequently, our definition of disasters is not specific to the sample of counties with mutual funds that we study further below.

[Insert Figure 1 about here]

[5] We use income rather than wealth throughout the paper because data on wealth are not available at the county-year level or finer granularities.

In Figure 1, we graph descriptive statistics for natural disasters. We focus on counties in which mutual funds are located. While our analysis is at the county-month level, we graph statistics at the year level for ease of interpretation. At this stage, we separate disasters driven by fatalities as opposed to damages.

Panel A shows that the rate of disasters does not trend over time, declining very slightly during the past quarter of a century. This is the case for both fatalities and damages as drivers of disasters. Roughly 1% of county-months, on average, have a disaster driven by fatalities, which is the same proportion as county-months with damages driven fatalities.

Panel B similarly shows that the losses caused by disasters do not trend over time, though disaster losses are more volatility over time than are disaster rates. Given the heterogeneity of both population and income across counties and time, we scale fatalities in a county-month by the population of the county, and similarly we scale damages by the income of the county. For ease of interpretation, we report fatalities per million people, and we report damages in dollars per $1,000 of income. The year with easily the highest fatalities is 1995, whereas the years 1992, 1994, 2004, and 2011 stand out for their high damages. Over the past quarter of a century, the average county-month has experienced roughly 6 fatalities per million people and $6 of damages per $1,000 of income.

It is worth digging deeper into the wealth effects of our disasters. We focus here on disasters driven by damages rather than fatalities. While fatalities have negative wealth effects on affected households, they have no wealth on the population as a whole or an arbitrary member thereof. Figure 1 Panel B shows that the average conditional loss due to damages is a mere 0.6% of income. Looking more closely at the distribution of conditional losses (not tabulated), the 90th and 95th percentiles are 0.11% and 0.26%, respectively. The 99th percentile of the distribution is

0.83%, and the maximum is still only 2.07%. Assuming a ratio of wealth to income of four times (the ratio of measurable U.S. wealth to U.S. GDP), even the maximum conditional loss is only 0.5% of wealth. Even for disasters driven by damages, wealth effects are very likely to be very small. This is especially the case for mutual fund managers and investors, groups that are closer to the top of the wealth distribution than the middle let alone the bottom, even after a disaster, particularly once insurance is taken into account.

2.2. Selection of Mutual Funds

We merge our dataset of natural disasters in the U.S. with a dataset of all international equity mutual funds based in the U.S. Since we conduct our empirical analysis at the fund-year level, we collapse our disasters to the county-year level. Counties with a disaster in one or more months in a given year are deemed to have a disaster that year, whereas counties without a disaster in any month are deemed to have no disaster that year. Where applicable, we use the first month in a given year to determine the month of the disaster for the county-year in question.

We obtain most of our data on mutual funds from the CRSP Mutual Fund database. We select international equity funds (which invest only in non-U.S. stocks) and not global equity funds (which invest in both U.S. and non-U.S. stocks). This ensures that our sample portfolio managers are based in the U.S., but since they invest outside the U.S., the stocks in their portfolio cannot be affected by disasters experienced by the managers themselves. Our data comprehensively cover the universe of international equity funds based in the U.S. In 2013, for example, they cover three-quarters of the universe by assets and three-fifths of the universe by number of funds.[6] We obtain data on the location of mutual fund managers from Morningstar.

[6] For the initial sample of funds, from which our final sample of treatment and control funds are taken, total assets equal $1.5 trillion in 2013, the last year in our sample, and the number of funds is 824. By comparison, according to the Investment Company Institute's Fact Books, there was $2.0 trillion invested in global equity mutual funds in the

These data identify the location of the portfolio manager of our funds. A natural disaster the following year is experienced by approximately 17% of fund-years between 1991 and 2013.

Focusing on international equity mutual funds that experience a natural disaster, our sample of "treatment" funds comprises 1,757 fund-years. This corresponds to 731 unique funds and spans the years 1991-2013. Our treatment funds are located in 220 unique county-years and 62 unique counties. At the fund-year level, roughly 73% of disasters are driven in part by fatalities, and 29% are driven in part by damages, so a large majority of our disasters have no generalized wealth effects.

To verify that our funds are indeed international funds and not invested in the U.S., we obtain data on their holdings from the Thomson Mutual Funds database. We find that 80.1% of our treatment funds have domestic assets worth less than 1% of total (domestic plus foreign) assets. Only 13.4% of our treatment funds have domestic assets worth more than 5% of total assets. On average, our funds have only 5% of their assets invested in U.S. stocks.[7]

While there is considerable heterogeneity in the county-years that experience a disaster, we nevertheless take a difference-in-differences approach and compare otherwise similar funds that experience a disaster to funds that do not, both before and after the disaster. Specifically, we use propensity score matching to match each of our treatment fund-years to an equal number of "control" fund-years.

To estimate propensity scores, we use the fund's total net assets, turnover ratio, age, raw returns, and flows. These are the standard covariates used for propensity score matching in the literature. We also include as a covariate the prior probability of a disaster in the county,

---

same year (which includes both international only funds and domestic plus international funds) spread across 1,345 funds. Of all equity fund assets, 26% was invested in global funds and the rest in domestic funds.

[7] In our robustness tests, we find similar results for funds that have more than a trivial proportion of their assets invested in domestic stocks.

measured from 1970 onward, the beginning of our disasters data. We include this covariate to account for any differences between treatments and controls based on the local incidence of disasters. Additionally, we use match treatments and controls based on the target region of the world in which they invest. We do so to account for any differences in risk exposures around the world. Since some target regions are very thick with funds while others are very thin, we organize target regions into three groups: "general", "developed markets", and "emerging markets".[8] All covariates are measured during the year before the disaster.

We match treatment funds to control funds first on year and target region and then the closest propensity score. The result is that treatment and control funds are well matched based on propensity scores. Testing the two groups of funds for equality of means and medians, we find that the two groups are not significantly different from each other (p-values of 0.68 for differences in means and 0.84 for medians). We also test the equality of means and medians for the proportion of assets invested in domestic stocks, and we find that the differences are not significant. Overall, our treatment and control funds appear to be well matched to each other.

2.3. Methodology

Our difference-in-differences approach is ideally suited for examining and even testing the effect of natural disasters on risk taking by mutual fund managers. We therefore begin our main empirical analysis with graphical evidence of the evolution of risk taking around disasters. For each treatment fund, the year of the disaster is set to be event year 0. The five calendar years before the disaster are set to be years -5 through -1, and the five calendar years after the disaster are set to be years +1 through +5. For each control fund, event years -5 through +5 are set to be

[8] The "general" group (72% of our treatment fund-years) comprises funds that invest in stocks around the world without a focus on either developed or emerging markets. The "developed markets" group (6% of fund-years) comprises "Canada", " "European", and "Japan" funds. The "emerging markets" group (21% of fund-years) comprises "Emerging markets", "China", "India", "Latin America", "Pacific", and "Pacific ex Japan" funds.

the same calendar years as for the corresponding treatment fund. We can thus examine the evolution of risk taking during five years before and after a disaster experience.

Our sample thus comprises 34,344 fund-event year observations. These correspond to 1,757 treatment fund-years between 1991 and 2013, and the same number of matched control fund-years. Each treatment fund has up to 5-5+1=11 event years depending on when the fund starts and ends, and the same is the case for each control fund.

To test the change in risk taking, we take an even more rigorous, regression approach. Our regression specifications have several common features. In our main regression specifications, the unit of observation is the fund-event year, as before. We pool all the event year observations together for treatment and control funds, and we run regressions that compare the treatment funds during one of the years after the disaster (e.g., year +1) to themselves during the year before the disaster (e.g., year -1) as well as the same event years for the corresponding control funds. To this end, we include three dummy variables: one for the treatment funds, another for the post-disaster period, and a third for the interaction of the first two. The interaction dummy variable captures our outcome of interest: the change in risk taking for treatment funds after they experience a disaster.

While our propensity score matching ensures that, on average, our treatment funds are well matched to our control funds, we wish to ensure that we account for any differences between individual pairs of treatment and control funds. To this end, we include as control variables in our regressions the covariates from our matching. These covariates are the fund's total net assets, turnover ratio, age, raw returns, and flows. The first three of these variables are measured in natural logarithms. We also include fund fixed effects and year fixed effects to account for any unobserved heterogeneity across funds and across time. We cluster standard errors by fund. Finally, we winsorize variables as appropriate at the 1st and 99th percentiles.

2.4. Descriptive Statistics

[Insert Table 1 about here]

In Table 1, we present descriptive statistics for our sample. Variables are defined in Appendix Table 1. Our sample funds are relatively large, with assets of close to $900 million, on average (median assets of over $150 million). They turn over roughly three-quarters of their assets (median of two-fifths). They are also relatively old, almost 9 years old, on average (median age of nearly 7 years).

Turning to risk taking, the volatility that we can estimate for our unrestricted sample is about 4.4% per month on average (median of 4.0%). For the restricted sample that we need to estimate the global four-factor model, volatility is a bit higher, at 4.8% per month on average (median of 4.4%), but it is still comparable. For future reference, it is worth noting that the total volatility of our sample funds is mostly systematic rather than idiosyncratic. This is in line with our expectations for mutual funds, which are well diversified portfolios of stocks that are mainly exposed to various sources of systematic risk. Overall, ours is representative sample of international equity mutual funds.

Finally, the growth rate of total net assets is approximate 1.7% per month higher, on average, than the raw returns of our funds (median of 0.2%). Mean raw returns are roughly 0.5% per month (median of 0.8%). The mean (median) Sharpe ratio based on monthly returns is about 0.17 (0.21). Our sample funds tend to underperform their benchmarks, with mean (median) alphas of -0.26 (-0.23) per month based on the global four-factor model.

3. Main Results

We now turn examine whether risk taking changes as a result of natural disasters experienced by mutual fund managers. We begin by graphing risk taking starting five years before a disaster and ending five year thereafter. We measure risk taking as the volatility of monthly raw returns during each event year. For each event year, we graph the difference in risk taking between treatment and control funds.

[Insert Figure 2 about here]

Figure 2 shows the results. During the 2-3 years before managers experience a disaster, volatility trends roughly in parallel for treatment and control funds. In year 0, volatility starts to decrease. In year +1 compared to year -1, volatility falls by an economically significant 50 basis points. Thereafter, volatility rises each year, until it returns to its pre-disaster level in year +4 and flattens out. In summary, the disaster experiences of fund managers appear to result in a significant but temporary decrease in risk taking.

Next, we formally test whether risk taking decreases as a result of the disaster experiences. To this end, we run regressions of the volatility of monthly raw returns as previously described. We compare, years +1 through +5 in succession to year -1, for both treatment and control funds. The theoretical number of observations in each regression should be 1,757×2×2=7,028, but the actual number is lower owing to data limitations, and the number decreases each event year after the disaster.

[Insert Table 2 about here]

The results of Table 2 confirm the results of Figure 2. There is a statistically significant decrease in volatility of 49 basis points in year +1 compared to year -1. In year +2, volatility is still lower than in year -1 by a statistically significant 36 bps. In year +3, volatility is lower by 17 bps, but this decrease is no longer statistically significant compared to year -1. By four years after the disaster, the level of volatility is statistically indistinguishable from its level before the disaster. The results once again suggest that disasters lead to fund managers decreasing their risk taking significantly but temporarily.

We also examine whether the decrease in risk taking can be explained by the wealth effects of our disasters. To this end, we test whether disasters driven by damages (with wealth effects) have a different effect from disasters driven by fatalities (without wealth effects). Specifically, we create a dummy variable for disasters driven by damages, and we run the same regressions as in Table 2, but we add interactions with our new dummy variable. Our untabulated results are similar to those in Table 2, but the incremental effect of our triple interaction of interest (Treatment × After × Damages) is not statistically significant in any of the five years after the disaster. This suggests that our results cannot be explained by the wealth effect of our disasters.

Next, we examine whether total risk decreases because of systematic risk or idiosyncratic risk or both. Unlike for U.S. stocks, there is no general consensus in the literature about the standard asset pricing model for international stocks (Fama and French (1998, 2012, 2015) and Hou, Karolyi, and Kho (2011)). However, the literature does indicate that it would be appropriate to use the global four-factor to explain the returns on portfolios of global stocks such as mutual funds (Fama and French (2012)). Moreover, our purpose is simply to approximate the contributions of systematic and idiosyncratic risk on total risk, so a sensible asset pricing model satisfies our needs.

Consequently, we estimate the systematic and idiosyncratic components of total volatility from the global four-factor model using monthly returns. The factor returns pertain to developed markets. The four factors capture the return on the market portfolio as well as the returns to size, book-to-market, and momentum portfolios. We require a minimum of 24 months and a maximum of 36 months of returns for estimates both before and after a disaster. Our estimates before the disaster end in year -1, and our estimates after the disaster start in year +1. We obtain data on developed market factor returns from Ken French's website.

Finally, we run the same regressions as in Table 2 but with some limitations. We can only test a single difference-in-differences because there is only one non-overlapping three year period during the five year period before the disaster, and the same is true after the disaster. Moreover, our sample size decreases (by about 10%) because we require two years of returns before the disaster and the same thereafter. Furthermore, as Figure 2 shows, volatility is relatively flat during the three years before the disaster but rises steeply during the three years thereafter, so comparing before and after will tend to understate the response to the disaster.

[Insert Table 3 about here]

Table 3 presents the results. Total volatility decreases significantly, both economically and statistically, but by a lower magnitude than in Table 2 due to the limitations already mentioned. Additionally, both systematic and idiosyncratic volatility decrease, significantly in both economic and statistical terms. However, the contribution of systematic versus idiosyncratic risk to the decrease in total risk remains to be examined.

To decompose the change in total risk into its systematic and idiosyncratic components, we perform a basic variance decomposition (results not tabulated). Rather than using standard deviation to measure risk, we use variance. As a starting point, before a disaster, roughly 83% of total risk is systematic, on average, and about 17% is idiosyncratic, which is what we would expect for mutual funds. After a disaster, the decrease in total risk relative to its mean is 18.9%, and is similar for systematic risk (18.6%) and idiosyncratic risk (23.7%). Given the dominance of systematic risk over idiosyncratic risk, most of the change in total risk is explained by the change in systematic risk rather than idiosyncratic risk: roughly 88% versus 12%. In summary, the results suggest that disasters lead managers to decrease risk taking principally by taking less systematic risk.

4. Alternative Explanations

4.1. The Agency Explanation

One alternative explanation for the decrease in risk taking as a result of natural disasters is the manager-investor agency problem. To summarize, fund managers may be able to attract flows, and thereby increase their fees, by taking more risk. Natural disasters in the U.S. may hurt the performance of domestic funds and thus help the performance of international funds, at least in relative terms. If investors move their money from domestic funds to international funds, then managers of the latter have less incentive to take risk to attract flows. Since both the treatment and control funds are international funds, the fund's investors must be clustered within the fund's county. This agency explanation predicts greater inflows for our sample of international funds as a result of natural disasters.

[Insert Figure 3 about here]

We examine this prediction by graphing monthly flows during the three years centered on the month of the disaster. Every event month, we graph the difference in flows between treatment and control funds. The results are shown in Figure 3. It is worth noting that while cumulative monthly flows are increasingly negative during the first half of the year before the disaster, they are increasingly positive during the second half of the same year, so for the year as a whole, the difference between treatment and control funds is close to zero. Indeed, the difference between the two groups is trivial compared to the standard deviation of monthly flows (almost 7%, according to Table 1).

Figure 3 shows that after the disaster, there is essentially no change in flows for at least 18 months thereafter. This result has a number of important implications. First, it refutes the agency explanation, which predicts inflows after the disaster.[9] Second, it provides additional evidence that the decrease in risk taking cannot be explained by the wealth effects of our disasters, which predict greater outflows as investors use their savings to replace their income. Finally, whatever the effect of disasters on local investors, the fund's investors as a group appear to be indifferent to the performance implications, if any, of the decrease in risk taking.

To formally test whether disaster experiences result in a change in flows, we run the same regressions as in Table 2 but with some modifications. The dependent variable is now mean monthly flows rather than the volatility of monthly raw returns, and the independent variables now exclude annualized flows. Additionally, since Figure 2 and Table 2 both show that risk taking returns to normal by the fourth year after the disaster, we now only consider the first three years after the disaster.

[Insert Table 4 about here]

The results of Figure 3 are confirmed by the results of Table 4. The change in flows is neither statistically nor economically significant in years +1 and +2. In year +3, there is a decrease in flows that is marginally statistically significant (at the 10% level).[10] However, the economic significance of the decrease (0.43% per month) is similarly marginal, roughly 6% of

[9] Even if managers anticipate inflows to the fund and decrease the risk of the fund in anticipation, there should be a surge in flows in the months immediately after the disaster followed by a plunge, as the fund's returns fall short of investors' expectations, owing to the decrease in risk taking. It is implausible that investors would anticipate the decrease in risk but not move their money first in and then out of the fund. The agency explanation depends on flows following performance: the two cannot merely be jointly determined.

[10] The results in years +4 and +5 are once again statistically insignificant (not tabulated).

the standard deviation of mean monthly flows (see Table 1). Moreover, it is implausible that flows would not respond to a disaster for two years but then respond in year +3. The marginally significant decrease in flows in year +3 could possibly be a delayed response to the slight decrease in returns in year +1. In summary, the results indicate that disasters do not affect flows during the years thereafter. On the whole, the evidence refutes the agency explanation for the decrease in risk taking as a result of disasters.

4.2. The Managerial Skill Explanation

Another alternative explanation is that the change in risk taking reflects managerial skill. By way of summary, disasters may endow managers that experience them with an informative advantage. Combined with stock selection or timing abilities, this information advantage may allow these managers to outperform on a risk adjusted basis. This skill explanation predicts an increase in risk adjusted returns as a result of natural disasters.

[Insert Figure 4 about here]

To examine this prediction, we first graph monthly returns during the three years centered on the month of the disaster, just like in Figure 3. As Figure 4 shows, there is essentially no change in returns from the year before the disaster, and there is no immediate change for several months thereafter. This provides further evidence that our treatment funds do not hold international stocks with greater local exposure than our control funds. If they did, the value of these stocks should decrease as a result a disaster, and consequently the returns of these funds would also decrease.

During the year after the disaster, there is indeed a decrease in returns, cumulatively of about 1.5 percentage points in magnitude, which compares with an approximately 19% standard deviation of annualized raw returns. The decrease in returns of funds that experience disasters would appear to be consistent with the decrease in their risk. At the same time, it is not necessarily inconsistent with the skill explanation, which predicts an increase in risk adjusted returns but not necessarily raw returns.

[Insert Figure 5 about here]

In a related analysis, we also graph the death rate of our treatment and control funds during the five years after the disaster. Fund survival is closely tied to fund performance, but it provides a more comprehensive assessment of the effect of the disaster on the fund. Figure 5 shows that the proportion of funds that die after a disaster is no different for treatment funds compared to control funds. In other words, disasters do not appear to affect survival. Once again, this does not provide definitive evidence for or against the skill explanation, which makes a prediction about risk adjusted returns.

We formally test whether disaster experiences affect returns using the regressions in Table 2 with a few modifications. The dependent variable is now mean monthly raw returns rather than the volatility of monthly raw returns, and the independent variables now exclude annualized raw returns. Additionally, we only consider the first three years after the disaster, for the same reason as in Table 4.

[Insert Table 5 about here]

Table 5 Panel A presents the results. Monthly raw returns in year +1 are 11 basis points lower, or about 1.3 lower percentage points lower on an annualized basis. This corresponds roughly to the cumulative monthly raw returns in year +1 in Figure 4. However, the results are statistically insignificant for all of years +1 to +3. Moreover, even in terms of economic significance, the results are marginal by comparison to the approximate 1.8% standard deviation of mean monthly raw returns (see Table 1). In summary, the results suggest that disasters do not affect raw returns during the years thereafter.

However, it is risk adjusted returns that are predicted to increase by the skill explanation. We now turn to testing this prediction first using the Sharpe ratio. This risk-return measure is well suited to well diversified portfolios of stocks, as are our mutual funds, and it does not require us to assume a specific equilibrium asset pricing model. We run modified versions of the regressions in Table 2. In particular, the dependent variable is now the monthly Sharpe ratio, and we only consider the first three years after the disaster. Table 5 Panel B presents the results. None of the changes in the Sharpe ratio are significant in any of the years after the disaster, in neither statistical nor economic terms.

We also test the prediction of the skill explanation using the alpha. With this measure, we need to assume an equilibrium asset pricing model, but doing so allows us to capture risk adjusted returns. We estimate alpha from the global four-factor model, as in Table 3. Indeed, we run a modified version of the regressions in Table 3. Specifically, the dependent variable is now alpha, and the independent variables now exclude annualized raw returns. We note that have the same limitations as Table 3: we only have one period before and one period after the disaster; the sample size decreases slightly; and averaging over the years after the disaster will tend to understate the response to it. The results in Table 5 Panel C indicate that the change in alpha is neither statistically nor economically significant.

Taken as a whole, the results indicate that the disaster experiences of mutual fund managers do not affect the returns to their investors. This is the case on both a raw and risk adjusted basis. The latter evidence clearly refutes the skill explanation for the decrease in risk taking caused by disasters.

4.3. The Catering Explanation

A final alternative explanation is that managers cater to investors. Disasters may increase the risk aversion of investors while leaving the risk attitudes of managers unchanged. Both the treatment and control funds are international funds, so the fund's investors must be clustered within the fund's county. This explanation predicts that the change in risk taking is positively related to the clustering of investors within the county of the fund. We test this catering explanation using two proxies for such clustering: fund size (small versus large) and investor type (institutional versus retail). While investors in the smallest funds may be clustered locally, this is highly improbable for the largest funds. Similarly, institutional funds may be dominated by locally clustered institutional investors, but this is very unlikely for retail funds. The catering explanation predicts a greater decrease in risk taking for the smallest funds and institutional funds.

We run the same regressions as in Table 2 but with a modification. Table 2 includes three dummy independent variables (for treatment funds, for the post-disaster period, and for their interaction). As an addition, we interact these dummy variables with a pair of dummy variables either for the smallest and largest funds or for institutional only and retail only funds. We also include the pair of dummy variables itself as independent variables. We sort funds based on total net assets and consider those in the bottom and top deciles as the smallest and largest, respectively. As before, we only consider the first three years after the disaster.

[Insert Table 6 about here]

The results are presented in Table 6. Both Panels A and B show that the main difference-in-differences (treatments versus controls, after versus before) have roughly the economic and statistically significance as in our main results (Table 2). However, the effects of small funds versus large funds, as compared to funds in the middle, are not significant (Panel A). Similarly, the effects of institutional only versus retail only funds, compared to funds that are mixed, are also insignificant (Panel B). In summary, the results indicate that there is no difference in risk taking between funds with investors that are plausibly concentrated locally and funds with investors dispersed around the country. This evidence seems to refute the catering explanation for the increase in risk taking generated by disasters.[11]

5. Cross-Sectional Contrasts and Robustness Tests

In this section, we first examine several cross-sectional contrasts that support the psychological interpretation of our main results. We then perform a number of robustness tests. For our tests, we use modified version of the regressions in Table 2, and we only consider the first three years after the disaster.

First, we examine whether managers react more strongly to disasters when they have fewer recent local disaster experiences. Managers experiencing a disaster for the first time should have a stronger psychological reaction to the disaster than managers that have already experienced disasters many times. By contrast, any rational reaction to a disaster should be similar to other disasters, whether on the basis of their wealth effects or other economic consequences. To test this prediction, in addition to the three dummy independent variables in Table 2 (for treatment funds, for the post-disaster period, and for their interaction), we add an interaction with another independent dummy variable. This fourth dummy independent variable captures fund-years in the bottom half of the rate of disasters in the county during the previous 10 years.

[Insert Table 7 about here]

---

[11] Since the agency explanation also requires that investors cluster locally, these results also provide additional evidence against that explanation.

Table 7 Panel A presents the results. As expected, the impact of a disaster is greater if it follows a period of few disasters than a period of many disasters. When there have been few disasters in the recent past, risk taking falls by 63 basis points in year +1, is still down by 57 bps in year +2, and is lower by 34 bps only by year +3 (though it is no longer statistically significant at this point in time). For comparison, risk taking in Table 2 is lower by 49, 36, and 17 bps in years +1 through +3, respectively (but it is not statistically significant in year +3 either). By contrast, when there have been many disasters in the recent past, risk taking falls by only 31 bps in year +1 and is no longer economically or statistically significant thereafter. In summary, managers do react more strongly to their first experience with disasters.

Second, we examine whether the managerial reaction to disasters is stronger in the first half of our sample period compared to the first half. We have already seen in Figure 1 that neither the rate of disasters nor the losses caused by disasters trend over time. However, it is possible that there is still a learning effect about the rate of or losses from disasters. (For example, given disaster preparedness efforts, expectations could have been for a decrease in the rate or and losses from disasters.) If there is learning, then the effect of disasters on risk taking should weaken over time. We test this prediction as in Panel A of Table 7, but this time the fourth dummy independent variable captures the first half of the sample period.

The results are presented in Panel B of Table 7. For all of years +1 through +3, the results for the entire sample period are similar in both economic and statistically significant to the results in Table 2. By contrast, the results for the first half of our sample period are not significantly different. In summary, we find no evidence of the learning effect, or, more generally, a change over time in the effect of disasters on risk taking.

Our third cross-sectional contrast is closely related to our second. We examine whether the managerial reaction to disasters is stronger for younger funds than older ones. Even there is not learning over time across all funds, there could still be learning across individual funds. Our test of this prediction is the same as in Panel B of Table 7 except that the fourth dummy independent variable now captures the bottom half of the sample by fund age. The results (not tabulated) are not significantly different for younger funds compared to older funds. Once again, we find no evidence of the learning effect.

We now turn to some robustness tests. For the sake of brevity, the results are not tabulated. It is possible that our funds both have significant local exposure because they invest in foreign firms that operate in the county of the fund. Note that this would require an extreme local bias on the part of fund managers and similarly extreme local operational focus on the part of the portfolio firms. (By far the most plausible example in our sample would be a fund manager in Chicago (Cook County, IL) investing much of his portfolio in foreign firms that also had much of their operations in Chicago.) To test this prediction, we split our sample into two groups based on their domestic exposure. The first group comprises the roughly 80% of our funds that have no more than 1% of their assets invested in domestic stocks (no domestic exposure), while the second group comprises the remaining funds (some domestic exposure). We run the same regressions as in Table 7, but now the fourth dummy independent variable captures funds with some domestic exposure. We not only find that the results for funds with no domestic exposure are similar to those in Table 2, but the results for funds with some domestic exposure are not significant.

It is also possible that our funds located in major financial centers are driving our results. For example, financial centers have a concentration of funds with both managers and investors that are more locally biased than usual. Alternatively, more intense competition between fund managers in financial centers may greatly magnify an otherwise small decrease in risk taking. We test this prediction by running the same regressions as in Table 2 but excluding funds located in financial centers. In our list of financial centers, we include New York, Philadelphia, Chicago, Boston, Los Angeles, and San Francisco. We find that the results are not significantly different for funds depending on whether they are located in financial centers.

6. Conclusion

We study the effect of personal catastrophic experiences, in the form of natural disasters in the U.S., on the risk attitudes of professional money managers, as embodied by U.S.-based managers of mutual funds that invest in non-U.S. stocks. Our approach has numerous advantages, including: focusing on professional risk takers; precisely measuring risk taking as portfolio volatility; and using psychological shocks that can affect managerial risk aversion but cannot affect the individual stocks in their portfolio.

In our empirical analysis, we compare managers in disaster in counties that experience a disaster to managers in counties without a disaster, as well as the period before a disaster to the period thereafter. We combine our difference-in-differences approach with controls for fund characteristics as well as unobserved heterogeneity across funds and time.

We find that risk taking decreases by approximately 50 bps during year after the disaster, an effect that gradually disappears during the following three years. Since the results are similar for disasters with only fatalities and only property damage, we can rule out wealth effects. Decomposition of risk taking indicates that the decrease is primarily attributable to systematic rather than idiosyncratic risk.

Given the advantages of our approach, the natural interpretation of our findings is that disaster experiences cause an increase in managerial risk aversion. Other possible but less plausible explanations include managerial agency, skill, and catering. Additional results rule out each of these alternative explanations.

Overall, we show that personal experiences with natural disasters lead mutual fund managers to increase their risk aversion and consequently decrease their risk taking. The decrease in risk is primarily systematic rather than idiosyncratic, and consequently there is no effect on risk adjusted returns to investors. Nevertheless, given that mutual fund investors make investments in fund that take risks in line with their own risk preferences, our results suggests that managers' personal disasters experiences cause a temporary misalignment of their risk preferences and those of investors.

References

Bailey, Warren, Alok Kumar, and David Ng, 2011, Behavioral biases of mutual fund investors, *Journal of Financial Economics* 102, 1-27.

Barber, Brad M., Xing Huang, and Terrance Odean, 2016, Which factors matter to investors? Evidence from mutual fund flows, *Review of Financial Studies* 29, 2600-2642.

Barberis, Nicholas, Ming Huang, and Tano Santos, 2001, Prospect theory and asset prices, *Quarterly Journal of Economics* 116, 1-53.

Bassi, Anna, Riccardo Colacito, Paolo Fulghieri, 2013, 'O sole mio: An experimental analysis of weather and risk attitudes in financial decisions, *Review of Financial Studies* 26, 1824-1852.

Bernile, Gennaro, Vineet Bhagwat, and P. Raghavendra Rau, 2015, What doesn't kill you will only make you more risk-loving: Early-life disasters and CEO behavior, forthcoming *Journal of Finance*.

Bharath, Sreedhar T., and DuckKi Cho, 2015, Ephemeral experiences, long lived impact: Disasters and portfolio choice, working paper.

Bordalo, Pedro, Nicola Gennaioli, and Andrei Shleifer, 2013, Salience and consumer choice, *Journal of Political Economy* 121, 803-843.

Bucciol, Alessandro, and Luca Zarri, 2015, The shadow of the past: Financial risk taking and negative life events, Journal of Economic Psychology 48, 1-16.

Busse, Jeffrey A., Amit Goyal, and Sunil Wahal, 2014, Investing in a global world, *Review of Finance* 18, 561-590.

Caballero, Ricardo J., and Arvind Krishnamurthy, 2009, Global imbalances and financial fragility, *American Economic Review Papers and Proceedings* 99, 584-88.

Cameron, Lisa, and Manisha Shah, 2015, Risk-taking behavior in the wake of natural disasters, *Journal of Human Resources* 50, 484-515.

Campbell, John Y., and John H. Cochrane, 1999, By force of habit: A consumption-based explanation of aggregate stock market behavior, *Journal of Political Economy* 107, 205-251.

Chevalier, Judith, and Glenn Ellison, 1997, Risk taking by mutual funds as a response to incentives, *Journal of Political Economy* 105, 1167-200.

Cremers, Martijn, Miguel A. Ferreira, Pedro Matos, and Laura Starks, 2016, Indexing and active fund management International evidence, *Journal of Financial Economics* 120, 539-560.

Cumby, Robert E., and Jack D. Glen, 1990, Evaluating the performance of international mutual funds, *Journal of Finance* 45, 497-521.

Dessaint, Olivier, and Adrien Matray, 2016, Do managers overreact to salient risks? Evidence from hurricane strikes, working paper.

Didier, Tatiana, Roberto Rigobon, and Sergio L. Schmukler, 2013, Unexploited gains from international diversification: Patterns of portfolio holdings around the world, *Review of Economics and Statistics* 95, 1562-1583.

Fama, Eugene F., and Kenneth R. French, 1998, Value versus growth: The international evidence, *Journal of Finance* 53, 1975-1999.

Fama, Eugene F., and Kenneth R. French, 2012, Size, value, and momentum in international stock returns, *Journal of Financial Economics* 105, 457-472.

Fama, Eugene F., and Kenneth R. French, 2015, International tests of a five-factor asset pricing model, working paper.

Ferreira, Miguel A., Massimo Massa, and Pedro Matos, 2016, Investor-stock decoupling in mutual funds, working paper.

Guiso, Luigi, and Monica Paiella, 2008, Risk aversion, wealth, and background risk, *Journal of the European Economic Association* 6, 1109-1150.

Guiso, Luigi, Paola Sapienza, and Luigi Zingales, 2016, Time varying risk aversion, forthcoming *Journal of Financial Economics*.

Heaton, John, and Deborah Lucas, 2000, Portfolio choice and asset prices: The importance of entrepreneurial risk, *Journal of Finance* 55, 1163-1198.

Hirshleifer, David, and Tyler Shumway, 2003, Good day sunshine: Stock returns and the weather, *Journal of Finance* 58, 1009-1032.

Hou, Kewei, G. Andrew Karolyi, and Bong-Chan Kho, 2011, What factors drive global stock returns?, *Review of Financial Studies* 24, 2527-2574.

Huang, Jennifer, Clemens Sialm, and Hanjiang Zhang, 2011, Risk shifting and mutual fund performance, *Review of Financial Studies* 24, 2575-2616.

Jotikasthira, Jotikasthira, Christian Lundblad, and Tarun Ramadorai, 2012, Asset fire sales and purchases and the international transmission of funding shocks, *Journal of Finance* 67, 2015-2050.

Kempf, Alexander, and Stefan Ruenzi, 2008, Tournaments in mutual-fund families, *Review of Financial Studies* 21, 1013-1036.

Kempf, Alexander, Stefan Ruenzi, and Tanja Thiele, 2009, Employment risk, compensation incentives, and managerial risk taking: Evidence from the mutual fund industry, *Journal of Financial Economics* 92, 92-108.

Kumar, Alok, 2009, Dynamic style preferences of individual investors and stock returns, *Journal of Financial and Quantitative Analysis* 44, 607-640.

Loewenstein, George F., Christopher K. Hsee, Elke U. Weber, and Ned Welch, 2001, Risk as feelings, *Psychological Bulletin* 127, 267-286.

Loewenstein, George, 2000, Emotions in economic theory and economic behavior, *American Economic Review* 90, 426-432.

Lu, Yan, Sugata Ray, and Melvyn Teo, 2016, Limited attention, marital events, and hedge funds, forthcoming *Journal of Financial Economics*.

Malmendier, Ulrike, and Stefan Nagel, 2011, Depression babies: Do macroeconomic experiences affect risk taking?, *Quarterly Journal of Economics* 126, 373-416.

Pool, Veronika K., Noah Stoffman, Scott E. Yonker, and Hanjiang Zhang, 2014, Do shocks to personal wealth affect risk taking in delegated portfolios?, working paper.

Roll, Richard W., 1992, Weather, in Peter Newman, Murray Milgate, and John Eatwell, eds.: *The New Palgrave Dictionary of Money and Finance* (Macmillan Press, London).

Saunders, Edward M., 1993, Stock prices and Wall Street weather, *American Economic Review* 83, 1337-1345.

Shu, Tao, Johan Sulaeman, P. Eric Yeung, 2012, Local religious beliefs and mutual fund risk-taking behaviors, *Management Science* 58, 1779-1796.

Shu, Tao, Johan Sulaeman, P. Eric Yeung, 2016, Cost of bereavement: How does parental loss affect mutual fund managers?, working paper.

Wright, Phillip G., 1928, *The Tariff on Animal and Vegetable Oils* (MacMillan, New York).

Table 1
Descriptive Statistics

This table presents descriptive statistics for the main variables used in this paper. The sample comprises 34,344 fund-event year observations. These correspond to 1,757 treatment fund-years between 1991 and 2013, and the same number of matched control fund-years. Treatment fund-years experience a natural disaster in the U.S., whereas control fund-years do not. Event years start five years before and end five years after the disaster year. All funds are international equity mutual funds based in the U.S. Variables are defined in Appendix Table 1.

	Mean	Standard deviation	25^{th} percentile	Median	75^{th} percentile
Independent variables					
- Total net assets ($ millions)	864	2,190	50	164	651
- Annual turnover ratio (%)	74.5	61.5	32.0	57.0	98.0
- Age (Years)	8.8	7.0	3.8	6.8	12.2
- Annualized raw returns (%)	6.7	19.0	-7.4	9.5	17.7
- Annualized flows (%)	20.5	73.6	-12.7	3.2	27.9
Dependent variables					
- Volatility of monthly raw returns (%)	4.44	1.89	3.03	4.02	5.48
- Total volatility of monthly returns (%)	4.80	1.84	3.39	4.36	5.94
- Systematic volatility of monthly returns (%)	4.37	1.69	3.05	3.98	5.47
- Idiosyncratic volatility of monthly returns (%)	1.76	1.14	1.02	1.40	2.15
- Mean monthly flows (%)	1.70	6.83	-1.14	0.23	2.37
- Mean monthly raw returns (%)	0.49	1.87	-0.56	0.78	1.60
- Monthly Sharpe ratio	0.169	0.393	-0.133	0.210	0.457
- Monthly alpha (%)	-0.26	0.55	-0.50	-0.23	0.03

Table 2
The Effect of Natural Disasters on Mutual Fund Risk Taking: Total Risk

This table shows the effect on risk taking of U.S. natural disasters experienced by U.S. managers of international equity mutual funds. The sample comprises 34,344 fund-event year observations. These correspond to 1,757 treatment fund-years between 1991 and 2013, and the same number of matched control fund-years. Treatment fund-years experience a natural disaster in the U.S., whereas control fund-years do not. Event years start five years before and end five years after the disaster year. All funds are international equity mutual funds based in the U.S. The dependent variable is the volatility of monthly raw returns. The dependent variable is regressed on three dummy variables: one for the treatment funds, another for the post-disaster period, and a third for the interaction of the first two. The other independent variables are the fund's total net assets, annual turnover ratio, age, annualized raw returns, and annualized flows. The first three of these variables are measured in natural logarithms. Variables are defined in Appendix Table 1. The dependent variables are multiplied by 100. Fixed effects are included for funds and years. Standard errors are clustered by fund. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Only selected results are tabulated.

	Dependent variable is volatility of monthly raw returns				
	Year +1	Year +2	Year +3	Year +4	Year +5
Treatment dummy variable × After dummy variable	-0.49***	-0.36***	-0.17	0.03	0.13
	(-4.21)	(-2.89)	(-1.10)	(0.18)	(0.90)
Treatment dummy variable	0.07	0.09	0.10	0.07	0.12
	(0.96)	(1.10)	(1.21)	(0.91)	(1.59)
After dummy variable	-0.60***	-0.64***	-0.83***	-0.86***	-0.81***
	(-6.16)	(-6.29)	(-6.20)	(-6.90)	(-6.34)
Observations	6,992	6,783	6,594	6,372	5,857
Adjusted R^2	0.539	0.481	0.400	0.395	0.441

Table 3
The Effect of Natural Disasters on Mutual Fund Risk Taking: Systematic versus Idiosyncratic Risk

This table shows the effect on risk taking of U.S. natural disasters experienced by U.S. managers of international equity mutual funds. The sample comprises 34,344 fund-event year observations. These correspond to 1,757 treatment fund-years between 1991 and 2013, and the same number of matched control fund-years. Treatment fund-years experience a natural disaster in the U.S., whereas control fund-years do not. Event years start five years before and end five years after the disaster year. All funds are international equity mutual funds based in the U.S. The dependent variable is the total, systematic, and idiosyncratic volatility of raw returns in Panel A through Panel C, respectively. Volatility is estimated from the global four-factor model using monthly returns over three years before the disaster and three years after the disaster. The dependent variable is regressed on three dummy variables: one for the treatment funds, another for the post-disaster period, and a third for the interaction of the first two. The other independent variables are the fund's total net assets, annual turnover ratio, age, annualized raw returns, and annualized flows. The first three of these variables are measured in natural logarithms. Variables are defined in Appendix Table 1. The dependent variables are multiplied by 100. Fixed effects are included for funds and years. Standard errors are clustered by fund. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Only selected results are tabulated.

	Dependent variable is volatility of monthly returns		
	Total	Systematic	Idiosyncratic
Treatment dummy variable × After dummy variable	-0.36**	-0.32**	-0.16***
	(-2.35)	(-2.11)	(-3.55)
Treatment dummy variable	0.03	0.03	0.02
	(0.30)	(0.35)	(0.49)
After dummy variable	-0.80***	-0.68***	-0.30***
	(-6.28)	(-5.32)	(-7.33)
Observations	6,156	6,156	6,156
Adjusted R^2	0.430	0.319	0.805

Table 4
The Effect of Natural Disasters on Mutual Fund Flows

This table shows the effect on flows of U.S. natural disasters experienced by U.S. managers of international equity mutual funds. The sample comprises 34,344 fund-event year observations. These correspond to 1,757 treatment fund-years between 1991 and 2013, and the same number of matched control fund-years. Treatment fund-years experience a natural disaster in the U.S., whereas control fund-years do not. Event years start five years before and end five years after the disaster year. All funds are international equity mutual funds based in the U.S. The dependent variable is mean monthly flows. The dependent variable is regressed on three dummy variables: one for the treatment funds, another for the post-disaster period, and a third for the interaction of the first two. The other independent variables are the fund's total net assets, annual turnover ratio, age, and annualized raw returns. The first three of these variables are measured in natural logarithms. Variables are defined in Appendix Table 1. The dependent variables are multiplied by 100. Fixed effects are included for funds and years. Standard errors are clustered by fund. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Only selected results are tabulated.

	Dependent variable is mean monthly flows		
	Year +1	Year +2	Year +3
Treatment dummy variable × After dummy variable	-0.03	-0.28	-0.43*
	(-0.13)	(-1.21)	(-1.80)
Treatment dummy variable	0.24	0.30	0.39**
	(1.32)	(1.57)	(2.16)
After dummy variable	-0.95***	-1.15***	-1.12***
	(-5.54)	(-6.02)	(-6.04)
Observations	6,985	6,771	6,581
Adjusted R^2	0.314	0.291	0.292

Table 5
The Effect of Natural Disasters on Mutual Fund Performance

This table shows the effect on the performance of U.S. natural disasters experienced by U.S. managers of international equity mutual funds. The sample comprises 34,344 fund-event year observations. These correspond to 1,757 treatment fund-years between 1991 and 2013, and the same number of matched control fund-years. Treatment fund-years experience a natural disaster in the U.S., whereas control fund-years do not. Event years start five years before and end five years after the disaster year. All funds are international equity mutual funds based in the U.S. The dependent variable is the mean monthly raw return in Panel A, the monthly Sharpe ratio in Panel B, and the monthly alpha in Panel C. Alpha is estimated from the global four-factor model using monthly returns over three years before the disaster and three years after the disaster. The dependent variable is regressed on three dummy variables: one for the treatment funds, another for the post-disaster period, and a third for the interaction of the first two. The other independent variables are the fund's total net assets, annual turnover ratio, age, and annualized flows in all panels plus annualized raw returns in Panel B. The first three of these variables are measured in natural logarithms. Variables are defined in Appendix Table 1. The dependent variables are multiplied by 100. Fixed effects are included for funds and years. Standard errors are clustered by fund. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Only selected results are tabulated.

Panel A: Mean Monthly Raw Returns			
	Dependent variable is mean monthly raw return		
	Year +1	Year +2	Year +3
Treatment dummy variable × After dummy variable	-0.11 (-1.05)	-0.05 (-0.47)	0.07 (0.60)
Treatment dummy variable	0.01 (0.19)	0.04 (0.67)	0.06 (0.91)
After dummy variable	-0.03 (-0.31)	-0.25*** (-2.75)	-0.41*** (-4.36)
Observations	6,992	6,783	6,594
Adjusted R^2	0.276	0.349	0.364

Panel B: Monthly Sharpe Ratios			
	Dependent variable is monthly Sharpe ratios		
	Year +1	Year +2	Year +3
Treatment dummy variable × After dummy variable	-0.97 (-0.43)	-0.84 (-0.35)	0.25 (0.10)
Treatment dummy variable	0.70 (0.62)	1.14 (0.94)	1.69 (1.41)
After dummy variable	2.71 (1.45)	-0.60 (-0.30)	-4.59** (-2.25)
Observations	6,992	6,783	6,594
Adjusted R^2	0.333	0.361	0.355

Panel C: Monthly Alphas	
	Dependent variable is monthly alphas
	Year +1 to Year +3
Treatment dummy variable × After dummy variable	-0.04 (-0.80)
Treatment dummy variable	0.04 (1.29)
After dummy variable	-0.03 (-0.62)
Observations	6,156
Adjusted R^2	0.229

Table 6
Natural Disasters on Mutual Fund Risk Taking: The Role of Local Investor Clusters

This table shows the moderating role of local investor clusters on the effect of natural disasters on mutual fund risk taking. The same regressions are run as in Table 2 but with minor modifications. The three dummy independent variables (treatment funds, post-disaster period, and their interaction) are interacted with a pair of dummy independent variables either for the smallest and largest funds or for institutional only and retail only funds. The pair of dummy variables itself is also included as independent variables. The smallest and largest funds are in the bottom and top deciles, respectively, of total net assets. The dependent variables are multiplied by 100. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Only selected results are tabulated.

Panel A: Difference-in-Differences for the Smallest Funds versus the Largest Funds

	Dependent variable is volatility of monthly raw returns		
	Year +1	Year +2	Year +3
Treatment dummy var. × After dummy var. × Smallest funds dummy variable	0.35	0.40	0.45
	(1.21)	(1.31)	(1.28)
Treatment dummy var. × After dummy var. × Largest funds dummy variable	0.04	0.08	0.19
	(0.16)	(0.26)	(0.53)
Treatment dummy variable × After dummy variable	-0.53***	-0.41***	-0.24
	(-4.34)	(-3.21)	(-1.54)
Other dummy variables?	Yes	Yes	Yes
Observations	6,992	6,783	6,594
Adjusted R^2	0.541	0.482	0.403

Panel B: Difference-in-Differences for Institutional Only Funds versus Retail Only Funds

	Dependent variable is volatility of monthly raw returns		
	Year +1	Year +2	Year +3
Treatment dummy var. × After dummy var. × Retail only funds dummy variable	0.19	0.12	0.07
	(0.83)	(0.44)	(0.23)
Treatment dummy var. × After dummy var. × Institutional only funds dummy variable	0.12	0.04	0.03
	(0.64)	(0.18)	(0.14)
Treatment dummy variable × After dummy variable	-0.58***	-0.40*	-0.20
	(-3.39)	(-1.96)	(-0.84)
Other dummy variables?	Yes	Yes	Yes
Observations	6,992	6,783	6,594
Adjusted R^2	0.542	0.491	0.404

Table 7
Cross-Sectional Contrasts

This table shows cross-sectional contrasts for the effect of natural disasters on mutual fund risk taking. The same regressions are run as in Table 2 but with minor modifications. The three dummy independent variables (treatment funds, post-disaster period, and their interaction) are interacted with another a dummy independent variable. This fourth dummy independent variable captures either fund-years in the bottom half of the rate of disasters in the county during the previous 10 years, or the first half of the sample period. The dependent variables are multiplied by 100. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Only selected results are tabulated.

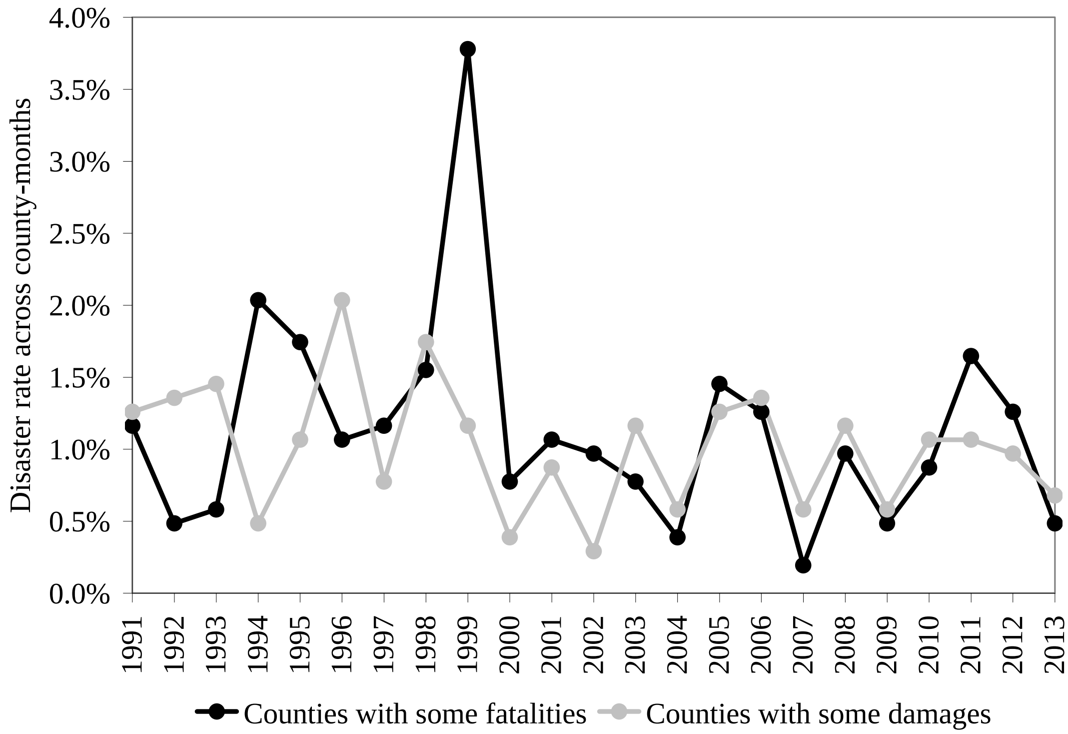
Panel A: Difference-in-Differences for Low versus High Rate of Prior Disasters

	Dependent variable is volatility of monthly raw returns		
	Year +1	Year +2	Year +3
Treatment dummy var. × After dummy var. × Few recent local disasters dummy variable	-0.32 (-1.57)	-0.46** (-1.99)	-0.38 (-1.34)
Treatment dummy variable × After dummy variable	-0.31** (-2.03)	-0.11 (-0.59)	0.04 (0.15)
Other dummy variables?	Yes	Yes	Yes
Observations	6,992	6,783	6,594
Adjusted R^2	0.551	0.495	0.415

Panel B: Difference-in-Differences for First versus Second Half of Sample Period

	Dependent variable is volatility of monthly raw returns		
	Year +1	Year +2	Year +3
Treatment dummy var. × After dummy var. × First half dummy variable	0.11 (0.52)	-0.11 (-0.48)	-0.14 (-0.48)
Treatment dummy variable × After dummy variable	-0.54*** (-3.75)	-0.31* (-1.66)	-0.11 (-0.46)
Other dummy variables?	Yes	Yes	Yes
Observations	6,992	6,783	6,594
Adjusted R^2	0.545	0.502	0.406

Panel A: Disaster rate



Panel B: Loss given disaster

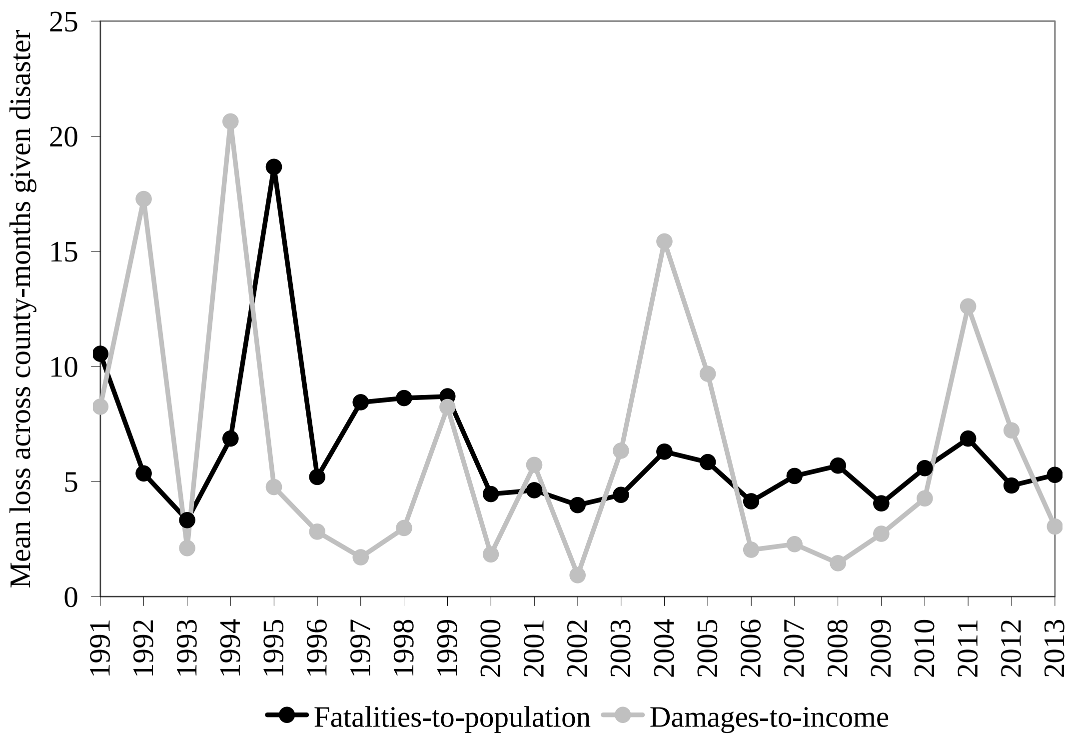


Figure 1. The disaster rate and the loss given disaster over time. This figure presents the disaster rate and the loss given disaster across county-months. The sample comprises all counties in which a mutual fund is located in any year between 1991 and 2013. Disasters driven by fatalities are presented separately from disasters driven by damages. Results are presented at the year level rather than the month level for ease of interpretation.

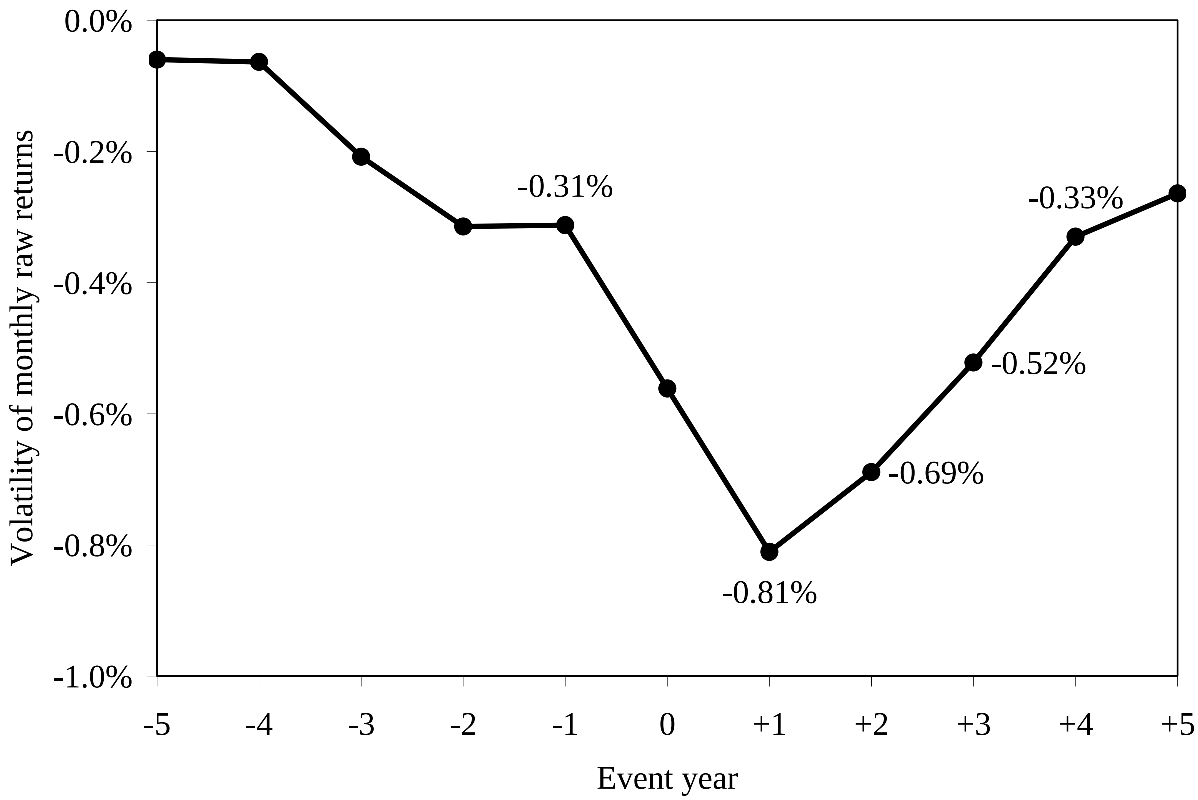


Figure 2. Fund risk taking around disaster experiences. This figure presents risk taking before and after disasters experienced by mutual fund managers. The sample comprises 1,757 fund-years for treatment funds and the same number of fund-years for matched control funds. The sample spans the years 1991-2013. Risk taking is measured as the volatility of monthly raw returns. All funds are international equity mutual funds based in the U.S.

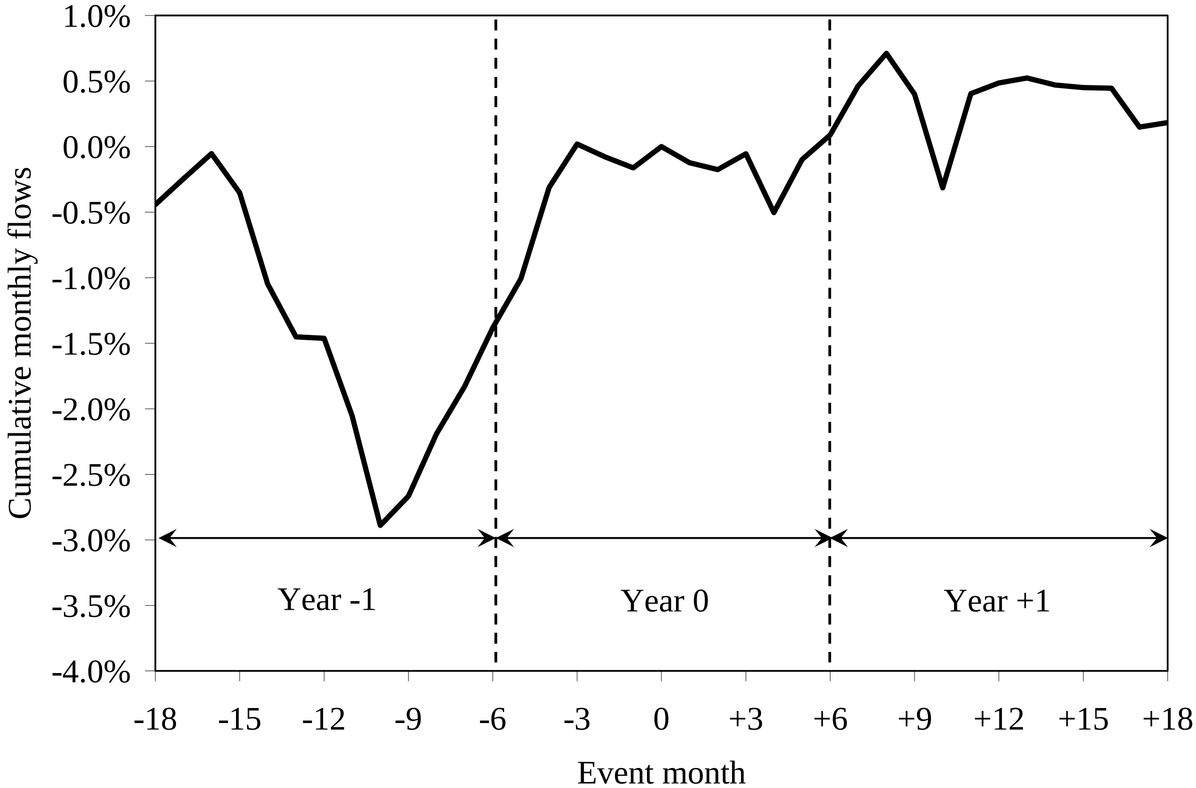


Figure 3. Fund flows around disaster experiences. This figure presents cumulative monthly flows before and after disasters experienced by mutual fund managers. The sample comprises 1,757 fund-years for treatment funds and the same number of fund-years for matched control funds. The sample spans the years 1991-2013. All funds are international equity mutual funds based in the U.S.

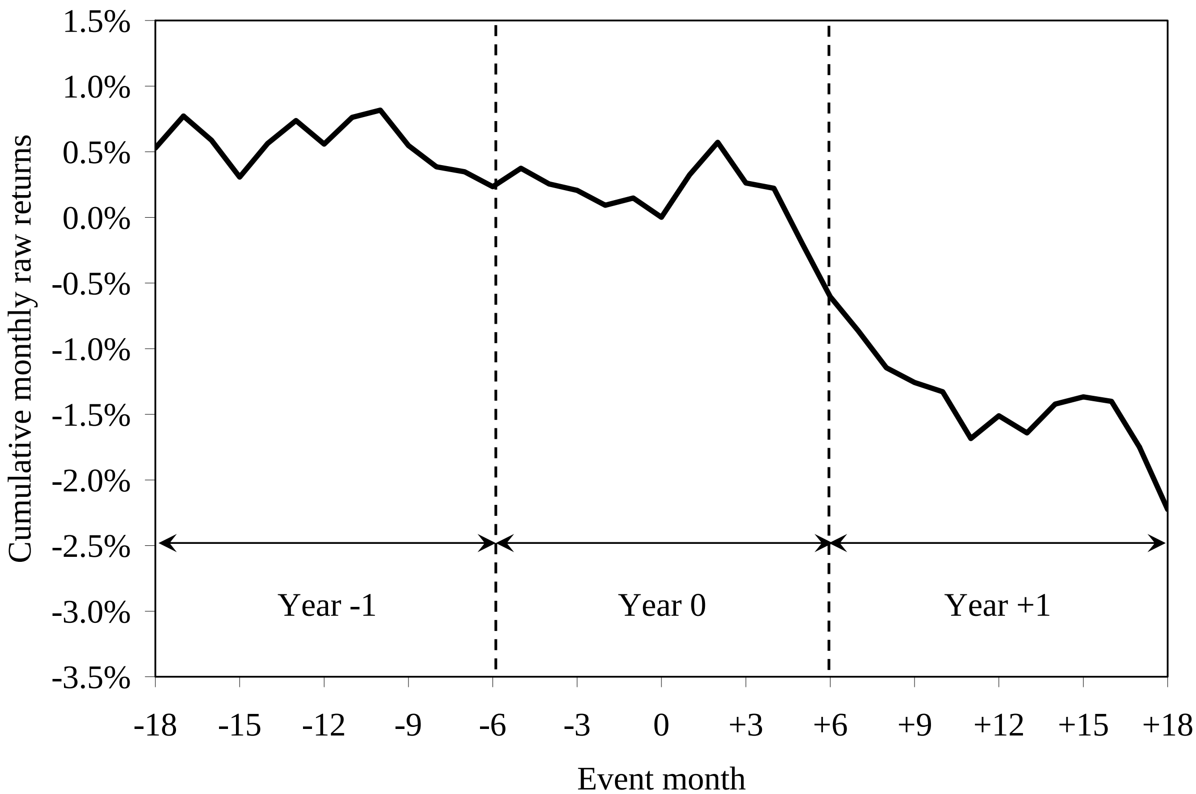


Figure 4. Fund returns around disaster experiences. This figure presents cumulative monthly raw returns before and after disasters experienced by mutual fund managers. The sample comprises 1,757 fund-years for treatment funds and the same number of fund-years for matched control funds. The sample spans the years 1991-2013. All funds are international equity mutual funds based in the U.S.

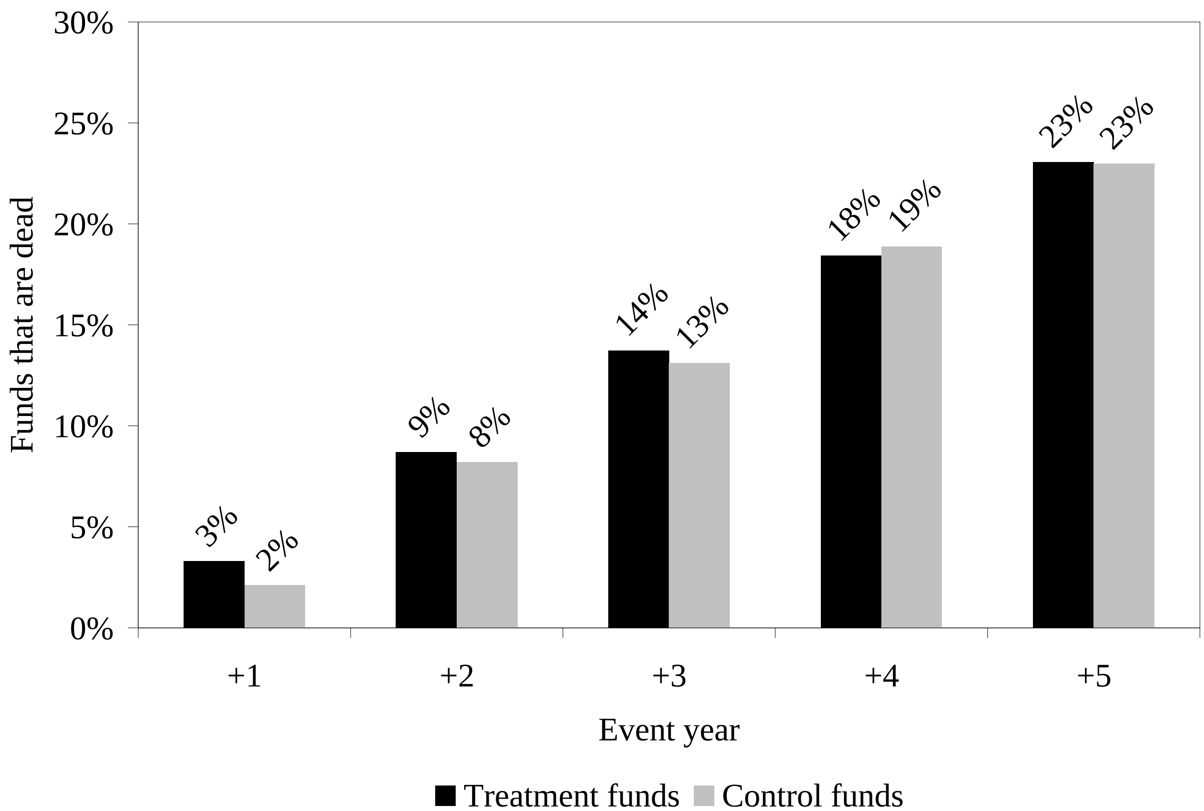


Figure 5. Fund deaths after disaster experiences. This figure presents the proportion of funds that die after disasters experienced by mutual fund managers. The sample comprises 1,757 fund-years for treatment funds and the same number of fund-years for matched control funds. The sample spans the years 1991-2013. All funds are international equity mutual funds based in the U.S.

Appendix Table 1
Variable Definitions

Name	Definition
Disaster variables	
- Fatalities driven disaster	A minimum of 2.5 fatalities per million population in the county-month (approximately the top percentile of fatalities-to-population)
- Damages driven disaster	A minimum of $500 of damages per million dollars of income in the county-month (approximately the top percentile of damages-to-income)
- Disaster	A fatalities driven disaster and/or a damages driven disaster
Independent variables	
- Total net assets	The total net assets of the fund at the end of the year
- Annual turnover ratio	The annual turnover ratio of the fund
- Age	The age of the fund at the end of the year
- Annualized raw returns	The raw returns of the fund during the year annualized from monthly returns
- Annualized flows	The flows of the fund during the year annualized from monthly flows. Monthly flows are calculated as the growth rate of the total net assets of the fund minus the returns of the fund.
- Prior probability of disaster	The probability of a disaster in the county measured from 1970 until the current year
Dependent variables	
- Volatility of monthly raw returns	The standard deviation of monthly raw returns during the year
- Systematic, idiosyncratic, and total volatility of monthly returns and monthly alpha	These variables are estimated from the global four-factor model using monthly returns. The factor returns pertain to developed markets. Estimates before and after the disaster both require a minimum of 24 months and a maximum of 36 months of returns. Estimates "before" end the year before the disaster, and estimates "after" start the year after the disaster.
- Mean monthly flows	The mean of the monthly flows of the fund during the year. Monthly flows are calculated as the growth rate of the total net assets of the fund minus the returns of the fund.
- Mean monthly raw returns	The mean of the monthly raw returns of the fund during the year
- Monthly Sharpe ratio	The ratio of the mean monthly raw returns of the fund to the volatility of monthly raw returns