Terrorist Attacks and Investor Risk Preference: Evidence from Mutual Fund Flows

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Abstract

Using domestic and transnational terrorist attacks in the U.S. from 1970-2010, we find that in the month after a spike in attacks, mutual fund investors display a significant increase in risk averse portfolio choices. The drop in demand for risky funds is evident in the cross-section of equity and bond funds; it varies with the risk level of the fund and the assets in which it is invested. The response to attacks depends on the investors' proximity to the attacks and the attacks' saliency. In accordance with related studies, the change in investor risk preference is transitory.

Key Words: Terrorism, Risk Preference, Risk Aversion, Mutual Fund Flows
JEL Classification: G11, G14, H56

War on Terrorism in the "Battlefield of the Mind"

Terrorism is a psychological warfare. Terrorists try to manipulate us and change our behavior by creating fear, uncertainty, and division in society.

--- Patrick J. Kennedy

1. Introduction

The attacks on September 11, 2001 is the most devastating example, in the U.S., of what terrorist activity can do to a society and its individuals. From then on, there has been much written about the effect of terrorism in the fields of sociology, political science, and history.[1] With respect to the consequence of terrorism on financial markets, the majority of existing studies focus on the impact of a few large-scale attacks on stock markets around the world. It is surprising that much less is known about whether, and how terrorism affects human behavior, such as their investment decisions.

In this paper, we seek to understand the role of changing risk preferences due to increases in terrorist activity, on individuals' portfolio choices. More specifically, using mutual fund flows as a proxy for aggregate investor preferences, we measure the change in demand for risky investments following spikes in the number of terrorist attacks. We study mutual fund flows because they are largely the outcome of individual investors' investment decisions. As retail investors (i.e. households) hold the vast majority (89%) of the nearly $16 trillion in mutual fund assets (ICI FactBook, 2015, Figure 2.2), mutual fund flows predominantly reflect the asset allocation of individual investors. We believe mutual fund flows truthfully represent the risk preference or emotion of individuals as there is no mechanism for arbitrageurs to directly counter the trades. Investor choice of mutual fund trading is more direct evidence than prior studies that are based on stock market returns and insurance premiums. Aggregate stock prices adjust to temporary supply versus demand conditions, making the reason for buying or selling difficult to determine. Similarly, the change of insurance premiums after natural disasters can be attributed to both the change of supply and demand for catastrophe insurance.[2] The "price" for a mutual fund is held constant and any shock in demand

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[1] See Hoffman (2006) and Borum (2007).

[2] Johnson, Hershey, Mezaros and Kunreuther (1993) and Browne and Hoyt (1999) note that individual's insurance purchase decision can be significantly impacted by government subsidies and expenditures by the federal government on flood mitigation

for risky assets shows up in volume (flows). Thus, if changes to investors' risk preference over time affects individuals' investment decisions, it is reasonable to expect the effects would be apparent in mutual fund flows (Kamstra, Kramer, Levi and Wermers, 2015).

Terrorism triggers fear and depressions that have huge and enduring effects on human being's risk preference.[3] According to Guiso, Sapienza and Zingales (2013), the value-function of each individual can exhibit large changes after terrorist attacks for two reasons. First, in the presence of standard utility models, changes in the outside environment or the perception of future attacks (Caballero and Krishnamurthy, 2009) can affect investors' estimation of market volatility and future uncertainty. In other words, the exposure to the risk of terrorist attacks is positively related to the perceived probability of extreme negative market shocks. Even if investors believe the risk of attacks is independent from their portfolio risk, terrorist attacks may still impose increased background risk to investors' final wealth with regards to employment, wage income, and home value.[4] Second, negative sentiment may affect risk tolerance and the level of individual risk aversion. For example, Loewenstein (2000) claims that emotions such as fear and depression, experienced at the time of the decision-making, can alter the measured risk aversion of each individual. To wit, the negative shock to risk preference caused by terrorism is likely to affect individuals' investment decisions by reducing their tendency to take risks.

Based on a comprehensive list of domestic and transnational terrorist attacks from 1970 to 2010, we find strong evidence that mutual fund investors exhibit a significant shift in their demand for risky mutual funds after an attack month. We define a month as an attack month if the number of attacks in a given month is greater than three times the average number of attacks per month over the previous 12 months. Using aggregate mutual fund data from the Investment Company Institute (ICI), we find that in the month after a spike in the number of the attacks, aggregate flows to equity funds drop by 43%, while

lead to a drop in flood insurance demand. In terms of supply, following losses due to Hurricane Katrina Allstate dropped homeowner coverage for coastal counties in SC, NC and AL, while also stopping writing new policies in MD and VA (Clark, 2006).

[3] For example, several studies have shown that in the months after a terrorist attack, a significant proportion of the local community experiences symptoms of post-traumatic stress disorder (Vlahov et al., 2002; Galea et al., 2002; Hughes et al., 2011).

[4] Eeckhoudt, Gollier, and Schlesinger (2005) and Guiso and Paiella (2008) show that an increase to the level of the background risk will lead investors to decrease the level of risk in their portfolio.

aggregate flows to government bond, and money market funds increase by 49% and 66% respectively, relative to non-attack months. Furthermore, by breaking down net flows, and using net exchanges of funds within the same fund family, we find significant results that investors are directly moving money out of equity and into government bond funds. Finally, using CRSP mutual fund data we find that results in the aggregate hold at the individual fund level. In the month after the attacks the average equity mutual fund faces a drop in flows of 40% relative to a non-attack month, while bond funds experience an increase of 22%. On the other hand, flows into the average money market fund increase by 54% in the month following the attacks. In terms of inflation adjusted monthly dollar flows, those results are equivalent to $3.96 million less flows for equity funds, and $0.585 million and $10.85 million more flows for bond funds and money market funds, respectively.

If fear is driving some part of the change in risk preference, investors located closer to an attack may be more sensitive to the consequences of the attacks than those living outside of the immediate area (Galea et al., 2001). In addition to proximity, attacks with greater media coverage may trigger a larger emotional response in the form of fear (Becker and Rubinstein, 2011). We find consistent results to both. Consistent with the idea that institutional investors limit the role that emotions play in their investments, we find that institutional equity funds experience a much weaker reaction after the attacks than retail equity funds. In further tests we examine whether the effect of attacks differs for equity funds with different risk characteristics. We find that, in the month after the attacks, equity funds with more exposure to systematic risk, as measured by fund market beta, experience significantly higher outflows than low and mid beta funds. In addition to systematic risk, we find that investors alter their flows into funds at different rates based on the investment style of the fund. Following a spike in attacks, we find that investors prefer large capitalization equity funds to small and mid-cap funds. Similarly, flows into growth funds are significantly lower than income equity funds. Finally, government bond funds receive significantly more flows than corporate and municipal funds. These beta and style results point us in the direction that terrorist attacks are changing investors' risk preference, such that they are looking into funds that are able to insulate them from market volatility caused by the attacks.

Karolyi and Martell (2006) find that, on average, firms lose $410 million when they are the targets of a terrorist attack. If, following attacks, investors downgrade their expectation of future cash flows for the stocks in their portfolio, we would observe a shift to safer assets (Pool, Stoffman and Yonker, 2014). To find evidence of such a cash flow effect, we start by examining investor survey data from the Investor Intelligence, University of Michigan Survey of Consumers, and the Yale Stock Market Confidence Indices. Results from these investor surveys show that following the spike in attacks, investors do not significantly change their expectations on stock market performance, in either the short run or in the long run. In addition, we find no evidence of a significant change in the level of volatility or the equity risk premium in the month following the spike in attacks. Next, we examine funds whose stock performance is not directly affected by the attacks. Using classifications from Chesney, Reshetar, Karaman (2010) and Sandler and Enders (2008) we test the effect of the attacks on the industries that are most susceptible to terrorism and the other unaffected industries respectively. The significant results on unaffected industries suggest that our main findings are unlikely driven by inflows or outflows to industries that are directly affected by terrorist attacks. If investors' asset allocation decisions are a result of their updated posteriors of future cash flows, we would expect the change in flows to be permanent rather than transitory. We examine two and three months after attacks and find that by the third month the effect of the attacks on flows has reversed for equity funds and is insignificant for bond and money market funds.

Over a battery of robustness checks we find that our results hold using different econometric specifications, additional sample selection criteria and alternative definitions of an attack month. For example, we include fund style fixed effects to test for possible unexplained heterogeneity in different assets classes and time-varying demand shocks. We drop the largest attacks in terms of casualties to rule out the possibility that large attacks such as 9/11 or the Oklahoma City bombing are driving our results. To alternate specifications of an attack month, we use the standard deviation of the number of attacks over the previous year, as well as including the number of fatalities and wounded in the calculation. In a final robustness test we run a falsification test on the sample by creating a randomized distribution of attacks and do not find any significant results.

Our paper is closely related to previous studies that examine the link between changes in investors' risk preference and their asset allocation decisions. Bharath and Cho (2014) find that past disaster experience lowers an individual's risky asset market participation and the share of risky assets in the portfolio. In addition, a recent paper by Kamstra, Kramer, Levi and Wermers (2015) find that the movement of large amounts of money between different mutual fund categories is correlated with seasonality in investor risk aversion. We believe our paper complements these studies in the following two ways. First, human-made disasters such as terrorism are more psychologically pathogenic than natural disasters, so for some people, the consequences of terrorism may be more severe (Mathewson, 2004). Second, seasonal changes in mood are largely predictable because the reduction in daylight is triggered by the onset of seasonal change. The exogenous nature of terrorist attacks assures that the subsequent risk shift is independent of fund past performance, which avoids common concerns of endogeneity. In addition to these papers, we extend the literature on the effect of emotions on risk attitudes, portfolio choice, and stock returns. Bassi, Colacito and Fulghieri (2013) and Saunders (1993) find that sunlight and good weather have a positive effect on risk-taking behavior: individuals are more risk tolerant on sunny days. To shed more light on this line of research, we provide new evidence on sentiment driven investing behavior that is based directly on quantities of fund shares chosen by investors.

Finally, we provide direct evidence that absence of any change in wealth; external events can cause individuals to make significantly less risky portfolio choices. This turns out to be important, as most asset pricing models require large fluctuations in the aggregate risk aversion (Campbell and Cochrane, 1999). While existing psychology literature predicts that fear leads to pessimistic risk estimates and risk-averse choices, our paper is the among the first to present large-scale empirical evidence, in addition to those collected through survey, that support such a prediction.[5]

The reminder of this paper will proceed as follows. Section 2 reviews the literature and articulates our hypotheses. Section 3 describes the data. Section 4 presents our main results, followed by a battery of

[5] See, for example, Lerner and Keltner (2000, 2001)

cross-sectional tests. Section 5 rules out the alternative explanations. Section 6 examines the fund performance after the terrorist attacks. Section 7 contains robustness checks. Section 8 concludes the paper.

2. The Link Between Terrorism and Mutual Fund Flows

A defining characteristic of a terrorist attack is the intent of the perpetrators to cause harm to their intended victims and create fear in a larger population. In contrast to previous sentiment studies using natural disasters or weather patterns, it is the attempt to intimidate that separates our study. Mathewson (2004) notes that, because of their nature, terrorist attacks have a larger impact on victims than similar catastrophic natural disasters.

Terrorist attacks can trigger investors' concern about global economic activity and corporate earnings; weakening equity markets and widening high-yield bond spreads. Increased concern may cause investors to hold a less risky portfolio if they believe stock market will become more volatile after the attacks. The updated beliefs of future attacks are likely to increase the degree of uncertainty about near future economic outlook and amplify downside risk with extreme market conditions. After 9/11, there was a sharp increase in global equity market price volatility and transaction volumes. All major stock markets experienced rapid, sharp price declines, reflecting expectations about the adverse impact of the tragedy on corporate profitability and portfolio reshuffling, as investors' demand for liquid, less risky assets increased (Choudry, 2005). Using evidence from six different financial markets, Arin et al. (2008) show that terror has a significant, yet short term, impact on both stock market and the stock market volatility.

The prevalence of PTSD or depression following terrorist attacks has been well documented in many psychological studies. For example, Hobfoll, Canetti-Nisim and Johnson (2006) use survey results from adult Jewish and Palestinian citizens of Israel to show that exposure to terrorism is significantly related to higher probability of PTSD and depression. Existing psychological literature provides ample evidence linking depression to increased risk aversion and less risky financial decision making. Kuhnen and Knutson (2008) and Carton et al. (1992) are among those who establish a link between depression and risk aversion. In Kunhen and Knutson's study, subjects who were shown a negative image before making a choice between a risky and a riskless asset were significantly less likely to select the risky asset than those shown a positive image. Carton et al. find that depressed subjects exhibit significantly lower sensation seeking scores [6] than a matched control group. Wong and Carducci (1991) and Horvath and Zuckerman (1993) explore the link between sensation seeking and everyday financial decisions and find high sensation seekers make riskier household finance decisions.[7] Kamstra, Kramer and Levi (2003) show that an increase in depressive moods, related to seasonal affective disorder (SAD) has a significant and large economic effect on global stock markets. Kamstra et al. (2015) extend the study of SAD and find the onset of SAD is linked to a shift of aggregate mutual fund flows from risky equity funds to safer money market funds. In related studies examining the relationship between weather and risk preferences, Bassi, Colacito and Fulghieri (2013) and Saunders (1993) show that poor weather conditions and less jovial moods are linked to lower risk tolerance. To wit, there is a wealth of evidence to suggest that individuals who are depressed or are experiencing depressive moods exhibit more risk averse financial choices.

A decrease in the appetite for risk could also be prompted by a change in the way that individual investors process risk following the event. Bernile et al. (2015) show that CEOs who were more likely to be victims of natural disasters at a young age implement less risk averse corporate policies. One channel described in their paper is related to the idea of 'co-option' from Futuyma (1998), which suggests that parts of the brain that were not previously involved in economic decisions and were impacted by the event are now involved and responsible for the increased risk aversion.

Using these previous studies as our guide, we hypothesize that following terrorist attacks, depressed or fearful individuals will become less risk tolerant, leading to more risk averse portfolio choices. In the context of investing in mutual funds, our hypothesis predicts a decrease in flows into riskier mutual fund classes (i.e. equity funds) and an increase of flows into safer fund classes (i.e. bond and money market funds).

[6] Sensation seeking is similar to risk aversion in that people who are high sensation seeking may receive higher utility from riskier activities

[7] Financial decisions that subjects had to make ranged from investing in stocks, bonds, or CD's; to determining if there are sufficient funds in a bank account and buying car insurance.

3. Data and Methodology

Many of the previous studies on terrorism focus on a small sample of major events. We believe a true examination of the effects of terrorism on individual investors must come from using all possible attacks and not a few major events. Therefore, we do not limit our study to the large-scale attacks; instead we incorporate all attacks, large or small, in our sample. To do so, we use a comprehensive database of all domestic and transnational[8] terrorist attacks in the U.S. from 1970 – 2010. We rely on Enders, Sandler and Gaibulloev (2011) to define our set of terrorist attacks.[9] This includes 1,206 total attacks from January 1970 to December 2010. We aggregate attack data to the monthly level and use the monthly number of attacks, regardless of their nature (domestic or transnational) to create our main attack variable.[10] We then define the attack month dummy as one if the number of attacks in that month is greater than 3 times the average number of attacks per month over the previous 12 months.[11] Using this definition, we are left with 39 of the 492 months from 1970-2010 being defined as attack months (months in which there is a spike in attacks).

$$Attack_t = 1 \; if \; Number \; of \; Attacks_t > 3 * \left[\sum_{t-1}^{t-13} Number \; of \; Attacks\right] \Big/ 12$$

We use spikes in the number of attacks as our measurement of terrorism for the following reasons. In our sample, 67% of all months have at least one attack. We believe our attack variable is able to identify the months with an abnormal number of attacks that may have the largest impact on investors. We focus on the number of attacks because Llussa and Tavares (2008) show that the number of terrorist attacks has a larger effect on consumption and investment than the number of individuals killed or wounded from attacks using similar terrorism data to ours. Additionally, Eckstein and Tsiddon (2004) show that the effect of terrorism is larger when there is a prolonged period of attacks than following one major event.

[8] An attack becomes transnational when one of the attackers or victims is not from the U.S.

[9] Notes on their methodology for aggregating and classifying the data can be found in the "Comparing GTD and ITERATE Time Series" section of their paper.

[10] In unreported tests we also use the aggregated number of attacks, injuries and deaths to create our attack variable and get qualitatively similar results.

[11] In the robustness section, we apply alternate definitions for attack month and the results are similar.

Frey, Luechinger and Stutzer (2004) point out that if the severity of attacks is changing over time, terrorism effect could be lost in a measure using only the accumulation of attacks. In order to address this concern, we create a measure of attack severity in each month. Our severity measure is created by totaling the number of individuals killed and wounded in each month and dividing it by the total number of attacks. We then examine the level of the severity measure in our attack months and find no significant difference in the severity of attacks in attack and non-attack months.[12] In addition to this, we incorporate the number of people killed and wounded in our attack dummy as a robustness check.

For our initial tests, we use the ICI database to test our results on aggregate equity, bond, and money market fund flows. The ICI database reports sales, redemptions, exchanges in, and exchanges out of funds on a monthly basis going back to 1984.[13] Using ICI data enables us to examine not only the change in overall net flows, but whether that change is being cause by a change in outflows from the fund or in flows. Following Kramer et al. (2015) we can use net exchanges as a strict test to see if investors are in fact taking money out of riskier asset classes and moving them into a lower risk class of funds. ICI defines 33 categories of funds, and for the most part we follow the groupings of Kramer et al. (2015) into creating of our five categories of funds. That is, we take the 33 individual categories of funds and aggregate them into equity, corporate, municipal, and government bonds, and finally money market funds.[14] To control for heterogeneity in fund categories, we run category and year fixed effect regressions with category level controls as well as other macroeconomic variables.

In order to capture fund characteristics pertaining to fund flows, we next turn to fund level analysis using mutual fund data from CRSP. As the CRSP mutual fund database is organized at the fund share class level, we first aggregate to the fund level because we believe investors are making their investment decisions based on the assets in which the fund is invested. Running regressions at the share class level

[12] We run this test both including and excluding 9/11 and find similar results

[13] ICI defines exchanges as a transfer from one type of fund in the family to a differently style of fund in that same family.

[14] We use all equity funds in our classifications for equity. Corporate bonds are comprised of foreign and domestic corporate bonds. For government bonds, we include non-taxable government money market funds as government bond funds to include all government securities in the same grouping.

would be double-counting funds that are comprised of the same assets.[15] This leaves us with a sample of 6,423 equity funds, 4,950 bond funds and 1,549 money market funds.

We use monthly fund returns and total asset values as the basis for our calculation of fund flows. Funds are classified as equity, bond or money market funds. We compute flows as a percentage of funds' total assets into the fund in each month. Flows are calculated as follows.

$$Percent\ Flows = \frac{Net\ Assets_t - Net\ Assets_{t-1} * (1 + Return_{t-1})}{Net\ Assets_{t-1}}$$

Fund flows are winsorized at the 99% level and we drop all funds with missing returns and assets when creating our sample. CRSP objective codes are used to classify funds into equity, bond or money market funds. For later tests, four-digit CRSP objective codes are used to classify funds into style categories.[16]

Following Kamstra et al (2015) we include capital gains as the return to the investor from the current month to the previous November to control for investors' reluctance to incur capital gains tax. We include the personal savings rate from BEA to control for the effect of liquidity needs on investor's investment decisions. We add seasonal dummies to adjust seasonal changes in aggregate fund flows. To control for auto correlation in flows we add one and three months lagged flows in all of our regressions. We use the one month lagged return of the S&P 500 to control for stock market conditions as well as the return on the 5-year treasury and the change in inflation to control for macroeconomic factors that could impact bond investors' decisions.

Figure 1 plots the number of attacks in each month of our sample and Figure 2 plots the rolling twelve-month average of the number of attacks per month, and the months in which we define our attack variable to equal one. Three things stick out in these figures. First, as we would expect there is no clear pattern in number of attacks per month in figure 1. Second, Figure 2 shows that the months in which we

[15] For equity funds we rely on MFlinks to aggregate flows from the share class level to the fund level. For bond and money market funds we hand match funds and combine all fund share classes at the fund level.
[16] CRSP Objective codes are used to combine Lipper, Strategic Insights and Wiesenberger fund classification codes. The first digit codes represent debt or equity, and funds are classified into more precise classifications as you move from the first to the 4th digit.

define our attack variable equal to one are spread out over our entire sample period. Finally, the number of attacks in the early portion of our sample is much greater than the latter half. As in Sandler and Enders (2004), we see a decreasing trend in the number of attacks over time, especially starting in the post-cold war era. This differentiation will enable us to examine investors' response to attacks in different time periods as the frequency of attacks differs. When the frequency of attacks varies, investors recognize these trends in attacks such that their change in behavior could be a response to updated beliefs on future attacks.

The attacks on September 11th provide an interesting case study in the context of our research. In two distinct ways these attacks are extreme outliers in our sample of attacks. In the sense of the size and scope of the attack it was by far the largest in the history of the United States. With respect to casualties the almost 3,000 deaths caused by the 9/11 attacks was over 17 times greater than the next closest attack in our sample.[17] Second, the magnitude and location of the attacks meant that the Federal Reserve (FED) felt it necessary to take action to provide liquidity and stability to financial markets. Among steps that were taken by the Federal Reserve, they included a $61 billion purchase of treasury securities and $45 billion in loans to banks through the discount window.[18] In addition to these steps by the Fed, the NYSE did not open until the Monday following the attack. Because of these extraordinary steps, we felt it was necessary to exclude the effects of September 11th from our baseline tests. Due to intervention from the Fed and the suspension of NYSE trading, we may see confounding effects in the month following the 9/11 attack. Unlike the other attacks in our sample, investors may be reacting to the attack, the fed actions, the market closure or a combination of all three in the month following 9/11.[19]

4. Results

4.1. Aggregate Fund Flows

[17] The next closest attack in terms of casualties was the Oklahoma City Bombing with 168 deaths.
[18] This compared to a $59 million over the previous 10 Wednesdays.
[19] In our robustness section, we add 9/11 to our main test and find qualitative, yet a bit weaker result.

Table 2 presents the baseline results using aggregate flow data from ICI. The dependent variable in all specifications is aggregate flow in month *t+1*, while the attack month is defined in month *t*. In Column 1 of Panel A we find a significant drop in flows to equity funds of 35 basis points in the month following a spike in attacks. This represents a drop of 43% relative to non-attack months, which have an average flow of 81 basis points. In Columns 2 and 3 we do not see a significant change in subsequent flows to corporate and municipal bond funds. In Columns 4 and 5, we see that government bond and money market funds experience a significant increase in flows, confirming our main hypothesis. Government bond funds receive an increase in flows of 25 basis points. This is relative to average flows of 51 basis points in non-attack months, representing an increase of 49% relative to non-attack months. Money market funds in Column 5 see an increase in flows of 64 basis points, which is an economically large increase of 66% relative to the average non-attack month flow of 80 basis points. The large increase of flows into money market funds echoes individuals' consumption behavior after the attacks. For example, Eckstein and Tisddon (2004) find a negative effect of terrorism on annual consumption per capita by about 5%, while Llussa and Tavares (2008) show a similar drop in consumption after a rise in the number of attacks. As these previous studies show and Frey et al. (2007) reiterates, terrorism induces individuals to place their money in safe heavens rather than buying durable consumer goods. To summarize, consistent with our hypothesis, aggregate flows to equity, bond and money market funds reveal an increase in risk averse investment decisions made by mutual fund investors following the terrorist attacks.

In Panel B we repeat the tests in Panel A, using the net exchange one month after the attacks as the dependent variable. The net exchange variable is created by subtracting exchanges out from exchanges in for that month and dividing the difference by the one-month value of lagged total net assets. In contrast to net flows, net exchanges directly reflect investors' decision to shift investment between mutual funds in the same family (Ben-Rephael, Kandel, and Wohl, 2012). Panel B confirms our results for equity and bond funds from Panel A. For equity, we see a drop in net exchanges of 11.1 basis points while we see an increase in net exchanges of 11.5 basis points for government bond funds. Such evidence clearly suggests that investors are directly transferring their funds out of risky equity funds and into less risky government bond funds.

In Panel C we shift our focus to outflows from the fund and new inflows into the fund.[20] To do this we create our total inflows and total outflows variable as a percent of lagged total assets. Total inflow is defined as the sum of all new sales and exchanges into the fund. Total outflows are defined as the total redemptions plus the exchanges out of the fund. In Column 1 we see that the drop in equity flows is being driven by an increase outflows from equity funds. On the other hand, Column 4 shows us that the increase in flows to government bond funds is being driven by an increase in the value of inflows to the funds. With respect to money market funds, Column 5 shows us that money market funds experience a reduction in their redemptions and exchanges out in the month after the attack.

While our main hypothesis is confirmed in Panel A, the results in Panel B and C help to identify if net changes are being caused by changes in outflows, inflows or both. Equity fund investors redeem their holdings or exchange them within the family into a safer bond fund. In direct contrast to equity funds, the increase in flows to government bond funds is a result of an increase in new sales and exchanges into the funds. For money market fund investors, we see a drop in outflows from the fund. In each case, investors are making more risk averse investment choices by decreasing their investments in risky asset classes by shifting funds to safer fixed income funds.

4.2. Sub-Period Analysis

In this section we examine how terrorism impacts fund flows and investors' portfolio choices in different time periods. We first split our sample into three distinct periods using two major geopolitical events: The end of the cold war in 1992 and the attacks on 9/11 in 2001.

Table 3 presents the results in three sub-periods (Cold War period ending in 1992, Post 9/11 period starting 2002, and the years in between). Overall, we see a clear trend that over the course of our sample, investor reaction to attacks, for equity funds, has diminished since the end of the cold war. For equity funds,

[20] Outflows are defined as the sum of redemptions and exchanges out. Inflows are defined as the sum of new sales and exchanges into the fund.

in the period after 9/11 we see a negative and significant reaction to attacks; it is however significantly less than what we observe in the period between the cold war and 9/11. As with equity funds, money market fund investors also exhibit significantly smaller reactions in the latter time period. In the post-Cold War period, money market fund investors increase flows by roughly 95 basis points, following the attacks on 9/11 the attack coefficient drops to 43 basis points and is insignificant. In contrast to equity and money market funds, we see a consistent coefficient on the attack dummy for bond funds. In each of the three time periods we split our sample into, we find that flows into bond funds increase by 23 to 30 basis points in the month following a spike in attacks. In addition to splitting our sample by these major events, in un-tabulated results we find that recessionary periods, as defined by NBER, do not drive our main results.[21] In total, we find that the results in equity and bond funds are not being driven by any one period of the sample or by changes in the business cycle.

4.3. Individual Fund Results

To further test our main hypothesis, we run panel regressions on a sub-sample of individual equity, bond, and money market funds. We use individual fund data because results at the aggregate fund level my not be reflective of assets allocation decision at the individual fund level. More importantly, CRSP individual fund data enables us to better control for differences in fund flows related to differences in performance, asset allocation and fund characteristics. In all regressions, we control for year and fund fixed effects as we intend to compare flows in attack months to those in non-attack months within each fund. Other control variables are taken from previous literature and load with the sign and significance that we expect.

The results are presented in Table 4. The dependent variable in Panel A is fund flows in month $t+1$, while the attack variable is defined in month t. In Column 1 we examine equity funds, the attack variable has a coefficient of -38.4 basis points and is significant at the one percent level. For the average equity fund

[21] The correlation between recession and our attack month dummy is only 0.08, not significant at the 5% level.

this equates to a drop in flows of roughly 40% relative to non-attack months (the average flows in non-attack months is 95 basis points).

Columns 2 and 3 in Panel A replicates the model in Column 1 with our sample of bond and money market funds. If investors prefer safer assets after an attack, we should, and do in fact see an increase in flows to bond and money market fund in the month after the attacks. The results are smaller economically for bond funds, but the change in flows to money market are much larger relative to equity and bond funds. The coefficient on bond funds is 11.9 basis points and is significant at the 1% level. The average percent flows into bond funds in attack months' increases by 22% relative to non-attack months (the average flows in non-attack months is 53 basis points). Following attacks, flows into money market funds have an increase of 54% relative to non-attack months.

4.4. Proximity and Saliency Tests

Results from Galea et al. (2001) and Antoniou et al. (2016) show that people living closer to terrorist attacks are more affected than those living outside of the immediate area of the attack. We do not have individual investor location data, but previous studies have shown that investors are more likely to invest in mutual funds headquartered in their local area. (Coval and Moskowitz, 1999). Hence, to test the effect of the proximity to the attack on investors, we examine attacks that are within 100 miles of the mutual fund headquarters.

In Panel A of Table 5 we examine the difference between flows into funds that are headquartered in close proximity to the attack and those that are outside of the immediate area of the attack. To do this we run a piecewise regression, splitting the equity funds in our sample into two separate groups: local funds and non-local funds. Local funds are those located less than 100 miles from any attack that occurred in that month. Non-local funds are those that are located outside the immediate area of the attack.[22] Consistent with previous studies, we find that the change in flows for both equity and bond mutual funds is larger for funds that are located closer to an attack. Column 1 in Table 5 shows that equity funds located less than

[22] We are limited in this sample by the availability of mutual fund locations and exact locations of all the attacks in our sample. Location data for funds from CRSP starts in 2000.

100 miles from an attack suffer a drop in flows of 47.8 basis points, while funds outside of that radius only experience a drop of 29.6 basis points. Column 3 examines the flows into local and non-local bond funds. Similar to the results we see for equity funds, we find that bond funds located with 100 miles of an attack see a 32 basis point increase inflows. Funds located outside of 100 miles do not see a significant change in flows. In Columns 2 and 4 we extend the definition of a local fund to those headquartered within 200 miles of any attack in that month. For both equity and bond funds, the response by investors diminishes as we extend the definition of a local fund. If flows into and out of the funds that are located close to the attack are made up primarily of local investors, then it is reasonable to assume that these local investors will be more impacted by the attack and show a greater increase in risk averse behavior. Therefore, this result follows from the previous literature that investors are more likely to invest in mutual funds located closer to them.

Media coverage of disasters and atrocities may be particularly upsetting and hence trigger particularly large emotional response in the form of fear. By bringing images of terrorism into people's homes, and advertising the effects, media coverage appears to generate anxiety and distress (Slone, 2000; Schlenger et al. 2002). To test the effect that media coverage of the attack has on flows we search for mentions of each attack in four national newspapers: The New York Times, The Wall Street Journal, USA Today, and The Washington Post. In Panel B of Table 5 we run a piecewise regression where we split our main attack variable into high coverage months and low coverage months. In Columns 1 and 3 we define high coverage months as those months in the top 10% of the median word count distribution, and low coverage months as those attack months in the bottom 90% and those without news mentions. [23] The result in Column 1 indicates that equity funds see a drop in flows of 60 basis points in high coverage attack months compared to a drop in flows of 37.3 basis points in the low coverage attack months (different at the 5% level). In the high coverage attack months' flows into bond funds increase by 1%, which is significantly greater than the increase in flows of 7.4 basis points in low coverage attack months.

[23] To create our distribution of median word counts we search all attacks months for news mentions in the four national newspapers and create a distribution of median word counts for all months with at least one news article.

In Columns 2 and 4 we alter the definition of a high coverage attack month to be those months with the median number of words per article in the top 25% of the distribution of all attack months with at least one article in the four national newspapers. Low coverage months are those with median word counts in the bottom 75% and those with no news mentions. For both equity and bond funds we continue to observe a significant stronger effects for high coverage months than for the low coverage months when we relax the criteria for a high coverage month to the top 25%.

4.5. Fund Characteristics

In our initial test of fund characteristics, we examine the flow differences between institutional and non-institutional share classes. We identify institutional share classes using the CRSP Institutional fund identifier. For each fund, CRSP identifies the share classes that are sold to institutional investors. We then create an institutional dummy that takes the value of one if CRSP identifies the share class as institutional. In this test we would expect that institutional investors would be less reactionary than retail investors. For example, Barber and Odean (2008) show that individual investors are more likely to trade on large news days than institutional investors. In Column 1 the coefficient on the institutional fund and attack interaction term confirms that for equity funds, institutional investors respond less than retail investors.[24] The coefficient on the interaction term in Column 1 is 26.9 basis points and significant at the one percent level and totally negates the drop in flows from retail investors of 23.7 basis points. This positive response from institutional investors reflects the idea that they recognize the short-term impact on the market attacks cause and do not significantly change their investment activity. In the case of bond funds in Column 2, we do not see a significant difference between retail and institutional funds, but we do see a negative interaction term.

Columns 3 and 4 test investors preference for domestic and foreign funds after the attacks. Chesney et al. (2011), show that following attacks on U.S. soil as well as overseas, the U.S. market is the most resilient global market index. Consistent with the idea that investors are shying away from riskier funds,

[24] Sample size is large in columns 1 and 2 of table 6 because we run regressions at the share class level

we find that foreign equity funds suffer larger outflows than domestic equity funds. The coefficient on the interaction term in column 3 is -22.8 basis points and is significant at the 1% level.

Along with the fee structure and the assets in which it is invested, risk is among the most important fund characteristics that influence investors' investment decisions. In Table 7 we attempt to determine investors' response to funds that would be most impacted by an increase in market volatility. To do so, we examine changes in demand for high and low beta funds. To calculate the market beta for each fund we run a rolling 36-month regression of excess fund returns on the Fama French factors (i.e. one-, three-, and three-factor plus momentum). [25] In each month, we then rank all funds into quartiles based on the beta calculated over the previous 36-months.We take the market beta calculated from the 36 month, rolling one-factor beta regression and create a high and low dummy for the highest and lowest 25% of betas in each month, respectively. We then repeat this for the three and four-factor market beta regressions. Table 7 presents results consistent with the idea that fund heterogeneity, with respect to market risk, plays an important role in the flow of funds following the attacks. If investors perceive that the market is becoming more volatile after attacks, then we would expect that riskier funds, measured by market beta, would suffer larger outflows than lower beta funds. This is indeed what we find. Following a spike in attacks, high beta funds experience significantly larger outflows than mid and low beta funds. The increased drop in flows for high beta funds ranges from 32 basis points in the market model, to 17basis points for the four-factor model in column 3.

4.6. Fund Styles

In our baseline result in Table 4, we find that investors respond to attacks with reduced flows to equity funds and increased flows to bond and money market funds. In this subsection, we examine how this increase in risk averse choices manifests itself in the cross-section of equity and bond funds. For all columns in table 8 we assign funds a style based on their 4 digit CRSP objective code. In Columns 1 to 3 of Table 8 we repeat our main tests on a sub-sample of small, mid and large capitalization funds. According to Fama

[25] Factor data is taken directly from Ken French's data library.

and French (1993) small cap funds have historically outperformed large and mid-cap stocks because they present an increased level of risk.[26] If investors do view small cap funds as riskier, then we would expect to see a difference in the level of outflows to those small and large cap funds.

Table 8 shows us that investors do no alter their flows into all equity funds at an even rate. Large funds do not experience a significant drop in flows; mid and small-cap funds experience a significantly large drop of 64 and 44 basis points respectively. This result leads us to believe that investors are not only making a decision between equity and bond funds, but also shifting investment from riskier mid and small cap funds to less volatile large cap funds.

Columns 4 to 6 of Table 8 conduct a similar test, but we focus on the investment style of the funds. We use funds that classified as growth, growth and income, or income equity funds by CRSP. The negative coefficients on growth, and growth and income funds suggest that in response to terrorist attack, investors prefer funds that provide a larger portion of their returns through dividends. If investor's views about future market volatility are changing after attacks, it is rational for them to invest in funds that can provide return for the investor in terms of dividends, instead of only relying on price appreciation.

The last three Columns in Table 8 shift the focus from equity funds to bond funds. Using the same CRSP objective codes we classify bond funds as government, corporate or municipal. Municipal bond funds and corporate bond funds represent much higher risk than a government bond fund, meaning we should see a larger increase in flows to the safer government bond funds. Following the same methodology as Columns 4-6, we run our main regression on the sub sample of government, municipal and corporate bonds. Government bond funds receive a significant boost in flows of 65 basis points, significantly more than both, municipal and corporate bond, which do not see a significant increase in flows. This result is consistent with our findings in Table 2 that corporate and municipal bond funds receive a significantly smaller increase in flows relative to government bond funds.

[26] In our sample, small cap funds have the highest level of risk, but not the highest return. Mid cap funds outperform small cap over our sample. Both mid and small cap funds have higher volatility than large cap funds

5. Is This a Cash Flow Effect?

We have proposed that the response by investors after terrorist attacks is driven by a change in investor sentiment and their risk tolerance. However, investors downwardly adjusting their perception of future stock prices following an attack would cause a similar change in investment patterns. Karolyi and Martell (2006) examine the impact that attacks can have on a firm's stock price. Their findings show that firms suffer a significant loss in market valuation on the day of a firm specific attack. Similarly, Sandler and Enders (2004) show that there is a significant negative effect of terrorism on the country's tourism industry. In this case, investors' response to attacks could be proactive moves to insulate their portfolio from any correlation that it has to the returns of stocks in the domestic tourism industry. In the context of mutual fund industry, Pool et al. (2014) use shocks to housing value to examine fund managers risk taking and find that negative shocks to personal wealth lead to mutual fund managers to take less risk in the funds they manage. In this section, we show that changes in risk taking behavior following terrorist attacks is not contaminated by any significant change in wealth.

To rule out the possibility that individuals are altering their level of investment in risky funds due to a reduction in their expectation of future cash flows, we start with an examination of three common investor sentiment surveys: Investor Intelligence's summary of professional investors' survey, the University of Michigan Survey of Consumers and the Yale Stock Market Confidence Indices. Examining the levels of the surveys before and after attack months enables us to measure the change in investors' perception of future market performance.[27] Investor Intelligence collects and summarizes the outlook of over 120 financial market newsletters. Their survey begins in 1963 and is available for our entire sample period.[28] For our examination we track the percent of newsletters classified as "bearish" as well as follow Greenwood and Shleifer (2014) and use the percent of newsletters classified as "bullish" minus the percent classified as "bearish" to create two measures of market outlook. Both the Yale and University of Michigan

[27] These are attack months as defined by our attack variable.
[28] The survey was released monthly in 1963, then moved to bi-weekly until 1969 and weekly through 2010. For our use, we use the monthly average of the weekly and bi-weekly reporting to be consistent with our main tests.

surveys ask investors similar questions related to investors' expectation of market returns over the next 12 months. The Michigan survey asks respondents how likely do they think it is that a $1,000 investment in the stock market will be worth more one year from now, than it is today. The Yale survey directly asks respondents (both individuals and institutional investors) how they think the Dow will perform (in percent) over the next year.[29] Both surveys are measured in a similar manner. The Yale surveys report the percentage of respondents expecting the return for the Dow to be greater than zero. Respondents in the Michigan survey report the percent chance they believe the market will increase over the next year. The average of all responses in each survey is then used as the dependent variable in our regression. While the Yale and Michigan surveys are similar in both the question being asked and the time horizon (12 months) being studied, the Investor Intelligence survey focuses on shorter-term market views.[30] Using these different surveys gives helps us examine how both short and long-term market views may be influenced by spikes in terrorist attacks. Table 9 presents the results of the changes in these market outlook surveys in the month following a spike in attacks. In all tests we control for the lagged level of the outlook index, all non-fund specific controls from our main tests, and year fixed effects. The results show that investors, both individual and institutional, do not significantly change expectations on near or longer term market performance following attacks.

While survey results show that investors' beliefs about the future are unchanged in the month following the attacks, investors could be responding to a drop in the equity risk premium or an increase in market volatility. To test such a possibility, we regress the one-month ahead risk premium on our attack variable and all non-fund specific controls from our main regression. We measure the equity risk premium in two different ways. We first use the return on the S&P 500 minus the one-month Treasury bill. Second, we proxy for the market return using all stocks from the NYSE, AMEX and NASDAQ.[31] Regardless how we measure the risk premium, the result suggests that there is no significant drop in the risk premium in the

[29] The question used from the Michigan surveys was not asked until June 2002. The Yale index was initiated in 1989 and publishes two separate sentiment indexes that measure whether or not individual and institutional investors believe the Dow Jones will have a positive return in the next year. Prior to July 2001 the index was only published on a quarterly basis.
[30] Greenwood and Shleifer (2014) note that the editors of Investor Intelligence focus on the forecast of returns over the near term
[31] Excess return on the market is taken from Ken French's data library.

month following the attacks. To examine the change in market volatility, we calculate the standard deviation of daily returns of the S&P 500 for each month then replicate the equity risk premium test described above, with one-month ahead volatility as the dependent variable. Again, we find that there is no significant increase in daily market volatility in the month following a spike in attacks.

In later tests we examine whether there is a significant drop in flows even in industries that are not directly affected by terrorist attack. We also alter the window around the attacks to test the persistence of the effect.

5.1. Directly Affected Funds

Terrorist attacks affect different industries in different ways. Sandler and Enders (2004) show the negative effect of terrorism on the tourism industry. Chesney et al. (2011) examine the insurance, financial, and defense industries in the wake of attacks. They find that the insurance industry is negatively affected by attacks, while the financial and defense industries are more insulated from attacks, and may even benefit. If investors believe that terrorist attacks cause a negative shock to industry performance, they should move funds into the industries that are insulated from attacks and move out of industries that are the most negatively impacted.

Testing these results in our equity fund sample poses an issue, in that, going back to 1970 there are very few, if any industry specific funds or industry specific indexes. To create our sample of transportation, defense, insurance, and bank specific funds we take returns for those industries and run 12-month rolling regressions of equity fund returns on the returns from those industries to estimate the industry exposure (industry beta) for each fund.[32] Industries are defined using the Fama-French 49 industry classification and value-weighted industry returns are taken from Ken French's data library. We classify the funds in each month that have a beta in the top 5% as the high correlation funds to each industry. Those high industry beta funds are excluded from the other industry regressions as to not contaminate the results for a certain

[32] Definitions and SIC codes for those industries can be found at Ken French's data library: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html#Research. We use the transportation industry as a rough approximation for tourism.

industry.[33] We then create an interaction term by multiplying the high industry beta dummy by our original attack dummy to test the flows into those high industry beta funds in the attack month.

Results in Table 10 show that our baseline results are not driven by funds highly correlated to these directly affected industries. Even while picking out these highly correlated funds, the main attack variable continues to be negative and significant in each column of the table. The result in Column 1 shows that investors agree with Sandler and Enders (2004), in that, the transportation industry is extremely susceptible to terrorism. In the wake of an attack the funds highly correlated to the transportation industry experience a drop in flows of 81 basis points relative to other equity funds. In Column 3 we isolate funds that are highly correlated to the insurance industry. Similar to the transportation industry, we see a negative but insignificant coefficient on the insurance and attack interaction term. This result follows from Chesney et al. (2011), who show that the insurance industry is negatively affected by terrorist attacks.

The rest of Table 10 looks at funds correlated to the banking and defense industries and shows that investors have no significant preference to these funds after the attacks. The results here confirm the findings of Chesney et al. (2011), showing that both the banking and defense industries are insulated from the effects of terrorism. After controlling for funds highly correlated to these industries we still find that flows to all other funds are negatively impacted by the attacks. While we do see evidence of a wealth effect in the transportation industry, it does not appear that a cash flow effect is driving our main results. Examining the main attack variable in each column, we still see strong evidence of a decrease in demand for all equity funds.

5.2. Persistence in Fund Flows after Attacks

In our final test, we examine the persistence of the attacks effect on investors' asset allocation decisions. We do this by replicating the regressions from our main results in Table 4, but setting the dependent variable as flows in two and three months after the attacks. The results are presented in Table

[33] An example of this is as follows: If fund A is classified as a high bank fund, it will be excluded from the transportation, defense and insurance regressions.

11.[34] For equity funds the effect of the attack is present, but declining in magnitude after two months. The result reverses in the third month after the attack and disappears in the fourth month after the attack. This transitory nature of the effect of attacks is similar to the results of Antoniou et al. (2016), who find that firms become more risk averse after attacks, but only for a short time. Bond funds experience an immediate reversal in flows in the second month with any significant change in flows disappearing in the third month after the attack. Finally, money market funds still see a positive and significant inflow during the second month after the attack. We do not see a reversal in money market flows like equity and bonds funds, but the effect becomes insignificant in the third month after the attack. While we cannot totally rule out the possibility that perceptions of future cash flows are causing the change in investing activity, we do believe the persistence results, combined with those in sections 4.7-4.9, point to the fact that investors' risk tolerance are more likely causing the change of their mutual fund investments.

6. Mutual Fund Performance After Attacks

In this section we examine the impact fund flows after attacks have on future fund performance. As Berk and Green (2004) points out, return-chasing fund flows acts as the equilibrating force that equalizes the expected abnormal returns across funds. This leads to the lack of performance persistence in the long run. On the other hand, if mutual fund investors are moving out of risky equity funds immediately after the attacks, then the fund managers are forced to sell assets to meet those unexpected redemptions. Forced trades caused by non-informative investor flows are likely hurting future fund performance because such trading does not reflect fund managers' strategic allocation decisions. For example, fire sales by funds that are experiencing extreme outflows generate temporary downward price pressure on securities held in common by these funds (Coval and Stafford, 2007). Hence, we expect to observe worse performance after attacks, especially for those with outflows.

[34] We alter the sample in this test so that there are no attacks in the second or third month after the original attack month. We do this so the coefficients we see in month two and three are only being effected a single attack.

To measure the effect that outflows, following an attack, have on future performance we create a decile rank variable that takes discreet values between 1 and 10. In each month we rank funds based on the level of flows and sort them into 10 deciles. The funds with the highest outflows in the current month are given a rank of 10 and the funds with the lowest outflows a rank of 1. We then interact this outflow rank variable with the attack month dummy in the prior month. Fund performance is measured by the benchmark-adjusted return, defined as the difference between the fund return and the return of a benchmark assigned by Morningstar.[35]

Table 12 presents the results of the future performance tests. In each column the dependent variable is the benchmark-adjusted return in month t+1 after the attacks in month t-1. We focus on the benchmark-adjusted performance two months after the attacks to capture the effect fund flows in the month after the attack have on future performance. Examining the future performance after the flows in month *t* following an attack in month *t-1* allows us to gauge the impact of the attacks on fund performance. These flows are important because they reflect investors' reaction to the attacks. In column 1, we regress future fund returns on the attack month dummy and flow rank variable. The attack variable is negative and significant with a coefficient of -19.67 basis points. This 19 basis point drop translates to a 30% drop in performance in month two after the attacks, relative to non-attack months. The average benchmark-adjusted return in the sample in non-attack months is 64.27 basis points. The positive coefficient on the outflow rank variable implies an inverse relationship between flows and future fund performance, which is consistent with the implications in Berk and Green (2004). It is likely that the fund flows after the attacks are partially driven by fund performance. To address that, in column 2 we add one, two, and three month lagged return. We find that the result in column 1 does not seem to be driven by past returns. The attack dummy remains negative and significant with a slight increase in magnitude to -21.5 basis points. To see whether the effect of attacks on future performance is stronger for funds with more outflows, we interact the attack dummy with the outflow rank variable in column 3. The results in column 3 show that the performance of the fund after the attacks

[35] Not all funds have a matched benchmark from Morningstar. If a fund has a missing benchmark in Morningstar, we use S&P 500 index as the benchmark.

is significantly affected by the outflows from the previous month. Moving from the bottom decile to the top decile of fund outflows in the month after the attacks reduces the following month's performance by 20 basis points. Outflows after the attacks may force the managers to liquidate certain holdings to meet unexpected redemptions. This unexpected selling can then lead to lower performance in the following month, similar to the results from Coval and Stafford (2007) and Chen et al. (2008).

7. Robustness Tests

To further test the robustness of our results we use an alternate specification of the attack variable. We start by testing whether it is the large-scale attacks that are driving our results. To do this, we sort attack months based on the number of casualties and drop the months that are in the top five percent.

Panel A of Table 13 reports results using this specification. After dropping the largest attacks (in terms of casualties), we find that the coefficients on the attack variable are still negative and significant at the 1% level for equity funds, and positive for bond fund and money market funds. In equity and bond funds, we see a small increase in the size of the coefficient, while money market funds see no significant change in the coefficient on the attack variable when we drop the largest attacks, in terms of casualties. For our main tests we exclude 9/11, Panel B of Table 13 expands the sample to include the attacks on 9/11. Again, we see that the sign and significance of the attack coefficients do not change when including 9/11 in the sample.

In un-tabulated results we randomize the attack months in a falsification test. To do so we randomly assign 39 dummies without replacement to all months in our sample. [36] We then replicate Table 4 using this randomized attack dummy and find no significant results. To control for possible unobserved heterogeneity in fund styles we run our tests to include style fixed effects rather than fund fixed effects. In another econometric specification we use time trend variable instead of our year fixed effects. In both of these alternate specifications we find results consistent in both sign and significance as our main table. Finally,

[36] 39 is the number of months in the sample which the attack dummy takes a value of one.

we alter the definition of an attack month to determine if our results are driven by our attack month definition. In addition to using our main attack variable, we use the mean plus the standard deviation of the number of attacks over the past year. To account for the severity of attacks we include the number of people killed and wounded in the attacks to the calculation of the attack dummy.[37] Using these variations of an attack month we continue to find consistent results.

8. Conclusion

Previous literature has created the link between terrorism and its impact on the financial markets, industries, and specific firms, with a focus on certain events and a smaller group of stakeholders. Our paper is among the first few to examine the effect of terrorism on a much larger portion of the population (i.e. individual investors) with a significantly larger sample of terrorist events. Using a comprehensive set of all domestic and transnational attacks in the U.S. between 1970 and 2010, we find that in the month after a spike in attacks, mutual fund investors significantly reduce their investment in equity funds while increasing their investment in bond and money market funds. The size of this impact does seem to be related to the amount of national news coverage and the investor's proximity to attacks. The significance of the proximity and saliency of the attacks lends to the idea that the fear induced by terrorism is the main force driving the shift to safer assets. Tests of fund heterogeneity shows that investors are responding to different risk profiles in terms of market beta and varying investment styles within asset classes. Based on results of fund industry correlation, investor sentiment surveys, and altering measurement windows we believe that the reactions shown by investors is more likely due to changing views on risk and not on their perception of future stock returns.

It is important, though, to remember that our results were obtained using mutual fund flows aggregated at the fund level. Further research is needed to investigate whether trading behavior of individuals, using brokerage data, is altered by their risk preference following attacks. Our study also

[37] In a similar way to define the attack month in the main test, we assign the alternate attack dummy a value of one if that sum of the casualty and fatalities in each month is greater than three or four times the average for the previous twelve months.

provides some guidance in designing government policy and economic remedies to ease the fear and depression of the general public that affect their investment and consumption behaviors.

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Figure 1: Number of Attacks

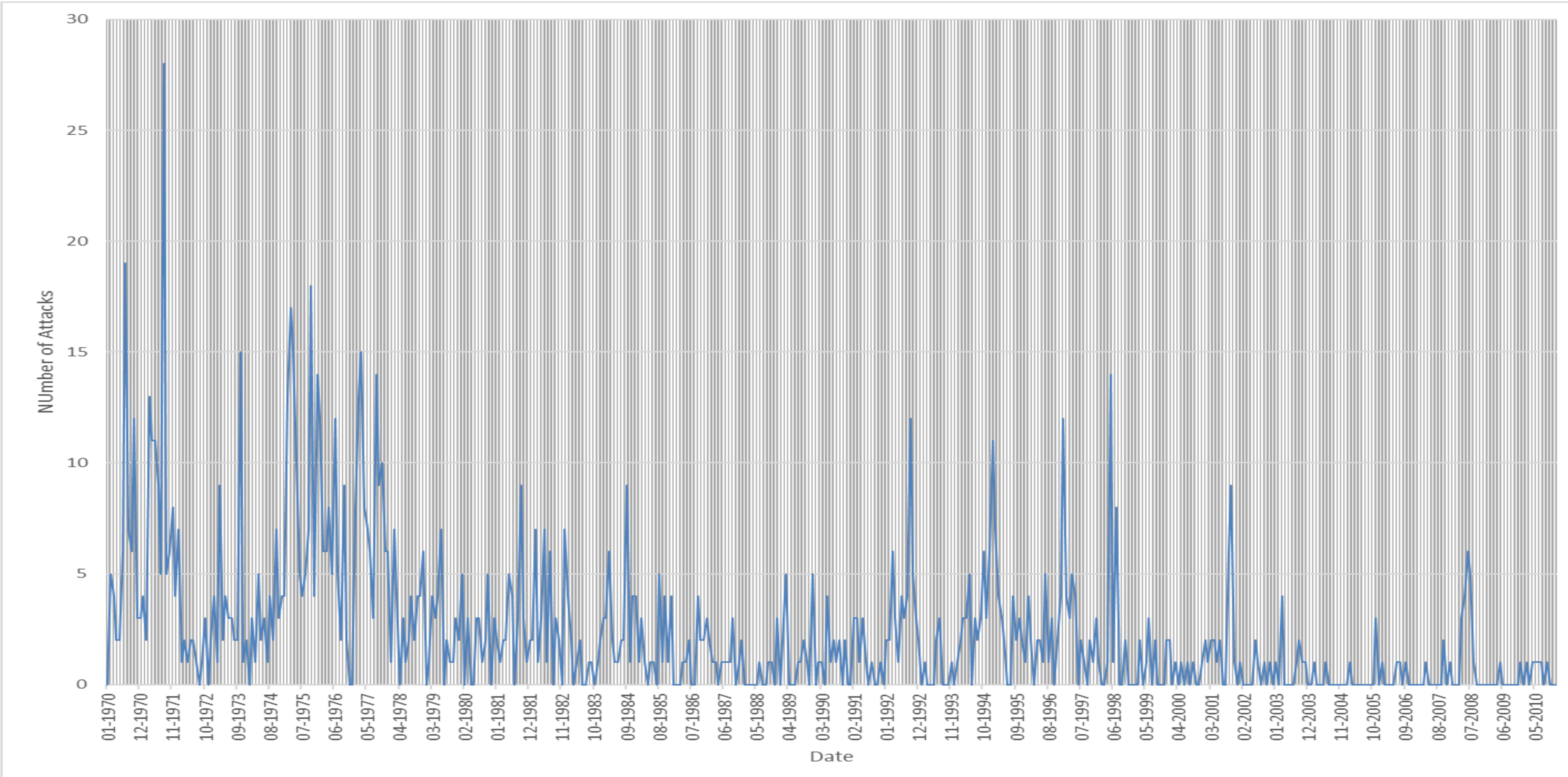

Figure 1 graphs the total number of attacks for each month in our sample

Figure 2: 12 Month Rolling Average of Attacks

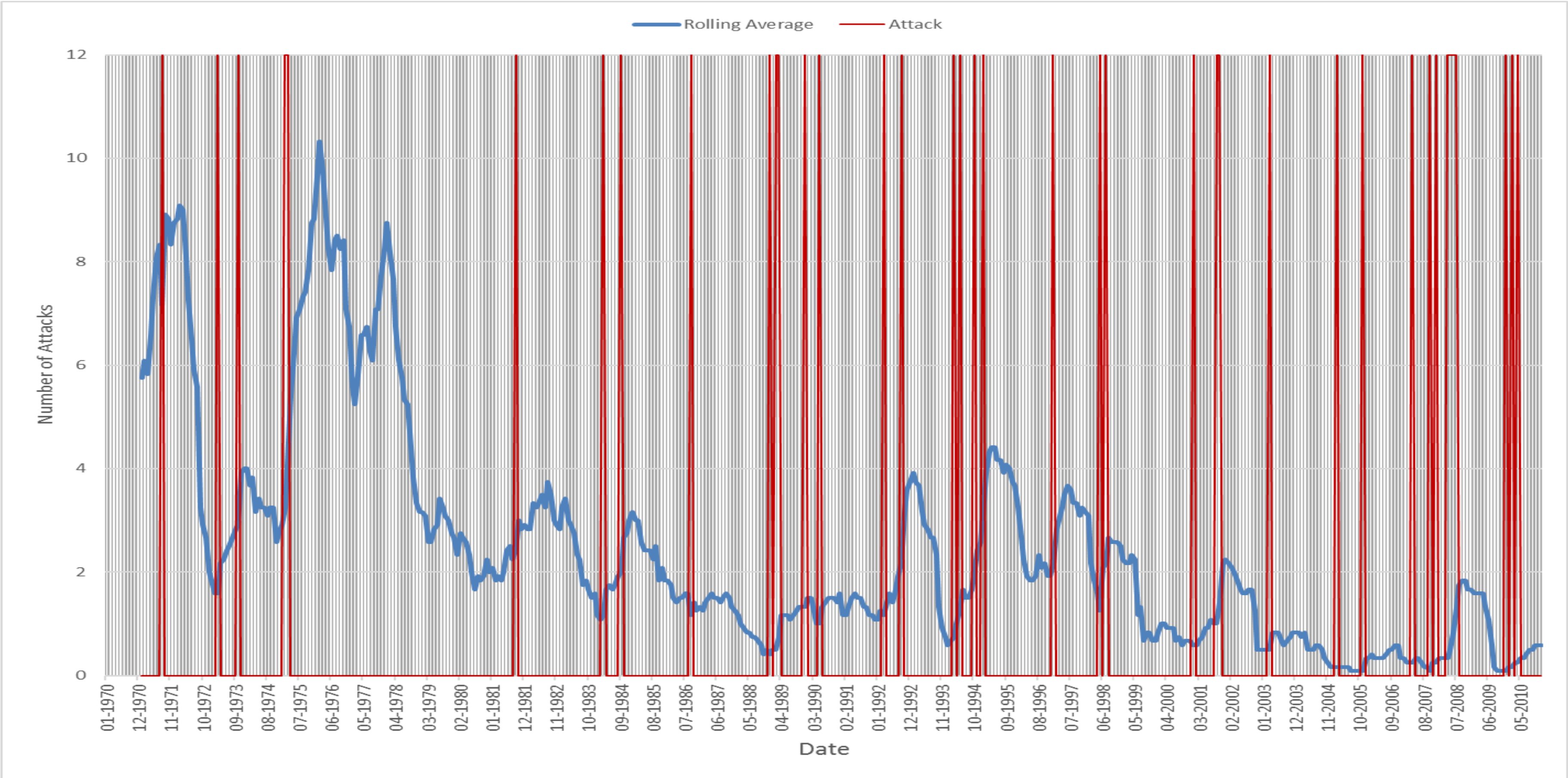

Figure 2 graphs the rolling average of the total number of attacks per month over the past 12 months. Vertical lines represent the months in which the attack variable takes the value of one.

Table 1: Summary Statistics

This table presents summary statistics for the variables used in the paper. Attack is a dummy variable that takes the value of 1 if the number of attacks in that month is greater than 3 times the average number of attacks per month over the past 12. Return is the annual return for the fund and Assets is the log of total fund assets in millions. Expense ratio is the annual expense ratio reported by CRSP. 5 Year Treasury, CPI and S&P 500 are the values of the 5-year government bond return, the change in CPI and the value weighted return for the SP 500 on an annualized basis. Capital gains is the cumulative return since the previous November. Personal savings is the BEA personal savings rate for the month.

Variables	Mean	Standard Deviation	10th Percentile	Median	90th Percentile
Flow	0.019	0.129	-0.042	-0.003	0.079
Attack	0.117	0.322	0.000	0.000	1.000
Return	0.060	0.117	-0.36	0.072	0.492
Assets	3.404	2.497	0.000	3.611	6.395
Expense Ratio	0.011	0.006	0.003	0.010	0.020
Capital Gains	0.040	0.119	-0.076	0.031	0.161
Personal Savings	0.054	0.016	0.030	0.053	0.081
S&P 500	0.084	0.176	-0.720	0.18	0.804
5 Year Treasury	0.072	0.048	-0.144	0.072	0.276
CPI	0.024	0.013	-0.024	0.024	0.084

Table 2: Aggregate Flows

In this table we present our main results using aggregate flow data from ICI. The dependent variable in Panel A is net flows as a percentage of one month lagged assets. In panel B we use net exchanges as a percent of lagged total net assets as the dependent variable. In panel C we use inflows and outflows as a percent of lagged total net assets as the dependent variable. All dependent variables are measured in month *t+1* following the attack month. Attack is a dummy variable that takes the value of one if the number of terrorist attacks in that month is greater than three times the average number of attacks per month over the past 12 months. Return and Assets are the 1 month lagged values of the fund returns and natural log of total assets, respectively. 5-year treasury, CPI and SP 500 are the lagged values of the 5-year government bond return, the change in CPI, and the value weighted return for the SP 500. Flow is the 1 (3) month lagged flows for the fund measured in the same basis as the dependent variable. Robust standard errors in parentheses *, **, and *** indicate significance at the 10, 5 and 1% level respectively.

Panel A: Net Flows					
	(1)	(2)	(3)	(4)	(5)
VARIABLES	Equity	Corporate	Municipal	Gov't	Money Market
Attack $_t$	-0.351**	-0.039	0.020	0.254**	0.649**
	(0.130)	(0.071)	(0.099)	(0.075)	(0.325)
Personal Savings $_t$	-0.060	-0.001	-0.054	-0.009	-0.128
	(0.094)	(0.076)	(0.035)	(0.107)	(0.147)
Capital Gains $_t$	-0.004*	-0.010	-0.009	0.003	0.158***
	(0.002)	(0.007)	(0.005)	(0.009)	(0.060)
Return $_t$	0.004***	-0.002	0.016	0.023	0.119**
	(0.000)	(0.003)	(0.008)	(0.015)	(0.055)
Flow $_t$	0.457***	0.158**	0.309*	0.314**	-0.123***
	(0.051)	(0.059)	(0.121)	(0.073)	(0.031)
Flow $_{t-2}$	0.141***	0.278***	0.208***	0.309***	0.142***
	(0.023)	(0.046)	(0.025)	(0.056)	(0.036)
Market Return $_t$	-0.783				
	(1.123)				
Winter $_t$	0.358***	0.165	0.152	-0.533	1.646***
	(0.050)	(0.102)	(0.127)	(0.505)	(0.297)
Spring $_t$	0.260	-0.046	-0.174	-0.486*	-0.867***
	(0.177)	(0.155)	(0.164)	(0.213)	(0.284)
Fall $_t$	0.068	-0.250	-0.443*	-0.395**	0.435*
	(0.085)	(0.143)	(0.159)	(0.138)	(0.261)
5 Year Treasury $_t$		0.103**	0.085	0.178***	0.248***
		(0.032)	(0.047)	(0.036)	(0.075)
CPI $_t$		-0.075	-0.039	0.111*	-0.686**
		0.165	(0.205)	(0.049)	(0.315)
Observations	2,618	1,876	1,088	1,404	930
R-squared	0.456	0.444	0.661	0.511	0.244
Fund Fixed Effects	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes

Panel B: Net Exchanges					
	(1)	(2)	(3)	(4)	(5)
VARIABLES	Equity	Corporate	Municipal	Gov't	Money Market
Attack $_t$	-0.111**	0.006	-0.034	0.115*	0.055
	(0.040)	(0.027)	(0.062)	(0.048)	(0.054)
Personal Savings $_t$	-0.021	0.023	0.016	0.013	0.009
	(0.024)	(0.015)	(0.018)	(0.007)	(0.018)
Capital Gains $_t$	0.000	-0.003	0.001	0.007	-0.007
	(0.000)	(0.002)	(0.001)	(0.004)	(0.024)
Return $_t$	0.000	0.001	0.001	0.000	0.031*
	(0.000)	(0.002)	(0.001)	(0.002)	(0.010)
Flow $_t$	0.054***	0.014	0.033*	0.029	-0.008
	(0.009)	(0.009)	(0.013)	(0.017)	(0.003)
Flow $_{t-2}$	0.031*	0.033*	-0.001	-0.009	0.020
	(0.014)	(0.015)	(0.012)	(0.007)	(0.008)
Market Return $_t$	-0.059				-0.059
	(0.294)				(0.294)
Winter $_t$	0.062**	-0.003	-0.025	-0.109**	-0.122
	(0.022)	(0.058)	(0.021)	(0.033)	(0.167)
Spring $_t$	0.081	-0.016	-0.006	-0.128**	-0.065
	(0.050)	(0.064)	(0.022)	(0.031)	(0.070)
Fall $_t$	0.032	-0.025	-0.015	-0.060	-0.003
	(0.037)	(0.065)	(0.047)	(0.029)	(0.073)
5 Year Treasury $_t$		4.783***	-0.809	4.004**	0.378
		(0.717)	(1.498)	(1.303)	(1.674)
CPI $_t$		-3.247	-1.368	-0.490	6.132
		(5.768)	(4.620)	(3.617)	(3.480)
Observations	2,618	1,876	1,088	1,404	930
R-squared	0.162	0.121	0.213	0.312	0.143
Fund Fixed Effects	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes

Panel C: Total Inflows and Outflows						
	Equity		Government		Money Market	
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Outflows	Inflows	Outflows	Inflows	Outflows	Inflows
Attack $_t$	0.131**	-0.221*	0.120	0.345	-0.354	0.102
	(0.055)	(0.103)	(0.229)	(0.200)	(0.160)	(0.233)
Personal Savings $_t$	-0.108	-0.169**	-0.044	0.102**	-0.595**	-0.763
	(0.084)	(0.067)	(0.044)	(0.035)	(0.138)	(0.405)
Capital Gains $_t$	0.003**	-0.001	-0.028	-0.023	-0.672	-0.509*
	(0.001)	(0.002)	(0.042)	(0.042)	(0.325)	(0.145)
Return $_t$	-0.002	0.002*	0.006	0.033	0.285	0.400
	(0.001)	(0.001)	(0.029)	(0.032)	(0.136)	(0.198)
Flow $_t$	0.106	0.558***	0.267**	0.516***	0.048	-0.076
	(0.099)	(0.084)	(0.059)	(0.042)	(0.205)	(0.322)
Flow $_{t-2}$	-0.093*	0.050	0.095**	0.411***	0.193*	0.328
	(0.041)	(0.035)	(0.021)	(0.053)	(0.053)	(0.212)
Market Return $_t$	-2.666***	-3.408***				
	(0.739)	(0.967)				
Winter	0.407***	0.766***	0.321*	-0.089	-0.162	1.429
	(0.076)	(0.111)	(0.140)	(0.324)	(0.187)	(1.103)
Spring	0.089	0.347*	0.436	0.076	1.481	0.604
	(0.056)	(0.178)	(0.279)	(0.220)	(0.765)	(0.899)
Fall	0.193**	0.260**	0.587*	0.316	0.580	0.948
	(0.071)	(0.094)	(0.222)	(0.461)	(0.523)	(0.363)
5 Year Treasury $_t$			-0.099**	0.068	-0.120	0.103**
			(0.028)	(0.036)	(0.055)	(0.017)
CPI $_t$			-0.407**	-0.068	-1.433**	-2.012**
			(0.105)	(0.156)	(0.298)	(0.329)
Observations	2,618	2,618	1,404	1,404	940	940
R-squared	0.265	0.408	0.245	0.304	0.357	0.649
Fund Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

Table 3: Effect of Attack in Different Time Periods

This table contains fund fixed effects regressions using percent flow one month after an attack month for different time periods in our sample. The dependent variable is the percent flow into the fund in the month *t+1* following the attack month. Attack is a dummy variable that takes the value of 1 if the number of attacks in that month is greater than three times the average number of attacks per month over the past 12 months. We define the Cold War as the sample ending in 1992, Cold War – 9/11 period as all years between 1993 and 2001, and use years after the 9/11 attacks as the post 9/11 sample. All other control variables are defined the same way as table 2. Robust standard errors in parentheses *, **, and *** indicate significance at the 10%, 5%, and 1% level respectively.

	Equity			Gov't Bonds			Money Market		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
VARIABLES	Cold War	Cold War – 9/11	Post 9/11	Cold Wat	Cold War – 9/11	Post 9/11	Cold War	Cold War – 9/11	Post 9/11
Attack	-0.350	-0.527***	-0.257**	0.244*	0.234*	0.309*	0.566	0.952**	0.435
	(0.198)	(0.118)	(0.077)	(0.096)	(0.099)	(0.129)	(0.249)	(0.138)	(0.310)
Observations	701	954	963	1,191	1,202	1,203	285	318	321
R-squared	0.271	0.616	0.405	0.694	0.711	0.677	0.376	0.349	0.272
Number of style	9	9	9	5	5	5	3	3	3
Fund Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 4: Individual Fund Results

This table contains our main results using individual fund level data from CRSP. The dependent variable is the percent flow into the fund in the month *t+1* following the attack month. Expense ratio is the annual expense ratio reported by CRSP. Aggregate Flow is the total fund flows into all funds in the same category for that month. All other control variables are defined the same as in Table 2. Robust standard errors in parentheses *, **, and *** indicate significance at the 10%, 5%, and 1% level respectively.

VARIABLES	(1) Equity	(2) Bond	(3) Money Market
Attack $_t$	-0.384***	0.119***	0.530***
	(0.035)	(0.028)	(0.131)
Return $_t$	0.132***	0.155***	0.452
	(0.007)	(0.009)	(0.317)
Assets $_t$	-0.766***	-0.708***	-2.114***
	(0.032)	(0.034)	(0.128)
Expense Ratio $_t$	0.027	-0.285***	0.389
	(0.037)	(0.101)	(0.434)
S&P 500 $_t$	-0.097***		
	(0.007)		
Capital Gain $_t$	0.019***	0.020***	0.271***
	(0.002)	(0.004)	(0.076)
Savings $_t$	0.063***	-0.018	-0.161**
	(0.017)	(0.015)	(0.071)
Winter $_t$	0.182***	0.408***	1.060***
	(0.027)	(0.025)	(0.124)
Summer $_t$	-0.209***	0.191***	0.952***
	(0.025)	(0.023)	(0.122)
Fall $_t$	-0.278***	-0.168***	0.839***
	(0.028)	(0.030)	(0.151)
Past Year Avg. Return $_t$	0.220***	0.384***	0.474
	(0.012)	(0.032)	(0.874)
Flow $_t$	0.101***	0.079***	-0.146***
	(0.009)	(0.006)	(0.006)
Flow $_{t-2}$	0.074***	0.100***	0.000***
	(0.005)	(0.004)	(0.000)
Aggregate Flow $_t$	0.003*	0.004*	0.002*
	(0.002)	(0.002)	(0.001)
5 Year Treasury $_t$		0.059***	-0.016
		(0.008)	(0.030)
CPI $_t$		-0.097***	-0.581***
		(0.025)	(0.110)
Observations	605,584	482,770	141,653
R-squared	0.045	0.046	0.049
Number of Funds	6,423	4,950	1,549
Fund Fixed Effects	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes

Table 5: The Effect of Proximity and Saliency on Fund flows

In this table we examine the effect proximity and saliency of attacks has on flows into the funds. The dependent variable is the percent flow into the fund in the month *t+1* following the attack month. In Panel A we measure the proximity to each attack during a single "attack month" using the office location for each fund. We define a fund as a local fund if it is within 100 or 200 miles of at least one of the attacks. In Panel B we split our main attack variable into high and low word months. High word months are those attack months where the median number of words per news article is in the top 10% or 25% of attack months with at least one article in the New York Times, USA Today, Wall Street Journal or Washington Post. Low word months are those attack months with the median number of words per article in the bottom 90% or 25% of attack months or those attack months with no news mentions. All controls variables are the same as defined in Table 4. Robust standard errors in parentheses *, **, and *** indicate significance at the 10%, 5%, and 1% level respectively.

Panel A: Proximity				
	Equity		Bond	
	(1)	(2)	(3)	(4)
VARIABLES	100 mi.	200 mi.	100 mi.	200 mi.
Local Funds $_t$	-0.478***	-0.254***	0.320**	0.124
	(0.147)	(0.077)	(0.150)	(0.102)
Non-Local Funds $_t$	-0.296***	-0.300***	0.047	0.073
	(0.042)	(0.044)	(0.051)	(0.052)
Observations	397,034	397,034	148,071	148,071
R-squared	0.037	0.037	0.052	0.052
Number of Funds	5,811	5,811	1,698	1,698
Fund Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes

Panel B: Saliency				
	Equity		Bond	
	(1)	(2)	(3)	(4)
VARIABLES	Top 10%	Top 25%	Top 10%	Top 25%
High Coverage $_t$	-0.609***	-0.834***	1.049***	0.241***
	(0.119)	(0.101)	(0.134)	(0.073)
Low Coverage $_t$	-0.373***	-0.330***	0.074**	0.102***
	(0.035)	(0.034)	(0.029)	(0.030)
Observations	605,584	605,584	482,770	482,770
R-squared	0.052	0.052	0.046	0.046
Number of Funds	6,423	6,423	4,950	4,950
Fund Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes

Table 6: Effect of Attack across Fund Type

In this table we examine the effect of the attack on flows across different fund types. The dependent variable is the percent flow into the fund in the month *t+1* following the attack month. Attack is a dummy variable that takes the value of one if the number of attacks in that month is greater than three times the average number of attacks per month over the past 12 months. In Columns 1 and 2 we examine how flows into retail and institutional level share classes differ. We use the CRSP institutional fund flag to define the Institutional dummy. In Columns 3 and 4 we examine foreign vs domestic funds. We identify funds as foreign based on CRSP objective codes. All other control variables are defined the same as in Table 4. Robust standard errors in parentheses *, **, and *** indicate significance at the 10%, 5%, and 1% level respectively.

VARIABLES	(1) Equity	(2) Bond	(3) Equity	(4) Bond
Attack $_t$	-0.237***	0.230***	-0.341***	0.115***
	(0.033)	(0.040)	(0.038)	(0.029)
Attack * Institutional $_t$	0.269***	0.066		
	(0.071)	(0.110)		
Attack * Foreign $_t$			-0.228***	0.078
			(0.076)	(0.140)
Observations	1,416,084	829,891	605,584	482,770
R-squared	0.041	0.033	0.052	0.046
Number of Fund Share Classes	21,247	9.765	6,423	4,950
Fund Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes

Table 7: Terrorists Attacks and Fund Beta

In this table we examine how fund flows after attacks differ for funds that have generated different level market Betas over the 36 months prior to the attack month. To calculate fund market betas, we run 36 month rolling regressions based on the one-factor, Fama-French three-factor and Fama-French three-factor plus momentum models. We define High Beta funds as the funds with a beta in the top 25% of all funds in that month and Low Beta funds as those in the bottom 25% of all funds in that month. The dependent variable is the percent flow into the fund in the month t+1 following the attack month. All other control variables are defined the same as in Table 4. Robust standard errors in parentheses *, **, and *** indicate significance at the 10%, 5%, and 1% level respectively.

VARIABLES	(1) 1 Factor Beta	(2) 3 Factor Beta	(3) 4 Factor Beta
Attack $_t$	-0.261***	-0.279***	-0.290***
	(0.041)	(0.040)	(0.039)
High Beta $_t$	-0.058	-0.160***	-0.175***
	(0.045)	(0.041)	(0.040)
Low Beta $_t$	0.168***	0.217***	0.241***
	(0.046)	(0.044)	(0.043)
High Beta * Attack $_t$	-0.327***	-0.194**	-0.175**
	(0.081)	(0.082)	(0.081)
Low Beta * Attack $_t$	-0.054	-0.114	-0.087
	(0.079)	(0.079)	(0.081)
Observations	461,983	461,983	461,983
R-squared	0.047	0.047	0.047
Number of Funds	5,371	5,371	5,371
Fund Fixed Effects	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes
Controls	Yes	Yes	Yes

Table 8: Effect of Attacks across Fund Style

In this table we examine the effect of the attack on flows across different fund styles. The dependent variable is the percent flow into the fund in the month *t+1* following the attack month. Attack is a dummy variable that takes the value of one if the number of attacks in that month is greater than three times the average number of attacks per month over the past 12 months. In Columns 1-3 we examine equity funds that differ in terms of the capitalizations of the stocks they hold in their portfolio. Funds are assigned to small, mid or large cap. In Columns 4-6 we classify funds as growth, growth and income, income. In Columns 7-9 we classify bond funds as government, municipal and corporate. Funds are assigned based on their CRSP objective codes. All other control variables are the same as Table 4. Robust standard errors in parentheses *, **, and *** indicate significance at the 10%, 5%, and 1% level respectively.

	Capitalization			Equity Style			Bond Style		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
VARIABLES	Small	Mid	Large	Growth	Growth and Income	Income	Gov't	Muni	Corp
Attack $_t$	-0.446***	-0.641***	-0.144	-0.375***	-0.279***	-0.182	0.651***	0.044	-0.018
	(0.081)	(0.134)	(0.162)	(0.050)	(0.061)	(0.170)	(0.1467	(0.030)	(0.331)
Observations	73,067	40,450	8,717	196,898	84,343	13,880	23,369	173,591	3,380
R-squared	0.073	0.072	0.037	0.064	0.074	0.108	0.057	0.066	0.057
Number of Funds	820	530	94	2,405	1,053	224	352	1,528	98
Fund Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 9: Investor Market Outlook

In this table we examine the change in investors future market outlook following a spike in attacks. In Column 1 the dependent variable is the percentage of newsletters classified as "bearish" by Investor Intelligence. Column 2 uses the "bullish percent" minus "bearish percent" from the Investor Intelligence as the dependent variable. Columns 3 and 4 use the institutional investor's and individual investor's response from the Yale Stock Market Confidence Index as the dependent variable, respectively. Column 5 uses the mean response to the question "How likely do you think it is that the market will increase over the next year?" from the University of Michigan Survey of Consumers as the dependent variable. All dependent variables are in month *t+1* following an attack month. All other control variables are defined the same as in Table 2. Robust standard errors in parentheses *, **, and *** indicate significance at the 10%, 5%, and 1% level respectively.

VARIABLES	(1) Bearish %	(2) Bullish % - Bearish %	(3) Yale Survey Institutional	(4) Yale Survey Individual	(5) Univ. of Michigan Survey
Attack $_t$	0.806	-2.480	-0.951	0.295	0.539
	(0.773)	(1.626)	(0.626)	(0.603)	(0.931)
S&P 500 $_t$	-56.733***	101.236***	-3.791	3.100	31.786***
	(4.724)	(9.832)	(3.844)	(4.118)	(6.304)
Winter $_t$	-0.614	0.438	1.234**	-0.120	-0.106
	(0.626)	(1.357)	(0.618)	(0.470)	(0.842)
Spring $_t$	-0.081	-1.231	0.314	-0.815*	0.197
	(0.538)	(1.175)	(0.604)	(0.433)	(0.735)
Summer $_t$	0.742	-1.728	-0.927*	-0.624	0.428
	(0.577)	(1.239)	(0.504)	(0.422)	(0.695)
Market Outlook $_t$	0.600***	0.455***	0.737***	0.709***	0.541***
	(0.042)	(0.042)	(0.066)	(0.093)	(0.085)
5 Year Treasury $_t$	-48.245***	93.218***	-12.733	-2.406	5.138
	(15.121)	(30.882)	(15.720)	(11.441)	(21.278)
CPI $_t$	24.075	-63.839	9.549	0.428	-113.559*
	(76.764)	(149.105)	(54.964)	(40.364)	(66.084)
Observations	479	479	113	113	102
R-squared	0.852	0.779	0.848	0.945	0.862
Year FE	Yes	Yes	Yes	Yes	Yes

Table 10: Industry Correlation Results

In this table we examine how flows into equity funds that are highly correlated with certain Fama-French 48 industries reaction after attacks. The dependent variable is the percent flow into the fund in the month *t+1* following the attack month. Attack is a dummy variable that takes the value of one if the number of attacks in that month is greater than three times the average number of attacks per month over the past 12 months. We run 36-month rolling regressions against the FF 48 industry returns for the transportation, defense, insurance and bank industries and denote the funds in the top 10% of betas for each month as high correlation. Any fund that is classified as a high correlation fund for one industry is excluded from the regressions for the other three industries. All other control variables are defined the same as in Table 4. Robust standard errors in parentheses *, **, and *** indicate significance at the 10%, 5%, and 1% level respectively.

VARIABLES	(1) Transportation	(2) Defense	(3) Insurance	(4) Banks
Attack $_t$	-0.335***	-0.409***	-0.409***	-0.407***
	(0.034)	(0.035)	(0.035)	(0.035)
High Transportation*Attack $_t$	-0.817***			
	(0.209)			
High Transportation $_t$	-0.070			
	(0.085)			
High Defense*Attack $_t$		-0.098		
		(0.184)		
High Defense $_t$		0.009		
		(0.062)		
High Insurance*attack $_t$			-0.299	
			(0.197)	
High Insurance $_t$			-0.149*	
			(0.082)	
High Banks * Attack $_t$				0.019
				(0.314)
High Banks $_t$				-0.047
				(0.083)
Observations	492,819	505,008	490,542	490,368
R-squared	0.053	0.060	0.061	0.060
Number of Funds	6,315	6,303	6,302	6,309
Fund Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes

Table 11: Flow Persistence after the Attack

In this table we replicate the results from Table 4 but use fund flows from 2 and 3 months after the attack. The dependent variable is the percent flow into the fund in the month *t+2* and *t+3* following the attack month. Attack is a dummy variable that takes the value of one if the number of attacks in that month is greater than three times the average number of attacks per month over the past 12 months. Control variables are the same as Table 4. Robust standard errors in parentheses *, **, and *** indicate significance at the 10%, 5%, and 1% level respectively.

	Equity		Bond		Money Market	
	(1)	(2)	(4)	(5)	(7)	(8)
VARIABLES	+ 2	+ 3	+ 2	+ 3	+ 2	+ 3
Attack $_t$	-0.060	0.355***	-0.135***	-0.027	0.349*	-0.165
	(0.049)	(0.053)	(0.031)	(0.032)	(0.205)	(0.185)
Observations	353,863	353,549	420,235	418,734	93,434	94,101
R-squared	0.045	0.046	0.042	0.042	0.039	0.052
Number of Funds	6,225	6,219	4,912	4,911	1,546	1,547
Fund Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes

Table 12: Attack and Future Fund Returns

In this table we examine the effect that attack driven flows have on future fund performance. The dependent variable is the benchmark-adjusted fund return in month t+1, where the attack month is defined in month t-1. The variable Flow Rank is a rank variable that assigns the decile rank based on flows of each fund in month t. The funds with the lowest flows in the month receive a rank of 10 and the funds with the highest flows in the month is given a rank of 1. Fund Age is the fund age in years. Fund Turnover Ratio is the turnover ratio for the fund provided by CRSP. All other control variables are defined the same as in table 4. Robust standard errors in parentheses *, **, and *** indicate significance at the 10%, 5%, and 1% level respectively.

VARIABLES	(1)	(2)	(3)
Flow Rank $_t$ * Attack $_{t-1}$			-0.025***
			(0.006)
Attack $_{t-1}$	-0.197***	-0.215***	-0.078**
	(0.009)	(0.009)	(0.034)
Flow Rank $_t$	0.029***	0.027***	0.029***
	(0.003)	(0.003)	(0.003)
Expense Ratio $_t$	-2.164*	-3.281*	-3.280*
	(1.108)	(1.901)	(1.902)
Fund Age $_t$	-0.083***	-0.019	-0.020
	(0.012)	(0.012)	(0.012)
Fund Turnover Ratio $_t$	-0.036***	-0.038***	-0.038***
	(0.008)	(0.009)	(0.009)
SP 500 $_{t-1}$	-14.906***	0.703	0.731
	(0.077)	(0.653)	(0.653)
Assets	-0.058***	-0.064***	-0.064***
	(0.004)	(0.005)	(0.005)
Return $_t$		-0.021***	-0.021***
		(0.002)	(0.002)
Return $_{t-1}$		-0.171***	-0.172***
		(0.007)	(0.007)
Return $_{t-2}$		-0.469***	-0.456***
		(0.093)	(0.093)
Constant	9.008***	-0.763***	-0.782***
	(0.079)	(0.225)	(0.225)
Observations	313,443	309,708	309,708
R-squared	0.186	0.188	0.188
Number of Funds	3,153	3,122	3,122
Fund Fixed Effects	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes

Table 13: Excluding Large Attacks

This table replicated the results in Table 4 using a reduced sample of attacks. The dependent variable is the percent flow into the fund in the month *t+1* following the attack month. Attack is a dummy variable that takes the value of one if the number of attacks in that month is greater than three times the average number of attacks per month over the past 12 months. In Panel A we rank all attack months based on the number of casualties and drop the attacks in the highest 5%. Panel B includes all months and 9/11. All other control variables are defined the same as in Table 4. Robust standard errors in parentheses *, **, and *** indicate significance at the 10%, 5%, and 1% level respectively.

Panel A: Number of Casualties			
	(1)	(2)	(3)
VARIABLES	Equity	Bond	Money Market
Attack $_t$	-0.407***	0.150***	0.558***
	(0.035)	(0.028)	(0.131)
Observations	590,692	472,201	139,132
R-squared	0.053	0.045	0.049
Number of Funds	6,423	4,950	1,549
Fund Fixed Effects	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes
Controls	Yes	Yes	Yes

Panel B: Include 9/11			
	(1)	(2)	(3)
VARIABLES	Equity	Bond	Money Market
Attack $_t$	-0.265***	0.149***	0.450***
	(0.032)	(0.027)	(0.120)
Observations	611,350	487,152	143,145
R-squared	0.058	0.046	0.049
Number of Funds	6,423	4,950	1,549
Fund Fixed Effects	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes
Controls	Yes	Yes	Yes