THREE ESSAYS IN BEHAVIORAL FINANCE

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ABSTRACT

Over the last two decades, there has been a significant increase in research related to behavioral finance. As Barberis and Thaler (2002) point out, there are two main aspect of behavioral finance: limits to arbitrage and the effects of psychology. My dissertation will focus on the second aspect, the effects of psychology on individual investor behavior.

The *first essay* examines an important question in this behavioral finance literature: changes in aggregate risk aversion. I use changes in the level of terrorism in the United States as a shock to the aggregate mood of American investors, and examine changes in flows to mutual funds as a proxy for investor risk preferences. After examining investors vulnerable to changes in mood after attacks, and ruling out any possible effect due to changes in expect risk, and changes to expected returns, the *first essay* concludes that mood driven risk aversion is the likely cause of the change in behavior.

In the *second essay,* we use the insights gained from *Essay 1* regarding the change in behavior of U.S. investors following an increase in terrorist attacks. Using household level of equity market participation and individual trading data the *second essay* examines the array of decisions investors make. The *second essay* finds that households participate less in equity markets, trade less, but purchase more local stocks in response to terrorist attacks. Additionally, this change in behavior is especially apparent in households where the designated head is a male.

Finally, in the *third essay* we turn away from terrorism, and examine the effects that local NFL team performance on equity market participation. Examining the most popular spectator sport in the U.S. the *third essay* shows that poor performance by local NFL teams correlates with

fewer households in that state owning equity. While previous studies argue that sentiment is the driver of sports related behavior, the *third essay* find that gambling losses may also play a role in the drop in equity market participation following seasons with a low number of wins.

Taken together, the dissertation demonstrates the importance of examining external shocks and the effect they have on the behavior of investors. From terrorism to something as seemingly benign as the NFL, the dissertation adds to the behavior finance literature by identifying new shocks that effect the investing behavior of individuals.

DEDICATION

This dissertation is dedicated to my parents, Jim and Terry Young. They have always supported me and I will be forever thankful for all they have done to help me achieve my goals.

LIST OF ABBREVIATIONS AND SYMBOLS

BEA	Bureau of Economic Analysis
CEO	Cheif Executive Officer
CRSP	Center for Reserach in Security Prices
CPI	Consumer Price Index
et al.	Et alia (and others)
GTD	Global Terrorism Database
G8	Group of Eight
ICI	Investment Company Institute
ITERATE	International Terrorism: Attribution of Terrorist Events
i.e.	id est (that is)
NFL	National Football League
PSID	Panel Study of Income Dynamics
PTSD	Post Traumatic Stress Disorder
SAD	Seasonal Affective Disorder
WRDS	Wharton Research Data Services
VIX	Chicago Board Options Exchange Volatility Index

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TERRORIST ATTACKS AND INVESTOR RISK PREFERENCE: EVIDENCE FROM MUTUAL FUND FLOWS

INTRODUCTION

Is risk aversion time varying? If we link changes in risk aversion to changes in discount rates, Cochrane (2011) summarizes the importance of this question by arguing that discount rate variation is the central ingredient of the current asset pricing literature. However, there is limited direct evidence for large fluctuations in aggregate risk aversion, which is required for most asset pricing models. Using terrorism in the United States as a non-economic shock to retail investors, the goal of this paper is to gain further insight into the causes of short-term fluctuations in risk aversion. The immediate emotional fallout of terrorism includes anxiety, fear, and depression, all of which can cause changes in risk aversion.[1]

We use mutual fund flows, and specifically the flows to equity funds and government bond funds, as proxies for aggregate investor risk preferences. As retail investors hold 89% of the nearly $16 trillion in mutual fund assets (ICI Fact Book, 2017, Figure 2.3), mutual fund flows predominantly reflect their asset allocations. We believe flows are a true representation of demand for these funds because there is no direct mechanism for arbitrageurs to counter the

[1] Kuhnen and Knutson (2008) show that negative images lead individuals to be more likely to choose a guaranteed payoff when given the choice of a risky asset. Carton et al. (1992) find that people with depression exhibit lower sensation seeking (akin to risk taking) when matched based on age and gender to those without depression. Wong and Carducci (1991) conclude that higher sensation seeking leads households to make more risky everyday household finance decisions (buying stocks, bonds, balance in a bank account, car insurance etc.)

trades (i.e. there is no short selling in mutual funds). Thus, changes in investor risk preference and their investment decisions will likely be apparent in these flows (Kamstra et al., 2015).

Our proxy of retail investor risk preference through mutual fund flows is more direct evidence than prior studies based on stock market returns. Aggregate stock prices adjust to temporary supply versus demand conditions, making the reason for buying or selling difficult to determine. With respect to demand, the possibility of price pressure from institutional traders, trading in the opposite direction of individuals following attacks, adds to the difficulty of isolating the true effect on prices. Additionally, aggregate prices are influence by short-term changes in liquidity, while the "price" for a mutual fund is held constant and any shock in demand for risky assets shows up in volume (flows)

Terrorism has far-reaching impacts on America's collective sense of security. The ongoing risk has changed everything from defense and immigration policy, to an awareness of homegrown terrorism and the heightened sense of personal safety in a crowd. In economics and finance, researchers have mainly focused on the response to the largest individual attacks by financial markets and macroeconomic factors, including government and private investment, as well as personal consumption.[2] Much less work to date has examined how the aggregation of attacks, or the level of terrorism nationally affects individual investors in terms of their risk preferences and subsequent investment decisions.

From 1984 to 2010, we find strong evidence that the level of terrorist activity in the United States correlates with aggregate investor risk preference, and causes significant drops in

[2] Arin et al. (2001) examine the effects of terrorism on six different global financial markets. Chesney et al. (2011) examine the effects of terrorist attacks on global financial markets and certain industries. Eckstein et al. (2004) look at the effect on the Israeli economy, as do Llussá et al. (2011).

investor demand for risky funds. We use the number of attacks each month[3] as our measure of terrorism because a single large attack may been seen by investors as random and have only an isolated effect. Whereas a nationwide increase in attacks, over the course of a month, is likely to be seen as a larger trend and create fear in a much larger proportion of the population. Applying aggregate mutual fund data from the Investment Company Institute (ICI), we find that a one standard deviation increase in the level of terrorism (the equivalent of going from one attack to three in a month) leads to a 5.10 basis-point (or 7.05%) drop in aggregate equity fund flows, and a 5.01 basis-point (or 10.32%) increase in aggregate government bond fund flows. In 2010 dollars, this equates to a $75.09 million drop in aggregate equity fund flows and a $56.81 million increase in aggregate flows to government bond funds, per month. Further, using net exchanges of funds, as a more direct measure of sentiment and short-term investment decisions (Ben-Rephael et al. (2012)), we find that investors are moving money directly out of equity funds and into government bond funds within the same fund families.

Using mutual fund data from the Center for Research in Securities Prices (CRSP), we find that the aggregate results hold at the individual fund level. Following a one standard deviation increase in the level of terrorism, the average equity mutual fund faces a drop in flows of $197,000 while the average bond fund experiences an increase in flows of $155,000, in 2010 dollars. Consistent with the transient nature of depressive moods following attacks, as discussed in Schlenger et al. (2002), we find a reversal in flows for equity funds in the second month after the increase in terrorism, and in the third month for government bond funds.

[3] The number of attacks has been previously used by Drakos (2010) and Llussá and Tavares (2008). Similarly, Giannetti and Wang (2016) use the number of corporate fraud revelations in their study of corporate fraud and stock market participation.

If emotional changes, post-traumatic stress disorder (PTSD), and depression-like symptoms are the cause of changing risk aversion, it is reasonable to assume that investors more likely to experience these symptoms will exhibit larger changes in investing behavior. Galea et al. (2002) find that those who lived closest to ground zero reported higher rates of PTSD or symptoms of depression following 9/11. Schlenger et al. (2002) survey individuals in New York City, Washington DC, and other major US cities, and find slightly higher levels of "clinically significant distress" in these areas relative to smaller US cities. Consistent with the idea that investors living in the area of an attack and other major cities are more likely to experience PTSD-like symptoms, we find that our results at the aggregate level are concentrated in individuals most likely to experience psychological distress. Importantly, we also find that investors unlikely to experience a change in mood, those living in small cities far away from the attacks, do not exhibit a significant change in behavior.

Individual investors' responses to terrorism also depends on the share class, risk characteristics, and investment styles of the funds. Flows to institutional and retirement share classes are unresponsive to transitory changes in investor risk preference. Equity funds with more exposure to systematic risk, as measured by fund market beta, experience a significantly larger drop in flows. Investors prefer large-capitalization equity funds to small- and mid-cap funds. Similarly, flows into growth funds are much lower than into income funds. Government and municipal bond funds receive significantly more flows than do corporate funds. These beta and style results further confirm the main results of this study by showing that the changing risk preferences of mutual fund investors cause changes in demand in the cross section of equity and bond funds.

Once we have established a decrease in demand for risky mutual funds following an increase in terrorism, we focus on isolating the risk aversion channel by examining alternate channels that could cause a change in flows. First, we look to see if our initial results are due to investors updating their views on future market risk. To proxy for changing views on future market volatility, we calculate the average daily level of the VIX for each month in our sample and measure the change in the average daily VIX level during the month of an increase in terrorist activity. Additional tests determine whether investors are responding to a change in realized standard deviation or higher moments (skewness or kurtosis) of daily S&P 500 returns. Finally, we use the Yale Crash Risk Index to proxy for investors' views on future tail risk. Insignificant changes to each of these lead us to believe that emotionally driven risk aversion, rather than perceptions of market risk, is most likely responsible for the main results at the aggregate level. While there is always a possibility that the surge in risk aversion is driven by the change in the perceived probability of an extreme negative stock market realization,[4] our evidence is consistent with Bharath and Cho (2014) and Kaplanski et al. (2015) finding that in most cases, sentiment does not affect an individuals' expectations of risk.

We next look into the possibility that expectations of reduced cash flows/profitability, or lower future stock returns (so called wealth effect) cause the change in investor behavior. First, we examine the relationships between terrorism and corporate investment, and personal consumption. Our findings show that the rate of total corporate investment, including investment into R&D and equipment, is unaffected by the level of terrorism. In contrast, and consistent with risk shifting in mutual fund flows, individuals' consumption of durable goods drops following

[4] To perfectly rule out that possibility, one would need a laboratory experiment that the distribution of the stock returns is given. However, the problem with laboratory experiment is that it is impossible to generate a shock that is similar to those experienced in real life.

attacks, while non-durable goods consumption remains unaffected. Second, using consumer sentiment surveys[5] we show that retail investors do not significantly change their short- or long-term expectations of economic and financial performance. Finally, in the wake of terrorist attacks outside the United States, U.S. investors reduce their holdings of domestic equity funds. This result is the opposite of what we expect to see if investors are concerned about future returns of the equity markets in the country where the attacks took place.

We conduct a number of robustness checks that include different econometric specifications, additional sample selection criteria, and alternative definitions of attacks. We include fund-style fixed effects to test for possible unexplained heterogeneity in different assets classes and time-varying demand shocks. To further test the robustness of the attack variable, we create rank variables and attack month dummy variables to ensure that the design of our terrorism variable is not driving our main results. Lastly, we use an alternate sample of attacks and school shootings taken from Antoniou et al., 2016. In all alternate specifications of attack variables, results are consistent with the main findings.

Given our use of a non-economic shock, and fund flows as a proxy for risk aversion, the most similar study to ours is Kamstra et al. (2017). Kamstra et al. extend the study of SAD and the stock market (Kamstra et al., 2003) and find that its onset correlates with a shift of aggregate mutual fund flows, from risky equity funds to safer money market funds. This paper complements those earlier studies in two important ways. First, seasonal mood changes are largely predictable—unlike terrorist attacks, which appear to the victims as random. Second, SAD correlates with changes in fund flows, as well as changes in aggregate stock returns and expectation of returns. Studies by Kaplanski et al. (2015) and Barath, and Cho (2014) find that

[5] Consumer survey data is taken from the Investors Intelligence; the University of Michigan Survey of Consumers; and the Stock Market Confidence Indices from Yale University

Season Affective Disorder (SAD) and natural disasters, respectively, significantly affect expectations of future returns. Using tests of consumer sentiment surveys and foreign vs domestic flows we separate our study by showing that aggregate risk aversion can vary independent of a change in the expectations of returns. Using survey data, Guiso et al. (2017) find that investors' risk aversion increases following the 2008 financial crisis, even for those who did not suffer any financial loss. Our results combined with those in Guiso et al. (2017) provide important empirical evidence for most asset-pricing models, which require large fluctuations in aggregate risk aversion (Campbell and Cochrane, 1999).

The primary focus of this paper is time variation in risk aversion triggered by terrorism. However, the study of a topic as significant as terrorism presents an important addition to the understanding of investor behavior, in and of itself. As Waxman (2011) notes, terrorist attacks have changed the way we live and travel, making terrorism an important issue in our social and political conversations.[6] This paper extends on previous studies by showing that all terrorist activity, not only major events, have economic consequences.

The reminder of this paper proceeds as follows: Section 2 reviews the literature and lays out our hypotheses. Section 3 describes the data and methodology. Section 4 presents our main results. Section 5 identifies the channels through which risk preference is changing. Section 6 discusses the possibility of wealth effect following terrorist attacks. Section 7 contains robustness checks, and Section 8 concludes.

[6] In a recent survey by the Pew Research Center, 80% of voters registered for the 2016 presidential election said that terrorism is "very important" to their vote; this was second only to the economy (Pew Research Center, July, 2016)

LITERATURE REVIEW: THE LINK BETWEEN TERRORISM AND MUTUAL FUND FLOWS

The generally accepted definition of terrorism is violence that strikes without warning and targets innocent civilian populations for the purpose of intimidation or coercion for political or social ends. It is a form of psychological warfare. As Mathewson (2004) notes, terrorists strike to “immobilize” populations through extreme fear and anxiety as an unseen, hovering existential threat.

The prevalence of post-attack depression and PTSD symptoms is well documented in the psychological literature. Hobfoll et al. (2006) survey hundreds of Israeli and Palestinian citizens of Israel and show that exposure to terrorism, especially close exposure, correlates significantly with a higher probability of PTSD and depression. Galea et al. (2002) study the psychological effects among residents below 110th Street in Manhattan in the months after 9/11, and find a similar increase in PTSD among people living closest to ground zero.

The extant literature on terrorism and depressive moods in the U.S. focuses mostly on the largest attacks, specifically 9/11. Hobfoll et al. (2006) studies citizens of Israel, which because of cultural differences and the nature of terrorism in that part of the world, may respond to terrorism differently. To supplement psychological studies on terrorism we can use studies on negative images to create a similar link between depressive moods, risk aversion and terrorism. Kuhnen and Knutson (2008) and Guiso, Sapienza and Zingales (2017) both find a link between negative images and increases in individual risk aversion. In Kuhnen and Knutson’s study, subjects 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. Guiso et al. use scenes from a horror movie and find similar results. If we assume that images and stories about terrorism are negative, then we can use these studies to compliment those directly examining terrorism to provide a link between terrorist activity, psychological distress, and risk aversion.

It is important to identify and acknowledge the emotional toll terrorism inflicts, it is equally important to note that most people exhibit resilience to long-term effects. Shalev et al. (1998) study people admitted to emergency rooms for trauma and find that a significant percentage of the patients see a reduction in symptoms four months later. With respect to terrorist attacks, Schlenger et al. (2002) find that in the second month after 9/11, the level of psychological distress nationally was inside historical norms.

Existing psychological literature provides ample evidence linking depressive moods to increased risk aversion. Carton et al. (1992) find that depressed subjects exhibit significantly lower sensation-seeking scores than a matched control group (sensation seeking is similar to risk aversion in that people who score high in sensation seeking may receive higher utility from riskier activities). Wong and Carducci (1991) and Horvath and Zuckerman (1993) explore the link between sensation seeking and everyday financial decisions, and find that high-sensation seekers make riskier household finance decisions.[7] In related studies examining the relationship between weather and risk preferences, Bassi et al. (2013) and Saunders (1993) show that poor weather conditions and less jovial moods correlate with lower risk tolerance, and that sunlight and fair weather have positive effects on risk-taking behavior. The wealth of evidence suggests that individuals experiencing depressive moods exhibit an increase in risk aversion.

A perception of heightened risk could also prompt an increase in the appetite for financial risk. Bernile et al. (2017) show that CEOs who in early life likely experienced natural disasters resulting in high or extreme fatalities tend to lead their firms more aggressively than do CEOs

[7] Financial decisions that subjects have to make range from investing in stocks, bonds, or CDs to determining if there are sufficient funds in a bank account and buying car insurance.

who likely experienced natural disasters resulting in low to moderate fatalities. This is perhaps because of an organic "co-opting," as Futuyma (1998) suggests, in which trauma alters certain brain functions, making it necessary to "co-opt" other parts of the brain to perform those functions for survival. Thus, the survivors of terrorist attacks may exhibit an increase in risk preferences.

Terrorist attacks can also trigger investor concern about risks to global economic activity and corporate earnings, weakening equity markets, and widening high-yield bond spreads. Investors may decide to hold less risky portfolios if they believe stock market volatility relates positively to terrorism. If they perceive a greater risk of more attacks, this will likely amplify their concerns about near-term economic outlook and downside risk. After 9/11, there was a sharp increase in global equity 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 increased demand for liquid and less risky assets (Choudhry, 2005). Using evidence from six different financial markets, Arin et al. (2008) show that terror has a significant albeit short-term impact on both stock market and the stock market volatility.

On the other hand, the change of investor risk preferences after attacks may be driven by a much more proximal wealth effect, be it personal, corporate, or industrywide. Karolyi and Martell (2006) examine 75 terrorist attacks on 45 public US and foreign firms between 1995 and 2002, and find that on average the firms lose $410 million per terrorist attack. Pool et al. (2014) use county assessor records to study the home values of 737 managers of US domestic equity funds and conclude that when managers experience idiosyncratic shocks to their personal wealth, they are more likely to lower the risk profiles of the funds they manage. Moving into safer holdings is one of ways they do this. In Section 6, we test for this wealth effect in our fund flows of individual investors, to determine if it is a factor in our results.

Using these previous studies as our guide, we hypothesize that in the month following an increase in the level of terrorism, depressed or fearful individuals become less risk tolerant, leading to a short-term increase in risk aversion. In the context of investing in mutual funds, we also hypothesis that flows into riskier mutual fund classes (i.e., equity funds) will decrease and that flows into safer fund classes (i.e., bond funds) will increase.

DATA AND METHODOLOGY

Many of the previous studies on terrorism focus on a small sample of major attacks. As our focus is a comprehensive assessment of terrorism's effects on individual investors, we feel that using a larger set of salient events better captures the effect of aggregate levels of terrorism on retail investors. Thus, our measure of terrorism includes more attacks, and a longer period. We rely on Enders et al. (2011), who use the University of Maryland's Global Terrorism Database (GTD) and the International Terrorism: Attributes of Terrorist Events (ITERATE) database, to define our initial sample of attacks. The Enders data go back to 1970, but we begin our measure in January 1984, when the Investment Company Institute starts its mutual fund coverage. This gives us 460 attacks from January 1984 to December 2010.

We then apply a filter to the sample to check for news coverage of each event. We use the global news database Factiva to search for local and national media coverage of the 460 attacks in the weeks following their occurrence. We drop any attacks that do not result in casualties, including loss of life, and any attacks that do not receive press coverage. From the original sample of 460 attacks, the filter removes 51, leaving 409 attacks that for the final sample from 1984 to 2010.

Next we take the natural log of 1 plus the number of attacks in each month to create a time-series continuous variable of terrorist attacks. Because the number of attacks in each month has a lower bound of zero, we take the natural logarithm to remove the skewness of the attack variable. We use the number of attacks as the measurement of terrorism because our goal is to measure the response to a national increase in terrorism, rather than the responses to individual attacks. Individual attacks may be isolated incidents, but a nationwide increase in the number of attacks is likely to affect a much larger population as investors see that the terrorism is widespread. Using the number of attacks is not new to the terrorism literature, and other areas of the finance literature use a similar methodology.

Llussá and Tavares (2008) show that the number of attacks has a larger effect on consumption and investment than does the number of casualties. With respect to the market response to terrorism, Drakos (2010) uses attacks of all sizes and finds that globally, there is a drop in national markets on the day of an attack. In addition to using all attacks, Drakos finds that even events described as having “minor” psychosocial effects cause a significant drop in market returns. When examining events that have moderate and major psychosocial effects, the paper finds mixed results. Moderate events have no significant effect on prices, but major events do cause a significant drop. This is evidence that both, “smaller” events can have significant impacts on behavior, and that estimating the expected reaction to attacks of different sizes is extremely difficult. Thus, we include these “smaller” events because we focus on the level of terrorist activity, and these events have proven to cause significant shifts in behavior.

More recently, and in a study unrelated to terrorism, Giannetti and Wang (2016) use a similar methodology to measure the effect that trust, through corporate scandals, has on stock market participation. As with our measure of terrorism, they use the number of corporate fraud cases revealed in a state as the variable of interest, rather than focusing on the largest or using some measure of size. Much like they show that the number of fraud cases in a state affects trust, we argue that the number of terrorist attacks is more likely to increase the anxiety, fear, and depression that lead to an increase in risk aversion. In Section 7, the robustness section, we show that the results are qualitatively similar regarding an alternative definition of terrorism, including the use of large attacks and school shootings.

For our initial tests, we use the ICI database to test the results on aggregate equity and bond fund flows. The ICI database defines 33 mutual fund style categories and reports flow data on a monthly basis going back to 1984. Monthly data for each fund style consists of total net assets, new sales, redemptions, exchanges in, and exchanges out; the data are aggregates from all individual mutual funds in each style category. We then create a net flows variable for each fund style in each month as the net of inflows and outflows of the same fund style divided by lagged total net assets:

$$Net\ Flows_{i,t} = \frac{New\ Sales_{i,t} - Redemptions_{i,t} + \ Exchanges\ In_{i,t} - Exchanges\ Out_{i,t}}{Total\ Net\ Assets_{i,t-1}}$$

The ICI defines "exchanges" as transfers from one style of fund to a different style of fund within the same fund family. Thus, we can examine not only the change in overall net flows but also the sources of the inflows and the destination of the outflows. Following Kamstra et al. (2017), we 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 lower-risk classes of funds. We create a net exchange variable by subtracting exchanges out of the fund style from exchanges into the fund style in month *t*, divided by lagged total net assets:

$$Net\ Exchanges_{i,t} = \frac{Exchanges\ In_{i,t} - Exchanges\ Out_{i,t}}{Total\ Net\ Assets_{i,t-1}}$$

Once we create our net flow and net exchange variables, we follow the groupings used in Kamstra et al. (2017) to build our four asset classes of funds—equity, corporate bonds, municipal bonds, and government bonds—that we will use as separate fund groups to run our main regressions. We use all equity funds in our equity class of funds. Corporate bonds include foreign and domestic corporate bonds. For municipal and government bonds, we use non-taxable government money market funds as a means to include all government securities in the same grouping. To control for heterogeneity in fund styles, we run fund-style and year fixed-effect regressions with style level controls, as well as other macroeconomic variables.

For both, the net flows and net exchanges variable, we measure the change in the month *t+1*, while the terrorism variable is measured in month *t*. Previous studies examining the stock market response to individual attacks have historically tested the response to attacks on the day of attacks. Because our fund flows are only available monthly, and we are focused on the response to an increase in the level of terrorism over the previous month, rather than the response to an individual attack, we use flows in month *t+1* rather than contemporaneously in month *t.* In robustness tests, we find that fund flows are responsive to large attacks contemporaneously, but that the effect does not carry over to month *t+1*.

To capture fund characteristics pertaining to fund flows, we turn to fund-level analysis, using CRSP mutual fund data. Because the CRSP mutual fund database is organized at the fund share class level, we first aggregate to the fund level, assuming that investors make their investment decisions based on the fund's holdings. Running regressions at the share class level would be double-counting funds that comprise the same assets. 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. This leaves us with a sample of 5,951 equity funds and 4,203 bond funds. To ensure consistency over all of our tests using CRSP data, we only examine individual fund data going back to 2000, when CRSP data coverage of fund location begins.

We use monthly fund returns and total asset values as the basis for our calculation of a fund's net flows. We compute flows as a percentage of a fund's total assets into the fund in each month, and calculate the Net flows as follows:

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

Fund's net flows are winsorized at the 99% level, and we drop all funds with missing returns and assets when creating our sample. We apply CRSP objective codes to classify funds into equity or bond funds. For later tests, we use four-digit CRSP objective codes to classify funds into style categories.[8]

Again following Kamstra et al. (2017), we include capital gains as the return to the investor from the current month to the previous November to control for investor reluctance to incur capital gains tax. We include the personal savings rate from the Bureau of Economic Analysis (BEA) to control for the effect of liquidity needs on investor investment decisions. We add seasonal dummies to adjust for seasonal changes in aggregate fund flows. To control for auto correlation in flows, we add one- and three- month lagged flows in all of the 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 five-year Treasury and the change in inflation to control for macroeconomic factors that could affect bond investor decisions.

[8] CRSP Objective codes combine Lipper, Strategic Insights, and Wiesenberger fund classification codes. The first-digit codes represent debt or equity, and funds are divided into more precise classifications as one moves from the first to the fourth digit.

Table 1-1 reports the summary statistics for control variables and total number of attacks. For the entire sample, the mean and median number of attacks in a month are 1.29 and 1.00, respectively, with a standard deviation of 1.96 attacks. Figure 1 plots the number of US attacks in each month of the sample. Two things stand out in these figures. First, as we would expect, Figure 1-1 shows no clear pattern in the number of attacks per month. Second, the number of attacks in the early years of the sample is much greater than the later years. As in Sandler and Enders (2004), we see a decreasing trend in the number of attacks over time.[9] This differentiation though the years will help us examine investor responses to attacks in different periods. For example, as investors come to recognize trends in frequency, they may make investment decisions based on updated beliefs about the risk of future attacks.

We exclude the effects of Tuesday, September 11, 2001, from our baseline tests for the following reasons: It is an extreme outlier in the sample. The attacks that day caused almost 3,000 deaths, more than 17 times the deaths of the next closest attack, the 1995 Oklahoma City bombing, in which 168 people died. Second, the magnitude and location of the attacks prompted the Federal Reserve to take dramatic action, including a $61 billion purchase of Treasury securities and $45 billion in loans to banks through the discount window (this compares to $59 million over the previous ten Wednesdays). The New York Stock Exchange remained closed until the following Monday. Thus, it is likely that investors reacted not just to the attacks, but to the Fed's intervention and market closure, or some combination of all three in the month following 9/11.[10]

[9] Enders and Sandler (2004) attribute the decreasing trend in the post-Cold War period to reduced state sponsorship of terrorism, increased efforts to thwart terrorism, and the demise of many leftist groups.
[10] Section 7 includes a robustness test that adds 9/11 to the main test. We find a qualitatively similar result.

MAIN RESULTS

In this section, we present the results from our main tests. Using aggregate fund data from ICI and individual fund data from CRSP, we examine the fund flows in the month following a rise in the level of terrorism.

Aggregate Fund Flows

Table 2 presents the baseline results using aggregate ICI flow data. The dependent variable in all specifications is aggregate net flows at the fund style level in month *t+1*, while the attack variable is defined in month *t*. In Panel A, Column 1, we find a negative and significant coefficient on the terrorism variable for aggregate equity funds. A one standard deviation increase in the level of terrorism in month *t* (the equivalent of going from one attack to three in a month) leads to a drop of 5.10 basis points in flows in month *t+1*. This drop represents a 7.05% drop in flows, relative to average flows to equity funds of 72 basis points. In Columns 2 and 3, we do not see a significant change in subsequent flows to corporate and municipal bond funds. In Column 4, we see that government bond funds experience a significant increase in flows, confirming our main hypothesis that investors will exhibit more risk averse behavior. Following a one standard deviation increase in the level of terrorism, government bond funds receive an increase in flows of 5.01 basis points in the month after the attacks. This is relative to average flows of 48 basis points, representing a 10.32% increase.

In terms of inflation-adjusted dollar flows, these results equate to a $75.09 million drop in aggregate equity fund flows and a $56.81 million increase in aggregate flows to government bond funds with a one standard deviation increase in terrorist activity the previous month. To summarize, consistent with our hypothesis, aggregate flows to equity and bond funds reveal an increase in risk-averse investment decisions in the period following an increase in terrorism.

In Panel B we repeat the tests in Panel A, using the net exchange one month after the attacks as the dependent variable. We create the net exchange variable 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 Panel A's net flows, net exchanges are a direct reflection of investor decisions to shift assets between mutual funds in the same family (Ben-Rephael et al., 2012). Panel B confirms the results for equity and bond funds from Panel A. For equity, we see a coefficient of -4.6 basis points, and for government bonds, a coefficient of 6.6 basis points. Such evidence clearly suggests that investors are transferring funds out of equity and into less risky government bond funds in a response to an increase in terrorism.

In Panel C, we shift focus to exchanges in, and out of equity and government funds. We build the variables for exchanges in and exchanges out as percentages of lagged total net assets. We use exchanges in and exchanges out, rather than new sales and redemptions, because the former better represent the short-term changes in investor risk preference. Ben-Rephael et al. (2012) note that exchanges between funds offer better representations of sentiment driven asset allocation decisions because long-term savings and withdrawal decisions influence new sales and redemptions. In Column 1, we see that the drop in equity flows is driven by an increase in exchanges out of equity funds. On the other hand, Columns 3 and 4 show us that an increase in the exchanges into the funds and a drop in exchanges out of the government bond funds causes the increase in flows to government bond funds.

While Panel A confirms our main hypothesis, the results in Panel B and C help further determine whether net flows are attributable to changes in outflows, or inflows, or both. The results suggest that equity fund investors exchange their holdings into safer government bond funds within the same family of funds. In direct contrast to equity funds, the increase in flows to government bond funds is a result of an increase in exchanges into, and a drop in exchanges out of, the family funds. In each case, investors make more risk-averse investment choices by decreasing their investments in risky asset classes.

Sub-Period Analysis

To see how terrorism affects fund flows and investor portfolio choices in different periods, we split the sample in half along its midpoint, 1998. We then examine investor reactions to terrorism in different business cycles, such as during a recession. Table 1-3 presents the results for the two halves of our sample, pre-1998 and post-1998, as well as results for NBER recession periods. Columns 1 to 4 presents the time period results using net flows. In Column 1, we see a negative and significant coefficient of -12.4 basis points on the terrorism variable; the insignificant coefficient on the post-1998 interaction term suggests that the effect has been mostly consistent throughout the entire sample period.

The effect of terrorism on government bond funds increases over time, a contrast to the effect it has on equity funds. In Column 2, the coefficient on the terrorism variable is 3.1 basis points but insignificant, while the interaction term for the post-1998 sample is 19.8 basis points and significant at the 5% level. Columns 3 and 4 examine the effects of terrorism on investor decisions during recessions, by including an interaction term between a given recession and the terrorism variable.

For both equity and government bond funds, we show that investor behavior during recessions does not drive our results; the sign and significance of the coefficients on the terrorism variable are the same as Panel A of Table 1-2. For equity funds, we find that the interaction between the recession dummy and the terrorism variable is -0.18 and significant at the 5% level, suggesting that the effect of terrorism becomes larger during a recession. This result is consistent with Galea et al. (2002), who find that individuals who suffer financial hardship in the wake of a terrorist attack are likely to experience more severe and lasting psychological effects. Columns 5 to 8 of Table 1-3 replicates the time period tests, using net exchanges as the dependent variable. For both equity and government bond funds, we find that results using net exchanges are mostly consistent to those using net flows.

Individual Fund Results

To further test our main hypothesis, we run panel regressions on a sample of individual equity and bond funds. We use individual fund data because results at the aggregate fund level may not reflect assets allocation decisions at the individual fund level. More importantly, CRSP individual fund data enable us to better control for differences in fund flows related to differences in performance, asset allocation, and fund characteristics. All regressions control for year and fund fixed effects, as we intend to compare flows in months of high levels of terrorism with flows in unaffected months within each fund. We take other control variables from previous literature, and load with the sign and significance that we expect.

Table 1-4 presents the individual fund results. The dependent variable in Panel A is a fund's net flows in month *t+1*, while the terrorism variable is defined in month *t*. In Column 1, equity funds, the terrorism variable has a coefficient of -12.2 basis points and is significant at the 1.00% level. For the average equity fund, this equates to a drop in flows of roughly 10.87% following a one standard deviation increase in the level of terrorism in the month *t*. Column 2 replicates the model in Column 1 with the sample of bond funds. If investors prefer safer assets in response to an increase in terrorism, we should, and do in fact, see an increase in flows to bond funds in the following month. The coefficient on bond funds is 15.3 basis points and is significant at the 1.00% level. This represents an increase in flows of 15.68% following a one standard deviation increase in the level of terrorist activity. In terms of inflation-adjusted total dollar flows, equity funds receive a drop in flows of $197,000, and bond funds receive an increase in flows of $155,000.

Vulnerability Tests

If an increase in risk aversion induced by psychological distress is the cause for the change in flows we observe, then we believe the most direct test is identifying investors most likely to experience anxiety, fear, and depression related to terrorism.

Terrorism related PTSD and psychological distress correlate with direct exposure to the event and one's direct experience with loss: loss of loved ones, loss of personal property, loss of employment, loss of social network (Galea et al., 2002; Schlenger et al., 2002). Identifying those most likely be fearful of future attacks, as a result of increasing terrorism in the current period, is more difficult. Yet given that terrorists generally strive to sow great destruction and reap great publicity, they would most likely find it easier to accomplish these by targeting a metropolitan area (Graham, 2004). If one assumes that terrorists will likely attack larger cities, then it is also reasonable to assume that the people living in these cities may have some anxiety about possible attacks following an increase in the level of terrorism nationally. Schlenger et al. (2002) find that two months after 9/11, the residents of other large metropolitan centers (Boston, Philadelphia, Chicago, Houston, and Los Angeles) reported levels of significant psychological distress that were not significantly different from those reported by residents in New York and Washington DC.

To take into account these two factors, we assume that investors are likely to be more vulnerable to significant psychological distress if they either live in close proximity to an attack or live in a large metropolitan city. We do not have individual investor location data; previous studies however, have shown that investors are more likely to invest in mutual funds headquartered in their local area. (Coval and Moskowitz, 1999). Hence, we will use the location of the mutual fund as a proxy for the location of the investors that invest in the fund.

In Table 1-5, Panel A, we test these assumptions and examine the difference between flows into funds whose investors could be vulnerable to post-attack significant psychological distress (vulnerable funds), and those whose investors are less vulnerable (less vulnerable funds). To do so, we run a piecewise regression, splitting the funds in our sample into vulnerable funds and less vulnerable funds. In Panel A, we define vulnerable funds as those located in the same city as the attack and those located in another large city. To define a large city, we use Beale urban rural codes; thus, in Columns 1 and 2, a large city is a metropolitan area of more than 250,000. In Columns 3 and 4, we change the definition of a large city, to one with a population greater than 1 million. We consider all funds that fall outside these definitions to be less vulnerable.

Consistent with Schlenger et al. (2002), and the idea that psychological distress leads to higher levels of risk aversion, we find that the change in flows is greater for funds more likely owned by investors experiencing significant psychological distress (i.e., those living near the attack or in a large city). For example, Column 1 shows that the coefficient on the terrorism variable for vulnerable equity funds is -19.8 basis points, while the coefficient on the less vulnerable funds is insignificant. Column 2 examines the flows into vulnerable bond funds. Similar to the results we see for equity funds, we find that the coefficient on the terrorism variable for vulnerable bond funds is 17.6 basis points. Less vulnerable bond funds do not see a significant change in flows. In Panel B, we extend our study of vulnerable funds by alternating the definition of a directly affected fund to those located in the same state of the attack. For both equity and bond funds, and for both definitions of the larger city, the results are consistent with those in Panel A.

To summarize, we find that vulnerable funds, those held by the individuals most likely to experience significant psychological distress following attacks, exhibit significantly larger changes in flows than do less vulnerable funds. It is also important to note that less vulnerable funds do not exhibit a significant change in flows. If increased risk aversion, caused by psychological distress is the cause of the change in flows then two things must be true: affected individuals have a significantly larger response than those unaffected, and the behavior of unaffected individuals should not change. Our results in Table 1-5 meet both of these criteria and directly support our initial hypothesis that investor behavior in response to an increase in terrorism is likely driven increased risk aversion induced by psychological distress.

Fund Beta

If terrorism leads investors to become more risk averse, we should observe larger outflows from riskier funds. To test this, we examine changes in demand for high-beta equity funds. To calculate each fund's market beta, we use factor data from Ken French's data library and run a rolling 36-month regression of excess fund returns on the Fama-French factors (i.e., one-factor, three-factor, and three-factor plus momentum). Table 1-6 presents results consistent with the idea that, with respect to market risk, fund heterogeneity plays an important role in the change of fund flows in response to an increase in terrorism. If investors are becoming more risk averse in response to an increase in terrorism, we would expect riskier funds, measured by market beta, to suffer a larger drop than would lower-beta funds; and this is indeed what we find. Following an increase in terrorism, funds with a market beta greater than 1 experience significantly lower flows than funds with betas less than 1. The coefficient on the interaction between a high-beta fund and the terrorism variable ranges from -2.6 basis points in the market model in Column 1 to -4.1 basis points for the three-factor model in Column 2.

Fund Styles

We next examine how the increase in risk aversion manifests itself in the cross section of equity and bond funds, using the mandated style of the fund. For all sub-groups in Table 1-7, with the exception of retirement funds, we assign each fund a style based on its four-digit CRSP objective code. To define our set of retirement funds, we use a word search to look for funds with “retirement” or “Class R” in their names.

Panel A of Table 1-7 shows us that investors do not change their equity fund allocations at even rates. In Columns 1−3 we repeat our main tests on a sub-sample of small-, mid-, and large-capitalization funds. According to Fama and French (1993), small-cap funds historically outperform large- and mid-cap stocks because they present greater risk.[11] Thus if investors consider small-cap funds riskier, we would expect to see a difference in outflows from those small- and large-cap funds. Large-cap funds do not experience a significant drop in flows; the coefficients on mid- and small-cap funds are -16.3 and -28.4 basis points, respectively. This result suggests that investors are not only deciding between equity and bond funds, but also shifting investments within equity funds from riskier mid- and small-cap funds to less volatile large-cap funds.

Columns 4 to 6 show results of a similar test, with the focus now on the funds’ investment styles: growth, growth and income, or income equity funds, as defined by CRSP. The negative coefficients on growth funds suggest that investors prefer funds that provide a larger portion of their returns through dividends, rather than price appreciation in the month following

[11] 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.

an increase in terrorism. If investors' risk aversion increases, it is rational for them to invest in funds that can provide return in the form of dividends, instead of only relying on price appreciation.

Columns 7 and 8 extend our examination a fund's institutional and retirement share classes. In this test, we assume that institutional and retirement investors are less reactionary than retail investors. Barber and Odean (2008), for example, show that individual investors are more likely than institutional investors to trade on large news days. In the case of retirement share classes, Beshears et al. (2009) find that decisions by retirement investors can be affected by their default choice, and not reflect true demand. In addition, it is likely that some retirement plans limit the flexibility investors have, and thus cause those share classes to be less responsive to increases in terrorism. With the above arguments, we would expect that for both institutional and retirement share classes, there would be no significant change in flows related to the level of terrorism. Insignificant coefficients on the terrorism variable in Columns 7 and 8 confirm the assumption that the investors of these share classes are less reactionary than are retail investors.

Panel B of Table 1-7 shifts the focus from equity funds to bond funds. Using the same CRSP objective codes, we classify bond funds as government, corporate, or municipal. We follow the same method for identifying institutional and retirement share classes as we do for equity funds. Municipal bond funds and corporate bond funds represent higher risk than do government bond funds, meaning we should see a greater increase in flows to the safer government bond funds. Following the same methodology as Panel A, we run our main regression on the sub-sample of government, municipal, and corporate bonds. The terrorism coefficient on government bond funds is 25.5 basis points, while the coefficient on the terrorism variable for corporate bonds is only 11.3 basis points and insignificant. This result is consistent with our findings in Table 1-2, that corporate bond funds receive a significantly smaller increase in flows relative to government bond funds. In Columns 4 and 5 we extend our analysis to share classes held by institutional or retirement investors. Consistent with the results from Panel A, neither institutional nor retirement share classes experience significant flow increases in the wake of an increase in terrorism.

HOW IS RISK PREFERENCE CHANGING?

In this section, we look into the possibility that a change in the perception of future market volatility could be driving the main results with respect to fund flows.

In addition to change in risk aversion as a factor that drives terrorism related fund flow changes, we consider change in the perception of future market volatility, i.e., when investors believe that future market volatility correlates with the level of terrorism. If risk aversion stays constant but investors believe market volatility will rise, then we would expect to see a similar drop in demand for risky funds. Here we test to distinguish between the risk aversion channel and market volatility channel.

With respect to expectations of future market risk, Caballero and Krishnamurthy (2009) suggest that the exposure to risk (i.e. an increase in terrorism) positively relates to a perceived probability of future market risk through the expectation of extreme market shocks. While the Caballero and Krishnamurthy paper uses a theoretical model, studies related to ours have found that sentiment shocks are much more likely to influence expectations of returns, rather than expectations of risk. Using household data, Kaplanski et al. (2015) examine this idea by studying the effect of various sentiment factors on the investing behavior of Dutch citizens. Creating a sentiment index made up of general feeling, SAD, and sporting results; they find no significant relationship between sentiment and the short-term expected risk of the AEX or S&P 500. With respect to long-term views, there is a significant effect between the sentiment and the 1 year ahead expected risk of the S&P 500 but not with the AEX. Overall, the authors note "sentiment affects expected returns more intensely than expected risk". Examining households directly experiencing natural disasters, Bharath and Cho (2014) again find that expectations of future risk are unaffected by natural disasters, while expectations of returns are significantly negatively affected.

If investors think market risk will increase, then we should see an increase in the VIX to reflect updated expectations. We use the VIX because it acts as a much-cited measure of near-term (one-month) expectations of S&P index option prices. We use the average VIX level in month *t* to determine whether investor views on future market volatility change in relation to an increase in the level of terrorism. Columns 1 and 2 of Table 1-8 present these results. In both settings, we find no change in the VIX in the month of the attacks.

It is possible that investors are responding to increases in *realized* market volatility, not just to expectations reflected in the VIX. To examine the change in actual market volatility, we calculate the standard deviation of the S&P 500 for each month using daily returns, and then replicate our main tests with volatility in month *t* as the dependent variable. These results appear in Columns 4 and 5. Similar to the results using the VIX, an increase in the level of terrorism does not lead to an increase in realized market volatility.

In addition to any change in the expected and realized market volatility, it is possible that investors are reacting to an increase in the level of tail risk in the market (i.e. higher moments). Following Kelly and Jiang (2014), we use the skewness and kurtosis of market returns as a coarse proxy of market tail risk. For each month, we calculate realized skewness and realized kurtosis using daily S&P 500 returns. We run tests with the dependent variable defined in the same month as the terrorism variable because it is likely that any changes in the market would show up in the immediate aftermath of the attacks. Consistent with our findings in Panel A of Table 1-8, Panel B shows us that the third and fourth moments are unaffected by the level of terrorism (In unreported tests, we run each measure of Table 1-8's market risk in month *t+1*, and find similar results).

As noted above, previous literature on retail investors finds that the correlation between changes in expected risk and sentiment are generally very weak. Overall, the results from Table 1-8 provide evidence consistent with these previous findings. Results from the VIX and realized market volatility, in conjunction with previous literature, lead us to conclude that our main results at the aggregate level are more likely attributable to an emotionally driven change in risk aversion, rather than individuals updating their beliefs about future market volatility.

IS THERE A WEALTH EFFECT?

Up to this point, we have proposed that investor risk aversion drives the drop in demand for risky funds related to an increase in terrorism. This section examines the possibility that a wealth effect is driving our main results. If terrorism leads investors to downgrade their perception of future stock prices, we would observe a similar change in investment patterns as we do in Table 1-2.

Karolyi and Martell (2006) examine the impact of terrorist attacks against a firm's stock price, and find that market valuation drops significantly that same day the firm is the target of an attack. Sandler and Enders (2004) show that terrorism causes a significant negative effect on the domestic tourism industry. In such a case, investors may act to shelter their portfolios to preserve wealth against downturns in other industries affected by tourism. Pool et al. (2014) look at the prices fund managers paid for their own homes and the subsequent losses in those home values following the 2007−2008 real estate bubble, and find that drops in their own personal wealth led them to take less risk in the funds they manage. Thus, we want to look more closely at whether a significant change in value—of portfolio, or a publicly traded firm, and of related industries—plays a role in investor risk-taking behavior.

Corporate Investment and Personal Consumption

If investors believe that terrorism will negatively affect future corporate cash flows, they may in fact be responding to reduced corporate investment. Antoniou et al. (2016) find that following large terrorist attacks and school shootings, corporations tend to reduce their R&D expenditures, borrow less, and hold more cash. Just as firms adjust their investment activities, Eckstein and Tisddon (2004) and Llussá, and Tavares (2008) find that increases in terrorism correlate with drops in personal consumption. These two studies examine terrorism in Israel, which has come of age in a hostile region and where attacks sometimes come in waves. We focus on examining corporate investment and personal consumption activities in the US.

As our measure of corporate investment, we use the rate of non-residential private fixed investment from the Bureau of Economic Analysis (BEA). We further break down the total non-residential private fixed investment into the equipment and R&D portions of investment.[12] Since corporate investment data is only available quarterly, we re-create our main terrorism variable at the quarterly level to match the frequency. In each case, we use the rate of investment in quarter *t+1*, while our terrorism variable is defined in quarter *t*. In each model, we control for the lagged level of investment, the lagged return on the S&P 500, the lagged return on five-year Treasury bills, and the change in the Consumer Price Index (CPI), as well as year fixed effects. We do not

[12] Non-residential private fixed investment is BEA series PNF; our measure of equipment investment is BEA series Y033RL1Q225SBEA; and research and development investment is BEA series Y006RL1Q225SBEA.

include the seasonal dummies since the BEA already seasonally adjusts each series. Table 1-9 shows the results.

The findings do not show a significant drop in the quarter following an increase in terrorist activity for our measures of total corporate investment, or for either equipment or R&D. If corporations are not altering their investment activities under these scenarios, then it does not seem likely that the drop in fund flows is a reaction to decreasing corporate investment.

In Columns 4–6 of Table 1-9, we extend our analysis to the relationship between terrorism and personal consumption. We use monthly personal consumption expenditures from the BEA, and separate total consumption into non-durable and durable goods.[13] Similar to our models for corporate investments, we control for the lagged value of consumption and the return on the S&P 500. In Column 4, we find a significant drop in consumption following attacks. Consistent with previous results from Eckstein and Tisddon (2004), and Llussá and Tavares (2008), a drop in durable goods consumption (Column 5), seems to drive the drop in overall consumption. Non-durable goods consumption remains unchanged (Column 6). The drop in the consumption of durable goods is consistent with the notion that investors believe the future contains uncertainty and thus are limiting their large expenditures.

Market Outlook Survey

We next examine the possibility that increases in terrorism correlate with lower expectations of future market performance lead individual investors to reduce their investment in risky funds. In related studies on sentiment in general and natural disasters, Kaplanski et al. (2015) and Barath and Cho (2014) both find that negative shocks to sentiment lead to more pessimistic views on future returns. We use responses in three well-known investor sentiment

[13] Personal consumption data comes from BEA series PCE; durable goods consumption is from BEA series PCEDG; and non-durable goods consumption is BEA series PCEND.

surveys—Investors Intelligence's summary of professional investors' survey, the University of Michigan Survey of Consumers, and the Yale Stock Market Confidence Indices—to measure changes in investor perception of future market returns in response to increases in terrorism.

Investors Intelligence collects and summarizes the outlooks of more than 120 financial market newsletters; it started in 1963 and is available weekly for our entire sample period.[14] We track the percentage of newsletters classified as "bearish" and, following Greenwood and Shleifer (2014), use the percentage of newsletters classified as "bullish" minus the percentage of "bearish" to create two measures of market outlook. For all measures of the Investors Intelligence surveys, we use the survey responses from the first week of month $t+1$ as the dependent variable.

The Yale and University of Michigan surveys ask investors similar questions related to expectations of market returns over the next 12 months. The Michigan survey asks respondents how likely it is that a $1,000 investment in the stock market will be worth more one year from now. The Yale survey asks respondents (both individuals and institutional investors) how they think the Dow will perform (in percent) over the next year.[15] 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 rise over the next year. We use the average of all responses in each survey as the dependent variable in our regression. Along with the expectations of returns from the Yale survey, we use the Yale Crash Risk Index to proxy for investor views on future tail risk.

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[14] The survey was released monthly in 1963, then moved to bi-weekly until 1969 and weekly through 2010.For our use, we us the first survey from month $t+1$ to be consistent with our main tests.

[15] 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.

To create the Crash Risk Index, Yale asks respondents what they think is the likelihood of a catastrophic market crash within the next six months.[16]

While the Yale and Michigan surveys are similar in both the questions and the time horizon (12 months), the Investors Intelligence survey focuses on shorter-term market views.[17] Using these different surveys helps us understand how attacks can affect both short- and long-term market views. Table 1-10 presents the results of the changes in these market outlook surveys following 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 help present an important distinction between our work on time varying risk aversion and related studies by Kaplanski et al. (2015), Barath and Cho (2014) and Guiso et al. (2017). In these previous studies related to sentiment and risk taking, a significant link between the sentiment shock (weather, sports, natural disasters and financial crisis) and investors' expectations of future market returns. Using these widely cited surveys on aggregate consumer of market returns, we conclude that the expectation on future market performance is unlikely the primary cause of our main results.

The survey results show that investor beliefs about future market returns remain unchanged following an increase in terrorism, but what if investors are responding to a decrease in the equity risk premium? To test this possibility, we regress the risk premium on our terrorism variable and all non-fund specific controls from the main regression. We measure the equity risk premium in two ways: First, we use the return on the S&P 500 minus the one-month T-bill. We then proxy for the market return using all stocks from the NYSE, AMEX, and NASDAQ, and repeat the test.[18] Regardless of how we measure the risk premium, the untabulated results

[16] An answer of 100% represents a view that a crash is certain in the next six months.
[17] Greenwood and Shleifer (2014) note that the editors of Investors Intelligence focus on the forecast of returns over the near term.
[18] Excess return on the market is taken from Ken French's data library.

indicate that no significant change in the risk premium occurs in the month following an attack. This finding is consistent to Brounen and Derwall (2010), who show that the only large-scale US attack causing a negative event day cumulative abnormal return was 9/11.

Directly Affected Funds

Terrorisms affects different industries in different ways. Sandler and Enders (2004), as noted, explore the negative effects of terrorism on the tourism industry. Chesney et al. (2011) examine its effects on the insurance, financial, and defense industries. They find that the insurance industry is negatively affected, while the financial and defense industries are more insulated from terrorism and may even benefit. If investors believe that terrorism causes a negative shock to industry performance, they would likely move funds into the insulated industries and out of those that are more vulnerable.

While some funds clearly focus on financial or bank holdings, there are few if any that cover the transportation, defense, or insurance sectors. This makes it more difficult to test the hypotheses in our equity fund sample. To proxy for industry-specific funds, we create a sample of transportation, defense, insurance, and bank-specific funds by taking the returns for those industries and running 12-month rolling regressions of equity fund returns on the industry returns to estimate the industry exposure (industry beta) for each fund. (We use the Fama-French 49 industry classifications and we take value-weighted industry returns from Ken French's data library. We use the transportation industry as a rough approximation for tourism.[19] We classify the funds in each month whose industry betas are in the top 10% as the high-correlation funds to each industry, and these we exclude from the other industry regressions so as not to contaminate

[19]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.

the results for a certain industry.[20] We then create an interaction term by multiplying the high industry beta dummy by our terrorism variable to test the differences of flows into those high industry beta funds in the month following an attack.

As the results in Table 1-11 show, funds that correlate highly to vulnerable industries do not drive our baseline results. Even after identifying each vulnerable industry, the main terrorism variable continues to be negative and significant, as shown in each column of the table. Examining the interaction terms in Table 1-11 also allows us to examine investors' industry preferences in the month following the attacks. If mutual fund investors are updating their beliefs about future cash flows, prior studies show that those changes would most likely be evident in these four industries. Yet the insignificant interaction terms in Table 1-11 lead us to believe that investors do not significantly change their views of future industry performance.

Just as terrorism affects industry performance, the effect on different international markets depends on where attacks take place. If US investors are altering their flows based on updated beliefs of future returns following terrorism on US soil, then we should observe a decrease in flows to domestic funds relative to international funds. Similarly, regarding terrorism outside US, we should only observe a drop in flows in foreign funds, since US market performance is unlikely to be affected by terrorism in foreign countries.

We identify terrorism in foreign countries using the same method we use for our US terrorism variable, but we aggregate attacks in the seven other G8 countries (Canada, France, Germany, Italy, United Kingdom, Russia and Japan) and exclude attacks in the US in each month. We use these countries because they are very similar to the US, and terrorism in these countries is most likely relevant to US investors. In addition to our main set of control variables,

[20] 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.

we add the lagged return on the global market index to control for global market conditions that could affect investment into foreign mutual funds.[21] We separate our ICI mutual fund sample into foreign and domestic equity funds separately. Table 1-12 presents these results. We examine the response to foreign terrorism by foreign funds in Column 1, and domestic funds in Column 2. We find that investors respond to an increase in foreign terrorism by reducing flows only to domestic equity funds—the opposite of what we would expect if investors believe that terrorism on foreign soil negatively affect foreign market performance. In Columns 3 and 4, we use our US terrorism variable and repeat the tests in Columns 1 and 2. We find that investors reduce flows to both foreign and domestic equity funds following terrorism on US soil. Once again, the result is not consistent with the notion that investors would respond to their updated expectations of future market performance.

Terrorism and Stock Prices

From our analysis, it is reasonable to ask, why terrorism does not causes a change in stock prices, if it causes a significant increase in risk aversion? For an initial answer to this question, we focus on the economic magnitude of our variable in comparison to a sentiment shock that we know has an impact on both prices and flows; SAD. In our main results, we find an approximate drop of $75 million in flows to equity funds after an increase in terrorism. Kamstra et al. (2017) studying seasonality in fund flows; estimate that SAD was responsible for a $13 billion reduction in equity flows in September of 2006 with a similar size reversal in March. This drop in flows is roughly 175 times larger than the drop in flows we see following a one standard deviation in our terrorism variable. As the response to terrorism is orders of magnitude smaller than SAD, it is unlikely that terrorism would have a measurable effect on

[21] Global market index data are downloaded from Ken French's website.

market prices. Previous literature also leads us to believe it is unlikely we would see an effect on prices. Chen and Siems (2004) do not find an abnormal market impact of either the first World Trade Center or the Oklahoma City bombings, and in general find that US markets are more resilient to terrorism than global markets. Lastly, we do not see an effect on institutional fund flows related to terrorism. If institutions are not altering their flows into funds, it is unlikely they would be altering their trading behavior, which would be an important factor if we were to observe an effect on prices.

While we do not see an effect on aggregate prices, we do not feel this is a limiting factor in our study of time variation in risk aversion. The goal of our study is to determine if risk aversion can change independent of a change in expected risk, or in future cash flows (returns). We believe this is an important addition to the literature given that fact that there is a large shift in aggregate mutual fund flows and durable goods consumption as a response to terrorism.

ROBUSTNESS TESTS

In this section, we test the robustness of our findings using alternate sample selection criteria and alternate definitions of the terrorism variable. For brevity, we only report the coefficient on attacks for each alternate definition, so that each row of the table represents a separate regression. We start by testing alternate specifications of terrorism to test the robustness of our main terrorism variable. We start by creating rank variables, based on the number of attacks in each month. In Model 1, we rank all months with at least one attack and sort them into quartiles. In Model 2, we repeat these ranks but sort the attack months into terciles. Using alternate sample selections and rank variables, we find consistent results for both equity and government bond funds to our main results in Table 1-2.

In Models 3 and 4, we create dummy variables to test if our continuous or rank variables are driving our results. In Model 3, we create a dummy variable that gives a value of 1 to any month in which the number of attacks is greater than the median number of attacks per month. In Model 4, we create a dummy variable that identifies months with sharp increases in the number of attacks relative to recent trends. We assign the value of 1 to any month in which the number of attacks is greater than three times the average number of attacks per month over the previous 12 months. Again, we find that using dummy variables to designate certain months as attack months yields consistent results to our main tests.

In a final robustness test, we use a sample of terrorist attacks and school shootings used in a related paper by Antoniou et al. (2016). Their sample differs from ours in that they use on only attacks that caused at least one death and were covered in the national news. Additionally, they use school shootings that meet the same criteria. We include this test, as it is likely that investors would respond to these larger attacks and school shootings in a similar manner to our measure of terrorism. In Model 5 in Table 1-13, we create a dummy variable from the events in their sample and replicate our main tests from Table 1-2. Consistent with the idea that investors respond to large attacks and shootings in a similar fashion to the level of terrorism, we find that the results using this dummy are similar to our main results.

This test also provides an interesting result with respect to timing of the response to large individual attacks versus our measure of nationwide terrorism. Flows respond contemporaneously to the large attacks in the Antoniou et al. (2016) sample, but the effects do not carry over to month *t+1*. For our main variable, we see a negative but insignificant response in month *t*, but a negative and significant response up to and including month *t+2*. We feel this is indicative of investors responding to similar but different shocks. The first is an immediate, but short-lived response to a single large attack or shooting which investors may seem as random. The second is a slightly delayed but longer-lived reaction to multiple events spread over the entire country, a possible signal of increased terrorism in the future.

CONCLUSION

Previous studies have identified terrorism's impact on financial markets, industries, and specific firms; yet have worked with small samples, focusing on a few major attacks and relatively a small group of stakeholders. By expanding the study of terrorism to a larger set of events and stakeholders (409 attacks and investors in nearly 6,000 equity funds and more than 4,000 bond funds) this paper is able to help answer two important questions. First, we help answer a seemingly simple, yet important and difficult question in the asset pricing literature. What causes risk aversion to vary over time? Second, we provide insight into the effect that increases in terrorist activity have on the behavior of retail investors. Answering the first question is important in a theoretical sense, as Campbell and Cochrane (1999) show that most asset-pricing models require large fluctuations in aggregate risk aversion. The answer to the second question provides some guidance in designing government policy and economic remedies to ease the fears and anxieties that affect the public's investment and consumption behaviors.

Looking at the level of terrorist activity on US soil from 1984 to 2010, we find that in the immediate month following a rise, mutual fund investors reduce their investment in equity funds significantly, while increasing their investment in bond funds. The fund flows changes do seem to correlate with the probability that fund investors are experiencing fear, depression, and other significant distress. They also show that most of these reactions dissipate in the second month. Tests of fund heterogeneity shows that investors respond to different risk profiles, in terms of market beta and varying investment styles within asset classes. They do not seem to respond to changing perceptions of future wealth, based on results of the tests we run of corporate investment, fund industry correlation, investor sentiment surveys, and flows to foreign funds. In subsequent tests, we find no significant change in the VIX and market risk in the month following a terrorist attack. These results, along with investor outlook surveys of crash risk, suggest that increasing risk aversion is most likely the cause for an increase in risk preferences.

It is important to remember that we base these results on mutual fund flows aggregated at the fund level. Further research at the brokerage level will help us better understand the relationship between risk preference and trading behavior.

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APPENDIX

Figure 1-1: Number of Attacks

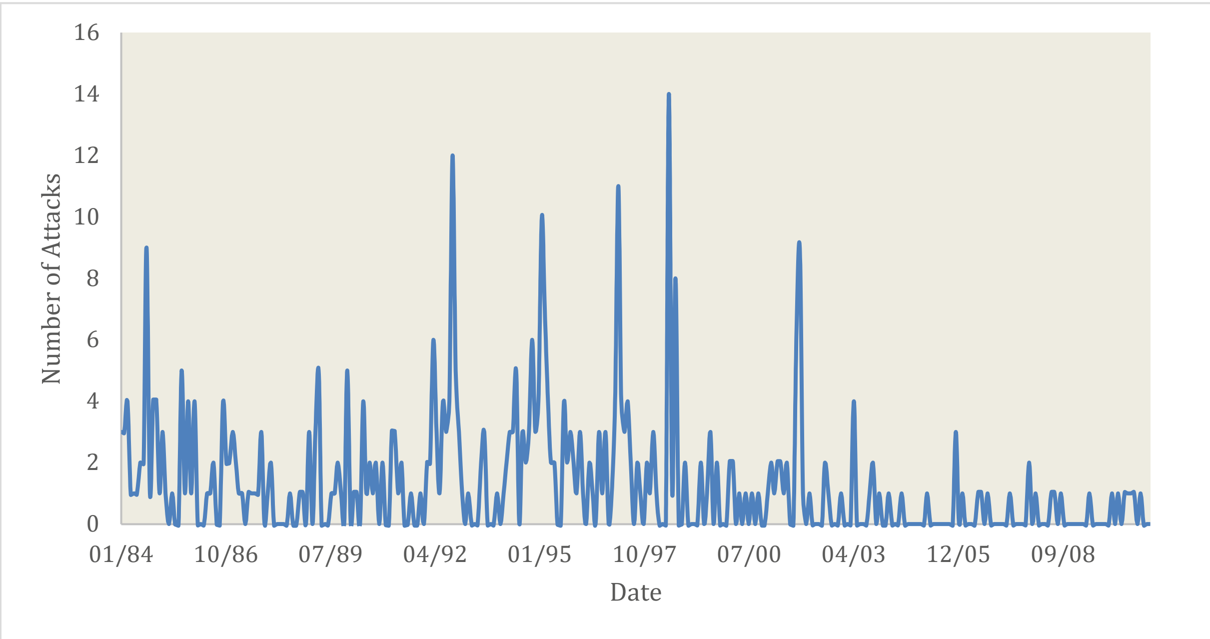

Figure 1 graphs the total number of attacks for each month in our sample. The sample period runs from January 1984 to December 2010. In each month, we sum the number of attacks that involve human casualties or injuries, or mention in the news.

Table 1-1: Summary Statistics

This table presents summary statistics for the variables used in the paper. Net Flows (CRSP) is fund's net flows in percentage. Net Flows (ICI) is aggregate net flows in percentage at the fund style level (styles represent the 33 subcategories grouped to make up the equity, municipal, corporate, and government bonds classes). Attack is the total number of attacks in each month that involve human casualties or injuries, or mention in the news. Return is the annual return for the fund, and Assets is the log of total net assets in millions. Expense ratio is the annual expense ratio reported by CRSP. The 5Year Treasury, CPI, and S&P 500 are the values of the five-year government bond return, the change in CPI, and the value-weighted return for the S&P 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
Net Flows (CRSP)	0.592	6.615	-3.801	-0.221	5.455
Net Flows (ICI)	0.790	2.222	-1.257	-0.467	3.141
Attacks	1.290	1.964	0.000	1.000	3.000
Return	0.060	0.117	-0.360	0.072	0.492
Assets	4.781	1.951	2.351	4.812	7.219
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 1-2: Aggregate Flows and Terrorist Attacks

In this table we present our main results using aggregate flow data from ICI. The dependent variable in Panel A is aggregate net flows at the fund style level (styles represent the 33 subcategories that are grouped to make up the equity, municipal, corporate, and government bonds classes). In Panel B we use net exchanges in percentage at the fund style level as the dependent variable. Exchanges are defined by ICI as a transfer from one style of fund in the family to a different style of fund in that same family. Net exchanges are created by subtracting exchanges out of the style, from exchanges into the style, then divided by lagged total net assets. In Panel C, we use Exchanges Out and Exchanges Into fund styles, as a percentage of lagged total net assets, as the dependent variable. All dependent variables are measured in the month following the attacks. Attacks is the total number of attacks in each month that involve human casualties or injuries, or mention in the news. Savings is the lagged personal savings rate from the BEA, and Capital Gains is the cumulative style return from the previous November. Return and Assets are the one-month lagged values of the style returns and natural log of total style assets, respectively. five-year Treasury, CPI and S&P 500 are the lagged values of the five-year government bond return, the change in CPI, and the value weighted return for the S&P 500. Flow is the one- (three-) month lagged aggregate flows in each style category. All models include fund style fixed effects and year fixed effects. Robust standard errors in parentheses *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Panel A: Net Flows				
	(1)	(2)	(3)	(4)
VARIABLES	Equity	Corporate	Municipal	Gov't
Log (1 + Attacks) $_t$	-0.096**	-0.060	0.005	0.110***
	(0.029)	(0.079)	(0.021)	(0.024)
Personal Savings $_t$	-0.048	-0.001	-0.074	0.008
	(0.056)	(0.075)	(0.052)	(0.059)
Capital Gains $_t$	-0.002	-0.013**	0.001	0.025
	(0.002)	(0.005)	(0.001)	(0.014)
Return $_t$	0.769	1.874	2.258	-0.981
	(1.358)	(2.231)	(1.628)	(1.005)
Flow $_t$	0.295***	0.159**	0.311*	0.287***
	(0.026)	(0.064)	(0.111)	(0.052)
Flow $_{t-2}$	0.177***	0.302***	0.233***	0.309***
	(0.025)	(0.050)	(0.019)	(0.059)
S&P 500 $_t$	-0.489			
	(1.602)			
Winter $_t$	0.380***	0.162	0.162	-0.314
	(0.048)	(0.104)	(0.123)	(0.377)
Spring $_t$	0.203	-0.055	-0.158	-0.367**
	(0.127)	(0.161)	(0.155)	(0.106)
Fall $_t$	0.027	-0.250	-0.464*	-0.213
	(0.067)	(0.139)	(0.157)	(0.264)
5 Year Treasury $_t$		0.099***	0.061	0.167***
		(0.026)	(0.043)	(0.034)
CPI $_t$		-0.091	-0.068	0.116
		(0.205)	(0.184)	(0.132)

Observations	2,643	1,897	1,100	1,411
R-squared	0.455	0.455	0.654	0.602
Fund Style Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Panel B: Net Exchanges				
	(1)	(2)	(3)	(4)
VARIABLES	Equity	Corporate	Municipal	Gov't
Log (1 + Attacks) $_t$	-0.046***	-0.003	-0.010	0.066**
	(0.012)	(0.012)	(0.017)	(0.017)
Personal Savings $_t$	-0.025	0.016	0.006	0.003
	(0.024)	(0.016)	(0.021)	(0.010)
Capital Gains $_t$	0.000	-0.002**	0.001	0.007
	(0.001)	(0.001)	(0.000)	(0.004)
Return $_t$	0.199	0.336*	0.985**	0.431
	(0.459)	(0.153)	(0.281)	(0.660)
Flow $_t$	0.052***	0.013	0.031*	0.028
	(0.007)	(0.009)	(0.012)	(0.016)
Flow $_{t-2}$	0.030*	0.033*	0.003	-0.008
	(0.014)	(0.015)	(0.008)	(0.007)
S&P 500 $_t$	-0.261			
	(0.580)			
Winter $_t$	0.063**	-0.009	-0.037	-0.098**
	(0.024)	(0.057)	(0.028)	(0.030)
Spring $_t$	0.074	-0.015	-0.007	-0.117**
	(0.049)	(0.063)	(0.024)	(0.028)
Fall $_t$	0.020	-0.030	-0.015	-0.058*
	(0.037)	(0.063)	(0.049)	(0.026)
5 Year Treasury $_t$		0.045***	-0.013	0.038*
		(0.007)	(0.016)	(0.016)
CPI $_t$		-0.032	-0.020	-0.018
		(0.060)	(0.044)	(0.040)
Observations	2,643	1,897	1,100	1,411
R-squared	0.153	0.119	0.204	0.312
Fund Style Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes

Panel C: Exchanges In vs. Exchanges Out				
	Equity		Government	
	(1)	(2)	(3)	(4)
VARIABLES	Exchanges Out	Exchanges In	Exchanges Out	Exchanges In
Log (1 + Attacks) $_t$	0.029*	-0.006	-0.034**	0.064**
	(0.013)	(0.015)	(0.009)	(0.020)
Personal Savings $_t$	-0.022	-0.075***	-0.017	-0.002

	(0.018)		(0.020)	(0.008)	(0.012)
Capital Gains $_t$		0.001	0.001	0.005	0.015*
	(0.001)		(0.001)	(0.006)	(0.006)
Return $_t$	-0.146		-0.033	-0.570	-0.655
	(0.245)		(0.235)	(0.288)	(0.791)
Flow $_t$		0.007	0.094***	0.009	0.044*
	(0.011)		(0.017)	(0.014)	(0.020)
Flow $_{t-2}$	-0.018		0.021	0.030*	0.024
	(0.018)		(0.017)	(0.012)	(0.012)
S&P 500 $_t$	-0.345		-1.007**		
	(0.262)		(0.357)		
Winter $_t$	0.155***		0.233***	0.147**	0.004
	(0.044)		(0.049)	(0.035)	(0.018)
Spring $_t$		0.023	0.112*	0.074**	-0.077*
	(0.024)		(0.054)	(0.020)	(0.032)
Fall $_t$		0.039	0.062**	0.081*	-0.014
	(0.032)		(0.026)	(0.029)	(0.019)
5 Year Treasury $_t$				-1.358	3.161**
				(0.690)	(0.717)
CPI $_t$				-4.848**	-9.240*
				(1.256)	(3.926)
Observations		2,643	2,643	1,411	1,411
R-squared		0.453	0.458	0.369	0.340
Fund Style Fixed Effects		Yes	Yes	Yes	Yes
Year Fixed Effects		Yes	Yes	Yes	Yes

Table 1-3: Effect of Attack in Different Time Periods

This table contains the main results for different time periods in our sample. The dependent variable in Panel A is the aggregate net flow from ICI data in the month following the attacks. The dependent variable in Panel B is the net exchange in the month following the attacks. Attacks is the total number of attacks in each month that involve human casualties or injuries, or mention in the news. Columns 1 and 2 examine the difference between the effect of attacks in the first and second halves of the sample. Columns 3 and 4 examine the effect of attacks during recessionary periods. We define recessions as NBER contractionary periods. Columns 5 to 8 repeat the tests from Columns 1 to 4 using Net Exchanges as the dependent variable. All other control variables are the same as in Table 2. All models include fund style fixed effects and year fixed effects. Robust standard errors in parentheses *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Net Flows					Net Exchanges			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	Equity	Gov't	Equity	Gov't	Equity	Gov't	Equity	Gov't
Log (1 + Attacks) $_t$	-0.124**	0.031	-0.077**	0.123***	-0.074***	0.065**	-0.033**	0.077***
	(0.050)	(0.026)	(0.033)	(0.023)	(0.019)	(0.017)	(0.012)	(0.015)
Post 1998 Dummy * Log (1+Attacks) $_t$	0.051	0.198**			0.057**	0.009		
	(0.055)	(0.067)			(0.018)	(0.016)		
Post 1998 Dummy $_t$	-0.275	0.326			-0.190**	0.098		
	(0.170)	(0.311)			(0.066)	(0.064)		
Recession $_t$			-0.123	0.265			-0.153**	-0.188
			(0.080)	(0.295)			(0.046)	(0.102)
Recession * Log (1+Attacks) $_t$			-0.180**	-0.212			0.042	0.254**
			(0.073)	(0.211)			(0.038)	(0.075)
Observations	2,643	1,411	2,643	1,411	2,643	1,411	2,643	1,411
R-squared	0.455	0.604	0.455	0.602	0.155	0.319	0.155	0.319
Fund Style Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 1-4: Individual Fund Flows and Terrorist Attacks

This table contains our main results using individual fund level data from CRSP. The dependent variable is each fund's net flows in the month after attacks. Attacks is the total number of attacks in each month that involve human casualties or injuries, or mention in the news. Return is the one-month lagged fund return, and Assets is the log of lagged total fund assets. Expense ratio is the annual expense ratio reported by CRSP. Savings is the lagged personal savings rate from the BEA and Capital Gains is the cumulative fund return from the previous November. Past Year Avg. Return is the average monthly fund return over the past 12 months. Flow is the one- (three-) month lagged fund flows. Aggregate Flow is the lagged total fund flows into all funds in the same fund style. For equities in Column 1, fund styles are defined by Morningstar nine-style-box category, and for bond funds in Column 2, we aggregate total flows by municipal, corporate, and government bonds. Savings, Capital Gain, five-year Treasury, CPI, and S&P 500 are defined the same way as in Table 2. All models include fund fixed effects and year fixed effects. Robust standard errors in parentheses *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

VARIABLES		(1) Equity	(2) Bond
Log (1 + Attacks) $_t$	-0.122***		0.153***
		(0.032)	(0.024)
Return $_t$	0.116***		0.167***
		(0.008)	(0.010)
Assets $_t$	-1.076***		-0.820***
		(0.047)	(0.040)
Expense Ratio $_t$		0.040	-0.065
		(0.033)	(0.188)
S&P 500 $_t$	-0.097***		
		(0.007)	
Capital Gain $_t$	0.017***		0.028***
		(0.002)	(0.004)
Savings $_t$		0.034*	-0.080***
		(0.021)	(0.018)
Winter $_t$	0.129***		0.317***
		(0.033)	(0.028)
Summer $_t$	-0.140***		0.109***
		(0.030)	(0.027)
Fall $_t$	-0.251***		-0.322***
		(0.033)	(0.034)
Past Year Avg. Return $_t$	0.169***		0.240***
		(0.013)	(0.036)
Flow $_t$	0.080***		0.116***
		(0.011)	(0.007)
Flow $_{t-2}$	0.070***		0.107***
		(0.006)	(0.004)
Aggregate Flow $_t$		0.003	0.010***
		(0.002)	(0.002)
5 Year Treasury $_t$			0.047***
			(0.009)
CPI $_t$			-0.134***
			(0.027)
Observations	428,210		321,887
R-squared		0.039	0.054
Number of Funds		5,951	4,203
Fund Fixed Effects		Yes	Yes
Year Fixed Effects		Yes	Yes

Table 1-5: The Effect of Proximity and Saliency on Fund Flows

In this table we examine the effect of the vulnerability of investors to depressive moods and PTSD on flows into funds. The dependent variable is each fund's net flow in the month after attacks. Attacks is the total number of attacks in each month that involve human casualties or injuries, or mention in the news. In Panel A we define a vulnerable fund as one located in the same city of an attack during the month or in a large city. The rest of the funds are defined as less vulnerable funds. In Panel B we define a vulnerable fund as one located in the same state of an attack during the month or in a large city. The rest of the funds are defined as less vulnerable funds. We define a large city using Beale Urban Rural Codes. In Columns 1 and 2 of both panels, a large city is defined as a metro area with a population greater than 250,000 (Beale codes 1 and 2). In Columns 3 and 4 we define a large city as a metro population of over 1,000,000 (Beale code 1). All controls variables are the same as defined in Table 4. All models include fund fixed effects and year fixed effects. Robust standard errors in parentheses *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Panel A: Attack City + Large City				
	Large City > 250,000		Large City > 1,000,000	
	(1)	(2)	(3)	(4)
VARIABLES	Equity	Bond	Equity	Bond
Log (1 + Attacks) $_t$ * Vulnerable Funds $_t$	-0.189**	0.176***	-0.247***	0.175***
	(0.080)	(0.039)	(0.041)	(0.040)
Log (1 + Attacks) $_t$ * Less Vulnerable Funds $_t$	-0.044	0.306	0.176	0.207
	(0.070)	(0.374)	(0.130)	(0.169)
Observations	382,376	147,984	382,376	147,984
R-squared	0.039	0.053	0.039	0.053
Number of Funds	5,026	1,698	5,026	1,698

Panel B: Attack State + Large City				
	Large City > 250,000		Large City > 1,000,000	
	(1)	(2)	(3)	(4)
VARIABLES	Equity	Bond	Equity	Bond
Log (1 + Attacks) $_t$ * Vulnerable Funds $_t$	-0.217***	0.176***	-0.255***	0.174***
	(0.064)	(0.039)	(0.040)	(0.040)
Log (1 + Attacks) $_t$ * Less Vulnerable Funds $_t$	-0.026	0.307	0.187	0.225
	(0.057)	(0.374)	(0.132)	(0.171)
Observations	382,376	147,984	382,376	147,984
R-squared	0.039	0.053	0.039	0.053
Number of Funds	5,026	1,698	5,026	1,698

Table 1-6: Terrorists Attacks and Fund Beta

In this table we examine the change of flows after attacks for funds with different levels of market risk, as measured by market beta. To calculate fund market betas, we run 36-month rolling regressions based on the one-factor (Column 1), Fama-French three-factor (Column 2), and Fama-French three-factor plus momentum factor (Column 3). We define high beta funds as the funds with a market beta greater than 1. The dependent variable is each fund's net flow in the month after attacks. Attacks is the total number of attacks in each month that involve human casualties or injuries, or mention in the news. All other control variables are defined the same as in Table 4. All models include fund fixed effects and year fixed effects. 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
Log (1+Attacks) $_t$	-0.106***	-0.114***	-0.111***
	(0.039)	(0.039)	(0.039)
High Beta $_t$	-0.098*	-0.110**	-0.148***
	(0.056)	(0.047)	(0.047)
High Beta * Log (1+Attacks) $_t$	-0.026***	-0.041***	-0.037***
	(0.006)	(0.006)	(0.006)
Observations	252,281	252,281	252,281
R-squared	0.038	0.038	0.038
Number of Funds	5,079	5,079	5,079
Fund Fixed Effects	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes
Controls	Yes	Yes	Yes

Table 1-7: Effect of Attacks Across Fund Style

In this table we examine the effect of the attacks on flows across different fund and share class styles. Attacks is the total number of attacks in each month that involve human casualties or injuries, or mention in the news. Panel A and B examine flows to different equity fund styles and bond fund styles, respectively. In Columns 1−3 we examine equity funds that differ in terms of the capitalizations of the stocks they hold in their portfolios. The dependent variable is each fund's net flow in the month after attacks. Funds are assigned to small-, mid-, or large-cap categories. In Columns 4−6 we classify funds as growth, growth and income, and income. Funds are assigned based on their CRSP objective codes. In Columns 7 we identify institutional share classes using the CRSP institutional fund flag. In Column 8 we identify retirement share classes using a text search for the terms "retirement" or "Class R" in the fund name. In Columns 1−3 of Panel B, we classify bond funds as government, municipal and corporate. In Columns 5 and 6 of Panel B, we classify bonds fund share classes as institutional or retirement in the same manner we do for equity funds. All other control variables are the same as in Table 4. Fund fixed effects and year fixed effects are included in all regressions. Robust standard errors in parentheses *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Panel A: Equity Funds

	Capitalization			Equity Style			Share Class	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	Small	Mid	Large	Growth	Growth and Income	Income	Retirement Class	Institutional Class
Log (1 + Attacks) $_t$	-0.163**	-0.284**	-0.067	-0.151***	-0.051	-0.061	-0.058	-0.086
	(0.079)	(0.127)	(0.165)	(0.051)	(0.059)	(0.130)	(0.177)	(0.061)
Observations	56,253	35,001	7,937	117,116	54,505	11,719	62,624	19,005
R-squared	0.057	0.061	0.026	0.053	0.063	0.117	0.047	0.044
Number of Funds	736	503	93	1,738	755	205	2,002	462
Fund Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Panel B: Bond Funds					
	Bond Style			Share Class	
	(1)	(2)	(3)	(4)	(5)
VARIABLES	Gov't	Muni	Corp	Retirement Class	Institutional Class
Log (1 + Attacks) $_t$	0.255**	0.151***	0.113	0.162	0.150*
	(0.119)	(0.025)	(0.082)	(0.254)	(0.087)
Observations	13,267	117,676	20,479	19,005	203,209
R-squared	0.068	0.060	0.051	0.044	0.027
Number of Funds	202	1,375	328	462	3,550
Fund Fixed Effects	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes

Table 1-8: Market Volatility after the Attacks

In this table we examine the change in the level of the VIX index and the market volatility in the month following attacks. Attacks is the total number of attacks in each month that involve human casualties or injuries, or mention in the news. For the VIX data we use the updated methodology that was introduced September 22, 2003. The updated methodology changes the measurement of the VIX from the implied volatility of at the money S&P 100 index (OEX) prices, to the weighted average of S&P 500 index (SPX) put and call prices over a range of strike prices. We then use historical data from the CBOE going back to 1990 for our tests in Columns 1 and 2. We use the average value of the VIX in the month after the attacks as the dependent variable. In Columns 3 and 4 we examine the change in realized market volatility. To measure market volatility, we calculate the standard deviation of the daily returns for the S&P 500 and use the month ahead value as the dependent variable. In Panel B we use the realized market kurtosis and realized market skewness, using daily returns. Columns 1 and 2 reports market kurtosis, and columns 3 and 4 report market skewness. All models include year fixed effects. Robust standard errors in parentheses *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Panel A: VIX and Market Volatility	Average Value of VIX $_t$		Realized Market Volatility $_t$	
	(1)	(2)	(3)	(4)
VARIABLES				
Log (1+Attacks) $_t$	-0.420	-0.449	0.000	0.000
	(0.405)	(0.405)	(0.001)	(0.001)
VIX $_{t-1}$	0.658***	0.607***		
	(0.075)	(0.079)		
Volatility $_{t-1}$			0.438***	0.349***
			(0.111)	(0.113)
S&P 500 $_{t-1}$		-8.844		-0.018***
		(6.834)		(0.006)
Spring $_t$		-0.738		0.000
		(0.638)		(0.000)
Winter $_t$		-0.221		0.000
		(0.624)		(0.000)
Fall $_t$		0.806		0.001*
		(0.792)		(0.001)
Observations	251	251	324	324
R-squared	0.775	0.782	0.529	0.550

Panel B: Skewness and Kurtosis				
	Realized Market Kurtosis $_t$		Realized Market Skewness $_t$	
	(1)	(2)	(3)	(4)
VARIABLES				
Log (1+Attacks) $_t$	-0.057	-0.080	-0.052	-0.058
	(0.112)	(0.112)	(0.062)	(0.063)
Kurtosis $_{t-1}$	-0.144***	-0.161***		
	(0.053)	(0.056)		
Skewness $_{t-1}$			-0.084	-0.077
			(0.056)	(0.057)
S&P 500 $_{t-1}$		1.915*		-0.493
		(1.070)		(0.658)
Spring $_t$		0.396***		0.036
		(0.148)		(0.086)
Winter $_t$		0.386**		0.032
		(0.189)		(0.095)
Fall $_t$		0.533***		0.050
		(0.181)		(0.088)
Observations	324	324	324	324
R-squared	0.134	0.163	0.132	0.134

Table 1-9: Corporate Investment and Personal Consumption

In this table we examine effect of terrorism on corporate investment and personal consumption expenditures. Attacks is the total number of attacks in each month that involve human casualties or injuries, or mention in the news. We use quarterly total private non-residential investment (series PNFI) from the BEA as our measure of corporate investment in Column 1. In Columns 2 and 3, we use the equipment and R&D portions of total investment (BEA series Y033RL1Q225SBEA and Y006RL1Q225SBEA). In Column 4 we use monthly personal consumption expenditures (series PCE) from the BEA as the dependent variable. Columns 5 and 6 then use the non-durable and durable portions of consumption (series PCEND and PCEDG). In each case, the BEA seasonally adjusts the investment and consumption rates so we do not include seasonal dummies in our models. Five-year Treasury, CPI, and S&P 500 are the lagged values of the five-year government bond return, the change in CPI, and the value weighted return for the S&P 500. All models include year fixed effects. Robust standard errors in parentheses *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Corporate Investment				Personal Consumption Expenditures		
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Total Investment	Equipment	R&D	Total Consumption	Non-Durable Goods	Durable Goods
Log (1 + Attacks) $_t$	0.225	1.163	0.332	-0.117**	-0.035	-0.873**
	(0.273)	(1.709)	(0.642)	(0.058)	(0.082)	(0.337)
Investment $_t$	0.081	0.051	-0.321***			
	(0.141)	(0.153)	(0.094)			
Consumption $_t$				-0.400***	-0.055	-0.364***
				(0.098)	(0.101)	(0.103)
S&P 500 $_t$	0.958	-11.662	-6.291	-0.603	1.104	-0.818
	(3.138)	(22.880)	(8.134)	(0.618)	(1.259)	(3.369)
CPI $_t$	0.429	-0.749	4.823***	3.678	-10.979	14.958
	(0.776)	(4.052)	(1.819)	(7.493)	(22.897)	(49.051)
5 Year Treasury $_t$	-0.065	-0.318	0.296	3.875**	-3.629	18.321*
	(0.122)	(0.718)	(0.283)	(1.855)	(3.903)	(9.536)
Observations	108	108	108	324	324	324
R-squared	0.688	0.608	0.638	0.256	0.066	0.192
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Table 1-10: Investor Market Outlook

In this table we examine the change in investors future market outlook following a spike in attacks. Attacks is the total number of attacks in each month that involve human casualties or injuries, or mention in the news. 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 (II) as the dependent variable. Columns 3 and 4 use the institutional investor and individual investor responses from the Yale Stock Market Confidence Index as the dependent variable, respectively. Column 5 represents the percent probability that investors believe the market will experience a crash in the next six months. Column 6 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. Investor Intelligence conducts weekly surveys, so we use the value from the first survey of month *t+1*, all other dependent variables are in month *t+1*. Market Outlook is the lagged value of the dependent variable in each column. All other control variables are defined the same as in Table 2. All models include year fixed effects. Robust standard errors in parentheses *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Bearish %	Bullish % - Bearish %	Yale Survey Institutional	Yale Survey Individual	Yale Crash Risk	Univ. of Michigan Survey
Log (1+Attacks) $_t$	-0.026	0.349	-0.243	0.120	0.455	1.248
	(0.373)	(0.713)	(0.590)	(0.408)	(0.621)	(0.799)
S&P 500 $_t$	-69.916***	150.636***	-3.539	-2.805	-5.065	16.950*
	(5.678)	(11.126)	(3.915)	(3.456)	(5.876)	(9.201)
Winter $_t$	-0.121	-0.518	1.688***	0.310	0.361	0.258
	(0.601)	(1.223)	(0.512)	(0.393)	(0.580)	(0.704)
Spring $_t$	0.958*	-2.440**	-0.177	-0.563	1.143*	-0.188
	(0.534)	(1.153)	(0.503)	(0.416)	(0.655)	(0.826)
Summer $_t$	-0.050	-1.373	1.588***	-0.445	0.562	-0.614
	(0.567)	(1.257)	(0.574)	(0.483)	(0.617)	(0.846)
Market Outlook $_t$	0.608***	0.561***	0.754***	0.713***	0.830***	0.587***
	(0.041)	(0.041)	(0.052)	(0.082)	(0.060)	(0.101)
5 Year Treasury $_t$	-9.054	17.447	12.753	-10.502	-29.777*	-1.724
	(16.013)	(33.941)	(14.428)	(11.721)	(16.860)	(23.233)
CPI $_t$	192.893**	-424.581**	1.691	-18.981	-72.779	-24.098
	(77.650)	(175.957)	(39.914)	(41.177)	(51.381)	(69.518)
Observations	322	322	111	111	111	102
R-squared	0.856	0.825	0.863	0.949	0.939	0.836
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

Table 1-11: Industry Correlation

In this table we examine the change in flows to equity funds that are highly correlated with certain Fama-French 49 industries after attacks. The dependent variable is each fund's net flow in the month after attacks. We estimate the funds exposure to each industry (industry beta) by running 12-month rolling regressions against the Fama-French 49 industry returns for the transportation (Column 1), defense (Column 2), insurance (Column 3), and bank industries (Column 4). We take the industry beta from the rolling regression and denote the funds in the top 10% of industry 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. Attacks is the total number of attacks in each month that involve human casualties or injuries, or mention in the news. All other control variables are defined the same as in Table 4. Fund fixed effects and year fixed effects are included in all regressions. 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
Log (1+Attacks) $_t$	-0.079**	-0.061*	-0.065**	-0.075**
	(0.032)	(0.032)	(0.032)	(0.032)
High Transportation* Log (1+Attacks) $_t$	0.114			
	(0.212)			
High Transportation $_t$	-0.346***			
	(0.104)			
High Defense* Log (1+Attacks) $_t$		0.060		
		(0.157)		
High Defense $_t$		-0.037		
		(0.078)		
High Insurance* Log (1+Attacks) $_t$			-0.225	
			(0.222)	
High Insurance $_t$			0.018	
			(0.103)	
High Banks * Log (1+Attacks) $_t$				-0.031
				(0.299)
High Banks $_t$				-0.085
				(0.117)
Observations	346,800	357,235	345,541	345,372
R-squared	0.049	0.050	0.050	0.048
Number of Funds	5,821	5,812	5,808	5,821
Fund Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes

Table 1-12: Foreign and Domestic Fund Results

In this table we use aggregate flows from ICI to examine the change of flows into equity funds invested in foreign and domestic equities after attacks. The dependent variable is aggregate net flows in percentage in foreign funds (Column 1 and 3) and domestic funds (Column 2 and 4). We define emerging markets, global and international equity styles as foreign. All other equity styles are classified as domestic. The Attack – Ex US variable in Column 1 and 2 is defined using the same methodology as our U.S. terrorism variable in Column 3 and 4, except that attacks are aggregated in each month from the other seven countries that comprise the G8, with the exception of the US. All other control variables are defined the same as in Column 1 of Table 2, Panel A. We add the lagged value of the global market index as an additional control variable. Fund style fixed effects and year fixed effects are included in all regressions. Robust standard errors in parentheses *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

VARIABLES	(1) Foreign	(2) Domestic	(3) Foreign	(4) Domestic
Log (1 + Attacks) – Ex US $_t$	0.006	-0.043**		
	(0.057)	(0.011)		
Log (1 + Attacks) $_t$			-0.082**	-0.046*
			(0.013)	(0.017)
Observations	725	1,215	725	1,215
R-squared	0.584	0.635	0.584	0.638
Fund Style Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes

Table 1-13: Alternate attack specifications

This table replicates the results in Table 4 using a reduced sample of attacks and alternate specifications of the terrorism variable. The dependent variable is aggregate net flows in percentage in equity funds (Column1) and governance bond funds (Column 2). In Model 1 we rank all attack months based on the number of casualties and drop the attacks in the highest 5%. In Model 2 (Model 3) we create a rank attack variable in which we sort all months with attacks into quartiles (terciles). In Model 4 we define an attack month if the number of attacks in that month is greater than the median number of attacks per month in our sample. In Model 5 we create an attack month dummy that equals 1 if the number of attacks in the current month is greater than three times the average number of attacks per month over the past 12 months. In Model 6 the attack dummy is equal to 1 if there is an attack or school shooting from the Antoniou et al. (2016) sample. All other control variables are defined the same as in Table 2. All models include fund style fixed effects and year fixed effects. Robust standard errors in parentheses *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)
VARIABLES	Equity	Gov't Bond
(Model 1) Attack Month Rank – Quartile $_t$	-0.045***	0.044**
	(0.011)	(0.010)
(Model 2) Attack Month Rank – Tercile $_t$	-0.051***	0.060***
	(0.013)	(0.007)
(Model 3) Attack – Month Above Median of Attacks $_t$	-0.231***	0.153***
	(0.042)	(0.030)
(Model 4) Attack – 3x Rolling Average $_t$	-0.236**	0.244*
	(0.073)	(0.091)
(Model 5) Attack/School Shooting Dummy $_{t+1}$	-0.201***	0.268*
	(0.029)	(0.115)
Observations	2,2643	1,411
R-squared	0.456	0.603
Number of Funds	9	5
Fund Style Fixed Effects	Yes	Yes
Year Fixed Effects	Yes	Yes
Controls	Yes	Yes

CHAPTER II – ESSAY 2:

EQUITY MARKET PARTICIPATION AND HOUSEHOLD TRADING: EVIDENCE FROM TERRORIST ATTACKS

INTRODUCTION

Households are constantly faced with financial decisions. With regards to creating long term wealth, participating in the equity market is arguably the most important (Campbell, 2006). Accepting the risk return trade off the equity market presents, then introduces the household to an additional array of choices: when to trade, how much to trade, and what to trade. While Campbell points out the importance of owning stocks, Grinblatt and Keloharju (2001) note that understanding the extraordinary degree of trading activity is itself one of the great challenges for finance academics. As these are both important topics themselves, the majority of studies focus on these decisions separately. The goal of this paper is to use a single non-economic shock, terrorism, to examine the effect time varying risk preference has on both the decision to invest in the stock market, and different aspects of household trading behavior.

We start by examining overall trading activity in the form of purchase and selling behavior; then further examine the decision to invest in the equity market;. In the lead up to the 2016 presidential election, voters listed terrorism as the campaign issue that was most important to them, behind only the economy (Pew Research Center, July, 2016). In addition to voting decisions, terrorism and terrorist attacks affect individual consumption, short-term stock prices, mutual fund flows and corporate decision making[22]. With these findings on the wide-ranging effects of terrorism, it is possible that further examination may help add to understanding market related decisions households make.

To determine if terrorism affects trading activity, we use two sources of individual investor data and a comprehensive list of terrorist attacks from the past 40 years. While previous studies on terrorism use only a handful of large events, we use a larger sample of all salient attacks. This approach is similar to Wang and Young (2017), and consistent with Llussá and Tavares (2008) finding that the number of attacks have a larger effect on consumption than does the casualties from attacks. A comprehensive list of terrorist attacks is taken from Enders et al. (2011), then paired down to ensure that all attacks included are likely to be salient to household investors[23]. Initial tests on trading behavior use data from a large discount brokerage. The brokerage data allows for a more complete analysis on the value and direction of common stock trades, and the characteristics of stocks traded. Tests of equity market participation use survey data from the Panel Study of Income Dynamics at the University of Michigan (PSID). This data allows for a broad examination of market participation and savings behavior of households from 1984 to 2013.

For households participating in the stock market, the percentage of wealth invested, and trading activity play a significant role in household stock market outcomes. To further examine the effect of terrorism on trading activity we use data from a large discount brokerage. From 1991 to 1996, the value of households' net purchases, as a percentage of total equity holdings,

[22] Arin et al. (2001) examine the effects of terrorism on six different global financial markets. Chesney et al. (2011) examine the effects of terrorist attacks on global financial markets and certain industries. Eckstein et al. (2004) look at the effect on the Israeli economy, as do Llussá et al. (2011). Wang and Young (2018) study mutual fund flows and Antoniou et al. (2016) look at the effect of attacks and school shootings on corporate investment and cash holdings.

[23] An attack is included and considered salient if it is covered in the news or involved injuries or casualties.

drops significantly in the month following an increase in the level of terrorism. A one standard deviation increase in the number of attacks, roughly equivalent of going from the mean of two attacks in a month to four attacks, leads active traders[24] to reduce their net purchases by 10%. In terms of dollars, this equates to a drop of $1,623. Consistent with results from PSID data, breaking down the value and number of both buys and sells shows that the drop in net purchases is caused by a drop in overall trading activity.

A significant difference between ours, and related studies on corporate scandals and natural disasters by Giannetti and Wang (2016) and Barath and Cho (2014), is that terrorism can affect individuals far outside just the local area of an attack. Galea et al. (2002) and Schlenger et al. (2002) show that individuals living in large cities as well as those living close to the attacks are most likely to be affected. Using household location data from a subsample of the brokerage data, we find that the effect of terrorism can be seen both at the local level, and in households located in large metropolitan cities outside the immediate area of the attacks. In related tests, we find evidence of a flight home effect and an increase in demand for local stocks. Following attacks, households located in the state of an attack, increase their purchases of locally headquartered stocks.

In addition to the location of the investor, gender and relationship status are significant predictors of an individual's response to terrorism. Biais et al. (2005) find that men are much more susceptible to the effects of psychological variables, while the same effects are non-existent in women. In addition to gender, Roussanov and Savor (2014) study the risk taking of married CEOs and show that relationship status, with respect to married or single head of households',

[24] Households in the individual trading data are classified as active traders, affluent household, and general accounts. We use active traders because general and affluent traders trade at a much lower frequency and results may suffer from an inattention bias.

may play a significant factor in behavior as well. Consistent with these studies, households with a married couple respond to terrorism more than their single counterparts. Further tests show that the response by married households is driven by those where the male is designated the head of the household. Neither single nor married females alter their trading behavior in response to terrorism.

We next examine the extent to which the effects of terrorist attacks on trading behavior are transient. Using the brokerage data we find that the effect of terrorist attacks on net purchases persists for a total of 4 months. This includes the month directly after attacks and a following three months. Additionally, as a robustness test we do not find any significance on the attack variable for the month before the attacks took place. Over a number of robustness tests, we find that the main results hold up to alternate specifications of the attack variable. To ensure that the continuous attack variable is not driving the results, we create a tercile rank variable as well as a high attack dummy variable and find consistent results in both the PSID and trading samples.

Using household survey data from PSID and aggregating the number of salient attacks each year, we find that households significantly reduce their level of market participation in years with higher terrorist activity. Following a one standard deviation increase in the level of terrorism, akin to going from 9 attacks in a year to 16 attacks, there is a 6% drop in the likelihood that households own equity. A further study of household savings accounts, reveals a significant increase in the value of savings, relative to household wealth. Along with fewer households owning equity in a year with a high terrorist activity, the number of individuals reporting more buys than sells decreases significantly. In terms of the dollar value of net purchase, an increase in terrorism leads households to significantly reduce the value of their equity purchases.

Historically, papers examining the effects of noneconomic events on mood and behavior have focused mainly on aggregate price effects, but have also recently used aggregate mutual fund flows as well (Kamstra et al., 2015, Wang and Young, 2018). Similar to Kaplanski et al. (2015) we turn our attention to the household level in our examination of terrorism. With respect to Kaplanski et al., we differ in that our study focuses on the outcome of investor decision making (market participation and trading) while they focus on the effect of mood, sporting results and Seasonal Affective Disorder on future expectations of risk and return. In addition to adding to a growing literature directly examining aggregate behavioral factors on households, rather than prices or flows, our two sources of household data enables us to contribute to multiple strands of literature related to individual investor behavior: Trading activity, home bias, and equity market participation.

Use of individual investor trading data, allows us to provide further insight into determinates of trading behavior and stock selection. Shum and Faig (2006) explore portfolio allocation and conclude that predicting the value of stocks owned is much more difficult than predicting who will be invested in the stock market. Using terrorism to examine transient changes risk preference helps add to the understanding of the determinants of portfolio allocation and may help explain the lack of predictive power shown by Shum and Faig (2006). With respect to market stability, Cueva et al. (2015) and Kandasamy et al. (2014) find that female traders are less susceptible to the effects of increased cortisol[25], and thus provide stability to financial market. The result of our gender tests provide some of the first large-scale real world support for these resent experimental studies. Finally, we add to the extensive literature on local bias in

[25] Increased levels of cortisol are linked with depression, depressive moods and increased stress as well (Burek et al., 2005)

investing by documenting a significant flight home effect through increased trading in local stocks after local attacks.

Previous studies identify both economic and behavioral factors that limit equity market participation. Vissing-Jorgensen (2002) find that the mean and volatility of nonfinancial income, and fixed costs of investing all affect an individual's willingness to participate in the market. Giannetti and Wang (2016) studying corporate scandals, and Barath and Cho (2014) examining natural disasters have found that each can reduce the likelihood that households invests in the equity market. We add to the literature on behavioral factors that affect participation and extend on Barath and Cho (2014) by examining an effect that is transient in its effect on households, and has a much larger scale impact, in terms of the population affected. With regards to Giannetti and Wang (2016) and their examination of trust and corporate scandals, terrorism differs in that it is noneconomic in nature. Lastly, building on the findings of Wang and Young (2018), we show that expectations of returns do not need to change to affect the participation decision.

Wang and Young (2018) examine terrorism's effect on aggregate risk preference and mutual fund flows. Antoniou et al. (2016a) and Antoniou et al. (2016b) study the shift in corporate policies and change in equity analyst forecasts following attacks, respectively. This study extends on these in a few important ways. This is the first study that directly examines the behavior of individual households. As demographic data is unavailable for mutual fund flows, we are able to study the effect that individual characteristics have on the response to terrorism. Lastly, our buy and sell tests add to these studies by showing that increased uncertainty brought on by attacks may be a factor in the risk adverse decision making shown by previous studies.

The reminder of this paper will proceed as follows. Section 2 reviews the literature and articulates the hypotheses. Section 3 describes the data. Section 4 examines the effect of terrorism using individual brokerage data. Section 5 presents the results on market participation. Section 6 provides robustness test, and Section 7 concludes the paper.

LINKING TERRORISM, MARKET PARTICIPATION AND TRADING BEHAVIOR

When planning and committing attacks, terrorists have two main goals: cause destruction, and create fear in the civilian population. Whether an individual lives in close proximity to an attack or observes the aftermath from afar, there are clear links between the attacks, and investor's financial decision making.

The most direct evidence of a link between terrorism and market related household decisions comes from recent papers in the finance also examining the effects of terrorism. Wang and Young (2017) use terrorism to shock aggregate risk preference and find that increases in the number of attacks lead to a drop in flows to equity mutual funds and increases in flows to government bond funds. Antoniou et al. (2016) and Antoniou et al. (2017) conduct a similar test, but examine the decision making for corporations and equity analysts, respectively. Similar to Wang and Young, these papers find that corporations take less risks and that changes in mood lead analysts to issue more pessimistic forecasts. As mutual fund flows are primarily driven by retail investors, corporate decisions and analysts forecasts show that emotionally driven changes to risk preference as a result of increases in terrorism and large attacks can alter the decision making of both retail investors, and more informed decision makers.

The conclusions from the recent financial literature that changes in behavior related to terrorism are driven by mood are supported by a wealth of evidence from medical studies. Both in the U.S. and overseas, previous studies show that the level of depressive moods and even PTSD increases in the civilian population directly affected by attacks. Following the attacks of September 11th, Galea et al. (2002) and Schlenger et al. (2002) find that the level of depression and the number of individuals exhibiting the symptoms of PTSD increases significantly. Over longer stretches, Hobfoll, Canetti-Nisim and Johnson (2006) find citizens of Israel who are exposed higher levels of terrorism are more likely to exhibit signs of depression and PTSD. In this case, a response to attacks could be less due to firm or market factors and related to depressive moods.

Thus far the psychological studies referenced focus on local households, however, a significant factor in terrorism is the attempt to intimidate a large group of individuals that were not directly targeted by the attacks. For these individuals not directly targeted by the attack, news coverage of the attack can trigger a shift in behavior. In both the psychology literature and traditional finance literature, negative images have been shown to lead individuals to alter behavior. Kuhnen and Knutson (2008) find that individuals exposed to negative images are more likely to choose a riskless asset when given the choice between a risky asset and a guaranteed payoff. In a similar study, Guiso, Sapienza and Zingales (2014) find that students shown scenes from a horror movie are willing to pay more to avoid a risky lottery than students not shown the movie scene. Using results from these studies as a baseline, it is possible that the effect of terrorist attacks may be felt in individuals that live outside the immediate area of the attack. Along with results from the lab, empirical evidence shows that an individual's consumption of news through television is directly related to depressive moods. Schlenger et al. (2002) show that in the aftermath of 9/11, rates of PTSD in large cities such as Boston, Chicago, Houston etc. were not significantly different than rates in Washington D.C and New York. Wang and Young (2017) present evidence supporting this hypothesis. Their study finds that the change in flows to mutual funds is evident in funds located close to an attack as well as those in large metropolitan cities. It is easy to understand that those individuals living closest to attacks would be affected by them, but these studies show it is clear that a much larger population of investors are susceptible the effects of terrorist attacks as well.

Another possible link between attacks and market participation for those households living closest may come through a wealth effect to local firms. Karolyi and Martell (2006) show that, on average, firms suffer a $400 million loss in market capitalization on the day they are the targets of a terrorist attack. In addition to firm stock price, Antoniou et al. (2016a) examine the corporate policies of firms close to attacks and find they invest less in R&D and hold more cash in the aftermath of a terrorist attack or school shooting. For the households in the local area of the attack they are more likely to be invested in these local firms (Coval and Moskowitz, 1999) and would likely be more sensitive to their price movements or policy changes.

With respect to market returns, Brounen and Derwall (2010) and Arin et al. (2008) both find a significant but short term drop in domestic stock markets following an attack in that country. Even if there is no drop in price for local firms, households may update their expectations of future returns. Antoniou et al. (2016b) find results consistent with the idea that individuals may become more pessimistic about future returns. Examining equity analysts they find that analysts located close to terrorist attacks make more pessimistic forecasts. If sophisticated equity analysts are more bearish about firm earnings in the future, then it is likely that this effect could be found in households as well.

Finally, households may be responding to larger macro-economic effects. Enders, Sandler and Parise (1992) find tourists recognize the risk of terrorist attacks, and will vacation in countries with less terrorism, leading to a significant drop in tourism revenue. For the other macroeconomic effects of terrorism Enders and Sandler (1996) provide a broad overview of other negative effects attacks can have. They note that attacks can lead to lower foreign direct investment, and lead governments to shift assets and resources to defending the country from future attacks. While these effects may be less of a factor in the decision making of individual investors, they help to show the broad impact terrorism has on an economy.

If households are experiencing a change in mood, or updating their views of future returns or corporate cash flows, there is ample evidence that this will carry over to their market participation. Previous studies on market participation have examined similar questions but focused on time invariant personal characteristics. Puri and Robinson (2005) and Dominitz and Manski (2005) examine the effect that the level of personal optimism has on expectation of returns and investing activity and find that more optimistic individuals invest more in the stock market. In this case a change in mood and return expectations may be linked, in that the mood of the individual could alter their view on the market. In either case, it is likely that terrorist attacks will lead to a change in behavior.

Just as mood has been shown to affect market participation, a similar case can be made about the effect of mood on trading behavior. Various studies have examined what causes individuals to make trades. Odean (1999) shows overconfidence leads investors to trade too much, while Barber and Odean (2001) show that this effect is larger in males. Linking confidence and depression, Stone et al. (2001) find that depressed individuals exhibit less confidence in decision making relative to their nondepressed counterparts. If depressive moods are a cause of the changing behavior, then a decrease in investor confidence could lead to a drop in trading activity.

In addition to market participation and trading, other shocks have been used to examine short-term changes in asset allocation decisions by investors. Using the onset of seasonal affective disorder (SAD), Kamstra, Kramer and Levi (2003) find that changes in moods has a significant and large impact on global market returns. Kamstra et al. (2015) conduct a similar study and find that the changes to aggregate mutual fund flows are driven by the onset of SAD. Over shorter time horizons, Bassi, Colacito and Fulghieri (2013) and Saunders (1993) find that poor weather can lead individuals to make less risky trades.

Using results from previous studies as a guide, we hypothesize that an increase in terrorism will alter household risk preferences and lead them to be less willing to participate in the stock market. This effect will be present in both those living close to the attack and those living farther away in large metropolitan areas. Finally, using brokerage data we hypothesis that attacks will lead to a short term drop in the net value of household purchases.

DATA AND METHODOLOGY

In this section we describe the data sources that will be used throughout the paper. We start with the terrorism data and then describe the PSID data and the brokerage trading data.

Terrorism Data

To start the examination, we use a comprehensive list of domestic, and transnational terrorist attacks from Enders, Sandler and Gaibulloev (2011). We start with the Enders et al. data set and use the same method as Wang and Young (2017) to define my final set of attacks. To filter out attacks that may not be large enough that investors to notice, we drop any attack that does not involve human casualties, death or is not mentioned in a newspaper. This leaves a total of 457 attacks for the sample using the PSID data and 155 attacks in the individual trading sample.

We use this set of terrorist attacks because it gives a more complete representation of the nature of terrorism. By including all salient attacks, we are able to capture the effects of all types of terrorist attacks. Studying consumption and investment data from Israel, Llussá and Tavares

(2008) show that the number of attacks has a larger effect than do the number of casualties as a result of the attacks. Similarly, Wang and Young (2017) provide evidence that the number of attacks is significantly correlated with aggregate risk preference and mutual fund flows. Additionally, as we are attempting to measure the effects of a widespread increase in terrorist activity, we feel the number of attacks nationally is a more appropriate measure than single large attacks.

Figure 1 reports the summary statistics for the control variables for both sets of household data and the terrorist attacks over those time periods. For the PSID data, the average number of attacks in a year is 9.48 with a standard deviation of 7.01. The brokerage data is aggregated at the monthly level, with the average number of attacks being 2.21 with a standard deviation of 2.37.

Brokerage Data and Variables

To study short term trading behavior, we use individual trading data from a large discount brokerage. The data covers 1991 – 1996 and is geographically distributed across states similarly to U.S. census data (Korniotis and Kumar (2013)). It has been previously used in a series of important papers that examines household trading behavior and performance (Barber and Odean (1999), Barber and Odean (2000), Barber and Odean (2001)). The individual trading data differs from the PSID data in that it is observable at a higher frequency; daily trades and monthly holdings. Additionally, we are able to differentiate between common stock trades and mutual fund trades. This is not possible in the PSID data, as both are grouped under equity holdings. As PSID data is only available every two years after 1999, individual trading data allows us to measure the change in behavior monthly and is better suited for the transient nature of the effects of terrorist attacks.

Additionally, the breadth of the individual trading data allows for a more robust analysis of trading behavior. For each trade made by a household, the date of the trade, the price paid for the stock and the total shares bought is reported. We then aggregate trades each month to conduct the main tests of net trade value, values of buys, and values of sales. For each of these tests we divide the dollar value of the trades by total household equity holdings. Along with the date of each trade, we have the total account holdings at the end of each month. Total household equity is calculated each month by summing the total value of all stocks owned. To create the net trade variable we take the total net value of all trades made in month *t* and divide it by the total equity holdings at the end of month *t-1*.

$$Net\ Trade\ Value = \frac{Dollar\ value\ of\ Buys_{i,t} - Dollar\ Value\ of\ Sells_{i,t}}{Total\ Account\ Value_{i,t-1}}$$

For all tests we include controls for the one month lagged dependent variable to control for recent trends in trading patterns, the past month return of the stocks being traded and the past months return on the S&P 500. Seasonal dummies are included to control for seasonal variation in returns and individual risk aversion. Year and household fixed effects are included to control for any unobserved heterogeneity. Finally, robust standard errors are clusters at the household level.

Each household in the individual trading data is defined as an active trader, affluent household, or general. The full sample of tests using the brokerage data is conducted on just the sample of active traders. We focus on only the active traders because using the general and affluent traders introduces a possible inattentiveness issue. Over the sample period the average number of trades made by "active traders" is 410, while the average number of trades made by “general” households is 62. The infrequent trading of the general households presents two issues. The first is that infrequent trading may mean that trades made may not be in response to terrorist attacks and could be planned long in advance. Second, any results may be skewed by a large amount of zeros in the dependent variable. Removing households that trade infrequently reduce these issues in the paper. As well, even active traders do not make trades in each month of the sample. To ensure that zeros are not driving the results, the main tests are done both including and excluding months with no trades made to avoid any issues of sample selection bias. This is important, as, especially for active traders, not making trades is a decision as well.

PSID Data and Variables

The Panel Study of Income Dynamics at the University of Michigan (PSID) was introduced in 1968 and follows 5,000 families and 18,000 individuals. Giannetti and Wang (2016) recently used PSID data to study stock market participation following the revelation of corporate scandals. Individual investment and savings data is available starting in 1984 and reported every five years up to 1999 then every other year up to 2013. We follow Giannetti and Wang to define control variables, with the exception of controlling for market returns using the return on the S&P 500. Giannetti and Wang match their corporate scandals at the state level, and therefor use the returns of the firms in the state of the attack as a control. Because the effect of terrorism extends outside of the immediate area of the attack, we use the S&P 500 as a control for returns.

To match the frequency of the PSID survey data we aggregate the number of attacks annually when using the PSID data. We then match the number of attacks in year *t-1,* to year *t* of the survey answers. This is done because the surveys taken in year *t* refer to behavior in year *t-1*. As an example, for the survey year 1999, we match the number of attacks in 1998 because the behavior the survey asks about in 1999 refers to actions in 1998. We again take from previous literature to define and select the variables of interest.

For the PSID data we create the following variables to examine the market participation, trading and savings behavior. *Hold Equity* is a dummy variable that takes the value of 1 if the individual owns in stocks during the current year. These holdings can come in the form of direct positions in publicly traded companies, mutual funds or trusts. We create the variable *Equity Ratio* by taking the value of an individual's equity holdings and dividing it by their total wealth, excluding equity. *Save Ratio* is similar to the equity ratio variable, but instead takes the value of savings accounts divided by total wealth. In addition to reporting whether or not households hold equity and how much of it, a portion of the survey reports a summary of their trading activity each year. To summarize trading behavior of each household we use survey responses to a question asking about the nature of the trades that the household made the previous year. *Buy* is a dummy variable that takes the value of 1 if the household reported that they made more stock purchases than sales. *Sell* is a dummy variable that takes the value of 1 if the household sold more stock than they purchase. Finally, *Net Buy* is created by taking 1 plus the natural log of the estimated value of the net purchases made by the household in the past year. We take the natural logarithm to remove any skewness from the variable. To control for the effects of income and wealth on investment behavior, all regressions include the controls for the reported household income and wealth. Other control variables include, the age of the head of household, children in the household, and whether or not the head of the household is married. Additionally, all models include household, state, and year fixed effects.

HOUSEHOLD TRADING ACTIVITY

In this section we present the results using individual trading data from a large discount brokerage. Discount brokerage data allows us to extend the analysis on the lack of market participation and trading activity through actual trade data, rather than only relying on households' estimation of trade volume.

Short Term Trading Behavior

In Table 2-2 we start the examination on individual trading by testing the net purchase value, as a percentage of equity holdings, made by individual investors in the month after an increase in the number of attacks. Households are classified as active traders, affluent, or general accounts. For someone who is an infrequent trader it is possible that trades made in a month are not a direct response to increased terrorism but could have been planned in advance. For this reason, we focus on active traders throughout the sample, as it is more likely their trades are influenced by recent events. When evaluating the net trades, months in which households do not make trades presents some issues. For active traders, not trading is a decision that they are making, as their norm is to make trades each month. To make sure the results are not skewed by months with no trades we conduct the tests on all months in Panel A of Table 2-2 and Panel B of Table 2-2 repeats the same tests but only on months that include trades.

In Column 1 of Table 2-2 we find that in the month after an increase attacks, active traders reduce the net value of their trades by 0.011, significant at the 1% level. In the short term, this result is consistent with the survey results from the PSID data. If attacks lead households to be less willing to participate over the course of a year, then it follows that in the immediate aftermath, household's will reduce the value of their net purchases. In Columns 2 thru 5 of Table 2-2, we further test the change in different aspects of trading activity.

Table 2-2 and Column 1 of Table 2-2 show that investors reduce their exposure to the equity market in response to an increase in the number of terrorist attacks. A drop in net purchases may be driven by multiple factors: a change in the value of trades made, or a change in the number of trades made. Columns 2 thru 5 of Table 2-2 furthers examines the change in trading behavior in terms of the value and number of trades made in both directions, buys and sells. Columns 2 and 3 starts by examining the value of the trades, as a percentage of total equity holdings. The dependent variable in Columns 2 and 3 is the total value of all stock purchases (sales), as a percentage of one month lagged equity holdings, respectively. For active investors we find that, as a percentage of their total equity holdings, the value of their stock purchases drops significantly in the month following an increase in the number of attacks. In Column 3 we repeat this test, now using the value of sales, as a percentage of lagged equity holdings, as the dependent variable. Similar to the value of buys, the result in Column 3 shows that investors reduce the value of the stock sales.

Columns 4 and 5 of Table 2-2 shifts the focus from the value of trades, to the number of trades made by investors. As with the value of buys and sells, we find that investors significantly reduce the number of both buys and sells made in the month following an increase in attacks. Taken together, the results from Panel A of Table 2-2 provide further evidence that terrorist attacks lead investors to not only reduce their market participation in terms of value of equity, they also reduce their trading activity as a whole. The results from Panel A of Table 2-2 echo the results from the survey data presented in Table 2-2.

Panel B of Table 2-2 repeats the tests from Panel A, but excludes months in which the household did not make a trade. While we do focus the tests on only the household that trade most frequently, there are still a number of months in which households do not trade. To ensure that these months with no trades are not biasing the main results, we repeat all main tests on a sample including only months in which the household made at least one trade. Panel B of Table

2-2 presents these results. In each case, we find that the results from Panel A are unchanged when excluding the months without trades. For all Columns, the sign and significance of the attack variable is the same as the main results.

Overall, the results in Table 2-2 shed more light on the trading activity of investors in the immediate aftermath of terrorist attacks. The results in Table 2-2 use survey data to provide evidence that market participation and trading activity drops significantly when there are a high number of attacks in a year. Table 2-2 expands on those results, and finds that the drop in net purchase value is a result of a drop all trading activity; the value and number of buys and sells. At first glance, readers may expect to see an increase in the number and value of sells, alongside a decrease in the number and value of purchases. Guiso and Paiella (2008) show that risk aversion varies with "any source of uncertainty characterizing the environment". It is possible that an increase in the number of terrorist attacks leads investors feeling uncertain as to its effect on the economy, stock market, or the country at large. Table 2-2 shows that investors are less willing to participate in the market, Table 2-2 further sheds light on those choices by showing that consistent with Guiso and Paiella, increased uncertainty may be a contributing factor.

Location and Local Area Characteristics

Previous studies show that those living closer to traumatic events and terrorist attacks, exhibit larger reactions following attacks. Antoniou et al. (2016) find that the reactions to terrorist attacks and school shootings are greater for those firms within close proximity of attack. If the goal of terrorist attacks is the create fear in a larger population, then it may be the case that individuals not directly affected by the attack will also exhibit a change in behavior. Wang and Young (2017) find evidence consistent with the idea that individuals not directly affected by the attacks may still exhibit a change in behavior following an increase in attacks.

To conduct these tests we use a subsample of the brokerage data, for which more information on the household is available, including the location of the house. For each month an attack takes place we create an *In State* dummy that takes the value of 1 if the household is located in one of the states in which an attack took place. We then interact this dummy with the main attack variable and rerun the main tests from Table 2-2 on this subsample of households.

Panel A of Table 2-3 presents the results for households living closest to the attacks. Consistent with previous studies the coefficient on the main attack variable in Column 1 is insignificant while the coefficient on the interaction term of in state households is -0.011 and significant at the 10% level. For the values of buys and sells, the interaction term while insignificant, is negative and positive, respectively. In Column 5 we find that those households living in the state of the attack do not reduce the number of sells in response to the attacks.

If individuals believe that an increase in terrorist attacks lead to an increased likelihood of future terrorist attacks, then individuals not directly affected by the attack may still exhibit a significant response to the attacks. Reports from the press echo the sentiment that terrorist attacks can lead individuals living in large metropolitan areas to be weary of future attacks. In a 2003 Chicago Tribune article, it is noted that the Sears Tower in Chicago was on a list of possible future targets that the 9/11 attackers planned to target in the future. Similarly, terrorism experts in academia and the FBI note that terrorist are looking to attack places of notoriety and places that will “have a large carnage count” (Graham, 2014). Schlenger et al. (2002) study the prevalence of PTSD following the attacks on 9/11 and find that the percentage of those in large cities (Boston, Philadelphia, Chicago, Houston, and Los Angeles) in the second month following the attacks was 1.2% higher than the rest of the country (12.3% vs. 11.1%).

Using this as a guide, we replicate the tests from Wang and Young (2017) and examine the response of investors directly affected by attacks, and those likely to be weary of future attacks. Consistent with Wang and Young, we define vulnerable investors as those living in the state of an attack, as well as individuals living in large metropolitan areas. To classify a city as large, we use Beale urban-rural codes matched to the zip code for each household. While this does replicate the test done in Wang and Young (2017), it presents an important addition to their test. They use the location of a mutual funds headquarters as a proxy for the location of the investors holding the fund. Using the physical address of the households in the subsample of individual investors, means that this is no longer a proxy for the location of the investor and able to more accurately identify the investors most vulnerable to depressive moods.

Panel B of Table 2-3 presents the results for investors both directly and indirectly affected by attacks. The results in Column 1 of Panel B are consistent with Wang and Young (2017) and the results in Panel A. The coefficient on attack variable is insignificant, but the coefficient on the interaction term between the attack variable and the vulnerable investors is -0.012 and significant at the 10% level. Columns 2 through 4 of Panel B repeat the buy and sell tests from Table 2-2. For buys in Column 2 we find a negative but insignificant coefficient on the interaction term. For the value of sells in Column 3, vulnerable investors seem to decrease the value of their sales by less than all other investors. In Columns 4 and 5 the number of buys and sells is used for the dependent variable. Column 5 shows another significant difference in the behavior of the vulnerable investors. Consistent with the results from Column 5 in Panel A, the coefficient on the interaction term is positive and significant. If terrorist attacks have significant effects on households that both directly and indirectly affected by the attacks, Panel B helps to confirm that hypothesis. If these individuals are more fearful from the attacks themselves, or of future attacks targeting their cities, then it is consistent that the drop in the value of net trades is driven by a drop in purchase behavior and less so by sell side behavior.

Results from similar studies on market participation focus only on household directly affected. Both Giannetti and Wang (2016) using corporate scandals and Barath and Cho (2014) using natural disasters match their independent variable at the state or county level. In Table 2-3 we show that while stronger effects are shown for households living in the state of an attack, the strongest results are for the households both in the state of the attack and those living in large metropolitan cities. This result is consistent to Wang and Young (2017) who conducted a similar test using the location of mutual fund headquarters.

Flight Home Effect

Numerous studies have shown that both household and institutional investors exhibit a significant local bias in their portfolio holdings. Coval and Moskowitz (1999) and Strong and Xu (2006) study the effect for fund managers, while Grinblatt and Keloharju (2001) and Seasholes and Zhu (2010) find the effect for household investors. More recently, Riff and Yagil (2016), in an experimental setting, found that home country bias increases during bear markets. This is similar to a flight home effect that Giannetti and Laeven (2012) found in the syndicated loan market during the financial crisis.

With these recent papers in mind, we test for a flight home effect for local investors following local terrorist attacks. We start our tests with the same sub-sample of investors used in the previous section to test the location effects, for which their household location is known. For each month we calculate the total dollar value of stocks purchased (sold) for stocks headquartered in the same state, as a percentage of the total dollar value of stocks bought (sold) in that month. We then calculate a similar variable using the number of stocks traded rather than the dollar value of trades.

Table 2-4 presents the results for our tests of the flight home effect. In Columns 1 and 2 we test the preference for local stocks following attacks using a piecewise regression and splitting the main attack variable into in-state and out-of-state households. In Column 1 we find that following a local attack, investors increase the dollar value of their purchases that are locally headquartered firms. For households living outside the state of the attack we do not see the same effect. In Column 2 we test for the changing proportion of locally headquartered sales and find no effect for either in-state or out-of-state households. Columns 3 and 4 repeat the tests from Columns 1 and 2, but instead use the number of trades that are locally headquartered rather than the dollar value of those trades. Using this as the dependent variable in Columns 2 and 4, we find similar results for both buys and sells.

Family Demographics

Along with the location of the investor, the demographic characteristics of individuals have been shown to be a significant determinant of trading behavior in response to new sources of risk. In this section we look to identify the groups of individuals most likely to exhibit a response to terrorist attacks. Roussanov and Savor (2014) explore the risk taking of married CEOs and find that married CEOs take less risk than their single counterparts. An important part of the Roussanov and Savor study is the finding that Single CEOs are unresponsive to changes in idiosyncratic risk, and that it seems to be the act of getting married that triggers this change. Recent work by Kandasamy et al. (2014) find that female traders' risk preferences are less responsive than male traders to increased levels of cortisol. This is important in the context of terrorism because higher levels of cortisol is linked to difficult life events (Cowen, 2002). These findings are similar to Biais et al. (2005) findings that males are more susceptible to psychological variable than females. We use these previous studies because they identify individual characteristics that are correlate with the introduction of new stimuli. Using these previous studies as a guide, we expect that married individuals will react more than those who are single, and that households where the female is the head will react less than those where the male is listed as the head.

In Table 2-5 we use piecewise regressions to examine the differences between these groups. Similar to the location data used in the previous section, demographic data is only available for a subsection of the individual trading data. For each household with demographic data we assign the gender of that household based on the gender reported for the head of the household. This means that even if the household is classified as married, it can still be given a gender based on the gender of the reported head of the household. In Columns 1 to 3 of Table 2-5 we split the main attack variable based on the gender of the head of household[26]. Consistent with Kandasamy et al. (2014), households where the head is male exhibit a significant change in their trading behavior, while households with female heads do not exhibit and change. Consistent with the main results, Columns 2 and 3 show that males reduce the value of their buys and sales by -0.058 and -0.036, respectively. Columns 4 to 6 shift the focus to examining the difference between married and single individuals. Here, we again find results consistent with the previous literature; the coefficient on the married individuals is -0.012 and significant at the 10% level, while the coefficient on single individuals is 0.006 and insignificant. Consistent with Roussanov and Savor (2014), married individuals' exhibit a significant change in behavior in response to a new sources of risk.

In Panel A of Table 2-5 we find significant differences in the trading activity between males and females, as well as single and married individuals. Panel B looks further into these

[26] If the household does not report the gender for the head of the household, it is not included in this regression

differences by running the relationship tests from Panel A on subsamples of males and females. Columns 1 to 3 of Panel B examine the effect of marriage on the sample of households where the male is designated as the head. Married males respond to attacks with a drop in the net value of their trades, as well as a drop in the value of buys and sells. The insignificant results for single males further echoes the Roussanov and Savor (2014) results by showing that marriage may be driving the behavior. Finally, neither married nor single females alter their trading behavior in the aftermath of an increase in attack.

Table 2-3 presents evidence that an investor's location relative to the attack has a significant impact on their trading behavior in the following months. Table 2-5, extends this by showing that personal characteristics, related gender and relationship status, are a determinant of an individual's trading behavior in the aftermath of attacks. Overall, results from Tables 4 and 5 provide more insight into the cross section of households and give a deeper understanding of the households that are most likely to react to an increase in attacks.

In additional to adding to the understanding that gender has on the response to terrorism, these results provide an interesting addition to the literature on the positive effect that female traders have on market stability. Cueva et al. (2015) and Kandasamy et al. (2014) that female traders are less susceptible to the effects of increased cortisol. In our context this is important, as cortisol levels are positively linked to stress and difficult life events. These initial studies are done in a laboratory setting, as reading hormone levels in a large group of traders would be exceedingly difficult. However, linking terrorism to higher levels or stress and cortisol, enable us to provide some of the first large-scale supporting evidence to these laboratory studies.

Duration of the Effect

Previous studies on market participation focus on events that are time-invariant or have long-lived effects. In this section we will use the brokerage data to examine how long terrorist attacks affect investors' behavior. In addition to using this test to examine the behavior of investors after the attack, we will use it as a test to ensure that there is no significant change in behavior before the attacks.

Table 2-7 presents the results on the effect of terrorist attacks in the months surrounding the attacks. For all Columns in Table 2-7 we repeat the main result from Column 1 of Table 2-2 using the net value of purchases but shifting the month, relative to the attack month. Columns 1 and 2 of Table 2-7 start by testing the month before the attacks and the month of the attacks. As expected, there is no significant relationship between the trading behavior in the month preceding the attacks and the attacks in the following month. We do not find any significant change in behavior in the month of the attacks in Column 2. This could be due to the response time of investors and the fact that attacks are spread out during the month and could come in the last few days. Column 3 repeats the test from Column 1 of Table 2-2. We next turn the attention to the months after the increase in attacks. In Columns 4 to 6 we find that the coefficient on the attack variable, while decreasing in magnitude, continues to be for the 4 months following the increase in attacks. Finally, the attack variable becomes insignificant in the fifth month after the increase in attacks. This result is consistent with Antoniou et al. (2016) who find that changes to corporate policies do not extend past the next quarter following the attacks.

HOUSEHOLD MARKET PARTICIPATION

In the previous section, we have shown that terrorist attacks significantly affect the trading activity of households. In this section, we take this examination one step further and test if terrorist attacks affect household equity market participation. If For the initial test of market participation we use data from the Panel Study of Income Dynamics. This allows us to test the effects of years with high number of terrorist attacks on the level of household market participation.

PSID Results

We start the analysis on the stock market participation of individuals using the survey data from the Panel Study of Income Dynamics. In Column 1 of Table 2-7 we start by examining the percentage of household equity that individuals hold in stocks. Here we do not find a significant change in the amount of equity held as a percentage of household assets. As the effects of terrorism have been shown to be transient (Schlenger et al, 2002, Wang and Young, 2017) this result may not be unexpected as aggregating the effect to the annual level may reduce the necessary variation needed to see the true effect. Column 2 measures the market participation in the year of an increased number of attacks. Here we find a significant drop in the number of individuals owning stock during a year with an increase in the number of terrorist attacks. Following a one standard deviation increase in the number of attacks (going from 6 attacks in a year to 16), households are 6% less likely to hold equity. Along with the ability to measure the effects of terrorism over a longer sample period, PSID data allows us to measure household savings behavior. In contrast the results in Column 1, individuals significantly increase their level of savings, as a percentage of their household assets. This increase equates to a 3% increase in the value of their savings. While household do not exhibit a drop in the value of their equity holdings, results in Columns 2 and 3 of Table 2-7 confirm the initial hypothesis that attacks lead households to reduce their participation in the stock market.

PSID data does not report detailed trading information for each household; however, in the years that equity market participation data is collected there are two survey questions that do give insight into the trading behavior. The first asks households if they bought more stocks than they sold in a year or if they sold more stocks than they bought. Second, the survey asks respondents to estimate the value of their net purchases in the previous year. The rest of Table 2-2 will test responses to these questions to further test the trading behavior of the individuals in the PSID sample. Columns 4 and 5 report the results using the dummy variables *Buy* and *Sell* respectively. Finally, Column 6 measures the value of the net purchases of the household over the previous year. We again find evidence that households are significantly reducing their exposure to the equity market by reducing the net value of their purchases over the course of the year.

The initial results using the PSID data help to show that in response to the attacks, households are less likely to hold equity. Consistent with this idea, we also find an increase in the level of savings. Interestingly, it seems that with respect to trading behavior, both buying and selling behavior drops in response to attacks.

ROBUSTNESS TESTS

In this section we use alternate specifications of the attack variable to test the robustness of the main results. It is possible that investors may not notice small differences in the number of attacks each month, but they are responding to a more general realization of a large vs. small number of attacks. To account for this possibility that the main results are driven by the small variations in the attack variable, we use two alternate specifications of an attack variable also used in Wang and Young (2017). First, we sort months into terciles based on the number of attacks each month and create a tercile rank variable to test the robustness of the continuous attack variable. We next test the possibility that continuous variables are driving the main result. To do this we create a dummy variable that is equal to one if the number of attacks in a month is greater than the number of median number of attacks per month over the full sample.

In Panel A of Table 2-8 we conduct the robustness tests on the PSID sample. In these tests we make similar to the adjustments made to the attack variable in the main tests to aggregate the attacks and the annual level. For the tercile rank variable, we rank years according to the number of attacks, then sort them into terciles. Similarly, we define the above median dummy as equal to one if the number of attacks in the year is greater than the median number of attacks in a year during the sample. We find results consistent with the main PSID tests using the alternate attack variables.

In Panel B we repeat the robustness tests on the main tests from brokerage data. Consistent with the alterations we make to the main variable, for Panel B we create the tercile rank and the above median variables at the monthly level. For the net purchases and trading behavior the results using these alternate attack variables are consistent with the main results in Table 2-2.

Edmans et al. (2007) note that the use of continuous variables, especially in sentiment studies, may have a low signal to noise ratio. Using dummy and rank robustness variables help to alleviate concerns that noise in the continuous attack variable is the cause of the main results. Additionally, these robustness tests use the same specifications as Wang and Young (2017).

CONCLUSION

Recently, there has been an increase in the number of studies examining financial decision making related to terrorism and terrorist attacks. Thus far, however, they haven't directly examined the effect that terrorism has on household market participation and short term trading behavior. Using household survey data from PSID we show that shocks to risk preference, triggered by an increase in terrorism, significantly affects household market participation and overall trading behavior. In addition to the market participation, PSID data reveals that households increase the level of their savings.

An examination of individual trading data reveals results consistent with the PSID survey data. Following an increase in terrorism, investors reduce the value and number of the trades they make. This includes a drop in the value and number of stock buys and sales. Evidence from the location of investors indicates the effects of terrorist attacks are felt by households both in the state of the attack and those in areas that may be vulnerable to future attacks. Further cross-sectional analysis reveals that married males exhibit a significant change to their trading behavior, relative to single males. For female investors, neither single nor married females respond to attacks. Finally, consistent with previous studies on terrorism, the effect is transient in nature, lasting up to 4 months after the increase in attacks.

Terrorism and terrorist attacks are an important aspect of modern society; they have influenced everything from defense and immigration policy. Until recently, knowledge of their effects on household investing behavior was limited. Using household market participation data as well as detailed trade data, this paper adds our understanding of the effects that terrorism has on household financial decisions. In addition to an overall understanding of the effects of terrorism, we are also able to add to the literature on home bias, and the potential stabilizing effects that female traders and on financial markets.

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APPENDIX

Table 2-1: Summary Statistics

This Table presents summary statistics for the variables used in the paper. Panel A presents summary statistics for variables used in the PSID regressions. Equity Ratio is the ratio of dollars held in stocks divided by total household wealth. Hold Stocks is a dummy variable that takes the value of 1 if the household owned stocks. Wealth and Income are the reported total assets of the household (net home equity) and the reported Income. Age is the age of the head of the household as designated by PSID. Children is the number of children. Market Return is the return on the S&P 500 in the year prior to the survey. Married is a dummy variable that takes the value of 1 if the head of the household is married. Panel B presents variables used in the individual trading regressions. Net Trades is the net dollar amount of buys and sells in a month divided by the lagged value of total account holdings. Value of Buys and Value of Sells are the value of buys and sells each month divided by the lagged value of total account holdings. Number of buy and Number of sells is the log of one plus the number of buys or sells made in each month. S&P 500 is the monthly return of the S&P 500. Portfolio return is the monthly return of the portfolio. Stock return is the weighted average previous month return of the stocks traded in the previous month,

Panel A: PSID Data

Variables	Mean	Standard Deviation	10th Percentile	Median	90th Percentile
Number of Attacks	9.418	7.017	4.000	7.000	19.000
Equity Ratio	0.042	0.128	0.000	0.000	0.128
Hold Equity	0.184	0.388	0.000	0.000	1.000
Wealth ($)	148379	336694	0	28300	399000
Income ($)	69077	113382	8636	39250	690600
Age	44.828	20.521	25.000	42.000	69.000
Children	0.875	1.185	0.000	0.000	3.000
S&P 500	0.059	0.190	-0.217	0.151	0.222
Married	0.452	0.498	0.000	0.000	1.000

weighted by trade size.

Panel B: Individual Trading Data

Variables	Mean	Standard Deviation	10th Percentile	Median	90th Percentile
Number of Attacks	2.219	2.373	0.000	2.000	5.000
Net Trades	0.011	0.255	0.000	0.000	0.000
Value of Buys	0.077	0.597	0.000	0.000	0.065
Value of Sells	0.047	0.267	0.000	0.000	0.032
Number of Buys	0.235	1.135	0.000	0.000	1.000
Number of Sells	0.157	0.921	0.000	0.000	0.000
S&P 500	0.013	0.028	-0.025	0.013	0.041
Buys Return	0.002	0.125	0.000	0.000	0.000
Sells Return	0.009	0.097	0.000	0.000	0.000
House Equity ($)	82,132	412,849	4,888	25,450	170,640

Table 2-2: Net Trades

Table 2 tests the net value of trades made by investors in the month following an increase in the number of attacks. *Attacks* is the number of attacks each month that cause injuries, deaths or were covered in the news. *Net Trades* is the total value of stocks sold subtracted from the value of stocks purchased, divided by 1 month lagged total equity holdings. *Buy (Sell) Value* is the value of purchases (sells) in the month divided by the 1 month lagged total equity holdings. *Number of Buys (Sells)* is the natural log of 1 plus the number of buys in each month. *Market return* is the return of the S&P 500 in month *t-1*. *Buys Return (Sells Return)* is the weighted average return of the stocks bought (sold) in the month *t-1*. *Total Equity* is the total value of stocks held by the household. Panel A includes all months, while Panel B only includes months where trades are made. All models include household fixed effects and year fixed effects. Robust standard errors in parentheses *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

VARIABLES	(1) Net Purchases	(2) Buy Value	(3) Sell Value	(4) Number of Buys	(5) Number of Sells
Log (1+ Attacks) $_{t-1}$	-0.006***	-0.012***	-0.011***	-0.018***	-0.016***
	(0.001)	(0.003)	(0.001)	(0.002)	(0.002)
Market Return $_{t-1}$	0.060**	0.423***	0.176***	0.748***	0.452***
	(0.030)	(0.074)	(0.031)	(0.043)	(0.041)
Winter $_{t}$	-0.006**	0.011**	0.011***	0.025***	0.042***
	(0.002)	(0.005)	(0.002)	(0.003)	(0.003)
Spring $_{t}$	-0.006***	0.016***	-0.000	0.016***	-0.003
	(0.002)	(0.005)	(0.002)	(0.003)	(0.003)
Summer $_{t}$	-0.014***	-0.017***	-0.009***	-0.028***	-0.022***
	(0.002)	(0.005)	(0.002)	(0.003)	(0.003)
Buys Return $_{t}$	0.006	0.132***	0.057***	0.136***	0.101***
	(0.006)	(0.019)	(0.009)	(0.015)	(0.016)
Sells Return $_{t}$	0.073***	0.152***	0.302***	0.262***	0.594***
	(0.010)	(0.022)	(0.022)	(0.017)	(0.041)
Net Purchases $_{t-1}$	-0.071***				
	(0.009)				
Log (House Equity) $_{t}$	-0.072***	-0.021**	-0.053***	0.094***	0.022***
	(0.004)	(0.009)	(0.003)	(0.003)	(0.002)
Buy Value $_{t-1}$		0.120***			
		(0.015)			
Sell Value $_{t-1}$			0.231***		
			(0.012)		
Num. of Buys $_{t-1}$				0.217***	
				(0.004)	
Num. of Sells $_{t-1}$					0.191***
					(0.005)
Observations	255,830	255,830	255,830	255,830	255,830
R-squared	0.035	0.019	0.090	0.104	0.092
Number of households	5,726	5,726	5,726	5,726	5,726

Household Fixed Effects	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes

Panel B: Months with Trades

VARIABLES	(1) Net Purchases	(2) Buy Value	(3) Sell Value	(4) Number of Buys	(5) Number of Sells
Log (1+ Attacks) $_{t-1}$	-0.011***	-0.017***	-0.018***	-0.020***	-0.021***
	(0.002)	(0.006)	(0.002)	(0.003)	(0.003)
Market Return $_{t-1}$	0.033	0.413***	0.167***	0.597***	0.382***
	(0.053)	(0.131)	(0.052)	(0.061)	(0.063)
Winter $_t$	-0.018***	-0.005	0.006*	0.003	0.041***
	(0.004)	(0.009)	(0.004)	(0.005)	(0.005)
Spring $_t$	-0.014***	0.016*	-0.006	0.019***	-0.018***
	(0.004)	(0.009)	(0.004)	(0.005)	(0.005)
Summer $_t$	-0.027***	-0.024***	-0.015***	-0.025***	-0.025***
	(0.004)	(0.009)	(0.004)	(0.004)	(0.004)
Buys Return $_t$	0.004	0.105***	0.046***	0.120***	0.080***
	(0.006)	(0.018)	(0.008)	(0.012)	(0.014)
Sells Return $_t$	0.037***	-0.008	0.214***	-0.017	0.381***
	(0.009)	(0.021)	(0.017)	(0.013)	(0.029)
Net Purchases $_{t-1}$	-0.093***				
	(0.008)				
Log (House Equity) $_t$	-0.145***	-0.087***	-0.132***	0.116***	-0.021***
	(0.006)	(0.015)	(0.005)	(0.004)	(0.003)
Buy Value $_{t-1}$		0.110***			
		(0.017)			
Sell Value $_{t-1}$			0.213***		
			(0.013)		
Num. of Buys $_{t-1}$				0.157***	
				(0.005)	
Num. of Sells $_{t-1}$					0.139***
					(0.005)
Observations	137,879	137,879	137,879	137,879	137,879
R-squared	0.070	0.018	0.110	0.076	0.059
Number of households	5,700	5,700	5,700	5,700	5,700
Household Fixed Effects	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes

Table 2-3: Proximity and Local Characteristics

Table 3 examine the effect that location has on investor's reaction to attacks. *Attacks* is the number of attacks each month that cause injuries, deaths or were covered in the news In Panel A, *In State* is a dummy variable that takes the value of 1 if the household occupants lived in the state of the attack. In Panel A, *Vulnerable* is a dummy variable that takes the value of 1 if the household occupants lived in the state of the attack or lives in a large city outside the state of the attack. A city is considered large if it is located in a county with a population greater than 1,000,000. All dependent variables and controls are defined the same as in Table 2. All models include household fixed effects and year fixed effects. Robust standard errors in parentheses *, **, and *** indicate significance at the 10, 5 and 1% level respectively.

Panel A: In State	(1)	(2)	(3)	(4)	(5)
VARIABLES	Net Trade	Buy	Sell	Count Buy	Count Sell
Log (1+ Attacks) $_{t-1}$	-0.004	-0.023***	-0.018***	-0.018***	-0.024***
	(0.003)	(0.007)	(0.003)	(0.004)	(0.004)
Log (1+ Attacks) $_{t-1}$ * In State	-0.011*	-0.016	0.007	0.005	0.023**
	(0.006)	(0.012)	(0.007)	(0.011)	(0.010)
Observations	61,366	61,366	61,366	61,366	61,366
R-squared	0.044	0.019	0.096	0.112	0.097
Number of households	1,367	1,367	1,367	1,367	1,367
Controls	Yes	Yes	Yes	Yes	Yes
Household Fixed Effects	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes

Panel B: Vulnerability	(1)	(2)	(3)	(4)	(5)
VARIABLES	Net Trade	Buy	Sell	Count Buy	Count Sell
Log (1+ Attacks) t-1	-0.004	-0.024***	-0.018***	-0.018***	-0.024***
	(0.003)	(0.007)	(0.003)	(0.004)	(0.004)
Log (1+ Attacks) t-1 * Vulnerable	-0.012*	-0.003	0.017*	0.017	0.036***
	(0.007)	(0.015)	(0.009)	(0.012)	(0.012)
Observations	61,366	61,366	61,366	61,366	61,366
R-squared	0.044	0.019	0.096	0.112	0.097
Number of households	1,367	1,367	1,367	1,367	1,367
Controls	Yes	Yes	Yes	Yes	Yes
Household Fixed Effects	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes

Table 2-4: Flight Home Effect

Table 4 examines a possible flight home effect exhibited by investors following attacks. In Columns 1 and 2 the dependent variable is the percentage of a month's total buys (sells), based on dollar value, that are firms located in the same state as the investor. In Columns 2 and 3 the percentage of the number of individual stocks purchased is used rather than the dollar value of purchases. *Attacks* is the number of attacks each month that cause injuries, deaths or were covered in the news. *In State* is a dummy variable that takes the value of 1 if the household occupants lived in the state of the attack. All dependent variables and controls are defined the same as in Table 2. All models include household fixed effects and year fixed effects. Robust standard errors in parentheses *, **, and *** indicate significance at the 10, 5 and 1% level respectively.

VARIABLES	(1) % of Buys (Dollar Value)	(2) % of Sells (Dollar Value)	(3) % of Buys (Number of Trades)	(4) % of Sells (Number of Trades)
In State * Attacks	0.008**	0.006	0.009*	0.005
	(0.004)	(0.004)	(0.005)	(0.005)
Out of State * Attacks	0.001	-0.001	0.000	-0.001
	(0.001)	(0.001)	(0.002)	(0.002)
Observations	105,392	97,332	105,392	97,332
R-squared	0.559	0.597	0.518	0.542
Number of households	1,331	1,308	1,331	1,308
Controls	Yes	Yes	Yes	Yes
Household Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes

Table 2-5: Gender and Family Characteristics

In this Table we examine the effect that gender and relationship status have on investor behavior after an attack. *Net Trades, Net Buy, and Net Sell* are defined the same as in Table 2. *Attacks* is the number of attacks each month that cause injuries, deaths or were covered in the news. *Male* is a dummy that takes the value of 1 if the head of the household identifies as a male. Fem*ale* is a dummy that takes the value of 1 if the head of the household identifies as a female. *Single* is a dummy that takes the value of 1 if the head of the household is single. Married is a dummy that takes the value of 1 if the head of the household is married. All controls are defined the same as in Table 2. All models include household fixed effects and year fixed effects. Robust standard errors in parentheses *, **, and *** indicate significance at the 10, 5 and 1% level respectively

VARIABLES	(1) Net Trades	(2) Net Buy	(3) Net Sell	(4) Net Trades	(5) Net Buy	(6) Net Sell
Male * Log (1+ Attacks) $_{t-1}$	-0.006	-0.058***	-0.036***			
	(0.006)	(0.012)	(0.007)			
Female * Log (1+ Attacks) $_{t-1}$	-0.017	0.021	-0.011			
	(0.017)	(0.030)	(0.018)			
Single * Log (1+ Attacks) $_{t-1}$				0.006	-0.024	-0.011
				(0.011)	(0.023)	(0.011)
Married * Log (1+ Attacks) $_{t-1}$				-0.012*	-0.059***	-0.039***
				(0.007)	(0.014)	(0.008)
Observations	25,674	25,674	25,674	20,449	20,449	20,449
R-squared	0.090	0.372	0.085	0.097	0.396	0.085
Number of Households	1,050	1,050	1,050	841	841	841
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Household Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

Panel B	Male			Female		
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Net Trades	Net Buy	Net Sell	Net Trades	Net Buy	Net Sell
Single * Log (1+ Attacks) $_{t-1}$	0.008	-0.031	-0.015	-0.019	0.007	-0.002
	(0.013)	(0.027)	(0.012)	(0.019)	(0.048)	(0.028)
Married * Log (1+ Attacks) $_{t-1}$	-0.014**	-0.068***	-0.043***	-0.001	0.089	0.019
	(0.007)	(0.014)	(0.008)	(0.031)	(0.058)	(0.042)
Observations	18,859	18,859	18,859	1,338	1,338	1,338
R-squared	0.101	0.393	0.078	0.091	0.419	0.170
Number of Households	767	767	767	62	62	62
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Household Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

Table 2-6: Duration of Trading Effect

Table 2-6 tests the duration of the effect of attacks on trading behavior and repeats the test from Column 1 of Table 2 on the net purchase value of individual households but alters the month of the dependent variable, relative to the month of the attack variable. The controls for both panels are the same as Table 2 and Table 3, respectively. Robust standard errors in parentheses *, **, and *** indicate significance at the 10, 5 and 1% level respectively.

VARIABLES	(1) Month t-2	(2) Month t-1	(3) Month t	(4) Month t+1	(5) Month t+2	(6) Month t+3	(7) Month t+4
Log (1+ Attacks) t-1	-0.001	-0.000	-0.006***	-0.005***	-0.003**	-0.003**	-0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Observations	244,900	250,359	255,830	258,674	255,977	253,268	250,566
R-squared	0.018	0.055	0.035	0.011	0.010	0.010	0.009
Number of house	5,711	5,726	5,726	5,734	5,731	5,726	5,719
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Household Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 2-7: PSID and Market Participation

Table 2-7 examines the market participation, savings and trading behavior of households during the year of an increase in the number of attacks. . *Attacks* is the number of attacks each year that cause injuries, deaths or were covered in the news. *Equity Ratio* is the ratio of dollars held in stocks divided by total household wealth. *Hold Stocks* is a dummy variable that takes the value of 1 if the household owned stocks. *Save Ratio* is the ratio of dollars held in savings accounts divided by total household wealth. *Buy* is a dummy variable that takes the value of 1 if the household reported that they made more stock purchases than sales. *Sell* is a dummy variable that takes the value of 1 if the household sold more stock than they purchase. Finally, *Net Buy* is created by taking 1 plus the natural log of the estimated value of the net purchases made by the household in the past year. *Equity Ratio* $_{t-2}$ is the reported household equity ratio from the previous survey. *Wealth* and *Income* are the log of the total household assets, and total household income, respectively. *Age* is the age of the head of the household as designated by PSID. *Children* is the number of children. *Market Return* is the return on the S&P 500 in the year prior to the survey. *Married* is a dummy variable that takes the value of 1 if the head of the household is married. All models include household fixed effects state fixed effects and year fixed effects. Robust standard errors in parentheses *, **, and *** indicate significance at the 10, 5 and 1% level respectively

VARIABLES	(1) Equity Ratio	(2) Hold Stocks	(3) Save	(4) Buy	(5) Sell	(6) Net Buy
Log (1+ Attacks) $_{t-1}$	0.004	-0.122**	0.063***	-0.053***	-0.018***	-1.629***
	(0.016)	(0.050)	(0.016)	(0.010)	(0.007)	(0.359)
Equity Ratio $_{t-2}$	0.000	0.009	0.007	0.018	0.045***	3.920***
	(0.012)	(0.021)	(0.012)	(0.012)	(0.009)	(0.454)
Log(wealth)	0.013***	0.025***	-0.014***	0.001***	0.001**	0.224***
	(0.001)	(0.001)	(0.002)	(0.000)	(0.000)	(0.012)
Log(Income)	0.003**	0.011***	0.004*	0.003***	-0.002**	0.078***
	(0.001)	(0.003)	(0.002)	(0.001)	(0.001)	(0.027)
Log(Head age)	-0.123***	0.076	-0.439***	0.094**	0.034	2.023***
	(0.031)	(0.076)	(0.055)	(0.040)	(0.022)	(0.759)
Child	-0.003**	-0.002	-0.005**	-0.004**	-0.002	-0.013
	(0.001)	(0.004)	(0.002)	(0.002)	(0.001)	(0.036)
Market Return	0.128	7.620**	-3.105***	1.114**	0.140	82.623***
	(1.022)	(3.317)	(0.873)	(0.550)	(0.391)	(20.721)
Married	0.011**	-0.017	0.044***	-0.003	0.001	-0.230*
	(0.005)	(0.012)	(0.009)	(0.006)	(0.005)	(0.124)
Observations	49,524	51,530	49,524	51,530	51,530	44,458
R-squared	0.037	0.045	0.032	0.023	0.008	0.053
Number of Households	12,565	13,251	12,565	13,251	13,251	13,002
Household Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
State Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

Table 2-8: Robustness Tests

Table 2-8 tests the robustness of the attack variable on both the individual trading sample as well as the PSID sample. To save space, each row represents a separate regression. *Above Median* takes the value of 1 if the number of attacks in the month is greater than the median number of attacks per month. *Tercile Rank* is created by sorting attack months into terciles, then creating a rank variable. Panel B repeats these tests on the PSID sample. *Above Median* and *Tercile Rank* are created at the yearly level using the same method as the monthly variables in panel A. For Panel A, all controls are the same as Table 2. For Panel B, all controls are the same as Table 2. All models include household fixed effects and year fixed effects. State fixed effects are included in Panel A. Robust standard errors in parentheses *, **, and *** indicate significance at the 10, 5 and 1% level respectively.

Panel A: PSID Robustness

VARIABLES	(1) Ratio	(2) Hold Stocks	(3) Save	(4) Buy	(5) Sell	(6) Net Buy
Above Median	0.002	-0.045***	0.023***	-0.030***	-0.011***	-1.004***
	(0.004)	(0.009)	(0.007)	(0.003)	(0.002)	(0.216)
Tercile Rank	0.001	-0.021***	0.011***	-0.014***	-0.005***	-0.502***
	(0.002)	(0.004)	(0.003)	(0.001)	(0.001)	(0.108)
Observations	64,480	70,502	64,480	70,502	70,502	48,223
R-squared	0.038	0.040	0.040	0.021	0.006	0.042
Number of Households	16,664	17,841	16,664	17,841	17,841	13,607
Household Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
State Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

Panel B: Brokerage Data	(1)	(2)	(3)	(4)	(5)
VARIABLES	Net Purchases	Buy Value	Sell Value	Number of Buys	Number of Sells
Above Median	-0.011***	-0.028***	-0.008***	-0.026***	-0.024***
	(0.002)	(0.005)	(0.002)	(0.003)	(0.003)
Tercile Rank	-0.004***	-0.009***	-0.007***	-0.013***	-0.010***
	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)
Observations	255,830	255,830	255,830	255,830	255,830
R-squared	0.035	0.019	0.090	0.104	0.091
Number of house	5,726	5,726	5,726	5,726	5,726
Controls	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
Household Fixed Effects	Yes	Yes	Yes	Yes	Yes

CHAPTER III – ESSAY 3:

THE NFL AND HOUSEHOLD INVESTING ACTIVITY

INTRODUCTION

For the fans of the team, and the individuals in the surrounding community, professional sports can play an important role in their lives. In the finance literature the most widely studied topic is the effect that team outcomes have on returns. Asset prices are a fundamental area of study in finance, however, understanding the rate and determinants of household stock market participation is especially important; as it is a significant factor in long-term household wealth (Campbell, 2006). If sports related sentiment is driving short-term changes to markets and firm stock returns[27], then it follows that the shocks to investor sentiment caused by the performance of local sports teams may affect local households' participation in the stock market.

Our goal is to extend the literature on the financial impact of sports by examining the effect that local team results have on the equity market participation of the individuals in the surrounding area. To measure the effect of sports related sentiment, we focus on the results of local NFL teams. We use the NFL because it is by all accounts the most popular sport in the U.S. and therefore, means that it is likely the individuals in the local area are affected by the teams' results. According to Gallup, 41% of adults say that their favorite sport to watch is football; baseball is second at 10%. Additionally, over 60% of fans report that they are fans of the sport[28]. With these surveys in mind, we feel the NFL results serve as the best measure of sports

[27] Edmans et al. (2007) and Chang et al. (2012), Kaplanski and Levy (2010)
[28] http://news.gallup.com/poll/1705/football.aspx

sentiment for our main tests.

To study equity market participation we use household survey data from the Panel Study of Income Dynamics at The University of Michigan (PSID). The PSID data allows us to follow households over parts of four decades on a bi-annual basis[29]. Hand collected NFL data from 1983 to 2012 is obtained from the Sunshine Forecast's website[30]. In addition to the teams and score of each game, the point spread for each game is collected as well. Using publicly available PSID data we are only able to identify the state in which each household is located. To account for states with multiple NFL teams in a single year we only include households in states with a single team in our tests.

As continuous sentiment variables may suffer from a low signal to noise ratio[31] we create high and low win dummies to test the effect of high and low wins seasons on equity market participation. For a team in the bottom 10th percentile of historical win totals[32], we find a 2.5% drop in local households owning equity, a 9% drop relative to the average rate of market participation. In terms of the actual number of game wins, teams in the bottom 10th percentile of historical wins, win between zero and four games in a 16 game season. For these poor performing teams, local investors reduce their equity holdings as a percentage of household wealth, are less likely to hold stocks, and reduce the value of their net purchases. Consistent with Edmans et al. (2007), we find that households react to poor performances, but this result is asymmetric. Households do not alter their stock market participation during seasons when their local team performs well.

[29] PSID surveys households every 5 years starting in 1984, then moves to every other year in 1999.
[30] http://www.repole.com/sun4cast/index2014.html
[31] This is brought up by Edmans et al. (2007). As they also study sporting results, we feel it is especially important for our study.
[32] In a 16 game season this is the equivalent to winning between 0 and 4 games.

In addition to reacting to the win/loss performance of a team, an individual's response to their team's performance may be shaped by expectations. To proxy for the expectations of investors and win probabilities for each game, we use the point spread (spread) of the game as the basis for the expected outcome. We then recreate our initial tests using the win/loss percentage of a team versus the spread[33]. Consistent with the idea that expectations may play a role in sentiment and reaction to a team's performance, we find that individuals reduce their market participation during a season in which the local team performs poorly against the spread. In addition to using the performance of the team versus the spread, we find that the performance of the team in the current season, relative to the previous season has a significant effect on behavior.

When examining the response to sporting events, it is important to try and identify individuals that are actually fans of the team, and likely to be affected by the performance. To identify households with different levels of fandom, we examine those where the current head of the household grew up in their current state (fans), and those where the household moved into the state (transplants). Consistent with Edmans et al. (2007) argument that the spread matters less to fans, we find that those "fan" households respond to the low wins dummy, but not the low spread wins dummy. If fans respond to the wins and losses because their expectations are biased, then fans with expectations that are less biased should respond to the expected outcome of the game. Consistent with this, we find that transplant households respond to the record versus the spread, but not the win-loss record. By identifying likely fans of a team and those less likely to be a devoted fan, we find the response to the local NFL team can vary significantly across individuals in the area.

[33] If team A is favored to win by 5 points in game vs team B, then wins by 4 points, team A is considered to have a loss vs the spread and team B is considered to have a win vs the spread.

The spread is a useful proxy for the fans expectation of the game (Hausch and Ziemba, 1995), but it does introduce a possible confounding effect; dollar losses from gambling. Gambling on sports is illegal in 49 of the 50 U.S. states[34], but it is estimated that $80 - $380 billion is wagered illegally annually on the NFL[35]. To examine the gambling channel we start at the aggregate level and identify 6 different game types based on the ex-ante expected outcome, the actual outcome and the outcome versus the spread. After decomposing seasons into high numbers of these different types of games, we find that seasons with a high number of losses that were expected wins, produce the most consistent results, in terms of reduced stock market participation. Along with a drop in participation for teams with low wins, we find those seasons with a high number of wins that were also expected wins, but were losses versus the spread, leads to a drop in market participation. These seasons are evidence that for some households, gambling losses may affect a household's ability to participate in the stock market.

To further attempt to differentiate between sentiment and gambling at the aggregate level, we examine close losses versus the spread and larger losses versus the spread. If our sentiment results are solely due to gambling, then we should see no differences in the response to these two types of spread losses, as the dollar losses are the same. Here we find that seasons with a high number of large losses versus the spread cause a significant drop in market participation, but that participation is unaffected by small losses versus the spread, and significantly different than the large spread losses. Consistent with the sentiment channel. However, the subsample of transplant households show no significant difference between close and large spread losses; and actually respond significantly to close spread losses. This is the result we would expect if gambling was a

[34] Sports betting is legal in Nevada, but over the course of our sample, there is no NFL team in Nevada.
[35] https://www.washingtonpost.com/sports/sports-gambling-in-us-too-prevalent-to-remain-illegal/2015/02/27/f1088e4c-b7d3-11e4-9423-f3d0a1ec335c_story.html?noredirect=on&utm_term=.c24a78f1dec6

factor for some households, as the wealth effect from a large and close spread loss are the same. Next, we follow the previous literature on risk taking, gambling, and religiosity and identify households that are either catholic or protestant. Using subsamples of Catholic and Protestant households, we find that protestant households reduce their equity market participation in response to the low spread win seasons. The opposite of what we should see if gambling was driving the reaction to the spread variable. Overall, we find support for both the sentiment and gambling channels, as we are unable to unable to totally rule either one out.

Lastly, we use household trading data from a large discount brokerage to directly examine household trading behavior over the course of the season. During seasons with a low number of wins, households respond by significantly reducing the value of their stock purchases, and increase the percentage of their sales that are locally headquartered firms. These results are consistent with the main results using PSID data, and hold when matching households to teams in the same CBSA, something we are not able to do using PSID data.

The effect that sporting events has on sentiment, and in turn, market returns has be widely documented. There is a wealth of evidence showing the effect of soccer on international markets (Ashton et al.,2003; Edmans et al., 2007); Kaplanski and Levy, 2010; Palomino et al., 2009). More recently, Chang et al. (2012) extend this study to the effect of the NFL teams on local NASDAQ firm performance. We extend the literature on sports and sentiment in the following meaningful ways. First, we add to this literature by showing that outside of short-term market drops, the performance of NFL teams have significant effects on individual's equity market participation. Second, we focus our study on the performance of NFL teams. With the exception of Chang et al., the majority of these studies focus on the results of international soccer matches, and would be less applicable to American households.

We also add to the literature on gambling and gambling attitudes on investing behavior. This literature started with examining the link between investors gambling attitudes and the type of stocks purchases (Kumar, 2009, Kumar et al., 2011). More recently, Dorn et al. (2014) documented a partial substitution effect with regards to decreased trading activity around lotteries with higher than normal payoffs. Our results extend on these, and show that a wealth effect through gambling losses may cause limit households ability to participate in the equity market. As the issue of legalized sports gambling has become a national issue in the United States, this finding can help inform future policy choices.

Finally, we add the literature on the determinants of household equity market participation[36]. Recent studies examine personal levels of optimism and trustworthiness, as well as outside factors including accounting scandals and natural disasters.[37] Similar to Barath and Cho (2015) and Giannetti and Wang (2017) examining natural disasters and corporate scandals respectively, we show that local state shocks have significant effects on equity market participation. Ours differs from these studies as NFL results do not directly affect firm cash flows and the negative shock to sentiment from football is much different that the fear induced risk aversion caused by natural disasters. Additionally, we are the first to show that sporting outcomes can lead to a drop in equity market participation.

The reminder of this paper will proceed as follows. Section 2 reviews the literature and articulates the hypotheses. Section 3 describes the data. Section 4 describes our main results using PSID data, while section 5 examines the effect of expectations versus the wealth effect of gambling. Section 6 examines household trading behavior and section 7 concludes the paper.

[36] Mankiw and Zeldes (1991), Poterba and Samwick (1995) and Vissing-Jorgensen (2002)
[37] Puri and Robinson (2005), Dominitz and Manski (2005), Guiso, Sapienza and Zingales (2008), Giannetti and Wang (2016) and Bharath and Cho (2014)

FOOTBALL AND SENTIMENT

Edmans et al. (2007) argue that a sentiment variable must "drive mood in a substantial way", it must affect a large portion of the population, and it must be correlated across the majority of individuals within a given area. As with their use of international soccer results, we feel our use of local NFL results meets each of these criteria for American households. With respect to NFL results driving mood changes, there is a wealth of evidence that links local NFL team performance with changes in mood and behavior that will be correlated across the individuals in a state.

The first thing we must examine is the popularity of the NFL in America and the likelihood that people living in a state are a fan of the team and follow their performance. One way to measure this is to examine the TV ratings for the NFL and determine the number of people watching games each week. According to USA Today, in 2014 an estimated 70% (205 million) of Americans watched at least part of one NFL game. Consistent with this, over the past 6 years, the Sunday night football game on NBC has been the highest rated show on primetime television; averaging 20.3 million viewers. Of more importance to our study however, is the popularity of the teams locally. Again, according to USA Today, the NFL games of local teams are often the highest rated show each week and each year. As an example, from 2011 to 2014 the average rating for an NFL team in their local TV area is a 28. This equates to 28% of all TVs in the area watching every game. For more popular teams, this number can be as high as 50% in some seasons. For large games such as the Super Bowl, this can be above 80%[38]. Anecdotally, it is understood that the NFL is popular in the US, but television viewership helps to confirm that the interest in the league and local teams is large enough to affect local investor's behavior in a

[38] https://ftw.usatoday.com/2015/11/nfl-tv-ratings-rankings-no-1-show-snf-mnf-local-markets

meaningful way.

If the performance of local NFL teams is going to cause a change in investing behavior, it follows that it will have a significant effect on other behavior as well. White (1989) finds that following a loss in a playoff game, the murder rate in the surrounding area of the losing team increases significantly relative to the local area of the winning team. More recently, Card and Dahl (2011) find that domestic violence increases following an unexpected loss of the local NFL team, while Chen and Spamann (2014) find a significant correlation between the performance of local teams and asylum grants in U.S. immigration courts. Eren and Mocan (2016) find that following an unexpected loss of a prominent college football team in the state, for the week following, local judges increase sentence lengths. Each of these studies make it clear that with respect to U.S. investors, the performance of local NFL teams satisfy the three main hurdles that a mood variable must pass, as set out by Edmans et al. (2007).

Along with changes in mood, it is also possible that a change in behavior may be driven by physical changes to the individual. Examining testosterone levels of individuals after watching their favorite teams lose Bernhardt et al. (1998) find that the fans of the losing team experience a significant drop in testosterone levels. In a slightly different, but related study, Carre and Putnam (2009) find that for elite hockey players, watching a video of a past game they won causes a significant increase in the level of testosterone. In either the case of changes in mood or physical changes, it is clear that sports, and more significantly for U.S. investors, the NFL has a significant impact on the local area of the team.

Physical and mood changes, however, are not the only possible explanation as to why individuals would change their behavior in response to the performance of their local NFL team. Coval and Moskowitz (1999) show that individuals are more likely to invest in stocks that are locally headquartered. Using this result as a basis for the start of their study, Chang et al. (2012) show that smaller NASDAQ firms suffer negative next day returns following the loss of a local NFL team. While this result is also attributed to local investor sentiment, it could be the fact that the sentiment effect is driving the stock result and that is in turn leading investors to exit the stock market. Later tests will examine this possibility to determine to what extent, if any, a market effect is causing our main results.

Poor performance by local teams may cause a price impact to local firms, but there is also the possibility that a more direct effect through gambling could cause individuals to lower their level of stock market participation. Previous studies in finance have found that the propensity to gamble is directly linked to stock market decisions. Kumar (2009) shows that gambling preferences lead investors to prefer stocks with lottery like payoffs. Dorn et al. (2014) go further and show that participation in lotteries with higher than normal payouts lead to a drop in household trading behavior. While gambling is only legal in Nevada, which does not have an NFL team during our sample years, illegal gambling is still prevalent through local bookmakers and overseas online sites. Estimates vary widely, but range from $80 - $380 billion that is wagered illegally annually on the NFL[39].

If previous studies show that poor results of the local NFL team can significantly affect individuals' behavior through negative sentiment and possibly lower testosterone levels, we should expect to see this carry over to individual trading activity and market participation. Puri and Robinson (2005) and Dominitz and Manski (2005) show that the level of individual optimism correlates significantly with individual market participation. A notable difference between our study and theirs is that they focus on time invariant personal characteristics, where

[39]https://www.washingtonpost.com/sports/sports-gambling-in-us-too-prevalent-to-remain-illegal/2015/02/27/f1088e4c-b7d3-11e4-9423-f3d0a1ec335c_story.html?noredirect=on&utm_term=.c24a78f1dec6

we focus on shocks to sentiment that cause a drop in market participation. Outside of time invariant personal characteristics other studies have showed the effect that outside events can have on individual's market participation and trading activity. Barath and Cho (2016) document the negative effect that natural disasters have on individual's market participation. Similarly, Wang and Young (2018) documents a similar result following an increase in the number of terrorist attacks.

Using these previous studies as a guide, we hypothesis that the performance of the local NFL team will correlate significantly with the market participation and trading activity of individuals in that year. Further, we hypothesize that this effect will be asymmetrical and concentrated in the team years with the poorest performance. For fans of the local team, we hypothesize that their allegiance to the team will positive skew their expectations, meaning the outcome of the game relative to the rational expectation, provided by the points spread, will have less effect on their behavior than the actual outcome of the game. Finally, consistent with prior research on gambling preferences, we hypothesize that gambling losses may limit some households ability to participate in the stock market.

DATA AND METHODOLOGY

We start our analysis with a data set of all NFL game results from 1983 to 2012 obtained from the Sunshine Forecast's website[40]. This includes all regular season games, playoffs and the Super Bowl. Along with the score for each game, we also obtain the points spread for the game as well. We use the point spread in later tests as a proxy for the expected outcome of the game.

Our initial tests use data from the Panel Study of Income Dynamics at the University of Michigan (PSID) to examine the stock market participation of individuals. The household market

[40] http://www.repole.com/sun4cast/index2014.html

participation data starts in 1984 and runs through 2013. It follows 5,000 families over that time period. The main variables of interest we use from the PSID data is the value of equity holdings, whether or not the household owns equity, and the value of their stock purchases. This data is available every five years from 1984 to 1999, then every other year starting in 2001 and going to 2013. An important note about the data is that the survey dated in 2013, refers to behaviors of the household in the previous year.

The structure of the PSID data means that we must make certain choices for our main tests. The first issue is that public PSID data only allows us to identify the home state of the household. This creates an issue because in certain years, there are multiple teams located in a single state. As an example, over the course of our full sample, there are multiple teams that are located in New York, California, Ohio, Missouri, and Pennsylvania. Our main assumption is that a household located in a certain state is more likely to be a fan of the team located in that state. If there are multiple teams located in the state that assumption becomes weak and we do not know which team we should match to a certain household. To account for this we only include state years in which there is only one team in that state.

The second issue that we must account for is that the survey reports behavior over an entire year. With respect to the NFL, their season spans over the course of two years. Many times the regular season is the fall and winter of year *t*, with the playoffs for that season coming in the early months of the following year *t+1*. That is, 2012 will include the playoffs from the 2011 season and the regular season from 2012. To address this, our main tests only use the results from the full regular season.

We follow Giannetti and Wang (2016) and Guiso, Sapienza and Zingales (2008) in defining our main variables of interest. *Equity Ratio* is the value of equity holdings as a percentage of household assets. It is important to note that equity holdings may come as part of mutual fund holdings, or ownership of the stock itself. *Hold Equity* is a dummy variable that takes the value of one if the household owns stock in the current year. *Enter (Exit)* is a dummy variable that takes the value of one if the household did not (did) own stock in the previous survey but does (does not) own stock in the current survey. These were initially used by Brunnermeier and Nagel (2008). Finally, *Net Buy* is the estimated value of net purchases made by the household.

To control for other factors that may affect stock market participation and the decision to enter or exit, we control for household and market wide factors. At the household level we control for the lagged equity ratio, household wealth and income, the age of the head of the household, if they have children and if they are married. To account for market effects that could affect the decision, we control for the return on the S&P 500 and a return of an index of locally headquartered stocks. All models use household, state and year fixed effects, while standard errors are clustered at the household level.

Household Trading Data

In addition to PSID data, data from a large discount brokerage will be used to study the more immediate reaction of individuals. This data has been used in the past by Barber and Odean (2000, 2001, and 2002) to study the trading behavior of individual investors. It covers 1991 to 1996 and includes all trades made by each household over the course of that time. The benefit of this data over the PSID data is that we are able to observe more information about the trading behavior of the households, relative to the PSID data. This includes the size and direction of the trade, as well as the stock that was traded. Another benefit of the brokerage data is that we have zip code level data for the location of a sample of those households. For these tests, we use the location of the team's stadium to identify the Core Based Statistical Area (CBSA) that the team is located in[41]. We then match teams to individuals in the same CBSA. This does help to eliminate some of the issues with regards to multiple teams in the same state, but over the course of the sample there are still instances of multiple teams in the same CBSA. This includes the L.A. Rams and L.A. Raiders from 1991 to 1994, the Oakland Raiders and San Francisco 49ers in 1995 and 1996, and finally the N.Y. Jets and N.Y. Giants over the full sample.

TEAM PERFORMANCES AND STOCK MARKET PARTICIPATION

We start our analysis on the effect of local NFL outcomes on household stock market participation using the survey data from the Panel Study of Income Dynamics (PSID). In Table 3-2 we test the effect that high and low win seasons have on an array of stock market participation variables. We define our high and low win variables based on historical averages of all teams in our sample. Using the distribution of season results, we define the low (high) win dummy to be a season where a team has a win total that is in the bottom (top) 10% historically. Column 1 starts by examining the value of household equity, relative to household wealth. Consistent with previous literature that poor sporting outcomes lead to negative sentiment, we find that a poor season performance by the local team leads households to reduce the value of their equity holdings. Following a season with a historically low number of wins, households respond by reducing the value of their equity holdings by 7 basis points. Relative to the average equity ratio is represents a drop of roughly 15%.

In column 2 we follow previous studies and define the *Hold Equity* dummy to directly

[41] A Core Based Statistical Area is a U.S geographic area that containing one substantial population nucleus, together with adjacent communities that have a high degree of economic and social integration with the core. CBSA is a new standard defined by the Office of Management and Budget in 2003 to replace the previous definitions of metropolitan areas in 1990. Formal definitions of CBSA can be found at Census Bureau's website (https://www.census.gov/geo/reference/gtc/gtc_cbsa.html)

identify whether or not the households own equity. Consistent with the results in column 1, we find that the rate of local stock market participation drops significantly. Following a low win season, the likelihood of a household owning equity drops by 2.5%. In columns 3 and 4 we define dummy variables to test whether households are entering or exiting the stock market. While insignificant, the coefficients on the *Low Wins* dummy in the enter and exit regressions do have the sign that we would expect if poor performance leads to lower levels of stock market participation. Finally, in Column 5, we find that the value of net purchases drops significantly. This result, combines with the drop in equity holdings and market participation help to confirm the initial hypothesis that poor local team performance has a negative effect on household stock market participation.

As sentiment variables such as mood and weather have been shown to have both positive and negative effects, we also examine seasons in which the local team performs well. In contrast to the effects of low win seasons, we do not find any significant positive effect on stock market participation when the local team performs well. In fact, we actually find weak evidence of a drop in the number of households owning equity in Column 3 of Table 3-2. This is initial evidence that gambling losses may play a factor in the results we see. We explore this point further in Section 5, but if a team is expected to, and wins a lot of games, but does not cover the point spread, then that could lead to gambling losses and a drop in market participation. Looking back on the previous literature on sporting outcomes, our lack of significant a positive coefficients on our high win dummy is not totally unexpected. The asymmetric response to wins and losses is consistent with Edmans et al. (2007) and their study of World Cup games and local market indices.

Using the win-loss record of the team is an obvious starting point, but it does not account for the expected outcome of each game. Prior results in the literature have shown conflicting results with respect to the effect of expected outcomes of games and individuals responses. Edmans et al. (2007) argue that an allegiance bias will lead fans of the team to have more positive expectations than a neutral observer would have on the game. Using NFL data, Chang et al. (2012) find that unexpected losses have a larger effect on local prices than regular losses. To proxy for individuals expected outcome of a game, we use the team's win-loss record versus the gambling spread (spread). The spread does not necessarily represent the true expected outcome, as the bookmakers may alter the lines based on the gamblers sentiment, but it has been shown to be a close approximation (Hausch and Ziemba, 1995) that have been used in prior studies (Edmans et al., 2007, Chang et al., 2012).

Panel B of Table 3-2 reruns the same tests as Panel A, but we now define the low wins dummy with respect to the team's record versus the spread. Consistent with our results in Pane A, we find that a low number of wins versus the spread leads households to reduce their equity holdings, and results in fewer households owning equity. Column 4 of Panel B shows that when using the spread record, we actually find a significant increase in the number of households exiting the stock market. As in Panel A, we include a high spread wins dummy in Panel B. Here, we again find that a high number of spread wins, has no significant effect on household stock market participation.

In Panel C of Table 3-2, we drop the high win dummies and include both the low wins and the low spread win dummies into the same regressions. After including the both the low regular win and low spread win dummies we find that, the response to the low wins and low spread wins dummy are virtually identical. The same can be said for the rest of the table as well. Additionally, the negative coefficient in Column 3 becomes statistically significant. In contrast to the coefficient on the low spread wins dummy, the inclusion of the spread record leads the coefficients on the low wins dummy to become mostly insignificant. The signs on the coefficients remain the same as Panel A, but only the coefficient in Column 2 remains the same.

Overall the results in Table 3-2 confirm the initial hypothesis that poor performance by the local NFL team will lead to a drop in household stock market participation. Panels B and C add to this by showing that households respond to the record of the team versus the spread. The similarity of the coefficients however, lead to more questions about who is responding to the spread versus the actual outcomes, and to what extent the spread is actually picking up sentiment.

Past Team Performance

Our main results in Table 3-2, use historical win totals from all teams to create our low win dummy. However, it is likely that a team's performance relative to their recent past is likely to have an impact on how investors view their team's current season performance. In Table 3-3, we look past just the number of wins in the current season, and create a dummy variable that takes into account a team's performance in the previous season. In Panel A of Table 3-3, we create two dummy variables to measure the team's performance in the current season, relative to the previous season. The variable *Worse* takes the value of 1 if the team had less wins in the current season than they did in the previous season, and 0 otherwise. The variable *Better* takes the value of 1 if the team had more wins in the current season than they did in the previous season, and 0 otherwise.

In Panel A of Table 3-3 we find results that are consistent with our hypothesis and those found in table 2. After altering the definition of a poor season, to take into account the previous seasons results, we find a significant drop in the market participation of local households if the team performed worse than they did in the previous season. This drop in market participation is accompanied by an increase in households exiting the stock market. Consistent with the asymmetric response we saw in Table 3-2, performing better than the previous season does not alter household behavior.

A possible issue with the dummy variables defined in Panel A, is that households are unlikely to exhibit a significant shift in behavior, if their local team's performance in the current season is only slightly worse than the previous season. For example, if the team were to win 5 games in the current season after winning 6 in the previous season, that is likely not a major disappointment. In Panel B we create a continuous variable that measures the change in wins from the previous season. To do this, we subtract the number of wins in the previous season from the number of wins in the current season. Using this continuous integer we find a positive relationship between the increase in the number of wins in the current season and the number of households owning equity. Additionally, we see an inverse relationship between the increase in wins variable and the number of households exiting the equity market.

Table 3-2 provides evidence that poor performance by a team, relative to league wide historical averages, have a significant negative effect on stock market participation. In Table 3-3 we take this one step farther and account for previous season's performance. Even after accounting for the past performance of the team, we find that poor performance relative to the previous season has a negative effect on stock market participation. This again helps to confirm our initial hypothesis that NFL team performance will have a negative effect on market participation, and that investor expectations will play a role.

Fans and Expectations

Our results in Table 3-2 point to the idea that NFL fans respond to both the record of the team, in terms of actual wins and losses, as well as the record versus the spread. This however, directly contradicts the findings in Edmans et al. (2007) and their allegiance bias. To further explore which record the households are responding to, we look to identify households that are more likely to be a fan of the local team. To do this, we assume that if the head of the household is still living in the same state they grew up in, they are more likely to be a fan of that team and have a strong allegiance to the local team. Conversely, individuals that did not grow up in their current state, are less likely to be a fan of the local team. Even if these transplant households are fans of the team, it is possible that the suffer less of an allegiance bias, and their expectations are more in line with the unbiased expectations.

We use the PSID data to determine the state that the head of the household grew up in. This is defined as the state in which they spend the most time in from the ages of 6-16. This works well for us, as it seems likely that team allegiances would be formed around these ages. Here we assume that the “fan” households, are more likely to exhibit the allegiance bias and respond to the actual win-loss record of the team. While the “transplant” households are less likely to have this allegiance bias, or at least it is a smaller bias than the “fan” households. If this is the case, then these households may be more likely to respond to the record of the team relative to expectations.

We start our analysis in Table 3-4 by rerunning regression from Panel C of Table 3-2 that includes both the low wins dummy and the low spread wins dummy. Columns 1 to 5 examine only those “fan” households, while Columns 6 to 10 examine the “transplant” households. Consistent with our hypothesis, the “fan” households only respond to the actual win-loss record of the team. For “fan” households, a poor season leads to less equity holdings, less households owning stocks, more households exiting and a drop in the value of purchases. In the same model, we do not see any significant coefficients on the low spread wins dummy. Additionally, for our main variable of interest, we can say that the drop in households owing equity is statistically different for the low wins dummy versus the low spread wins dummy. Repeating this test on the sample of “transplant” households we find the opposite results. For these households, they do not respond to the actual win-loss record of the team, but strong respond to the record versus the spread. We again here find that, for these households, the response to the low spread wins dummy is statistically different than the low wins.

Table 3-4 provides some interesting results. In the case of “fan” households, we find significant support for the allegiance bias of devoted fans. When contrasting the “fans” and “transplant” households we find an interesting result with regard to the response to sentiment variables that should have seemingly homogenous responses in the local area. In the past, it has been assumed that sporting results have the same or similar effect on the majority of the local area. Here we show that this may be too strong of an assumption for related literature to make going forward. Table 3-4 also helps to confirm an important underlying assumption of our study; that the investors in the local area that are most likely to be fans, are responding to their teams performance.

EXPECTATIONS VS GAMBLING

Up to this point we have only used the gambling spread as a proxy for the expected outcome of the game. However, as we noted in Section 4, the negative coefficient on the high wins dummy in Column 2 of Table 3-2 points to the idea that gambling could play a role in our results. Even though gambling on sports is illegal in the U.S. (with the exception of Nevada), betting on the NFL is still a large underground industry. Whether it is through foreign online sites or local bookmakers, gambling represents an important aspect of our story that needs to be examined. Estimates on the dollar value gambled vary widely, but range from $80 - $380 billion wagered illegally annually. We spend this section attempting to control for, and examine to what extent, if any, gambling plays in the results that we see in response to a low number of spread losses.

Game Types

In our initial attempt to examine the effects that gambling may have, we identify games and seasons that would be more likely to cause a wealth effect through gambling losses versus a negative sentiment effect. In Table 3-5, we break down game types into 6 different categories that we define that are based on the expected outcome, the actual outcome and the outcome vs the spread. In Panel A of Table 3-5, we include dummy variables that capture seasons with a high number of these game types. The goal of this test is to further understand the role that ex ante expectations may play in our results, while also being able to isolate a certain effect while keeping all else constant. Overall Table 3-5 does not either totally rule out the gambling effect or show that the results versus the spread are caused only by gambling losses. In further evidence that gambling losses may in fact play a role in the drop in market participation we find that seasons with a high number of expected wins, actual wins, but spread losses, causes a drop in the number of households owning equity. If our results were only being driven by sentiment then, even with the asymmetric response we see with our main results in Table 3-2, we should see a positive response, or at the very least no response. The drop in market participation for seasons that by either the actual win, or spread win measure should be positive, gives our first evidence that for some households, dollar losses gambling may affect market participation.

In Table 3-6 we look to further examine the competing sentiment and gambling hypothesis. Here we look to keep the wealth effect from gambling constant, while letting the possible sentiment effect of spread losses vary. To do this we define seasons as having a high number of losses that were large spread losses or having a high number of close spread losses. We define a large spread loss as being greater than 7 points[42], and a close spread loss as being 7 points or less. We use this score differential because it is equal to one touchdown and it would mean the team was within one score of beating or tying the spread at the end of the game. Conversely, when a bettor losses their bet, the money lost is the same no matter how close they were to winning the bet. In this test, if gambling were to be totally driving our results versus the spread, we should see statistically indistinguishable results between the close and large spread losses.

In Panel A of Table 3-6, for each of our market participation measures, we see a significant coefficient in the direction that would mean lower participation. In the case of *Hold Equity* and *Exit*, these are statistically different than the high close spread loss dummy. Again, if dollars lost gambling were driving this, we should see significant coefficients on the close spread loss dummy, or at least they should be indifferent from each other.

In Table 3-4, we split our sample into "fan" and transplant households. Doing this we find that the reaction to regular wins and spread wins differ significantly between the types of households. Fan households do not respond to the spread, while transplant households seem to only respond to the spread. Because this test is using spread losses, we again split our sample using this criteria in Panels B and C. In Panel B, we repeat the tests from Panel A on the sample of "fan" households. Here we find what we would expect if fan households' response is more likely to be driven by sentiment. In all Columns except number 3, we find that fan households are less likely to participate in the market. Additionally, for each of these columns, we are able to

[42] The results are quantitatively the same if we alter the definition of a close loss to 3 points or less.

say that the coefficient on the large spread loss dummy is significantly different than the close spread loss dummy.

In Panel C of Table 3-6 we run the same tests as Panel A on the subsample of transplant households. Similar to Table 3-4, we find significantly different results between the “fan” and transplant households. If gambling losses are playing a role in the results versus the spread then we should see no significant difference between the close and large spread losses. This is what we find in Panel C. In response to close spread losses, transplant households are less likely to hold equity and reduce the value of their purchases. It is also significant that we are not able to find any significant difference between the coefficient on the large and close spread losses, and the sign of the coefficients are the same in each column. Each of these results in Panel C provide further evidence that gambling losses may be playing a role in the response we see versus the spread.

Table 3-6 provide further evidence that both sentiment and gambling are a factor in our main results. Similar to Tale 4, Table 3-6 shows that the response to the local NFL team varies significantly by households. For “fan” households, it seems that sentiment from large losses are the more likely cause of a drop in equity market participation. Conversely, we find further evidence that gambling losses are limiting the ability of transplant households to participate in the stock market.

Demographics and Gambling Propensity

Identifying game types may help to understand the possible interaction of the sentiment and gambling effects, but using household and statewide characteristics may help to provide further insight into any gambling effect. In the financial literature there have been numerous studies using the idea that gambling preferences vary widely by religion (Kumar, 2009; Bali et al., 2011; Adhikari and Agrawal, 2016). To further examine gambling we identify households that regularly attending church services at Protestant or Catholic churches. This test varies somewhat from previous studies as we directly identify the denomination at the household level, while previous studies examine the ratio of Catholics to Protestants in the area.

In Table 3-7, we again find evidence that, at the aggregate level, gambling losses do not seem to be the sole channel that contributes to the response to the spread results that we find in our initial results. If the results are being driven by gambling losses, we should find that Catholic households respond to the low spread wins, while Protestant households do not. For our tests in Table 3-7, we split households into Catholic and Protestant sub samples and re-run the test from Panel C of Table 3-2. Columns 1 to 5 use the Catholic sample and Columns 6 to 10 run the test on the protestant subsample. For the Catholic households, we find that for the most part, the coefficients are virtually the same for our measures of market participation. We do find a significant negative coefficient on the low wins dummy in Column 2 and a significant negative coefficient on the low spread wins dummy in Column 3. Moving to the Protestant households we find further evidence that the low spread wins dummy is not only driven by gambling. As previous literature has noted, the Protestant religion takes an extremely negative view on gambling, while the Catholic religion does not. In Column 7 we find a significant negative coefficient on the Low Spread Wins dummy for the subsample of Protestant sample of households.

The results in Table 3-7 do not rule out either the sentiment or gambling channel, but it helps to show that we are not able to rule out either channel. The fact that Protestant households respond to the low spread wins dummy is a sign that for at least some households, sentiment is driving the response to the spread wins.

HOUSEHOLD TRADING

PSID data allows us to examine stock market participation across four decades, but it doesn’t allow us to examine more detailed household trading data. To further examine the effect that local team results have on household’s stock market participation we use data from a large discount brokerage. This data set does face limitations, in that it is only available for a short time period (1991 – 1996), but it allows us to examine actual trades made by the households, as well as match households based alternate measures of proximity, rather than only the state of the team.

Household Trading Tests

In Panel A of Table 3-8, we use the same sample teams as we used in the PSID data. To be consistent we match households to the local team in their state, and only include those states with a single NFL team. Because our results using the PSID data come over the course of a season, we attempt to replicate this using the brokerage data. For each of our measures, we create them at the monthly level and apply the low win dummy to each month during the season. Consistent with our findings in the PSID data that individuals limit their stock market participation during a season in which their local team performs poorly. We find that households significantly reduce the value of their stock purchases. We find this for the full sample of households in Column 2 of Table 3-8, and for a subsample of households that trade more frequently in Column 5 of Table 3-8. For households that trade infrequently it may be less likely that their trades are affected by NFL games, in this case, the active traders provide a good test to ensure that the results in the full sample are likely to be a response to the local team.

In Panel B of Table 3-8 we repeat the tests from Panel A, but match households to team based on the core based statistical area (CBSA). We use this test for two reasons. First, as there are multiple states that have multiple teams, matching on CBSA avoids the problem we face with the PSID data. Second, If NFL teams are having a significant effect on local households, then we should still see the effects that we do at the state level when we match at the CBSA level.

Overall, the results from the brokerage data help to confirm that NFL results are directly causing a change in trading behavior. While previous studies have used the same identification method as we do using the PSID data, matching an event from any point in the year to the survey questions, they have also used trading data to further confirm the results. Additionally, using the trading data we are able to show that we still find significant results when matching to the households living closest to the team.

Home Bias

Another benefit from using the brokerage data is that we are able to examine the types of stocks that are traded. With respect to the type of stocks traded in response to local team performance, we focus our examination on the location of the stocks that households trade during seasons with poor performance. As we have noted earlier, the majority of studies related to sports and investor behavior focus on asset prices. In accordance with the findings that local firm prices suffer following losses of the local team, we test for any time variation in home bias in response to seasons with poor performance. To measure the frequency or infrequency of local trading, we measure the percentage of the total dollar value of buys and sells that were comprised of local firms.

Table 3-9 reports our results for the time variation in home bias in response to low win season. As with our tests in Table 3-8, we run our home bias test on all traders, as well as active traders; matched both at the state level and the CBSA level. For both our full sample and our sample of active traders, matching teams at the state level, we find a significant increase in the percentage of their dollar value of sales that are local firms. In Column 6 of Table 3-9, we again find increased proportion of local firms sold, when matching households and teams by CBSA. While these results are not totally unexpected, given the findings of previous studies, they are to our knowledge the first that directly examine households trading.

CONCLUSION

While there have been numerous studies that examine the financial implications of local sporting results. These have almost entirely focused on short term effects on asset prices. Initial studies have focused on the results of international soccer tournaments, and more recently studies have examined local trading around NFL games. Using household survey data from the PSID, we are able to extend on these studies and examine the effect that local NFL results on household equity market participation.

We add to the long literature on household's equity market participation by showing that poor season long performance of local NFL teams leads to a drop in households owning equity. In addition to fewer households owning equity, households respond to poor performance by reducing the value of their equity holdings and decreasing the value of their stock purchases. We find this result using both the regular win-loss record of the team as well as using the record versus the gambling spread and the record relative to the past season, to take into account effects of ex-ante expectations. Prior studies have assumed that all individuals in the local area respond to sporting results in a similar manner. Splitting our sample of households into those that are living in the same state they grew up in (fans), and those that are transplants, we find that the response of these two groups varies significantly. As predicted by Edmans et al. (2007) the fan households respond to the regular win-loss record, while the transplant households only respond to the record versus the spread.

Using the spread as a basis for expectations also brings the possibility of gambling losses being a cause of our results. After identify games that would be more likely to be affected by sentiment versus gambling losses we are unable to rule out either the sentiment channel or the gambling channel. We find supporting evidence of the gambling channel through a small drop in participation after seasons with a high number of wins that were expected based on the spread. Support for the sentiment channel is shown by the fact that the response to large losses versus the spread is significantly different than small losses versus the spread, if this was solely gambling, then the dollar losses of these two games would be the same.

Finally, using individual trading data we find evidence of decreased value of purchases during seasons with poor performance. We find these results when we match households at the state level, as well as matching on CBSA. Additionally, consistent with previous studies, we find a decrease in home bias during these low win seasons. Over the course of these seasons, we find an increase the proportion of local stocks sold.

Using NFL and household survey data we are able to add to two important strands of literature. First, we find a previously unexamined cause of changes in stock market participation; local sporting results. Second, as we are unable to rule out gambling as a cause, we add to the literature on gambling preferences as investing behavior. We add to this literature as we are some of the first evidence to show that losses from gambling on sports can cause individuals to participate less in the stock market.

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APPENDIX

Table 3-1: Summary Statistics

Equity Ratio is the ratio of dollars held in stocks divided by total household wealth. *Hold Stocks* is a dummy variable that takes the value of 1 if the household owned stocks. *Wealth* and *Income* are the reported total assets of the household (net home equity) and the reported Income. *Enter* is a dummy that takes the value of 1 if the household holds stocks in the current survey, but did not in the previous survey. *Exit* is a dummy that takes the value of 1 if the household is not in the market during the current survey, but was in the previous survey. *Low(high) Wins* is a dummy that takes the value of 1 if the number of wins is in the bottom (top) 10% historically. *Low (High) Spread* Wins uses the *Wins* is a dummy that takes the value of 1 if the number of spread wins is in the bottom (top) 10% historically. *Worse (Better)* is a dummy that takes the value of 1 if the record in the current season is worse (better) than the previous season. *State Firm Returns* is a market capitalization weighted index of locally headquartered firms. Age is the age of the head of the household as designated by PSID. *Children* is the number of children. *Market Return* is the return on the S&P 500 in the year prior to the survey. *Married* is a dummy variable that takes the value of 1 if the head of the household is married. Panel B presents variables used in the individual trading regressions. Net Trades is the net dollar amount of buys and sells in a month divided by the lagged value of total account holdings. Value of Buys and Value of Sells are the value of buys and sells each month divided by the lagged value of total account holdings. Home Buy (Sell) % is the percentage of monthly buys(sells) that are locally headquartered stocks. S&P 500 is the monthly return of the S&P 500. Portfolio return is the monthly return of the portfolio. Stock return is the weighted average previous month return of the stocks traded in the previous month, weighted by trade size.

Variables	Mean	Standard Deviation	10th Percentile	Median	90th Percentile
Equity Ratio	0.046	0.133	0.000	0.000	0.150
Hold Stocks	0.194	0.395	0.000	0.000	1.000
Enter	0.052	0.223	0.000	0.000	0.000
Exit	0.055	0.229	0.000	0.000	0.000
Net Buy	1.637	3.773	0.000	0.000	9.434
Low Wins	0.167	0.373	0.000	0.000	1.000
Low Spread Wins	0.210	0.407	0.000	0.000	1.000
Worse	0.398	0.489	0.000	0.000	1.000
Wealth ($)	148379	336694	0.000	28300	399000
Income ($)	69077	113382	8636	39250	690600
Age	44.828	20.521	25.000	42.000	69.000
Children	0.875	1.185	0.000	0.000	3.000
Market Return	0.059	0.190	-0.217	0.151	0.222
Married	0.452	0.498	0.000	0.000	1.000
Season State Firm Return	0.027	0.087	-0.052	0.009	0.156
Pre-Season State Firm Return	0.047	0.079	-0.033	0.042	0.149
S&P 500	0.050	0.198	-0.365	0.15	0.293

Panel B: Individual Trading Data

Variables	Mean	Standard Deviation	10th Percentile	Median	90th Percentile

Low Wins	0.137	0.344	0.000	0.000	1.000
Net Trades	0.011	0.255	0.000	0.000	0.000
Value of Buys	0.077	0.597	0.000	0.000	0.065
Value of Sells	0.047	0.267	0.000	0.000	0.032
Home Buy %	0.162	0.345	0.000	0.000	1
Home Sell %	0.167	0.352	0.000	0.000	1
S&P 500	0.013	0.028	-0.025	0.013	0.041
Buys Return	0.002	0.125	0.000	0.000	0.000
Sells Return	0.009	0.097	0.000	0.000	0.000
House Equity ($)	82,132	412,849	4,888	25,450	170,640

Table 3-2: Team Performance and Participation

In this table we examine the effects that the performance of the local NFL team has on market participation. The main variables of interest are determined using the number of wins the local NFL team had in the year of the survey. *Low (High) Wins* is a dummy variable that takes the value of 1 if the number of wins in the season are in the bottom (top) 10^{th} percentiles of historical season win totals. Panel B repeats this process for wins versus the spread. *Equity Ratio* is the ratio of dollars held in stocks divided by total household wealth. *Hold Stocks* is a dummy variable that takes the value of 1 if the household owned stocks. *Enter)* is a dummy variable that takes the value of 1 if the household owns equity in the current survey year, but did not in the previous. *Exit* is a dummy variable that takes the value of 1 if the household did not own equity in the previous year, but does in the current survey. Finally, *Net Buy* is created by taking 1 plus the natural log of the estimated value of the net purchases made by the household in the past year. *Equity Ratio* $_{t-1}$ is the reported household equity ratio from the previous survey. *Wealth* and *Income* are the log of the total household assets, and total household income, respectively. *Age* is the age of the head of the household as designated by PSID. *Children* is the number of children. *Market Return* is the return on the S&P 500 in the year prior to the survey. *Married* is a dummy variable that takes the value of 1 if the head of the household is married. All models include household fixed effects state fixed effects and year fixed effects. Robust standard errors in parentheses *, **, and *** indicate significance at the 10, 5 and 1% level respectively

VARIABLES	(1) Equity Ratio	(2) Hold Equity	(3) Enter	(4) Exit	(5) net Buy
Low Wins	-0.007**	-0.025***	-0.009	0.011	-0.168*
	(0.004)	(0.009)	(0.007)	(0.007)	(0.094)
High Wins	-0.004	-0.015*	-0.002	0.003	-0.089
	(0.004)	(0.008)	(0.007)	(0.006)	(0.095)
Season State Firm Return	-0.000	0.012	0.021	-0.027	-0.671
	(0.015)	(0.039)	(0.031)	(0.035)	(0.490)
Pre-Season State Firm Return	0.029	0.031	0.046	-0.055	-0.472
	(0.017)	(0.046)	(0.036)	(0.041)	(0.544)
Equity Ratio $_{t-1}$	-0.034*	-0.050	-0.522***	0.800***	4.449***
	(0.020)	(0.036)	(0.023)	(0.043)	(0.807)
Wealth	0.006***	0.012***	0.006***	-0.003***	0.109***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.011)
Income	-0.002	0.004	0.002	0.003*	0.024
	(0.002)	(0.003)	(0.003)	(0.002)	(0.032)
Age	-0.011	0.029	-0.039	0.045	1.360
	(0.024)	(0.062)	(0.031)	(0.035)	(1.287)
Child	-0.001	-0.002	0.006	0.007**	0.007
	(0.002)	(0.006)	(0.004)	(0.003)	(0.062)
S&P 500	-0.757***	-3.084***	-0.323	0.146	-29.439***
	(0.222)	(0.539)	(0.340)	(0.324)	(9.653)
Married	0.001	-0.037**	-0.002	0.011	-0.296
	(0.007)	(0.018)	(0.013)	(0.013)	(0.193)
Observations	19,543	21,168	21,168	21,168	15,843
R-squared	0.032	0.033	0.066	0.123	0.039
Number of Households	5,564	5,859	5,859	5,859	4,708

Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
State Fixed Effects	Yes	Yes	Yes	Yes	Yes

Panel B: Spread Wins

	(1)	(2)	(3)	(4)	(5)
VARIABLES	Equity Ratio	Hold Equity	Enter	Exit	net Buy
Low Spread Wins	-0.005	-0.024***	-0.007	0.017***	-0.132
	(0.003)	(0.008)	(0.006)	(0.007)	(0.088)
High Spread Wins	0.003	0.004	0.011	0.001	0.051
	(0.004)	(0.009)	(0.007)	(0.007)	(0.101)
Season State Firm Return	-0.004	0.003	0.009	-0.025	-0.725
	(0.015)	(0.039)	(0.031)	(0.034)	(0.498)
Pre-Season State Firm Return	0.035**	0.060	0.055	-0.071*	-0.329
	(0.018)	(0.046)	(0.037)	(0.041)	(0.541)
Equity Ratio t-1	-0.033	-0.046	-0.521***	0.798***	4.483***
	(0.020)	(0.036)	(0.023)	(0.042)	(0.806)
Wealth	0.006***	0.012***	0.006***	-0.003***	0.109***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.011)
Income	-0.002	0.004	0.002	0.003*	0.025
	(0.002)	(0.003)	(0.003)	(0.002)	(0.032)
Age	-0.012	0.024	-0.041	0.048	1.293
	(0.024)	(0.062)	(0.032)	(0.035)	(1.290)
Child	-0.001	-0.002	0.006	0.007**	0.007
	(0.002)	(0.006)	(0.004)	(0.003)	(0.062)
S&P 500	-0.768***	-3.092***	-0.375	0.110	-29.340***
	(0.223)	(0.539)	(0.342)	(0.327)	(9.637)
Married	0.001	-0.038**	-0.002	0.011	-0.297
	(0.007)	(0.018)	(0.013)	(0.013)	(0.194)
Observations	22,355	24,369	24,369	24,369	17,006
R-squared	0.038	0.036	0.072	0.120	0.046
Number of Households	6,366	6,743	6,743	6,743	4,966
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
State Fixed Effects	Yes	Yes	Yes	Yes	Yes

Panel C					
	(1)	(2)	(3)	(4)	(5)
VARIABLES	Equity Ratio	Hold Equity	Enter	Exit	net Buy
Low Wins	-0.005	-0.018**	-0.007	0.007	-0.121
	(0.004)	(0.009)	(0.007)	(0.007)	(0.098)
Low Spread Wins	-0.005	-0.022***	-0.009	0.016**	-0.122
	(0.003)	(0.008)	(0.006)	(0.006)	(0.088)
Observations	19,543	21,168	21,168	21,168	15,843
R-squared	0.032	0.033	0.066	0.124	0.039
Number of Households	5,564	5,859	5,859	5,859	4,708
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
State Fixed Effects	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes

Table 3-3: Full Season Expectations

Table 3-3 examines the effects that performance in the current season has on the response to current season win totals. In Panel A we create two dummy variables *Worse* (*Better)* that takes the value of 1 if the team performed worse (better) in the current season than it did in the previous season. In Panel B we create a variable *Change in Wins* that is the number of wins in the current season, subtracted from the number of wins in the current season. All control variables are defined the same as in Table 2. All models include household fixed effects state fixed effects and year fixed effects. Robust standard errors in parentheses *, **, and *** indicate significance at the 10, 5 and 1% level respectively

VARIABLES	(1) Equity Ratio	(2) Hold Equity	(3) Enter	(4) Exit	(5) net Buy
Worse	-0.001	-0.022**	-0.006	0.017*	-0.114
	(0.004)	(0.011)	(0.009)	(0.010)	(0.122)
Better	-0.000	-0.013	-0.002	0.008	-0.139
	(0.005)	(0.012)	(0.010)	(0.010)	(0.132)
Observations	19,543	21,168	21,168	21,168	15,843
R-squared	0.031	0.032	0.066	0.123	0.038
Number of Households	5,564	5,859	5,859	5,859	4,708
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
State Fixed Effects	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes

Panel B: Win Differences

VARIABLES	(1) Equity Ratio	(2) Hold Equity	(3) Enter	(4) Exit	(5) net Buy
Change in Wins	0.000	0.002**	0.001	-0.002**	-0.001
	(0.000)	(0.001)	(0.001)	(0.001)	(0.009)
Observations	19,543	21,168	21,168	21,168	15,843
R-squared	0.031	0.032	0.066	0.124	0.038
Number of Households	5,564	5,859	5,859	5,859	4,708
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
State Fixed Effects	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes

Table 3-4: Fans and Transplants

In this table we examine the groups of households that respond to each of our initial performance variables: raw wins and spread wins. Here we split our sample based on where the head of the household grew up. We split the main sample into those households that are currently living in the state they grew up in, and those that have moved to a different state. All other variables are defined the same as in Table 2. All models include household fixed effects state fixed effects and year fixed effects. Robust standard errors in parentheses *, **, and *** indicate significance at the 10, 5 and 1% level respectively

	Currently living in Same State as Grew Up					Currently Living in State other than where grew up				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
VARIABLES	Equity Ratio	Hold Equity	Enter	Exit	net Buy	Equity Ratio	Hold Equity	Enter	Exit	net Buy
Low Wins	-0.007*	-0.030***	-0.008	0.017*	-0.166	-0.004	0.003	-0.006	-0.014	-0.069
	(0.004)	(0.011)	(0.008)	(0.009)	(0.113)	(0.007)	(0.016)	(0.012)	(0.013)	(0.194)
Low Spread Wins	-0.002	-0.010	-0.005	0.012	-0.051	-0.010*	-0.046***	-0.017*	0.026**	-0.280*
	(0.003)	(0.010)	(0.008)	(0.008)	(0.110)	(0.006)	(0.014)	(0.010)	(0.011)	(0.148)
Observations	12,786	13,998	13,998	13,998	10,663	6,757	7,170	7,170	7,170	5,180
R-squared	0.025	0.030	0.065	0.148	0.035	0.054	0.051	0.076	0.107	0.057
Number of Households	3,562	3,771	3,771	3,771	3,056	2,130	2,236	2,236	2,236	1,749
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 3-5: Decomposing Game Types

In Table 3-5 we further decompose games into 6 different types based on the expected outcome of the game, the actual outcome of the game, and the outcome versus the spread. For example, *E[Win] + Win + Spread Loss* is a dummy that takes the value of 1 if the team has a high number of games in a season that were expected wins, the team won, but lost versus the spread. For each combination we define a dummy variable if the team had a number of those game types that were in the top 10% of historical total. In Panel A, we include all six dummies in the regressions. In Panel B, we include all game types that include a spread loss. All other variables are defined the same as in Table 2. All models include household fixed effects state fixed effects and year fixed effects. Robust standard errors in parentheses *, **, and *** indicate significance at the 10, 5 and 1% level respectively.

VARIABLES	(1) Equity Ratio	(2) Hold Equity	(3) Enter	(4) Exit	(5) net Buy
E[Win] + Win + Spread Loss	-0.004	-0.019*	0.007	0.003	-0.072
	(0.004)	(0.010)	(0.008)	(0.008)	(0.111)
E[Win] + Win + Spread Win	0.000	0.007	0.000	-0.003	0.022
	(0.003)	(0.009)	(0.007)	(0.007)	(0.093)
E[Win] + Loss + Spread Loss	-0.004	-0.013*	-0.008	0.012*	-0.090
	(0.003)	(0.007)	(0.006)	(0.006)	(0.078)
E[Loss] + Win + Spread Win	0.001	0.013*	0.004	-0.014**	0.031
	(0.003)	(0.008)	(0.007)	(0.006)	(0.089)
E[Loss] + Loss + Spread Win	0.000	0.005	0.005	-0.005	0.044
	(0.004)	(0.009)	(0.007)	(0.007)	(0.105)
E[Loss] + Loss + Spread Loss	-0.003	-0.009	0.002	0.009	-0.001
	(0.003)	(0.009)	(0.007)	(0.007)	(0.096)
Observations	19,337	20,940	20,940	20,940	15,689
R-squared	0.032	0.033	0.066	0.124	0.039
Number of Households	5,365	5,641	5,641	5,641	4,560
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
State Fixed Effects	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes

VARIABLES	(1) Equity Ratio	(2) Hold Equity	(3) Enter	(4) Exit	(5) net Buy
E[Win] + Loss + Spread Loss	-0.004	-0.013*	-0.008	0.011*	-0.090
	(0.003)	(0.007)	(0.006)	(0.006)	(0.079)
E[Win] + Win + Spread Loss	-0.005	-0.022**	0.004	0.008	-0.089
	(0.003)	(0.009)	(0.007)	(0.008)	(0.100)
E[Loss] + Loss + Spread Loss	-0.003	-0.012	0.002	0.011*	-0.005
	(0.003)	(0.008)	(0.007)	(0.007)	(0.093)
Observations	19,337	20,940	20,940	20,940	15,689
R-squared	0.032	0.033	0.065	0.123	0.039
Number of Households	5,365	5,641	5,641	5,641	4,560
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
State Fixed Effects	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes

Table 3-6: Decomposing Spread Losses

In Table 3-6, we conduct and initial test to differentiate the response to a team's record versus the spread between gambling losses and sentiment based on expectations. We create two dummy variables based on the number of close and large losses versus the spread. A close lose is considered less than 7 points and a large loss is anything greater than 7 points. All other variables are defined the same as in Table 2. All models include household fixed effects state fixed effects and year fixed effects. Robust standard errors in parentheses *, **, and *** indicate significance at the 10, 5 and 1% level respectively.

VARIABLES	(1) Equity Ratio	(2) Hold Equity	(3) Enter	(4) Exit	(5) net Buy
High large Spread Loss	-0.005*	-0.021***	-0.012**	0.014**	-0.151**
	(0.003)	(0.007)	(0.006)	(0.006)	(0.077)
High Close Spread Loss	-0.000	-0.008	-0.002	-0.002	-0.030
	(0.003)	(0.007)	(0.006)	(0.006)	(0.078)
Observations	19,543	21,168	21,168	21,168	15,843
R-squared	0.032	0.033	0.066	0.124	0.039
Number of Households	5,564	5,859	5,859	5,859	4,708
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
State Fixed Effects	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes

Panel B: "Fan" households

VARIABLES	(1) Equity Ratio	(2) Hold Equity	(3) Enter	(4) Exit	(5) net Buy
High large Spread Loss	-0.005*	-0.019**	-0.011	0.012*	-0.113
	(0.003)	(0.009)	(0.007)	(0.007)	(0.101)
High Close Spread Loss	0.006**	0.007	0.002	-0.009	0.127
	(0.003)	(0.009)	(0.007)	(0.008)	(0.098)
Observations	11,583	12,653	12,653	12,653	9,775
R-squared	0.024	0.022	0.066	0.158	0.024
Number of Households	3,071	3,212	3,212	3,212	2,673
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
State Fixed Effects	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes

Panel C: Transplant Households					
	(1)	(2)	(3)	(4)	(5)
VARIABLES	Equity Ratio	Hold Equity	Enter	Exit	net Buy
High Close Spread Loss	-0.005	-0.009	-0.012	0.007	-0.146
	(0.006)	(0.013)	(0.009)	(0.010)	(0.135)
High Close Spread Loss	-0.005	-0.023**	-0.004	0.003	-0.250*
	(0.005)	(0.011)	(0.009)	(0.010)	(0.130)
Observations	6,170	6,512	6,512	6,512	4,752
R-squared	0.038	0.045	0.070	0.112	0.041
Number of Households	1,878	1,941	1,941	1,941	1,551
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
State Fixed Effects	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes

Table 3-7: Gambling Preferences

In Table 3-7 we use personal and state characteristics to further explore the possibility that gambling may play a role in our main results. In Panel A we identify households that identify as Catholic or Protestant, then interact that with the low spread wins dummy. All other variables are defined the same as in Table 2. All models include household fixed effects state fixed effects and year fixed effects. Robust standard errors in parentheses *, **, and *** indicate significance at the 10, 5 and 1% level respectively.

	Catholic Households					Protestant Households				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
VARIABLES	Equity Ratio	Hold Equity	Enter	Exit	Net Buy	Equity Ratio	Hold Equity	Enter	Exit	Net Buy
Low Wins	-0.011	-0.049**	-0.025	0.010	-0.226	-0.003	-0.015	-0.008	0.012	-0.118
	(0.009)	(0.022)	(0.018)	(0.017)	(0.242)	(0.004)	(0.011)	(0.008)	(0.009)	(0.117)
Low Spread Wins	-0.002	-0.018	-0.024*	0.017	-0.185	-0.003	-0.018*	0.001	0.012	-0.089
	(0.007)	(0.018)	(0.014)	(0.015)	(0.203)	(0.004)	(0.011)	(0.008)	(0.009)	(0.114)
Observations	3,281	3,421	3,421	3,421	2,474	12,249	13,334	13,334	13,334	10,232
R-squared	0.041	0.047	0.083	0.128	0.059	0.030	0.029	0.068	0.133	0.038
Number of Households	887	913	913	913	740	3,545	3,759	3,759	3,759	3,028
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 3-8: Household Trading Activity

In Table 3-8 we use data from a large discount brokerage to examine trading activity of households during low wins seasons. Consistent with Table 2, we match households to the team in their home state, conditional in there only being 1 team in that state. In Panel B, we match households and teams based on their core based statistical area. *Net Trades* is the total value of stocks sold subtracted from the value of stocks purchased, divided by 1 month lagged total equity holdings. *Buy (Sell) Value* is the value of purchases (sells) in the month divided by the 1 month lagged total equity holdings. *Market return* is the return of the S&P 500 in month *t-1*. *Buys Return (Sells Return)* is the weighted average return of the stocks bought (sold) in the month *t-1*. *Total Equity* is the total value of stocks held by the household. Panel A includes all months, while Panel B only includes months where trades are made. All models include household fixed effects and year fixed effects. Robust standard errors in parentheses *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	All Traders			Active Traders		
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Net Trades	Buys	Sells	Net Trades	Buys	Sells
Low Wins	-0.006	-0.041**	-0.007	0.001	-0.043**	-0.013
	(0.009)	(0.021)	(0.009)	(0.009)	(0.019)	(0.010)
Market Return	0.391***	0.771***	0.478***	0.347***	0.481	0.286**
	(0.094)	(0.233)	(0.088)	(0.108)	(0.321)	(0.127)
winter	-0.015*	0.013	0.017**	-0.005	0.006	0.010
	(0.008)	(0.019)	(0.007)	(0.009)	(0.018)	(0.009)
spring	-0.004	0.037*	-0.015*	-0.004	-0.005	-0.012
	(0.008)	(0.022)	(0.008)	(0.008)	(0.025)	(0.011)
summer	-0.015*	-0.008	-0.020***	-0.004	-0.022	-0.006
	(0.009)	(0.021)	(0.008)	(0.008)	(0.020)	(0.008)
Buys Prior Return	-0.011	0.099**	0.047***	-0.010	0.200***	0.079***
	(0.011)	(0.041)	(0.014)	(0.028)	(0.071)	(0.029)
Sells Prior Return	0.068***	-0.117***	0.249***	0.109***	0.167*	0.272***
	(0.016)	(0.040)	(0.031)	(0.029)	(0.088)	(0.053)
Net Purchases $_{t-1}$	-0.111***			-0.061		
	(0.016)			(0.054)		
Log(House Equity)	-0.121***	0.061***	-0.120***	-0.088***	0.001	-0.039**
	(0.010)	(0.021)	(0.008)	(0.018)	(0.038)	(0.015)
Buy Value Lag		-0.034			0.122**	
		(0.032)			(0.055)	
Sell Value Lag			0.116***			0.285***
			(0.030)			(0.041)
Observations	40,084	40,084	40,084	17,862	17,862	17,862
R-squared	0.075	0.009	0.086	0.044	0.022	0.109
Number of Households	4,477	4,477	4,477	428	428	428
Household Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
State Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

Panel B: Individuals Matched to Team CBSA						
	All Traders			Active Traders		
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Net Trades	Buys	Sells	Net Trades	Buys	Sells
Low Wins	0.001	-0.079*	-0.020	0.011	-0.110*	-0.050
	(0.018)	(0.045)	(0.018)	(0.023)	(0.057)	(0.032)
Observations	9,127	9,127	9,127	3,716	3,716	3,716
R-squared	0.100	0.008	0.117	0.062	0.086	0.196
Number of households	1,013	1,013	1,013	87	87	87
Household Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
State Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

Table 3-9: Local Trading

In Table 9 we examine the location of the firms traded during seasons with poor performance. In Columns 1 and 2 the dependent variable is the percentage of a month's total buys (sells), based on dollar value, that are firms located in the same state as the investor. Columns 3 and 4 repeat the tests on active traders. Columns 5 to 8 repeat the tests from Columns 1 to 4, but match households and teams based on their CBSA. All controls are defined the same as in Table 9. All models include household fixed effects and year fixed effects. Robust standard errors in parentheses *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	Team Matched on State				Team Matched on CBSA			
	All Traders		Active Traders		All Traders		Active Traders	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	Buys	Sells	Buys	Sells	Buys	Sells	Buys	Sells
Low Wins	0.000	0.013*	-0.002	0.028**	-0.008	0.044***	0.041	0.010
	(0.007)	(0.007)	(0.013)	(0.012)	(0.016)	(0.016)	(0.026)	(0.020)
Market Return	-0.097	0.239***	-0.166	0.219*	-0.116	0.225	0.069	-0.005
	(0.065)	(0.069)	(0.112)	(0.120)	(0.136)	(0.139)	(0.186)	(0.206)
Winter	-0.006	-0.003	-0.010	0.003	-0.005	0.024*	-0.008	0.015
	(0.006)	(0.006)	(0.009)	(0.010)	(0.012)	(0.013)	(0.016)	(0.019)
Spring	-0.009	0.003	0.004	0.003	-0.026*	0.023	0.013	-0.023
	(0.007)	(0.007)	(0.011)	(0.011)	(0.013)	(0.015)	(0.021)	(0.024)
Summer	0.003	0.007	0.006	0.003	-0.019	0.019	0.019	-0.024
	(0.006)	(0.007)	(0.010)	(0.011)	(0.014)	(0.015)	(0.019)	(0.021)
Buys Prior Return	-0.016*	-0.015	-0.000	-0.008	-0.012	-0.032**	-0.003	-0.051
	(0.009)	(0.009)	(0.021)	(0.015)	(0.016)	(0.016)	(0.024)	(0.055)
Sells Prior Return	0.016	0.027***	0.022	0.029*	-0.005	0.053**	0.030	0.035
	(0.011)	(0.010)	(0.020)	(0.018)	(0.018)	(0.023)	(0.034)	(0.046)
Net Purchases $_{t-1}$	-0.002	-0.011**	0.004	-0.006	-0.008	-0.010	-0.005	-0.008
	(0.003)	(0.004)	(0.006)	(0.006)	(0.007)	(0.008)	(0.007)	(0.005)
Log(House Equity)	-0.006*	-0.006***	-0.003	-0.001	-0.005	-0.009*	-0.004	0.007
	(0.003)	(0.002)	(0.006)	(0.003)	(0.007)	(0.005)	(0.012)	(0.006)
Observations	24,051	19,493	6,091	5,034	5,457	4,343	1,252	1,028
R-squared	0.002	0.003	0.004	0.006	0.003	0.009	0.013	0.016
Number of households	3,967	3,643	410	401	909	826	82	80
Household Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes