Terrorist Attacks and Household Trading

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Using two sources of household data, we show that an increase in terrorist attacks leads individual investors to reduce stock market participation and overall trading activities. The effects of attacks are evident both in households located in the state of the attack, as well as those living in large metropolitan cities. We find support for a flight home effect through the increase in trading of local stocks following attacks. Adding to the recent literature on gender and market stability, we find that the main results are concentrated in male traders and households with married couple. In addition to a drop in equity market participation, households respond by increase the value of their savings.

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JEL Classification: G11, G14, H56

1. Introduction

Understanding the degree of trading activity by individuals is itself one of the great challenges for finance academics (Grinblatt and Keloharju, 2001). Many households make trading decisions that are hard to reconcile with standard finance theory. Indeed, existing literature largely focuses on household investors' suboptimal behaviors in the equity market: limited market participation (Mankiw and Zeldes, 1991; Vissing-Jorgensen, 2002) and excessive trading (Odean 1999; Balduzzi and Sunden, 2003).[1] According to Campbell (2006), the discrepancies between observed and optimal behaviors among household investors can be partially explained by nonstandard behavioral models that incorporate loss aversion and sentimental bias. Building on this idea from Campbell (2006), the goal of this paper is to shed light on households' trading activities and equity market participation by examining the effect of terrorism on household investment decisions.

We start by examining households' trading activities in the month after terrorist attacks. We then further examine the characteristics of stock purchases and possible mechanisms that could be causing any changes in behavior. 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.[2] With these findings on the wide-ranging effects of terrorism, it is possible that further examination would help add to understanding why households deviate from optimal trading decisions that could maximize their welfare.

[1] An overview of the individual trading literature can be found in Barberis and Thaler (2003).

[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). Wang and Young (2018) study mutual fund flows and Antoniou et al. (2016a) look at the effect of attacks and school shootings on corporate investment and cash holdings.

To determine the effects of terrorism on household trading we use two sources of individual investor data, combined with 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 (2018), and consistent with Drakos (2010) finding that events causing "minor" psychosocial effects can still alter behavior. A comprehensive list of terrorist attacks is taken from Enders et al. (2011), and paired down to ensure that all attacks are likely to be salient to household investors.[3]

From 1991 to 1996, we find that the value of households' net purchases, as a percentage of total equity holdings, 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 to reduce their net purchases by 20%.[4] In terms of dollars, this equates to a drop of $1,472, relative to an average monthly net purchase of $7,235. Breaking net trades into buys and sells, we find that a drop in the value of both buying and selling accompanies the net drop in trade value.

If terrorism is causing households to reduce their net purchases and limit trading activity, it is possible that it will also limit their willingness to participate in the equity market all together. 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. Overall, these initial results show that terrorist attacks lead households to limit two important stock market related behaviors: trading activity and equity ownership.

[3] An attack is included and considered salient if it is covered in the news or involved injuries or casualties.
[4] 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.

A significant difference between terrorism, 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 effects of terrorism are evident both at the local level, and in households located in large metropolitan cities outside the immediate area of the attacks.

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', may play a significant factor in behavior as well. Consistent with these studies, we find that households with a male designated as the head and households with married couples significantly change their behavior following attacks. On the other hand, households with a single or female head do not alter their behavior in response to attacks. Cueva et al. (2015) and Kandasamy et al. (2014) find that female traders are less susceptible to the effects of increased cortisol,[5] and thus provide stability to financial markets. The result of our gender tests provide some of the first large-scale real world support for these resent experimental studies.

To this point, our tests have focused on identifying the change in behavior and examining the cross section of households. We next examine the characteristics of stocks purchased and possible mechanisms that lead to such change. We focus on buys because the possible universe of stocks is unconstrained, whereas the characteristics of stocks sold is dependent on the stocks already in the portfolio.

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

We find that following attacks, investors respond by purchasing fewer risky stocks, as characterized by high idiosyncratic volatility and skewness. This is consistent with findings in both Antoniou et al. (2016a) and Wang and Young (2018) that through fear and depression, investors become more risk averse after attacks. Next, we follow the literature on home bias in investing, and the effect of patriotism on holdings,[6] and examine the time variation in home bias as it relates to local attacks. Interestingly, we find that following an attack in an investor's home state, households devote a larger percentage of their purchases to stocks headquartered in that state. With this result, we add to the home bias literature by documenting a flight home effect whereby households rebalance their portfolios in favor of local stocks after local attacks.

A previously unexamined factor in related studies on terrorism is the effect that attacks have on investors' attention to financial markets. With respect to terrorism, multiple studies have shown a strong correlation between the effects of terrorism and news coverage, and for those individuals that consume more news coverage of the event.[7] If during periods of higher levels of terrorism individuals focus their attention on news coverage of the events, rather than coverage of the stock market, it is possible that their reduced attention to market/firm related news is a factor in the reduction of trading activity that we observe (Peress and Schmidt, 2016). Following Barber and Odean (2008) to identify high attention stocks, we find that individuals are less likely to purchase high attention stocks following an increase in attacks.

Lastly, we examine the extent to which individuals recognize industry risk following attacks and how that affects their behavior. Using stocks that Chesney et al. (2011) identify as most affected by terrorist attacks, we find that investors are generally rational in their response to attacks. Chesney et al. find that the defense industry is least affected by attacks, while the insurance industry is most commonly negative affected. In accordance with these common outcomes, we find that

[6] Building on Coval and Moskowitz (1999), Grinblatt and Keloharju (2001) and Seasholes and Zhu (2010) find that individual investors exhibit home bias in their portfolios. In a related paper Morse and Shrive (2011) find that countries that are more patriotic exhibit more home bias.
[7] See Sloane (2000); Schlenger et al. (2002); Melnick and Eldor (2010).

investors increase their purchases of stocks in the defense industry and decrease their investment of stocks in the insurance industry.

Finally, we 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, the month directly after attacks and a following three months. Additionally, we do not find any significance on the attack variable for the month before the attacks took place. 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.

In response to low proportion of households holding stocks, previous studies identify fixed costs that limit equity market participation.[8] One type of fixed costs can be measured by time and money that are involved with investing in stock market. For example, Vissing-Jorgensen (2003) find that the complication of tax returns through equity ownership affects an individual's willingness to participate in the market. Alternatively, fixed costs may be related to psychological factors that make equity ownership uncomfortable for some households (Campbell, 2006). Both Guiso, Sapienza, and Zingales (2005) and Giannetti and Wang (2016) find that lack of trust can reduce the likelihood that households invests in the equity market. In addition to trust, Barath and Cho (2016) show that exposure to natural disasters lead households to limit market participation. We add to the literature by identifying terrorism as another important example of psychological-related fixed costs that limit individuals to participate in the equity market.

In addition to equity market participation, individual brokerage data allows us to examine variations in trading activity. This is important, as Shum and Faig (2006) find that predicting households the value of stock owned is much more difficult than predicting which houses will own stock. Numerous studies have examined the relationship between personal characteristics and

[8] According to the Federal Reserve Board's Survey of Consumer Finances, only 50% of American families have any exposure (direct or indirect) to the stock market.

trading activity,[9] but much less has been done on the way external factors affect trading at the household level. While weather, seasonal change and calendar effects have been used previously, a terrorist attack is unexpected by households and elicits much different emotions; including fear and patriotism.[10] Exploring terrorism effect on trading activity provides new insight into the way the nonstandard behavioral models discussed in Campbell (2006) can explain variation in individual trading behavior.

Finally, most papers examining the effects of terrorist attacks on mood and behavior have focused mainly on aggregate price effects or investors as a whole. For example, Wang and Young (2018) examine terrorism's effect on aggregate risk preference through mutual fund flows, while Kamstra et al. (2015) examine the effect of Seasonal Affective Disorder (SAD) on 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 is among the first set of studies that directly examines the behavior of individual households related to terrorism. 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. This is important as most of the existing literature consider household investors as less sophisticated, uninformed and noise traders (Barber and Odean (2008); Grinblatt and Keloharju (2009)). Using terrorist attacks, we add to existing studies on household investors, and show that their investment decisions are significantly affected by the emotional fall out of certain non-economic shocks.

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 and household survey data. Section 5 presents the results on stock selection after attacks. Section 6 provides robustness test, and Section 7 concludes the paper.

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[9] Gribblatt, Keloharju and Linnainmaa (2012), Grinblatt and Keloharju (2009), Odean (1999), Barber and Odean (2001), Barnea, Cronqvist and Siegel (2010).
[10] See Kaustia and Rantapuska (2016), Loughran and Schultz (2004).

2. 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 is a wealth of evidence from medical studies that terrorism can increase the negative sentiment and depressive moods of individuals. 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.

If terrorism and terrorist attacks are altering the sentiment and moods of the affected individuals, then there is clear evidence that it is likely to affect trading behavior. Examining trading behavior of Finnish individuals, Grinblatt and Keloharju (2009) find that individual level of sensation seeking strongly correlates with trading behavior.[11] Various other 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.

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 outside the area of the attack. 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, findings show that negative images lead individuals to alter behavior. Kuhnen and

[11] Sensation seeking is akin to risk taking and is negatively affected by depressive moods (Carton et al., 1992).

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 (2017) 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 are. Using these studies as a baseline, it is possible that the effect of terrorist attacks will 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. 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.

Just as mood affects trading behavior, it can have a similar effect on stock market participation. 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.

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.

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 should 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.

3. Data and Methodology

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

3.1. Terrorism Data

To measure the level of terrorism in the United States, we use a comprehensive list of domestic, and transnational terrorist attacks from Enders, Sandler and Gaibulloev (2011) who use the University of Maryland’s Global Terrorism Database (GTD) and the International Terrorism: Attributes of Terrorist Events (ITERATE) database, to create their final database of attacks. We start with the Enders et al. data set and use the same method as Wang and Young (2018) to define my final set of attacks. The Enders et al. data goes back to 1970, but we are limited by the dates of the individual trading and PSID data. 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 national or local newspaper. This leaves a total of 457 attacks for the sample using the PSID survey 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 because of the attacks. Similarly, Wang and Young (2018) provide evidence that the number of attacks correlates 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 beleive 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. The brokerage data is aggregated at the monthly level from 1991 to 1996, with the average number of attacks being 2.21 with a standard deviation of 2.37. For the PSID data, the average number of attacks in a year from 1984 to 2012 is 9.48 with a standard deviation of 7.01.

3.2. Brokerage Data and Variables

To study household 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 papers that examines household trading behavior and performance (Barber and Odean (1999), Barber and Odean (2000), Barber and Odean (2001)). The individual trading data includes individual account's daily trades and monthly holdings. For an additional sub-sample of the brokerage data, demographic information is available for the households. This includes location, gender, relationship status etc. 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 are available.

To create our main variables of interest we 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. We calculate total household equity 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.

The brokerage firm from which the data was obtained, classified households as either an active trader, affluent household, or general.[12] 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

[12] From Barber and Odean (2000): "The firm labels households that make more than 48 trades in a year as active traders, households with more than $100,000 in equity are labeled as affluent. If a household qualifies as either active or affluent, it is assigned the active trader label"

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 to avoid any issues of sample selection bias. This is important, as, especially for active traders, not making trades is a decision as well.

3.3. 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 (2016) 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.

As our study is focused on examining both trading behavior and market participation, we use these two different data sources as each is suited for a certain question. The brokerage data provides rich data on individuals trades, but for only a short period of time. 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.

While the brokerage data is better suited to examine trading behavior, the PSID data is arguably better suited to examine household equity market participation. While data is not available as frequently as the brokerage data, it is available over a longer period of time. Starting in 1984 and continuing through 2013. Additionally, the brokerage data, by construction, is only made up of households that already own equity, whereas the PSID data includes households that do not own equity. We are also able to control for changes in wealth and income in the PSID data, as opposed to the brokerage data, where income and wealth are only reported once in the sample.

4. 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.

4.1. Short Term Trading Behavior

In Table 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 were previously planned. 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 and Panel B of Table 2 repeats the same tests but only on months that include trades.

In Column 1 of Table 2 we find that in the month after an increase attacks, active traders the significantly reduce the value of their net purchases. In Column 1 the coefficient on the attack variable is -0.006, and significant at the 1% level. Further examining the magnitude of this result, we find that 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 to reduce their net purchases by $1,472. This drop is also economically significant as an average monthly net purchase in our sample is $7,235. If attacks lead households to be less willing to take risks following attacks, then it follows that in the immediate aftermath, household's will reduce the value of their net purchases. In Columns 2 and 3 of Table 2, we further test the change in different aspects of trading activity.

Column 1 of Table 2 shows that investors reduce their exposure to the equity market in response to an increase in attacks. It is possible that multiple different factors could contribute to a drop in the net value of purchases: A drop in the value of buys, and increase in the value of sells, or some combination of both. Columns 2 and 3 of Table 2 furthers examines the change in trading behavior in terms of the value of trades made in both directions. 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. Taken together, the results from Panel A of Table 2 provide further evidence that terrorist attacks lead investors to not only reduce their market exposure in terms of net purchases, they also reduce their trading activity as a whole.

Panel B of Table 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 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 shed light on the trading activity of investors in the immediate aftermath of terrorist attacks. The net trade results in Table 2 are consistent with previous findings that individuals take less risk in response to terrorist attacks. Results in Columns 2 and 3 of Table 2 find that this drop in net purchases correspond with a drop in the value of both buys and sells. In addition to the finding that investor are less willing to add to their portfolio after attacks, these findings show that individual investors less will to trade as well.

4.2. Equity Market Participation

In the previous section, we find that terrorist attacks significantly affect the trading activity of households. In this section, we take this examination one step further and test the hypothesis that if terrorist attacks affect short term trading behavior, can they affect equity market participation? For the initial test of market participation, we use survey data from the Panel Study of Income Dynamics (PSID). This allows us to test the effects of years with high number of terrorist attacks on the level of household market participation.

In Column 1 of Table 3 we start by examining the percentage of household assets 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 to 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 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 3 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.

In Table 2 we find that investors reduce their net purchases and overall trading activity following an increase in terrorist attacks. Using the PSID data in Table 3 compliments the results in Table 2 by showing that in addition to a reduction in trading activity, households are less likely to hold equity response to the attacks. Consistent with the findings using the trading data, buying and selling behavior drops in response to attacks.

4.3 Local Area Characteristics

Previous studies show that those living closer to traumatic events and terrorist attacks, exhibit larger reactions following attacks. Antoniou et al. (2016a) 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 (2018) 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 on this subsample of households.

Panel A of Table 4 presents the results for households living closest to the attacks. Previous studies have shown that those living closest to attacks are the ones most significantly affected. Consistent with these 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. The significant interaction term indicates that the stronger response, reducing the value of net trades, is only found in those households living closest to the attacks. This stronger reaction by those living closest to the attacks is consistent with findings in both the finance and psychology[13] literature examining the effects on proximity to terrorist 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

[13] Antoniou et al. (2016a) find that a drop in risk taking is larger for firms located closer to an attack, while Galea et al. (2002) and Schlenger et al. (2002) both find stronger psychological effects for individuals living in New York and Washington, DC after 9/11.

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 (2018) and examine the response of investors directly affected by attacks, and those likely to be weary of future attacks. Consistent with Wang and Young (2018), 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. Our test is different than Wang and Young (2018) because 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 allow us to more accurately identify the investors most vulnerable to depressive moods.

Panel B of Table 4 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 (2018) 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. This is equivalent to a 7.55% drop in net trade value following a one standard deviation increase in the number of terrorist attacks. Columns 2 and 3 of Panel B repeat the buy and sell tests from Table 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. If terrorist attacks have significant effects on households that are 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 they drive the drop in net purchases we see in Table 2.

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 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 (2018) who conducted a similar test using the location of mutual fund headquarters.

4.4 Family Demographics

Along with the location of the investor, demographic characteristics are 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 (2014) 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 are to increased levels of cortisol. This is important in the context of terrorism because higher levels of cortisol are 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 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 5, we split our main sample into four groups to test the differences in reaction based on the head of the household's gender or marital status. 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 5 we repeat the main tests from Table 2 on a sample of male households, while Columns 4 to 6 of Table 5 repeat the tests on a sample of female households.[14] 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 -0.03 and -0.022, respectively. These represent a drop of 5% and 7% in the value of buys and sells, relative to non-attack months, in response to a one standard deviation increase in the level of terrorism. Panel B of Table 5 shifts the focus to the marital status of the household. Here, we again find results consistent with the previous literature. In Columns 1 to 3, households where the head is not married, do not significantly alter their trading behavior. In Consistent with Roussanov and Savor (2014), in Columns 4 to 6, we find that married households exhibit a significant shift in their trading patterns.

Table 4 presents evidence that an investor's location relative to the attack has a significant impact on their trading behavior in the following months. Table 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 the effect of gender 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

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

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

5. Stock Characteristics

In the previous section, we focused on how the cross-sectional differences between households affect the trading behavior in the aftermath of attacks. In this section, we will further examine the types of stocks that investors purchase following an increase in attacks. We focus on purchases, as the universe of stocks that investors can buy is always more or less the same. On the other hand, the stocks that an investor is able to sell is constrained by their previous purchases and current portfolio holdings. This method is similar to that of Kaustia and Rantapuska (2016), in their study of seasonal effects on households trading.

5.1 Risky Stocks

The most common finding in previous studies related to individual behavior following terrorist attacks is that they take less risk. Wang and Young (2018) find that mutual fund investors shift their flows from equity mutual funds to safer government bond funds following an increase in attacks. Examining corporate policies, Antoniou et al. (2016a) find that in the aftermath of a school shooting or terrorist attack, corporations hold more cash, invest less in R&D and generally take less risk. In Table 6, we examine the affect that terrorism has on individual investors' purchases of risky stocks. To define risky stocks, we focus on the idiosyncratic volatility and skewness of stocks. For each day that an investor buys a stock, we rank all stocks based on their idiosyncratic volatility (skewness). If a stock has an idiosyncratic volatility (skewness) that is in the top have of the sample, we identify it as a risky stock. For each household in each month, we then calculate the ratio of the value of risky stocks bought to the total value of stocks purchased.

We focus on the firm specific volatility and skewness as previous studies (Kumar (2009); Dorn and Huberman (2010)) show that they are predominantly held by retail investors. As these risky stocks are held, and actively traded by retail investors, it provides a setting where we can test the effect that attacks have on the purchase of risky stocks. Additionally, just as different industries are affected by terrorism differently, Drakos (2004) notes that it is possible for different firms to be affected differently as well. If investors are more weary of risk, then after an attack it may be the case that firm or industry specific risk is a factor they are more aware of. We use firm specific skewness to proxy for the tail risk of the individual firm (Kelly and Jiang, 2014), as terrorist attacks are rare events, it is expected that they are related to risks at the extreme.

In running tests with stock characteristics, one problem that we face is that of a high number of zeros and the possibility of inflated zeros. In this test, there is two possible ways for the risky stock purchase ratio to be zero: the household may not purchase stock, or the household may purchase stock but not buy any risky stocks. We take two separate measures to account for this problem. First, we run the same panel regressions, but on a sample of households that most frequently trade risky stocks. Second, using that same subsample, we use a Zero Inflated Poisson model to account for the possibility of inflated zeros.[15]

Consistent with previous literature, our results in Table 6 show that investors reduce their purchases of risky stocks following an increase in the level of terrorism. In Columns 1 to 3 of Table 6, we find that for each of our specifications, households reduce the proportion of their purchases that are stocks with high idiosyncratic volatility. In Columns 4 to 6 of Table 6 we use idiosyncratic skewness to proxy for the tail risk of a firm. Using this alternate measure of risk, we again find that households are fewer less risky stocks.

5.2. Flight Home Effect

[15] Using the Zero Inflated Poisson (ZIP) model, we are able to address the inflated zero problem by modeling two different types of zeros independently. A Poisson model is used in this case to model the purchase of high-risk stocks, while a logit model is used to predict excess zeros that arise from not making any purchases in the given month.

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. Additionally, Morse and Shrive (2011) find that countries that are more patriotic exhibit greater home bias. This is similar to a flight home effect that Giannetti and Laeven (2012) found in the syndicated loan market during the financial crisis.

Another possible link between attacks and local stocks 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. If investors are responding to this wealth effect, then we would expect a drop in local buying, as opposed to an increase in local buying predicted by the flight home effect.

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 to test the location effects, for which their household location is known. For each month we calculate the total dollar value of stocks purchased for stocks headquartered in the same state, as a percentage of the total dollar value of stocks bought in that month.

Table 7 presents the results for our tests of the flight home effect. To test a flight home effect, we use the same instate dummy that we created in Table 4, and interact it with the attack variable. Using the full sample 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 repeat the test, but now using the Zero Inflated Poisson model to control for the inflated zero problem. Using this specification, we again find that households increase their purchase of local stocks.

At first glance, this result may seem counterintuitive, as it is easy to imagine negative economic shocks from terrorism may scare off local investors after attacks. However, a common impact of attacks is to increase the level of patriotism in the local community (Li and Brewer, 2004). Building on the findings of Morse and Shrive (2011), we are able to reject the predictions of the wealth effect hypothesis and show that increased patriotism after attacks can significantly increase local bias exhibited by household investors.

5.3 Attacks and Attention

As the goal of a terrorist attack is to create fear, examining the news coverage of attacks is common across studies related to terrorism. In our case however, we will take a slightly different stance on the effect of news coverage on investor behavior. As pointed out by Yuan (2015), finance models generally assume that investors have unlimited attention. However, research on psychology tells a very different story. Numerous studies have shown that attention is limited by the capabilities of the brain, and is not unlimited as some models assume. In line with the findings in finance, and the attention constraints of individual investors, it is possible that attention-grabbing events unrelated to the market will affect trading behavior.

With respect to terrorism, multiple studies have shown that larger effects are seen for those terrorism events with more news coverage, and for those individuals that consume more news coverage of the event (Sloane, 2000; Schlenger et al., 2002). Additionally, Melnick and Eldor (2010) find that media coverage is the main driver of the economic effects of terrorism. If during periods of higher levels of terrorism individuals focus their attention on news coverage of the events, rather than coverage of the stock market, it is possible that their reduced attention to market/firm related news is a factor in the reduction of trading activity that we observe.

To test the effect of attention in Table 8, we follow Barber and Odean (2008) and identify stocks that are attention grabbing. We define stocks has high attention if they are in the top 10% or 5% of the previous day in terms of return, or abnormal volume. As we focus on purchases, we exclude stocks that were in the bottom 10% of the previous day return, as those stocks would most likely be sold.[16] Using this definition, and the same sub sample and zero inflated poisson models as previous tests, the findings in Table 8 confirm the hypothesis that attacks may shift investors' attention away from stock market related news.

While this is an interesting finding in and of itself, it may also help explain why, in our main results we find that both buying and selling behavior decrease after attacks. Barber and Odean (2008) and Da, Engleberg and Gao (2011) both find evidence that investors' trading behavior is directly linked to their level of attention. Barber and Odean find that investors are more likely to buy attention grabbing stocks. These can be stocks in the news, high abnormal trade volume, or extreme one day returns. In similar settings, Seasholes and Wu (2007) and Huddart and Lang, and Yetman (2009) confirm the results of Barber and Odean. Using a measure of attention derived from google searches for Russell 3000 stocks, Da, Engleberg and Gao find that their measure of attention predicts short-term prices and longer term price reversals. Yuan (2015) finds a similar market wide attention effect for record-breaking events about the Dow and front-page news about the market. This increased level of attention leads to aggregate individual investor net selling, outflows from mutual funds and selling in individual brokerage accounts. Results from these previous studies, and our findings of decreased trade in attention grabbing stocks helps to support the idea that households increased focus on non-market related news following attacks could be a factor in the drop in buying and selling that we find in Table 2.

5.4 Industry Specific Risk

[16] We repeat the tests including these stocks in the high attention definition and find the same results.

One significant factor in terrorism is that attacks are more likely to affect certain industries. Chesney et al. (2011) provide one of the most comprehensive studies on this topic. Using a global sample of attacks, the study finds that attacks most commonly affect the insurance industry, while the defense industry is less often affected. Additionally, previous studies have identified the tourism industry as one that is significantly affected by tourism. Lastly, we use the banking industry as a final test of household's response to industry risk. We classify firms into industries based on the Fama-French 49 industry classification.[17]

In Table 9, we present the results for the industry risk tests. Here we only use the zero inflated Poisson model to run the industry tests as the rate of industry specific purchases is much lower than the other stock characteristics, increasing the number of zeros overall and the number of inflated zeros. Carter and Simkins (2004) find that after the attacks on September 11th, the response by investors, with respect to airline stocks, was rational, in that, the largest price drops were found in airlines that were most susceptible to bankruptcy. For our measure of industry risks in Table 9, we find similar results. If investors believe that an increase in attacks, may lead to future attacks, then it would make sense to shift their purchases away from affected industries and towards more those that are more insulted.

This is what we see in the first two Columns of Table 9; In Column 1, we find that households increase their purchases of stocks in the defense industry. Column 2 finds that for the industry most susceptible to terrorism, households significantly reduce their purchases of insurance stocks. In Column 3 and 4 we test the response to the transportation and banking industry respectively. As there is no direct industry classification for tourism, we use the transportation industry as our proxy for tourism. In Column 3 we do not find a significant response by individuals to the transportation industry. Lastly, in Column 4 we examine the purchase behavior of banking

[17] To identify firms in the defense, transportation, banking and insurance industries we use FF49 industry two digit SIC codes starting with 26, 41, 45 and 46, respectively. The full list of accompanying SIC codes for each FF49 industry code can be found at Ken French's data library: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html#Research.

stocks and find a significant drop in purchases. While the result for banking is less straightforward than the insurance or defense industries. The results from Chesney et al. (2011) do show that that the industry does suffer through a number of attacks in their sample. Additionally, the coefficient on the attack variable in Column 4, is almost half of what we see for the insurance industry in Column 2. Overall, the first two columns are clear evidence that households appear to recognize the specific risks that terrorism and terrorist attacks present to certain industries.

6. Robustness Tests

6.1. 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 10 presents the results on the effect of terrorist attacks in the months surrounding the attacks. For all Columns in Table 10 we repeat the main result from Column 1 of Table 2 using the net value of purchases but shifting the month, relative to the attack month. Columns 1 and 2 of Table 10 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. 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 significant 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. (2016a) who find that changes to corporate policies do not extend past the next quarter following the attacks.

6.2. Alternate definition of attacks

Next, 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 based on Wang and Young (2018). 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. 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.

In Panel A of Table 11 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 at 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.

7. 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 have not directly examined the effect that terrorism has on household trading activity and market participation. Our paper adds to the literature on household finance by directly examining household trading behavior, while also contributing to the understanding of the effect of terrorism on equity market participation. Following an increase in terrorism, investors reduce the value and number of the trades they make. Evidence from the location of investors indicates the effects of terrorist attacks are stronger 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. Examining the characteristic of stocks purchased following attacks reveals that households purchase fewer risky stocks, more local stocks and less attention grabbing stocks after attacks. Finally, consistent with previous studies on terrorism, the effect is transient in nature, lasting up to 4 months after the increase in attacks.

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. Finally, consistent with the findings using the brokerage data, in years with higher number of terrorist attacks households report that they trade less during those years.

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 detailed trade data, as well as household market participation surveys, 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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Table 1: Summary Statistics

This Table presents summary statistics for the variables used in the paper. Panel A 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. Buys and 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 index. Stock return is the weighted average previous month return of the stocks traded in the previous month, weighted by trade size. Household equity is the total value of stock held by the household and the end of each month. Panel B 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 A: 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
Buys	0.077	0.597	0.000	0.000	0.065
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
Household Equity ($)	82,132	412,849	4,888	25,450	170,640

Panel B: 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

Table 2: Net Trades

This table 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. In Column 1, *Net Trades* is the total value of stocks sold subtracted from the value of stocks purchased, divided by 1 month lagged total equity holdings. In Column 2(3), *Buy (Sell)* 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.

VARIABLES	(1) Net Trades	(2) Buy	(3) Sell
Log (1+ Attacks) $_{t-1}$	-0.006***	-0.012***	-0.011***
	(0.001)	(0.003)	(0.001)
Market Return $_{t-1}$	0.060**	0.423***	0.176***
	(0.030)	(0.074)	(0.031)
Winter $_{t}$	-0.006**	0.011**	0.011***
	(0.002)	(0.005)	(0.002)
Spring $_{t}$	-0.006***	0.016***	-0.000
	(0.002)	(0.005)	(0.002)
Summer $_{t}$	-0.014***	-0.017***	-0.009***
	(0.002)	(0.005)	(0.002)
Buys Return $_{t}$	0.006	0.132***	0.057***
	(0.006)	(0.019)	(0.009)
Sells Return $_{t}$	0.073***	0.152***	0.302***
	(0.010)	(0.022)	(0.022)
Net Purchases $_{t-1}$	-0.071***		
	(0.009)		
Log (House Equity) $_{t}$	-0.072***	-0.021**	-0.053***
	(0.004)	(0.009)	(0.003)
Buy Value $_{t-1}$		0.120***	
		(0.015)	
Sell Value $_{t-1}$			0.231***
			(0.012)
Observations	255,830	255,830	255,830
R-squared	0.035	0.019	0.090
Number of households	5,726	5,726	5,726
Household Fixed Effects	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes

Panel B: Months with Trades			
VARIABLES	(1) Net Trades	(2) Buy	(3) Sell
Log (1+ Attacks) $_{t-1}$	-0.011***	-0.017***	-0.018***
	(0.002)	(0.006)	(0.002)
Market Return $_{t-1}$	0.033	0.413***	0.167***
	(0.053)	(0.131)	(0.052)
Winter $_{t}$	-0.018***	-0.005	0.006*
	(0.004)	(0.009)	(0.004)
Spring $_{t}$	-0.014***	0.016*	-0.006
	(0.004)	(0.009)	(0.004)
Summer $_{t}$	-0.027***	-0.024***	-0.015***
	(0.004)	(0.009)	(0.004)
Buys Return $_{t}$	0.004	0.105***	0.046***
	(0.006)	(0.018)	(0.008)
Sells Return $_{t}$	0.037***	-0.008	0.214***
	(0.009)	(0.021)	(0.017)
Net Purchases $_{t-1}$	-0.093***		
	(0.008)		
Log (House Equity) $_{t}$	-0.145***	-0.087***	-0.132***
	(0.006)	(0.015)	(0.005)
Buy Value $_{t-1}$		0.110***	
		(0.017)	
Sell Value $_{t-1}$			0.213***
			(0.013)
Num. of Buys $_{t-1}$			
Num. of Sells $_{t-1}$			
Observations	137,879	137,879	137,879
R-squared	0.070	0.018	0.110
Number of households	5,700	5,700	5,700
Household Fixed Effects	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes

Table 3: PSID and Market Participation

Using PSDI survey data, this table 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. In Column 1, *Equity Ratio* is the ratio of dollars held in stocks divided by total household wealth. In Column 2, *Hold Stocks* is a dummy variable that takes the value of 1 if the household owned stocks. In Column 3, *Save Ratio* is the ratio of dollars held in savings accounts divided by total household wealth. In Column 4, *Buy* is a dummy variable that takes the value of 1 if the household reported that they made more stock purchases than sales. In Column 5, *Sell* is a dummy variable that takes the value of 1 if the household sold more stock than they purchase. Finally, in Column 6, *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 * 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 4: Proximity and Local Characteristics

This table 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: Same State

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

Panel B: Vulnerability

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

Table 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. In Panel A, Column 1-3 includes individual account of which the head of the household identifies as a male. Column 4-6 includes individual account of which the head of the household identifies as a female. In Panel B, Column 1-3 includes individual account of which the head of the household is single. Column 4-6 includes individual account of which 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

Panel A: Gender

	Male			Female		
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Net Trades	Buys	Sells	Net Trades	Buys	Sells
Log (1 + Attacks)	-0.005	-0.030***	-0.022***	-0.003	-0.014	-0.007
	(0.003)	(0.009)	(0.004)	(0.009)	(0.018)	(0.012)
Observations	42,876	42,876	42,876	4,007	4,007	4,007
R-squared	0.054	0.019	0.102	0.050	0.086	0.169
Number of house	961	961	961	91	91	91
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: Relationship

	Single			Married		
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Net Trades	Buys	Sells	Net Trades	Buys	Sells
Log (1 + Attacks)	0.007	-0.020	-0.009	-0.011***	-0.037***	-0.023***
	(0.007)	(0.022)	(0.007)	(0.004)	(0.011)	(0.005)
Observations	8,575	8,575	8,575	28,823	28,823	28,823
R-squared	0.084	0.013	0.103	0.052	0.032	0.111
Number of house	200	200	200	643	643	643
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 6: Risky Stocks

In this table, we examine the propensity of investors to buy high risk stocks following an increase in attacks. In Columns 1 to 3 we identify stocks that have high idiosyncratic volatility. In Columns 4 to 6 we examine stocks that have high idiosyncratic skewness. To identify stocks as high risk, we calculate the idiosyncratic volatility (skewness) based on the 252-day rolling regression. Then for each day in the sample we define those stocks in the top half as high idiosyncratic volatility (skewness). The depended variable is defined as the percentage of total purchases in each month that are high idiosyncratic volatility (skewness) stocks. *Attacks* is the number of attacks each month that cause injuries, deaths or were covered in the news. In columns 2 and 4 a subsample of the households is taken to include only those households that frequently trade high idiosyncratic volatility (skewness) stocks (top 25th percentile). In columns 3 and 6 the same subsample is used, but we run a zero inflated Poisson model. The controls are the same as Table 2. Robust standard errors in parentheses *, **, and *** indicate significance at the 10, 5 and 1% level respectively.

	High Idiosyncratic Volatility			High Idiosyncratic Skewness		
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Full Panel	Sub Panel	ZIP	Full Panel	Sub Panel	ZIP
Log (1 + Attacks)	-0.006***	-0.012***	-0.027***	-0.008***	-0.011***	-0.028***
	(0.001)	(0.003)	(0.007)	(0.001)	(0.003)	(0.007)
Observations	255,830	65,567	65,567	255,830	66,819	66,819
R-squared	0.052	0.060		0.060	0.073	
Number of house	5,726	1,389		5,726	1,414	
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 7: Flight Home Effect

This table examines a possible flight home effect exhibited by investors following attacks. The dependent variable is the percentage of a month's total buys, based on dollar value, that are firms located in the same state as the investor. *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. Column 1 uses a fixed effect OLS model and Column 2 uses a zero inflated Poisson model. 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.

	% of Buy That are local stocks	
	(1)	(2)
VARIABLES	Full Panel	Zero Inflated
In State * Log (1 + Attacks)	0.008*	0.088***
	(0.004)	(0.022)
Log (1 + Attacks)	0.002	0.014
	(0.001)	(0.011)
Observations	105,392	105,392
R-squared	0.559	
Number of house	1,331	
Controls	Yes	Yes
Year Fixed Effects	Yes	Yes
House Fixed Effects	Yes	Yes

Table 8: Attacks and Attention

In this table, we examine the propensity of investors to buy attention stocks following an increase in attacks. To identify high attention stocks, we follow the methodology from Barber and Odean (2008). In Columns 1 to 3 we identify high attention as the top decile and in Columns 4 to 6 we identify stocks in the top 5% as high attention. The dependent variable is defined as the percentage of total purchases in each month that are high attention stocks. *Attacks* is the number of attacks each month that cause injuries, deaths or were covered in the news. In columns 2 and 4 a subsample of the households is taken to include only those households that frequently trade high attention stocks (top 25th percentile). In Columns 3 and 6 the same subsample is used, but we run a zero inflated Poisson model. The controls are the same as Table 2. Robust standard errors in parentheses *, **, and *** indicate significance at the 10, 5 and 1% level respectively.

VARIABLES	(1) Full Panel Top 10%	(2) Sub Sample Panel Top 10%	(3) ZIP Top 10%	(4) Full Panel Top 5%	(5) Sub Sample Panel Top 5%	(6) ZIP Top 5%
Log (1 + Attacks)	-0.008***	-0.010***	-0.079***	-0.004***	-0.007***	-0.099***
	(0.001)	(0.002)	(0.010)	(0.001)	(0.002)	(0.014)
Observations	255,830	66,847	66,847	255,830	67,029	67,029
R-squared	0.033	0.048		0.036	0.057	
Number of house	5,726	1,394		5,726	1,423	
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 9: Terrorism Related Industries

In this table, we examine the propensity of investors to buy stocks that are directly related to an increase in the level of terrorism. We follow Chesney et al. (2011) in identifying the Defense, Insurance, Transportation and Banking industries as being closely related to terrorism. In our tests, we classify firms into these industries based on the Fama-French 49 industry classification. The dependent variable is defined as the percentage of total purchases in each month that firms in a terrorism related industry. *Attacks* is the number of attacks each month that cause injuries, deaths or were covered in the news. In columns 2 and 4 a subsample of the households is taken to include only those active households that frequently trade high attention stocks (top 25th percentile). In columns 3 and 6 the same subsample is used, but we run a zero inflated Poisson model. The controls are the same as Table 2. Robust standard errors in parentheses *, **, and *** indicate significance at the 10, 5 and 1% level respectively.

	Zero Inflated Poisson			
	(1)	(2)	(3)	(4)
VARIABLES	Defense	Insurance	Transportation	Banks
Log (1 + Attacks)	0.203*	-0.135***	-0.008	-0.060***
	(0.106)	(0.029)	(0.053)	(0.023)
Observations	14,634	91,932	66,205	64,751
,R-squared				
Number of house	306	1,465	1,438	1,396
Controls	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Household Fixed Effects	Yes	Yes	Yes	Yes

Table 10: Duration of Trading Effect
This table 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. All dependent and control variables are defined the same as Table 2. Robust standard errors in parentheses *, **, and *** indicate significance at the 10, 5 and 1% level respectively.

	Net Trades						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
VARIABLES	Month t-2	Month t-1	Month t	Month t+1	Month t+2	Month t+3	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 11: Robustness Tests

Table 11 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. The dependent variables in Columns 1 to 3 are defined the same as in Table 2. In Column 1, *Net Trades* is the total value of stocks sold subtracted from the value of stocks purchased, divided by 1 month lagged total equity holdings. In Column 2(3), *Buy (Sell)* is the value of purchases (sells) in the month divided by the 1 month lagged total equity holdings. In Panel B, the dependent variable in each column is defined the same as in Table 3. *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: Brokerage Data

VARIABLES	(1) Net Trades	(2) Buy	(3) Sell
Above Median	-0.011***	-0.028***	-0.008***
	(0.002)	(0.005)	(0.002)
Tercile Rank	-0.004***	-0.009***	-0.007***
	(0.001)	(0.002)	(0.001)
Observations	255,830	255,830	255,830
R-squared	0.035	0.019	0.090
Number of house	5,726	5,726	5,726
Controls	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes
Household Fixed Effects	Yes	Yes	Yes

Panel B: PSID Robustness						
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Ratio	Hold Stocks	Save	Buy	Sell	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