Violence and investor behavior: Evidence from terrorist attacks

Vikas Agarwal
Georgia State University

Pulak Ghosh
Indian Institute of Management Bangalore

Haibei Zhao*
Lehigh University

August 2018

Abstract

We use terrorist attacks as a natural experiment to examine the effect of violence on investors' trading behavior in the stock market. Using a large-scale dataset of daily trading records of millions of investors, we find that investors located in the areas more affected by the attacks tend to trade less compared to the investors in less affected areas. This effect does not seem to be driven by the changes in asset fundamentals, risk preferences, lack of attention, local bias, or trader experience, but instead by the impairment of cognitive ability due to fear and stress after exposures to violence.

JEL Classification: G41, D91

Keywords: violence, terrorism, cognitive ability, individual investors

* Vikas Agarwal is from Georgia State University, J. Mack Robinson College of Business, 35 Broad Street, Suite 1234, Atlanta GA 30303, USA. Email: vagarwal@gsu.edu. Tel: +1-404-413-7326. Fax: +1-404-413-7312. Vikas Agarwal is also a Research Fellow at the Centre for Financial Research (CFR), University of Cologne. Pulak Ghosh is from the Indian Institute of Management Bangalore, Decision Sciences and Information Systems. E-mail: pulak.ghosh@iimb.ac.in. Haibei Zhao is from Lehigh University, College of Business and Economics, 621 Tylor Street, RBC 323, Bethlehem PA 18015, USA. Email: haz816@lehigh.edu. We thank Shashwat Alok, Paul Brockman, Eliezer Fich, Sugata Ray, Stephan Siegel, and seminar participants at the Lehigh College of Business Research Retreat for valuable comments. This paper is funded by the NSE-NYU Stern School of Business Initiative for the Study of the Indian Capital Markets. The views expressed in this paper are those of the authors and do not necessarily represent those of the NSE or NYU.

What is supposed to be a lifesaving instinct becomes anchored in your body, flooding your system with corrosive hormones that can damage your health, affect the way you think and change the decisions you make. Terrorists are counting on that effect. They want you to be full of fear. Of them. All the time.

– CNN, July 15, 2016

1. Introduction

Terrorist attacks can have severe consequences for human health, such as post-traumatic stress disorder (PTSD), subjective well-being, and physical well-being (Schuster et al., 2001; Galea et al., 2002; Schlenger et al., 2002; Camacho, 2008; Shenhar-Tsarfaty et al., 2015; Ahern, 2018). Terrorist attacks can also have adverse effects on economic outcomes, such as impediments to economic growth, international trade, consumption and production, and the gross domestic product (Abadie and Gardeazabal, 2003; Blomberg, Hess, and Orphanides, 2004; Eckstein and Tsiddon, 2004; Blomberg and Hess, 2006). However, little is known about how such violent and traumatic events affect investors' financial decision making.

In this paper, we use terrorist attacks as a natural experiment to examine the change in individual investors' trading behavior after exposure to violence and trauma. We focus on the November 2008 Mumbai attacks which caused hundreds of fatalities, involved the use of lethal weapons, caused tremendous panic and fear among the general public, and are referred to as "India's 9/11" (Rabasa et al., 2009). We utilize a proprietary large-scale dataset which contains all the trading records on the National Stock Exchange (NSE) of India, a first time in the literature. The rich dataset has trading records at the trader-day-stock level, as well as the location information for each trader, such as zip code, city, and state. These unique features of the data allow us to compare the changes in the trading behavior for the treated investors (those located closer to the attack scenes) after the attacks with the changes in the trading behavior of the control group (those further away from the scenes). In addition, we are able to include individual trader fixed effects to control for factors such as investor wealth, trading experience, and financial sophistication that are not likely to vary within a few days around the attacks; and day fixed effects to control for changes in aggregate market conditions such as overall market return, risk, and liquidity.

We find that after the Mumbai attacks on November 26, 2008, there is less trading activity by individual investors located in Mumbai compared with the other individuals located outside Mumbai. The changes in trading behavior of the affected investors are economically significant. For example, the total trading volume per trader per day decreases by 2,885 Indian Rupees (henceforth INR) for an average individual investor located in Mumbai after the attacks, which is 9.2% of the daily volume for an average investor. We further assign the individual traders into different groups based on their geographical distance to Mumbai. We find that the magnitude of the changes in trading activity decreases monotonically with the increases in the distance from the attack scenes, with no significant decline in trading activity if investors are more than 500 kilometers from Mumbai.

To understand the mechanism of the loss in trading activity, we formulate several hypotheses that predict less investor trading after the terrorist attacks, and exploit the richness of our large-scale data to disentangle between different hypotheses. First, fear and stress after the terrorist attacks can adversely affect the traders' ability to retrieve and analyze information, and impair their cognitive ability to perform complex trading tasks (hereafter *cognitive ability hypothesis*). Interestingly, there is mixed, and sometimes contrasting evidence from the science literature regarding the consequences of stress. On one hand, stress hormones such as cortisol and adrenaline can help prepare the body to fight or flight, enable us to stay more awake and focused, and enhance information retrieval. On the other hand, such hormones can impair memory functions, information acquisition, and cognitive abilities.[1] Our evidence based on millions of individual investors is consistent with the adverse consequences of stress demonstrated in the lab settings. To further investigate the cognitive ability hypothesis, we examine the trade performance of the individual investors. We find that despite trading less, the performance of Mumbai traders is also worse post attacks compared with the control group (non-Mumbai traders). This result lends further support to the cognitive ability hypothesis, suggesting that traders' cognitive abilities are impaired enough to result in worse trading decisions.[2]

Second, terrorist attacks can have adverse effects on the economic activity and firm fundamentals. A decrease in investors' trading activity can be due to asset reallocation or risk management considerations, instead of changes in investors' behavioral traits (hereafter *fundamental value hypothesis*). However, the changes in asset fundamentals is unlikely to drive our findings since we explicitly control for the changes in market conditions through day fixed effects. Furthermore, investors located closer to or further away from the sites of attacks should alter their investment behavior in a similar fashion if there are shocks to asset fundamentals due to the attacks.

Third, violence and traumatic events can affect individuals' preference to take risks. Prior literature has documented both increase (Callen et al., 2014) and decrease (Voors et al., 2012) in risk aversion due to violence exposures. In our setting, investors may become more risk averse after the attacks, and are less willing to take financial risks and trade in the stock market (hereafter

[1] For the contradictory roles of the physiologic systems on brain function and human behavior when individuals face stress, see Wolkowitz et al. (1990); Sapolsky (1996); Kirschbaum et al. (1996); McEwen and Sapolsky (1995); De Quervain, Roozendaal, and McGaugh (1998); McEwen (1998); Newcomer et al. (1999); de Kloet et al. (1999); De Quervain et al. (2000); Lupien et al. (1999); Lupien et al. (2002); Kim and Diamond (2002); Lupien et al. (2007); Liston et al. (2009); Putman et al. (2010); and Kandasamy et al. (2014).

[2] It is possible that although Mumbai investors trade less post attacks, they trade on the stocks that have more information asymmetry and therefore require more cognitive ability to process. This conjecture is not supported in the data as we do not find that Mumbai traders show a greater propensity to trade stocks with more information asymmetry.

risk preference hypothesis). However, when we separately examine the purchase and sale activities of Mumbai-based investors, we find that both activities decline after the attacks compared with the control group. This finding is inconsistent with the risk preference hypothesis, which would predict less purchase and more sale if investors become more risk-averse after the attacks, and vice versa.[3]

A fourth hypothesis is that terrorist attacks can reduce the investors' perceived life expectancy or increase their mortality risk, and investors may rationally adjust their consumption and investment behavior facing these changes (hereafter *life expectancy hypothesis*). If distant investors are less likely to suffer from death in future attacks, it is possible that they are less likely to alter their trading behavior compared with Mumbai investors. However, lower life expectancy would suggest more current consumption, thus more selling and less purchasing of stocks. Inconsistent with the life expectancy hypothesis, we observe that Mumbai investors decrease both buying and selling of stocks after the attacks. Relatedly, the likelihood of being harmed during terrorist attacks is very low (Becker and Rubinstein, 2011; Ahern, 2018), which should also make it difficult for the life expectancy hypothesis to explain the large economic magnitude of trading volume change that we observe.

Fifth, Mumbai-based investors may pay more attention to their local events compared to the other traders, and exhibit less trading activity if they have difficulty allocating attention to the stock market (hereafter *investor attention hypothesis*).[4] This hypothesis, however, is inconsistent with at least two pieces of evidence. First, we compute conditional measures of trading activity and find that conditional on investors already paying attention to the stocks, those exposed more to terror still tend to trade less. Second, the limited attention hypothesis predicts the largest decline

[3] These findings are in sharp contrast to those of Lee and Andrade (2011), who find that students exposed to fear induced by horror movies sell more stocks in an experiment involving 80 students.

[4] The attention hypothesis does not unambiguously predict less trading. If traders care about the performance of their financial investments, news coverage on the attacks may make them pay more attention to the stock market.

during the first few days after the attacks when Mumbai residents are most tuned to the news coverage on the events. In contrast, we find a U-shaped decrease in the investor trading activity after estimating the treatment effects over time (see Figure 1). While this finding contradicts the limited attention channel, it is consistent with the prior science literature showing that acute exposures to stress hormones may promote learning and memory functions while prolonged exposures inhibit these functions (McEwen, 1998; Lupien, et al., 2002; Liston et al., 2009; Putman et al., 2010; Kandasamy et al., 2014), and the damages to human body are reversible after the danger is past (McEwen, 1998).

The last competing hypothesis is related to the local bias in trading of Mumbai investors. Firms located in Mumbai may suffer from property damages or business interruptions due to the attacks. If the implications of such damages are easier to assess for Mumbai-based investors, then they may trade differently on their local stocks than non-Mumbai traders (hereafter *local bias hypothesis*). We find that Mumbai investors do not exhibit a different propensity to trade Mumbai stocks after the attacks. Moreover, the local bias hypothesis would predict simultaneously more purchase and less sale of their local stocks by Mumbai traders if they identify a stock undervaluation, and vice versa. Instead, we find that both their buys and sells decline after the attacks. We also examine the performance of Mumbai and non-Mumbai stocks, and do not find any significant difference between their performances after the attacks.

Lastly, we conduct two tests to examine the trading behavior of different types of investors. First, we hypothesize that the trading behavior of institutions can be different from individuals. Traders in a group setting may be able better to manage the trading tasks facing fear and stress after exposure to violence. Also, institutions may adopt trading algorithms that are not influenced by human emotions. We find that institutions located in Mumbai do not exhibit different trading behavior after the attacks than more distant institutions. Second, individuals with more past trading experience may be better able to manage trading tasks, and are less affected after the attacks. We develop several measures of past trading experience for individual investors, and do not find evidence that past trading experience help weaken the effect of terror on investor trading activity.

Our paper contributes to several strands of literature. The recent literature on finance and economics documents a number of novel, though sometimes mixed, findings on how trauma and fear affect individuals' financial choices, predominantly the effect on agents' risk preferences.[5] We use terrorist attacks as a natural experiment for exposures to violence and fear, and find evidence consistent with a new channel related to the loss of cognitive ability behind the change in individuals' financial behavior. Our large-scale evidence complements prior findings from the lab and field experiments that typically involve smaller numbers of test subjects.

Second, we contribute to the literature on the adverse effects of terrorism on economic activity. Over the past decade, there has been around a ten-fold increase in the number of terrorist attacks around the world (Ahern, 2018). Therefore, it is increasingly important to examine the impact of the attacks to study policy implications. Our high frequency trading records allow us to track individual investors' reaction around the terrorist attacks, and better identify and quantify the effects of terror through the individuals' real-world financial transactions.

2. Data and variable construction

2.1 Trading data

[5] Callen et al. (2014) and Voors et al. (2012) find that individuals become more and less risk-averse after wars and violence experiences, respectively. Eckel, El-Gamal, and Wilson (2009) find more risk-seeking behavior among women after hurricane Katrina. Cohn et al. (2015) find the financial professionals in their experiment become more fearful and risk averse after being primed with financial crisis. Guiso, Sapienza, and Zingales (2018) find that students treated with horror movies show more risk aversion.

Our dataset on investor trading consists of a large trader-day-stock level panel data covering the complete daily trading records of over 14 million traders on the Indian National Stock Exchange (NSE) between 2004 and 2017. The NSE is the primary stock exchange in the Indian market where the vast majority of the stock trading takes place, especially during recent years. For each trader-day-stock observation, we have information on the ticker symbol of the stock traded, the number of shares purchased and sold, as well as the average price per share paid or received for the purchase or sale. Each trader has a unique and masked identifier in the dataset, which allows us to track the same trader over time. The dataset also includes the location information for the traders, such as their zip code, city, and state. Finally, each trader is flagged as individual investor or institutional (including banks, mutual funds, etc.) investor.

We aggregate the trader-day-stock observations to the trader-day level and calculate four measures of trading activity for each individual during a day: the probability of trading (*probtrade*), the total volume in thousand INR (*totvol*), the number of stocks traded (*nstock*), and the total number of shares traded (*totshr*). Specifically, *probtrade* is an indicator variable that is equal to one if the investor makes any stock purchase or sale during the day, and zero otherwise.[6] *totvol* is the total trading volume per trader per day in thousand INR, including both purchases and sales. *nstock* is the number of stocks traded per trader per day. *totshr* is the total number of shares traded per trader per day. We consider these four variables as unconditional trading activity measures since they are set to be equal to zero if the individual does not make any trade during a day. Next, we compute three *conditional* trading activity measures (conditional on a trader making a trade during the day), denoted *CONDvol*, *CONDnum*, and *CONDshr*. They are set to be equal to *totvol*,

[6] We do not include the individuals who do not ever trade during the period of terrorist attacks. This is because these observations will be dropped from the regressions after we include individual fixed effects.

nstock, and *totshr* when an individual makes any trade during a day, and are set to missing and dropped from the analysis otherwise.

Table 1 shows the summary statistics of the individual trading data around the 2008 Mumbai attacks. An average trader has a 22% probability of making any trade in a given day during this period, and the average trading amount per trader per day is 31.45 thousand INR as we observe in Panel A. We also report the correlations between the unconditional and conditional trading activity measures in Panels B and C, respectively. All measures are positively correlated with each other as one would expect, since when a trader exhibits less trading activity, all measures should decline, and vice versa. The numbers also show that although the correlations are positive, they are far from being perfectly correlated, suggesting that we capture different aspects of trading activity through these measures.

2.2 Stock data

We obtain the daily stock return and firm financials data from COMPUSTAT Global, and match these data with the individual trading data using a ticker symbol–ISIN (International Securities Identification Numbers) link file provided by the NSE. The NSE tick size is 0.05 Indian Rupees, and we observe that many of the stocks with very low share prices have either extreme daily returns due to bid-ask bounce, or zero returns due to stale pricing. We therefore exclude the stocks with share prices below 5 INR to reduce the noise in calculated stock returns. Excluded observations total to 3% of the stock-day observations, which is comparable to the threshold used in Kahraman and Tookes (2016) in their study of stock liquidity in the Indian market. This exclusion has minimal impact on our empirical results.

We compute three measures of investor's propensity to trade stocks with different characteristics. The first measure is the propensity to trade Mumbai stocks by a given trader during a day (*tradeMum*). For each stock, we first construct a stock-level indicator variable that is equal to one if the company's headquarter is located in Mumbai, and zero otherwise (*Mumstock*). We obtain the company's headquarter location information from COMPUSTAT Global. We then take a weighted average of these indicator variables across all stocks traded by a trader during a day, weighted by the INR amount of each stock trade to compute *tradeMum*.

Our second measure is the propensity to trade stocks with high illiquidity levels (*amihud*). We first compute the stock-level Amihud (2002) measure:

$$Amihud = \frac{1}{N}\sum_{t=1}^{\mathrm{N}}\frac{\left|\mathrm{R}_t\right|}{P_t \times Vol_t}, \tag{1}$$

where t is the index for days, N is the number of trading days during the past calendar quarter, R_t is the daily stock return, P_t is the stock's closing price on day t, and Vol_t is the stock's total trading volume on day t. We then take a weighted average of the Amihud measures across all stocks traded by a trader during a day, weighted by the INR amount of each stock trade to compute *amihud*.

Our third measure is the propensity to trade stocks with high return volatility (*retvol*). We first compute the stock-level return volatility using the stock's daily returns during the past calendar quarter. We then take a weighted average of the return volatilities across all stocks traded by a trader during a day, weighted by the INR amount of each stock trade to compute *retvol*.

Our last two measures related to liquidity and volatility capture the information asymmetry and uncertainty associated with the stocks (e.g. Kyle, 1985; Glosten and Milgrom, 1985). Stocks with more illiquidity or volatility should be more difficult to value and require more information processing by the investors.

2.3 Terrorist attacks

In our empirical analysis, we focus on the 2008 Mumbai attacks that took place in Mumbai, India, around 20:00 Indian Standard Time on November 26, 2008. The attacks caused hundreds of fatalities and injuries, lasted several days, held random civilians as hostages, and had multiple targeted areas including the historic Taj hotel, a community center, a restaurant, a hospital, and railway stations. Most of the dead hostages showed signs of torture and the bodies were beyond recognition. One doctor noted, "I have seen so many dead bodies in my life, and was yet traumatized. A bomb blast victim's body might have been torn apart and could be a very disturbing sight. But the bodies of the victims in this attack bore such signs about the kind of violence of urban warfare that I am still unable to put my thoughts to words".[7] The event was covered extensively in the news and social media, and induced a great amount of fear among the public.

Since the stock market was closed on November 27 due to the attacks, our post event date starts from November 28, 2008 when the market reopened. We use an event window of 7 trading days before and 21 trading days after the event date to isolate the effect of terrorist attacks on investors' trading behavior. The ending date of our event window is December 30, 2008, right before the New Year's Eve to avoid any confounding effects of the national holiday. We choose a shorter event window for the pre-event period to avoid any confounding effect of the global financial crisis (e.g., rumors in October 2008 that ICICI, India's largest private bank, will go bankrupt due to its holdings of Lehman Brothers). Table A1 in the Appendix shows that extending the pre-period to 21 trading days has little impact on our main results.

3. Empirical methodology and results

[7] See http://www.rediff.com/news/2008/nov/30mumterror-doctors-shocked-at-hostagess-torture.htm.

We expect to observe that investors located in Mumbai are more affected by violence and trauma after the 2008 Mumbai attacks. A number of studies use the proximity to attack sites to measure the extent of an individual's exposure to terrorist attacks. For example, Galea et al. (2002) find that 7.5% of the surveyed adults living in Manhattan reported symptoms consistent with post-traumatic stress disorder (PTSD) after 9/11, while the prevalence of PTSD was 20.0% among respondents living near the World Trade Center. Sharot et al. (2007) show that participants living close to the 9/11 attacks exhibit selective activation of the amygdala when asked to recall the event, and argue that close personal experience to terror is critical in triggering the neural mechanisms underlying the emotional reactions. Ahern (2018) uses the travel time to Madrid or London to measure the extent of exposures to two terrorist attacks that took place in these cities.

We investigate the differences in individuals' trading behavior for those who are more exposed to the attacks (treatment group) compared to those that are less exposed (control group), before and after the events. Specifically, we estimate the following difference-in-differences (DD) model using trader-day level observations:

$$Trade_{i,t} = \alpha + \beta \times Mumbai_i \times post_t + \omega_i + \kappa_t + \varepsilon_{i,t}, \tag{2}$$

where $Trade_{i,t}$ denotes proxies of trading behavior such as share or volume trading activity for trader *i* during day *t*; $post_t$ is an indicator variable that is set to one if *t* is after the event date, and zero otherwise; $Mumbai_i$ is an indicator variable that is set to one if the trader is located in Mumbai, and zero otherwise; ω_i is the individual trader fixed effects; and κ_t is the day fixed effects. The indicator variable $Mumbai_i$ is included, but absorbed by the individual fixed effects; similarly, $post_t$ is absorbed by the day fixed effects.

The trader fixed effects ω_i help control for various factors that can affect the investors' trading behavior, such as investor wealth, trading experience, and financial sophistication that are unlikely to change over the few days around the event date. The day fixed effects κ_t control for any change in the aggregate market conditions such as fluctuations in market risk, return, and liquidity. Our main variable of interest is the interaction term between $Mumbai_i$ and $post_t$. A positive (negative) coefficient on β would indicate that Mumbai traders exhibit more (less) trading activity after the attacks, compared with more distant traders in the control group who are less exposed to the attacks.

3.1 Baseline results

Table 2 reports the estimation results of Equation (2). We find that the probability of trading, the trading volume, the number of stocks traded, and the number of shares traded, all decline significantly after the attacks for investors located in Mumbai. For example, the coefficient of –0.015 in Panel A, Column (1) indicates that the probability of trading any stock during a given day (*probtrade*) decreases by 1.5% for an average individual trader located in Mumbai after the attacks, which is 6.8% of the sample average of 22% shown in Table 1. Column (2) of Panel A shows the total volume per trader per day decreases by 2.885 thousand INR (which is around $57 using the currency conversion rate between INR and U.S. dollars at the time of the attacks), or 9.2% of the sample mean of *totvol*. The number of stocks traded per day per trader decreased by 8.1% as we observe in Column (3) of Panel A, which is 8.9% of the sample mean of *nstock*. The total number of shares traded per trader per day decreased by 14.4 shares in Column (4) of Panel A, or 10.3% of the mean value of *totshr*.

To put these numbers in perspective, consider the aggregate decrease in trading volume for Mumbai traders during the post-attack period. The total number of Mumbai individual traders is 337,129 for the sample used in Table 2 (consisting of 4 trading weeks), representing 18% of the total number of individual traders during the same period. Since the unit of observation is per trader per day, the total decline of trading volume over the 21 days subsequent to the attacks is ₹2,885×337,129×21, which is around 20.4 billion INR, an economically large figure.

The measures of trading activity in Columns (2) through (4) of Panel A are unconditional, i.e., they are set to zero if an individual does not trade during a day. Since in Column (1) we observe a decrease in the probability of trading, a natural question is whether the effects in panel A only reflect a lower probability of trading, or a decline in trading activity conditional on trading as well. In Panel B of Table 2, we examine this issue by focusing on the conditional measures of trading activity. As mentioned in the data section, for the conditional trading measures, the non-trading observations are set to missing and dropped from the analysis. We continue to observe negative and significant coefficients on *post*×*Mumbai* in all three specifications, suggesting that traders are both less likely to trade, and tend to trade a smaller amount conditional on trading.[8]

Since the post-event period ends on December 30, 2008, there may be concerns about a confounding effect of tax-loss selling which may affect individual investors' trading behavior. However, we can rule out this possibility for two reasons. First, unlike December-end as the fiscal year ending in the US, the financial year ends on March 31st in India. Second, there is no obvious economic reason why Mumbai investors should have a different propensity to sell their shares compared with more distant investors. Nonetheless, in untabulated results, we use November 26

[8] The difference between the number of observations in Panel B of Table 2 (10,934,570) using the conditional measures of trading and the number reported in summary statistics (11,331,241) is due to the fact that investors who only trade on one day during our sample period will be dropped from the regressions due to inclusion of individual fixed effects.

in the years of 2007 and 2009, and the same lengths of pre- and post-event windows to conduct placebo tests for investors' trading behavior. We do not find that Mumbai investors exhibit any difference in their trading behavior around the placebo dates.

3.2 Investor distance from Mumbai

In our baseline results, we find that investors located in Mumbai are more affected by the terrorist attacks, measured by changes in their trading behavior. In this section, we investigate whether investors located closer to Mumbai are more affected by the attacks. Specifically, we construct four indicator variables based on the geographical distance between investors' zip code and the city center of Mumbai: *Dist0_50*, *Dist50_200*, *Dist200_500*, and *Dist500_1000*. The two numbers in each variable name indicate the range of distance in kilometers from Mumbai. For example, *Dist50_200* is equal to one if the trader is located between 50 and 200 kilometers from Mumbai, and zero otherwise. We then interact the distance variables with the post attack indicator variable (*post*) to estimate the treatment effects for close and distant traders.

Table 3 reports the results on changes in investor trading behavior based on their distance to Mumbai. We observe that the treatment effects decrease monotonically as traders move further away from Mumbai. The effects are the strongest for investors located within 50 kilometers of Mumbai, then become weaker for those located between 50 and 200 kilometers, much weaker for those located between 200 and 500 kilometers, and eventually disappear when the distance from Mumbai is over 500 kilometers. Moreover, the results are consistent across both unconditional and conditional measures of trading behavior.

The chance of being harmed directly in possible future attacks may be very low for individuals located several hundred kilometers away from Mumbai. One interpretation of our finding on *Dist200_500* is that those individuals may have more friends or relatives who are

Mumbai residents than those living even further away. In other words, individuals may suffer indirectly from the attacks through their social networks.

3.3 Change in trading behavior over event time

We find in previous sections that investors exhibit different trading behavior based on cross-sectional variations in their distances to Mumbai. Next, we examine the time-series changes in individuals' trading behavior subsequent to the attacks. Specifically, we allow the treatment effects to vary over time by estimating the following equation:

$$Trade_{i,t} = \alpha + \sum_{t} \beta_t \times Mumbai_i \times \kappa_t + \omega_i + \kappa_t + \varepsilon_{i,t}, \tag{3}$$

where the coefficients β_t measure the treatment effects on Mumbai traders for each event date κ_t.

Figure 1 plots the evolution of β_t over time for the trading activity measures *probtrade*, *totvol*, *nstock*, and *totshr* in the four subplots, respectively. We observe that the trading activity initially decline after the event date of attacks (denoted by the vertical dashed lines), and then recover to the pre-event level around three trading weeks (or about four calendar weeks) after the attacks. Interestingly, the trading activity does not drop immediately after the attacks but rather 2-3 days afterwards till we see a significant decrease.

This finding resonates well with the evidence from the science literature. Tests conducted in the lab show that immediate elevation of the stress hormone level can promote learning and memory functions (Lupien, et al., 2002; Lupien et al., 2007; Putman et al., 2010). In contrast, prolonged exposure to the stress hormones impairs memory retrieval and cognitive abilities (Sapolsky 1996; McEwen 1998; de Kloet et al., 1999; Liston et al., 2009). Kandasamy et al. (2014) conduct a lab experiment by artificially raising the test subjects' stress hormone (specifically cortisol) levels to analyze their financial choice. They find that immediately after an elevation of the hormone, there is no difference between the treated and the control group during the following day. However, the treated group becomes more likely to overweight small probability events during the seventh day of the test after prolonged exposure to high stress hormone levels, suggesting that acute (hours) and chronic (days to weeks) exposures to stress have different effects on human behavior.

Our results on the reversal of the treatment effect are also consistent with the physiologic systems' reaction to stress over time. The human body first activates the adaptive system after detection of a dangerous situation and releases various stress hormones, then shuts down the system after the threat is past, and eventually restores the hormones to baseline levels (see Figure 2 of McEwen, 1998). The reversal of symptoms is also documented in the setting of the 9/11 attacks. Prior survey-based studies find that following the event of 9/11, most people report problems related to irritability, nightmares, distressing thoughts and loss in concentration (Schuster et al., 2001). However, most recover from initial symptoms 5 to 8 weeks after the 9/11 attacks (Galea et al., 2002).[9]

4. Analyses and discussion of the mechanism

We first discuss several mechanisms that can explain our prior findings in Section 4.1. We then examine how different types of agents react to violence exposures in Section 4.2.

4.1 Mechanism influencing investors' trading behavior

4.1.1 Cognitive ability

Our main finding on the decline in trading activity in the previous section is consistent with the cognitive ability hypothesis, which predicts that fear and stress after exposure to violence and

[9] Our results in Figure 1 suggest that traders take a bit less time (four calendar weeks) to recover than the period documented for the 9/11 attacks in previous studies (e.g. Galea et al., 2002). The terrorist attacks we examine, although associated with a large number of fatalities, are perhaps still less dramatic than the 9/11 attacks.

trauma impair the traders' ability to perform complex trading tasks. In this section, we examine the trade performance of the individual investors to find additional support for the cognitive ability channel. If terrorist attacks adversely affect the traders' cognitive ability, we should observe worse trade performance for Mumbai investors after the attacks compared to the more distant investors. Examining trade performance provides a powerful test for the cognitive ability channel, since trading involves real-world financial transactions based on individuals' own financial stakes. Individuals therefore should have great incentive to utilize their ability and maximize performance.

We start by following Puckett and Yan (2011) and compute a trade-level performance measure (for additional details, see Section II.B of Puckett and Yan, 2011). For each trader-day-stock observation, we compute the abnormal return of buy and sell trades separately, then weight the stock-level abnormal returns by the traded amount on the stock to calculate the total abnormal return. Specifically, we first separate the buys and sells for each trader in a given day. For each buy trade, we calculate the holding period return from the trade execution date to the ending date of our sample (December 30, 2008). We then subtract the DGTW (Daniel et al., 1997) benchmark return from the holding period return to compute the abnormal return on this buy trade.[10] Next, for each trader, the abnormal returns for all buy trades are weighted by the amount of buying for each trade to compute the total abnormal returns for all buys. We repeat the same procedure to compute the total abnormal returns for all sells. Finally, the total abnormal returns for all buys and total abnormal returns for all sells are weighted by the aggregate amount of buys and sells, respectively, to compute the total performance for the trader.

[10] The benchmark is matched with the traded stock on size, book-to-market, and momentum, and calculated over the same period as the stock return. The total number of stocks traded on the NSE in our sample is around 900, which is substantially smaller than those on the U.S. exchanges. Therefore, instead of forming 5×5×5=125 benchmark portfolios, we form 3×3×3=27 portfolios based on size, book-to-market, and momentum.

Note that although we evaluate each trade from the execution date to the ending date of the sample, this approach also accounts for the round-trip trades since we use the same ending date to compute the holding period returns for all trades. For example, suppose a trader buys 100 shares of Reliance Industries at ₹300 per share and sells 100 shares at ₹310 per share, and the price on the last date is ₹330 per share. The total profit for this trader should be 100×(₹310–₹300), which is exactly equal to the amount under our methodology (100×(₹330–₹300)+ 100×(₹310–₹330)).[11]

One difference between our setting and that in Puckett and Yan (2011) is that they do not examine trade performance before and after a specific event date. In our setting, instead of having one performance for each trader, we have two performance measures for trader *i*: one based on all trades placed before the event date ($Performance_{i,Before}$), and the other based on all trades placed after the event date ($Performance_{i,After}$). We then estimate the following equation:

$$Performance_{i,T} = \alpha + \beta \times post \times Mumbai_i + \omega_i + \kappa_t + \varepsilon_{i,t} \qquad (4)$$

where *T*=*Before* or *After*; and *post* is equal to one if the performance is measured after the event date, and zero otherwise.

We report the estimation results of Equation (4) in Table 4. The negative and significant coefficient on $post \times Mumbai$ suggests that the performance of Mumbai investors is worse after the attacks compared with the more distant investors in the control group. The average performance decline for each Mumbai trader is 0.492%, which is economically significant considering that the performance is measured over only several weeks around the attacks.[12]

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[11] ₹ is the official symbol for the INR.

[12] This result also rules out the possibility that Mumbai investors are more financially sophisticated or have better access to news on the financial market, which would predict that their performance should be better, and not worse, than more distant investors.

Although the performance results are consistent with the cognitive ability hypothesis, one form of endogeneity can affect the interpretation of these results. If Mumbai investors trade more on stocks that have more information asymmetry and demand more cognitive ability to process, then the total amount of trading tasks they perform may be more, instead of less than the more distant traders. To test this conjecture, we use the two measures for the propensity to trade stocks with more information asymmetry (computed in the data section), i.e., stocks with high return volatilities (*retvol*), and stocks with high illiquidity levels (*amihud*). We then regress the two measures on the post event indicator variable (*post*), the Mumbai investor indicator variable (*Mumbai*), and the interaction term between *post* and *Mumbai*. The results reported in Table 5 show that Mumbai traders do not exhibit a greater propensity to trade stocks with more information asymmetry after the attacks. If anything, they choose to trade those with less information asymmetry, as indicated by the negative and significant coefficient on *post*×*Mumbai* when we use the *retvol* measure in Column (1).

4.1.2 Asset fundamentals

Terrorist attacks can have adverse implications on the economy or the operations of local firms, which raises a question that whether our results are due to shocks to investor psychology or to asset fundamentals. The 9/11 attacks in the U.S. caused a 14% drop in the Dow Jones Industrial Average over the week after the stock market reopened, representing the largest one-week drop in history for the index at that time. For comparison, in Figure 2 we plot the daily market returns by value-weighting the returns of all the stocks in our sample. In stark contrast with the 9/11 attacks, the market returns were generally positive after the 2008 Mumbai attacks. This suggests that the 2008 Mumbai attacks did not cause large scale economy-wide damages that are comparable to the

9/11. In addition, in all of our analyses we control for day fixed effects that should absorb any change in aggregate market conditions and asset fundamentals.

Moreover, investors from every city and state have the discretion to purchase and sell the stocks. Therefore, emotionless “rational” agents should trade in a similar fashion based on shocks to the fundamental values, instead of trading differently based on their distance from the attack scenes as we show previously (unless their assessments on the asset fundamentals are different, a possibility we entertain in Section 4.1.6).

4.1.3 Risk preference

Violence and trauma can lead to severe emotional consequences such as depression, fear and stress, thus changing individuals’ risk preferences and their trading behavior. This hypothesis is based on at least two strands of literature, each with mixed evidence. First, in the economics literature, Malmendier and Nagel (2011) find that individuals are more risk averse after experiencing the Great Depression. Callen et al. (2014) use controlled recollection of violence in a field experiment in Afghanistan, and find that individuals become more risk averse after recollection of fearful events. Guiso, Sapienza, and Zingales (2018) find that students treated with horror movies exhibit higher risk aversion. In contrast, Voors et al. (2012) find more risk-seeking behavior after the individuals have exposure to civil wars in Burundi. Second, in the science literature, Piazza et al. (1993) and van den Bos et al. (2009) find that more stress hormones induce greater risk-seeking behavior, while Kandasamy et al. (2014) find that individuals became more risk-averse after raising their stress hormone levels.

Our findings so far are largely consistent with agents becoming more risk averse after the attacks, since we observe less trading activity (Table 3) and less propensity to trade stocks with high volatility (Table 5). However, the total trading activity measures do not separate the purchases and sales of the stocks, while the risk preference hypothesis predicts different signs on these activities. To further examine this issue, in Table 6 we re-construct our trading activity measures based on stock buys and stock sales, respectively (for example, *probbuy* is an indicator variable that is equal to one if an individual makes a buy trade during a day, and zero otherwise). We observe that both purchase and sale activities decline after the attacks, either using unconditional (Panels A and C) or conditional (Panels B and D) measures of trading activity. These findings are not consistent with the risk preference hypothesis, which would predict less purchase and more sale if investors become more risk averse in order to reduce their risk exposures to the financial market; or more purchase and less sale if investors become less risk averse. Overall, we find mixed evidence for the risk preference hypothesis.

4.1.4 Life expectancy

If terrorist attacks reduce the traders' life expectancy or increase their mortality risk, traders may adjust their consumption and investment by altering their trading behavior. However, it is well documented in the literature that the likelihood of being harmed during terrorist attacks is very low, and the main effect of terror on human beings is through fear instead of change in life expectancy or mortality rate (Becker and Rubinstein, 2011; Ahern, 2018). Given the small probability of being fatally harmed, we should not observe as great of a change in trading behavior as we document in previous results. In addition, if individuals feel their lives are in danger, they should change their behavior more during the first few days of the attacks, when there is a greater threat for follow-up attacks. Our findings in Figure 1 does not support this hypothesis, as we observe a U-shaped response instead of a sharp decrease in trading activity during the first few days after the attacks. Finally, the life expectancy hypothesis would again predict asymmetric trading behavior for buys and sells. If agents demand more current consumption, they should sell more and buy less on the stock market, which is not what we observe in Table 6.[13]

4.1.5 Investor attention

If investors have limited attention and the news coverage on local events draws much of their attention, then they may allocate less attention to the stocks and trade less even if they do not suffer from stress or loss of cognitive ability. We argue that our findings are not driven by the allocation of limited attention for several reasons. First, our results on the conditional measure of trading activity suggest that conditional on investors allocating attention to the stocks, they still trade less. Second, the limited attention hypothesis would predict the greatest decline in trading activity during the first few days after the attacks, when investors are most influenced by the news coverage on terrorist attacks. However, our results on the evolution of treatment effects over time in Figure 1 do not show an immediate decline but rather a U-shaped pattern for the change in trading activity, which as mentioned earlier, matches the scientific evidence of the effect of chronic stress (Kandasamy et al., 2014). Third, both the cognitive ability channel and the limited attention channel predict less trading after the attacks. However, conditional on investors paying attention to the stocks and conditional on them trading less, only the cognitive ability channel predicts worse trade performance, while the limited attention channel does not have performance implications. We find the trading performance for Mumbai investors is indeed worse compared with individuals in the control group in Section 4.1.1.

Finally, it is likely that after terrorist attacks, investors may also have difficulty commuting via public transportation, and therefore have less time to pay attention to the stocks. However, this conjecture again contradicts with the results from Figure 1 since if commuting is a problem, we

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[13] The results on buys and sells also rule out certain behavioral channels such as investors being more pessimistic after trauma, which would again predict asymmetric trading behaviors for buys and sells.

should observe the greatest decline in trading activity during the first few days after the attacks. In addition, our conditional trading activity measures are conditional on investors allocating time and attention to the stocks, despite any commuting issues. Lastly, one would expect that the professional investors should be more likely to be affected by commuting issues since they may have a greater need to commute to their trading desks and utilize their proprietary resources to trade, while our results later in Section 4.2.1 suggest the opposite.

4.1.6 Local bias

It is well documented that investors exhibit local bias when making investment decisions, and one primary reason is that they have access to better information on local stocks than the other market participants. This hypothesis suggests that in our setting, Mumbai investors may trade differently (i.e., strategically) if they have better information on their local stocks. However, investors should again demonstrate asymmetric trading behavior regarding purchases and sales, e.g., buy more and sell less if they view their local stocks as undervalued. Moreover, if Mumbai investors have informational advantage, they should perform better compared with the other traders, while in Section 4.1.1 we observe the opposite.

To further investigate the local bias hypothesis, we conduct two tests. First, we examine the performance of Mumbai and non-Mumbai stocks in Panel A of Table 7. We regress the daily stock returns (*return*) on the post event indicator variable (*post*) that is equal to one if the company's headquarter is in Mumbai (*Mumstock*), and the interaction between *post* and *Mumstock*. We do not observe any difference in the stock returns between Mumbai stocks and non-Mumbai stocks after the attacks, as indicated by the insignificant coefficient on *post*×*Mumstock*.

Second, in Panel B of Table 7, we examine whether Mumbai investors exhibit a different propensity to trade Mumbai stocks post attacks. The dependent variable is *tradeMum*, the propensity of trading Mumbai stocks for an average trader during a day. We find that the interaction term between *Mumbai* and *post* is insignificant, suggesting that Mumbai investors' do not change their propensity to trade Mumbai stocks after the attacks.

Overall, we find neither that Mumbai investors have a different propensity to trade their local stocks, nor that Mumbai stocks exhibit different performance compared with non-Mumbai stocks after the terrorist attacks. Therefore, the local bias in investment behavior cannot explain our findings.

4.2 Institutional investors and trading experience

We first study the trading behavior of institutional investors in Section 4.2.1. We then discuss the role of past trading experience in mitigating the effect of violence exposures on individual investors in Section 4.2.2.

4.2.1 Institutional Investors

We show in previous sections that terrorist attacks have important implications on individuals' trading behavior. A natural question is whether the professional investors are less affected by the attacks. Prior literature shows that trading experience and learning can mitigate behavioral biases (Dhar and Zhu, 2006; Seru, Shumway, and Stoffman, 2010; Linnainmaa, 2011). Interestingly, Lo and Repin (2002) document less physiological reactions under stress from experienced traders compared with less experienced traders. Traders working inside the financially institutions are usually perceived to have the ability to manage stressful situations, therefore they could be less subject to or could better handle the stress after the attacks.

Further, in the modelling framework of Becker and Rubinstein (2011), agents can choose to invest, manage, and overcome fear if they are more affected by terror. They find that (a) suicide bomber attacks decrease the chance of drivers to serve as bus drivers, but have no effect on the existing bus drivers to quit their jobs; (b) suicide bomber attacks on average have negative effects on the likelihood to take bus rides, but not so for the high frequency bus users; and (c) average consumers visit coffee shops less frequently post attacks, yet frequent visitors do not change their habits. These arguments and results also suggest that in our setting, institutional investors may be less affected since they should have better ability and/or more incentives to manage and overcome fear after exposures to violence. Institutions frequently use computer models and algorithms to automate the process of trading, which would again predict less reaction after the attacks.

We study institutional trading behavior in Table 8. We first report the summary statistics of the trading activity measures for institutional investors around the 2008 Mumbai attacks in Panel A of Table 8, where the measures are constructed similarly as those for individual investors. We observe that the trading volume, the number of stocks traded, and the number of shares traded by institutions are all much greater than individual investors. For example, the unconditional trading volume for individual traders per day (*totvol*) is 31 thousand INR, while for institutions it is 879 thousand INR.

Panels B and C of Table 8 report the results on the changes in institutional trading activity after the 2008 Mumbai attacks. In sharp contrast with our previous findings for individual investors, we do not observe any statistically significant change in trading behavior for institutions located in Mumbai compared with the other institutions after the attacks. We note that although the estimated coefficients on *Mumbai*×*post* in Panels B and C of Table 8 are sometimes larger than those for individual investors, this is due to the fact that the magnitude of institutional trading is much larger on average than individual traders, as we see in Panel A of Table 8.

4.2.2 Investor experience

We find in the previous section that institutional trading is not affected by the attacks, and one possible explanation is institutions have more trading experienced than individuals. It is therefore natural to examine among individual investors, whether those with more trading experience can also manage the violence exposures better and show less decline in trading activity. To investigate this possibility, we develop four indicator variables that measure the trading experience for individual traders (*exp*), which are equal to one if: 1. the individual trader's total trading volume during the past year is ranked in the top quartile among all individual traders; 2. the individual trader's number of shares traded during the past year is ranked in the top quartile among all individual traders; 3. the length of time from the individual trader's account registration date on the NSE to the event date is ranked in the top quartile among all individual traders; and 4. the length of time from the individual trader's first trading date on the NSE to the event date is ranked in the top quartile among all individual traders; and zero otherwise.

We report the results on individual trading experience in Table 9. Panels A through D use the four aforementioned trading experience measures for *exp*, respectively. Interestingly, we only find evidence that experience helps alleviate the decline in the probability of trading (*probtrade*) for Mumbai investors post the 2008 attacks, as indicated by the positive and significant coefficients on *exp*×*Mumbai*×*post* in the first Column in all four panels. However, experience does not help alleviate the decline in the other measures of trading activity. These results suggest that our finding on the institutional investors is either because institutional investors have even more trading experience than the top-ranked individual investors, or because there are alternative factors affecting the different behaviors among institutions and individuals (e.g. institutions can adopt trading algorithms that are not affected by human emotions or individuals when working in groups can deal better with the stress and trauma).

In addition to the past experience of trading on the stock market, past traumatic experience may help the individuals better cope with the fear and stress. For example, those who have experienced the 2006 Mumbai attacks may have less trouble resuming their normal activities after the 2008 attacks. We construct an indicator variable that is equal to one if the individual opens a trading account before July 11, 2006 (date of the Mumbai train bombing in 2006), and zero otherwise. We then conduct a similar test as in Table 9 by interacting this indicator variable with *Mumbai*×*post*. Untabulated results are very similar to those in Table 9, suggesting that either prior traumatic experience does not help investors manage the new attacks, or the experience from the milder 2006 attacks is not significant enough for investors to cope with a much more severe terrorist event such as the 2008 attacks.

5. Concluding remarks

Terrorist attacks, even with small damages to property and direct cost to the economy, can create a disproportional amount of fear and anxiety and impose indirect costs on human well-being (Becker and Rubinstein, 2011). In this paper, we use terrorist attacks as a natural experiment to examine the effects of stress on investors' trading behavior in the stock market. Using the records from millions of trading accounts, we document several novel findings. First, individual investors located closer to the attack sites trade less after the attacks compared with those located further away. Second, potential alternative channels such as change in asset fundamentals, risk preference, mortality rate, attention effect, and local bias do not support the evidence we present. Instead, our overall results show that the driving force behind less trading by and poor trading performance of the individual investors is likely to be on account of the loss of cognitive abilities due to stress and fear after exposures to violence. Lastly, we find that institutional trading activity is not affected by the exposure to violence.

Our study contributes to the literature on how violence and trauma affect financial decision making, as well as the adverse effects of terrorism on economic activity. Although we focus on the terrorist attacks as an extreme form of stress, our results have implications for decision making under less severe forms of stress such as day-to-day chronic stress that can cause similar physiologic responses of human bodies (McEwen, 1998; Coates and Herbert, 2008).

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Table 1: Summary statistics

Panel A reports the summary statistics of the variables on individual investor trading around the 2008 Mumbai terrorist attacks. *probtrade* is an indicator variable that is equal to one if the investor makes any stock trade during the day, and zero otherwise. *totvol*, *nstock*, and *totshr* are the total trading volume in thousand Rupees per trader per day (including both purchases and sales), the number of stocks traded per trader per day, and the total number of shares traded per trader per day, respectively; and are all set to zero when there is no trade. *CONDvol*, *CONDnum*, and *CONDshr* are measures of conditional trading activity, which are equal to *totvol*, *nstock*, and *totshr* respectively when the trader makes any trade during the day; and are set to missing when there is no trade. Panels B and C report the correlation tables for the conditional and unconditional trading measures, respectively.

Panel A: Trading activity

Variable	Observations	Mean	STD	25%	Median	75%
probtrade	53,422,200	0.22	0.41	0.00	0.00	0.00
totvol	53,422,200	31.45	187.94	0.00	0.00	0.00
nstock	53,422,200	0.91	2.68	0.00	0.00	0.00
totshr	53,422,200	140.14	588.75	0.00	0.00	0.00
CONDvol	11,331,241	139.63	362.21	8.22	27.62	101.81
CONDnum	11,331,241	4.11	4.28	1.00	2.00	5.00
CONDshr	11,331,241	877.38	1923.95	55.00	200.00	760.00

Panel B: Correlations between unconditional trading measures

	probtrade	*totvol*	*nstock*	*totshr*
probtrade	1.00			
totvol	0.34	1.00		
nstock	0.64	0.49	1.00	
totshr	0.45	0.65	0.59	1.00

Panel C: Correlations between conditional trading measures

	CONDvol	*CONDnum*	*CONDshr*
CONDvol	1.00		
CONDnum	0.40	1.00	
CONDshr	0.64	0.39	1.00

Table 2: Terrorist attacks and individual investors' trading behavior

This table reports the change in individual investors' trading behavior around the 2008 Mumbai attacks by estimating the difference-in-differences specifications in Equation (2). *post* is an indicator variable that is equal to one if the corresponding date is after the event date of the attacks (November 26, 2008), and zero otherwise. *Mumbai* is an indicator variable that is equal to one if the trader is located in Mumbai, and zero otherwise. The dependent variables are defined previously in Table 1. Panels A and B report the results for the unconditional and conditional measures of trading activity, respectively. The regressions control for the individual and day fixed effects, and the standard errors are double clustered at the individual and day levels. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Unconditional measures of trading activity

	(1) *probtrade*	(2) *totvol*	(3) *nstock*	(4) *totshr*
Mumbai×*post*	–0.015***	–2.885***	–0.081***	–14.376***
	(–5.61)	(–5.37)	(–5.11)	(–5.63)
Individual FE	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes
Observations	53,422,200	53,422,200	53,422,200	53,422,200
Adj. R^2	0.397	0.476	0.555	0.417

Panel B: Conditional measures of trading activity

	(1) *CONDvol*	(2) *CONDnum*	(3) *CONDshr*
Mumbai×*post*	–5.422***	–0.109***	–29.905***
	(–3.50)	(–4.31)	(–3.91)
Individual FE	Yes	Yes	Yes
Day FE	Yes	Yes	Yes
Observations	10,934,570	10,934,570	10,934,570
Adj. R^2	0.591	0.571	0.548

Table 3: Distance from Mumbai and individual investors' trading behavior

This table reports the change in individual investors' trading behavior around the 2008 Mumbai attacks based on their distance from Mumbai. *Dist0_50*, *Dist50_200*, *Dist200_500*, and *Dist500_1000* are indicator variables that are equal to one if the individual is located 0 to 50, 50 to 200, 200 to 500, and 500 to 1,000 kilometers from Mumbai, respectively; and zero otherwise. The dependent variables are defined previously in Table 1. Panels A and B report the results for the unconditional and conditional measures of trading activity, respectively. The regressions control for the individual and day fixed effects, and the standard errors are double clustered at the individual and day levels. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Unconditional measures of trading activity

	(1) *probtrade*	(2) *totvol*	(3) *nstock*	(4) *totshr*
Dist0_50×post	–0.016***	–3.064***	–0.089***	–15.696***
	(–5.56)	(–5.40)	(–5.05)	(–5.48)
Dist50_200×post	–0.012***	–2.760***	–0.073***	–14.890***
	(–4.92)	(–3.93)	(–4.55)	(–4.63)
Dist200_500×post	–0.003	–1.426***	–0.035***	–7.672***
	(–1.47)	(–3.42)	(–3.20)	(–4.02)
Dist500_1000×post	0.000	0.523**	–0.004	1.260
	(0.04)	(2.14)	(–0.72)	(1.43)
Individual FE	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes
Observations	53,422,200	53,422,200	53,422,200	53,422,200
Adj. R^2	0.397	0.476	0.555	0.417

Panel B: Conditional measures of trading activity

	(1) *CONDvol*	(2) *CONDnum*	(3) *CONDshr*
Dist0_50×post	–5.481***	–0.116***	–31.997***
	(–3.56)	(–4.42)	(–4.00)
Dist50_200×post	–4.073*	–0.086***	–27.678**
	(–1.85)	(–3.18)	(–2.38)
Dist200_500×post	–2.089*	–0.046*	–20.759***
	(–1.71)	(–1.97)	(–3.30)
Dist500_1000×post	1.363	0.005	5.727
	(1.45)	(0.34)	(1.06)
Individual FE	Yes	Yes	Yes
Day FE	Yes	Yes	Yes
Observations	10,934,570	10,934,570	10,934,570
Adj. R^2	0.591	0.548	0.571

Table 4: Trade performance

This table reports the results on individual investors' trade performance around the 2008 Mumbai attacks. We first separate the buys and sells for each trader during a day. For each buy trade at the trader-stock-day level, holding period return is calculated from the trade execution date to the last date of the sample period (December 30, 2008). DGTW (Daniel et al., 1997) benchmark return is subtracted from the holding period return to calculate the abnormal return. DGTW benchmarks are formed based on value-weighted returns of 3×3×3 benchmark portfolios sorted on size, book-to-market, and momentum. The two size breakpoints are based on Nifty 200 and Nifty 500 stocks, respectively. The two book-to-market breakpoints are based on tercile ranks of book-to-market ratios of all stocks. The book value of equity is based on the values on March 31, 2007, the fiscal year-end date for Indian companies. The two momentum breakpoints are based on tercile ranks of cumulative stock returns during the previous year, from October 2006 to October 2007. The abnormal returns for all buys are then weighted by the traded amount to calculate the total buy performance. The same process is repeated to compute the total sell performance. Total buy performance and total sell performance are then weighted by the aggregate buying and aggregate selling amounts to compute the total performance in percentage (*Performance*). *Performance* is computed separately for the pre-event and the post-event periods for each trader, using all trades placed during these two periods by the trader, respectively. The regressions control for individual fixed effects and the post event indicator variable, and the standard errors are clustered at the individual trader level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Performance
Mumbai×post	–0.492***
	(–7.29)
Time FE	Yes
Individual FE	Yes
Observations	1,168,988
Adj. R^2	0.0699

Table 5: Information asymmetry of stocks traded

This table reports the results on the propensity to trade stocks with more information asymmetry. *retvol* is a weighted average of the stocks' return volatility for all stocks traded by an individual during a day, weighted by the amount of each stock traded. *amihud* is a weighted average of the Amihud (2002) measures for all stocks traded by an investor during a day, weighted by the amount of each stock traded (scaled after multiplying by 10^8 for expositional convenience). The regressions control for the individual and day fixed effects, and the standard errors are double clustered at the individual and day levels. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1) *retvol*	(2) *amihud*
Mumbai×post	–0.012**	0.021
	(–2.31)	(0.58)
Individual FE	Yes	Yes
Day FE	Yes	Yes
Observations	10,106,675	9,951,080
Adj. R^2	0.435	0.318

Table 6: Purchases and sales

This table reports the change in individual investors' purchase and sale activities around the 2008 Mumbai attacks by estimating the difference-in-differences specifications in Equation (2). The dependent variables on investor trading activity are computed based on stock purchases in Panels A and B, and based on sales in Panels C and D. Panels A and B report the results for the unconditional and conditional measures of purchase activity, respectively. Panels C and D report the results for the unconditional and conditional measures of sale activity, respectively. The regressions control for the individual and day fixed effects, and the standard errors are double clustered at the individual and day levels. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Unconditional measures of purchase activity

	(1) *probbuy*	(2) *totvol*	(3) *nstock*	(4) *totshr*
Mumbai×post	–0.011***	–1.501***	–0.036***	–6.271***
	(–4.06)	(–5.21)	(–4.03)	(–4.52)
Individual FE	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes
Observations	53,422,200	53,422,200	53,422,200	53,422,200
Adj. R^2	0.399	0.464	0.513	0.380

Panel B: Conditional measures of purchase activity

	(1) *CONDvol*	(2) *CONDnum*	(3) *CONDshr*
Mumbai×post	–3.625***	–0.077***	–16.257***
	(–3.98)	(–3.29)	(–3.10)
Individual FE	Yes	Yes	Yes
Day FE	Yes	Yes	Yes
Observations	10,934,570	10,934,570	10,934,570
Adj. R^2	0.574	0.536	0.524

Panel C: Unconditional measures of sale activity

	(1) *probsell*	(2) *totvol*	(3) *nstock*	(4) *totshr*
Mumbai×post	–0.013***	–1.384***	–0.045***	–8.105***
	(–6.27)	(–5.02)	(–5.09)	(–5.83)
Individual FE	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes
Observations	53,422,200	53,422,200	53,422,200	53,422,200
Adj. R^2	0.422	0.465	0.526	0.387

Panel D: Conditional measures of sale activity

	(1) *CONDvol*	(2) *CONDnum*	(3) *CONDshr*
Mumbai×post	–1.727**	–0.039***	–13.331***
	(–2.11)	(–3.09)	(–3.35)
Individual FE	Yes	Yes	Yes
Day FE	Yes	Yes	Yes
Observations	10,934,570	10,934,570	10,934,570
Adj. R^2	0.581	0.565	0.521

Table 7: Local stocks

Panel A reports the results on stock performance around the 2008 Mumbai attacks using stock-day level observations. The dependent variable *return* is the daily stock return in percentage. *Mumstock* is an indicator variable that is equal to one if the company's headquarter is located in Mumbai as reported in COMPUSTAT Global, and zero otherwise. The regressions control for the stock and day fixed effects, and the standard errors are double clustered at the stock and day levels. Panel B reports the results on individual investors' propensity to trade Mumbai stocks. *tradeMum* is the average propensity of trading Mumbai stocks at the trader-day level, defined as the trading amounts on each stock weighted by the *Mumstock* measure for the corresponding stock. The regressions control for the individual and day fixed effects, and the standard errors are double clustered at the individual and day levels. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Stock performance

	(1) *return*	(2) *return*
post×Mumstock	–0.005	0.043
	(–0.04)	(0.36)
Stock FE	Yes	No
Day FE	Yes	Yes
Observations	28,656	28,656
Adj. R^2	0.243	0.189

Panel B: Propensity to trade Mumbai stocks

	tradeMum
Mumbai×post	–0.001
	(–0.89)
Individual FE	Yes
Day FE	Yes
Observations	9,632,890
Adj. R^2	0.368

Table 8: Institutional investors

Panel A reports the summary statistics of the trading activity measures for institutional investors around the 2008 Mumbai attacks. Panels B and C report the change in institutional investors' trading behavior around the 2008 Mumbai attacks. The regressions control for the institution and day fixed effects, and the standard errors are double clustered at the institution and day levels. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Summary statistics of trading activity

Variable	Observations	Mean	STD	25%	Median	75%
probtrade	1,416,390	0.19	0.39	0	0	0
totvol	1,416,390	879	11,451	0	0	0
nstock	1,416,390	1.15	6.38	0	0	0
totshr	1,416,390	3,832	42,310	0	0	0
CONDvol	251,207	4,584	25,833	17	68	378
CONDnum	251,207	6.01	13.52	1	2	5
CONDshr	251,207	19,708	93,112	110	529	3,000

Panel B: Unconditional measures of trading activity

	(1) *probtrade*	(2) *totvol*	(3) *nstock*	(4) *totshr*
Mumbai×post	0.008	–46.700	0.042	58.289
	(1.53)	(–0.56)	(1.24)	(0.20)
Individual FE	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes
Observations	1,416,390	1,416,390	1,416,390	1,416,390
Adj. R^2	0.371	0.720	0.841	0.725

Panel C: Conditional measures of trading activity

	(1) *CONDvol*	(2) *CONDnum*	(3) *CONDshr*
Mumbai×post	6.647	0.163	845.425
	(0.01)	(0.84)	(0.53)
Individual FE	Yes	Yes	Yes
Day FE	Yes	Yes	Yes
Observations	251,207	251,207	251,207
Adj. R^2	0.790	0.873	0.793

Table 9: Investor experience

This table reports the change in individual investors' trading behavior around the 2008 Mumbai attacks for investors with different trading experience. *exp* is an indicator variable that is equal to one if the investor's aggregate trading volume in the past year is in the top 25% in Panel A, if the trader's aggregate number of shares traded in the past year is in the top 25% in Panel B, if the length of time from the trader's account registration date on NSE to the event date is in the top 25% in Panel C, and if the length of time from the trader's first trading date to the event date is in the top 25% in Panel D; and zero otherwise. All possible double interactions and level variables are included in the regressions but omitted in the table for brevity. The regressions control for the individual and day fixed effects, and the standard errors are double clustered at the individual and day levels. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Experience based on past volume

	(1) *probtrade*	(2) *totvol*	(3) *nstock*	(4) *totshr*	(5) *CONDvol*	(6) *CONDnum*	(7) *CONDshr*
$exp \times Mumbai \times post$	0.009**	–2.109	–5.495	–0.027	–1.715	2.458	0.046
	(2.47)	(–0.81)	(–0.80)	(–0.94)	(–0.34)	(0.11)	(1.05)
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	53,422,200	53,422,200	53,422,200	53,422,200	10,934,570	10,934,570	10,934,570
Adj. R^2	0.377	0.458	0.397	0.539	0.542	0.495	0.520

Panel B: Experience based on past shares

	(1) *probtrade*	(2) *totvol*	(3) *nstock*	(4) *totshr*	(5) *CONDvol*	(6) *CONDnum*	(7) *CONDshr*
$exp \times Mumbai \times post$	0.010***	–2.176	–7.685	–0.026	–3.777	–7.894	0.025
	(3.01)	(–0.90)	(–1.08)	(–0.90)	(–0.78)	(–0.34)	(0.61)
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	53,422,200	53,422,200	53,422,200	53,422,200	10,934,570	10,934,570	10,934,570
Adj. R^2	0.377	0.458	0.397	0.540	0.542	0.495	0.520

Panel C: Experience based on the account registration date

	(1) *probtrade*	(2) *totvol*	(3) *nstock*	(4) *totshr*	(5) *CONDvol*	(6) *CONDnum*	(7) *CONDshr*
$exp \times Mumbai \times post$	0.003**	–0.602	–0.947	0.008	–1.906	3.123	0.020
	(2.55)	(–1.02)	(–0.56)	(1.16)	(–0.69)	(0.19)	(0.71)
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	53,422,200	53,422,200	53,422,200	53,422,200	10,934,570	10,934,570	10,934,570
Adj. R^2	0.377	0.458	0.397	0.539	0.542	0.495	0.520

Panel D: Experience based on the first trading date

	(1) *probtrade*	(2) *totvol*	(3) *nstock*	(4) *totshr*	(5) *CONDvol*	(6) *CONDnum*	(7) *CONDshr*
$exp \times Mumbai \times post$	0.004**	–0.309	0.068	0.001	–2.165	0.287	–0.011
	(2.58)	(–0.46)	(0.04)	(0.19)	(–0.82)	(0.02)	(–0.36)
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	53,422,200	53,422,200	53,422,200	53,422,200	10,934,570	10,934,570	10,934,570
Adj. R^2	0.377	0.458	0.397	0.539	0.542	0.495	0.520

Figure 1: Changes in trading behavior over event time

This Figure plots the treatment effects (defined in Equation (3)) over the event time. pre1, post1, post2 and post3 on the x-axis indicate one trading week before and 1, 2, and 3 trading weeks after the event.

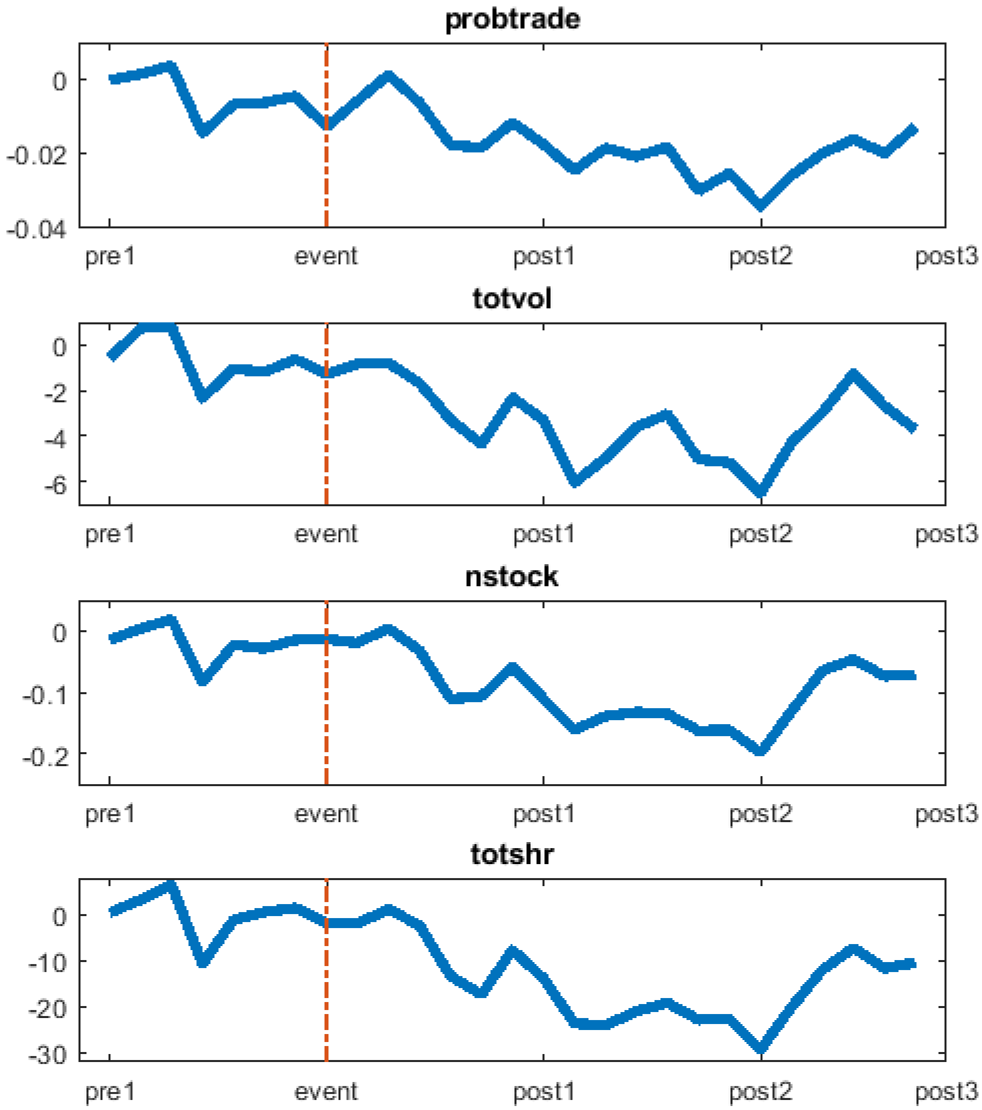
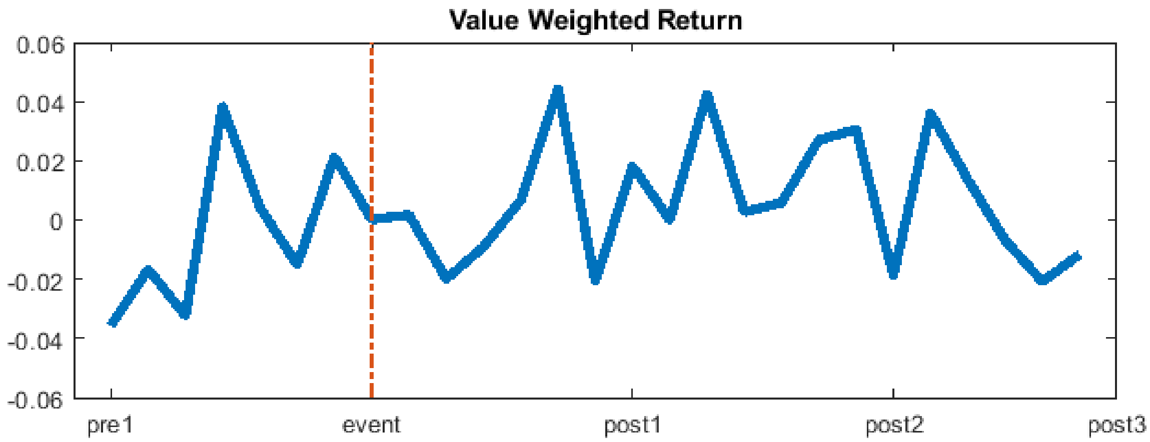


Figure 2: Stock market returns around the 2008 Mumbai attacks

This figure plots the daily stock market returns around the November 26, 2008 Mumbai attacks using value-weighted returns of all stocks in our sample. *pre1*, *post1*, *post2*, and *post3* on the x-axis indicate one trading week before, and 1, 2, and 3 trading weeks after the event. The value-weighted market return on the y-axis is in decimals.



Appendix

Table A1: Terrorist attacks and individual investor trading behavior: Alternative event window

This table reports the change in individual traders' trading behavior around the 2008 Mumbai attacks using the difference-in-differences specifications in Equation (2). The event window is extended to 21 days before and 21 trading days after the event date. Panel A and B report the results under unconditional and conditional measures of trading activity, respectively. The regressions control for the individual and day fixed effects, and the standard errors are double-clustered at the individual and day levels. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Unconditional measures of trading activity

	(1) *probtrade*	(2) *totvol*	(3) *nstock*	(4) *totshr*
Mumbai×post	–0.012***	–2.936***	–0.061***	–12.206***
	(–3.87)	(–5.02)	(–3.11)	(–4.13)
Individual FE	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes
Observations	81,667,234	81,667,234	81,667,234	81,667,234
Adj. R^2	0.341	0.400	0.492	0.355

Panel B: Conditional measures of trading activity

	(1) *CONDvol*	(2) *CONDnum*	(3) *CONDshr*
Mumbai×post	–6.794***	–0.086***	–27.951***
	(–5.49)	(–3.13)	(–4.53)
Individual FE	Yes	Yes	Yes
Day FE	Yes	Yes	Yes
Observations	16,160,617	16,160,617	16,160,617
Adj. R^2	0.508	0.490	0.465