Violence and investor behavior: Evidence from terrorist attacks

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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 and perform worse compared to their peers. 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.

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1. Introduction

Individuals and households are key participants in the stock market. Prior literature documents a number of factors that affect individuals' stock investment behavior.[1] However, an emerging literature in science, finance, and economics highlights that different forms of stress can also have profound implications on individuals' preferences and decision making, such as workplace stress (Coates and Herbert, 2008; Cohn et al., 2015), depression and panic after macroeconomic shocks (Malmendier and Nagel, 2011; Guiso, Sapienza, and Zingales, 2018), and fear and trauma after exposure to war and violence (Voors et al., 2012; Callen et al., 2014). We build on these strands of literature and examine whether and how stress affects individuals' stock investment behavior.

At first glance, stress should be correlated with cognitive ability and is likely to adversely affect investment decisions. However, it is challenging to establish a causal relation of stress on investment behavior because stress and poor financial performance are usually endogenously determined and reinforce each other. In addition, large-scale datasets that contain both measures of cognitive ability and individual investments are difficult to obtain (Korniotis and Kumar, 2010). To address these issues, we use terrorist attacks as a natural experiment to examine the change in individuals' stock trading behavior after exposure to violence and trauma, arguably the most extreme form of stress. We focus on the November 26, 2008 Mumbai attacks which had 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). In addition, we utilize a

[1] Such factors include gender (Barber and Odean, 2001), age (Korniotis and Kumar, 2011; Betermier, Calvet, and Sodini, 2017), IQ (Grinblatt, Keloharju, and Linnainmaa, 2011, 2012), experience (Seru, Shumway, and Stoffman, 2010; Linnainmaa, 2011), local bias (Grinblatt and Keloharju, 2001a; Ivkovic and Weisbenner, 2005), social interactions (Ivkovic and Weisbenner, 2007; Kaustia and Knupfer, 2012), and behavioral biases (Barber and Odean, 2000; Grinblatt and Keloharju, 2001b).

proprietary large-scale dataset which contains *all* trading records on the National Stock Exchange (NSE) of India, a first time in the literature. This rich dataset has millions of 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 allow us to use the difference-in-differences methodology (DID) and compare the changes in trading behavior for the treated investors (those located in Mumbai) after the attacks with those of the controls (those outside of Mumbai).

We find that after the Mumbai 2008 terrorist attacks, there is significantly less trading activity by Mumbai individual investors compared with those located outside of 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 Mumbai individual investor after the attacks, which is 9.2% of the daily volume for an average investor during our sample period. 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 attack site, and observe 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 a large body of science literature regarding the consequences of stress.[2] 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, which would predict that the traders should be more attentive to the news and trade more actively. On the other hand, stress hormones can impair memory functions, information acquisition, and cognitive ability. Our evidence based on millions of individual investors is consistent with the adverse consequences of stress demonstrated in the laboratory settings. To further investigate the cognitive ability hypothesis, we compute the trade performance and find that in addition to trading less, the performance of Mumbai traders is worse post attacks compared with that of the control group. This result lends further support to the cognitive ability hypothesis, suggesting that traders' cognitive abilities are impaired enough to result in worse trading decisions.

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 *asset fundamentals hypothesis*). However, the changes in asset fundamentals are unlikely to drive our findings since we explicitly control for the variation in aggregate market conditions such as return, risk and liquidity through day fixed effects in our DID estimations. Our setting thus differs from past studies on the effects of fear and depression after macroeconomic shocks that affects all investors at the same time (Malmendier and Nagel, 2011; Guiso, Sapienza, and Zingales, 2018). Moreover, in the absence of fear and stress, investors located closer to or further away from the

[2] 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, Gillin, and Hauger (1999); Lupien et al. (2002); Kim and Diamond (2002); Lupien et al. (2007); Liston, McEwen, and Casey (2009); Putman et al. (2010); and Kandasamy et al. (2014).

attack site should alter their investment behavior in a similar fashion when faced with shocks to asset fundamentals due to the attacks. we further show that in stark contrast with the 9/11 attacks in the U.S., the stock market did not suffer from significant declines after the 2008 Mumbai attacks, either in terms of the aggregate stock market returns or the returns of Mumbai-based firms.

Third, violence and traumatic events can affect individuals' preference to take risks. Prior literature has documented both increase (Malmendier and Nagel 2011; Callen et al., 2014) and decrease (Voors et al., 2012; Bernile, Bhagwat, and Rau, 2016) in risk aversion due to exposure to trauma. In our setting, investors may become more risk averse after the attacks, and less willing to take financial risks and trade in the stock market (hereafter *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 difficult to reconcile 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] Further, the risk preference hypothesis would predict an insignificant relation between traders' exposure to violence and their performance, since we use a risk-adjusted performance measure that already nets out the risk component.

Fourth, Mumbai-based investors may pay more attention to their local events compared to the other traders, and exhibit less trading activity if they are distracted and have difficulty allocating attention to the stock market (hereafter *investor attention hypothesis*).[4] Alternatively, people may be grieving or caring about their families. To examine this hypothesis, we first compute conditional measures of trading activity and find that conditional on investors already

[3] Our findings are also 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 drive them to pay more attention to the stock market.

paying attention to and focusing on the stocks, those more exposed to terror and violence still tend to trade less. Second, the attention hypothesis predicts the largest decline during the first few days after the attacks when Mumbai residents are most tuned to the news coverage on the events. For example, when we examine Google Trend search activity from India on the topic "2008 Mumbai attacks" during our sample period, we find that between the attack date and the third trading day after the attacks, there was a large spike followed by a sharp reversal of search activity (Figure 1). In stark contrast to this pattern, the investor trading activity does not exhibit significant change until the fourth trading day post attacks, accompanied by a significant decline and a reversal several trading weeks after the attacks (Figure 2). While inconsistent with the attention hypothesis, this finding is consistent with the prior science literature showing that acute exposures to stress hormones can actually promote learning and memory functions while prolonged exposures inhibit these functions (McEwen, 1998; Lupien, et al., 2002; Liston, McEwen, and Casey, 2009; Putman et al., 2010; Kandasamy et al., 2014), and the damages to human body are reversible after the danger is past (McEwen, 1998).[5]

The last competing hypothesis we examine is related to the local bias of trading by 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 in their local stocks compared to the 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

[5] The U-shaped pattern in trading activity also rules out the possibility that individual investors may have trouble commuting to their trading venues. Also, we find that investors outside of the city center of Mumbai who did not experience commuting issues also show a decline in trading activity. Finally, institutional investors are more likely to be affected as employees may not be able to commute to their trading desks but we do not find any evidence of decline in the trading activity of Mumbai institutional investors.

predict better trade performance of Mumbai traders post attacks, while our results suggest the opposite. We also examine the performance of Mumbai and non-Mumbai stocks, and do not find any significant difference between their performances after the attacks.

Finally, we conduct two additional 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. For example, institutional investors may have better ability and/or more incentives to manage and overcome fear. Institutions may also 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 distant institutions. Second, individuals with more past trading experience such as the active traders may need less of their cognitive ability to manage the trading tasks, and therefore are less affected by the attacks. We develop several measures of past trading experience for individual investors, and find little evidence that past trading experience helps weaken the effect of violence on investors' cognitive ability and trading behavior.

Our study is perhaps most closely related to Grinblatt, Keloharju and Linnainmaa (2011, 2012), who show that IQ (as a static measure of cognitive ability) is positively related to stock market participation and trade performance. Through identifying shocks to cognitive ability, we uncover a causal relation between cognitive ability and trading intensity or performance. Our paper also contributes to recent experimental and survey-based studies that document a number of novel, though sometimes mixed, findings on how trauma and fear affect individuals' financial choices, predominantly through the change in agents' risk preferences.[6] We use a major terrorist attack as

[6] Callen et al. (2014) and Voors et al. (2012) find that individuals become more and less risk-averse after war 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.

a natural experiment for fear and stress on millions of investors, and find evidence consistent with a channel related to cognitive ability behind the change in individuals' financial behavior. Our evidence based on a large group of individuals therefore complements prior findings from the laboratory and field experiments that typically involve much smaller numbers of test subjects.[7]

In addition, we contribute to the literature on investor emotions and stock market. Hirshleifer and Shumway (2003) find morning sunshine in the city of a country's leading stock exchange is positively related to the country's aggregate stock market returns. Kamstra, Kramer, and Levi (2000, 2003) show that daylight savings and winter blues can cause depression and affect market returns. Edmans, Garcia, and Norli (2007) show that losses in soccer games lead to negative market returns for losing country. Da, Engelberg, and Gao (2015) find that internet search volume related to negative sentiment predicts stock market returns and volatility. We contribute to this literature by showing how stress affects investors' trading behavior, thereby providing more direct evidence of how investor emotions matter for the stock market.

Our results have several important policy implications. First, if physical health has a causal impact on financial health, then government aid programs should also be administrated towards promoting physical health, instead of simply providing financial aid for individuals suffering from trauma. Second, if investors suffer from fear and panic during the crisis after market turmoil and severe financial losses, their loss of cognitive ability would hinder information production and cause asset values to deviate further from fundamentals, therefore amplifying the asset volatility.

[7] An exception is the contemporaneous paper by Wang and Young (2018) that studies terrorist attacks and household trading. Our study differs from theirs in several important ways. First, they do not examine trade performance or cognitive ability, our central hypothesis. Second, they focus on the changes in trading for all traders (single difference), while we compare the change for treatment and control (DID). The only exception is in Table 4 where they do not find close and distant investors have different buying and selling behavior (possibly because they include less severe attacks, e.g., only 3 attacks have more than 1 fatality shown in University of Maryland's Global Terrorism Database during their sample period).

Finally, the lack of trading and stock market participation, another consequence of cognitive ability impairment, could exacerbate the liquidity dry-ups during market downturns.

2. Data and variable construction

2.1 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. Terrorists targeted multiple random areas including the historic Taj hotel, a community center, a restaurant, a hospital, and railway stations. The attacks caused hundreds of fatalities and injuries due to lethal weapons, and lasted several days over which random civilians were held as hostages. 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".[8] The attacks were the longest one ever carried out by a terrorist group (Acharya, Mandal, and Mehta, 2009). The event was covered extensively in the news and social media, and induced a great amount of fear among the public.[9]

Since the stock market was closed on November 27, 2008 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

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

[9] In contrast to the Mumbai attacks of 2008, we do not find any change in investor trading behavior around other less significant attacks, such as the Mumbai train bombing in 2006.

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 findings.

2.2 Trading data

Our original 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 investor (including banks, mutual funds, etc.).

2.2.1 Measures of trading activity

We aggregate the trader-day-stock observations to the trader-day level and calculate four measures of trading activity for each trader during a day: the probability of trading (*probtrade*), the total volume in thousand Indian Rupees (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 trader makes any stock purchase or sale during the day, and zero otherwise. *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 trader 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*, *nstock*, and *totshr* when a trader 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 for the four trading weeks around the 2008 Mumbai attacks. Panel A shows that an average trader in our sample period has a 22% probability of making any trade in a given day during this period. It is important to note that the probability of trading appears to be large as we do not include the individuals who never trade during the period of terrorist attacks. This is because these observations will be dropped from the regression analysis after we include individual fixed effects. The mean and median daily trading amounts are INR 139,630 (about $2,840) and INR 27,620 (about $561), respectively conditional on an individual making any trade on a day.[10] These amounts are much smaller than the statistics reported for individual investors in developed countries such as the United States. For example, Barber and Odean (2000) report mean and median trade sizes for individual buy orders of $11,205 and $4,988, respective based on data from a discount broker; while Kelley and Tetlock (2013) report an average trade size of $11,566 based on data from multiple retail brokers. Such amounts are much larger than those in our data, especially given that our trading volume are aggregated at the trader-day level while those in prior studies are at the per trade level.

Finally, 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

[10] Throughout the paper, we use an exchange rate of $1 = INR 49.20 at the time of the attacks.

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. For example, although the volume measure better reflects the economic magnitude of trade size, the share measure captures the change in trading activity that is not driven by a change in the share price.

2.2.2 Measures of stock characteristics

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 INR 0.05, and we observe that many of the stocks with very low share prices have either extreme daily returns due to the bid-ask bounce, or zero returns due to stale pricing. We therefore exclude the stocks with share prices below INR 5 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 stock market. This exclusion has minimal impact on our empirical results.

Finally, we compute 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 information on company's headquarter location from COMPUSTAT Global database. 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*. *tradeMum* is therefore the daily fraction of trading in Mumbai stocks as a proportion of the trader's total daily trading volume.

3. Empirical methodology and results

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 show that the proximity to attack sites measures the extent of an individual's exposure to trauma. For example, Galea et al. (2002) find that 7.5% of the surveyed adults living in Manhattan reported symptoms of post-traumatic stress disorder (PTSD) after the 9/11, while the figure was 20% among respondents living near the World Trade Center. Schlenger et al. (2002) report that the prevalence of PTSD after the 9/11 was substantially higher in the New York City, and was within the expected ranges for the other metropolitan areas and the rest of the country. Sharot et al. (2007) show that participants living close to the 9/11 attacks exhibit selective activation of the amygdala (the "fear center" of our brain) when asked to recall the event, and argue that close personal experience to terror is critical in triggering the neural mechanisms underlying our emotional reactions.

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

$$Trade_{i,t} = \alpha + \beta \times Mumbai_i \times post_t + \omega_i + \kappa_t + \varepsilon_{i,t}, \tag{1}$$

where $Trade_{i,t}$ denotes measures of 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 IQ, age, trading experience, and financial sophistication that are unlikely to change significantly 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, liquidity, and interest rates. 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 (1). 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 much for investors located in Mumbai compared to their peers. 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 INR volume per trader per day decreases by INR 2,885 (about \$59), 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 individual traders based in Mumbai 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 (about $0.4 billion), 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 due to lack of investor attention in the aftermath of attacks, 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 even after conditioning on trading.[11] Finally, in Panels C and D, we include the interaction between an indicator variable for the pre-event (*pre*) and *Mumbai* to test the parallel trend assumption of the DID methodology.[12] The interaction term is insignificant, indicating that our results are not driven by the pre-event differences in trading behavior between

[11] 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 trade only on one day during our sample period will be dropped from the regressions due to inclusion of individual fixed effects.
[12] The construction of *pre* does not include the first trading day to allow us to estimate the equation with both the *pre*×*Mumbai* and *post*×*Mumbai* interaction variables.

Mumbai and non-Mumbai investors, such as fear of recession and associated job losses, or flight to liquidity due to the financial crisis. The parallel trend results also indicate that the 2008 Mumbai attacks were unexpected by the traders.

We conduct several additional robustness checks for the findings on investor trading behavior after the attacks. First, we use a 7-day window in the pre-event period to avoid any confounding effect of the U.S. financial crisis and its spillover effect on the Indian stock market. We extend the pre-period from 7 to 21 trading days in Table A1 in the Appendix, and show that our inferences are unchanged when we use the alternative event window. Second, 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, unlike December-end as the fiscal year ending in the U.S., the financial year ends on March 31st in India. Moreover, there is no obvious economic reason why Mumbai investors should trade differently for tax reasons compared with more distant investors. Nonetheless, in Appendix Table A2, we use November 26 in the years of 2007 and 2009 as placebo dates of the attacks, and do not find that Mumbai investors exhibit any difference in their trading behavior around the placebo dates. Third, it is likely that investors located in metropolitan areas are different from other investors and react differently to major events like terrorist attacks. In Appendix Table A3, we keep traders from the other 9 cities ranked by total population as controls, and still find the treated investors in Mumbai trade less. Lastly, we use OLS in our baseline results as it is easier to interpret the economic magnitude on the estimated coefficients. Since the distributions of the trading activity measures are skewed as shown in Table 1, in Appendix Table A4, we take the logarithmic transformation of both the unconditional and conditional measures of trading. The results show that our results are not affected by outliers in trading activity.

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 the 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 investors' trading behavior based on their distance to Mumbai. We observe that the treatment effects decrease monotonically as traders move further away from Mumbai. The economic magnitude of the effects is the highest for investors located within 50 kilometers of Mumbai, then becomes lower for those located between 50 and 200 kilometers, much lower for those located between 200 and 500 kilometers, and eventually becomes insignificant 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 the significant finding for *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 Dynamic effects of the change in trading behavior

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:

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

where the coefficients β_t measure the treatment effects on Mumbai traders for each event date κ_t. The first trading day in the pre-period is excluded so that β_t can be estimated in presence of individual trader fixed effects.

Figure 2 plots the dynamic effect 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 declines after the event date of attacks (denoted by the vertical dashed lines), and then recovers 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 three trading days afterwards until we see a significant decrease.

This finding resonates well with the evidence from the science literature. Tests conducted in the laboratory show that immediate elevation of the stress hormone level can even 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, McEwen, and Casey, 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). Our results in Figure 2 suggest that traders take a bit less time (around 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 intense and destructive compared to the 9/11 attacks.

4. Analyses 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 exposure 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 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-based 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. The benchmark is matched with the traded stock on size, book-to-market, and momentum, and its return is calculated over the same period as that of 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 $5\times5\times5=125$ benchmark portfolios, we form $3\times3\times3=27$ portfolios based 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 2007 to October 2008.

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 overall performance for the trader.

Note that although we evaluate each trade from the execution date to the ending date of the sample, this approach also accounts for the roundtrip 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)).[13]

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 measure for each trader, we have two measures for each 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:

$$Performance_{i,T} = \alpha + \beta \times post \times Mumbai_i + \omega_i + \kappa_t + \varepsilon_{i,t} \tag{3}$$

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

[13] ₹ is the official symbol for the Indian currency, Indian Rupees (INR).

We report the estimation results of Equation (3) in Table 4. The negative and significant coefficient on *post*×*Mumbai* suggests that the performance of Mumbai-based investors is worse after the attacks compared with the more distant investors in the control group. The average performance decline for each Mumbai-based trader is 0.492% (or 8.9% of the standard deviation of individual traders' performance during this period), which is economically significant considering that the performance is measured over only several weeks around the attacks.[14]

Although the performance results are consistent with the cognitive ability hypothesis, it is possible that Mumbai investors trade more on the stocks that have more information asymmetry, which 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, measured by the Amihud (2002) price impact measure (untabulated).

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 3, 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

[14] 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.

9/11. In addition, in all of our analyses we control for day fixed effects that should absorb any change in aggregate market conditions such as market return, risk, liquidity and interest rates.

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 site as we show previously (unless their assessments on the asset fundamentals are different, a possibility we entertain later in Section 4.1.5).

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 more risk aversion. In contrast, Voors et al. (2012) find more risk-seeking behavior after the individuals have exposure to civil wars in Burundi. Bernile, Bhagwat, and Rau (2016) find a nonmonotonic relation between CEO’s early life exposures to fatal disasters and their risk-taking behavior. 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 on average after being exposed to the attacks.

However, the total trading activity measures do not separate the purchases and sales of the stocks, while the risk preference hypothesis predicts opposite effects on these activities. To further examine this issue, in Table 5 we reconstruct 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.[15]

Finally, we find in the previous section that Mumbai investors suffer from worse trade performance after the attacks. In contrast, the risk preference hypothesis should predict no relation between violence exposure and trade performance, since the performance measure we use already adjusts for the risk component by matching the stock on a portfolio of stocks with similar characteristics (Daniel et al., 1997).

4.1.4 Investor attention

It is challenging to completely separate the attention and stress channel since without paying any attention to the terror attacks and knowing about the event, investors should not suffer from fear and stress due to the attacks. Despite the challenges, we find several pieces of evidence that suggest the change in investor trading behavior is not driven by the attention effect. First, our

[15] Note that this argument does not apply to short selling, since less short selling is an indicator of less, instead of more, financial risk taking. Short selling is extremely rare in India during our sample period. Kahraman and Tookes (2016) document that the shorting market was launched in April 2008 and restricted to a small fraction of stocks that are eligible for futures and options trading. Suvanam and Jalan (2012) report that despite several attempts to promote the security borrowing and lending market by the regulators, the total security borrowing and lending volume reached $250 million in 2010, which is only 0.015% of the total equity trading volume on the NSE in 2010.

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 2 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).

To further compare the time-series changes in treatment effect with the changes in investor attention, we follow Da, Engelberg, and Gao (2011) and use Google Trend search as a measure of investor attention. Google accounted for 94% of all search queries performed in India in 2009 based on data from gs.statcounter.com, a number that is even greater than that that for the United States (e.g., 72% as of February 2009 as shown in Da, Engelberg, and Gao, 2011). The solid line in Figure 1 plots the Google Trend search activity from India on the topic "2008 Mumbai attacks" during our sample period. We find that between the attack date (November 26, 2008) and the third trading day after the attacks (December 02, 2008), there is a large spike followed by a sharp reversal of search activity. The search activity declines significantly by the fourth trading day on December 03, 2008, and eventually diminishes over the next calendar days. In stark contrast to this finding, the treatment effects of investors' trading activities over time in Figure 2 do not change significantly during the first three trading days. Moreover, the treatment effects start to decline after the fourth trading day accompanied by a reversal several weeks after the attacks, a period when there is minimal investor attention on the attacks.

One possibility is that although the nationwide search interest from India diminishes after the first trading weeks post the attacks, Mumbai residents continue to pay close attention to the events. The dashed line in Figure 1 plots the search activities from the state of Maharashtra of which Mumbai is the capital city. We observe that the changes in investor attention from this state are virtually the same as those at the nationwide level. According to Google Trend, 100% of the search interest from Maharashtra is from Mumbai investors.

Finally, another form of attention effect is that investors may have trouble commuting via public transportation after terrorist attacks, and therefore have less time to pay attention to the stocks. However, anecdotal evidence suggests that the public transportation system was not much affected after the attacks.[16] In addition, this conjecture is inconsistent with several findings we mention earlier. First, if commuting is a problem, we should observe the greatest decline in trading activity during the first few days after the attacks, while the results in Figure 2 suggest otherwise. Second, our conditional trading activity measures are conditional on investors allocating time and attention to the stocks, despite any commuting issues. Third, in Table 3, we find a significant decline in trading activities for investors outside of the city center of Mumbai (more than 50 kilometers away and up to 500 kilometers). These investors were unlikely to experience any commuting issues that take place in Mumbai due to the attacks. Lastly, one would expect that the institutional investors should be more likely to be affected by commuting issues since employees should 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.

4.1.5 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. For example, Coval and Moskowitz (1999) show that U.S. mutual funds tend

[16] For anecdotal evidence that the railway and airport operations were not significantly affected, see https://www.forbes.com/2008/11/29/mumbai-economic-cost-oped-cx_ap_1129panagariya.html#21cc45e73ff2.

to prefer locally headquartered firms. 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, and vice versa. 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 based stocks in Panel A of Table 6. 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 6, we examine whether Mumbai-based traders exhibit a different propensity to trade Mumbai stocks post attacks. The dependent variable is *tradeMum*, the daily fraction of trading in Mumbai stocks as a proportion of the trader's total daily trading volume. We find that the interaction term between *Mumbai* and *post* is insignificant, suggesting that Mumbai-based traders do not change their propensity to trade Mumbai stocks after the attacks.

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

4.1.6 Additional channels

In this section, we discuss several additional channels that can affect investor trading behavior after the attacks, such as mortality risk, pessimism, and investor wealth.

First, if terrorist attacks increase the mortality risk for individual investors, they 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 large a change in the trading behavior as we have documented so far. 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 2 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 supported by the results in Table 5.

Second, the results on buys and sells also rule out the possibility that investors being more pessimistic after traumatic events, which would again predict asymmetric trading behavior for buys and sells. Finally, investors may suffer from losses in property values, rental fees, or business income from tourist activities. However, anecdotal evidence suggests that except for the damages to the Taj hotel, the property losses in the Mumbai 2008 attacks were not severe and not comparable to the U.S. 9/11. In addition, if there are significant losses from property values, rental fees, or business income from tourist activities within the city of Mumbai, we should also expect that the business revenues of the Mumbai-based public companies to be adversely affected. We do not find any difference in the stock performance for Mumbai or non-Mumbai firms post the attacks in Table 6, either economically or statistically, suggesting that businesses operating in Mumbai did not suffer from material loss in such activities. Finally, the loss of wealth due to damages in real economic activities would again predict more stock sales if investors need to change illiquid financial investments into liquid wealth, while our results in Table 5 suggests otherwise.

4.2 Institutional investors and trading experience

In this section, we first study the trading behavior of institutional investors, and then discuss the role of past trading experience in mitigating the effect of violence on individual investors.

4.2.1 Institutional investors

So far we have shown 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 financial institutions are usually perceived to have the ability to manage stressful situations, therefore they could be less subject to or could better handle the fear and 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 of bus users 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 7. We first report the summary statistics of the trading activity measures for institutional investors around the 2008 Mumbai attacks in Panel A of Table 7, 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 those for individual investors. For example, the unconditional INR trading volume per individual trader per day (*totvol*) is INR 31,000 (around \$630), while for institutions it is INR 879,000 per institution per day (about \$17,865).

Panels B and C of Table 7 report the results on the changes in institutional trading activity after the 2008 Mumbai attacks. In sharp contrast to 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 7 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 observe in Panel A of Table 7.

4.2.2 Trader experience

We find in the previous section that institutional trading is not affected by the attacks, and one possible explanation is that institutions have more trading experience than individuals. It is therefore natural to examine among individual investors, whether those with more trading experience can also manage exposure to violence 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 a) the individual trader's total trading volume during the past year is ranked in the top quartile among all individual traders; b) the individual trader's number of shares traded during the past year is ranked in the top quartile among all individual traders; c) 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 d) 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. Note that the first two trading experience measures can also be interpreted as measures of investor activeness.

We report the results on individual trading experience in Table 8. 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 $exp \times Mumbai \times post$ 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 (e.g., institutions can adopt trading algorithms that are not affected by human emotions; or institutions can counsel their traders on how to manage stress).

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 8, suggesting that either prior traumatic experience does not help traders cope with the stress associated with 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. The latter is likely to be the case since we do not find Mumbai investors to trade differently after the 2006 Mumbai attacks (untabulated).

5. Discussions and implications

The medical and psychiatric studies have documented severe consequences of trauma on mental and physical well-being (Kessler et al. 1995; Yehuda, 2002; Boscarino, 2006), such as PTSD and suicide. We utilize a unique data set on individual investor trading and find that exposures to traumatic events also affect individuals' financial well-being, as measured by their trading activities and performance in the stock market. Our results have practical implications since a substantial fraction of population suffers from exposure to violence due to interpersonal violence, sexual or childhood abuse, natural disasters, wars, and torture, especially among women and veterans (Schlenger et al., 1992). One policy implication from our results is that if physical health has a causal impact on financial health, then government aid programs should also be administrated towards promoting physical health, instead of simply providing financial aid for individuals suffering from trauma.

Our findings also have implications on other forms of less extreme stress, such as panic and fear due to the financial crisis. Traditional models on financial crisis focus on the roles of change in asset fundamentals, risk management concerns, self-fulfilling runs, strategic behaviors, and financial fragility. Although anecdotal evidence suggests that behavioral factors such as panic and fear are also likely to contribute to the market turmoil and liquidity dry-ups, it is challenging to empirically test the effects of such factors as there are many other confounding effects during the crisis. Earlier literature typically uses exposure to macroeconomic events as measures of fear and depression which can affect all investors at the same time. Our data on investor locations allow us to isolate the effect of fear for investors close to or far away from the attacks at the same time for better identification. Our results generate several implications. If investors suffer from fear and panic during the crisis after market turmoil and severe financial losses, their loss of cognitive ability would hinder information production and cause asset values to deviate further from fundamentals, therefore amplifying the asset volatility in the marketplace. In addition, the lack of trading and stock market participation, another consequence of cognitive ability impairment, could exacerbate the liquidity dry-ups during market downturns.

6. Conclusions

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 site trade less after the attacks compared with those located further away. Second, potential alternative channels such as change in asset fundamentals, risk preference, 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 exposure to violence. Lastly, we find that institutional trading activity is not affected by the exposure to violence.

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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 Indian Rupees (INR) 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 (1). *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

Panel C: Unconditional measures of trading activity (parallel trend)

	(1) *probtrade*	(2) *totvol*	(3) *nstock*	(4) *totshr*
Mumbai×pre	–0.004	–0.309	–0.013	–0.175
	(–1.52)	(–0.60)	(–0.97)	(–0.08)
Mumbai×post	–0.018***	–3.118***	–0.091***	–14.507***
	(–10.18)	(–6.63)	(–6.90)	(–7.40)
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 D: Conditional measures of trading activity (parallel trend)

	(1) *CONDvol*	(2) *CONDnum*	(3) *CONDshr*
Mumbai×pre	0.114	–0.005	–1.119
	(0.08)	(–0.17)	(–0.09)
Mumbai×post	–5.334***	–0.113***	–30.615***
	(–3.70)	(–3.61)	(–2.37)
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 2007 to October 2008. 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: 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 (1). 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 6: 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 7: 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. All the variables are defined earlier in Table 1. 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 8: 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×Mumbai×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×Mumbai×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: Google Trend search activities on the 2008 Mumbai attacks

This figure shows the Google Trend search activities on the topic "2008 Mumbai attacks" from November 26, 2008 to December 30, 2008. The x-axis denotes the calendar dates and the y-axis denote the search interest over time. Search interest over time is defined as the percentage search volume during that date relative to the highest daily volume on the chart (November 27, 2008). The solid line denotes the search activities from India, and the dashed line denotes the search activities from the state of Maharashtra of which Mumbai is the capital. The symbols "*", "o", and "+" denote the search activities from India on the first, second, and the third trading day after the attacks, respectively.

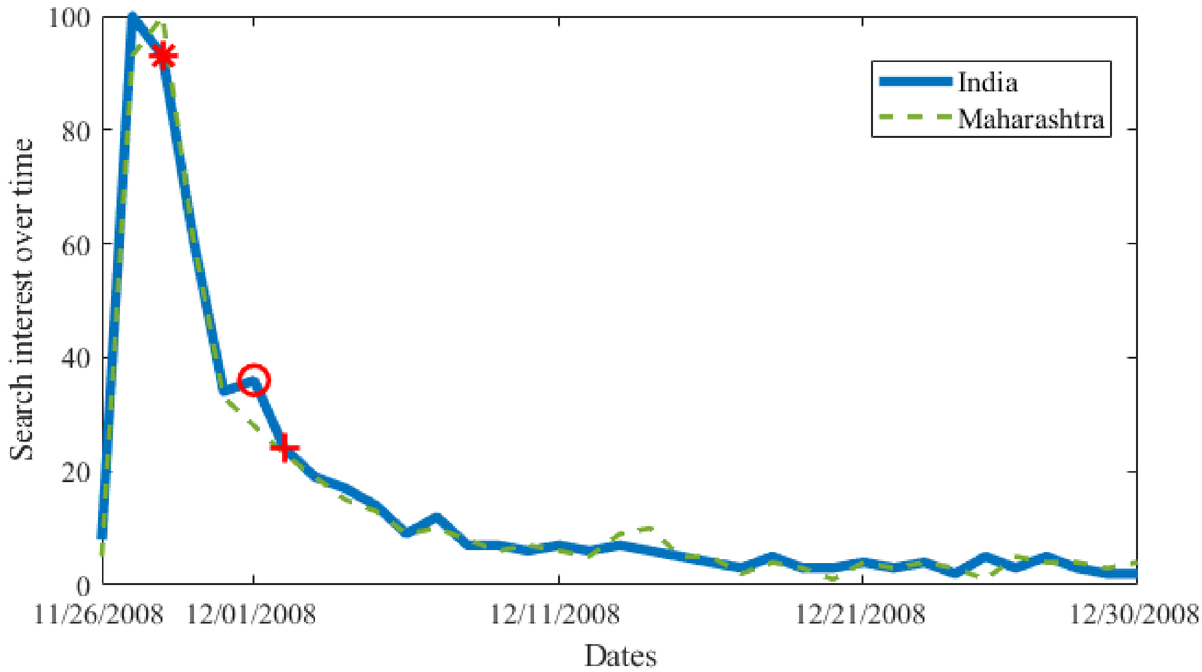


Figure 2: Changes in trading behavior over event time

This figure plots the changes in the trading activity of Mumbai-based traders relative to more distant traders over the event time as measured in Equation (2). *pre1*, *post1*, *post2*, and *post3* on the x-axis indicate one trading week before, and 1, 2, and 3 trading weeks after the event, respectively. The plotted variables are defined earlier in Table 1. The symbols "*", "o", and "+" denote the treatment effects on the first, second, and the third trading day after the attacks, respectively.

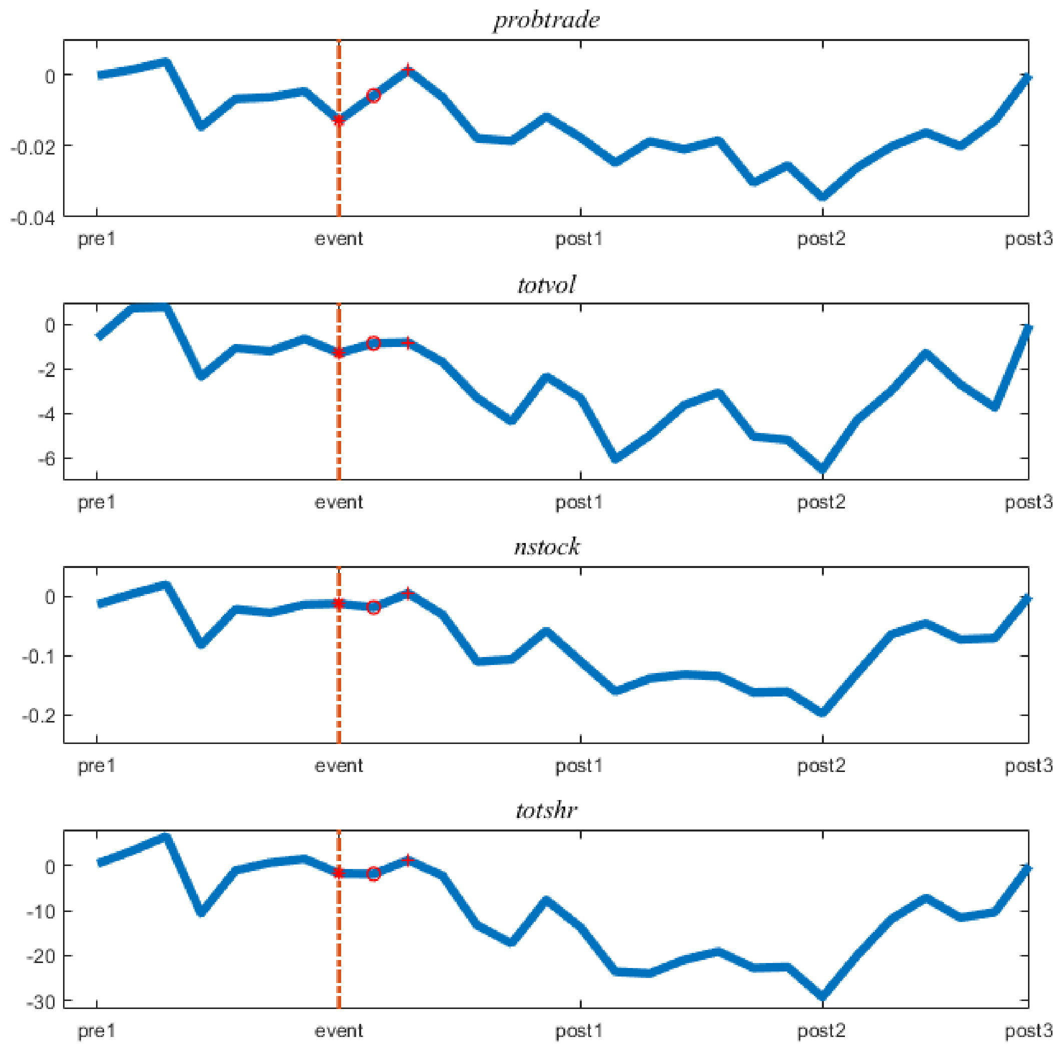
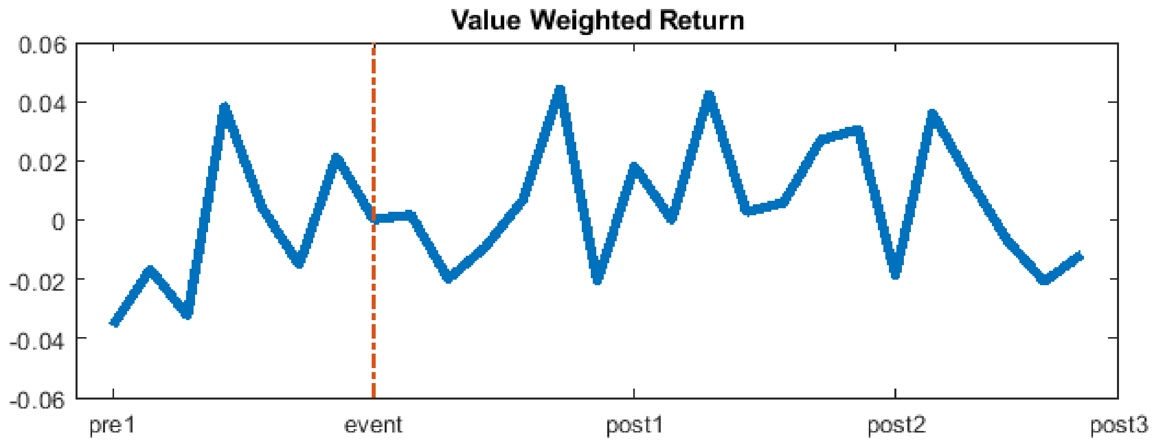


Figure 3: Stock market returns around the 2008 Mumbai attacks

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 investors' 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 (1). The event window is extended to 21 trading days before and 21 trading days after the event date of November 26, 2008. Panels 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

Table A2: Terrorist attacks and individual investors' trading behavior: Placebo event dates

This table reports the changes in individual traders' trading behavior around the placebo event dates. Panel A uses November 26, 2007 as the event date, and Panel B uses November 26, 2009 as the event date. 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: Trading activities around November 26, 2007

	(1) *probtrade*	(2) *totvol*	(3) *nstock*	(4) *totshr*	(5) *CONDvol*	(6) *CONDnum*	(7) *CONDshr*
Mumbai×post	–0.008	–0.848	–0.036	–4.608	–1.216	–0.031	–3.729
	(–1.55)	(–1.35)	(–1.47)	(–1.09)	(–0.76)	(–0.89)	(–0.40)
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	66,474,235	66,474,235	66,474,235	66,474,235	14,626,775	14,626,775	14,626,775
Adj. R^2	0.336	0.478	0.546	0.384	0.577	0.499	0.531

Panel B: Trading activities around November 26, 2009

	(1) *probtrade*	(2) *totvol*	(3) *nstock*	(4) *totshr*	(5) *CONDvol*	(6) *CONDnum*	(7) *CONDshr*
Mumbai×post	0.000	1.417**	0.006	1.028	2.091	0.007	7.43
	(0.14)	(2.25)	(0.61)	(0.55)	(1.37)	(0.42)	(1.00)
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	74,989,523	74,989,523	74,989,523	74,989,523	14,884,633	14,884,633	14,884,633
Adj. R^2	0.355	0.493	0.545	0.404	0.588	0.573	0.631

Table A3: Terrorist attacks and individual investors' trading behavior: Other major cities

This table reports the changes in individual traders' trading behavior. The treatment group includes traders located in Mumbai, and the control group includes traders located in New Delhi, Bangalore, Hyderabad, Ahmedabad, Chennai, Kolkata, Surat, Pune, and Jaipur. 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) *probtrade*	(2) *totvol*	(3) *nstock*	(4) *totshr*	(5) *CONDvol*	(6) *CONDnum*	(7) *CONDshr*
Mumbai×post	–0.013***	–2.556***	–0.068***	–11.071***	–6.560**	–0.098***	–16.226**
	(–5.87)	(–4.58)	(–4.92)	(–4.98)	(–2.61)	(–3.73)	(–2.05)
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	14,869,485	14,869,485	14,869,485	14,869,485	2,841,291	2,841,291	2,841,291
Adj. R^2	0.372	0.461	0.545	0.412	0.612	0.589	0.552

Table A4: Terrorist attacks and individual investors' trading behavior: Logarithm transformation

This table reports the changes in individual traders' trading behavior. The dependent variables are the logarithm of one plus *totvol*, *nstock*, *totshr*, *CONDvol*, *CONDnum*, and *CONDshr* in columns (1)-(6), 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.

	(1) log(*totvol*)	(2) log(*nstock*)	(3) log(*totshr*)	(4) log(*CONDvol*)	(5) log(*CONDnum*)	(6) log(*CONDshr*)
Mumbai×post	–0.061***	–0.024***	–0.088***	–0.044***	–0.017***	–0.030***
	(–6.17)	(–5.61)	(–5.99)	(–5.91)	(–5.02)	(–4.04)
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	53,422,200	53,422,200	53,422,200	10,934,570	10,934,570	10,934,570
Adj. R^2	0.499	0.514	0.432	0.683	0. 519	0.610