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 areas more affected by the attacks tend to trade less and perform worse compared with their peers. This effect does not seem to be driven by changes in asset fundamentals, risk preferences, lack of attention, local bias, or trader experience, but instead by 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 the 2008 Mumbai terrorist attacks as a natural experiment to study how an extreme shock to stress and fear affects individuals' trading activity and performance. The attacks had hundreds of fatalities, involved the use of lethal weapons, caused tremendous panic and fear among general public, and are referred to as "India's 9/11" (Rabasa et al., 2009). The attacks were the longest one ever carried out by a terrorist group (Acharya, Mandal, and Mehta,

[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).

2009) subjecting victims to prolonged stress and fear.[2] In addition, we utilize a 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 trader-day-stock level, as well as 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 changes in trading behavior for treated investors (those located in Mumbai) after the attacks with those of the controls (investors 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 affected investors are economically significant. For example, 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.

To understand mechanisms of the loss in trading activity, we formulate several hypotheses that predict lower 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 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 consequences of stress.[3] On one hand, stress hormones such as cortisol and

[2] 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 2005 Delhi bombings, 2006 Mumbai train bombing, 2008 Assam bombings, and 2010 Jnaneswari Express train derailment.

[3] 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

adrenaline can help prepare human body to fight or flight, enable us to stay more awake and focused, and enhance information retrieval, all of which would predict that individuals 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 individuals' trade performance and find that in addition to trading less, 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 so impaired as to result in worse trading decisions despite trading less than before the attacks.

Second, terrorist attacks can have adverse effects on 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, 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 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 absence of fear and stress, investors located closer to or further away from the 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 to the 9/11 attacks in the U.S., stock

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).

market did not suffer from significant declines after the 2008 Mumbai attacks, in terms of either aggregate stock market returns or 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 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.[4] 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 with 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*).[5] 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 paying attention to and focusing on the stocks, investors that are more exposed to terror and violence still tend to trade less. Second, the attention hypothesis predicts the largest decline during

[4] 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.

[5] 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.

the first few days after the attacks when Mumbai residents are most tuned to 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 post attacks, there was a large spike followed by a sharp reversal of search activity (Figure 1).[6] In stark contrast to this pattern, investor trading activity does not exhibit significant change until the fourth trading day post attacks when we observe a significant decline followed by a reversal several weeks after the attacks (Figure 2). While inconsistent with the attention hypothesis, this finding is consistent with prior science literature, which shows that acute exposures to stress hormones can actually promote learning and memory functions while prolonged exposures can inhibit these functions (McEwen, 1998; Newcomer et al., 1999; Lupien, et al., 2002; Liston, McEwen, and Casey, 2009; Putman et al., 2010; Kandasamy et al., 2014), and damages to human body are reversible after the danger is past (McEwen, 1998).[7]

The last competing hypothesis we examine relates to local bias of trading by Mumbai investors. Firms located in Mumbai may suffer from property damages or business interruptions due to the attacks. If implications of such damages are easier to assess for Mumbai-based investors, then they may trade differently in their local stocks compared with non-Mumbai traders (hereafter *local bias hypothesis*). We find that Mumbai investors do not exhibit a different propensity to trade Mumbai stocks after the attacks. Moreover, the local bias hypothesis would predict better trade performance of Mumbai traders post attacks if they possess better information than their distant

[6] Note that under the *topic* option on Google Trend, Google assigns all web queries related to "2008 Mumbai attacks" to the same topic. This is different from the *search term* option, where Google only calculates search interest related to the exact keywords, a noisier measure of the aggregate investor attention on the terror attacks.

[7] 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.

peers, while our results suggest the opposite. We also compare performance of Mumbai and non-Mumbai stocks, and do not find any significant difference between their performances after the attacks.

Finally, we conduct three additional tests to examine trading behavior of different types of investors. First, we hypothesize that 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 less likely to be influenced by human emotions. We find that institutions located in Mumbai do not exhibit different trading behavior after the attacks compared with the trading activity of distant institutions. Second, individuals with more past trading experience such as active traders may need less of their cognitive ability to manage 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. Third, consistent with the fact that algorithmic trading requires little human intervention, we find that Mumbai individuals that use such trading do not exhibit different trading behavior compared with non-Mumbai algorithmic traders.

Our paper 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 due to change in agents' risk preferences.[8] We use a major terrorist attack as a natural experiment for the impact of fear and stress on millions of investors,

[8] 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. Bernile, Bhagwat, and Rau (2016) find a nonmonotonic relation between firm CEO's disaster experience and subsequent risk-taking behavior. Guiso, Sapienza, and Zingales (2018) find that students treated with horror movies show more risk aversion.

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, and therefore complements prior findings from laboratory and field experiments that typically involve much smaller numbers of test subjects.

Our study is closely related to Grinblatt, Keloharju and Linnainmaa (2011, 2012), who show that IQ (as a static and fixed 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.[9] In addition, we contribute to the literature on emotions and stock market, such as weather (Hirshleifer and Shumway, 2003; Kamstra, Kramer, and Levi, 2000, 2003) and sports (Edmans, Garcia, and Norli, 2007) that affect investor sentiment at the aggregate market level. We examine trading behavior at the individual level, and therefore provide direct evidence of how investor emotions matter for the stock market to complement prior evidence from the earlier studies.[10]

Lastly, we contribute to prior literature on the adverse effects of terrorism on economic activity. Terrorist attacks can have severe consequences for human health and economic outcomes.[11] However, little is known about how such violent and traumatic events affect investors' financial decision making. Our high-frequency trading records allow us to track individual

[9] Several other studies also relate cognitive ability to financial decision making of individuals. Korniotis and Kumar (2011) use age as a measure of cognitive ability to study individual investors' investment decisions. They find that adverse effects of cognitive aging dominate positive effects of age on experience. Agarwal and Mazumder (2013) find that cognitive ability test scores are negatively associated with financial mistakes in credit card usages and home equity loan applications. Gamble et al. (2015) find that cognitive aging is associated with a decrease in financial literacy.

[10] Wang and Young (2018) in a contemporaneous paper study terrorist attacks and household trading, yet they do not examine trade performance or cognitive ability, which is our central hypothesis. In addition, they focus on the changes in trading for all traders (single difference), while we compare changes between treatment and control groups (DID).

[11] Terrorist attacks can lead to post-traumatic stress disorder (PTSD), and adversely affect subjective and physical well-being (Schuster et al., 2001; Galea et al., 2002; Schlenger et al., 2002; Camacho, 2008; Shenhar-Tsarfaty et al., 2015; Ahern, 2018). Terrorist attacks can also have adverse effects on economic outcomes, such as economic growth, international trade, consumption and production, and the gross domestic product (Abadie and Gardeazabal, 2003; Blomberg, Hess, and Orphanides, 2004; Eckstein and Tsiddon, 2004; Blomberg and Hess, 2006).

investors' reaction around a major terrorist attack to better identify and quantify the effects of terror on individuals' real-world financial transactions.

Our results have several important implications. First, 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 asset volatility. Second, the lack of trading and stock market participation, another consequence of cognitive ability impairment, could exacerbate liquidity dry-ups during market downturns. Finally, 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 help for individuals suffering from trauma.

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 after the stock market was closed. Terrorists targeted multiple random areas including the historic Taj hotel, a community center, a restaurant, a hospital, and several railway stations. Although the attacks did not cause significant property damage (except for the Taj hotel), there were hundreds of fatalities and injuries due to lethal weapons, and the attacks lasted several days over which random civilians were held as hostages. Most of the dead hostages showed signs of torture and their 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".[12] The event was covered extensively in the news and social media, and induced a great amount of fear among the public.

Since the stock market was closed on November 27, 2008 due to the attacks, our post-event date starts from November 28, 2008 when the market reopened. We use an event window of 10 trading days (14 calendar days) before and 20 trading days (33 calendar days) after the event to isolate the effect of terrorist attacks on investors' trading behavior. The ending date of our event window is December 29, 2008, right before the New Year's Eve to avoid any confounding effects of the national holiday. We choose a shorter event window for the pre-event period to avoid confounding effects of the global financial crisis and Diwali, a major festival celebrated throughout the country.[13]

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 stock trading takes place, especially during recent years. For each trader-day-stock observation, we have information on ticker symbol of stock traded, number of shares purchased and sold, as well as average price per share paid or received for stock 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 location information for traders, such as their zip

[12] See http://www.rediff.com/news/2008/nov/30mumterror-doctors-shocked-at-hostagess-torture.htm.
[13] The Nifty index on the National Stock Exchange plunged 12.2% on October 24, 2008, the largest percentage decline for the index, after the Reserve Bank of India (central bank of India) refrained from lowering the interest rate. There were rumors in October 2008 that ICICI, India's largest private bank, will go bankrupt due to its holdings of Lehman Brothers. Finally, trading volume on the NSE was 85% lower on October 28, 2008 than the previous day due to Muhurat trading on the Diwali holiday. Our sample period starts from November 12, 2008 to avoid the implications of these events, although we conduct robustness tests in Appendix Table A1 and show that extending the pre-period to 20 trading days has little impact on our main findings.

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 trader-day-stock observations at the trader-day level and calculate four measures of trading activity for each trader during a day: propensity of trading (*propensity*), total volume in thousand Indian Rupees (INR) (*totvol*), number of stocks traded (*nstock*), and total number of shares traded (*totshr*). Specifically, *propensity* is an indicator variable that is equal to one if a trader makes any stock purchase or sale during the day, and zero otherwise. *totvol* is total trading volume per trader per day in thousand INR, including both purchases and sales. *nstock* is number of stocks traded per trader per day. *totshr* is total number of shares traded per trader per day. We consider these four variables as unconditional trading activity measures since they are set to zero if a 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 our analysis otherwise.

Table 1 shows summary statistics of individual trading data for the 30 trading days around the 2008 Mumbai attacks. Panel A shows that an average trader in our sample period has a 24% probability of making a trade in a given day during this period. It is important to note that the *propensity* of trading appears to be large as we do not include those individuals who never trade during the period of terrorist attacks. This is because these observations will be dropped from our regression analysis after inclusion of individual fixed effects. The mean and median daily trading amounts are INR 140,190 (about $2,849) and INR 27,730 (about $563), respectively conditional on an individual making any trade on a day.[14] These amounts are much smaller than statistics reported for individual investors in more developed financial markets 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 trading volume is aggregated at the trader-day level in our study while that in prior studies is at the trade level.

Finally, we also report correlations between the unconditional and conditional trading activity measures in Panels B and C, respectively. All measures are positively correlated with each other as one would expect, since when a trader exhibits less trading activity, all measures should decline, and vice versa. The numbers also show that although the correlations are positive, the measures 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 change in trading activity that is not driven by a change in share price.

2.2.2 Measures of stock characteristics

We obtain daily stock return and firm financials data from Compustat Global, and match these data with 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 stocks with share prices below INR 5 to reduce noise in calculated stock returns. Excluded observations total to 3%

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

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 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 a company's headquarter is located in Mumbai, and zero otherwise (*Mumstock*). We obtain information on a 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 daily fraction of trading in Mumbai stocks as a proportion of a 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 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 their 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 prevalence of PTSD after the 9/11 was substantially higher in the New York City, and was within 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 ("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 with 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 are individual trader fixed effects; and κ_t are day fixed effects. The indicator variable, $Mumbai_i$, is included but absorbed by individual fixed effects; similarly, $post_t$ is absorbed by day fixed effects.

The trader fixed effects ω_i help control for various factors that can affect 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. Day fixed effects κ_t control for any changes 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 estimation results of Equation (1). We find that propensity of trading, trading volume, number of stocks traded, and number of shares traded all decline significantly after the attacks for investors located in Mumbai compared with their more distant peers. For example, the coefficient of –0.015 in Panel A, Column (1) indicates that propensity of trading any stock during a given day (*propensity*) decreases by 1.5% for an average individual trader located in Mumbai after the attacks, which is 6.3% of the sample average of 24% shown in Table 1. Column (2) of Panel A shows total INR volume per trader per day decreases by INR 2,826 (about $57), or 8.0% of the sample mean of *totvol*. Number of stocks traded per day per trader decreased by 8.2% as we observe in Column (3) of Panel A, which is 8.0% of the sample mean of *nstock*. Total number of shares traded per trader per day decreased by 14.4 shares in Column (4) of Panel A, or 9.2% 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, 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 20 trading days subsequent to the attacks is ₹2,826×337,129×20, which is around ₹19.1 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 propensity of trading, a natural question is whether the effects in Panel A only reflect a lower propensity 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 conditional measures of trading activity. As mentioned in the data section, for the conditional trading measures, 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.[15] Finally, in Panels C and D, we include interaction between an indicator variable for the pre-event (*pre*) and *Mumbai* to test the parallel trend assumption of the DID methodology.[16] The interaction term is insignificant, indicating that our results are not driven by pre-event differences in trading behavior between 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 10-day window in the pre-event period to avoid any confounding effects of the U.S. financial crisis and major festival of Diwali on the Indian stock market. Nonetheless, we extend the pre-period from 10 to 20 trading days in Table A1 in the Appendix, and show that our inferences are unchanged when we use this alternative event window. Second, since the post-event period ends on December 29, 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. Consistent with this argument, 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

[15] The difference between the number of observations in Panel B of Table 2 (10,640,279) using the conditional measures of trading and the number reported in summary statistics (11,262,958) 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.
[16] The construction of pre-event dummy *pre* does not include the event day (November 26, 2008) to allow us to estimate the equation with both the *pre*×*Mumbai* and *post*×*Mumbai* interaction variables.

behavior around the placebo dates. Third, investors located in metropolitan areas may react differently to major events like terrorist attacks compared with investors residing in smaller cities. In Appendix Table A3, we only keep traders from nine other metropolitan 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 estimated coefficients. Since the distributions of some trading activity measures are skewed as shown in Table 1, we repeat our analysis using logarithmic transformation of both the unconditional and conditional measures of trading (see Table A4 in the Appendix). The results show that our inferences are not affected by skewness in trading activity.

3.2 Dynamic effects of the change in trading behavior

Next, we examine 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 β_t measures the dynamic treatment effects on Mumbai traders for each event date κ_t. The event day 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 for the trading activity measures *propensity*, *totvol*, *nstock*, and *totshr* in the four subplots, respectively. We observe that 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 the end of December (or about four calendar weeks) after the attacks. It is important to note that 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 science literature. Tests conducted in the laboratory show that immediate elevation of stress level can promote learning and memory functions (Lupien, et al., 2002; Lupien et al., 2007; Putman et al., 2010). In contrast, prolonged exposure to 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 test subjects' stress hormone (specifically cortisol) levels to analyze their financial choices. They find that immediately after an elevation of the hormone, there is no difference between treated and control group during the following day. However, the treated group becomes more likely to overweight small probability events during the seventh day of their 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 treatment effect are also consistent with physiologic systems' reaction to stress over time. The human body first activates its adaptive system after detection of a dangerous situation and releases various stress hormones, 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 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 with 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 exposure to violence 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 traders' ability to perform complex trading tasks. In this section, we examine trade performance of individual investors to find additional support for the cognitive ability channel. If terrorist attacks adversely affect traders' cognitive ability, we should observe worse trade performance for Mumbai-based investors after the attacks compared with investors that are more distant. 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 abnormal returns of buy and sell trades separately, then weight stock-level abnormal returns by the traded amount on the stock to calculate the total abnormal return. Specifically, we first separate buys and sells for each trader in a given day. For each buy trade, we calculate its holding period return from trade execution date to the ending date of our sample (December 30, 2008). We then subtract the corresponding DGTW (Daniel et al., 1997) benchmark return from the holding period return to compute the abnormal return on this buy trade. DGTW benchmark is matched with the traded stock on size, book-to-market, and momentum, and benchmark return is calculated over the same period as that of the holding-period return. The total number of stocks traded on the NSE in our sample is around 900, which is substantially smaller than those on the U.S. exchanges. Therefore, instead of forming 5×5×5=125 benchmark portfolios, we form 3×3×3=27 portfolios based on size, book-to-market, and momentum. The two size breakpoints are based on market values of Nifty 200 and Nifty 500 stocks as of the first trading day before our sample period, 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 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.[17]

Next, for each trader, abnormal returns for all buy trades are weighted by the amount of buying for each trade to compute total abnormal returns for all buys. We repeat the same procedure to compute total abnormal returns for all sells. Finally, the total abnormal returns for all buys and total abnormal returns for all sells are weighted by aggregate amounts of buys and sells, respectively, to compute the overall abnormal performance for the trader.

Note that although we evaluate each trade from its execution date to the ending date of our sample period, this approach also accounts for roundtrip trades since we use the same ending date to compute 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 stock price on the

[17] In untabulated results, we find that using alternative methods to construct the breakpoints has minimal impact on our results of investor performance, such as taking market values of Nifty 200 and 500 stocks 6 months before our sample period, constructing the momentum breakpoints based on prior 6 months' (instead of prior one year's) stock returns, and equal-weighting (instead of value-weighting) the benchmark portfolio returns.

last date is ₹330 per share. 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)).[18]

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 trade performance is measured after the event date, and zero otherwise.

We report estimation results of Equation (3) in Panel A of Table 3. The negative and significant coefficient on *post*×*Mumbai* in Column (1) suggests that performance of Mumbai-based investors is worse after the attacks compared with the control group (more distant investors). The average performance decline for each Mumbai-based trader is 0.539% (or 8.9% of the standard deviation of individual traders' performance during this period), which is economically significant considering that trade performance is measured over only several weeks after the attacks. This result also rules out the possibility that Mumbai investors are more financially sophisticated or have better access to financial news, which would predict that their performance should be better, and not worse, than investors that are more distant.

Column (2) of Panel A, Table 3 shows dynamic effects of change in Mumbai investors' performance by splitting the post-event period into three periods, denoted by three indicator

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

variables *post1* (first 7 trading days post attacks), *post2* (next 7 trading days post attacks), and *post3* (last 6 trading days post attacks). We observe that the coefficient on *post1*×*Mumbai* is insignificant, while those on *post2*×*Mumbai* and *post3*×*Mumbai* are significantly negative. These results are consistent with our prior finding in Figure 2 regarding the dynamic change in trading activities.[19] Newcomer et al. (1999) give oral doses of cortisol to a group of treated subjects for four days, and find significant impairment of cognitive ability measured by memory performance on the fourth and tenth days after the first day of experiment. However, they do not observe any difference one day after the experience begins. Interestingly, they also do not find any difference in subjects' ability to pay sustained attention. Newcomer et al. (1994) find similar deferred effect of glucocorticoid on memory performance. Our results support findings in these scientific studies that acute and chronic exposures to stress have different implications for human behavior.

Next, we examine investors' trading in "new" stocks that they are less familiar with and thus may require more cognitive skills for information processing. For any individual trading in a stock on a given day, we check whether this individual has traded the same stock during the last 6 months. We define "new stocks" as those without prior trading records, and "old stocks" as those with prior trading records. We then compute the total number of new stocks traded per trader per day (*newstock*). Column (1) of Panel B, of Table 3 shows a negative and significant coefficient on *post*×*Mumbai* using *newstock* as dependent variable, suggesting that due to deterioration in cognitive ability, Mumbai investors are less likely to acquire new information and trade in new stocks. In Column (2) of Panel B, we use the proportion of new stocks traded relative to all stocks (so the proportions of trading in old and new stocks add up to one) as the dependent variable. We again find a negative and significant coefficient on *post*×*Mumbai*, i.e., when agents face loss in

[19] We use weekly indicator variables for the post period in Column (2) instead of daily treatment effects in Figure 2 to reduce noise in performance estimation.

cognitive ability, they gravitate towards performing the tasks that they are familiar with rather than undertaking new ones.

A natural question is whether our performance results in Panel A of Table 3 are driven by trading in new stocks. In Panel C of Table 3, we separate all trades for all traders into trading in new stocks (Column (1)) and old stocks (Column (2)). We observe a decline in performance for Mumbai traders in both new and old stocks, indicating that deterioration in cognitive ability also impairs Mumbai traders' performance on stocks that they are familiar with. The magnitude of the treatment effects are economically close, a fact that is perhaps not surprising because although new stocks may require greater cognitive ability to analyze, traders already choose to trade less on them as shown in Column (2) of Panel B.

Finally, it is possible that Mumbai investors trade more on stocks that have more information asymmetry, and require more cognitive ability to process. In Appendix Table A5, 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.

4.1.2 Asset fundamentals

Terrorist attacks can have adverse implications on economic activities or operations of local firms, which raises a question that whether our results are due to shocks to investor psychology or due 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 daily market returns around the Mumbai attacks by value-weighting returns of all stocks in our sample. In stark contrast to the 9/11 attacks, market returns were generally positive after the 2008 Mumbai attacks. This suggests that the 2008 Mumbai attacks did not cause large scale economywide damages that are comparable to the 9/11. In addition, in all of our analyses we control for day fixed effects that should absorb any change in aggregate market conditions such as market return, risk, liquidity, and interest rates.

Moreover, investors from every city and state have discretion to purchase and sell stocks. Therefore, emotionless "rational" agents should trade in a similar fashion based on shocks to stock fundamental values, instead of trading differently based on their distance from the attack site as we show previously (unless their assessments on 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 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.

Prima facie, it may appear that our finding of less trading activity after the attacks is consistent with agents becoming more risk averse, yet it is not possible to ascertain if this is indeed the case without separating the trading activity into purchases and sales. Risk preference hypothesis would predict more sales and less buys after the attacks for increase in risk aversion after the attacks. To test this alternative hypothesis, in Table 4 we reconstruct our trading activity measures based on stock buys and stock sales, respectively (for example, *propbuy* 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 after exposure to stress and violence.[20]

Finally, we find in Section 4.1.1 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 a given stock with a portfolio of stocks with similar characteristics (Daniel et al., 1997).

4.1.4 Investor attention

[20] We 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. However, 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 volume in this market reached $250 million in 2010, which is only 0.015% of the total equity trading volume on the NSE in 2010.

Our prior results on trading activity and performance seem also consistent with an attention effect, i.e., Mumbai investors may pay more attention to the terror attacks compared with other investors that are distant, and therefore allocate less attention to their stock investments. That is, investors may not suffer from any fear and stress, but still could trade less and perform worse due to lack of attention. However, we find several pieces of evidence that suggest the change in investor trading behavior does not seem to be driven by the attention effect. First, our results on the conditional measures of trading activity and trade performance show that conditional on investors already allocating attention to their stocks, they still trade less and perform worse. Second, the attention hypothesis would predict the greatest decline in trading activity during the first few days after the attacks, when investors are most influenced by news coverage on the attacks. However, our results on the dynamics 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 prior scientific evidence on the deferred effect of chronic stress (Kandasamy et al., 2014).

To further compare the time-series changes in treatment effect with 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 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 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 in attention followed by a sharp reversal of search activity. Search activity declines significantly by the fourth trading day on December 03, 2008, and eventually diminishes over the next few calendar days. In stark contrast to this finding, the treatment effects in Figure 2 do not change significantly during the first three trading days. Moreover, the treatment effects start to decline only 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 nationwide search interest from India diminishes after the first week post the attacks, Mumbai residents continue to pay close attention to the events. The dashed line in Figure 1 plots search activities from the state of Maharashtra of which Mumbai is the capital city. We observe that investor attention from this state is virtually the same as those at the nationwide level, suggesting that our results in Figure 2 are not driven by continuing attention on the attacks by Mumbai residents (according to Google Trend, 100% of search interest from Maharashtra is from Mumbai). The virtually identical search patterns from Maharashtra and India also show that variations in investor attention are likely to be similar for our treated and control groups. Since we use difference-in-differences approach in our empirical analysis, this evidence further suggests that our results on investor trading and performance are unlikely to be purely driven by the attention effect that is independent of fear and stress.

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.[21] 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

[21] 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.

attention to the stocks, despite any commuting issues. Lastly, one would expect that institutions should be more affected by commuting issues since their 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 their local stocks than other market participants. For example, Coval and Moskowitz (1999) show that U.S. mutual funds tend to prefer locally headquartered firms. Local bias hypothesis suggests that in our setting, Mumbai investors may trade differently (i.e., strategically) if they have better information on their local stocks. For example, Mumbai investors may profit from potential overreaction of other investors in Mumbai stocks due to the attacks. In this case, Mumbai 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 additional tests. First, we examine performance of Mumbai and non-Mumbai stocks in Panel A of Table 5. We regress the daily stock return (*return*) on the post event indicator variable (*post*), an indicator variable 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 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 5, we examine whether Mumbai-based traders exhibit a different propensity to trade Mumbai stocks post attacks. The dependent variable is *tradeMum*, 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 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, mortality risk or change in life expectancy would again predict asymmetric trading behavior for buys and sells. If agents prefer more current consumption after the attacks, they should sell more and buy less on the stock market, which is not supported by the results in Table 4.

Second, our results on buys and sells also rule out the possibility that investors are 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 tourism activities. However, anecdotal evidence suggests that except for damages to the Taj hotel, property losses in the Mumbai 2008 attacks were not severe and nowhere comparable to the 9/11 attacks in the U.S. In addition, if there were significant losses from property values, rental fees, or business income from tourism activities within the city of Mumbai, we should also expect business revenues of the Mumbai-based public companies to be more adversely affected. We do not find any difference in stock performance for Mumbai or non-Mumbai firms post the attacks in Table 5, either economically or statistically, consistent with businesses operating in Mumbai not suffering from material losses. Finally, 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 4 suggest otherwise.

4.2 Types of investors

In this section, we study trading behavior of different types of traders, such as institutional investors, experienced traders, and algorithmic traders.

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; Campbell, Ramadorai, and Ranish, 2014). Interestingly, Lo and Repin (2002) document less physiological reactions under stress from experienced traders compared with less experienced traders. Traders working inside financial institutions are usually perceived to have the ability to manage stressful situations, therefore they could be less subject to or could better handle 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 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 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 6. We first report summary statistics of the trading activity measures for institutional investors around the 2008 Mumbai attacks in Panel A of Table 6, where the measures are constructed similarly as those for individual investors. Not surprisingly, trading volume by institutions is much greater than that for individual investors. For example, the unconditional INR trading volume per individual trader per day (*totvol*) is INR 35,110 (around $714), while for institutions it is INR 984,000 per institution per day (about $20,000).

Columns (1) through (7) in Panels B of Table 6 report the results on changes in institutional trading activity after the 2008 Mumbai attacks. We do not observe any significant change in trading behavior for institutions located in Mumbai compared with distant institutions after the attacks.[22] In Column (8), we also find that post-event performance of Mumbai institutions are indifferent from that of the non-Mumbai institutions.

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 trading experience for individual traders (*exp*), which are equal to one if a) individual trader's total trading volume during the past year is ranked in the top quartile among all individual traders; b) individual trader's number of shares traded during the past year is ranked in the top quartile among all individual traders; c) length of time between the individual trader's account registration date on the NSE and the event date is ranked in the top quartile among all individual traders; and d) length of time between individual trader's first trading date on the NSE and 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 results on individual trading experience in Table 7. Panels A through D use the four aforementioned trading experience measures for *exp*, respectively. Interestingly, we only find

[22] We note that although the estimated coefficients on *Mumbai*×*post* in Panels B and C of Table 6 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 6.

evidence that experience helps alleviate decline in the propensity of trading (*propensity*) for Mumbai investors post the 2008 attacks, as indicated by the positive and significant coefficients on *exp*×*Mumbai*×*post* in the first column in all four panels. However, experience does not help alleviate decline in the other measures of trading activity. These results suggest that our finding on institutional investors is either because institutional investors have even more trading experience than the top-ranked individual investors, or because of 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; or traders who choose to work at institutions are better equipped or trained to handle stress).

In addition to past experience of trading on the stock market, past traumatic experience may help individuals better cope with 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 7 by interacting this indicator variable with *Mumbai*×*post*. Untabulated results are very similar to those in Table 7, 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).

4.2.3 Algorithmic traders

The last type of traders we examine is algorithmic traders. Algorithmic trading requires little human intervention and is unlikely to be affected by human emotions. We obtain a sample that contains all individual investors that use algorithmic trading during our sample period. We then compare the trading activity of Mumbai algorithmic traders with non-Mumbai algorithmic traders in Table 8. Consistent with our conjecture, none of the coefficients on $Mumbai \times post$ is significant at conventional levels. This evidence lends further support to the cognitive ability hypothesis since trading algorithms are based on technical trading rules and do not "suffer" from stress and fear. Note that the majority of individual investors cannot curtail the effects of fear and stress using algorithmic trading since retail algorithmic trading activities were rare during our sample period back in 2008 — possibly due to difficulty in setting up trading algorithms and high cost of accessing algorithmic trading platforms for individual investors.

5. Discussions and implications

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 financial crisis. Traditional models on financial crisis focus on factors such as 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 market turmoil and liquidity dry-ups, it is challenging to empirically test effects of such factors as there are many other confounding effects during periods of crisis. 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, compared with earlier studies that use exposure to macroeconomic events as measures of fear and depression which affect all investors at the same time. 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 asset volatility in the marketplace. In addition, the lack of trading and stock market participation, another consequence of cognitive ability impairment, could exacerbate 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 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 and algorithmic trading activities are not affected. Our study contributes to the literature on economic decision making under fear and stress, the most basic emotional states in our daily lives (Cowen and Keltner, 2017).

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Table 1: Summary statistics

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

Panel A: Trading activity

Variable	Observations	Mean	STD	25%	Median	75%
propensity	46,928,800	0.24	0.43	0.00	0.00	0.00
totvol	46,928,800	35.11	198.57	0.00	0.00	0.00
nstock	46,928,800	1.02	2.83	0.00	0.00	0.00
totshr	46,928,800	155.74	619.37	0.00	0.00	0.00
CONDvol	11,262,958	140.19	362.48	8.25	27.73	102.40
CONDnum	11,262,958	4.13	4.29	1.00	2.00	5.00
CONDshr	11,262,958	876.88	1,921.96	54.00	200.00	760.00

Panel B: Correlations between unconditional trading measures

	propensity	*totvol*	*nstock*	*totshr*
propensity	1.00			
totvol	0.33	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	0.41	1.00	
CONDshr	0.65	0.39	1.00

Table 2: Terrorist attacks and individual investors' trading behavior

This table reports 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 a trader is located in Mumbai, and zero otherwise. Dependent variables are defined previously in Table 1. Panels A and B report results for the unconditional and conditional measures of trading activity, respectively. The regressions control for individual and day fixed effects. Standard errors are reported in parentheses and are double-clustered at the individual-day level.

Panel A: Unconditional measures of trading activity

	(1) *propensity*	(2) *totvol*	(3) *nstock*	(4) *totshr*
Mumbai×post	–0.015***	–2.826***	–0.082***	–14.376***
	(0.003)	(0.592)	(0.017)	(2.733)
Individual FE	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes
Observations	46,928,800	46,928,800	46,928,800	46,928,800
Adj. R^2	0.352	0.450	0.528	0.388

Panel B: Conditional measures of trading activity

	(1) *CONDvol*	(2) *CONDnum*	(3) *CONDshr*
Mumbai×post	–5.594***	–0.102***	–28.958***
	(1.468)	(0.023)	(7.312)
Individual FE	Yes	Yes	Yes
Day FE	Yes	Yes	Yes
Observations	10,640,279	10,640,279	10,640,279
Adj. R^2	0.537	0.517	0.491

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

	(1) *propensity*	(2) *totvol*	(3) *nstock*	(4) *totshr*
Mumbai×pre	–0.001	–0.235	–0.013	–3.180
	(0.005)	(0.419)	(0.012)	(2.917)
Mumbai×post	–0.016***	–3.037***	–0.093***	–17.238***
	(0.002)	(0.405)	(0.013)	(2.087)
Individual FE	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes
Observations	46,928,800	46,928,800	46,928,800	46,928,800
Adj. R^2	0.352	0.450	0.528	0.388

Panel D: Conditional measures of trading activity (parallel trend)

	(1) *CONDvol*	(2) *CONDnum*	(3) *CONDshr*
Mumbai×pre	–0.231	0.022	–8.031
	(1.925)	(0.024)	(5.318)
Mumbai×post	–5.829***	–0.087***	–35.241***
	(1.943)	(0.024)	(5.464)
Individual FE	Yes	Yes	Yes
Day FE	Yes	Yes	Yes
Observations	10,640,279	10,640,279	10,640,279
Adj. R^2	0.536	0.517	0.491

Table 3: Trade performance

Panel A reports results on individual investors' trade performance around the 2008 Mumbai attacks. We first separate 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 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 abnormal return for a trade. 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 values as of March 31, 2007, 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 amount traded to calculate total buy performance. The same process is repeated to compute total sell performance. Total buy performance and total sell performance are then weighted by aggregate buying and aggregate selling amounts to compute total performance in percentage (*Performance*). In Column (1), *Performance* is computed separately for the pre-event and post-event periods for each trader, using all trades placed during these two periods by the trader, respectively. In Column (2), *Performance* is computed separately for the pre-event and 3 subperiods in the post-event periods for each trader. Indicator variables *post1*, *post2*, and *post3* denote the first 7 trading days, next 7 trading days, and last 6 trading days post attacks, respectively. Panel B reports results on individual investors' trading in new stocks. For any individual trading in a stock on a given day, trading on new stock is defined as those without a prior trading for this individual on the same stock during the last 6 months. In Column (1), the dependent variable is the total number of new stocks traded per trader per day (*newstock*). In Column (2), the dependent variable is the proportion of new stocks traded relative to all stocks (*prop_new*). Panel C shows individual investors' trade performance by separating all trades for all traders into trading in new stocks (Column (1)) and old stocks (Column (2)). The regressions control for individual and time fixed effects. Standard errors are reported in parentheses and are double-clustered at the trader-time level.

Panel A: Trade performance

	(1) *Performance*	(2) *Performance*
Mumbai×post	–0.539***	
	(0.100)	
Mumbai×post1		0.148
		(0.091)
Mumbai×post2		–0.943***
		(0.084)
Mumbai×post3		–0.832***
		(0.079)
Time FE	Yes	Yes
Individual FE	Yes	Yes
Observations	1,232,564	1,232,564
Adj. R^2	0.246	0.465

Panel B: Trading new stocks

	(1) *newstock*	(2) *prop_new*
Mumbai×post	–0.018***	–0.677***
	(0.004)	(0.145)
Time FE	Yes	Yes
Individual FE	Yes	Yes
Observations	10,640,279	10,640,279
Adj. R^2	0.196	0.249

Panel C: Trade performance on new and old stocks

	(1) *Performance*	(2) *Performance*
Mumbai×post	–0.537***	–0.590***
	(0.196)	(0.116)
Time FE	Yes	Yes
Individual FE	Yes	Yes
Observations	541,024	1,058,912
Adj. R^2	0.180	0.280

Table 4: Purchases and sales

This table reports change in individual investors' purchase and sale activities around the 2008 Mumbai attacks by estimating the difference-in-differences specifications in Equation (1). 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 results for the unconditional and conditional measures of purchase activity, respectively. Panels C and D report results for the unconditional and conditional measures of sale activity, respectively. The regressions control for individual and day fixed effects. Standard errors are reported in parentheses and are double-clustered at the individual-day level.

Panel A: Unconditional measures of purchase activity

	(1) *propbuy*	(2) *totvol*	(3) *nstock*	(4) *totshr*
Mumbai×post	–0.010***	–1.423***	–0.033***	–5.780***
	(0.003)	(0.331)	(0.011)	(1.592)
Individual FE	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes
Observations	46,928,800	46,928,800	46,928,800	46,928,800
Adj. R^2	0.357	0.438	0.484	0.350

Panel B: Conditional measures of purchase activity

	(1) *CONDvol*	(2) *CONDnum*	(3) *CONDshr*
Mumbai×post	–3.657***	–0.060***	–12.785***
	(0.827)	(0.020)	(4.753)
Individual FE	Yes	Yes	Yes
Day FE	Yes	Yes	Yes
Observations	10,640,279	10,640,279	10,640,279
Adj. R^2	0.519	0.452	0.451

Panel C: Unconditional measures of sale activity

	(1) *propsell*	(2) *totvol*	(3) *nstock*	(4) *totshr*
Mumbai×post	–0.014***	–1.402***	–0.049***	–8.600***
	(0.002)	(0.290)	(0.009)	(1.424)
Individual FE	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes
Observations	46,928,800	46,928,800	46,928,800	46,928,800
Adj. R^2	0.388	0.439	0.500	0.359

Panel D: Conditional measures of sale activity

	(1) *CONDvol*	(2) *CONDnum*	(3) *CONDshr*
Mumbai×post	–1.937***	–0.042***	–16.173***
	(0.759)	(0.012)	(3.906)
Individual FE	Yes	Yes	Yes
Day FE	Yes	Yes	Yes
Observations	10,640,279	10,640,279	10,640,279
Adj. R^2	0.526	0.486	0.460

Table 5: Local stocks

Panel A reports results on stock performance around the 2008 Mumbai attacks using stock-day level observations. Dependent variable *return* is daily stock return in percentage. *Mumstock* is an indicator variable that is equal to one if a company's headquarter is located in Mumbai as reported in COMPUSTAT Global, and zero otherwise. The regressions control for stock and day fixed effects, and standard errors are double clustered at the stock-day level. Panel B reports 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 trading amounts on each stock weighted by the *Mumstock* measure for the corresponding stock. The regressions control for individual and day fixed effects. Standard errors are reported in parentheses and are double-clustered at the individual-day level.

Panel A: Stock performance

	(1) *return*	(2) *return*
post×*Mumstock*	0.016	0.077
	(0.123)	(0.115)
Stock FE	Yes	No
Day FE	Yes	Yes
Observations	30,745	30,745
Adj. R^2	0.213	0.189

Panel B: Propensity to trade Mumbai stocks

	tradeMum
Mumbai×*post*	–0.001
	(0.001)
Individual FE	Yes
Day FE	Yes
Observations	9,288,768
Adj. R^2	0.368

Table 6: Institutional investors

Panel A reports summary statistics of trading activity measures for institutional investors around the 2008 Mumbai attacks. Panels B reports change in institutional investors' trading behavior and performance around the 2008 Mumbai attacks. All the variables are defined earlier. The regressions control for institution and day fixed effects. Standard errors are reported in parentheses and are double-clustered at the institution-day level.

Panel A: Summary statistics of trading activity

Variable	Observations	Mean	STD	25%	Median	75%
propensity	1,356,576	0.22	0.41	0	0	0
totvol	1,356,576	984	12,124	0	0	0
nstock	1,356,576	1.29	6.69	0	0	0
totshr	1,356,576	4,258	44,586	0	0	0
CONDvol	271,396	4,582	25,827	17	68	375
CONDnum	271,396	6.01	13.49	1	2	5
CONDshr	271,396	19,566	92,717	105	520	3,000

Panel B: Trading activity and performance

	(1) *propensity*	(2) *totvol*	(3) *nstock*	(4) *totshr*	(5) *CONDvol*	(6) *CONDnum*	(7) *CONDshr*	(8) *Performance*
Mumbai×post	0.010	–74.025	0.031	–34.276	–113.971	0.062	209.819	–0.397
	(0.006)	(92.248)	(0.039)	(311.468)	(495.522)	(0.194)	(1613.99)	(0.560)
Institution FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,356,576	1,356,576	1,356,576	1,356,576	271,396	271,396	271,396	45,257
Adj. R^2	0.349	0.719	0.839	0.723	0.763	0.856	0.764	0.201

Table 7: Investor experience

This table reports 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 a trader's aggregate trading volume in the past year is in the top 25% in Panel A, if a trader's aggregate number of shares traded in the past year is in the top 25% in Panel B, if length of time between a trader's account registration date on NSE and the event date is in the top 25% in Panel C, and if length of time between a trader's first trading date and 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 individual and day fixed effects. Standard errors are reported in parentheses and are double-clustered at the individual-day level.

Panel A: Experience based on past volume

	(1) *propensity*	(2) *totvol*	(3) *nstock*	(4) *totshr*	(5) *CONDvol*	(6) *CONDnum*	(7) *CONDshr*
exp×Mumbai×post	0.010***	–1.300	–1.057	–0.017	–3.067	5.917	0.032
	(0.003)	(2.766)	(7.046)	(0.283)	(4.868)	(20.403)	(0.043)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	46,928,800	46,928,800	46,928,800	46,928,800	10,640,279	10,640,279	10,640,279
Adj. R^2	0.352	0.450	0.388	0.528	0.537	0.491	0.517

Panel B: Experience based on past shares

	(1) *propensity*	(2) *totvol*	(3) *nstock*	(4) *totshr*	(5) *CONDvol*	(6) *CONDnum*	(7) *CONDshr*
exp×Mumbai×post	0.013***	–0.993	–1.560	–0.012	–3.816	–0.288	0.020
	(0.004)	(2.546)	(7.800)	(0.031)	(4.543)	(28.114)	(0.042)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	46,928,800	46,928,800	46,928,800	46,928,800	10,640,279	10,640,279	10,640,279
Adj. R^2	0.352	0.450	0.388	0.528	0.537	0.491	0.517

Panel C: Experience based on the account registration date

	(1) *propensity*	(2) *totvol*	(3) *nstock*	(4) *totshr*	(5) *CONDvol*	(6) *CONDnum*	(7) *CONDshr*
$exp \times Mumbai \times post$	0.004***	–0.411	0.675	0.013	–2.256	7.444	0.018
	(0.001)	(0.663)	(1.985)	(0.008)	(2.623)	(14.596)	(0.029)
Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	46,928,800	46,928,800	46,928,800	46,928,800	10,640,279	10,640,279	10,640,279
Adj. R^2	0.352	0.450	0.388	0.528	0.537	0.491	0.517

Panel D: Experience based on the first trading date

	(1) *propensity*	(2) *totvol*	(3) *nstock*	(4) *totshr*	(5) *CONDvol*	(6) *CONDnum*	(7) *CONDshr*
$exp \times Mumbai \times post$	0.005**	–0.058	1.321	0.007	–2.894	5.698	–0.011
	(0.002)	(0.725)	(2.064)	(0.008)	(2.704)	(14.610)	(0.031)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	46,928,800	46,928,800	46,928,800	46,928,800	10,640,279	10,640,279	10,640,279
Adj. R^2	0.352	0.450	0.388	0.528	0.537	0.491	0.517

Table 8: Algorithmic traders

Panels A and B report change in individual algorithmic traders' trading behavior around the 2008 Mumbai attacks. All the variables are defined earlier in Table 1. The regressions control for individual and day fixed effects. Standard errors are reported in parentheses and are double-clustered at the individual-day level.

Panel A: Unconditional measures of trading activity

	(1) *propensity*	(2) *totvol*	(3) *nstock*	(4) *totshr*
Mumbai×post	–0.014	–0.065	–0.031	–3.216
	(0.009)	(1.564)	(0.037)	(6.993)
Individual FE	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes
Observations	447,136	447,136	447,136	447,136
Adj. R^2	0.278	0.352	0.401	0.325

Panel B: Conditional measures of trading activity

	(1) *CONDvol*	(2) *CONDnum*	(3) *CONDshr*
Mumbai×post	1.002	–0.155	–24.184
	(5.299)	(0.125)	(26.734)
Individual FE	Yes	Yes	Yes
Day FE	Yes	Yes	Yes
Observations	77,295	77,295	77,295
Adj. R^2	0.484	0.450	0.442

Figure 1: Google Trend search activities on the 2008 Mumbai attacks

This figure shows Google Trend search activities on topic "2008 Mumbai attacks" from November 26, 2008 to December 30, 2008. The x-axis denotes calendar dates and the y-axis denote search activities over time. Search activities 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 search activities from India, and the dashed line denotes search activities from the state of Maharashtra of which Mumbai is the capital. The symbols "□", "o", and "+" denote search activities on the first, second, and third trading day after the attacks, respectively.

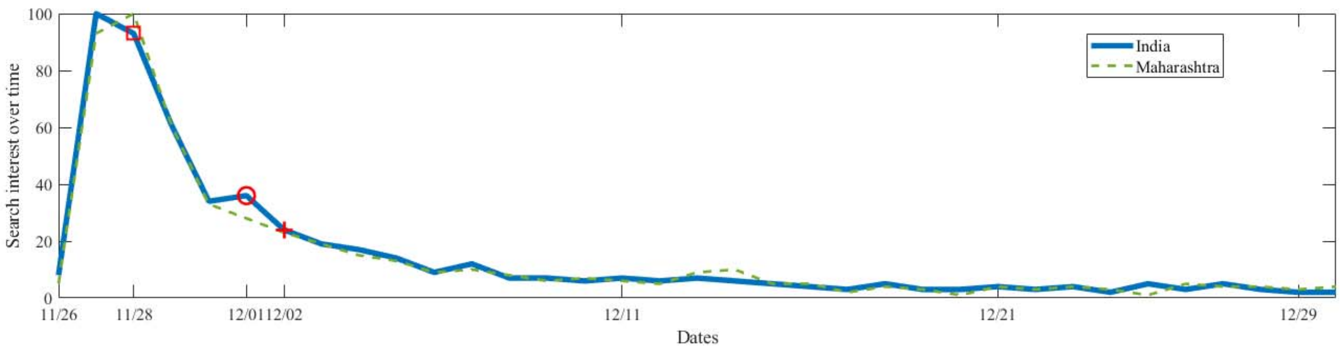


Figure 2: Dynamic treatment effects around the event date

This figure plots dynamic treatment effects (change in Mumbai traders' trading activity relative to other traders) around the event date November 26, 2008. Treatment effects are measured as in Equation (2). The x-axis denotes calendar dates and the y-axis denotes estimated treatment effects. Plotted variables are defined earlier in Table 1. Symbols "□", "o", and "+" denote treatment effects on the first, second, and third trading days after the event date of attacks, respectively.

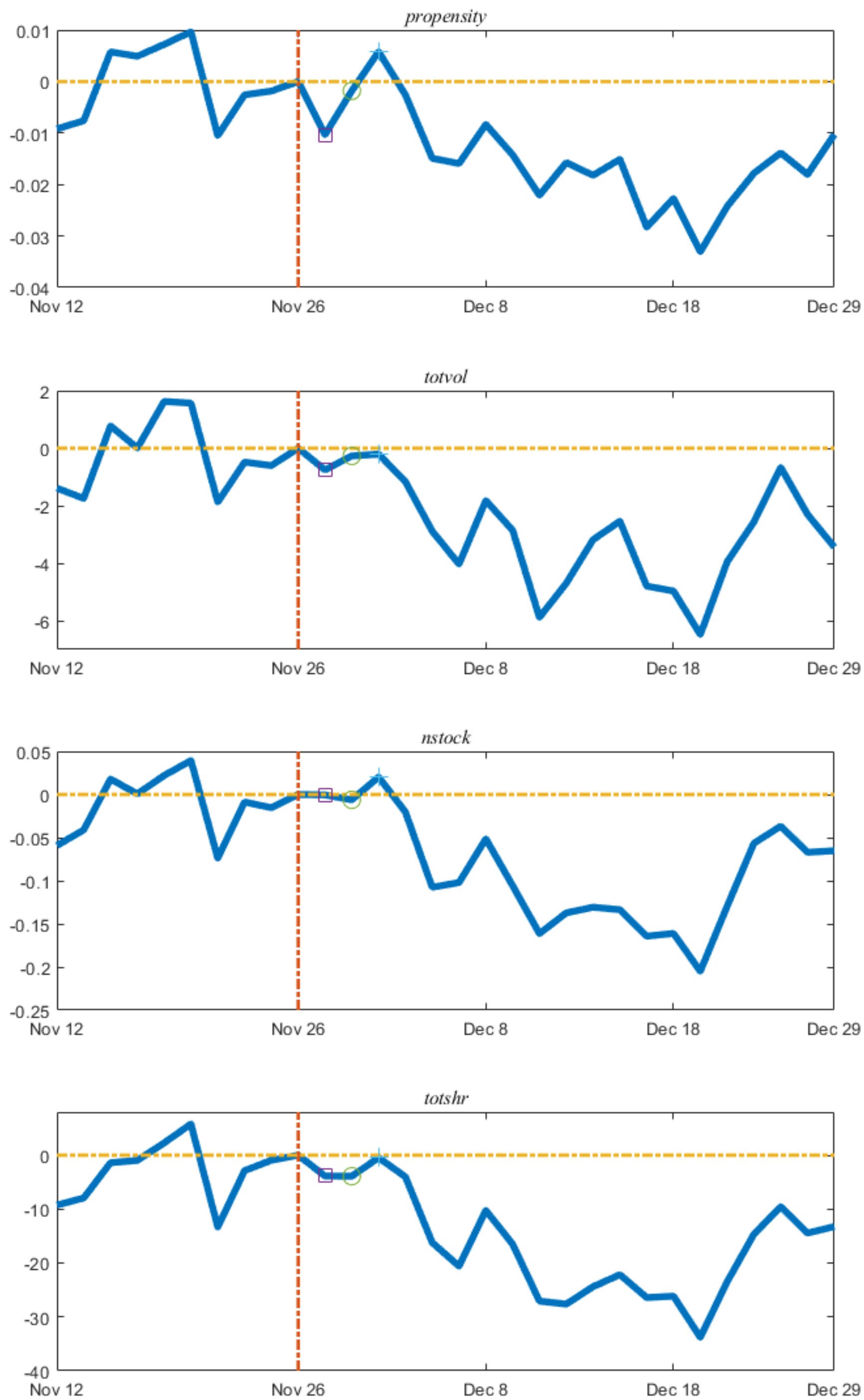
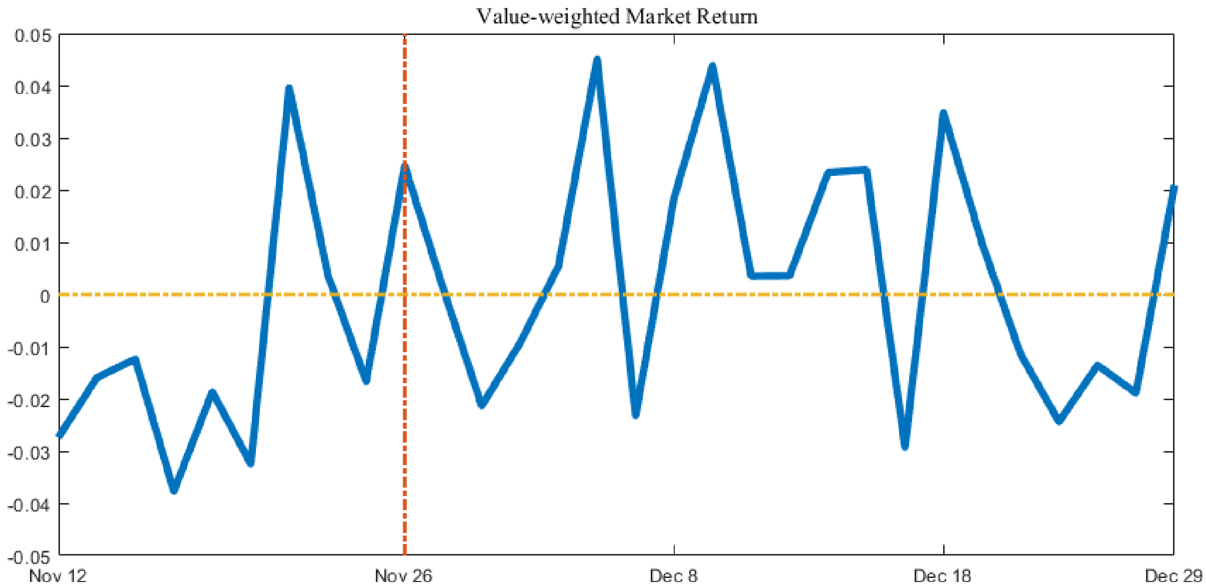


Figure 3: Stock market returns around the 2008 Mumbai attacks

This figure plots daily stock market returns around the event date (November 26, 2008) using value-weighted returns of all stocks in our sample. The x-axis denotes calendar dates and the y-axis denotes market returns in decimals.



Appendix

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

This table reports 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 20 trading days before and 20 trading days after the event date of November 26, 2008. Panels A and B report results under unconditional and conditional measures of trading activity, respectively. The regressions control for individual and day fixed effects. Standard errors are reported in parentheses and are double-clustered at the individual-day level.

Panel A: Unconditional measures of trading activity

	(1) *propensity*	(2) *totvol*	(3) *nstock*	(4) *totshr*
Mumbai×post	–0.011***	–2.550***	–0.052***	–10.912***
	(0.003)	(0.526)	(0.017)	(2.728)
Individual FE	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes
Observations	85,719,606	85,719,606	85,719,606	85,719,606
Adj. R^2	0.358	0.413	0.502	0.362

Panel B: Conditional measures of trading activity

	(1) *CONDvol*	(2) *CONDnum*	(3) *CONDshr*
Mumbai×post	–6.481***	–0.075***	–27.106***
	(1.216)	(0.025)	(6.188)
Individual FE	Yes	Yes	Yes
Day FE	Yes	Yes	Yes
Observations	15,757,687	15,757,687	15,757,687
Adj. R^2	0.511	0.495	0.468

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

This table reports changes in individual traders' trading behavior around 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 individual and day fixed effects. Standard errors are reported in parentheses and are double-clustered at the individual-day level.

Panel A: Trading activities around November 26, 2007

	(1) *propensity*	(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
	(0.005)	(0.628)	(0.024)	(4.220)	(1.641)	(0.035)	(9.322)
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) *propensity*	(2) *totvol*	(3) *nstock*	(4) *totshr*	(5) *CONDvol*	(6) *CONDnum*	(7) *CONDshr*
Mumbai×post	0.001	1.618**	0.006	2.481	1.345	0.017	8.874
	(0.002)	(0.719)	(0.010)	(1.969)	(0.941)	(0.018)	(6.826)
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	74,185,382	74,185,382	74,185,382	74,185,382	15,784,065	15,784,065	15,784,065
Adj. R^2	0.340	0.475	0.545	0.398	0.518	0.526	0.500

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

This table reports changes in individual traders' trading behavior. Treatment group includes traders located in Mumbai, and control group includes traders located in New Delhi, Bangalore, Hyderabad, Ahmedabad, Chennai, Kolkata, Surat, Pune, and Jaipur. The regressions control for individual and day fixed effects. Standard errors are reported in parentheses and are double-clustered at the individual-day level.

	(1) *propensity*	(2) *totvol*	(3) *nstock*	(4) *totshr*	(5) *CONDvol*	(6) *CONDnum*	(7) *CONDshr*
Mumbai×post	–0.012***	–2.384***	–0.066***	–9.956***	–6.113***	–0.092***	–14.515***
	(0.002)	(0.596)	(0.015)	(2.337)	(2.231)	(0.024)	(7.639)
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	13,774,816	13,774,816	13,774,816	13,774,816	2,931,115	2,931,115	2,931,115
Adj. R^2	0.346	0.452	0.537	0.383	0.558	0.535	0.491

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

This table reports changes in individual traders' trading behavior. The dependent variables are logarithm of one plus *totvol*, *nstock*, *totshr*, *CONDvol*, *CONDnum*, and *CONDshr* in columns (1)-(6), respectively. The regressions control for individual and day fixed effects. Standard errors are reported in parentheses and are double-clustered at the individual-day level.

	(1) log(*totvol*)	(2) log(*nstock*)	(3) log(*totshr*)	(4) log(*CONDvol*)	(5) log(*CONDnum*)	(6) log(*CONDshr*)
Mumbai×*post*	–0.060***	–0.024***	–0.088***	–0.038***	–0.016***	–0.027***
	(0.011)	(0.005)	(0.016)	(0.009)	(0.003)	(0.007)
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	46,928,800	46,928,800	46,928,800	10,640,279	10,640,279	10,640,279
Adj. R^2	0.481	0.497	0.411	0.679	0. 517	0.607

Table A5: Trading stocks with more information asymmetry

This table reports the average Amihud measure of stocks traded for a given individual during a day. The dependent variable *Amihud* is a weighted average of the Amihud (2002) measures across all stocks traded by a trader during a day, weighted by the INR amount of each stock trade (scaled after multiplying by 10^8 for expositional convenience) as a measure of stock's information asymmetry. The regressions control for individual and day fixed effects. Standard errors are reported in parentheses and are double-clustered at the individual -day level.

	(2) *Amihud*
Mumbai×post	0.002
	(0.359)
Time FE	Yes
Individual FE	Yes
Observations	9,129,580
Adj. R^2	0.315