Extreme stress and investor behavior: Evidence from a natural experiment

Vikas Agarwal, Georgia State University

Pulak Ghosh, Indian Institute of Management Bangalore

Haibei Zhao, Lehigh University*

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Abstract

We use the 2008 Mumbai terrorist attacks as a natural experiment to examine how exposure to extreme stress affects financial decision making, as measured by investors' stock trading activity and performance. We find that Mumbai investors trade less, perform worse, take longer time to react to corporate news announcement, are less likely to initiate trades on new stocks, and perform worse on familiar stocks compared with other traders. Collectively, our findings are most consistent with impairment of cognitive ability after exposure to prolonged and extreme stress.

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* Vikas Agarwal is from J. Mack Robinson College of Business, Georgia State University. Email: vagarwal@gsu.edu. Vikas Agarwal is also a Research Fellow at the Centre for Financial Research (CFR), University of Cologne. Pulak Ghosh is from Decision Sciences and Center of Public Policy, Indian Institute of Management Bangalore. Email: pulak.ghosh@iimb.ac.in. Haibei Zhao is from College of Business, Lehigh University. Email: haz816@lehigh.edu.
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1. Introduction

Traumatic experience such as exposure to intense violence can induce tremendous stress (Camacho, 2008; Becker and Rubinstein, 2011). Scientific studies show that extreme and prolonged stress can adversely affect cognitive skills through damage to the hippocampus (a brain area involved in learning and memory) and loss of brain neurons (McEwen and Sapolsky, 1995; Sapolsky, 1996; Bremner, 1999; Kim and Diamond, 2002). Identifying the effect of such extreme form of stress on financial decision making, however, is a challenging task. First, poor financial conditions can lead to stress-related health issues (Engelberg and Parsons, 2016), giving rise to reverse causality concerns. Second, stress from market-wide shocks affects all agents simultaneously and is confounded with many factors such as changes in investor wealth (Cohn et al., 2015; Guiso, Sapienza, and Zingales, 2018).

The 2008 Mumbai terrorist attacks provide us a distinctive natural experiment to examine how extreme and prolonged stress affects financial decision making in the stock market. Commonly referred to as "India's 9/11" (Rabasa et al., 2009), the attacks lasted for more than three days, the longest ever carried out by a terrorist group (Acharya, Mandal, and Mehta, 2009). Terrorists used lethal weapons to kill random civilians, held and tortured the hostages, and induced extreme and prolonged stress among Mumbai residents, including symptoms of posttraumatic stress disorders or PTSD (Contractor et al., 2014). Moreover, extensive real-time media coverage of this war-like massacre exacerbated and widely spread fear throughout Mumbai. We obtain a proprietary dataset that contains all investor-day-stock level trading records on the National Stock Exchange (NSE) of India, as well as information on investor location. These features allow us to use the difference-in-differences (DID) methodology around the attacks to compare changes in trading behavior for Mumbai investors (treatment group) that were more exposed to the attacks with those of non-Mumbai investors (control group). We include day fixed effects to control for the effect of asset fundamentals (e.g., market return, risk, and liquidity) that can simultaneously change investors' trading behavior.

We find that after the attacks, individual investors based in Mumbai exhibit significantly less trading activity compared with the controls, and the changes are economically significant. Daily trading volume for an average individual investor from Mumbai after the attacks decreased by 8% of the sample average. Motivated by prior literature that relates cognitive factors to trade performance (Korniotis and Kumar, 2011; Grinblatt, Keloharju, and Linnainmaa, 2012), we also find that despite trading less, Mumbai traders on average suffer from a decline of 0.539% in abnormal trade performance post attacks compared with the controls.[1] Moreover, Mumbai traders located closer to the site of attacks suffer from worse performance while more distant traders are unaffected. We further find that Mumbai investors are less likely to initiate trading on new stocks that would require more cognitive ability for information processing, perform worse on familiar stocks (i.e., those in which they invested prior to the attacks), and exhibit a longer response time, as measured by the elapsed time between corporate news announcements and trade placements. When we examine two "placebo" samples of institutional and algorithmic traders, we do not find significant change in trading activity and performance for the treated groups in both these samples.

We further explore both time-series and cross-sectional variations in exposure to stress. Prior studies show that stress symptoms vary with the distance from the site of attacks (Galea et al., 2002; Sharot et al., 2007). Therefore, we separate the traders based on their distance to Mumbai, and find the treatment effects of trading activity and performance decline monotonically with the

[1] There is mixed evidence on whether individual traders are skilled (Barber and Odean, 2000; Kaniel et al., 2012; Kelley and Tetlock, 2013). Our hypothesis does not rely on whether individual investors are systematically skilled as our focus is on the within-investor *change* in trade performance around the shock. It only requires those with skills to perform poorly, or those without skills to perform even worse.

distance. Moreover, stress level has to be significant and prolonged to cause damage to human cognition (McEwen and Sapolsky, 1995). We find insignificant changes in investor trading activity and performance around less severe attacks in India during our sample period, such as the 2005 Delhi bombings, 2006 Mumbai train bombing, 2008 Assam bombings, and 2010 Jnaneswari Express train derailment, suggesting that the stress exposures are not significantly large to induce cognitive impairment for individuals exposed to these events.

Next, we examine several alternative channels that can affect investor trading behavior. First, prior studies find traumatic experiences can change individuals' risk preferences but the evidence is mixed, documenting increase (Callen et al., 2014; Guiso, Sapienza, and Zingales, 2018), decrease (Voors et al., 2012; Eckel, El-Gamal, and Wilson, 2009), and non-monotonic change (Bernile, Bhagwat, and Rau, 2016) in risk aversion after traumatic events. One limitation of our data is that we do not observe investors' entire portfolio investments that may also include bonds, savings accounts, and cash holdings. Therefore, we can only examine if risk preference explains the stock trading behavior, but cannot draw a definitive conclusion about whether investors overall become more or less risk-averse. Considering only stock trades, greater risk aversion predicts *less* purchase and *more* sale as investors are less willing to take financial risks, and vice versa. However, we find that both purchase and sale activities decline after the attacks for Mumbai investors compared with the controls. In addition, we find that Mumbai investors do not change their propensity to trade (both buy and sell) risky stocks after the attacks.

Second, Mumbai investors may pay more attention to the attacks and less attention to the stock market. Given that attention is clearly a part of human cognitive ability (Kahneman, 1973; Liston, McEwen, and Casey, 2009; Gabaix et al., 2006), we believe it is neither necessary nor possible to fully separate out attention from other aspects of cognitive skills. In fact, any stress-induced inattention is consistent with cognitive impairment. However, it is still important to investigate whether our results are completely unrelated to stress and *only* due to inattention. We exploit investor-, stock-, and time-level variations in attention, and document three findings suggesting that attention is perhaps not the only cognitive factor driving the changes in investor behavior around the 2008 Mumbai attacks. First, conditional on investors trading and thus paying attention to stocks due to large financial stake (average volume of $2,849 per trader per day), Mumbai investors still perform worse, trade less on new stocks, perform worse on familiar stocks, and take longer time to respond to corporate news. Second, using stock ticker search activity to measure attention on stocks as in Da, Engelberg, and Gao (2011), we do not find investor attention from Maharashtra (of which Mumbai is the capital city) is different from the aggregate attention across India. Third, between the event date and the third trading day afterwards, there was an immediate spike in the attention on the attacks followed by a sharp reversal once the attacks were over (Figure 1). However, dynamic treatment effect estimates show that Mumbai investors' trading activity did not change significantly until the fourth trading day after the attacks (Figure 2). The delayed reaction of investor trading is consistent with the seminal theory of Selye (1946) and empirical evidence in the science literature (e.g., Wolkowitz et al., 1990; Newcomer et al., 1994; Newcomer et al., 1999; Kandasamy et al., 2014).[2]

Finally, we explore several additional channels that can affect investor trading behavior, such as asset fundamentals, local bias, pseudo market timing, wealth effect, commuting issues, and financial crisis. Our collective evidence is inconsistent with these alternative explanations.

[2] Appendix B discusses the related scientific evidence on prolonged stress.

Several pioneering studies examine how extreme stress such as depression, anxiety, and traumatic experience changes risk preferences.[3] However, we are the first to build on the large science literature showing the cognitive implications of extreme stress, and examine its consequences on individuals' trading behavior and performance.[4] While prior literature in economics documents that various types of stress have severe effects on mental and physical health (Camacho, 2008; Persson and Rossin-Slater, 2018; Borgschulte et al., 2019), our results reveal its adverse consequences on agents' financial wellbeing.

Our study also contributes to the literature on cognitive factors (e.g., genetic traits and aging) and financial decision making. Grinblatt, Keloharju and Linnainmaa (2011, 2012) show that IQ is positively associated with stock market participation and trade performance. Korniotis and Kumar (2011) and Agarwal and Mazumder (2013) find that cognitive aging is related to more financial mistakes. Huang, Xu, and Yu (2019) and Li et al. (2019) find air pollution in China affects cognitive functions and generates worse trade performance and stronger behavioral bias among individual investors. Through identifying a significant shock to cognitive skills due to extreme stress, we extend this literature by documenting a causal relation between cognitive ability and both trading intensity and performance.

2. Data and variable construction

2.1 Terrorist attacks

We focus on the 2008 attacks that took place in Mumbai, India, on November 26, 2008 at around 20:00 Indian Standard Time (after the stock market was closed). India has witnessed many

[3] See Kuhnen and Knutson (2011), Malmendier and Nagel (2011), Voors et al. (2012), Callen et al. (2014), Kandasamy et al. (2014), Cohn et al. (2015), Bernile, Bhagwat, and Rau (2016), and Guiso, Sapienza, and Zingales (2018).
[4] In a contemporaneous paper, Wang and Young (2018) study terror attacks and household trading but do not examine trade performance or cognitive ability.

domestic terror attacks over the years, and the nation has evolved to cope with the unfortunate events of terrorism. For example, although the 2006 Mumbai train bombings caused hundreds of fatalities and injuries, the train system was restored within a few hours, and workers and students resumed normal schedules the next day. However, the 2008 Mumbai attacks differ from prior terrorism events in several ways. First, prior attacks that caused a large number of fatalities were either bomb or train attacks (e.g., Punjab 1991, Rafiganj 2002, Mumbai 2006, and Jnaneswari 2010), or between conflict groups (e.g., Mandai 1980). In contrast, the 2008 Mumbai attacks were a war-like massacre that targeted multiple areas including the historic Taj hotel, a community center, a restaurant, a hospital, and several railway stations. The attacks lasted three days over which random civilians were held as hostages, and caused hundreds of fatalities and injuries due to lethal weapons. 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".[5]

Second, the event was covered extensively in the news and social media such as 24-hour live TV coverage, blogs, and tweets, which spread a great amount of fear among the public. Immediately after the attack started, many media channels gathered around the Taj hotel and started live broadcasting of the entire event for around 70 hours, including the movement of security forces as well as their operations. Residents of Mumbai suffered from great fear and stress since the terrorists could identify and anticipate inside movements of armed forces. In a survey of 818 adolescents exposed to the 2008 Mumbai terrorist attacks, Contractor et al. (2014) find that

[5] Krishnakumar, P. and V. Nanjappa. "Doctors shocked at hostages' torture." Rediff, www.rediff. com/news /2008 /nov/30mumterror-doctors-shocked-at-hostagess-torture.htm, Retrieved April 26, 2019.

96.2% of the survey participants gave a rating of 2 or greater (either “felt it a little” or more) on items related to fear, helplessness or horror. Same study shows that 12.7% of the participants have symptoms indicating a probable PTSD diagnosis. As a comparison, Galea et al. (2002) report that 20% of surveyed adults living near the World Trade Center reported symptoms consistent with a diagnosis of PTSD.

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 identify the effect of the terrorist attack 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.[6]

2.2 Trading data and stock characteristics

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 NSE from 2004 to 2017. The NSE is the primary stock exchange of India where the vast majority of stock trading takes place, especially during recent years. For each trader-day-stock observation, we have information on the ticker symbol of stock traded, number of shares purchased and sold, and average price per share paid or received for purchase or sale. Each trader has a unique and masked

[6] NSE’s Nifty index 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. Moreover, trading volume on the NSE was 85% lower on October 28, 2008 than the previous day due to *Muhurat* trading on the Diwali holiday.

identifier that tracks the trader over time. The dataset also includes traders' geographic location, such as their zip code, city, and state. Finally, each trader is identified as an individual or institutional investor (e.g., banks, mutual funds, etc.).

We aggregate trader-day-stock observations at the trader-day level and calculate four measures of overall trading activity for each trader during a day: the 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 purchase or sale during the day, and zero otherwise. *totvol* is the total trading volume per trader per day in thousand INR, including both purchases and sales. *nstock* is the number of stocks traded per trader per day. *totshr* is the total number of shares traded per trader per day. We consider these four variables as unconditional trading activity measures since they are set to 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 the descriptive 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 on any given day during this period. It is important to note that the propensity of trading appears to be large as we do not include individuals who were inactive and never traded during the period of terrorist attacks. This is because these individuals will be dropped from our regression analysis after the 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 ($1 = INR 49.20 at the time of the attacks). Although significant, these amounts are much smaller than statistics reported for U.S. individual investors. For example, Barber and Odean (2000) report mean and median trade sizes for individual buy orders of $11,205 and $4,988 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 at the trade level and therefore will be even larger than those in our data if aggregated to the trader-day level.

We report correlations between the unconditional and conditional trading activity measures in Panels B and C of Table 1, 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 they capture different aspects of trading activity. 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 stock price, and the number of stocks measures the ability to process information on different stocks, i.e., multitasking.

Finally, we obtain stock returns and firm financials data from Compustat Global and match them with the trading data using a ticker symbol–ISIN (International Securities Identification Numbers) link file provided by the NSE. We exclude stocks with share prices below INR 5 to reduce noise in calculated stock returns such as bid-ask bounce or stale pricing. Excluded observations total to 3% of the stock-day observations, and this exclusion has minimal impact on our results.

3. Empirical methodology and results

3.1 Baseline results

A number of studies show that proximity to attack sites measures the extent of an individual's exposure to stress.[7] We therefore compare trading behavior for Mumbai investors who are more exposed to the attacks (treatment group), with non-Mumbai investors that are less exposed (control group), both before and after the event. Specifically, we estimate the following difference-in-differences (DID) regression with trader-day level observations:

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

where $Trade_{i,t}$ denotes measures of trading activity for trader *i* during day *t*; $post_t$ is equal to one if t is after the event date, and zero otherwise; $Mumbai_i$ is equal to one if trader i is located in Mumbai, and zero otherwise; ω_i denotes individual trader fixed effects; and $\kappa_t$denotes day fixed effects. The indicator variable, $Mumbai_i$, is absorbed by the inclusion of individual fixed effects; similarly, $post_t$ is absorbed by day fixed effects.

Individual fixed effects help control for various factors that can affect investors' trading behavior, such as IQ, age, experience, and financial sophistication that are unlikely to change significantly over the few days around the event date. Day fixed effects 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 coefficient on the interaction term $Mumbai_i \times post_t$. 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.

Table 2 reports estimation results of Equation (1). We find that all trading activity measures decline significantly after the attacks for Mumbai investors compared with the controls. For

[7] For example, Galea et al. (2002) find a great prevalence of PTSD among those living near the World Trade Center than in Manhattan. 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.

example, the coefficient of –0.015 in Column (1) of Panel A indicates that the 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) 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 trader per day decreased by 8.2% as we observe in Column (3), 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), or 9.2% of the mean value of *totshr*.

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. In Panel B of Table 2, we focus on conditional measures of trading activity. As mentioned earlier, for these measures, non-trading observations are set to missing and dropped from the analysis. We continue to observe negative and significant coefficients on $Mumbai \times post$ 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.[8] Conditional on trading, the economic magnitude of decline in trading activity is generally smaller compared with the overall results in Panel A. For example, Column (1) of Panel B shows total INR volume per trader per day decreases by INR 5,594, or 4.0% of the sample mean of *CONDvol*, while the treatment effect in Column (2) of Panel A is 8.0% of the sample mean of *totvol*.

Finally, in Panels C and D, we include an interaction term between an indicator variable for the pre-event (*pre*) and *Mumbai* to test the parallel trend assumption of the DID methodology.

[8] The number of observations in Panel B of Table 2 (10,640,279) using the conditional measures differs from that reported in summary statistics (11,262,958) because investors who trade only on one day during our sample period are dropped from the regressions due to individual fixed effects.

The construction of pre-event indicator variable, *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. The interaction term is insignificant, indicating that our results are not driven by pre-event differences between the trading behavior of 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 suggest that the 2008 Mumbai attacks were unexpected by the Mumbai traders.

We conduct several robustness checks for the above findings, including alternative event windows, placebo event dates of November 26 in 2007 and 2009, controlling for any differential trading behaviors of investors in metropolitan areas, and skewness of trading activity measures. These results are reported in Online Appendix A. We double-cluster the standard errors at the trader and day levels as in Puckett and Yan (2011). As discussed in Online Appendix A, two-way clustering of standard errors is the most conservative compared with alternative approaches, since it simultaneously accounts for any time-series and cross-sectional correlations in the standard errors. Online Appendix A further discusses the related econometrics issues and shows that our results are robust using two-way clustering of the standard errors at the geographic region (e.g., zip code) and day levels, and bootstrapped standard errors.

3.2 Geographical and time-series variations in trauma exposures

In this section, we extend our baseline analysis by exploring both geographical and time-series variations in violence exposures. First, we construct four indicator variables based on the geographical distance between investors' zip code and the site of attacks, i.e., city center of Mumbai: *Dist0-30*, *Dist30-150*, *Dist150-400*, and *Dist400-1000* where the two numbers in each variable name indicate the range of distance in kilometers from Mumbai. For example, *Dist30-150* is equal to one if the investor is located between 30 and 150 kilometers from Mumbai, and zero otherwise. We then interact the distance variables with the post attack indicator variable (*post*) to estimate the treatment effects for close and distant traders. The distance cutoffs are selected such that there are around 10% of all traders in each distance group. This approach helps reduce the noise in estimated treatment effects as each treatment effect variable represents a significant number of investors.

Table 3 reports the estimation results based on investors' distance from Mumbai. We observe that the treatment effects decrease monotonically with this distance. Economic magnitude of the treatment effects is the greatest for investors located within 30 kilometers, and eventually becomes insignificant for those over 400 kilometers away. For individuals located several hundred kilometers from Mumbai, the direct impact of the attacks may be small. One interpretation of the significant finding for *Dist150-400* is that those individuals may have friends or relatives who are Mumbai residents and therefore may suffer indirectly.

3.3 Dynamic effects of the change in trading activity

Next, we examine dynamic changes in individuals' trading activity. Specifically, we estimate daily treatment effects as follows:

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

where β_t measures the dynamic treatment effects on Mumbai traders for each date κ_t. The event day (November 26) is excluded so that β_t can be estimated in presence of the individual fixed effects. Figure 2 plots the estimated β_t for *propensity*, *totvol*, *nstock*, and *totshr* in the four subplots, respectively. We observe that trading activity declines after the event date of attacks (denoted by the vertical dashed lines), and then recovers towards the end of our sample period.

Notably, the trading activity does not drop immediately after the attacks until three trading days after the event. This finding resonates well with the General Adaptation Syndrome theory of Hans Selye, and prior scientific evidence showing that chronic, but not acute, stress impairs cognitive abilities.[9] The General Adaptation Syndrome theory posits that there are three stages of reaction to stress: alarm reaction, resistance, and exhaustion. Facing stress, the human body first releases stress hormones and generate fight and flight responses. The body then tries to adapt to stress and restore to the normal state. Finally, significant and prolonged stress makes the restoration unsuccessful, as it drains the adaptive reserves, leads to exhaustion, and adversely affects performance. Online Appendix B reviews several scientific studies where participants receive continuous administration of high doses of stress hormones for several days, and cognitive impairment is observed only after prolonged exposure to the hormones.

Galea et al. (2002) document that most individuals recover from symptoms of PTSD and depression 5 to 8 weeks after the 9/11 attacks in the US. Figure 2 suggests that traders take a bit less time (around 3 calendar weeks) to start to recover after the 2008 Mumbai attacks. The attacks we examine, although generated a great amount of fear and stress, are perhaps still less intense and destructive compared with the 9/11. One caveat is that although we observe a recovery in trading activity during the last 10 days in our sample, given the confounding effect of the New Year, it is difficult to identify exactly when the investors fully recover from the attacks. However, even if the recovery period extends to the post New Year period, it would strengthen our result and indicate that the attacks have longer lasting effect than we document.

[9] Following Kandasamy et al. (2014), we define acute stress as short-lived exposure, ranging from minutes to hours, and chronic stress as sustained exposure ranging from days to weeks. Scientists also use chronic stress for even longer periods such as months or years.

4. Mechanisms influencing investors' trading behavior

4.1 Cognitive ability

Our main finding on the decline in trading activity in the previous section is consistent with the cognitive ability channel, i.e., violence-induced extreme stress impairs the ability to perform complex tasks such as trading.[10] In this section, we first examine trade performance that the literature has shown to reflect cognitive ability (Korniotis and Kumar, 2011; Grinblatt, Keloharju, and Linnainmaa, 2012). Trading involves significant and personal financial stakes, so traders should have strong incentives to utilize their cognitive skills and maximize performance. We then examine trading in new and old stocks, and traders' response time to corporate news announcement to further probe the cognitive ability channel.

4.1.1 Trade performance

We compute a trade-level performance measure following Puckett and Yan (2011) that extends the familiar DGTW measure of Daniel et al. (1997) to the trade level. This performance measure extends the buy-minus-sell weighted average returns used in prior studies (Odean, 1999; Barber et al., 2009) by adjusting for returns of a benchmark portfolio of stocks with similar characteristics. 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

[10] One possibility is that after the attacks, Mumbai investors trade more in stocks with greater information asymmetry that require more cognitive skills to process. We do not find evidence in favor of this conjecture. In addition, we do not find that the liquidity of Mumbai stocks went down after the attacks, which made them costlier to trade, and therefore hurt the performance of Mumbai investors. These results are reported in Online Appendix C1.

to the ending date of our sample (December 29, 2008).[11] 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. The DGTW benchmark is matched with the traded stock on size, book-to-market, and momentum, and the benchmark return is calculated over the same period as that of the holding-period return.[12] 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, total abnormal returns for buys and sells are weighted by aggregate amounts of buys and sells, respectively, to compute the overall abnormal performance for a 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 the stock at INR 300 per share and sells 100 shares at INR 310 per share, and the stock price on the last date is INR 330. Total profit for this trader should be 100×(INR 310 – INR 300), which is exactly equal to the amount under our methodology (100×(INR 330 – INR 300) + 100×(INR 310 – INR 330)).

To estimate the change in trade performance for each individual, we compute 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 ($Performance_{i,After}$), and estimate the following equation:

[11] Online Appendix C2 uses ending dates that are 1, 3, and 6 months after December 29, 2008 to ensure that our performance results are not sensitive to the end date of performance evaluation.
[12] The total number of stocks traded on the NSE in our sample is around 900, substantially smaller than that 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.

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

where T=*Before* or *After*; and *post* is equal to one if trade performance is measured after the event date, and zero otherwise.[13]

We report estimation results of Equation (3) in Panel A of Table 4. The negative and significant coefficient on $post \times Mumbai$ in Column (1) suggests that Mumbai investors perform worse after the attacks compared with the controls. The average performance decline for each Mumbai-based trader is 0.539% (or 8.9% of the standard deviation of *Performance*), which is economically significant considering that the performance is measured over only a few weeks after the attacks.[14] Column (2) examines the dynamic effects of performance change by partitioning the post-event period into three sub-periods, denoted by three indicator variables *post1* (first 7 trading days post attacks), *post2* (next 7 trading days), and *post3* (last 6 trading days). We use weekly indicator variables for the post period in Column (2) instead of daily (as in Figure 2) to reduce noise in performance estimation. The coefficient on *post1×Mumbai* is insignificant, while those on *post2×Mumbai* and *post3×Mumbai* are significantly negative. These results confirm the delayed response shown in Figure 2. Finally, Column (3) shows the treatment effects for different groups of investors based on their geographical distance to Mumbai. Similar to our earlier findings

[13] We use two-way clustering of standard errors that accounts for any cross-sectional and time-series correlations of standard errors. Although one can control for cross-sectional correlation of standard errors via calendar time portfolio or bootstrapping (Odean, 1999), we do not use the calendar time portfolio since it does not control for individual-level heterogeneity. Petersen (2009) shows that standard errors under two-way clustering is more conservative than bootstrapping.

[14] In the performance results, we require individuals to trade during both the pre- and post-event periods due to the inclusion of individual fixed effects. Therefore, one alternative interpretation of the performance result is that "smart" Mumbai investors self-select not to trade during the post-event period and are dropped out from our sample. However, when we examine the subsample of investors who *only* trade in the pre-event period, Mumbai investors have slightly worse performance compared with the other investors (–0.02%), i.e., any selection issue should bias against our finding.

on trading activity, we observe performance declines only for those located closer to the attack sites (up to 150 kilometers from Mumbai).

4.1.2 Trading new stocks

We then examine investors' trading in "new" stocks that they are less familiar with and thus 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 this stock during the last 6 months. We define "new stocks" ("old stocks") as those without (with) prior trading records. We then compute the total number of new stocks traded per trader per day (*newstock*). Column (1) of Panel B, Table 4 shows a negative and significant coefficient on *post*×*Mumbai* using *newstock* as dependent variable. Consistent with a 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, *prop_new*, as the dependent variable. Note that the proportions of trading in old and new stocks add up to one. We again find a negative and significant coefficient on *post*×*Mumbai*, i.e., when agents face cognitive impairment, they gravitate towards tasks that they are familiar with rather than undertaking new ones.

A natural question is whether our performance results in Panel A of Table 4 are driven by trading in new stocks. In Panel C of Table 4, we separate all trades for all traders into trading in new stocks in Column (1) and old stocks in Column (2). We observe a decline in performance for Mumbai traders in both new and old stocks, suggesting that deterioration in cognitive ability also impairs Mumbai traders' performance on stocks that they are familiar with. The magnitudes of the treatment effects are economically close, which 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 Panel B.

4.1.3 Response time after news announcement

Many prior studies use response time as a measure of cognitive ability (e.g., Hockley, 1984; Gabaix et al., 2006; Rubinstein, 2007). In addition, stock prices reflect the information in public news within a few minutes, and traders need to respond very fast to profit from the price adjustment (Busse and Green, 2002). If traders suffer from cognitive impairment, it would take them more time to digest the information in news and make quick trading decisions.

To examine traders' response time, we obtain the entire trade-by-trade data from the NSE for the 30 trading days in our sample period with time stamps for each trade. We then match the trade-level data with corporate news announcements by Indian listed companies reported in RavenPack (e.g., earnings announcements, credit rating changes, acquisitions, and CEO turnovers, etc.). Importantly, we only keep news announcements with novelty score equal to 100 to ensure that it is the first time such events are mentioned to the public. We then compute the number of seconds between news announcement and time for a trader to place a trade within a 3-minute (6-minute) window after the announcement (denoted as *Rtime3* and *Rtime6*, respectively). As before, our analysis includes individual fixed effects to estimate the *change* in their response time before and after the attacks.

Panel D of Table 4 reports the results on traders' response time after news announcements. Column (1) shows that within the 3-minute interval, it takes Mumbai traders 5.7 more seconds to respond to news and place a trade, which is 6.5% of the mean response time of 88 seconds. Column (2) shows that for the 6-minute window, there is no difference in response time, i.e., Mumbai traders have enough time to catch up and respond to news within 6 minutes. To rule out the possibility of a time-of-the-day effect, Columns (3) and (4) show insignificant results using placebo dates of news announcement (+1 and –1 day of the actual dates, holding announcement time unchanged). We also find insignificant results in Column (5) for institutional investors that are likely to be sophisticated and less affected by the attacks.

We next examine if longer response time after the attacks can partly explain the decline in trade performance. Panel E reports the relation between response time and trade performance. The dependent variable *Return* is the per share price paid (for buy orders) or received (for sell orders), scaled by the share price at the beginning of the trading day. We observe that for the 3-minute window, one more second of response time leads to a 0.036% decline in trade returns. For the 6-minute window, shorter response time does not contribute to better returns, suggesting that during this longer window, prices already incorporate information in the news. This result is consistent with Busse and Green (2002), which shows that shorter response time leads to better performance only if traders react very fast to public news. In addition, it indicates that our earlier performance result in Panel A can be partially attributed to longer response time of Mumbai investors due to cognitive impairment.

4.1.4 Less significant attacks

As discussed earlier, the 2008 Mumbai attacks were unprecedented in India due to the long-lasting exposure to violence and extensive media coverage. India has a long history of terrorism-related violence, and agents may manage and cope with less significant attacks.[15] To highlight the distinctive nature of the 2008 Mumbai attacks, Table 5 repeats our analysis for other bomb and train attacks in India with much shorter durations and less media coverage during our sample period, such as the 2005 Delhi bombings, the 2006 Mumbai train bombings, the 2008 Assam bombings, and the 2010 Jnaneswari express train derailment. We do not find significant difference

[15] India is ranked 3rd globally in terms of the number of terrorist incidents in 2017 (after Iraq and Afghanistan) based on the Global Terrorism Database (GTD) provided by the Study of Terrorism and Responses to Terrorism (START) at the University of Maryland.

between the trading activity and performance of the treated and control groups after these attacks, suggesting that the stress exposures during these events are not significantly large to induce cognitive impairment.

4.1.5 Institutional investors

In this section, we study a "placebo" sample of institutional investors that are less likely to be affected by violence-induced stress. First, professional agents may have better ability and/or more incentives to manage and overcome fear. Institutions frequently use computer models and algorithms to automate the process of trading, which would also predict less reaction after the attacks. Our dataset has separate identifiers for individuals and institutional investors, such as mutual funds and banks. We take the subsample of institutional investors and recompute the summary statistics of the trading activity measures.

Panel A of Table 6 reports summary statistics of the trading activity measures for institutional investors around the 2008 Mumbai attacks, where the measures are constructed in the same way 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). Panel B of Table 6 reports the changes in institutional trading activity and performance after the 2008 Mumbai attacks. We do not observe any significant change in trading behavior for institutions located in Mumbai compared with institutions located elsewhere after the attacks. We note that although the estimated coefficients on $Mumbai \times post$ in Panel B are sometimes economically larger than the treatment effects for individual investors (in Table 2), this is simply because the magnitude of institutional trading is much larger on average than individual traders, as we observe in Panel A of Table 6.

4.1.6 Algorithmic traders

Algorithmic trading is usually based on technical trading rules and therefore should not "suffer" from stress and fear after violence exposures. The NSE explicitly identifies algorithmic traders. We focus on the sample of all *individual* investors that use algorithmic trading during our event period (since we already show the results are insignificant for institutions). We compute the trading activity and performance measures as before, and compare these measures for Mumbai algorithmic traders with those for non-Mumbai algorithmic traders in Table 7. None of the coefficients on *Mumbai*×*post* is significant at conventional levels, thus lending further support to the cognitive ability channel.

Overall, results in this section support the cognitive ability channel. In the following sections, we investigate alternative consequences of exposures to extreme stress.

4.2 Risk preference

Violence and trauma can alter individuals' risk preferences and trading behavior although the evidence in prior literature is mixed. For example, 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. Eckel, El-Gamal, and Wilson (2009) find more risk-seeking behavior among women after hurricane Katrina. Bernile, Bhagwat, and Rau (2016) find a non-monotonic relation between CEOs' early life exposures to fatal disasters and their risk-taking behavior.

In Table 8, 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). Panels A and B show that both purchase and sale activities decline after the attacks. These findings are not supportive of the risk preference channel, which would predict less purchase and more sale if investors become more risk averse (to reduce their risk exposures to the stock market); or more purchase and less sale if investors become less risk averse. 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. For example, Kahraman and Tookes (2016) document that the shorting market was launched in April 2008 and was restricted to a small fraction of stocks eligible for futures and options trading. Suvanam and Jalan (2012) report that the total volume in the security lending market reached $250 million in 2010, which is only 0.015% of the total equity trading volume on the NSE in 2010.

To further probe the risk aversion channel, we test whether Mumbai investors change their propensity to trade risky stocks after the attacks as alternative way to measure investors' risk aversion. Specifically, we measure the propensity to trade risky stocks using the propensity to trade stocks with high return volatility (*AvgVol*), the propensity to buy stocks with high return volatility (*BuyVol*), and the propensity to sell stocks with high return volatility (*SellVol*). We first compute the stock-level return volatility using the stock's daily returns during the past calendar quarter. The quarter we use to compute the return volatility ends one day before our sample start date to ensure that the stock risk measure does not change due to the attacks. Using a rolling window (i.e., for each day, use the prior 90 days) to compute the measure has no impact on our result. We then take a weighted average of the return volatilities across all stocks traded by a trader during a day, weighted by the INR amount of each stock trade to compute *AvgVol*. Likewise, we take weighted average of the return volatilities across all stocks bought and sold by a trader during a day, weighted by the INR amount of each stock trade to compute *BuyVol* and *SellVol.*

In Panel C of Table 8, we regress the three measures of trading risky stocks on the post event indicator variable (*post*), the Mumbai investor indicator variable (*Mumbai*), and the interaction term between *post* and *Mumbai*. The results show that Mumbai traders do not exhibit any changes in the propensity to trade more risky stocks after the attacks.

Finally, we find in Section 4.1 that Mumbai investors have worse trade performance after the attacks. In contrast, change in risk preference predicts no change in performance, since the performance measure we use already adjusts for the risk component by matching with benchmark stocks that have similar characteristics (Daniel et al., 1997). Risk aversion also does not explain our finding on the change in response time after news announcement for Mumbai traders.

We acknowledge that our results only indicate that any change in risk preference is not manifested in Mumbai traders' stock trading behavior. Such evidence, however, does not allow us to conclude that the traders become more or less risk-averse overall, since they may hold more cash or invest less in other risky asset classes such as bonds and checking/savings bank accounts for which we do not have data.

4.3 Investor attention

Our prior results on trading activity and performance could also be 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.[16] Since attention is part of human cognitive ability, any stress-induced attention effect is consistent

[16] The attention channel does not unambiguously predict less trading. If traders care about the performance of their financial investments, news coverage on the attacks may promote more investor attention to the stock market.

with the cognitive ability channel. Therefore, our purpose in this section is to examine whether our results are completely unrelated to stress and *only* due to inattention. We discuss three sets of results that suggest attention is perhaps not the only cognitive factor that drives our findings.

First, conditional on trading, investors undoubtedly paid attention to the stocks. In addition, the average conditional trading volume is as high as INR 140,190 ($2,849) per trader per day, and it is difficult to argue that investors were trading such a significant amount without paying substantial attention.[17] Table 4 shows that conditional on trading, Mumbai investors still perform worse, trade less in new stocks, perform worse on familiar stocks that they have traded prior to the attacks, and take longer time to respond to information releases.

Second, we follow Da, Engelberg, and Gao (2011) (hereafter DEG) and use Google Trend search on stock tickers as a measure of investor attention on the stocks. Google accounted for 94% of all search queries performed in India in 2009 (gs.statcounter.com) that is even greater than the U.S. (e.g., 72% as of February 2009 as shown in DEG). As in DEG, we exclude keyword search activities that can be unrelated to stock trading, such as banking services, media, and telecommunication companies. For example, when searching for ICICI bank, people may be interested in using its banking services, instead of investing in its stock. In addition, we follow DEG and exclude tickers with a generic meaning such as BANG, FACT, ROMAN, TAKE, MIC, and MAX. Finally, stocks with no recorded Google search activity during both the pre- and post-event periods are dropped from our analysis due to the inclusion of stock fixed effects. Our final sample has 187 stocks traded on the NSE over the same time as in our main analysis. Table 9 reports the results from a DID regression of search activities for people from India and for those

[17] One advantage of our setting is that we measure attention directly at the individual level, conditional on investors' personal and significant financial exposure. Online Appendix C3 shows that conditional on significant aggregate trading volume (more than 5 million INR), traders still suffer from declines in trading activity and performance.

from Maharashtra (as Google does not retain city-level search activity for India). The coefficient on *treated×post* is insignificant, suggesting that there is no decline in search activity from Maharashtra on the stocks.

Third, the attention channel 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, dynamic treatment effects in Figure 2 and Table 4 do not show an immediate decline for the first few days after the attacks, which as mentioned earlier, matches prior scientific evidence of cognitive impairment only after prolonged and significant exposure to stress.

To further compare the time-series changes in treatment effect with changes in investor attention, we again use Google Trend search as a measure of investor attention. The solid line in Figure 1 plots Google Trend search activity from India on topic "2008 Mumbai attacks" during our sample period. Under the *topic* option, Google aggregates all web queries related to "2008 Mumbai attacks" to the same topic. This is different from the *search term* option, where Google only counts queries related to the exact keywords, a noisier measure of overall investor attention on the attacks. 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 attention spike 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 since the attacks were over after 9 terrorists were killed and the last one arrested. In stark contrast to this pattern, 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 afterwards, a period when there is minimal attention on the attacks, since the attacks were over by then.

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 that 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 DID approach in our analysis, this evidence further suggests that our results are unlikely to be entirely driven by an attention effect since attention on the attacks follows a similar pattern for both treatment and control group of investors.

4.4 Additional channels

In this section, we discuss several additional channels that can affect investor trading behavior, such as asset fundamentals, local bias, pseudo market timing, wealth effect, commuting issues, and financial crisis.

4.4.1 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 asset fundamentals. For example, 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, and thus affected investor trading (Burch, Emery, and Fuerst, 2016). Figure 3 shows daily market returns around the 2008 Mumbai attacks by value-weighting returns of all stocks in our sample. In stark contrast to the 9/11, market returns were generally positive after the 2008 Mumbai attacks. Consistent with anecdotal evidence, the 2008 Mumbai attacks did not cause large scale economy-wide damages. For example, excluding the Taj Mahal hotel, the property loss was estimated to be approximately \$8,691,667 (Contractor et al., 2014). In addition, in all our analyses we control for day fixed effects that absorb any change in aggregate market conditions such as market return, risk, liquidity, and interest rates.

Moreover, emotionless "rational" agents should trade in a similar fashion based on shocks to fundamental values of stocks, instead of trading differently based on their proximity from the site of attacks as we show previously (unless their assessments on asset fundamentals are different, a possibility discussed in the following section).

4.4.2 Local bias

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 perform better, which is not supported by our earlier finding in Table 4; and should 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, which is not supported by our earlier finding in Table 8.

To further investigate the local bias channel, we conduct two additional tests. First, we compare the returns of Mumbai and non-Mumbai stocks in Panel A of Table 10. 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 10, we examine whether Mumbai-based traders exhibit a different propensity to trade Mumbai stocks post attacks. The dependent variable is *tradeMum*, daily trading volume in Mumbai stocks as a proportion of a trader's total daily trading volume. We find that the coefficient on *Mumbai*×*post* is also insignificant, suggesting that Mumbai traders do not change their propensity to trade Mumbai stocks after the attacks. Overall, the local bias channel cannot explain our findings.

4.4.3 Pseudo market timing

Mumbai investors may have poor performance by chance due to pseudo market timing, i.e., they buy (sell) less prior to a period of good (bad) stock returns. Since our measure of abnormal performance already adjusts for the benchmark returns, it explicitly controls for any pseudo timing effect. We also find in Table 8 that Mumbai investors' buy and sell volume decline in similar magnitude, which further weakens the possibility of less net purchase under good market conditions, or vice versa.

4.4.4 Wealth effect

Investors may suffer from losses in property values, rental fees, or business income from tourism activities, i.e., a local wealth effect. However, as discussed earlier, property losses in the 2008 Mumbai attacks were not severe and nowhere comparable to the 9/11 in the U.S. In addition, if there were significant expected losses from business revenue and property damages within the city of Mumbai, we should also see the Mumbai-based publicly listed firms to be adversely affected. We do not find any difference in stock returns for Mumbai firms post the attacks compared with the controls (Table 10), either economically or statistically. Lastly, loss of wealth due to damages in real economic activities would again predict more stock sales if investors need to convert stock investments into cash to meet their consumption needs, while our results in Table 8 suggest otherwise.

4.4.5 Commuting issues

Investors may have trouble commuting via public transportation after the attacks and have less time to pay attention to stocks. However, anecdotal evidence suggests that the public transportation system was not much affected by the attacks.[18] In addition, 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. Moreover, our conditional trading activity measures are conditional on investors allocating time and attention to the stocks, despite any commuting issues. Lastly, 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 in Table 6 suggest the opposite.

4.4.6 Financial crisis

Our test of the parallel trend assumption in Table 2 shows that the pre-event trading behavior between Mumbai and non-Mumbai investors is similar in our sample period, suggesting that our results are not due to different reactions to the global financial crisis between the treatment and controls. To further control for differences between Mumbai and non-Mumbai investors, we adopt a matched sample approach using an entropy balanced sample of treatment and controls. We report the matched sample results under entropy balancing in Table C4 of the Online Appendix C. We continue to observe that Mumbai individuals trade less and perform worse after the attacks.

5. Conclusion

In this paper, we use a unique dataset and a major terror attack to tackle the challenging question of how stress affects financial decision making. Our setting has several advantages. First,

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[18] See, e.g., https://www.forbes.com/2008/11/29/mumbai-economic-cost-oped-cxap1129panagar iya.html#21cc 45e73ff2.

the exogenous nature of the 2008 Mumbai attacks, identifies a causal effect of extreme and prolonged stress on decision making. Second, our difference-in-differences methodology reveals the change in behavior for treated versus controls, thus helps isolate any confounding effects that affect all individuals simultaneously. Third, compared with lab or field experiments that typically have small sample sizes, our test involves millions of individuals and helps present large-scale evidence. Finally, trading involves significant financial stakes, which provide strong incentives for individuals to utilize their cognitive skills.

Using records from millions of trading accounts, we document several novel findings. First, individual investors located closer to the attack site trade less and perform worse 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 cannot explain our findings collectively. 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 cognitive impairment due to extreme and prolonged stress. Lastly, we find that institutional and algorithmic trading activities are not affected.

Our findings have implications for pricing efficiency and liquidity in financial markets. Cognitive impairment can hinder information production and cause asset values to deviate from fundamentals, therefore amplifying asset volatility. Also, reduction in stock market participation, another consequence of cognitive impairment, could exacerbate liquidity dry-ups during market downturns.

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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. The regressions control for individual and day fixed effects. Standard errors are reported in parentheses and are double clustered at the individual level and day level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

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
Time 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
Time 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
Time 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
Time 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: Geographical variations in exposures to violence

This table reports the change in individual investors' trading behavior around the 2008 Mumbai attacks based on their distance from Mumbai. *Dist0-30*, *Dist30-150*, *Dist150-400*, and *Dist400-1000* are indicator variables that are equal to one if the individual is located 0 to 30, 30 to 150, 150 to 400, and 400 to 1,000 kilometers from Mumbai, respectively; and zero otherwise. All regressions control for individual and day fixed effects. Standard errors are reported in parentheses and are double clustered at the individual level and day level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1) *propensity*	(2) *totvol*	(3) *nstock*	(4) *totshr*
Dist0_30×post	–0.016***	–3.126***	–0.095***	–16.456***
	(0.003)	(0.650)	(0.021)	(3.204)
Dist30_150×post	–0.013***	–2.448***	–0.072***	–15.901***
	(0.003)	(0.827)	(0.019)	(3.632)
Dist150_400×post	–0.002	–1.446**	–0.038***	–8.110***
	(0.002)	(0.634)	(0.014)	(2.639)
Dist400_1000×post	–0.001	0.119	–0.106	–1.9443
	(0.001)	(0.263)	(0.077)	(1.409)
Observations	46,928,800	46,928,800	46,928,800	46,928,800
Adj. R^2	0.397	0.476	0.555	0.417

Table 4: Cognitive ability

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 29, 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 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. 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 value-weighted by the amounts 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 Columns (1) and (3), *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 period 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 prior trading by individuals during the last 6 months. The dependent variables are the total number of new stocks traded per trader per day (*newstock*) in Column (1), and the proportion of new stocks traded relative to all stocks (*prop_new*) in Column (2). Panel C shows individual investors' trade performance in new stocks (Column (1)) and old stocks (Column (2)). Panel D reports the results on traders' response time after corporate news announcements. News announcements are from RavenPack with novelty score equal to 100 to ensure that it is the first time the events are mentioned. UTC time in RavenPack is converted to India local time. The dependent variable *Rtime3* (*Rtime6*) is the number of seconds between news announcement and trade placement within a 3-minute (6-minute) window after the announcement. Columns (1) and (2) show the baseline results. Columns (3) and (4) show the placebo results by changing the actual news announcement dates to +1 and –1 day of the actual dates (Placebo (+1) and Placebo (–1)), keeping the announcement time unchanged. Column (5) shows the response time for institutions. The regressions in Panels A through D control for individual and time fixed effects. Standard errors are reported in parentheses and are double clustered at the trader level and time level. Panel E reports the relation between response time and trade returns. *Return* is the per share price paid (for buy orders) or received (for sell orders), scaled by the share price at the beginning of the trading day (reported in percentage). The controls include stock and day fixed effects. Standard errors are reported in parentheses and are double clustered at the stock level and day level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Trade performance

	(1) *Performance*	(2) *Performance*	(3) *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)	
Dist0_30×post			–0.626***
			(0.107)
Dist30_150×post			–0.694***
			(0.161)
Dist150_400×post			0.181*
			(0.100)
Dist400_1000×post			–0.042
			(0.057)
Individual FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
Observations	1,872,942	2,859,486	1,872,942
Adj. R^2	0.246	0.465	0.246

Panel B: Trading new stocks

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

Panel C: Trade performance in new and old stocks

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

Panel D: Response time after news announcement

	Baseline		Placebo (+1)	Placebo (–1)	Institutions
	(1)	(2)	(3)	(4)	(5)
	Rtime3	*Rtime6*	*Rtime3*	*Rtime3*	*Rtime3*
Mumbai×post	5.698**	1.570	–6.155	–1.861	–0.616
	(2.620)	(3.413)	(3.753)	(3.209)	(2.933)
Individual FE	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes
Observations	61,173	173,087	38,903	46,309	39,823
Adj. R^2	0.086	0.118	0.116	0.118	0.018

Panel E: Reaction time and trade performance

	(1)	(2)
	Return (%)	*Return* (%)
Rtime3	–0.036**	
	(0.016)	
Rtime6		–0.003
		(0.003)
Stock FE	Yes	Yes
Time FE	Yes	Yes
Observations	83,110	188,849
Adj. R^2	0.044	0.045

Table 5: Less significant attacks

This table reports changes in individual investor trading behavior in Columns (1) through (4) and performance in Column (5) around the 2005 Delhi bombings, 2006 Mumbai train bombings, 2008 Assam bombings, and 2010 Jnaneswari express train derailment in Jhargram. *treated* is an indicator variable that is equal to one if an individual is located in the city where the terror attacks take place, and zero otherwise. All regressions control for individual and day fixed effects. Standard errors are reported in parentheses and are double clustered at the individual level and day level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1) *propensity*	(2) *totvol*	(3) *nstock*	(4) *totshr*	(5) *Performance*
			New Delhi 2005		
treated×post	–0.002	0.094	–0.026**	–4.137	0.074
	(–0.93)	(0.08)	(–2.26)	(–0.75)	(0.189)
			Mumbai 2006		
treated×post	0.000	0.440	–0.011	0.392	0.120
	(0.10)	(0.56)	(–0.97)	(0.15)	(0.103)
			Assam 2008		
treated×post	–0.001	3.231	0.035	1.387	–0.054
	(–0.21)	(1.65)	(1.15)	(0.17)	(0.742)
			Jhargram 2010		
treated×post	0.002	–1.530	0.012	4.237	0.071
	(0.34)	(–0.95)	(0.27)	(0.54)	(0.238)

Table 6: Institutional investors

Panel A reports summary statistics of the trading activity measures for institutional investors around the 2008 Mumbai attacks. Panel B reports changes in trading behavior and performance of institutional investors 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 level and day level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Summary statistics of institutional 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 of institutional investors

	(1) *propensity*	(2) *totvol*	(3) *nstock*	(4) *totshr*	(5) *Performance*
Mumbai×post	0.010	–74.025	0.031	–34.276	–0.397
	(0.006)	(92.248)	(0.039)	(311.468)	(0.560)
Institution FE	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes
Observations	1,356,576	1,356,576	1,356,576	1,356,576	45,257
Adj. R^2	0.349	0.719	0.839	0.723	0.201

Table 7: Algorithmic traders

This table reports changes in trading behavior and performance of individual investors that use algorithmic trading around the 2008 Mumbai attacks. All the variables are defined earlier. The regressions control for individual and day fixed effects. Standard errors are reported in parentheses and are double clustered at the individual level and day level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1) *propensity*	(2) *totvol*	(3) *nstock*	(4) *totshr*	(5) *Performance*
Mumbai×post	–0.014	–0.065	–0.031	–3.216	0.612
	(0.009)	(1.564)	(0.037)	(6.993)	(0.600)
Individual FE	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes
Observations	447,136	447,136	447,136	447,136	6,498
Adj. R^2	0.278	0.352	0.401	0.325	0.604

Table 8: Risk preference

Panels A and B report 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 Panel A, and sales in Panel B. Panel C reports the results on the propensity to trade risky stocks. *AvgVol* is a weighted average of the stocks' return volatility for all stocks traded by an individual during a day, weighted by the amount of each stock traded (multiplied by 10^4 for expositional convenience). *BuyVol* and *SellVol* are weighted averages of the stocks' return volatility for all stocks bought and sold by an individual during a day, weighted by the amount of each stock traded, respectively. The regressions control for individual and day fixed effects. Standard errors are reported in parentheses and are double clustered at the individual level and day level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Stock purchases

	(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
Time 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: Stock sales

	(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
Time 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 C: Trading risky stocks

	(1) *AvgVol*	(2) *BuyVol*	(3) *SellVol*
Mumbai×post	–0.264	–0.185	0.078
	(0.927)	(0.929)	(0.109)
Individual FE	Yes	Yes	Yes
Day FE	Yes	Yes	Yes
Observations	7,109,963	7,109,963	7,109,963
Adj. R^2	0.407	0.409	0.409

Table 9: Google Trend search activities on stock tickers

This table reports change in Google search activity on stock tickers for people in India and for those in Maharashtra around the 2008 Mumbai attacks. The dependent variable *attention* is the daily search activity on a given stock for India or Maharashtra. Keyword search activities that can be unrelated to stock trading are excluded, such as banking services, media, and telecommunication companies. Tickers with a generic meaning such as BANG, FACT, ROMAN, TAKE, MIC, and MAX are also excluded. Following Da, Engelberg, and Gao (2011), *attention* is scaled by the average attention measure for a given stock during the sample period to compute the abnormal attention level. *treated* is an indicator variable that is equal to one if search activity is from Maharashtra, and zero otherwise. The regression controls for stock and day fixed effects. Standard errors are reported in parentheses and are double clustered at the stock level and day level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1) *attention*
treated×post	–0.002
	(0.032)
Stock FE	Yes
Time FE	Yes
Observations	17,952
Adj. R^2	0.005

Table 10: 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 firm'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 and 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 level and day level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Stock performance

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

Panel B: Propensity to trade Mumbai stocks

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

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 29, 2008. The *x*-axis denotes calendar dates and the *y*-axis denotes search activities over time. Search activity 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.

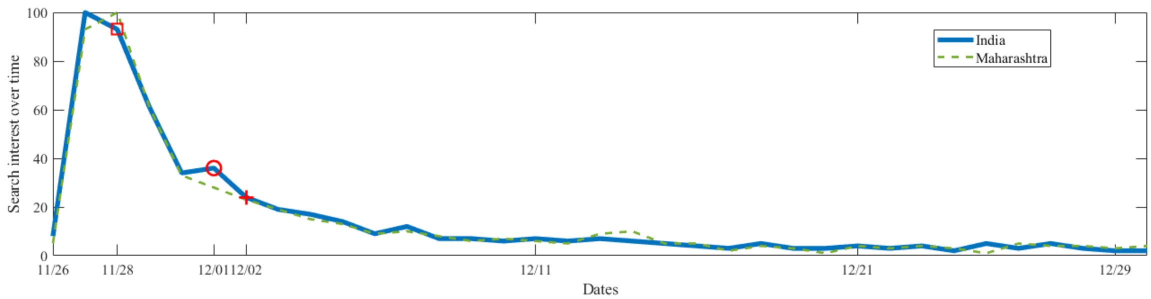


Figure 2: Dynamic treatment effects around the event date

This figure plots dynamic treatment effects (change in Mumbai traders' trading activity relative to other traders) around the event date of 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.

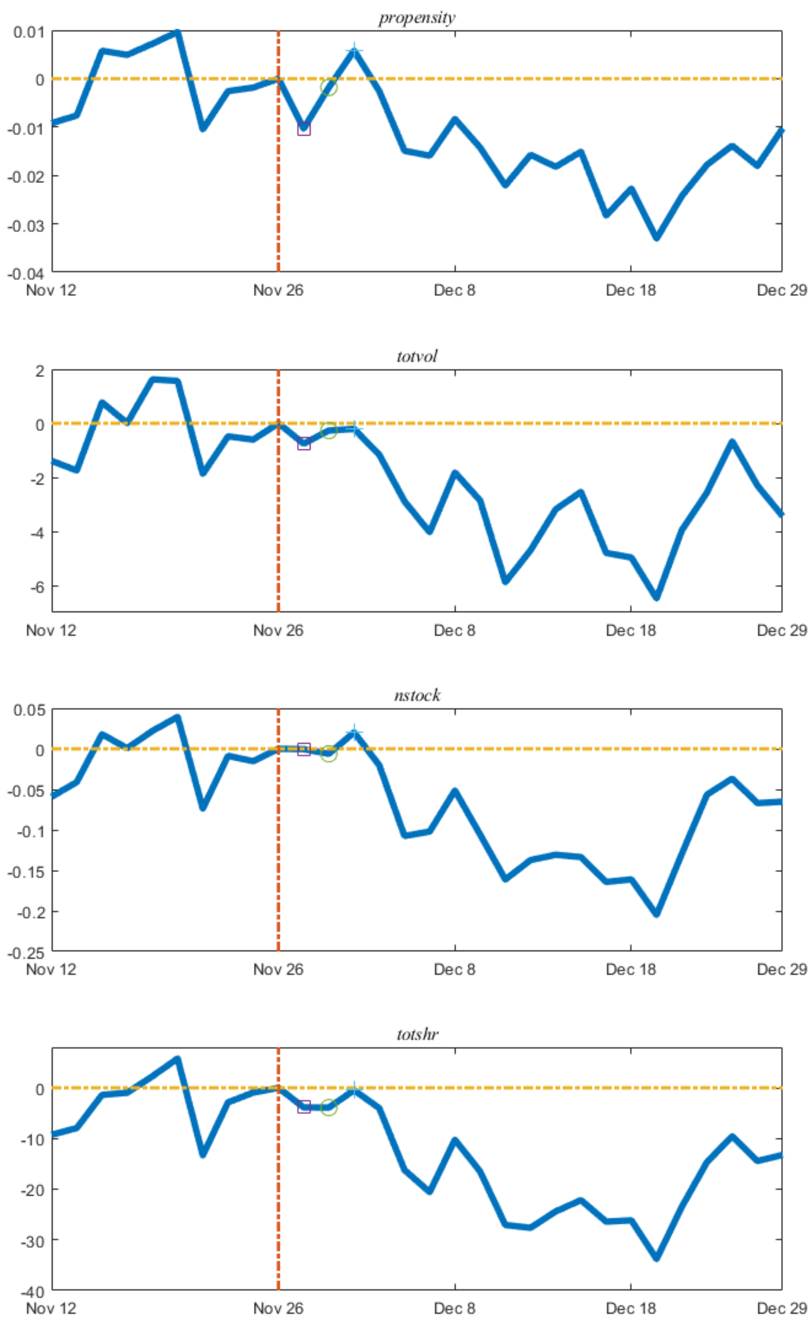
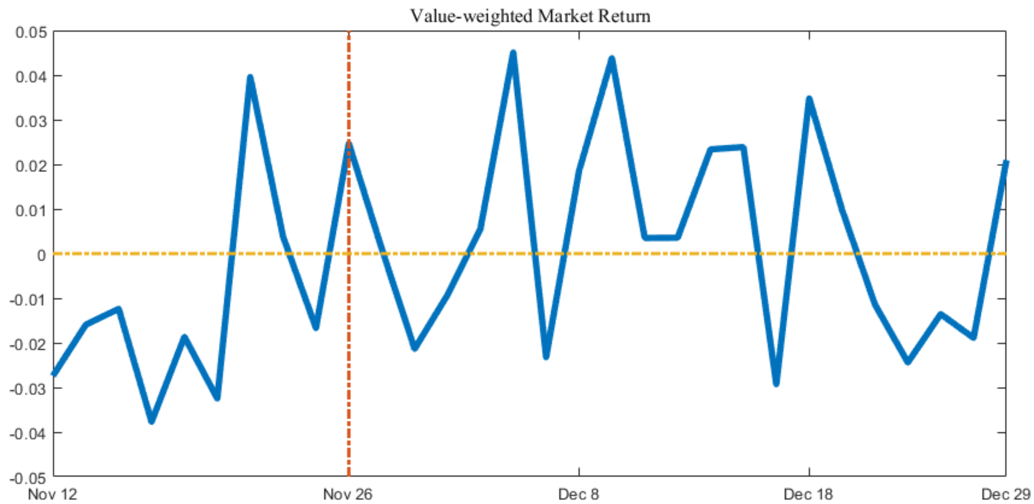


Figure 3: Stock market returns around the 2008 Mumbai attacks

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.



Online Appendix

Appendix A: Robustness of the change in trading activity

In this Appendix, we conduct several robustness checks for the change in trading activity we document in Table 2.

First, we use 10 trading days in the pre-event period to avoid any confounding effects of the global financial crisis and major Indian festival of Diwali. Table A1 extends the pre-period to 20 trading days and shows similar results.

Second, since the post-event period ends before December 29, there may be concerns about calendar effects such as tax-loss selling. However, unlike the U.S., the financial year ends on March 31st in India. Moreover, it is not obvious why Mumbai investors should trade differently for tax reasons compared to the controls. Table A2 shows that Mumbai investors do not trade differently around the placebo dates of November 26 in 2007 and 2009.

Third, Table A3 uses traders from nine other metropolitan cities in India (ranked by total population) as control group including New Delhi, Bangalore, Hyderabad, Ahmedabad, Chennai, Kolkata, Surat, Pune, and Jaipur, and shows our results are not driven by differential trading behaviors of investors in metropolitan areas.

Fourth, Table A4 takes the logarithmic transformation of the trading measures to allay concerns about skewness driving our results.

Fifth, we double cluster the standard errors at the individual and day levels throughout our analyses. Panel A of Table A5 shows that double clustering at the geographic region (i.e., zip code) and day levels has little impact on the standard errors.

Finally, throughout our analyses we use two-way clustering of standard errors as in Petersen (2009) and Thompson (2011). The two-way clustering of standard errors simultaneously accounts for any correlated standard errors for the same individual over time, and among different individuals at the same time. Petersen (2009) shows that the two-way clustering of standard errors is the most conservative method compared with alternative approaches. To further mitigate any concerns that our standard errors are understated, in Panel B of Table A5 we compute bootstrapped standard errors with 100 replications. Each replication is drawn with replacement and based on individual-level clusters. Consistent with Petersen (2009), the bootstrapped standard errors are smaller compared with those under two-way clustering. For example, the standard error for conditional trading volume *CONDvol* is understated by 18.6% (=1–1.273/1.564) using the bootstrap method compared with two-way clustering, and by 37.5% (=1–0.015/0.024) for the conditional number of shares traded *CONDshr*.

As further evidence of the conservative estimates of standard errors, note that many of our results are insignificant despite the large sample size, such as the parallel trend assumption (Panels C and D of Table 2), insignificant changes in trading activity and performance for those far away from Mumbai (Table 3 and Table 4), less significant attacks (Table 5), placebo samples of institutional investors and algorithmic traders (Tables 6 and 7), and placebo event dates (Table A2).

Table A1: 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 for 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 level and day level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

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
Time 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
Time 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: Placebo event dates

This table reports changes in individual traders' trading behavior around placebo event dates. Panel A uses November 26, 2007 as the placebo event date, and Panel B uses November 26, 2009 as the placebo event date. The regressions control for individual and day fixed effects. Standard errors are reported in parentheses and are double clustered at the individual level and day level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Trading activity 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
Time 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 activity 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
Time 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: Other major cities as controls

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 level and day level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	(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
Time 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: Logarithmic 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 level and day level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1) log(*totvol*)	(2) log(*nstock*)	(3) log(*totshr*)	(4) log(*CONDvol*)	(5) log(*CONDnum*)	(6) log(*CONDshr*)
Mumbai×post	–0.060***	–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
Time 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: Clustering of standard errors

This table reports changes in individual traders' trading behavior. In Panel A, standard errors are double clustered at the zip code level and day level. Panel B reports bootstrapped standard errors with 100 replications. The replications are drawn with replacement and based on individual-level clusters. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Region and day level double clustering

	(1) *propensity*	(2) *totvol*	(3) *nstock*	(4) *totshr*	(5) *CONDvol*	(6) *CONDnum*	(7) *CONDshr*
Mumbai×post	–0.015***	–2.826***	–0.082***	–14.376***	–5.594***	–0.102***	–28.958***
	(0.003)	(0.572)	(0.017)	(2.768)	(1.564)	(0.024)	(7.242)
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time 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	0.528	0.388	0.537	0.517	0.491

Panel B: Bootstrapped standard errors

	(1) *propensity*	(2) *totvol*	(3) *nstock*	(4) *totshr*	(5) *CONDvol*	(6) *CONDnum*	(7) *CONDshr*
Mumbai×post	–0.015***	–2.826***	–0.082***	–14.376***	–5.594***	–0.102***	–28.958***
	(0.001)	(0.238)	(0.004)	(0.761)	(1.273)	(0.015)	(7.077)
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time 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	0.528	0.388	0.537	0.517	0.491

Appendix B: Scientific evidence on chronic stress

Hans Selye developed a theory of chronic stress called General Adaptation Syndrome through a series of animal studies conducted in the early 19th century (see Selye (1946) for a survey of the related literature). The General Adaptation Syndrome involves three stages of alarm reaction, resistance, and restoration (Figure B1). The human body enters into the third stage only when stress is prolonged and extreme (Selye, 1976; McEwen and Sapolsky, 1995).

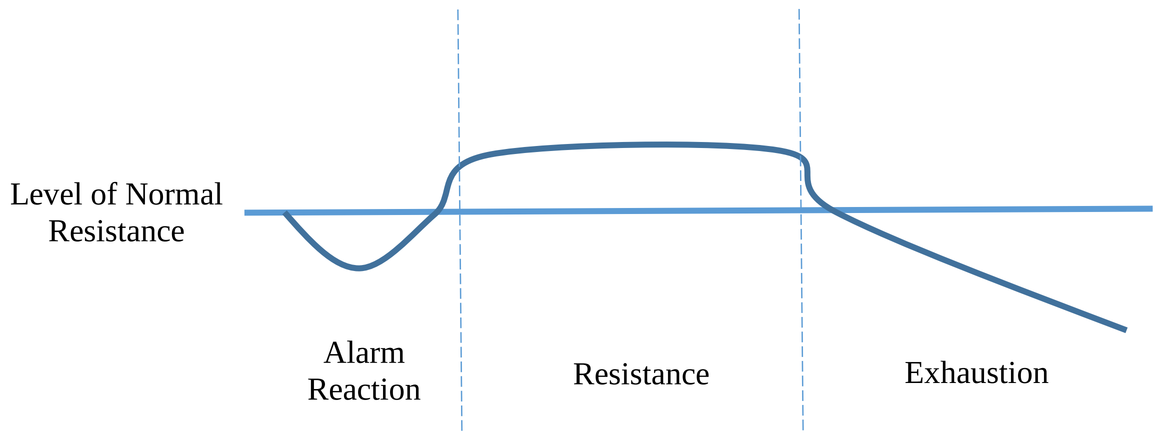
According to Selye (1946), the first stage lasts between a few minutes to 24 hours. Acute stress during this stage has mixed effects on cognition and may even enhance memory performance (e.g., "flashbulb memories" in Brown and Kulik, 1977). However, since the attacks we examine started on November 26, 2008 at around 20:00 Indian Standard Time which was after the stock market was closed, and the market was closed on November 27, 2008, investor response to acute stress during the first stage is not observable in our setting. Figure 2 shows that the second stage lasted for several days, and the third stage lasted at least for several weeks. In general, whether the body enters the third stage, and the durations of the second and third stages depend on the length and severity of stress exposures (Selye, 1976).

Later tests that involve human subjects show mixed evidence of immediate elevation of stress hormones that can even promote learning and memory functions (McEwen and Sapolsky, 1995; Lupien et al., 2007; Putman et al., 2010). In contrast, evidence on prolonged and significant stress exposure is less ambiguous and impairs cognitive abilities (Sapolsky 1996; de Kloet, Oitzl, and Joëls, 1999; Liston, McEwen, and Casey, 2009).

Recently, scientists use exogenous elevation of stress hormones to more precisely identify the effect of such hormones on cognitive abilities. Newcomer et al. (1999) give oral doses of cortisol to a group of treated subjects for four days and find significant impairment of memory performance on the fourth and tenth days after the first day of experiment, but no difference one day after the experience begins. Newcomer et al. (1994) find similar deferred effect of glucocorticoid on memory performance. Wolkowitz et al. (1990) observe impaired memory performance following 5 days of prednisone administration, but normal memory performance following an acute administration of dexamethasone. Kandasamy et al. (2014) artificially raise the test subjects' cortisol levels to analyze their financial choices. They find that immediately after an elevation of the hormone, there is no difference between the treated and the control group during the following day. However, the treated group becomes more likely to overweight small probability events during the seventh day of the test after prolonged exposure to high stress hormone levels. Our results on the dynamic treatment effect (Figure 2) support findings in these scientific studies that acute (hours) and chronic (days to weeks) stress have different effects on human behavior.

Figure B1: Three-stage stress theory of Hans Selye

This figure reproduces Figure 12 in Chapter 5 of Selye (1976). Facing a shock to stress, the body first generates alarm reaction, releases stress hormones and experiences a number of other physiological changes that can last between a few minutes to 24 hours (Selye, 1946). The body then adapts to the changes and tries to restore itself back to normal state during the resistance stage. Finally, after prolonged exposure to stress, adaption and restoration become unsuccessful and the body enters a stage of exhaustion.



Appendix C: Robustness tests on cognitive ability

C1: Information asymmetry and liquidity

Our main finding on the decline in trading activity is consistent with the hypothesis that violence-induced stress impairs traders' cognitive ability to perform trading tasks. However, it is possible that after the attacks, Mumbai investors trade more on stocks that have greater information asymmetry and require more cognitive skills to process. In this scenario, the overall cognitive ability demanded from the trading tasks may not decline. We investigate this possibility in Panel A of Table C1. First, we compute the Amihud (2002) measure of stocks (*Amihud*). The Amihud (2002) measure for a stock *k* is defined as:

$$Amihud_k = \frac{1}{N}\sum_{s=1}^{N}\frac{|R_{k,s}|}{P_{k,s} \times Vol_{k,s}}$$

where *s* is the index for days over a quarter, *N* is the number of trading days in the quarter, $R_{k,s}$ is the daily return of stock *k*, $P_{k,s}$ is the stock's closing price, and $Vol_{k,s}$ is the trading volume. The quarter we use to compute the Amihud (2002) measure does not overlap with our event period, i.e. the quarter ends one day before our sample starting date. This is to ensure that the Amihud measure does not change due to the attacks, although using a rolling window (i.e., for each day, use the prior 90 days) to compute the measure has no impact on our result. We then take 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 as a measure of information asymmetry for all stocks traded (*AvgAmihud*). Panel A of Table C1 shows an insignificant coefficient on *Mumbai*×*post*, i.e., Mumbai traders do not exhibit a greater propensity to trade stocks with more information asymmetry after the attacks.

Another possibility is that liquidity of Mumbai stocks went down after the attacks, which made them costlier to trade, and therefore hurt the performance of Mumbai investors. In Panel B of Table C1, we use the stock-level Amihud measure (*Amihud*) as a proxy for liquidity, and an indicator variable that is equal to one if a company's headquarter is located in Mumbai (*Mumstock*). We do not find evidence that the liquidity of Mumbai stocks went down after the attacks, as indicated by the insignificant coefficient on *post*×*Mumstock.*

C2*:* Alternative performance evaluation periods

In our main analysis, we compute the returns of each buy or sell trade from its trade execution date to the ending date of our sample period (December 29, 2008). To ensure that our performance results are not sensitive to the choice of end-date on which performance is computed, in this section we use alternative end dates that are 1, 3, and 6 months after December 29, 2008 on January 30, 2009, March 31, 2009, and June 30, 2009, respectively. After we compute the holding period returns for each trade, we follow the same procedure as in our main analysis to subtract the corresponding benchmark returns during the holding period, and value-weight all abnormal returns from buys and sells for each trader. Table C2 shows that our performance results are robust regardless of the end date chosen.

C3*:* High-volume traders

In Section 4.3, we argue that investors should pay significant attention conditional on trading due to the significant financial stakes. In this section, we further examine a subsample of individuals with high trading volume, i.e., traders whose aggregate trading activity is in the top quintile among all individual investors during our sample period. The minimum total trading volume for this group of traders is 5.02 million INR (around $102,094). Table C3 shows that conditional on trading such large amounts and likely involving significant attention on the stocks, Mumbai investors still trade less and perform worse after the attacks relative to the controls.

C4: Matched sample

In this section, we use a matched sample approach based on entropy matching to further control for any difference in trading activity and performance for treated and controls. Entropy balancing generalizes the traditional propensity score matching and achieves significantly improved matching between the treatment and control groups (Abadie, Diamond, and Hainmueller, 2010; Hainmueller, 2012). Unlike the propensity score matching where an observation in the control group is either retained or dropped, entropy balancing assigns a continuous set of weights to the controls and generates synthetic counterfactuals that match much more closely to the treatment. We report the results in Table C4. In each regression, the treatment and controls are matched on the corresponding dependent variable (e.g., in Column (1) of Panel A the treatment and synthetic controls have the same pre-event *propensity*).

Table C1: Information asymmetry

Panel A reports the average Amihud (2002) measure of stocks traded for a given individual during a day. The dependent variable *AvgAmihud* 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 (multiplied 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 level and day level. Panel B reports results on the change in stock-level information asymmetry around the 2008 Mumbai attacks using stock-day observations. Dependent variable *Amihud* is the stock-level Amihud (2002) measure. *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. Standard errors are reported in parentheses and are double clustered at the stock level and day level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Trading stocks with more information asymmetry

	(1) *AvgAmihud*
Mumbai×post	0.002
	(0.036)
Individual FE	Yes
Time FE	Yes
Observations	9,129,580
Adj. R^2	0.316

Panel B: Stock liquidity

	(1) *Amihud*
post×Mumstock	–0.230
	(0.783)
Stock FE	Yes
Time FE	Yes
Observations	29,186
Adj. R^2	0.956

Table C2: Alternative performance evaluation periods

This table 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 January 30, 2009, March 31, 2009, and June 30, 2009 in Columns (1), (2), and (3), respectively. DGTW (Daniel et al., 1997) benchmark return is subtracted from the holding period return to calculate abnormal return for a trade. DGTW benchmarks are 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. 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 value-weighted by the amounts 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*). *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. The regressions control for individual and time fixed effects. Standard errors are reported in parentheses and are double clustered at the trader level and time level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1) *Performance*	(2) *Performance*	(3) *Performance*
Mumbai×post	–0.962***	–0.770***	–2.118***
	(0.100)	(0.129)	(0.529)
Individual FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
Observations	1,872,873	1,872,834	1,871,780
Adj. R^2	0.219	0.348	0.296

Table C3: High-volume traders

Panels A and B report changes in trading behavior and performance for a subsample of individual investors whose aggregate trading activity is in the top quintile among all individual investors during our sample period. All the variables are defined earlier. The regressions control for individual and day fixed effects. Standard errors are reported in parentheses and are double clustered at the individual level and day level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Trading activity of high-volume traders

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	propensity	*totvol*	*nstock*	*totshr*	*CONDvol*	*CONDnum*	*CONDshr*
Mumbai×post	–0.015***	–8.000***	–0.182***	–38.195***	–16.950**	–0.113**	–67.499**
	(0.003)	(2.283)	(0.041)	(7.997)	(6.438)	(0.054)	(27.502)
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	9,385,760	9,385,760	9,385,760	9,385,760	2,166,676	2,166,676	2,166,676
Adj. R^2	0.296	0.393	0.456	0.306	0.420	0.461	0.393

Panel B: Trade performance of high-volume traders

	Performance
Mumbai×post	–0.746***
	(0.114)
Individual FE	Yes
Time FE	Yes
Observations	393,500
Adj. R^2	0.435

Table C4: Matched sample

Panels A and B report changes in trading behavior and performance of individual investors around the 2008 Mumbai attacks. In each regression, the treatment and controls are matched on the corresponding dependent variable using the entropy balance approach (Hainmueller, 2012). For example, in Column (1) of Panel A, the treatment and synthetic controls have the same pre-event *propensity*. The regressions control for individual and day fixed effects. Standard errors are reported in parentheses and are double clustered at the individual level and day level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Trading activity of individual traders

	(1) *propensity*	(2) *totvol*	(3) *nstock*	(4) *totshr*	(5) *CONDvol*	(6) *CONDnum*	(7) *CONDshr*
Mumbai×post	–0.016***	–2.995***	–0.083***	–15.566***	–5.089***	–0.120***	–28.875***
	(0.003)	(0.560)	(0.017)	(2.710)	(1.609)	(0.025)	(7.513)
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time 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	0.334	0.438	0.520	0.368	0.556	0.523	0.500

Panel B: Trade performance of individual traders

	Performance
Mumbai×post	–0.372***
	(0.100)
Individual FE	Yes
Time FE	Yes
Observations	1,872,942
Adj. R^2	0.279

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