

Negative Sentiment and Aggregate Retail Trading: Evidence from Mass Shootings*

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Abstract

I analyze the role of sentiment in aggregate retail investors' trading activity. Using mass shootings as exogenous, non-economic and negative shocks to investor sentiment, I find that retail investors on average net sell stocks of firms headquartered in the states where mass shootings took place in the previous week ("local stocks"). During the week after mass shootings, the average decrease in daily retail share volume order imbalance for local stocks is around 8% of the sample mean. Consistent with lower sentiment-driven trading, the retail net divestment from local stocks increases in the number of victims from mass shootings, and is more pronounced following unsolved shootings and shootings with teenager victims. Consistent with predictions from sentiment models, local stocks earn lower returns only in the week after shootings. Finally, institutional investors do not react to mass shootings, which suggests that retail investors are more prone to sentiment.

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1 Introduction

Retail investors are important participants in the U.S. equity market. As a group, they are becoming more active and gaining more market power. According to data from Bloomberg, retail trading accounted for 10% of U.S. equity trading volume in 2010. The number grew to almost 25% in 2021, which was larger than the share of mutual funds or hedge funds.¹ Given the increasing presence of retail investors and the academic evidence that they can move stock prices,² it is crucial to understand the determinants of aggregate retail investors' trading decisions.

The conventional wisdom from the literature on investor sentiment is that retail investors are noise traders who are subject to shifts in sentiment (De Long et al., 1990; Lee et al., 1991; Shleifer and Summers, 1990). In the presence of limits to arbitrage, such sentiment-driven traders push prices away from fundamental values and create higher volatility in the short run. While many academic studies focus on the return implications of both economic and non-economic shocks to investor sentiment,³ very few examine how the trading behavior of aggregate retail investors is affected by sentiment. In this paper, I fill the gap and investigate the role of sentiment in aggregate retail trading.

To measure daily buying and selling activity of aggregate retail investors, I use the algorithm proposed by Boehmer et al. (2021) (BJZZ, hereafter). BJZZ explores market microstructure features and identify retail trades of each common stock through the price improvement they receive from wholesalers (see Section 2.1 for details). One key advantage of using BJZZ's algorithm to study aggregate retail trading is that it captures order flows generated by a large population of retail investors, rather than small subsets.⁴ Moreover,

¹See <https://www.ft.com/content/7a91e3ea-b9ec-4611-9a03-a8dd3b8bddb5>, and <https://www.bnymellonwealth.com/articles/strategy/the-rise-of-retail-traders.jsp>.

²Barber et al. (2008), Kaniel et al. (2008), as well as some other studies, conclude that retail buying (selling) can reliably predict higher (lower) returns in the short run.

³For economic-induced sentiment and asset pricing implications, see Baker and Wurgler (2006), Baker and Wurgler (2007), Da et al. (2015), among others. For non economic-induced sentiment, see Edmans et al. (2007, 2022), Hirshleifer and Shumway (2003), Kaplanski and Levy (2010), among others.

⁴Many existing studies use proprietary brokerage account-level data, data from a single wholesaler, or

the algorithm captures retail flows for a large cross-section of publicly traded common stocks in the U.S. (more than 3000 common stocks on each day), which allows researchers to draw general conclusions about the overall retail trading behavior.

I use mass shootings in the U.S. as non-economic shocks to investor sentiment. Mass shootings are suitable as shocks to sentiment for several reasons. First of all, mass shootings take place frequently in the U.S. Based on data from Gun Violence Archive,⁵ there were more than 3000 shootings during 2013 and 2021 in which 4 people (excluding shooters) were injured or killed by the use of firearm. Secondly, these events are salient and are able to catch widespread attention, as they are often extensively covered in news (Smart and Schell, 2021). Moreover, mass shootings are shown to be random and hard to predict (Brodeur and Yousaf, 2019; Luca et al., 2020). Finally, mass shootings are extremely negative events that generate pessimism, emotional stress and fear. Evidence from finance and psychology literature shows that people who are aware of mass shootings and terrorist attacks become more pessimistic in risk assessment in unrelated domains, with a higher level of pessimism from people located closer to the incidents (Lerner and Keltner, 2001; Lerner et al., 2003; Cuculiza et al., 2021). Moreover, people tend to view places where mass shootings occurred more negatively and avoid being physically present in such places.⁶

In this paper, I study the impact of mass shootings on aggregate retail investors' daily trading activity. Motivated by theoretical predictions that retail investors are sentiment traders, as well as evidence that people tend to become pessimistic following mass shooting and develop negative attitudes toward places where shootings occurred, I posit that retail investors would on average divest from local stocks after mass shootings in an area. In this setting, I define "local" stocks as stocks of firms headquartered in the same state where mass shootings took place, as these firms are physically close to shootings. The idea is that,

small trade size as proxies for retail trading activity. See BJZZ for an overview of these studies and the issues of using these data.

⁵See <https://www.gunviolencearchive.org/>.

⁶See <https://www.apa.org/news/press/releases/2019/08/fear-mass-shooting>.

driven by lower sentiment from mass shootings and more negative views toward places of the shootings, aggregate retail investors would trade and allocate their capital away from local stocks.

Using a list of more than 3000 mass shootings in the U.S. from 2013 to 2021, I find that aggregate retail investors net sell local stocks during the week after the presence of local mass shootings. Following mass shootings in a state, retail investors on average sell more shares and place more sell trades of local stocks. This finding suggests that retail investors indeed divest from local stocks after local mass shootings. The net-selling effect is also large in magnitude. The daily retail share volume order imbalance, defined as the normalized difference between daily share volume of retail buy trades and sell trades, decreases about 8% of the sample mean during the week after local mass shootings. This is comparable to the change in daily retail share volume order imbalance following large Earnings Per Share (EPS) revisions documented in [McLean et al. \(2020\)](#). Moreover, using Google search volume data, I find that users actively search and acquire information about mass shootings on Google, which implies that retail investors likely pay close attention to mass shootings, and the main net-selling effect is plausible and not spurious correlation. Finally, through various robustness tests, I show that the main net-selling effect is not driven by empirical specification, different subsamples, holidays, or stocks/shootings in individual states.

Next, I examine whether the net retail divestment from local stocks is driven by lower sentiment due to mass shootings. If retail investors are affected by sentiment, then the net retail divestment should be stronger following local shootings that are more severe and tragic. I find evidence in support of this argument. Exploiting shooting-level heterogeneity, I show that retail investors net sell local stocks more intensely after local shootings with more victims. Moreover, the net outflows from local stocks is larger in response to shootings in which the suspects have not been arrested and teenagers were involved as victims. These results are consistent with more damaging shootings generating a higher level of pessimism, leading to larger retail divestment. In terms of return predictability, I find that local stock

returns indeed move in the direction of investor sentiment induced by mass shootings in the short-run. Specifically, local stocks earn lower daily returns only in the week following local mass shootings, but not in future weeks. This temporary mispricing aligns with the predictions from sentiment models in the literature.

In the final test, I explore institutional investors' buying and selling decisions following the same set of mass shootings. While retail investors are viewed as uninformed and sentiment-driven traders, institutional investors are often believed to be much more sophisticated and rational (De Long et al., 1990; Griffin et al., 2003). If such beliefs hold true, then institutional investors should not exhibit meaningful variations in their trading activity in response to mass shootings. To identify institutional order flows, following Farrell et al. (2022) and Mohr (2021), I apply Lee and Ready (1991) algorithm to sign each equity transaction as buy or sell transaction. Institutional buy (sell) flows are defined as the difference between buy (sell) flows and retail buy (sell) flows. The regression results show that local mass shootings have neither economically meaningful nor statistically significant impact on institutional investors' trading activity in local stocks. Therefore, the analysis implies that retail investors are more prone to sentiment when making trading decisions.

This paper contributes to several strands of literature. First of all, I extend the existing literature on investor sentiment. A vast majority of prior studies focus on the impact of investor sentiment on asset returns. The popular and common finding is that asset returns move in the direction of investor sentiment in the short run, and reverse to fundamental values in the long run. However, in this paper, I take a close look at the impact of sentiment on the daily buy and sell decisions of a large group of investors. Using mass shootings in the U.S. as a laboratory, I provide suggestive evidence that sentiment is not only an important driver of stock returns, but also a crucial determinant of aggregate retail investors' daily equity allocation decisions.

Secondly, I add to the literature that explores retail investors' trading behavior. Prior

research use proprietary data from specific brokerages, wholesalers, and exchanges to study retail traders' portfolios and draw several conclusions. For example, [Barber and Odean \(2008\)](#) argue that individual investors are net-buyer of attention-grabbing stocks. [Barber et al. \(2009\)](#) find that individual investors systematically lose money in their portfolios. Using data from a U.S. wholesaler, [Kelley and Tetlock \(2013\)](#) conclude that retail investors' net-buying activity has return predictability. However, the problem with using proprietary datasets is that only small subsets of retail order flows are studied ([Boehmer et al., 2021](#)), which limits one's ability to generalize findings. In this paper, I exploit an algorithm that identifies granular trading activity in a comprehensive range of stocks by a broad population of retail investors. This approach allows me to study how sentiment, induced by mass shootings across the U.S., affects aggregate retail investors' decision to trade local stocks.⁷

Finally, my findings shed light on the implications of mass shootings and terrorist attacks on financial markets. [Cuculiza et al. \(2021\)](#) and [Chen et al. \(2021\)](#) find that sell-side analysts and corporate managers who are close to terrorist attacks tend to issue more pessimistic earnings forecasts. Moreover, [Antoniou et al. \(2017\)](#) conclude that managers who experience terrorist attacks adopt more conservative corporate policies. In this paper, using a more comprehensive sample of mass shootings, I study retail investors trading behavior and show that retail investors divest from local stocks following local mass shootings. In a related paper, [Agarwal et al. \(2019\)](#) uses 2008 Mumbai terrorist attacks as a natural experiment and explore the impact of stress on investors' stock trading activity in India. Another related paper ([Wang and Young, 2019](#)) uses survey data and 1991-1996 account-level trading data from a brokerage to study changes in households' stock market participation and trading activity in response to terrorist attacks. Both studies find that retail investors who are close to terrorist attacks trade less and are less likely to trade new stocks/enter stock market. My paper differs from the above two studies in three important aspects. (1) Instead of digging

⁷For a list of papers that use BJZZ's algorithm to study retail investors, see [Chang et al. \(2022\)](#), [Farrell et al. \(2022\)](#), [Liaukonytė and Žaldokas \(2022\)](#), [McLean et al. \(2020\)](#), [Mohr \(2021\)](#), among others.

into local retail investors’ portfolios and stock market entry/exit choices, I focus on a large population of retail investors’ daily trading decisions targeting stocks local to mass shootings. (2) With a comprehensive dataset covering thousands of mass shootings, I exploit shooting-level heterogeneity (different types of shootings) and trace out corresponding variations in aggregate retail investors’ buying and selling behavior. (3) I compare the trading activity of retail and institutional investors in reaction to mass shootings and offer evidence that only retail traders are subject to sentiment in this setting. Overall, my findings suggest that mass shootings influence retail investors’ trading activity and local stock returns.

The remainder of the paper is organized as follows. In Section 2, I describe the data and construction of the key variables. In Section 3, I discuss the baseline findings and robustness checks. In Section 4, I conduct additional tests and provide evidence in support of sentiment-driven trading by retail investors. Section 5 briefly summarizes the findings and concludes the paper.

2 Data

I obtain data from several sources. The measures for retail trading activity come from Trade and Quote (TAQ) Millisecond Daily Files. Data on mass shootings in the U.S. is collected from Gun Violence Project (GVA). I use CRSP and Compustat to construct stock characteristics. Finally, state-level economic conditions are from U.S. Bureau of Economic Analysis (BEA). Section 2.1 to Section 2.3 describe each data source in detail and the construction of variables. Section 2.4 presents descriptive statistics.

2.1 Retail Investors Trading Activity

I follow BJZZ in identifying retail investor’s trading activity. According to BJZZ, most retail equity orders in the U.S. are executed off-exchange. Under regulation, such executions are

usually reported to a FINRA TRF (Trade Reporting Facility), and are included in TAQ “consolidated tape” (with exchange code “D”). After retail investors place equity trade orders, brokers can choose to internalize these orders via their own inventory, or route them to wholesalers for execution. In order to incentivize brokers to route orders, wholesalers often provide retail traders with some price improvement, in a small fraction of a penny, relative to the National Best Bid or Offer (NBBO).⁸ Importantly, as regulated by Regulation NMS (National Market System), institutional orders do not enjoy any subpenny price improvement. Instead, they are executed on exchange or in dark pools, either at whole or half-penny increments. Therefore, one can distinguish retail equity trades by examining the price improvement they receive.

The sample period is from January 1st, 2013 to December 31st, 2021. For each day, I keep all off-exchange trades (with an exchange code of “D”) from TAQ Millisecond Daily Files. I only consider common stocks with a share code of 10 and 11 in CRSP that are listed on NYSE, AMEX, and NASDAQ. To avoid influence from stocks with very low price, I drop all trades that have transaction price below \$1. Consistent with the aforementioned subpenny price improvement in retail orders, retail buy trades tend to have transaction prices that are slightly below a round penny, whereas retail sell trades have transaction prices that are slightly above a round penny. Following BJZZ, for each remaining trade of stock i at time t , I calculate the fraction of a penny associated with the transaction price, Z_{it} , as $Z_{it} = \text{mod}(P_{it}, 0.01)$, where P_{it} is the transaction price in TAQ.⁹ Based on values of Z_{it} , I define retail buy trades as trades with $Z_{it} \in (0.6, 1)$, and retail sell trades as trades with $Z_{it} \in (0, 0.4)$. I exclude trades that are executed at the whole penny ($Z_{it} = 0$) and around a half-penny ($Z_{it} \in [0.4, 0.6]$), since these trades are likely to be institutional trades.¹⁰

⁸The common amount of price improvement for a retail order is 0.01, 0.1, and 0.2 cent (Boehmer et al., 2021).

⁹ Z_{it} is the remainder of P_{it} divided by 0.01.

¹⁰While this method could leave out some retail trades that take place on exchanges or at the mid-quote, BJZZ and Farrell et al. (2022) argue that it “probably picks up a majority of the overall retail trading activity”.

After identifying retail buy and sell trades for stock i at time t throughout each trading day, I perform aggregation and calculate the following four variables for stock i on trading day t : $Mrbvol_{i,t}$ is the total share volume of retail buy orders, $Mrsvol_{i,t}$ is the total share volume of retail sell orders, $Mrbtrd_{i,t}$ is the number of retail buy trades, and $Mrstrd_{i,t}$ is the number of retail sell trades. In the final step, I compute retail order imbalances in order to capture the net-buying activity by retail investors. Specifically, for stock i on trading day t , I define the following order imbalance measures, in percentage:

$$Mroibvol_{i,t} = \frac{Mrbvol_{i,t} - Mrsvol_{i,t}}{Mrbvol_{i,t} + Mrsvol_{i,t}} \quad 100 \quad (1)$$

$$Mroibtrd_{i,t} = \frac{Mrbtrd_{i,t} - Mrstrd_{i,t}}{Mrbtrd_{i,t} + Mrstrd_{i,t}} \quad 100 \quad (2)$$

where $Mroibvol_{i,t}$ measures retail investors' net-buying activity, based on share volume. $Mroibtrd_{i,t}$ measures retail investors' net-buying activity, based on the number of trades. $Mroibvol_{i,t}$ and $Mroibtrd_{i,t}$ measure the extent to which aggregated retail investors are net-buyers ($Mroibvol_{i,t} > 0$ and $Mroibtrd_{i,t} > 0$) or net-sellers ($Mroibvol_{i,t} < 0$ and $Mroibtrd_{i,t} < 0$) of stock i on trading day t .

2.2 Mass Shootings

I assemble a list of mass shootings incidents that took place during 2013 and 2021 in the U.S. from Gun Violence Archive (GVA), an independent research group that aims to provide objective data on gun violence in near real-time.¹¹ GVA hosts a group of 20 researchers who actively collect information related to gun violence cases from over 7500 law enforcement, media, government and commercial sources. The maintained database from GVA is constantly updated, often on a daily basis, as new information about each case reveals. Important to this paper, GVA also makes the effort to guarantee that each case is validated and covered

¹¹The mass shootings data can be downloaded here: <https://www.gunviolencearchive.org/reports>

by at least 1 verifiable news article/report.¹² This provides assurance in the sense that at least some retail investors are aware of each mass shootings included in GVA database.

While there is no universal definition on what constitutes a “mass shooting”, organizations such as FBI as well as many data providers tend to define a mass shooting as an incident in which 4 or more people are killed by the use of firearms and no distinct periods between murders (Luca et al., 2020; Smart and Schell, 2020).¹³ However, there are potential concerns with this definition. With an emphasis solely on the number of fatalities, a large number of devastating shootings incidents are simply ignored.¹⁴ This would also be problematic in paper, because such incidents could also attract much attention from the public and thus are likely to alter sentiment. Therefore, to take into account a broader picture of severe gun violence in the U.S., I follow GVA and define a “mass shooting” as an incident in which at least 4 people are killed or non-fatally injured by the use of firearms, excluding the shooter.¹⁵ Unlike many other data providers, the definition of mass shootings in GVA is purely numerical, with no discrimination against the types of shootings (public, private, the relationship between shooters and victims, gang-related, etc).¹⁶ The objective is to capture a comprehensive set of attention-grabbing mass shootings incidents and understand retail investors’ reaction in terms of equity trading.

For each mass shooting included in GVA database, I collect information on the exact date of the shooting, the state where the shooting took place, the number of people injured, killed, as well as various shooting-level characteristics (whether the suspects have been ar-

¹²See <https://www.gunviolencearchive.org/methodology> for details regarding GVA’s data collection processes and methodologies

¹³For an overview of available mass shootings/gun violence databases, see Smart and Schell (2020).

¹⁴Consider a somewhat extreme but completely possible scenario: only 1 person is killed but 12 are injured. Such an incident would not be counted as a “mass shooting” by the popular definition. However, ex ante, it is hard to argue that such incident is any less serious/ominous than compared to an incident in which, say, 4 people are killed.

¹⁵Counting the number of people shot and killed rather than only killed also removes the role of progress in modern medical care system. See <https://massshootingtracker.site/about/> for details of this argument.

¹⁶Some other popular data providers on mass shootings employ screening on the types of shootings. For example, Mother Jones and Mass Shooter Database exclude armed robbery and gang violence related shootings.

rested, whether teenagers are victims, etc). For shootings that happened in the same state on the same day, I aggregate the casualties and count them as one incident. For shootings happened on Saturdays and Sundays, I shift the event dates to the next Monday, in order to match with retail trading activity and stock-level characteristics.¹⁷ In the end, my sample has a total of 3296 mass shootings between 2013 and 2021.

Figure 1 (a) plots the distribution of mass shootings across states during the sample period. For each state, I calculate the total number of shootings. A darker red color indicates more shootings incidents in a state. Other than mid-west and northern regions, shootings were fairly evenly distributed across states, which is consistent with Zhang (2019).¹⁸ Figure 1 (b) and (c) show a breakdown of mass shootings by sample year. Both the number and the severity of shootings (measured by the total number of injuries and deaths) increased gradually from 2013 to 2019 (with a small peak in 2016 and 2017). Notably, since 2020, both metrics have exploded. Figure 1 (d) plots the number of mass shootings by month. There were more cases during summer, compared to other seasons, which suggests a clear seasonality in mass shootings frequency. Table 1 presents more detailed information on shootings frequency and related casualties.

2.3 Stock and State Characteristics

I construct multiple stock-level characteristics. For each sample stock on each day, from CRSP, I calculate its previous 5 days (1-week) compounded returns ($Return_{i,w-1}$), returns at the previous month end ($Return_{i,m-1}$), and returns in the past 6 month ($Return_{i,m-2,m-7}$). All return variables are in percentage. Moreover, I obtain the natural logarithm of market capitalization at the previous month end ($Log_Size_{i,m-1}$). The realized return volatility ($Volatility_{i,m-1}$) is defined as the standard deviation of daily returns in the previous month. The turnover ($Turnover_{i,m-1}$) is defined as the ratio between trading volume and the num-

¹⁷Retail trading and daily stock returns are only available on trading days, which are weekdays.

¹⁸Zhang (2019) focuses on shootings with more than 4 people killed.

ber of shares outstanding in the previous month. From Compustat, I obtain the natural logarithm of the book-to-market ratio ($Log_BM_{i,m-1}$). To alleviate the impact of outliers, all stock-level characteristics are winsorized at the 1st and 99th percentile.

Several studies on gun violence find that mass shootings are fairly random and unpredictable to a large extent.¹⁹ Brodeur and Yousaf (2019) and Luca et al. (2020) find that local economic distress is the only significant predictor for mass shootings. Therefore, to proxy for local economic conditions and dynamics, I construct the natural logarithm of personal income per capita in the previous year ($Log_Pinc_{s,y-1}$) and the past-year real GDP per capita percentage growth rate ($GDP_Growth_{s,y-1}$) for each state. All state-level data come from U.S. Bureau of Economic Analysis (BEA).

To merge retail trading activity and stock-level characteristics. I use TAQ-CRSP linking table and CCM, both provided by WRDS. The combined sample is further merged with mass shootings data by states where firms' headquarters are located in and where the shootings took place.²⁰ Firms with missing headquarter state information in Compustat are dropped. In the end, the above sample is merged with state-level economic conditions. The final sample has 6396385 stock-day pairs. In each year, there are about 3000 unique stocks.

2.4 Summary Statistics

Table 2 presents summary statistics on key variables. Panel A shows that the average order imbalances are slightly negative (The mean for $Mroibvol_{i,t}$ and $Mroibtrd_{i,t}$ is -2.009% and -0.863%, respectively). This indicates that retail investors in my sample net sell a given stock on average. This is consistent with BJZZ and Kaniel et al. (2008), which studies earlier

¹⁹For example, factors such as political affiliations of the states, gun-control laws, and population composition cannot predict the occurrence of mass shootings (Luca et al., 2020).

²⁰Data on sample firms' headquarter states is reported in Compustat. However, about 2-3 % of Compustat firms change their headquarter states every year (<https://mingze-gao.com/posts/firm-historical-headquarter-state-from-10k/>). In untabulated results, I use the historical headquarter states information (adjusted for relocations) from SEC 10K/Q filings and find that the main findings hold.

periods and find that retail sells are more prevalent than retail buys.

The average weekly, monthly, and previous 6-month returns are 0.262%, 1.284%, and 8.326%, respectively. The average firm has a market capitalization of \$993.267 million, and a book to market ratio of 0.4. The average personal income per capita in a state is \$52944.53, and the real GDP grows at the rate of 1.66% annually.

3 Main Results

3.1 Attention on Mass Shootings

The baseline question I aim to investigate in this paper is whether retail investors' equity trading behavior in local stocks is affected by the presence of local mass shootings. Before attempting to answer the above question, it is important to first understand whether retail investors pay attention to gun violence and mass shootings at all. Suppose retail traders are not aware of/do not care about such incidents, it would be meaningless to dig into their trading decisions following mass shootings, since any results would be spurious correlation. Therefore, as the first step of analysis, I examine retail investors' attention on mass shootings incidents.

While it is hard to directly quantify retail investors' attention, it is possible to measure the revealed attitude of an arguably broader population, which at least overlaps with the group of retail investors. Specifically, I use Google Search Volume Index (SVI) of the term "shooting" to proxy for the amount of public attention on mass shootings. The underlying idea here is that, if the Google search volume of the term "shooting" is highly positively correlated with mass shootings severity, then retail investors, especially those who regularly use Google search engine, are very likely to be aware of mass shootings. This would further increase the plausibility of the conjecture that retail investors might adjust their equity trading decisions because of mass shootings.

Google SVI has been used in multiple academic studies to measure investor attention, information production, and sentiment (Da et al., 2011, 2015; Michaelides et al., 2019; Zhang, 2019). Published by Google Trends,²¹ Google SVI reports the frequency of all terms that users around the world ever searched on Google since 2004. The data can be filtered by geographic locations (countries, states, and counties), time period, and specific Google search tabs (“News”, “Images”, “Videos”, etc). The search volume is scaled by the time series maximum value (always assigned to be 100) within the selected geographic location, time period and search tab.²² Despite the unique way Google SVI is constructed, a larger SVI value corresponds to a higher search volume, which implies more attention on a specific topic.

I download both national and state-level Google SVI of the term “shooting” from January 2013 to December 2021. Also, I collect Google News SVI of the same term during this period. To proxy for mass shootings severity, I use the natural logarithm of the monthly count of injuries (Log_Injury_m), deaths (Log_Death_m), and victims (Log_Victim_m) from GVA database.²³ Table 3 Panel A shows the results from regressing national SVI on each one of the three mass shootings variables defined above. In each regression, I also control for SVI from the previous month. In column (1) to (3), the dependent variable is the SVI for general search of “shooting”. In column (4) to (6), the dependent variable is the SVI for news search of “shooting”. Across columns, the coefficients on Log_Injury_m , Log_Death_m , and Log_Victim_m are all positive and statistically significant at 1% level. There are two possible interpretations. First, people search more actively for information on mass shootings if shootings have a larger negative impact. Second, simply more people become aware of mass shootings when shootings are more deadly. Regardless of the exact interpretation,

²¹<https://trends.google.com/trends/?geo=US>.

²²For example, for the term “shooting” under the general search engine during the sample period, SVI in the U.S., is equal to 100 in October 2017, indicating that Google users searched “shooting” most frequently in this month, compared to rest of the period. In October 2017, a mass shooting that injured and killed over 500 people took place in Las Vegas, Nevada.

²³The count of victims equals the count of injuries and the count of deaths from mass shootings.

the key message from Table 3 Panel A is that Google users do pay close attention to mass shootings. Moreover, they pay relatively more attention if shootings caused more deaths.²⁴ Notice that not only do people search for mass shootings using the general search engine, they also learn about such incidents through news.

In addition to national-level data, Google also provides SVI data at the state-level. The search volume in each state would be determined by the frequency of a term searched by residents located only in that specific state. To provide support that the previous finding is not driven by search volume coming from a specific geographical area, I take a more granular look at the search behavior of residents within each state in response to local mass shootings. Specifically, I regress each state’s monthly SVI of “shooting” on the natural logarithm of the monthly count of injuries, deaths and victims from mass shootings that took place in the same state. Table 3 Panel B shows the results. In each regression, I control for state-level SVI from the previous month and include state and month fixed effects. The results indicate that people from a certain state actively acquire information regarding local mass shootings, and they increase their search activity if shootings are more deadly. Moreover, news articles serve as a channel through which local residents understand local shootings.

In conclusion, results from Table 3 suggest that Google users actively keep track of mass shootings. Although it is probably true that not all retail investors search on Google, it is reasonable to expect that at least a decent number of retail investors pay close attention to mass shootings and might factor such information into their equity trading decisions.

3.2 Mass Shootings and Retail Trading Activity

In this section, I directly analyze the impact of local mass shootings on retail investors’ trading behavior in local stocks. It is *ex ante* unclear how retail investors would react to mass shootings in a geographical area. On one hand, to the extent that retail investors

²⁴The coefficient of Log_Death_m is the largest among coefficients of all three independent variables on mass shootings severity.

are net-buyers of attention-grabbing stocks (Barber and Odean, 2008; Barber et al., 2022) and mass shootings bring more spotlight to firms in close proximity, retail investors might on average net purchase local stocks following local mass shootings. On the other hand, research on investor sentiment suggests that retail investors are noise traders who are subject to sentiment shifts (De Long et al., 1990; Lee et al., 1991; Shleifer and Summers, 1990). If mass shootings in an area make retail investors more pessimistic, it would imply that retail investors might net sell local stocks in response to local mass shootings.

To empirically examine the impact of local mass shootings on retail investors’ trading patterns, I estimate Equation 3 using panel regression with fixed effects:

$$Mroib_{i,s,t} = \alpha + \beta \text{ Shooting}_{s,w-1} + \text{Controls} + FEs + \epsilon_{i,s,t} \quad (3)$$

where $Mroib_{i,s,t}$ is the retail order imbalance for stock i with headquarter in state s on day t , measured using the share volume ($Mroibvol_{i,s,t}$) or the number of trades ($Mroibtrd_{i,s,t}$). $Shooting_{s,w-1}$ is a dummy variable that equals 1 if at least one mass shooting occurred in state s in the previous week, 0 if otherwise. Notice that $Shooting_{s,w-1}$ is overlapping in nature, which accounts for the possibility that retail investors may realize the existence of mass shootings at different times throughout a week, and trade subsequently.²⁵ In other words, there might be a lag between the date of the mass shootings and the date on which retail investors become aware of the shootings. Stock-level controls include past retail order imbalances, stock returns, firm size, return volatility, book-to-market ratio and turnover. These characteristics are shown to predict future retail trading activity (Boehmer et al., 2021; Bernhardt et al., 2022; Chang et al., 2022; McLean et al., 2020). I include these variables here in order to proxy for retail investors’ preference for cross-sectional stock characteristics and examine the incremental impact of local mass shootings on their trading decisions regarding

²⁵Results from Table 3 indicate that an important channel for retail investors to learn about mass shootings is news/media coverage. Initial news reports covering a mass shooting usually arrive within one day of the incident. However, news regarding material developments of the incident may arrive later.

local stocks. State-level control variables include past-year personal income per capita and real GDP growth rate for each state, which could affect the likelihood of mass shootings and local retail trading activity. All control variables are defined in Section 2.3. Stock control variables are winsorized at the 1st and 99th percentile to eliminate outliers. To absorb unobserved heterogeneity, I also include several dimensions of fixed effects. Specifically, year and month fixed effects account for time and seasonal trends that affect both retail trading activity and the frequency of mass shootings.²⁶ Industry fixed effect controls for the unobservable industry attributes that impact retail interest.²⁷ In Equation 3, β is the coefficient of interest. It measures the average change in local stocks' daily retail order imbalances in the week following same-state mass shootings. A positive (negative) β implies that retail investors net buy (net sell) local stocks after local shootings.

Table 4 presents the regression results. In column (1) to (3), the dependent variable is the retail order imbalance calculated using share volume. In column (4) to (6), the dependent variable is the retail order imbalance calculated using the number of trades. Across specifications, the coefficient on $Shooting_{s,w-1}$ is negative and statistically significant. This implies that, on average, retail investors net sell more shares and place more sell trades of local stocks in the week after mass shootings. In terms of economic magnitude, in column (3), where the dependent variable is daily retail order imbalance in share volume and year-month and industry fixed effects are included, the regression coefficient on $Shooting_{s,w-1}$ is -0.16%. Given that the unconditional sample mean of $Mroi\text{vol}_{i,s,t}$ is -2.009%, this implies that local firms experience daily net retail investment outflow of roughly 8% (-0.16%/-2.009%) in the week following same-state mass shootings. To put this magnitude into more context, McLean et al. (2020) finds that a firm's daily retail order imbalance increases about 7.7% on average following large Earnings Per Share (EPS) upward revisions. This comparison suggests that

²⁶Figure 1 shows that mass shootings frequency has a clear seasonality during the sample period. Also, Retail investors' share of U.S. equities trading volume stayed between 10% and 15% before 2020 and soared to almost 25% in 2021. See <https://www.bnymellonwealth.com/articles/strategy/the-rise-of-retail-traders.jsp>.

²⁷I use the Fama-French 49 industry classifications.

the impact of local mass shootings on retail investors' trading behavior is sizable. Moreover, the net-selling effect is even larger (11.6% of the sample mean) when order imbalance is measured using the number of trades ($Mroibtrd_{i,s,t}$).

The coefficients on stock-level control variables are qualitatively similar to BJZZ and [Bernhardt et al. \(2022\)](#). Retail order imbalances tend to be persistent, consistent with evidence from [Chordia and Subrahmanyam \(2004\)](#). Retail investors are contrarian, as they sell (buy) more when past returns are high (low). Moreover, retail investors invest more in large firms, growth firms, firms with higher return volatility and higher turnover. As for state-level economic conditions, firms in states with higher personal income per capita experience more net-selling activity by retail investors on average.

Results from [Table 4](#) show that, after mass shootings in a state, retail investors on average net-sell local stocks. This provides preliminary suggestive evidence that retail investors embrace pessimistic sentiment towards areas that experienced mass shootings incidents, and such sentiment translates to net investment outflows from local stocks.

3.3 Robustness

In this section, I provide several robustness tests of the baseline result in [Section 3.2](#) and show that the net-selling effect holds in different specifications, subsamples, and time periods.

In [Table 5 Panel A](#), instead of panel regression with fixed effects, I estimate [Equation 3](#) using [Fama and MacBeth \(1973\)](#) two-step approach. To account for serial correlation in the coefficients, I use [Newey and West \(1987\)](#) standard errors with 7 lags.²⁸ The results in [Table 5 Panel A](#) show that the coefficients on $Shooting_{s,w-1}$ stay negative and statistically significant at the 5% level across all specifications.

In [Table 5 Panel B](#), I re-estimate [Equation 3](#) using different time periods and subsamples.

²⁸I follow the lag selection criteria proposed in [Greene \(2003\)](#). Specifically, the number of lag = $T^{\frac{1}{4}} = 2267^{\frac{1}{4}} \approx 7$.

In column (1) and (2), I limit my sample till March 2020 for several reasons. First of all, the U.S. started to experience serious COVID-19 outbreak after March 2020. Secondly, there was a noticeable spike in the number of mass shootings (Table 1) during 2020 and 2021. Finally, retail equity trading volume grew rapidly during 2020 and 2021.²⁹ In column (3) and (4), I drop all observations from year 2016 to 2018, since the tick size pilot program adopted by SEC during this time could impact the probability of many stocks receiving any price improvement from brokers (BJZZ). The regression results in Table 5 Panel B are similar to estimates from Table 3, with magnitude even slightly larger.

Several studies document the abnormal return patterns and retail trading activity around holidays (Ariel, 1990; Da et al., 2015). To eliminate the potential confounding effects from holidays, in Table 5 Panel B column (5) and (6), I remove all sample weeks that contain a national holiday and re-estimate Equation 3.³⁰ Results confirm that the previous finding is not affected by holiday effects.

Finally, one might be concerned that the previous result is driven by shootings and retail investors' interest in firms located in a specific state. To alleviate such concern, I estimate Equation 3 in a loop, where I remove observations from one state in each iteration. Results are shown in Figure 2. The sign and magnitude of the coefficient on $Shooting_{s,w-1}$ in each iteration closely match the full-sample estimate. Therefore, it is clear that removing individual states is not likely to alter the result that retail investors divest from local stocks after local mass shootings.

4 Mass Shootings and Retail Investor Sentiment

Results in the previous section show that retail investors net sell local stocks in response to the presence of local mass shootings. This is consistent with negative sentiment-driven

²⁹Results are also robust if I drop all observations from year 2020 and 2021.

³⁰I obtain a list of historical national holidays and stock market closure dates in the U.S. from <http://www.market-holidays.com/>.

trading behavior by retail investors. In this section, I conduct multiple cross-sectional tests and provide further evidence that lower investor sentiment from mass shootings is a channel that explains retail investors' net-selling trading activity.

In Section 4.1, I explore shooting-level heterogeneity and find that retail investors divest more from local stocks following local mass shootings that had more victims, shootings in which suspects were yet to be arrested, and shootings that involved teenager as victims. In Section 4.2, I examine return predictability of local mass shootings on local stocks. Local stocks experience lower returns only in 1 week after local mass shootings, but not further. Finally, In Section 4.3, I find that institutional investors do not react to local mass shootings.

4.1 Shooting-level Heterogeneity and Retail Trading Activity

4.1.1 Severity of Mass Shootings

So far the analysis has focused on the existence of mass shootings and how it affects retail trading flows in local stocks. If retail investors are sentiment-driven traders, then it is reasonable to expect that they embrace more pessimistic sentiment towards more deadly shootings and consequently divest more from local stocks. Therefore, a significant connection between the severity of mass shootings and retail trading behavior would support the hypothesis that retail investors are affected by sentiment.

I re-estimate Equation 3 using alternative independent variables of interest. Specifically, I replace $Shooting_{s,w-1}$ dummy with three continuous variables that measure the severity of mass shootings: $Log_Injury_{s,w-1}$, $Log_Death_{s,w-1}$, $Log_Victim_{s,w-1}$. The three variables are the natural log of the total number of injuries, deaths, and victims from mass shootings occurred in state s during the previous week, respectively. Sentiment-driven trading would be consistent with coefficients on the above continuous independent variables being negative and statistically significant.

Table 6 presents the results. In column (1) to (3), the dependent variable is the daily retail share volume order imbalance. In column (3) to (6), the dependent variable is the daily retail trade order imbalance. Across columns, the coefficients on $Log_Injury_{s,w-1}$ are negative and statistically significant, which implies that retail investors engage in more net-selling of local stocks following local mass shootings that injure more people.

The coefficient on $Log_Death_{s,w-1}$ is also negative and statistically significant when the dependent variable is daily retail share volume order imbalance. This implies that retail investors on average sell more shares of local stocks if local shootings kill more people. When dependent variable is daily retail trade order imbalance, the coefficient in front of $Log_Death_{s,w-1}$ is negative but statistically insignificant. In terms of magnitude, one more person killed in local mass shootings triggers at least as much net-selling reaction from retail investors as one more person injured in such incidents. This suggests that retail investors might have even lower sentiment from observing shootings that killed more people. Finally, there is a negative and statistically significant impact of $Log_Victim_{s,w-1}$ on retail imbalances. Following mass shootings with more victims, retail investors become more pessimistic and move further away from local stocks.

In conclusion, Table 6 shows that retail investors divest from local stocks more intensely following more traumatic and severe mass shootings, which suggests that retail investors are prone to sentiment when making investment decisions.

4.1.2 Types of Mass Shootings

In this section, I further explore shooting-level heterogeneity and shed light on retail investors' sentiment-driven trading behavior. While the number of casualties examined in Section 4.1.1 is an important attribute that signals the severity of mass shootings, other characteristics could also help distinguish among incidents that are more damaging than others and thus more likely to shift investor sentiment. For example, mass shootings that

are unsolved, meaning that the suspects have not been arrested, presumably generate a sense of disappointment, uncertainty, and even fear among the public. Therefore, compared to solved shooting cases, unsolved ones tend to provoke stronger pessimism. As an another example, mass shootings in which teenagers are involved as victims often receive widespread attention in media and incur political debate on issues regarding gun controls.³¹ Compared to adults, teenagers are often deemed as more innocent and vulnerable, which implies that mass shootings that injure or kill teenagers tend to be perceived as more shocking, traumatic and destructive. Important to this paper, if retail investors are indeed affected by sentiment when making trading decisions, the observed net-selling pressure in local stocks should be more pronounced following the above-mentioned subsets of shootings. In other words, the hypothesis here is that retail investors divest from local stocks more heavily in reaction to local mass shootings that are unsolved and involve teenager victims.

To test the hypothesis, I make use of relevant data from GVA. For each mass shooting in the database, GVA provides granular information on the status of the case, as well as the demographic characteristics of suspects and victims. In particular, I identify shootings in which the suspects have not been arrested, or at least one of the victims (either injured or killed) was below 18 years old. Quite strikingly, among the 3296 mass shootings included in the sample, about 70% (2307) are unsolved and 31% (1022) have a victim below 18 years old. From this data, I construct four dummy variables. $Not_Arrested_{s,w-1}$ equals 1 if any shooting that took place in state s in the previous week was unsolved, 0 if otherwise. $Arrested_{s,w-1}$ equals 1 if all shootings that occurred in state s in the previous week were solved, 0 if otherwise. Moreover, $Teen_{s,w-1}$ equals 1 if at least one victim, from any mass shootings in state s in the previous week, was below 18 years old, 0 if otherwise. $Adult_{s,w-1}$ equals 1 if all victims, from mass shootings in state s in the previous week, were above 18 years old, 0 if otherwise. I horse-race the above dummy variables in Equation 4 and

³¹U.S. has the highest number of school-related mass shootings in the world (<https://qz.com/37015/how-school-killings-in-the-us-stack-up-against-36-other-countries-put-together/>). Such incidents are widely covered in news.

Equation 5 below:

$$Mroib_{i,s,t} = \alpha + \beta_1 \text{ Not_Arrested}_{s,w-1} + \beta_2 \text{ Arrested}_{s,w-1} + \text{Controls} + FEs + \epsilon_{i,s,t} \quad (4)$$

$$Mroib_{i,s,t} = \alpha + \beta_3 \text{ Teen}_{s,w-1} + \beta_4 \text{ Adult}_{s,w-1} + \text{Controls} + FEs + \epsilon_{i,s,t} \quad (5)$$

In Equation 4, β_1 and β_2 are coefficients of interest. They measure the average daily change in retail order imbalances following unsolved and solved mass shootings, respectively. In Equation 5, β_3 and β_4 are coefficients of interest. They measure the average daily change in retail order imbalances following mass shootings with teenage victims and adult victims, respectively. Based on the discussion in the beginning of this section, if retail investors are driven by sentiment, β_1 and β_3 should be both statistically significant and more negative than β_2 and β_4 .

Regression results are reported in Table 7. In Panel A across columns, the coefficients on $\text{Not_Arrested}_{s,w-1}$ are negative and statistically significant at 1% level, whereas the coefficients on $\text{Arrested}_{s,w-1}$ are negative but not statistically significant. In terms of magnitude, the reduction in retail order imbalances is much larger following shootings that were unsolved, compared to solved ones ($-0.196 < -0.046$ and $-0.123 < -0.026$). When the dependent variable is daily retail volume order imbalance, the difference between coefficients on two dummies is significantly different from 0. Results in Panel A aligns with the prediction that unsolved mass shootings lower retail investors' sentiment and consequently induce more divestment from local stocks.

In Panel B, the coefficient on $\text{Teen}_{s,w-1}$ is negative and statistically significant at 1% level, whereas coefficient on $\text{Adult}_{s,w-1}$ is negative but not statistically significant. In terms of magnitude, retail investors net sell more shares of local stocks and place more sell trades following shootings incidents in which teenagers were injured or killed, compared to incidents in which all victims were adults ($-0.255 < -0.106$ and $-0.134 < -0.081$). Again, when dependent variable is daily retail volume order imbalance, the difference between coefficients

in front of two dummies is significantly different from 0. This supports the argument that retail investors are influenced by more pessimism from mass shootings in which teenagers were involved as victims.

Overall, results from Table 7 suggests that shooting-level heterogeneity creates shifts in sentiment, which in turn leads to variations in retail outflows from local stocks.

4.2 Mass Shootings and Local Stock Returns Predictability

In this section, I investigate the asset pricing implications of local mass shootings on local stock returns. Literature on investor sentiment argues that, in the presence of sentiment-driven trading by uninformed noise traders and limits to arbitrage, sentiment changes can move prices away from fundamentals and lead to large mispricings in the short run (De Long et al., 1990; Baker and Wurgler, 2006, 2007). In this setting, if mass shootings indeed cause downward shifts in investor sentiment, and retail investors are affected by sentiment, then local firms' stock prices should experience notable decrease in the short run after shootings. Another prediction in sentiment models is return reversals: stock prices in the long run should come back to its fundamental value. When sentiment is low, stock prices should be temporarily low but come high in the future (Da et al., 2015). Therefore, in the long run, sentiment-driven effects of local mass shootings on local stock returns should be positive.

To test the return predictability of local mass shootings in the short-run, I estimate Equation 6, using Fama and MacBeth (1973) two-step approach:

$$Return_{i,s,t} = \alpha + \beta_5 Shooting_{s,w-1} + Controls + \epsilon_{i,s,t} \quad (6)$$

The dependent variable is the daily stock return of firm i headquartered in state s in week w . I include the same set of stock and state-level control variables as in prior analysis. To account for serial correlation in the coefficients, I use Newey and West (1987) standard

errors with 7 lags. β_5 measures the average daily change in local stocks' returns during the week after the presence of local mass shootings. If there exists sentiment-driven trading, then β_5 should be negative and statistically significant. The results are shown in Table 8 Panel A column (1) and (2). The coefficient on $Shooting_{s,w-1}$ is negative and statistically significant, regardless of whether control variables are included in the regression. In terms of magnitude, following mass shooting(s) in state s , the average daily drop in local firms' stock returns next week is about 0.012% (Table 8 Panel A column (2)), which is 15% of the unconditional sample mean of daily returns (0.079%). In column (3) and (4), I use the natural log of the number of injuries and victims as proxies for the severity of mass shootings. Results suggest that local stock returns decrease more following mass shootings with more victims. Overall, Table 8 Panel A provides strong evidence that the short-run price impact of local mass shootings on local stocks is negative, which aligns with the prediction of sentiment models.

To study the price impact of local mass shootings in longer horizons, I re-estimate Equation 6, using the daily returns of firm i headquartered in state s in week 2, 3, and 4 after the shooting as dependent variables. Table 8 Panel B reports the results. Local mass shootings do not seem to meaningfully predict local stock returns in the second week and beyond. The coefficients become statistically insignificant in column (2) to (4). Moreover, the magnitude of predictability decreases to almost 0 for returns in week 3 and 4. Although local stocks' returns do not exhibit a clear reversal after local mass shootings, the impact of mass shootings on local stock returns seems to be only temporary (lasts for 1 week).

Overall, results from Table 8, along with previous results, suggest that local mass shootings lower investor sentiment, which results in net-selling behavior by retail investors and a temporary drop in local stock returns.

4.3 Mass Shootings and Institutional Trading Activity

Prior analyses have focused on the trading behavior of retail investors following mass shootings in a geographical area. However, it is also interesting to understand how institutional investors trade local stocks in response to the same set of local mass shootings. Existing literature on sentiment models in behavior finance argues that, compared to retail investors, institutional investors are more sophisticated and rational (De Long et al., 1990; Griffin et al., 2003; Bank and Brustbauer, 2014). Therefore, when local mass shootings make retail investors pessimistic and consequently divest from local stocks, institutional investors should exhibit no differential treatment of local stocks in their portfolios.

To proxy for institutional buying and selling activity, I construct institutional order imbalances, which are the counterparts of retail order imbalances. Specifically, for the same sample period, I first classify each trade in TAQ database as buyer-initiated or seller-initiated, using the Lee and Ready (1991) algorithm. I drop all trades that cannot be assigned any direction after applying the algorithm. Then I aggregate buy and sell orders for each stock-day pair in my sample to calculate each stock’s daily buy (sell) share volume and number of trades. Finally, following Farrell et al. (2022) and Mohr (2021), I define institutional buy (sell) share volume as the overall buy (sell) share volume minus the retail buy (sell) share volume. Institutional buy (sell) trade count is defined similarly, based on the number of trades. Finally, institutional order imbalances are calculated in the same fashion as Equation 1 and Equation 2.³²

I re-estimate Equation 3, with daily institutional order imbalances as dependent variables. Regression results are reported in Table 9. Across columns, the coefficient on $Shooting_{s,w-1}$ is mostly negative and statistically insignificant. The absolute magnitude of coefficients is close to 0, which is considerably smaller than the baseline estimates for

³²Since it is possible that BJZZ’s algorithm for identifying retail trades has Type-2 error, the institutional trades could contain some trades that are actually from retail investors but are not picked up by the algorithm. While the proxies for institutional trading behavior could have some noise, they should still capture a majority of institutional trading activity.

retail investors. The result shows that, while retail investors on average divest from local stocks after local mass shootings, institutional investors do not materially adjust their trading activity in response to the same set of incidents. The above evidence is in support of the conventional wisdom that retail traders are more prone to sentiment, compared to institutional traders.³³

5 Conclusion

This paper studies the role of negative sentiment in aggregate retail investors' daily equity trading activity. Using a comprehensive list of mass shootings in the U.S. as exogenous and non-economic shocks to investor sentiment, I find that aggregate retail investors net sell stocks of firms headquartered in the state that experienced mass shootings in the previous week. Through Google search volume data, I find that retail investors are fully aware of mass shootings, which indicates that the observed net-selling effect is not spurious. Moreover, through multiple robustness checks, I find that the result holds across different subsamples and regression specifications.

I then offer suggestive evidence that such net-selling behavior is driven by lower investor sentiment from mass shootings. Overall, I find that retail outflows from local stocks is larger when shootings were more deadly and tragic. Specifically, retail investors net sell local stocks more heavily following shootings with more victims, as well as shootings in which the suspects have not been arrested and teenagers were involved as victims.

In term of stock return dynamics, I find that local stock returns move in the direction of lower investor sentiment from mass shootings in the short run. Specifically, local mass shootings predict lower local stock returns only in the next week, consistent with insights

³³There could be many reasons why aggregate institutional investors do not trade local stocks in response to local mass shootings in a meaningful fashion. One possible explanation might be that, albeit mass shootings being tragic events, institutional investors do not view them as negative shocks to local firms' future earnings streams.

from sentiment models in the behavioral finance literature. In the final part of the analysis, I show that institutional investors do not exhibit any meaningful changes in trading activity following local mass shootings, which implies that retail investors are more prone to sentiment.

Overall, my findings are consistent with the idea that retail investors are affected by sentiment when making trading decisions. Distinct from classic literature on retail trading, this paper focuses on the trading behavior of a much broader population of retail investors. Without relying on account-level data ([Barber and Odean \(2008\)](#) and others), this paper produces findings that show the importance of sentiment in aggregate retail investors' trading activity in common stocks in the U.S. Furthermore, in contrast to studies that only examines return implications of sentiment ([Edmans et al. \(2007, 2022\)](#) and others), I explore aggregate retail investors' daily buy and sell transactions and find that their trading decisions are likely to be affected by sentiment from observing mass shootings. Finally, this study sheds light on the impact of mass shootings on financial markets. My findings support the argument that mass shootings in the U.S. materially affect a fast-growing group of investors' stock trading activity and shift local stocks' short-term price dynamics.

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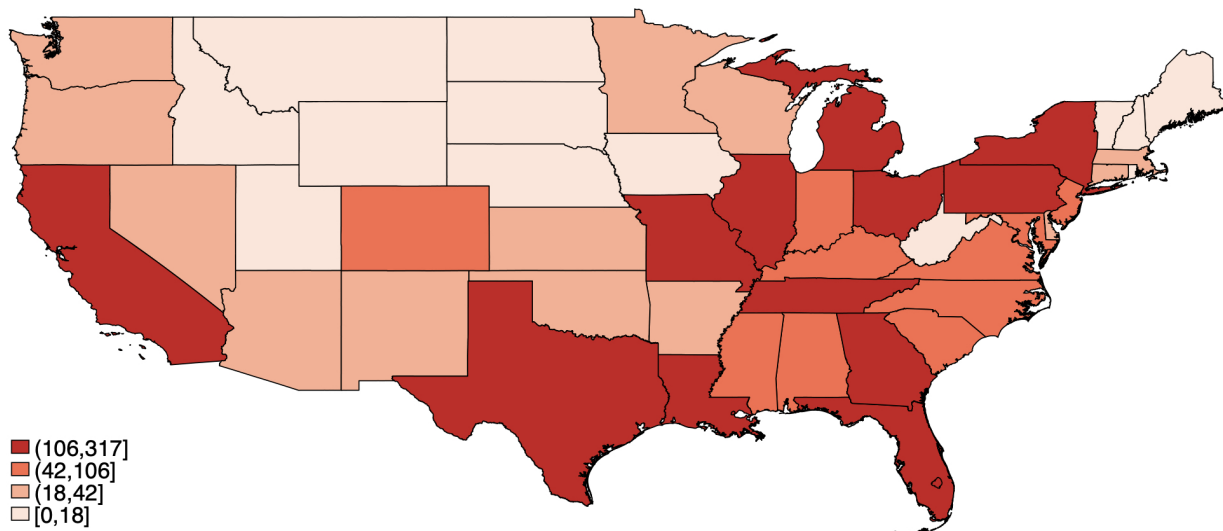
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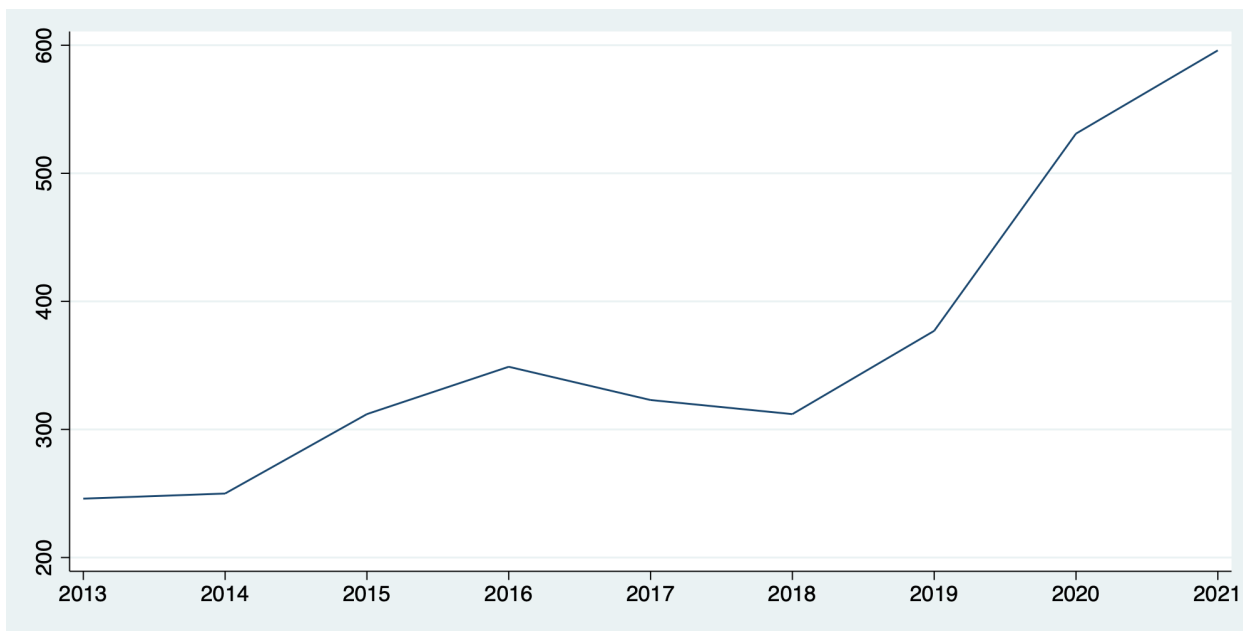
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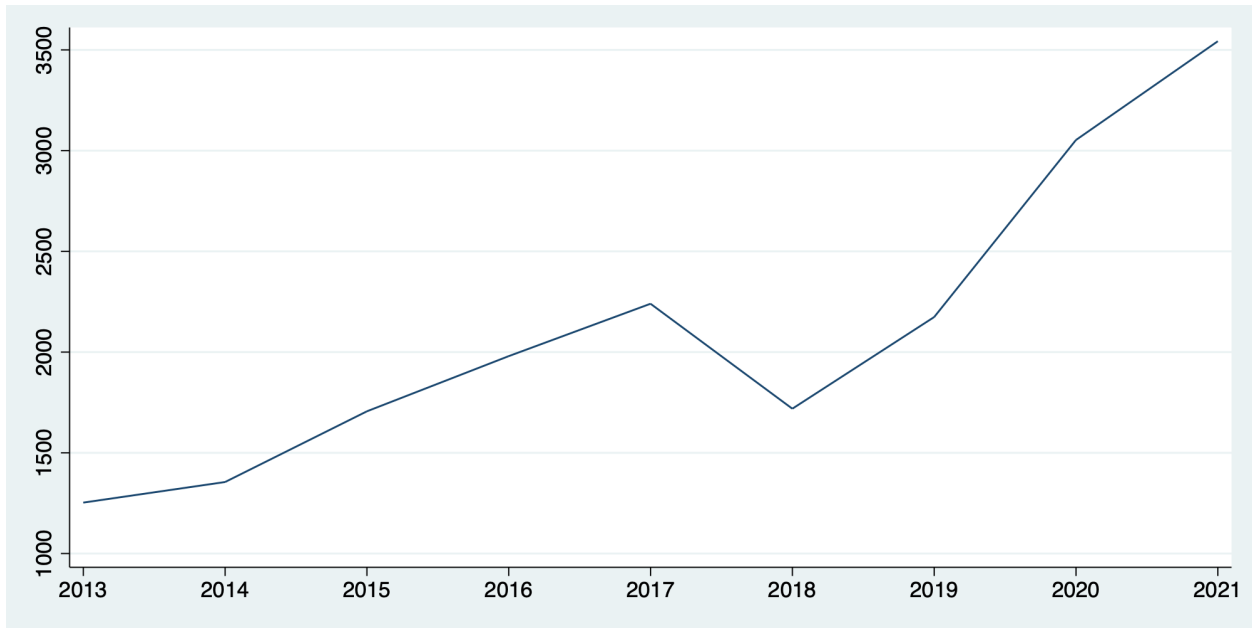
Figure 1: Mass Shootings In the U.S.



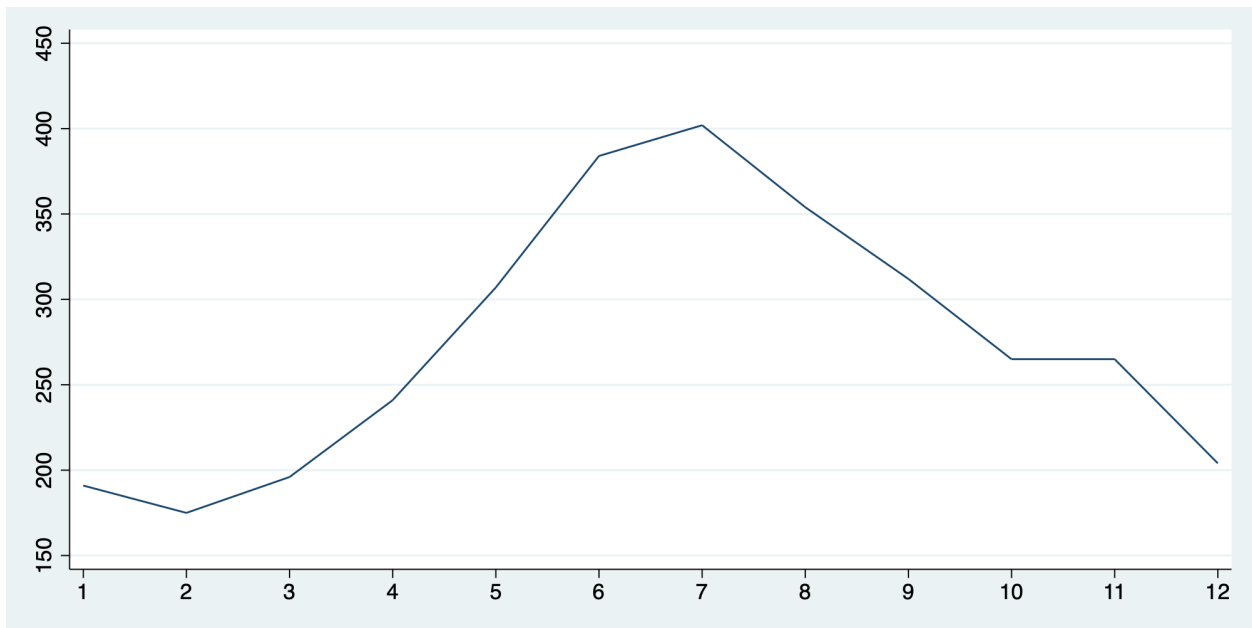
(a): The number of mass shootings by states



(b): The number of mass shootings by year



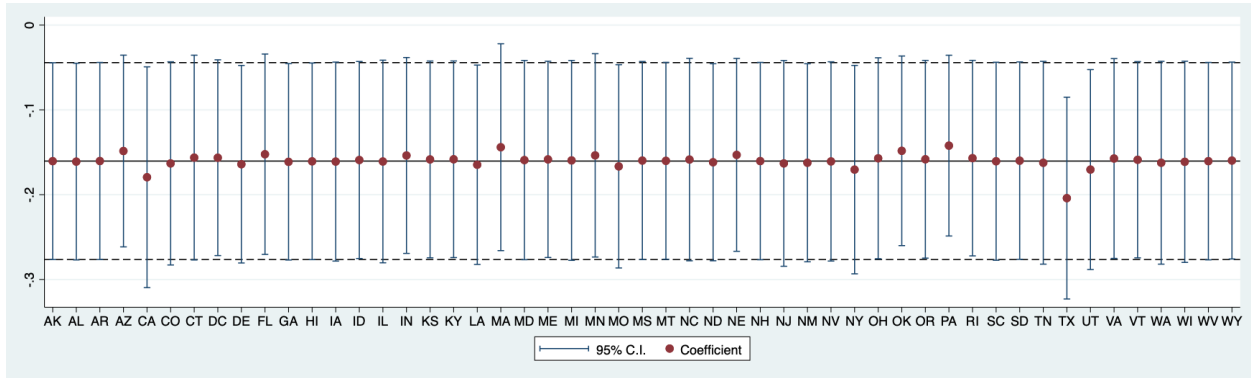
(c): The number of victims by year



(d): The number of mass shootings by month

This figure plots the distribution and frequency of mass shootings in the United States from January 1st, 2013 to December 31st, 2021. It consists of 4 different sub-figures. (a): the number of mass shootings in the U.S. by state. A darker red color indicates a higher count of qualified incidents. Mass shootings are defined as incidents in which at least 4 people are injured or killed by the use of firearms. (b): the number of mass shootings in the U.S. by sample year. (c): the number of victims (injuries + deaths) from mass shootings in the U.S. by sample year. (d): the number of mass shootings in the U.S. by month.

Figure 2: Robustness Check: Dropping Individual State



This figure plots the coefficients on $Shooting_{s,w-1}$ from estimating Equation 3 with year-month and industry fixed effect in 51 regressions. In each regression, observations from one specific state are removed from the sample. Y-axis is the value of the coefficient estimate, and X-axis is the abbreviated name of the state removed in each regression. The vertical bar around each red dot is the 95% confidence interval for each coefficient estimate. The black horizontal line and dashed lines are the coefficient estimate (-0.160) using the entire sample and the corresponding 95% confidence interval.

Table 1: **Mass Shootings Characteristics**

This table reports summary statistics on mass shootings in the U.S. from January 1st, 2013 to December 31st, 2021. A shooting event is defined as a mass shooting if more than 4 people (excluding shooters) are either injured or killed by the use of firearms. Panel A reports the total number of mass shootings, the number of injuries, and the number of fatalities in each sample year. Panel B reports the total number of mass shootings, the number of injuries, and the number of fatalities in each month. The sample period has 3296 mass shootings in total. Data source: Gun Violence Archive.

Panel A: Mass Shootings by Year

Year	# of Shootings	# of Injured	# of Killed
2013	246	963	290
2014	250	1085	270
2015	312	1337	369
2016	349	1530	450
2017	323	1802	438
2018	312	1338	381
2019	377	1709	465
2020	531	2540	513
2021	596	2839	704

Panel B: Mass Shootings by Month

Month	# of Shootings	# of Injured	# of Killed
1	221	859	301
2	209	829	325
3	234	1021	270
4	291	1225	324
5	365	1749	403
6	395	1968	471
7	402	1945	396
8	354	1633	355
9	312	1410	353
10	265	1570	370
11	265	1162	345
12	204	855	245

Table 2: **Summary Statistics**

This table reports the summary statistics of key variables. The sample period is from January 1st, 2013 to December 31st, 2021. Sample firms are common stocks listed on NYSE, NYSE MKT, and NASDAQ. Panel A reports statistics on retail investor trading activity. Panel B reports statistics on stock-level characteristics. Panel C reports statistics on state-level economic conditions. See Section 2 for variable definitions.

Variable	Obs	Mean	SD	P25	P75
<i>Panel A: Retail Trading Activities</i>					
$Mrbvol_{i,t}$	6396385	50792.11	369358	1296	20709
$Mrsvol_{i,t}$	6396385	50137.55	352087.4	1395	21405
$Mrbtrd_{i,t}$	6396385	194.969	1348.135	9	105
$Mrstrd_{i,t}$	6396385	175.979	1079.297	9	105
$Mroibvol_{i,t}(\%)$	6396385	-2.009	42.781	-24.949	20.558
$Mroibtrd_{i,t}(\%)$	6396385	-.863	35.359	-17.647	16.172
<i>Panel B: Stock-level Characteristics</i>					
$Return_{i,w-1}(\%)$	6396385	.262	6.096	-2.582	2.886
$Return_{i,m-1}(\%)$	6396385	1.284	12.826	-5.353	6.979
$Return_{i,m-2,m-7}(\%)$	6396385	8.326	34.934	-11.01	21.833
$Log_Size_{i,m-1}$	6396385	6.901	2.035	5.444	8.266
$Volatility_{i,m-1}(\%)$	6396385	2.611	1.824	1.416	3.192
$Log_BM_{i,m-1}$	6396385	-.912	.968	-1.458	-.239
$Turnover_{i,m-1}$	6396385	.199	.25	.073	.225
<i>Panel C: State-level Economic Conditions</i>					
$Log_Pinc_{s,q-1}$	6396385	10.877	.165	10.76	11
$GDP_Growth_{s,y-1}(\%)$	6396385	1.661	2.388	.845	3.308

Table 3: Mass Shootings and Google Search Volume

This table reports results from regressing Google Trends search volume of the term “shooting” on mass shooting casualties. The sample period is from January 1st, 2013 to December 31st, 2021. Panel A reports regression results using national-level data. Panel B reports regression results using state-level data. Dependent variables are Google web search volume and news search volume of the term “shooting”, defined as the proportion to all searches across all topics in a specific geographic area (the U.S. or each state) during the sample period. The highest level is scaled to 100 and the lowest level is scaled to 0. The independent variables are the natural logarithm of the count of injuries, deaths, and victims from mass shootings occurred in each month, either in the U.S. or in each state. ***, **, * denote significance at the 1%, 5%, and 10% level, respectively.

Dep. Var.	Web Search			News Search		
	(1)	(2)	(3)	(4)	(5)	(6)
<i>Panel A: National-Level</i>						
Log_Injury_m	5.782 [2.009]			8.809 [1.817]		
Log_Death_m		9.752 [2.272]			11.229 [2.109]	
Log_Victim_m			7.324 [2.146]			10.362 [1.932]
SVI_{m-1}	0.208 [0.079]	0.216 [0.076]	0.212 [0.078]	0.449 [0.067]	0.443 [0.065]	0.443 [0.065]
Observations	108	108	108	108	108	108
Adjusted R ²	0.101	0.175	0.127	0.416	0.438	0.439
<i>Panel B: State-level</i>						
$Log_Injury_{s,m}$	0.838 [0.122]			1.444 [0.324]		
$Log_Death_{s,m}$		1.93 [0.233]			2.181 [0.381]	
$Log_Victim_{s,m}$			0.918 [0.114]			1.369 [.294]
$SVI_{s,m-1}$	0.117 [0.022]	0.117 [0.022]	0.117 [0.022]	0.036 [0.018]	0.036 [0.018]	0.036 [0.018]
State FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5508	5508	5508	5508	5508	5508
Adjusted R ²	0.863	0.866	0.864	0.389	0.389	0.389

Table 4: Mass Shootings and Retail Order Imbalances

This table reports panel regression results from estimating Equation 3. The sample period is from January 1st, 2013 to December 31st, 2021. Dependent variables are retail order imbalances, measured in share volume or the number of trades. $Shooting_{s,w-1}$ is a dummy variable that equals 1 if mass shootings took place in state s in the previous week, 0 otherwise. See Section 2.3 for control variables' definitions. Different combinations of year, month, year-month, and industry fixed effects are included. Standard errors are clustered at states and reported in brackets. ***, **, * denote significance at the 1%, 5%, and 10% level, respectively.

Dep. Var.	Volume Imbalance			Trades Imbalance		
	(1)	(2)	(3)	(4)	(5)	(6)
$Shooting_{s,w-1}$	-0.185 [0.062]	-0.158 [0.067]	-0.160 [0.058]	-0.108 [0.063]	-0.117 [0.069]	-0.100 [0.039]
$Mroibvol_{i,d-1}$	0.048 [0.001]	0.048 [0.001]	0.047 [0.001]			
$Mroibtrd_{i,d-1}$				0.099 [0.004]	0.098 [0.004]	0.097 [0.004]
$Return_{i,w-1}$	-0.051 [0.005]	-0.054 [0.005]	-0.061 [0.005]	-0.042 [0.003]	-0.043 [0.003]	-0.049 [0.003]
$Return_{i,m-1}$	-0.034 [0.003]	-0.032 [0.002]	-0.037 [0.003]	-0.037 [0.003]	-0.035 [0.003]	-0.040 [0.003]
$Return_{i,m-2,m-7}$	-0.004 [0.001]	-0.004 [0.001]	-0.006 [0.001]	-0.003 [0.001]	-0.003 [0.001]	-0.005 [0.001]
$Log_Size_{i,m-1}$	0.340 [0.024]	0.342 [0.024]	0.294 [0.030]	0.450 [0.030]	0.454 [0.030]	0.378 [0.033]
$Volatility_{i,m-1}$	0.118 [0.019]	0.124 [0.019]	0.051 [0.028]	0.125 [0.022]	0.137 [0.023]	0.064 [0.028]
$Log_BM_{i,m-1}$	-0.242 [0.059]	-0.263 [0.059]	-0.347 [0.044]	-0.277 [0.061]	-0.295 [0.062]	-0.505 [0.039]
$Turnover_{i,m-1}$	0.644 [0.227]	0.593 [0.227]	0.410 [0.208]	1.667 [0.196]	1.606 [0.200]	1.648 [0.192]
$Log_Pinc_{s,y-1}$	-0.553 [0.415]	-0.568 [0.419]	0.278 [0.345]	-0.426 [0.363]	-0.441 [0.363]	0.645 [0.321]
$GDP_Growth_{s,y-1}$	0.026 [0.043]	0.025 [0.043]	0.011 [0.025]	-0.030 [0.037]	-0.031 [0.037]	-0.014 [0.022]
Year FE	Yes	Yes	No	Yes	Yes	No
Month FE	No	Yes	No	No	Yes	No
Year-Month FE	No	No	Yes	No	No	Yes
Industry FE	No	No	Yes	No	No	Yes
Observations	6396385	6396385	6396133	6396385	6396385	6396133
Adjusted R ²	0.31%	0.34%	0.4%	1.25%	1.29%	1.39%

Table 5: **Robustness Checks**

This table reports results on robustness checks. Panel A reports results from estimating Equation 3 using Fama and MacBeth (1973) regression. To account for serial correlation in the coefficients, the Newey-West standard errors with 7 lags are used. Panel B reports results from estimating Equation 3 using different sub-samples. The sample period is from January 1st, 2013 to December 31st, 2021. Dependent variables are retail order imbalances, measured in share volume or the number of trades. $Shooting_{s,w-1}$ is a dummy variable that equals 1 if mass shootings took place in a state in the previous week, 0 otherwise. See Section 2.3 for control variables' definitions. ***, **, * denote significance at the 1%, 5%, and 10% level, respectively.

<i>Panel A: Fama and MacBeth (1973) Regression</i>						
Dep. Var.	Volume Imbalance		Trades Imbalance			
	(1)	(2)	(3)	(4)		
$Shooting_{s,w-1}$	-0.126 [0.057]	-0.150 [0.059]	-0.104 [0.050]	-0.108 [0.051]		
Stock Controls	Yes	Yes	Yes	Yes		
State Controls	No	Yes	No	Yes		
Observations	6396385	6396385	6396385	6396385		
Adjusted R ²	0.43%	0.43%	1.41%	1.42%		
<i>Panel B: Sub-samples</i>						
	2013m1-2020m3		No 2016-2018		No Holidays	
	(1)	(2)	(3)	(4)	(5)	(6)
$Shooting_{s,w-1}$	-0.184 [0.067]	-0.174 [0.054]	-0.218 [0.053]	-0.125 [0.049]	-0.153 [0.066]	-0.091 [0.049]
Dep. Var.	Vol.	Trd.	Vol.	Trd.	Vol.	Trd.
Stock Controls	Yes	Yes	Yes	Yes	Yes	Yes
State Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5117056	5117056	4309146	4309146	5476694	5476694
Adjusted R ²	0.43%	1.23%	0.49%	1.75%	0.39%	1.38%

Table 6: Mass Shootings Severity and Retail Order Imbalances

This table reports panel regression results from estimating Equation 3, using the natural logarithm of the number of injuries, deaths and victims from mass shootings in state s in the previous week as independent variables. The sample period is from January 1st, 2013 to December 31st, 2021. Dependent variables are retail order imbalances, measured in share volume or the number of trades. Stock characteristics, state characteristics, year-month fixed effects and industry fixed effects are included. See Section 2.3 for control variables' definitions. Standard errors are clustered at states and reported in brackets. ***, **, * denote significance at the 1%, 5%, and 10% level, respectively.

Dep. Var.	Volume Imbalance			Trades Imbalance		
	(1)	(2)	(3)	(4)	(5)	(6)
$Log_Injury_{s,w-1}$	-0.084 [0.034]			-0.045 [0.020]		
$Log_Death_{s,w-1}$		-0.084 [0.037]			-0.048 [0.033]	
$Log_Victim_{s,w-1}$			-0.079 [0.029]			-0.042 [0.019]
Stock Controls	Yes	Yes	Yes	Yes	Yes	Yes
State Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6396133	6396133	6396133	6396133	6396133	6420449
Adjusted R ²	0.40%	0.40%	0.40%	1.39%	1.39%	1.39%

Table 7: Shootings-level Heterogeneity and Retail Sentiment

This table reports panel regression results from estimating Equation 4 (Panel A) and Equation 5 (Panel B). The sample period is from January 1st, 2013 to December 31st, 2021. $Not_Arrested_{s,w-1}$ is a dummy variable that equals 1 if any shooting that occurred in state s in the previous week was unsolved, 0 if otherwise. $Arrested_{s,w-1}$ equals 1 if all shootings cases that occurred in state s in the previous week were solved, 0 if otherwise. $Teen_{s,w-1}$ equals 1 if at least one victim was below 18 years old in mass shootings in state s in the previous week, 0 if otherwise. $Adult_{s,w-1}$ equals 1 if all victims in mass shootings in state s in the previous week were above 18 years old, 0 if otherwise. Stock characteristics, state characteristics, year-month fixed effects and industry fixed effect are included. See Section 2.3 for control variables' definitions. Standard errors are clustered at states and reported in brackets. ***, **, * denote significance at the 1%, 5%, and 10% level, respectively.

<i>Panel A: Unsolved vs. Solved Shootings</i>		
Dep. Var.	Volume Imbalance	Trades Imbalance
	(1)	(2)
$Not_Arrested_{s,w-1}$	-0.196 [0.066]	-0.123 [0.044]
$Arrested_{s,w-1}$	-0.046 [0.069]	-0.026 [0.061]
Wald test p-value	0.047	0.170
Observations	6396133	6396133
Adjusted R ²	0.4%	1.39%
<i>Panel B: Teenagers vs. Adults Victims</i>		
Dep. Var.	Volume Imbalance	Trades Imbalance
	(1)	(2)
$Teen_{s,w-1}$	-0.255 [0.065]	-0.134 [0.041]
$Adult_{s,w-1}$	-0.106 [0.066]	-0.081 [0.055]
Wald test p-value	0.029	0.427
Observations	6396133	6396133
Adjusted R ²	0.40%	1.39%

Table 8: Mass Shootings and Local Stock Returns

This table reports [Fama and MacBeth \(1973\)](#) regression results from estimating Equation 6. The sample period is from January 1st, 2013 to December 31st, 2021. In Panel A, the dependent variable is daily returns in week w for stock i headquartered in state s . In Panel B, the dependent variables are daily returns in week w , $w + 1$, $w + 2$, $w + 3$. $Shooting_{s,w-1}$ is a dummy variable that equals 1 if mass shootings took place in state s in the previous week, 0 otherwise. Other independent variables include the natural logarithm of the number of injuries and total victims from mass shootings in state s in the previous week. See Section 2.3 for control variables' definitions. To account for serial correlation in the coefficients, the Newey-West standard errors with 7 lags are used. ***, **, * denote significance at the 1%, 5%, and 10% level, respectively.

<i>Panel A: Daily Returns Next Week</i>				
Dep. Var.	Return $_{i,d}$			
	(1)	(2)	(3)	(4)
$Shooting_{s,w-1}$	-0.011 [0.006]	-0.012 [0.005]		
$Log-Injury_{s,w-1}$			-0.008 [0.003]	
$Log-Victim_{s,w-1}$				-0.007 [0.003]
Stock Controls	No	Yes	Yes	Yes
State Controls	No	Yes	Yes	Yes
Observations	6841074	6437521	6437521	6437521
Adjusted R ²	0.08%	4.32%	4.32%	4.32%
<i>Panel B: Longer Horizons</i>				
	w	w+1	w+2	w+3
	(1)	(2)	(3)	(4)
$Shooting_{s,w-1}$	-0.012 [0.005]	-0.006 [0.005]	0.001 [0.005]	-0.002 [0.006]
Stock Controls	Yes	Yes	Yes	Yes
State Controls	Yes	Yes	Yes	Yes
Observations	6437521	6410572	6406326	6390613
Adjusted R ²	4.32%	4.11%	4.05%	4.01%

Table 9: Mass Shootings and Institutional Order Imbalances

This table reports panel regression results from estimating Equation 3, with daily institutional order imbalances as dependent variables. The sample period is from January 1st, 2013 to December 31st, 2021. $Shooting_{s,w-1}$ is a dummy variable that equals 1 if mass shootings took place in a state in the previous week, 0 otherwise. See Section 2.3 for control variables' definitions. Standard errors are clustered at states and reported in brackets. ***, **, * denote significance at the 1%, 5%, and 10% level, respectively.

Dep. Var.	Volume Imbalance			Trades Imbalance		
	(1)	(2)	(3)	(4)	(5)	(6)
$Shooting_{s,w-1}$	-0.007 [0.048]	-0.003 [0.045]	0.007 [0.049]	-0.013 [0.043]	-0.002 [0.037]	0.015 [0.040]
$Nret_oibvol_{i,d-1}$	0.136 [0.001]	0.136 [0.001]	0.136 [0.001]			
$Nret_oibtrd_{i,d-1}$				0.203 [0.002]	0.202 [0.002]	0.202 [0.002]
$Return_{i,w-1}$	0.142 [0.007]	0.142 [0.007]	0.133 [0.007]	0.078 [0.007]	0.078 [0.007]	0.069 [0.007]
$Return_{i,m-1}$	0.014 [0.001]	0.014 [0.001]	0.018 [0.001]	0.015 [0.001]	0.015 [0.001]	0.018 [0.001]
$Return_{i,m-2,m-7}$	0.007 [0.001]	0.007 [0.001]	0.008 [0.001]	0.006 [0.001]	0.006 [0.001]	0.007 [0.001]
$Log_Size_{i,m-1}$	0.630 [0.023]	0.631 [0.023]	0.611 [0.025]	0.325 [0.015]	0.325 [0.015]	0.307 [0.016]
$Volatility_{i,m-1}$	-0.199 [0.018]	-0.198 [0.018]	-0.275 [0.023]	-0.116 [0.016]	-0.116 [0.016]	-0.173 [0.021]
$Log_BM_{i,m-1}$	0.037 [0.034]	0.035 [0.034]	0.018 [0.031]	0.016 [0.022]	0.015 [0.022]	0.007 [0.020]
$Turnover_{i,m-1}$	0.300 [0.171]	0.281 [0.170]	0.450 [0.169]	-0.283 [0.127]	-0.296 [0.126]	-0.145 [0.127]
$Log_Pinc_{s,y-1}$	-0.783 [0.381]	-0.784 [0.381]	-0.622 [0.360]	-0.355 [0.252]	-0.354 [0.253]	-0.303 [0.242]
$GDP_Growth_{s,y-1}$	0.030 [0.019]	0.030 [0.019]	0.028 [0.018]	0.020 [0.016]	0.020 [0.016]	0.018 [0.015]
Year FE	Yes	Yes	No	Yes	Yes	No
Month FE	No	Yes	No	No	Yes	No
Year-Month FE	No	No	Yes	No	No	Yes
Industry FE	No	No	Yes	No	No	Yes
Observations	6396385	6396385	6396133	6396385	6396385	6396133
Adjusted R-squared	2.65%	2.66%	2.75%	4.61%	4.64%	4.74%