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 in the U.S. 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, local stocks experience around 8% of the sample mean decrease in daily retail share volume order imbalance. 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 teenage victims. However, such trading behavior does not seem to be rational, as local mass shootings have little impact on local firms' financial and operating performances, as well as local economic conditions. 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. Data from Bloomberg reveals that retail trading accounted for only 10% of U.S. equity trading volume in 2010, but had more than doubled to almost 25% by the end of 2021, surpassing the share contributed by mutual funds or hedge funds.[1] This trend, combined with academic evidence that retail investors have the ability to move asset prices,[2] emphasizes the need to better understand the determinants of aggregate retail investors' trading decisions.

The conventional wisdom from the behavioral finance literature 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 asset return implications of both economic and non-economic shocks to investor sentiment,[3] very few examine how the daily 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 investors' daily investment decisions in the stock market.

To measure the daily buying and selling activity of aggregate retail investors, I use the algorithm developed by Boehmer et al. (2021) (BJZZ, hereafter). The algorithm examines market microstructure features and identifies retail trades of each common stock from the price improvement they receive from wholesalers (see Section 2.1 for more details). One key advantage of using BJZZ's algorithm to study aggregate retail trading is that it captures

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

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

[3] For the 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.

order flows generated by a large population of retail investors, rather than small subsets.[4] Moreover, the algorithm captures retail flows for a large cross-section of publicly traded common stocks in the U.S. (more than 3000 common stocks each day), allowing researchers to draw general conclusions about the overall retail trading behavior. Last but not least, the algorithm identifies retail investors' daily trading activity, which is much more granular than previously used data.

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. According to data from Gun Violence Archive,[5] there were more than 3000 shootings between 2013 and 2021 in which 4 people (excluding shooters) were injured or killed by the use of firearms. Secondly, these events are salient and are able to catch widespread attention, as they are often extensively covered in news (Smart and Schell, 2021). In addition, mass shootings are shown to be random, exogenous, and hard to predict (Brodeur and Yousaf, 2019; Luca et al., 2020). Finally, and most important to this paper, 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]

To the extent that retail investors are subject to sentiment and tend to develop negative/pessimistic attitudes toward places where mass shootings occurred, I aim to understand whether and how retail equity investors react to mass shootings incidents in the U.S. I ar-

[4]Many existing studies use proprietary brokerage account-level data, data from a single wholesaler, or small trade size as proxies for retail trading activity. See BJZZ for an overview of these studies and the issues with using the above-mentioned data.

[5]See https://www.gunviolencearchive.org/.

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

gue that, when making trading decisions, retail investors might consider mass shootings as negative events that make them pessimistic about either the local economy or local firms' operations, or both. Therefore, a central hypothesis in this paper is that retail investors might on average divest from local stocks after mass shootings in the same area. In this setting, I focus on states as the geographical areas of interest and define "local" stocks as stocks of firms headquartered in the same state where mass shootings took place. The reason is that the key operations of such firms are physically close to shootings and thus are more likely to be viewed by investors as bearing the impact and costs of mass shootings. The idea is, driven by lower sentiment from mass shootings and negative views toward the economic outlook of affected areas and businesses, aggregate retail investors would trade and allocate their capital away from local stocks.

Using a sample 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 relatively sell more shares and place more sell trades of local stocks on average, compared to buy. These findings suggest that aggregate retail investors indeed divest from local stocks after local mass shootings. The net-selling effect is also large in magnitude. Specifically, the daily retail share volume order imbalance, which measures the scaled difference between the 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). To ensure that the above-mentioned net-selling effect is not a spurious correlation, I study Google search volume data and find that users actively search and acquire information about mass shootings, which implies that retail investors likely pay close attention to mass shootings. Through various robustness tests, I show that the documented net-selling effect is not driven by empirical specification, different subsamples, holidays, or stocks/shootings in specific states in the U.S.

Next, I examine whether lower sentiment can explain aggregate retail investors' net divestment from local stocks following local mass shootings. If retail investors are affected by pessimism stemming from observing local mass shootings, 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 shooting incidents generating a higher level of pessimism, leading to larger retail outflows.

Given the finding that retail investors are driven by lower sentiment from mass shootings and net sell local stocks, an interesting follow-up question is whether such behavior is rational. To provide some evidence, I investigate the implications of local mass shootings on local firms' financial and operating performances and local economic conditions. I find that, during weeks following mass shootings in a state, local firms do not earn lower stock returns. Moreover, the number of shootings and the severity of shootings do not have any significant impact on local firms' quarterly operating performances (proxied by sales and net income over assets) and local states' quarterly economic conditions (proxied by unemployment rate and real GDP). Overall, the analysis suggests that local firms' performances and local states' macroeconomic conditions do not deteriorate in response to local mass shootings. This indicates that divestment from local stocks by aggregate retail investors is hard to justify.

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 a distinction holds, then, to the extent that institutional investors do not view local mass shootings as truly negative shocks to local firms' profitability, institutional investors should not exhibit meaningful variations in their trading activity in response to mass shootings. To identify institutional order flows, I follow Farrell et al. (2022) and Mohr (2021) and first apply Lee and Ready (1991) algorithm to sign each equity transaction as buy or sell transaction. Institutional buy (sell) flows are then 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 evidence suggests that retail investors are more prone to sentiment when making trading decisions. Moreover, together with the previous result that local mass shootings have no adverse effects on local firms and economies, it indeed seems to be the case that aggregate institutional investors, as a group, are more rational than retail investors in equity investing and trading.

This paper contributes to several strands of literature. First of all, I extend the existing evidence 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 stock buying and selling 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 uses 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] Leveraging heterogeneity at the mass shooting level, I show that aggregate retail investors are affected by sentiment when making equity trading decisions.

Finally, my findings shed light on the implications of violent crimes 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, which repeatedly happen in the U.S., 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 explores 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 the stock market. My paper differs from the above two studies in three important aspects. (1) Instead of digging into local retail investors' portfolios and stock market entry/exit choices, I focus on a large population of retail investors and their daily trading decisions targeting stocks local to mass shootings. (2) With a comprehensive dataset covering thousands of mass shootings (including some terrorist attacks) in the U.S., I am able

[7]For 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.

to exploit shooting-level characteristics and trace out corresponding variations in aggregate retail investors' buying and selling behavior, which allows me to pin down sentiment as a potential driver that affects retail investors' daily trading activity. (3) In addition to retail investors, I also study institutional investors and how they react to the same set of mass shootings incidents. Through comparison, I find that only retail traders are subject to sentiment in this setting, and their net divestment patterns are not justified by worsening local economic performances. Overall, my findings suggest that mass shootings affect retail investors' portfolio choices.

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. Moreover, I explore whether aggregate retail investors are rational, and how institutional investors react to the same set of mass shootings. 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 investors' trading activity. According to BJZZ, most retail equity orders in the U.S. are executed off-exchange. Under regulations, 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 exchanges 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 prices, I drop all trades that have transaction prices 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 $Z_{it} = mod(P_{it}, 0.01)$, 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

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

[9]Z_{it} is the reminder of P_{it} divided by 0.01.

$Z_{it} \in (0, 0.4)$. 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]

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 the daily retail order imbalances, as well as daily fractions of retail buying and selling activity. Specifically, for stock i on trading day t, I define the following order imbalance measures, in percentage:

$$Mroibvol_{i,t} = \frac{Mrbvol_{i,t} - Mrsvol_{i,t}}{Mrbvol_{i,t} + Mrsvol_{i,t}} * 100 \tag{1}$$

$$Mroibtrd_{i,t} = \frac{Mrbtrd_{i,t} - Mrstrd_{i,t}}{Mrbtrd_{i,t} + Mrstrd_{i,t}} * 100 \tag{2}$$

where $Mroibvol_{i,t}$ measures retail investors' net-buying activity, based on share volume. $Mroibvol_{i,t}$ measures retail investors' net-buying activity, based on the number of trades. $Mroibvol_{i,t}$ and $Mroibvol_{i,t}$ 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. [11]

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

[10] While 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".

[11] Notice that a positive (negative) retail order imbalance suggests that there is a relatively larger fraction of buying (selling) interest from retail investors.

objective data on gun violence in near real-time.[12] 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 by at least 1 verifiable news article/report.[13] This provides assurance in the sense that at least some retail investors are aware of each mass shooting included in GVA database.

While there is no universal definition of what constitutes a "mass shooting", organizations such as the 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).[14] However, there are potential concerns with this definition. With an emphasis solely on the number of fatalities, a large number of devastating shooting incidents are simply ignored.[15] This would also be problematic in this 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.[16] 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).[17] The objective is to capture

[12]The mass shootings data can be downloaded here: https://www.gunviolencearchive.org/reports

[13]See https://www.gunviolencearchive.org/methodology for details regarding GVA's data collection processes and methodologies

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

[15]Consider 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.

[16]Counting 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.

[17]Some 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.

a comprehensive set of attention-grabbing mass shootings incidents and understand retail investors' reactions 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 arrested, 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 that 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.[18] 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 shooting incidents in a state. Other than in mid-west and northern regions, shootings were fairly evenly distributed across states, which is consistent with Zhang (2019).[19] 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 shooting 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

[18] Retail trading and daily stock returns are only available on trading days, which are weekdays.

[19] Zhang (2019) focuses on shootings with more than 4 people killed.

the previous month end ($Return_{i,m-1}$), and returns in the past 6 months ($Return_{i,m-2,m-7}$). 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 number 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.[20] 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.[21] 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.

[20] For 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).

[21] Data 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.

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 periods and finds 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 correlations. Therefore, as the first step of the 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 the 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 the 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,[22] 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.[23] 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.[24] 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

[22] https://trends.google.com/trends/?geo=US.

[23] For 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.

[24] The count of victims equals the count of injuries and the count of deaths from mass shootings.

the 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, 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.[25] 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

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

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. Theoretical 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 a state make aggregate retail investors more pessimistic about local economic conditions or the operating activity of local firms, then aggregate retail investors might net sell and divest from 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:

$$Mroib_{i,s,t} = \alpha + \beta * Shooting_{s,w-1} + Controls + FEs + \epsilon_{i,s,t} \tag{3}$$

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 this specification accounts for the possibility that retail investors may realize the existence of mass shootings at different times throughout a week, and trade subsequently.[26] 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. By relating $Mroibvol_{i,s,t}$ to $Shooting_{s,w-1}$, I aim to capture the average change in daily retail order imbalance in a window (one week) after local mass shootings. Stock-level controls include past retail order imbalances, stock returns, firm size, return volatility,

[26] Results 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.

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 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.[27] Industry fixed effect controls for the unobservable industry attributes that impact retail interest.[28] I cluster standard errors at states.[29] In Equation 3, β is the coefficient of interest. As mentioned above, 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 with different levels of fixed effects, the coefficient on $Shooting_{s,w-1}$ stays negative and statistically significant. This implies that, on average, retail investors sell more shares and place more sell trades of local stocks in the week after mass shootings, relative to buy. In terms of economic magnitude, in column (3), where the dependent variable

[27]Figure 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.

[28]I use the Fama-French 49 industry classifications.

[29]All results hold if I cluster standard errors at states and time.

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 $Mroibvol_{i,s,t}$ 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 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 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, and 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.

Overall, results from Table 4 show that aggregate retail investors display a higher selling interest in local stocks following local mass shootings. This serves as preliminary 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. In Section 4, I provide further support that retail investors are indeed driven by lower sentiment from local mass shootings

3.3 Robustness

In this section, I conduct 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.[30] 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. 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.[31] 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.[32] 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

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

[31] Results are also robust if I drop all observations from year 2020 and 2021.

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

retail investors' interest in firms located in a specific state. For example, many shootings take place in large states, such as California and New York. In the meantime, a lot of firms have headquarters in these states as well. To alleviate such concern, I estimate Equation 3 in a loop, where I remove observations from a different state in each iteration. Results are shown in Figure 2. The coefficient on $Shooting_{s,w-1}$ in each iteration closely matches the full-sample estimate. Therefore, the result that retail investors divest from local stocks after local mass shootings is not driven by observations from an individual state.

4 Mass Shootings, Sentiment, and Rationality

Results in the previous section show that retail investors net sell local stocks in response to the presence of local mass shootings. Several important and interesting questions follow. First of all, can lower sentiment explain the observed net-selling behavior by aggregate retail investors? Also, is such an investment/trading strategy rational? Finally, how do aggregate institutional investors react to these incidents and shocks? In this section, I aim to provide answers to the above questions.

In Section 4.1, I explore shooting-level heterogeneity and test whether retail investors respond differentially to different types of shootings. In Section 4.2, I examine the impact of local mass shootings on local stock returns, local firms' operations, as well as local states' macroeconomic conditions to see whether the net-selling behavior by retail investors can be justified. In Section 4.3, I identify and study the daily trading patterns by aggregate institutional investors following the same set of mass shootings.

4.1 Shooting-level Heterogeneity and Retail Trading Activity

4.1.1 Mass Shootings Severity

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 the 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 Other Characteristics

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 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.[33] 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

[33] U.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.

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 Equation 5 below:

$$Mroib_{i,s,t} = \alpha + \beta 1 * Not\_Arrested_{s,w-1} + \beta 2 * Arrested_{s,w-1} + Controls + FEs + \epsilon_{i,s,t} \quad (4)$$

$$Mroib_{i,s,t} = \alpha + \beta 3 * Teen_{s,w-1} + \beta 4 * Adult_{s,w-1} + Controls + FEs + \epsilon_{i,s,t} \quad (5)$$

In Equation 4, $\beta 1$ and $\beta 2$ are coefficients of interest. They measure the average daily change in retail order imbalances following unsolved and solved mass shootings, respectively. In Equation 5, $\beta 3$ and $\beta 4$ 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 at the beginning of this section, if retail investors are driven by sentiment, $\beta 1$ and $\beta 3$ should be both statistically significant and more negative than $\beta 2$ and $\beta 4$.

Regression results are reported in Table 7. In Panel A across columns, the coefficients on $Not\_Arrested_{s,w-1}$ are negative and statistically significant at 1% level, whereas the coefficients on $Arrested_{s,w-1}$ 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 align 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 $Teen_{s,w-1}$ is negative and statistically significant at 1% level, whereas the coefficient on $Adult_{s,w-1}$ 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 the 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 suggest that shooting-level heterogeneity creates shifts in sentiment, which in turn leads to variations in retail outflows from local stocks.

4.2 Implications of Mass Shootings and Investors Rationality

In this section, I investigate whether retail investors are rational in net selling local stocks following local mass shootings. The answer to this question depends critically on the influence of mass shootings on local economies. Specifically, I examine how much mass shootings affect local firms' stock returns, operating performances, and local economic conditions. If shootings have muted or even positive effects, then it is hard to argue that retail investors make profits or avoid losses by divesting the local stocks.

First, to test the predictability of local mass shootings on local stocks, I estimate Equation 6, using Fama and MacBeth (1973) two-step approach:

$$Return_{i,s,w} = \alpha + \beta 5 * Shooting_{s,w-1} + Controls + \epsilon_{i,s,t} \tag{6}$$

The dependent variable is the daily stock return (in percentage) of firm i headquartered in state s in week w, $w+1$, $w+2$, $w+3$, which correspond to up to 4 weeks of daily returns following the presence of at least 1 local mass shooting. I include the same set of stock and state-level control variables as in the prior analysis. To account for serial correlation in the coefficients, I use Newey and West (1987) standard errors with 7 lags. $\beta 5$ measures the average daily change in local stocks' returns at different horizons after local mass shootings. The results are shown in Table 8 Panel A. The coefficient on $Shooting_{s,w-1}$ is very close to 0 and statistically insignificant, regardless of the horizons. Results suggest that local stock returns do not react to local mass shootings, not even during the first week. Overall, Table 8 Panel A suggests that net-selling retail investors do not seem to benefit from short-term stock price dynamics.

Instead of chasing short-term price trends, retail investors might be longer-term investors and care about firm fundamentals. If local firms' operating performances are adversely impacted by local mass shootings, aggregate retail investors might gain from divesting local stocks. To examine this possibility, I run a panel regression of local firms' quarterly sales and net income over total assets on the natural logarithm of local mass shooting counts and total victim counts. I include state and year-quarter fixed effects. Results in Table 8 Panel B suggest that local firms' operating performances are barely responsive to the frequency and severity of local mass shootings. Therefore, local firms' weaker operating performances following mass shootings cannot justify the net divestment by retail investors.

Finally, retail investors might allocate their capital away from local stocks because they fear that the local macroeconomic conditions would worsen after mass shootings. I proxy local states' macroeconomic conditions by quarterly unemployment rate and real GDP per capita. In Table 8 Panel C, I show that the above two indicators are not significantly correlated with mass shooting measures.

Overall, results from Table 8 do not provide any evidence that aggregate retail investors are rational in net-selling local stocks after mass shootings. This indicates that the strategy might be a behavioral bias.

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. 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 the 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.[34]

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 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 aligns with the conventional wisdom that retail traders are more prone to sentiment and less sophisticated, compared to institutional counterparts.[35]

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,

[34] Since 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.

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

through multiple robustness checks, I find that the result holds across different subsamples and regression specifications.

I 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 are 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.

I also find that such net-selling behavior by retail investors does not seem to be rational. Local firms' performances and local states' macroeconomic conditions do not deteriorate in response to local mass shootings, suggesting little gains for retail investors from divesting local stocks.

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 examine 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. Moreover, such a change in investment decisions appears to be a behavioral bias. 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' day-to-day portfolio choices.

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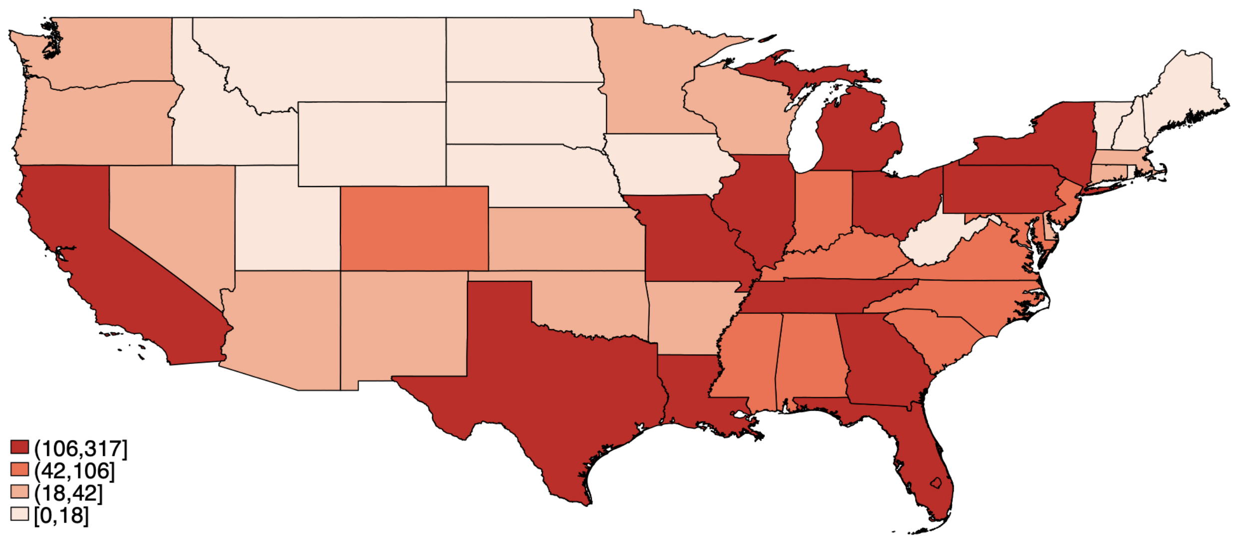
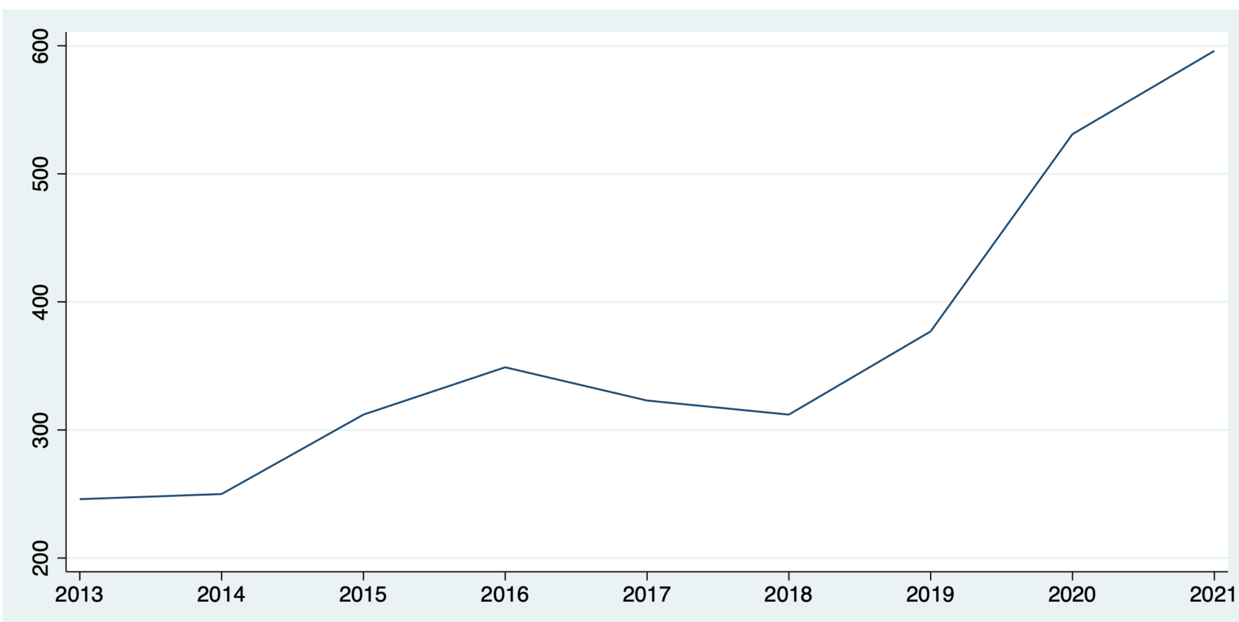
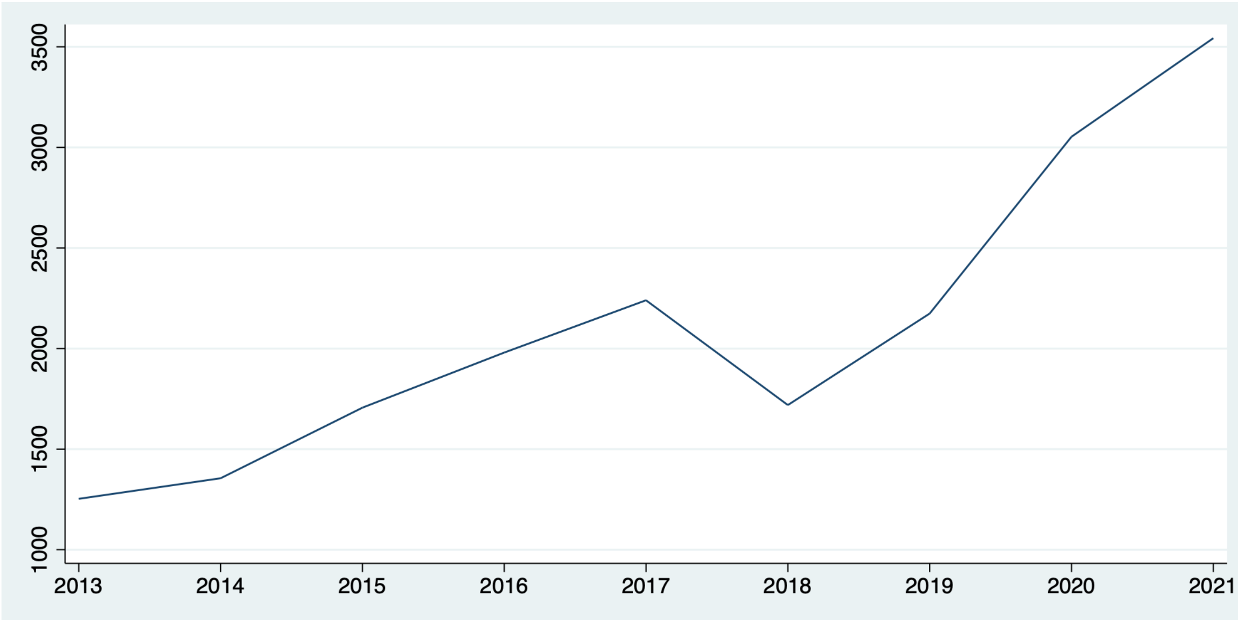
Figure 1: **Mass Shootings In the U.S.**



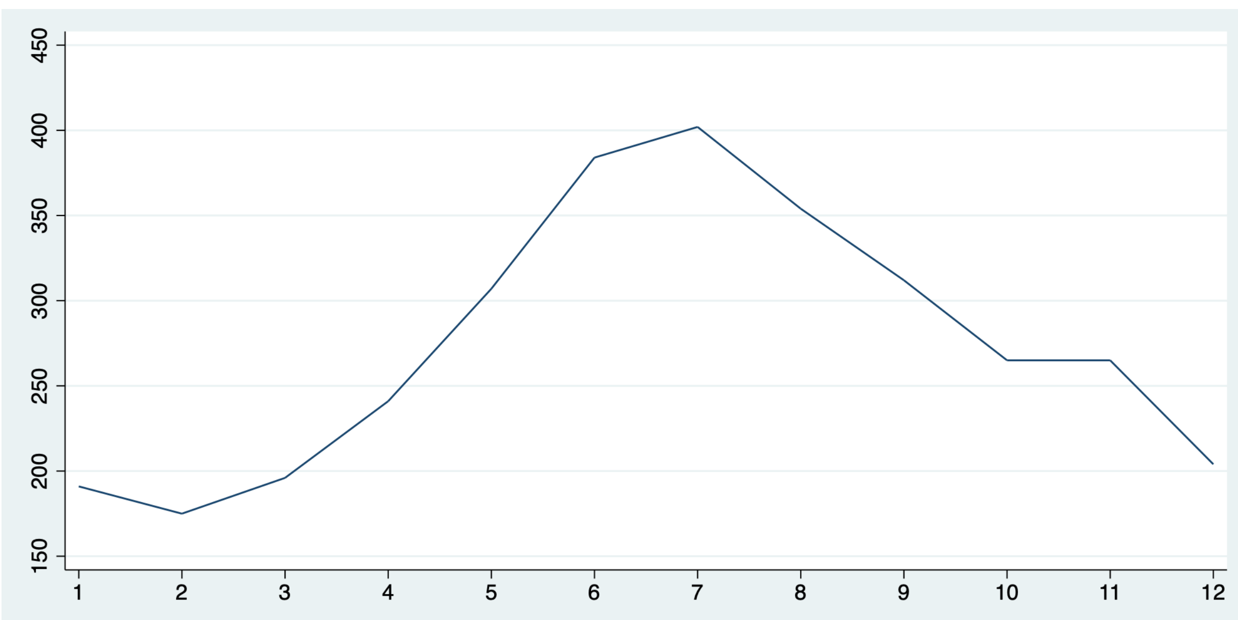
(a): The number of mass shootings by states



(b): The number of mass shootings by year



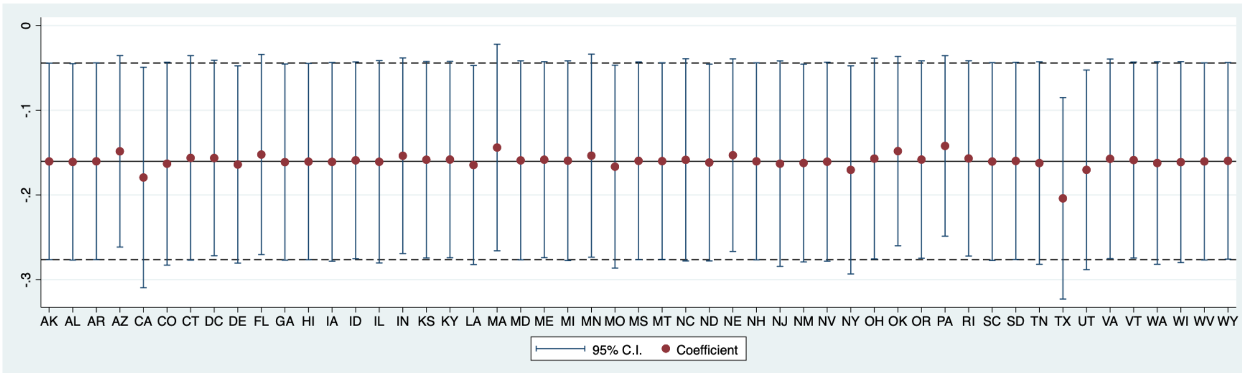
(c): The number of victims by year



(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
Panel A: Retail Trading Activities					
$Mrbvol_{i,t}$	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
Panel B: Stock-level Characteristics					
$Return_{i,w-1}(\%)$	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
Panel C: State-level Economic Conditions					
$Log\_Pinc_{s,q-1}$	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)
Panel A: National-Level						
Log_Injury_m	5.782***			8.809***		
	[2.009]			[1.817]		
Log_Death_m		9.752***			11.229***	
		[2.272]			[2.109]	
Log_Victim_m			7.324***			10.362***
			[2.146]			[1.932]
SVI_{m-1}	0.208**	0.216***	0.212***	0.449***	0.443***	0.443***
	[0.079]	[0.076]	[0.078]	[0.067]	[0.065]	[0.065]
Observations	108	108	108	108	108	108
Adjusted R^2	0.101	0.175	0.127	0.416	0.438	0.439
Panel B: State-level						
$Log\_Injury_{s,m}$	0.838***			1.444***		
	[0.122]			[0.324]		
$Log\_Death_{s,m}$		1.93***			2.181***	
		[0.233]			[0.381]	
$Log\_Victim_{s,m}$			0.918***			1.369***
			[0.114]			[.294]
$SVI_{s,m-1}$	0.117***	0.117***	0.117***	0.036**	0.036**	0.036**
	[0.022]	[0.022]	[0.022]	[0.018]	[0.018]	[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. The dependent variables are daily 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. 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.

Panel A: Order Imabalances

Dep. Var.	Volume Imbalance			Trades Imbalance		
	(1)	(2)	(3)	(4)	(5)	(6)
$Shooting_{s,w-1}$	-0.185***	-0.158**	-0.160***	-0.108*	-0.117*	-0.100**
	[0.062]	[0.067]	[0.058]	[0.063]	[0.069]	[0.039]
$Mroibvol_{i,d-1}$	0.048***	0.048***	0.047***			
	[0.001]	[0.001]	[0.001]			
$Mroibtrd_{i,d-1}$				0.099***	0.098***	0.097***
				[0.004]	[0.004]	[0.004]
$Return_{i,w-1}$	-0.051***	-0.054***	-0.061***	-0.042***	-0.043***	-0.049***
	[0.005]	[0.005]	[0.005]	[0.003]	[0.003]	[0.003]
$Return_{i,m-1}$	-0.034***	-0.032***	-0.037***	-0.037***	-0.035***	-0.040***
	[0.003]	[0.002]	[0.003]	[0.003]	[0.003]	[0.003]
$Return_{i,m-2,m-7}$	-0.004**	-0.004***	-0.006***	-0.003*	-0.003**	-0.005***
	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]
$Log\_Size_{i,m-1}$	0.340***	0.342***	0.294***	0.450***	0.454***	0.378***
	[0.024]	[0.024]	[0.030]	[0.030]	[0.030]	[0.033]
$Volatility_{i,m-1}$	0.118***	0.124***	0.051*	0.125***	0.137***	0.064**
	[0.019]	[0.019]	[0.028]	[0.022]	[0.023]	[0.028]
$Log\_BM_{i,m-1}$	-0.242***	-0.263***	-0.347***	-0.277***	-0.295***	-0.505***
	[0.059]	[0.059]	[0.044]	[0.061]	[0.062]	[0.039]
$Turnover_{i,m-1}$	0.644***	0.593**	0.410*	1.667***	1.606***	1.648***
	[0.227]	[0.227]	[0.208]	[0.196]	[0.200]	[0.192]
$Log\_Pinc_{s,y-1}$	-0.553	-0.568	0.278	-0.426	-0.441	0.645**
	[0.415]	[0.419]	[0.345]	[0.363]	[0.363]	[0.321]
$GDP\_Growth_{s,y-1}$	0.026	0.025	0.011	-0.030	-0.031	-0.014
	[0.043]	[0.043]	[0.025]	[0.037]	[0.037]	[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.

Panel A: Fama and MacBeth (1973) Regression

Dep. Var.	Volume Imbalance		Trades Imbalance	
	(1)	(2)	(3)	(4)
$Shooting_{s,w-1}$	-0.126**	-0.150**	-0.104**	-0.108**
	[0.057]	[0.059]	[0.050]	[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%

Panel B: Sub-samples

	2013m1-2020m3		No 2016-2018		No Holidays	
	(1)	(2)	(3)	(4)	(5)	(6)
$Shooting_{s,w-1}$	-0.184***	-0.174***	-0.218***	-0.125**	-0.153**	-0.091*
	[0.067]	[0.054]	[0.053]	[0.049]	[0.066]	[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**			-0.045**		
	[0.034]			[0.020]		
$Log\_Death_{s,w-1}$		-0.084**			-0.048	
		[0.037]			[0.033]	
$Log\_Victim_{s,w-1}$			-0.079***			-0.042**
			[0.029]			[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. Dependent variables are retail order imbalances, measured in share volume or the number of trades. $Not\_Arrested_{s,w-1}$ 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.

Panel A: Unsolved vs. Solved Shootings

Dep. Var.	Volume Imbalance	Trades Imbalance
	(1)	(2)
$Not\_Arrested_{s,w-1}$	-0.196***	-0.123***
	[0.066]	[0.044]
$Arrested_{s,w-1}$	-0.046	-0.026
	[0.069]	[0.061]
Wald test p-value	0.047	0.170
Industry FE	Yes	Yes
Year-Month FE	Yes	Yes
Observations	6396133	6396133
Adjusted R^2	0.4%	1.39%

Panel B: Teenagers vs. Adults Victims

Dep. Var.	Volume Imbalance	Trades Imbalance
	(1)	(2)
$Teen_{s,w-1}$	-0.255***	-0.134***
	[0.065]	[0.041]
$Adult_{s,w-1}$	-0.106	-0.081
	[0.066]	[0.055]
Wald test p-value	0.029	0.427
Industry FE	Yes	Yes
Year-Month FE	Yes	Yes
Observations	6396133	6396133
Adjusted R^2	0.40%	1.39%

Table 8: **Mass Shootings and Local Economy**

This table reports Fama and MacBeth (1973) regression results from estimating Equation 6 and panel regression results. The sample period is from January 1st, 2013 to December 31st, 2021. In Panel A, the dependent variables are daily stock returns in week w, $w+1$, $w+2$, $w+3$ after local mass shootings. In Panel B, the dependent variables are quarterly firm sales over assets and net income over assets (in percentages). In Panel C, the dependent variables are quarterly unemployment rate (in percentages) and the natural logarithm of the real GDP (in 2012 dollars). $Shooting_{s,w-1}$ is a dummy variable that equals 1 if mass shootings took place in state s in the previous week, 0 otherwise. $Log\_Shooting_{s,q}$ is the natural logarithm of the total number of mass shootings in state s during quarter q. $Log\_Victim_{s,q}$ is the natural logarithm of the total number of victims from mass shootings in state s and quarter q. 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 in Panel A. ***, **, * denote significance at the 1%, 5%, and 10% level, respectively.

Panel A: Local Stock Returns

	w	w+1	w+2	w+3
	(1)	(2)	(3)	(4)
$Shooting_{s,w-1}$	-0.001	-0.004	-0.001	0.002
	[0.003]	[0.004]	[0.004]	[0.004]
Stock Controls	Yes	Yes	Yes	Yes
State Controls	Yes	Yes	Yes	Yes
Observations	6396385	6369509	6365284	6349604
Adjusted R^2	5.54%	5.25%	5.18%	5.14%

Panel B: Local Operating Performance

	Sales/Assets		ROA	
	(1)	(2)	(3)	(4)
$Log\_Shooting_{s,q}$	-0.071		0.122	
	[0.080]		[0.085]	
$Log\_Victim_{s,q}$		-0.021		0.061
		[0.039]		[0.053]
Firm FE	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes
Observations	143603	143603	143649	143649
Adjusted R^2	85.14%	85.14%	55.35%	55.35%

Panel C: Local Economic Condition				
	Unemployment Rate		Log Real GDP	
	(1)	(2)	(3)	(4)
$Log\_Shooting_{s,q}$	-0.011		-0.000	
	[0.060]		[0.003]	
$Log\_Victim_{s,q}$		-0.030		0.000
		[0.026]		[0.001]
State FE	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes
Observations	1836	1836	1836	1836
Adjusted R^2	82.77%	82.77%	99.88%	99.88%

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. 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. 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	-0.003	0.007	-0.013	-0.002	0.015
	[0.048]	[0.045]	[0.049]	[0.043]	[0.037]	[0.040]
$Nret\_oibvol_{i,d-1}$	0.136***	0.136***	0.136***			
	[0.001]	[0.001]	[0.001]			
$Nret\_oibtrd_{i,d-1}$				0.203***	0.202***	0.202***
				[0.002]	[0.002]	[0.002]
$Return_{i,w-1}$	0.142***	0.142***	0.133***	0.078***	0.078***	0.069***
	[0.007]	[0.007]	[0.007]	[0.007]	[0.007]	[0.007]
$Return_{i,m-1}$	0.014***	0.014***	0.018***	0.015***	0.015***	0.018***
	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]
$Return_{i,m-2,m-7}$	0.007***	0.007***	0.008***	0.006***	0.006***	0.007***
	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]
$Log\_Size_{i,m-1}$	0.630***	0.631***	0.611***	0.325***	0.325***	0.307***
	[0.023]	[0.023]	[0.025]	[0.015]	[0.015]	[0.016]
$Volatility_{i,m-1}$	-0.199***	-0.198***	-0.275***	-0.116***	-0.116***	-0.173***
	[0.018]	[0.018]	[0.023]	[0.016]	[0.016]	[0.021]
$Log\_BM_{i,m-1}$	0.037	0.035	0.018	0.016	0.015	0.007
	[0.034]	[0.034]	[0.031]	[0.022]	[0.022]	[0.020]
$Turnover_{i,m-1}$	0.300*	0.281	0.450**	-0.283**	-0.296**	-0.145
	[0.171]	[0.170]	[0.169]	[0.127]	[0.126]	[0.127]
$Log\_Pinc_{s,y-1}$	-0.783**	-0.784**	-0.622*	-0.355	-0.354	-0.303
	[0.381]	[0.381]	[0.360]	[0.252]	[0.253]	[0.242]
$GDP\_Growth_{s,y-1}$	0.030	0.030	0.028	0.020	0.020	0.018
	[0.019]	[0.019]	[0.018]	[0.016]	[0.016]	[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%