Squeezing Shorts Through Social Media Platforms*

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Abstract

At the end of January 2021, a group of stocks listed on US stock exchanges experienced sudden price increases, which – coupled with high short interest – led to short-squeeze episodes. We find that these events were fueled by retail traders coordinating on social media platforms. Options markets also played a central role. Using unique data from social media platforms we provide a comprehensive account of these short squeezes and show that they significantly impeded market quality for the stocks at issue and their competitors. Thus, retail trader coordination can lead to market-distorting events and impair market efficiency.

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1. Introduction

One central question in financial economics is how efficiently information is incorporated in capital markets. In efficient capital markets, the price of an asset should reflect the arrival of new, value-relevant information. The mechanism by which this is accomplished is arbitrage. If the price of an asset is too low relative to its discounted future cash flows, arbitrageurs will buy it and drive the price up; if the price is too high, they will short sell it and drive the price down. Among the most important limits to this arbitrage process is the possibility of a short squeeze. Behavior intended to squeeze short sellers is considered market manipulation and losses to market participants can be substantial.[1] For example, during the 2008 Porsche-VW short squeeze alone, market participants lost upwards of USD 20 billion.[2]

At the end of January 2021, multiple companies listed on United States (US) stock exchanges experienced surges in their stock prices, which - coupled with high short interest - led to short squeezes in many of them. We find that these sudden price spikes were fueled by coordinated actions of retail traders through social media platforms, which ultimately deteriorated the market quality of the stocks concerned and their product market competitors.[3] While short squeezes initiated by large or sophisticated market participants have been studied in the past (see e.g., Kyle (1984), Jarrow (1992), and Allen, Haas, Nowak, and Tengulov (2021), among others), the impact of retail trader coordination through social media platforms on short sellers is largely unexplored. Historically retail traders have been viewed as "unsophisticated" traders that have very little market impact. However, if they coordinate through social media, their trading can lead to market-distorting events.

This paper focuses on the 13 "meme" stocks, which were at the center of the social media discussions and for which trading restrictions were put in place by brokers.[4] We find evidence of short squeezes in GameStop, which was one of the main stocks that individual traders focused on at the time, and an additional six of the 13 restricted meme stocks. For this set of seven stocks and concurrent with the sudden steep price increases we find a significant (i) de-

[1]Cherian and Jarrow (1995) survey the early manipulation literature and Spatt (2014) provides a recent review. Hart (1977), Kyle (1984), Vila (1989), Allen and Gale (1992), Allen and Gorton (1992), Benabou and Laroque (1992), Kumar and Seppi (1992), and Jarrow (1992, 1994) were among the first to study market manipulation. Later, Bagnoli and Lipman (1996), Chakraborty and Yılmaz (2004), Merrick Jr, Naik, and Yadav (2005), and Goldstein and Guembel (2008) contributed influential papers to the manipulation literature.

[2]"Hedge funds make £18bn loss on VW," BBC News, October 29, 2008 (Link).

[3]This evidence is timely given the recent focus of academic research on the interaction between social media platforms and financial markets. Indeed, Hirshleifer (2020) discusses "social economics and finance" as a new emerging field that aims to understand how social interactions influence market outcomes. Our study presents evidence consistent with social compounding, in which the views of a single (few) investor(s) can be compounded across social networks and have a large market impact. To our knowledge, the January 2021 events represent the first time that coordinated trading through social media specifically targeted stocks, some of which had high short interest.

[4]American Airlines, AMC, BlackBerry, Bed Bath & Beyond, Castor Maritime Inc., Express, GameStop, Koss, Naked Brand Group, Nokia, Sundial Growers Inc., Tootsie Roll, and Trivago NV. This set of stocks is the super-set of all stocks that were subject to trading restrictions by retail broker-dealers for the longest duration starting January 28 through early February 2021. Section 3 provides more details about our sample selection.

crease in shorting activity, ii) decrease in lendable quantity, iii) increase in available quantity, iv) decrease in average fees for stock borrowing transactions, and v) migration to the options market.

Using social media activity data from Reddit, Twitter, and StockTwits we provide evidence that the price increases of the meme stocks were fueled by retail traders coordinating through social media platforms. This evidence is corroborated by placebo tests based on a set of control companies with comparable short interest levels and industry classification as the squeezed stocks, but with no or low social media activity. For these control stocks, we do not find an increase in the association between retail trading activity and stock price movements during the short-squeeze window.[5] When the short squeezes approached their peak and retail brokers started to restrict purchases in the meme stocks, we document that both long and short investors used options likely to circumvent the impediments introduced in the stock market and to continue to express their positive and negative views.

Our sample allows us to compare restricted meme stocks that experienced short squeezes to restricted meme stocks that did not experience short squeezes. This, in turn, helps us differentiate the effects of the short squeezes on market efficiency and quality from other concurrent events, such as the introduction of trading restrictions by retail brokers and the retail trading hype on social media platforms. We find evidence of a decoupling of stock and option prices for the squeezed stocks, as suggested by put-call parity violation tests. This indicates relative mispricings and deterioration of market efficiency for the set of squeezed meme stocks. We also find worse market quality, as measured by bid-ask spreads and stock return volatility, for the stocks that experienced short-squeeze episodes compared to the other restricted stocks that did not experience short squeezes. Finally, we document negative spillover effects for the product market competitors of the stocks concerned.

While actions intended to cause short squeezes are illegal in most countries, including the US, it is currently unclear whether the type of coordination undertaken by investors in these episodes is covered by the rules governing stock market trading. The debate on the extent to which short selling and short squeezes should be regulated has been around for more than a century. For example, Allen, Litov, and Mei (2006) show that in the nineteenth and early twentieth century, squeezes and corners were not uncommon in US stock markets. Short squeezes and corners are regulated and subject to enforcement actions by US regulators. For example, they are regulated as part of the 1934 Securities and Exchange Act (the SEC Act), which broadly made illegal two categories of security market manipulation: action-based manipulation and information-based manipulation. In action-based manipulation, the manipulative strategy cen-

[5]Complementary to our analyses of trading activity in both the equity and the options market we investigate whether bots, i.e., accounts that post algorithmically using a computer algorithm, were contributing to the increase in social media posts. We do not find evidence of bot activity at any point in time over the sample period. This is not to say that bots did not exist or attempt to influence market participants' sentiment. Most social media platforms have committed themselves to screening for bot activity, and to remove bot activity once it has been recognized. See "WallStreetBets says Reddit group hit by "large amount" of bot activity," CBS News, February 2, 2021, (Link). For a detailed discussion, see Section A.1 in the Internet Appendix.

ters on implementing actions that change the actual or perceived value of the assets (Wycoff (1968)). To remove information-based manipulation, the SEC Act required firms to issue information to the public on a regular basis to, among other things, make the spreading of rumors more difficult. The SEC Act is actively enforced and with a number of well-publicized exceptions, it has been successful in eradicating action-based and information-based manipulation.[6]

Understanding what happened prior to and during these short-squeeze episodes is important for at least three reasons. First, US regulators are in the process of establishing the extent to which the January 2021 events have adversely impacted market quality and violated stock market regulations. For example, the SEC published a "Staff Report on Equity and Options Market Structure Conditions in Early 2021" (SEC October 2021 report) in which the agency discusses GameStop's January 2021 trading activity and claims to have found little evidence of a short squeeze in GameStop.[7] The report does not analyze any of the other stocks at issue. In contrast, in our paper, we provide evidence that a short squeeze developed in GameStop, as well as in six of the other restricted meme stocks. This evidence is based on detailed data from the securities lending market and suggests that coordination through social media platforms to target high short-interest stocks has made short selling more risky. This has driven short sellers out of meme stocks, which, in turn, can have a harmful impact on the information intermediation role of short sellers in particular and on market quality in general.[8] We find that market quality was adversely impacted for all meme stocks in our sample and their product

[6]A recent example of the stringent enforcement of the SEC Act is provided by the 2018 Tesla events. In particular, in August 2018 US regulators - the US Department of Justice (DOJ) and the SEC - investigated events surrounding Elon Musk's tweet that he was considering taking Tesla private. After the conclusion of the investigations, both Tesla and Mr. Musk had to pay penalties, and Mr. Musk had to step down as the chairman of Tesla's board (see Allen et al. (2021)).

[7]While the agency does find a steep decrease in short interest (from more than 100% to less than 25%) in a matter of two days or so, it concludes that "it was the positive sentiment, not the buying-to-cover, that sustained the weeks-long price appreciation of GameStop stock." See SEC October 2021 report, October 14, 2021, (Link). However, this finding is based on "buying-to-cover" and short interest positions data from December 24, 2020 onward and does not include short interest positions opened before this date, which can help explain the inconsistency in the SEC's finding between the steep drop in short interest and the little "buying-to-cover" activity found by the agency. In Figure 3 we plot the evolution of the average tenure of securities loans (among other relevant variables). Tenure represents the average length (in days) for which a securities loan was outstanding. We see that before the squeeze period, the average tenure for GameStop securities loans was around 85 days, meaning the average securities loan for GameStop was opened long before December 24, 2020. Tenure then drops by more than half to less than 40 days during the squeeze period, which indicates that many of the older outstanding loans were closed.

[8]Evidence from the empirical accounting and finance literatures suggests that short sellers are sophisticated market participants who are able to identify suspect financial reporting prior to public disclosures (Desai, Krishnamurthy, and Venkataraman, 2006). As a result, short sellers have an important information intermediation role (Pownall and Simko, 2005) and contribute to improved market efficiency (Drake, Myers, Scholz, and Sharp, 2015). For example, short sellers are shown to detect accounting irregularities (Dechow and Sloan, 1997; Karpoff and Lou, 2010). Further, short sellers are shown to provide predictive information to investors in trading against analysts' recommendations (Drake, Rees, and Swanson, 2011) and more generally in stock market trading (Beneish, Lee, and Nichols, 2015), in bond market trading (Kecskés, Mansi, and Zhang, 2013), as well as about large insider sales (Khan and Lu, 2013), auditor changes (Blau, Brough, Smith, and Stephens, 2013), risks considered by auditors (Cassell, Drake, and Rasmussen, 2011; Hope, Hu, and Zhao, 2017), and managers' voluntary disclosure choices (Li and Zhang, 2015). Thus, short sellers play an important role in price discovery and stock market efficiency (Jiang, Habib, and Hasan, 2022).

market competitors. Importantly, our analyses suggest a greater adverse impact on market quality for the subset of restricted meme stocks that experienced short squeezes.

Second, these short squeezes are unlike any other, historical short-squeeze events. While short squeezes did occur with some frequency historically, coordination among retail traders to target stocks with high short interest, as seen in these episodes, has not been seen before in quite this way. The reason is that this type of coordination is a phenomenon made possible only in recent years through social media platforms. Given that trading by retail investors (i) has seen a significant increase since the onset of the COVID-19 pandemic,[9] and (ii) is expected to remain at elevated levels,[10] it is important to understand whether retail investors' trading and coordination through social media platforms can lead to market-distorting events. Our study provides evidence that the January 2021 events were fueled by retail trading activity and that increased coverage of the meme stocks on social media platforms contributed to increased retail trading for these stocks.

Third, this paper sheds light on the role that social media platforms played during the January 2021 events, and how social media interacts with financial markets. The costs and benefits of social media have been the topic of intense debate since their development in the 1990s. While some financial researchers and regulators have repeatedly expressed concerns about social media platforms' potentially harmful effects on market efficiency and retail investors,[11] others point to the benefits arguing that traders' discussions on social media provide investment value and make retail investors become better informed. Much of the difference in opinions stems from the fact that individual users of social media platforms are traditionally considered to be mostly "unsophisticated" traders. However, with the rise of social media platforms, the degree of individual traders' "lack of sophistication" is not clear anymore. In particular, with the help of these platforms, individual traders can discuss and coordinate their trading strategies. Information is freely available and easily accessible, which can potentially make the retail trader group a powerful crowd that can move stock returns and volatility similar to what has previously been documented for large institutional investors. In the past, coordination among large institutional investors, which are usually considered "sophisticated traders," was often scrutinized and has previously led to convictions if regulators found evidence of market manipulation.[12] At the same time, retail traders enjoy special protection by the SEC. Therefore, to

[9]The Bank of International Settlement (BIS) describes how retail trader participation in capital markets has increased in 2021, and reports a surge in retail trader participation for exchange-traded funds, individual stocks, and (call) options. They also discuss that an increase in retail participation in the options market can lead to an increase in the market volatility of the underlying as options market makers attempt to hedge their trades in the underlying stock. See "The rising influence of retail investors," BIS, March 1, 2021, (Link).

[10]See e.g., "How the Meme Stock 'Revolution' Has Left Markets Changed a Year Later," Wall Street Journal, January 28, 2022, (Link)., and "Retail Trading Just Hit An All-Time High. Here's What Stocks Are The Most Popular," Forbes, February 3, 2023, (Link).

[11]See, for example, the "Investor Alert: Thinking About Investing in the Latest Hot Stock? Understand the Significant Risks of Short-Term Trading Based on Social Media," SEC, January 30, 2021, (Link); "Updated Investor Alert: Social Media and Investing – Stock Rumors", SEC, November 5, 2015, (Link).

[12]"Big Banks May Block Traders From Chat Rooms," Wall Street Journal, November 10, 2013, (Link).

analyze whether retail investor coordination through social media can have significant market impact, akin to that of sophisticated institutional investors, we analyze the January 2021 US stock market events, which represent one of the most prominent recent events of social media coordination.[13]

Our primary contribution is to the body of literature examining short squeezes and corners. While early literature focuses on either theoretical issues or empirical findings in the commodity, bond, and derivative markets (Kyle, 1984; Kumar and Seppi, 1992; Jarrow, 1992; Pirrong, 1993; Jegadeesh, 1993; Nyborg and Sundaresan, 1996; Cooper and Donaldson, 1998; Pirrong, 2001; Nyborg and Strebulaev, 2004; Merrick Jr, Naik, and Yadav, 2005; Ben-Abdallah and Breton, 2016), recent studies have branched out to examine squeezes and corners in equity markets (Brunnermeier and Pedersen, 2005; Allen, Litov, and Mei, 2006; Lamont, 2012; Riccò, 2019; Allen, Haas, Nowak, and Tengulov, 2021; Schultz, 2023; Stice-Lawrence, Wong, and Zhao, 2023).[14] Closely related to our contribution are Kyle (1984), Kumar and Seppi (1992), Merrick Jr, Naik, and Yadav (2005), and Allen et al. (2021). Kyle (1984) and Kumar and Seppi (1992) develop theories of squeezes in commodity futures markets, but many of their insights are also applicable to stock market squeezes. Kyle (1984) shows how short squeezes can arise even though all traders are fully rational. Kumar and Seppi (1992) argue that uninformed investors can profitably manipulate security prices by strategically trading the underlying of a futures contract. In their model, they show that manipulation (e.g., through a corner or squeeze) typically has an adverse effect on market liquidity. Merrick Jr, Naik, and Yadav (2005) study an attempted delivery squeeze in the long-term government bond futures contract traded in London and show that market prices and market depth were distorted. Allen et al. (2021) describe

[13] Despite the fact that the January 2021 events occurred in the middle of lockdowns, where retail investors had more available time, these are not isolated events, but rather represent a new market regime in which retail traders have a new and effective mechanism to coordinate and potentially dictate market outcomes. Throughout 2021 and 2022, retail traders have increased purchases of stocks and call options, which contributed to increasing prices of meme stocks, such as Bed Bath & Beyond Inc. and AMC Entertainment Holdings (see "Meme-Stock Investors are Back! Sort of, Anyway," The Wall Street Journal, August 13, 2022, (Link)). For example, in August 2022, the shares of both companies realized gains of at least 68%, with Bed Bath & Beyond stock having its best month in history. Further, in September 2022 retail investors crowded into Avaya Holdings Corp, driving up the software company's stock price by about 200%, despite the company's share and bond prices reflecting a high risk of bankruptcy (see "Meme-Stock Traders Embrace Avaya Despite Wall Street Fears," The Wall Street Journal, September 19, 2022, (Link)). Retail traders are now estimated to account for over a third of stock market trading and even up to 40% on peak trading days. (see "How the Meme Stock 'Revolution' Has Left Markets Changed a Year Later," Wall Street Journal, January 28, 2022, (Link)). Also professional traders have noticed this trend: a survey among professional traders shows that 85% of hedge funds and 42% of professional asset managers are now tracking retail trading message boards (see "Day Traders as 'Dumb Money'? The Pros Are Now Paying Attention," The Wall Street Journal, January 16, 2022, (Link)).

[14] More broadly, our findings are also related to the literature examining risks to short selling. Reed (2013) surveys the early short-selling literature and Jiang, Habib, and Hasan (2022) provide a more recent review. Specifically, in addition to rising stock prices short sellers face the risk that borrowing fees will increase before a short position is closed (e.g., Engelberg, Reed, and Ringgenberg (2018)) or that stock loans will be recalled (e.g., Chuprinin and Ruf (2017)). Banerjee and Graveline (2013) argue that under certain conditions, short sellers are at risk of paying higher borrowing costs than the premium they earn from selling the security. We highlight an additional risk to short sellers, namely the risk of a short squeeze induced by coordinated trading through social media platforms.

the evolution of securities laws in the European Union in general and Germany in particular and discuss the Porsche-Volkswagen (VW) short squeeze in 2008 as an example of the problems to which a lack of regulatory enforcement can lead. We contribute to this literature by documenting that in late January 2021 a short squeeze developed in GameStop and several of the other restricted meme stocks. These short squeezes are unique because they were not triggered by a large trader (as was the case, for example, in the Porsche-VW short squeeze), but by the coordinated efforts of a group of small retail investors, which many had previously considered uninformed. Further, these events occured in one of the most advanced countries in the world with arguably some of the most sophisticated financial market regulations, namely the US. We find that the short squeezes contributed to reduced market quality despite continuous information processing and real-time surveillance by U.S. market regulators. We also find that the short squeezes negatively impacted the market quality of the product market competitors of the stocks concerned.

Our findings also connect with the literature that explores the interaction between social media platforms and financial markets. This literature has largely focused on how companies use social media to reach stakeholders and interested parties (e.g., Blankespoor, Miller, and White (2014), Lee, Hutton, and Shu (2015) Blankespoor (2018), Nekrasov, Teoh, and Wu (2022), and Cong and Li (2023)). Recent research examines how investor opinions and analysis published on social media impact market prices (e.g., Chen, De, Hu, and Hwang (2014), Gomez, Heflin, Moon, and Warren (2022), Dim (2021), Farrell, Green, Jame, and Markov (2022)), as well as how coordinated trading or information sharing through social media platforms impacts capital markets (see e.g., Duz Tan and Tas (2020), Cookson and Niessner (2020), Jiao, Veiga, and Walther (2020), Lyócsa, Baumöhl, and Vỳrost (2022), Hu, Jones, Zhang, and Zhang (2021), and Cai, McLean, Zhang, and Zhao (2022), among others). For example, some papers document that information sharing on social media platforms is relied upon by individual investors, though it doesn't necessarily make them better informed (see, e.g., Ammann and Schaub (2021) and Kakhbod, Kazempour, Livdan, and Schuerhoff (2023)). Other papers show that information sharing on social media platforms contains predictive information for stock returns and increases trading volumes in the relevant stocks (Blankespoor, Miller, and White, 2014; Bartov, Faurel, and Mohanram, 2018; Farrell, Green, Jame, and Markov, 2022). Most of the prior literature argues that social media has a positive effect on financial markets. This, however, is not shared by all research. For example, more recently, Jia, Redigolo, Shu, and Zhao (2020) document that merger rumors on social media impede price discovery. Campbell, Drake, Thornock, and Twedt (2023) document, amongst other things, that when earnings announcements go viral on social media, this coincides with lower market liquidity and slower price formation. Our findings complement those of Jia et al. (2020) and Campbell et al. (2023) by showing that social media platforms can be an effective medium for retail trader coordination, which, in turn, can lead to market-distorting events and deteriorate market quality.

Closely related to our contribution is Pedersen (2022), who provides a theoretical model for the social media coordination events that took place in early 2021. However, Pedersen (2022) does not explore how short sale frictions interact with network effects and the impact of this interaction on market prices. Our study shows evidence consistent with network effects exacerbating limits to arbitrage.[15]

The remainder of this paper is organized as follows. Section 2 reviews the background of the January 2021 events. Section 3 describes the underlying data. Section 4 analyzes the securities lending market. Section 5 investigates if retail traders contributed to the price increases and analyzes the interaction between social media platforms and retail trading activity. Section 6 provides analyses related to the options market. Section 7 discusses the effects on market quality of the stocks at issue and their competitors. Section 8 concludes. The Internet Appendix provides further information and additional robustness tests.

2. Background

In this section, we review the January 2021 events as well as their resolution. We start by comparing the price increases for the meme stocks to the performance of the S&P 500 over the same time period. The left panel in Figure 1 shows how starting in the fourth week of January, the stock prices of the meme stocks increased by 100% to 1,500%. In contrast, the S&P 500 index remained almost constant over the same time period. The right panel in Figure 1 shows how starting with the increase in erratic price movements in the fourth week of January, social media activity of the meme stocks increased and moved closely with the price increases.

[Insert Figure 1 here.]

2.1. The short squeezes

During the second half of 2020 and going into 2021, retail investors participation in the stock market continued to increase, a trend that started during the Covid-19 pandemic in 2020.[16] This trend was amplified by commission-free trading that brokers like Robinhood offered through their platforms and apps.[17] The stocks of interest to these retail investors were mostly stocks

[15] Indeed, Pedersen (2022) points out that the interaction between short sale frictions and network effects is an important avenue for future research as a "bubble driven by social media effects can be greatly exacerbated if short sellers are forced to close their positions due to share recalls or risk controls." We find that the 13 meme stocks experienced similar increase in retail trading activity fueled by discussions on social media platforms, but the 13 stocks differ in that seven of them had high short interest and experienced short squeezes, while the other six stocks had low short interest and did not experience short squeezes. This, in turn, helps us analyze how limits to arbitrage (frictions resulting from short-squeeze constraints) interact with "network effects" through social media platforms. In other words, we provide evidence that the deterioration in market quality was more pronounced for the squeezed meme stocks relative to the non-squeezed meme stocks.

[16] See, e.g., Ozik, Sadka, and Shen (2021).

[17] "Memorandum to Members, Committee on Financial Services; Subject: February 18, 2021, Full Committee Hearing entitled, "Game Stopped? Who Wins and Loses When Short Sellers, Social Media, and Retail Investors Collide?," US House of Representatives, Committee on Financial Services, February 15, 2021.

well-known among consumers such as Bed, Bath & Beyond, GameStop, and AMC. Concurrent with increased retail trading in these stocks short sellers were betting that these stocks would perform poorly in the future. For example, one of the stocks at the center of the January 2021 events, GameStop, had short interest around 80%. However, not all institutional investors were taking short positions in the meme stocks. For example, in late 2020, activist investor Ryan Cohen disclosed a stake of more than 10% in GameStop, making him the company's biggest single investor at the time.

In January 2021, discussions focused on the meme stocks in general and GameStop in particular intensified on social media platforms. Many of the postings referenced that retail investors, such as Keith Gill (a trader who made an impact on social media) had entered into long positions in GameStop and called for others to do the same. Market participants entered into these long positions while being aware that significant short interest was outstanding for GameStop and some of the other meme stocks. Some short sellers, such as Citron Research, engaged publicly in an attempt to persuade the crowd that going long in these stocks was not a prudent investment strategy.[18] Retail traders were not discouraged. On the contrary: after Citron Research's posts, there was a marked uptick in social media activity for GameStop across Twitter, Stocktwits, and Reddit (see Figure 1). This increased activity was associated with an increase in GameStop's stock price from $30 to $347. The debate was spurred further by a tweet by Elon Musk on January 26 with the single word "Gamestonk!!" along with a link to the Reddit forum WallStreetBets. This tweet and the public debate were associated with a further increase in retail trading activity.[19] Eventually, the stock price of GameStop (and the other meme stocks) increased to levels such that investors shorting these securities were caught in a textbook short squeeze. For example, on January 27, the all-time highest intraday stock price for GameStop was $483 (nearly 190 times the price of $2.57 - the lowest stock price to date reached nine months earlier in April 2020). In pre-market trading hours the same day, it briefly hit over $500.[20] Many of the other meme stocks experienced stock price increases and social media surges similar to GameStop as shown in Figure 1.

[18] On January 19, Citron Research, an "online stock commentary source" (and at the time short in GameStop), published a post on Twitter that effectively called buyers of GameStop's stock "suckers" and promised to explain "the 5 reasons GameStop $GME buyers at these levels are the suckers at this poker game." See Citron Research Tweet on January 19, 2021.

[19] The debate appears to have attracted more and more retail investors to "further [go] long on GameStop" and the other stocks at issue. See Case 3:21-cv-00781, (Link).

[20] According to data from TAQ in pre-market trading the price briefly hit USD 500, an increase of 338% compared to the previous closing. The evolution of GameStop's stock price and order imbalances is shown in Figure A9 in the Internet Appendix. In addition, Figure A10 and Figure A11 plot the evolution of the stock prices and order imbalances of the other companies at issue, all of which experienced a similar stock price evolution as GameStop. It is worth noting that professional market analysts do not seem to have anticipated these steep price increases and were confused about the true fundamental value of the stocks at issue. See the Internet Appendix, Section A.3 for details on price target dispersions among stock analysts.

2.2. *The resolution*

Following the extraordinary price increases, on January 28, 2021 retail brokers restricted purchases of the meme stocks; customers could no longer open new positions in these stocks, although they could still close them. In addition to these purchasing restrictions, several brokers also increased the margin requirements for certain stocks and options.[21] After the markets closed, some of the brokers announced a relaxation in the restrictions. For example, Robinhood announced it would begin to allow "limited buys" of the affected securities starting the following day, although it was unclear at the time what this would entail. Several brokerage firms, including Robinhood, stated on January 29, 2021 that the restrictions were the result of clearing houses raising the required collateral for executing trades.[22] Because there is a two-day lag between the moment when investors purchase a security and the moment cash and securities are actually exchanged, brokerage firms have to post collateral at clearing houses to guarantee the proper settlement of their clients' orders. Clearing houses include the Depository Trust & Clearing Corporation (DTCC) for equities and the Options Clearing Corporation (OCC) for options. Brokerage firms claimed that the increased collateral could not be provided in time, and, as a result, trading had to be halted. The DTCC, for example, increased the total industry-wide collateral requirements from $26 billion to $33.5 billion, noting that the large trading volumes in specific stocks "generated substantial risk exposures at firms that clear these trades [...] particularly if the clearing member or its clients are predominantly on one side of the market."[23] As a result of increased collateral requirements brokerage firms searched for additional capital. For example, on January 29, 2021 it was reported that Robinhood had raised an additional USD 1 billion to protect the company from the financial pressure placed by the increased interest in particular stocks and met the collateral requirements of clearing houses.[24]

As of January 29, 2021 Robinhood was still imposing limits on the trading of several stocks. On January 30, 2021 Robinhood announced it had increased the restrictions from the trading of 13 securities to 50, including companies such as Rolls-Royce Holdings and Starbucks Corporation. However, this particular restriction was short lived, and on January 31, 2021 Robinhood announced it had removed several of these restrictions and would only limit the trading of eight securities.

On February 1, 2021, the prices of meme stocks started to decline. For example, the stock price for GameStop lost more than 80 percent of its value from its intraday high recorded during the previous week. Gamestop shares lost 60% of their value on February 2, closing below $100 for the first time in a week. Other stocks affected by the short squeeze and put under broker trading restrictions, such as AMC, also declined in value. Despite the decline, some Reddit users rallied to convince other users to hold on to the shares, arguing either that they would

[21] See "Anger as brokers curb retail investors' bets on GameStop," Financial Times, January 28, 2021, (Link).
[22] "Robinhood Fallout Sweeps Market After $1 Billion Lifeline," Bloomberg News, (Link).
[23] "Robinhood tightens GameStop trading curbs again as SEC weighs in," Financial Times, (Link).
[24] "Robinhood Fallout Sweeps Market After $1 Billion Lifeline," Bloomberg News, (Link).

increase in value or that such an action would send a political message.[25] On February 4, after market hours, Robinhood lifted all restrictions on long positions. Overall, losers and winners are yet to be determined.[26] However, market commentators estimate that short sellers have lost around $20 billion in betting against GameStop alone during January 2021.[27]

For the purposes of our analyses and based on the timeline of events, we define the short-squeeze period to be from January 26 through February 4 for the following reasons. First, the majority of the 13 stocks experienced sharp price increases on January 26 (see Figure 1). Second, the majority of the 13 stocks also experienced sharp decreases in short interest on January 26 (see e.g., Figure 3 for GameStop).[28] Third, the 13 stocks experienced a substantial increase in social media activity starting on January 26 (see Figure 1). The reverse is true for February 4, when the price and social media activity saw similarly substantial declines across the 13 stocks. This is also the day when retail brokers lifted the remaining trading restrictions. We therefore define this day as the end of the short-squeeze period.[29]

3. Data

Our unique data source is data on social media activity of the 13 banned meme stocks. We obtained the social media activity data by algorithmically scraping all user posts that mention the tickers of the 13 stocks over the period January through February 2021 from Reddit, Twitter, and Stocktwits, using their official APIs and Pushshift APIs.[30] Similarly, we retrieved user metadata, such as account creation date, through the same APIs.

We complement these data with accounting and stock price information from Compustat as well as the annual reports and investor relations websites of the meme stocks and their competitors. Data on analysts' target price forecasts and dispersion are retrieved from the I/B/E/S database. Intraday trades and quotes data are obtained from TAQ. Options markets data come from OptionMetrics. Data for the securities lending market are from IHS Markit. The data set includes the 13 stocks that experienced trading restrictions by the majority of

[25] "Reddit Traders Have Lost Millions Over GameStop. But Many Are Refusing To Quit." Forbes, February 4, 2021, (Link).

[26] The January 2021 events triggered investigations and discussions by US regulators and law makers. The Committee of Financial Services of the US House of Representatives held a full Committee hearing shortly after the events with key industry participants, including the CEOs of Robinhood and Citadel Securities, and followed up with two more full Committee hearings and multiple legislation proposals. The SEC and FINRA also proposed to modify several existing rules and introduce new rules. For example, the SEC proposed to amend Rule 15c6-1 to shorten the settlement window to T+1. Further, to bring transparency to the securities lending market, the SEC proposed a rule that would require all stock loans in a security to be reported within 15 minutes to FINRA. See SEC Release No. 34-93613; File No. S7-18-21.

[27] "GameStop short sellers are still not surrendering despite nearly $20 billion in losses this month," CNBC, January 29, 2021, (Link).

[28] See also Figures A15 and A16 for the remaining stocks at issue.

[29] Note that some of these stocks continued to experience high volatility with periods of large price increases after the end of these short-squeeze episodes, but none of these periods rose to the level of further short squeezes.

[30] Pushift API is a big-data storage and analytics platform that stores a copy of a social media platform's content (see, e.g., for Reddit (Link)).

brokers during January and February 2021.[31] To identify this set of stocks, we reviewed press releases, Twitter posts, and public press coverage on trading restriction implementations of the largest US retail broker dealers: Fidelity, Vanguard, Charles Schwab, TD Ameritrade, Webull, Robinhood, Interactive Brokers, and E-Trade. In identifying trading restrictions, we focus on outright trading bans and restrictions of purchases and sales. We do not consider adjustment of margin requirements for certain stocks or restrictions only on naked options positions. We note that this set of stocks was at the center of the restrictions put in place by Robinhood, whose platform handles about a third of the trading volume of all US retail brokers. For an example of Robinhood's announcement see Section A.4 in the Internet Appendix. Further, these stocks are also the relevant set of stocks in class action lawsuits filed by individual retail traders against several (retail) brokerages, hedge funds, and clearing houses (see, e.g., Case 3:21-cv-00781). We also include the product market competitors of the meme stocks,[32] as well as companies included in the broader stock market index S&P 500.

4. Did the sudden price increases lead to short squeezes?

In this section, we provide an analysis of the securities lending market in early 2021 for evidence of short squeezes. We also discuss a conceptual framework for our empirical analyses.

4.1. Empirical tests and results

There are several factors that represent risks to short sellers and that can contribute to a short squeeze. First, the price can move adversely to the short seller's position resulting in additional collateral requirements and related margin calls.[33] Second, the borrower can experience a recall of the shares. Third, there is a "re-rate" risk which is created by the possibility that each party to the securities lending transaction can request a change to the loan rate (Engelberg, Reed, and Ringgenberg (2018)). A necessary condition for a short squeeze is the existence of high short interest in a particular stock before a potential short-squeeze event coupled with a pronounced decrease in short interest during and after the potential short-squeeze event. We, therefore, start our analyses by examining whether the sudden price increases led to a decrease in the number of shares shorted (as measured by the ratio of quantity on loan relative to the shares

[31] We note that on January 28, Robinhood, among other brokers, initially implemented trading restrictions for 13 stocks (see Figure A14 in the Internet Appendix for Robinhood's announcement). On January 30, Robinhood expanded the set of stocks to approximately 50, but only a day later they reverted to the previous number of stocks. In addition, to our knowledge none of the other brokers (e.g., Freetrade, Trading 212, Charles Schwab, E-Trade, eToro, WeBull, etc.) implemented similarly strict or stricter trading restrictions for a wider set of companies than the initial 13. We therefore concentrate our analyses on the 13 stocks for which Robinhood initially put trading restrictions in place.

[32] We use CapitalIQ to identify firms' competitors. CapitalIQ sources information from companies' SEC filings and analyst reports.

[33] Collateral is usually set at 102%. In addition, there is a requirement of 50% margin with 30% maintenance margin, i.e., if the funds in the margin account decrease below 30%, the borrower receives a margin call and is required to deposit additional funds.

outstanding). Next, we describe the evolution of variables that proxy for the above-mentioned risks to short sellers.

The data suggest that, when analyzing short interest for each stock separately, the following seven stocks experienced a sharp decrease in short interest from a relatively high level before the period of the steep price increases, which is indicative of a short squeeze: GameStop, AMC Theaters, American Airlines, Bed Bath & Beyond, Express, Naked Brand Group, and Tootsie Roll. All other stocks had low short interest at the onset of events and do not show this pattern.[34] We therefore define two groups of stocks for all subsequent analyses: "squeezed stocks,' which consists of the above mentioned seven stocks, as well as "non-squeezed stocks," which consists of the remaining six stocks.

Figure 2 illustrates the difference in these two groups of stocks in terms of short interest. The red, dashed line shows the average quantity on loan (relative to shares outstanding) for the squeezed stocks; the blue line shows the average quantity on loan for the non-squeezed stocks. The squeezed stocks had a significantly higher quantity on loan outstanding before the period of interest than the non-squeezed stocks, and also experienced a steep reduction in the quantity on loan compared to the non-squeezed stocks. The non-squeezed stocks did not experience any change in the quantity on loan from before to after the period of interest, with a small increase in the quantity on loan during the period of interest.

Figure 2 also plots the returns for the squeezed and non-squeezed stocks. In this graph, the red, dashed line shows the average return of $1 invested on December 31, 2020 for the squeezed stocks. The blue line shows the average return for the non-squeezed stocks. Both lines are pegged to December 31, 2020. The difference in short-squeeze risk exposure appears to be associated with different return evolution for each group of stocks during the period of interest with a more pronounced price increase for the squeezed stocks compared to the non-squeezed stocks.[35]

[Insert Figure 2 here.]

Next, we turn to a more granular analysis of the securities lending market. While the SEC October 2021 report discusses GameStop's January 2021 trading activity and claims to have found little evidence of a short squeeze, the financial press has argued that a short squeeze did develop in GameStop.[36] To bridge this gap, we first analyze relevant securities lending market

[34]See Figure 3 in the Appendix and Figures A15 and A16 in the Internet Appendix for the evolution of short interest for each of the 13 stocks. In analyzing the short-squeeze events, we are only interested in the late January 2021 period, as this is the period when short interest significantly decreased. While the social media discussions continued into February and beyond, short interest was very low after January 2021 and no further short squeezes were therefore observed.

[35]In the spirit of the theoretical framework of Pedersen (2022), Figure 2 shows the extent to which each of the two groups of stocks experienced a "bubble" and indicates a more pronounced price bubble for the squeezed stocks compared to the non-squeezed stocks.

[36]"The GameStop Short Squeeze Shows an Ugly Side of the Investing World," Wall Street Journal, January 27, 2021, (Link); "GameStop Investors Still Await Riches From Epic Short Squeeze," Wall Street Journal, February 5, 2022, (Link).

variables that describe the demand and supply for GameStop's stock: quantity on loan, tenure, lendable quantity, available quantity, and stock average fees (SAF).[37] As shown in Figure 3 in the three weeks before the start of the short squeeze the amount of shorted GameStop shares fluctuated between 75% and 80%.[38] Starting on January 26, as the stock price started to rapidly increase, shares shorted started to decrease. On January 27, when GameStop's stock experienced an all-time intraday high of USD 483, shares shorted had dropped to approximately 30%. On January 28, Robinhood, among other brokers, started implementing trading limitations in GameStop and other stocks. This led to a brief reversal with GameStop's stock price decreasing. However, the trading limitations did not seem to have had an impact on the quantity on loan outstanding for GameStop. In fact, quantity on loan for GameStop continued to decrease even as GameStop's stock price kept decreasing over time. This evidence is consistent with the behaviour of a short squeezed stock, i.e., short sellers decrease their demand in response to the sudden increase in the share price.[39]

Next, we look at tenure, which represents the average number of days, from start date of the loan, for all loan transactions for GameStop. In other words, what is the average length for which a securities loan is outstanding. We see that before the squeeze period begins, tenure is around 85 days. It then drops to less than 40 days during the squeeze period. This drop in tenure indicates that many of the older outstanding loans were closed either because short sellers could not keep up with margin requirements as the share price of GameStop increased or because the end-lender recalled the shares or requested a rate increase (or because of all of these reasons).

We also analyze the supply side of the securities lending market by analyzing data for lendable quantity, available quantity, and stock average fees (SAF). Lendable quantity is the quantity of shares available to lend to borrowers by the end-lender. Before the squeeze period, this quantity was around 55%, which then subsequently dropped sharply during the squeeze period to about 25%. This evidence indicates that end-lenders decreased the supply of lendable quantity, in other words they likely recalled these shares in order to close out of the positions and cash in profits from the increasing GameStop price.

Available quantity on the other hand is the quantity of shares that is available for borrowing at the broker (lending agent). Before the squeeze period, this quantity was close to 0%,

[37] Markit records stock lending activity when it becomes known to the market; that is, as of the settlement date. The current standard settlement cycle is two trading days (SEC Release No. 34-80295). To match stock lending activity to the occurrence of an underlying short sale, we account for the trade settlement period by shifting stock loan transactions back by two trading days.

[38] We note that the ratio of quantity on loan relative to the shares outstanding of the respective stock represents a lower bound for the shares shorted. When using total shares available to the public (i.e., float) instead of shares outstanding, shares shorted for GameStop often exceeded 100%.

[39] Our conclusion that a short squeeze developed in GameStop is in line with the findings in a recently released report addressed to SEC Chair Gensler by Mitts et al. (2022). However, this report does not analyze any of the other stocks at issue. In contrast, our analyses include all meme stocks that experienced trading restrictions and their product market competitors. Further, we shed light on the role that retail trading and social media platforms played during the January 2021 events, and importantly, how these events and the resulting short squeezes impacted market quality and efficiency.

meaning all shares available for lending at the lending agent were lent out. At the same time stock average fees for GameStop were approximately 34%. What we observe during the short-squeeze period is that available quantity steadily increased and reached about 7% to 8% after the squeeze period. This indicates that lending agents were holding an increasing amount of GameStop shares that were not lent out. This in turn suggests that the decrease in short interest that we observe was not entirely due to end-lender recalls but also borrowers decreasing their demand for borrowing GameStop shares. In other words, short sellers voluntarily closed positions likely because they could not keep up with margin calls. We also find that stock average fees decreased during the short-squeeze period and after to below 10% (in fact almost 0% in the second half of February of 2021). Since price is a function of supply and demand – the lower the demand from short sellers the lower the lending agent will set the price in order to induce short sellers to borrow.

[Insert Figure 3 here.]

To test more broadly if the findings for GameStop hold for the other stocks and how these variables changed over time for the squeezed and non-squeezed stocks, we differentiate between the following time periods: 1) the pre-squeeze period is captured by the constant, α, and is defined as two weeks (ten trading days) before the short-squeeze period started, i.e., before January 26, 2021; 2) *SSqueeze* is a dummy that is one during the short-squeeze period, which is from January 26, 2021 through February 04, 2021, and zero otherwise; and 3) *Post-SSqueeze* is a dummy that is one during the two weeks (ten trading days) after February 04, 2021, and zero otherwise. We restrict the sample to two weeks around the event days for the sake of symmetry.[40] We estimate the following regression model:

$$Y_{i,t} = \alpha + \beta_1 SSqueeze + \beta_2 Post\text{-}SSqueeze + \beta_3 Controls_{i,t-1} + \varepsilon_{i,t}, \qquad (1)$$

where $Y_{i,t}$ represents one of the securities lending market variables discussed for GameStop. To control for differences in companies' size, market trading activity, and market performance we additionally include the variables size (market capitalization), trading volume, price dispersion, as well as daily returns (see e.g., Engelberg, Reed, and Ringgenberg (2012) and O'Hara and Ye (2011)). All control variables are lagged by one trading day ($Controls_{i,t-1}$).

Table 1 provides summary statistics and definitions of the dependent variables, and Table 2 presents the regression results. To take into account potential time-series and cross-sectional correlation, for all regressions throughout, we report t-statistics based on robust standard errors clustered by firm and time.[41] For the set of squeezed stocks (Panel A), we observe on average

[40]In robustness tests, for all regression estimations throughout this paper, we define the Pre-SSqueeze and Post-SSqueeze periods as 15 (20) trading days before and after the event period. The results are quantitatively and qualitatively very similar to the reported results (untabulated). In another set of robustness tests, for all regression estimations throughout this paper, we define the start of the SSqueze period to be January 25, 2021. Also these results are quantitatively and qualitatively very similar to the reported results (untabulated).

[41]We note that the small number of firm groups, i.e., 13 firm clusters in our study, might introduce a bias when

a statistically significant decrease during the short-squeeze period in quantity on loan of 22.1 percentage points or 65% (relative to the average quantity on loan for that group of 34.1% before the short-squeeze period).[42] After the squeeze period, quantity on loan remained at the lower level.[43] The coefficient on tenure is not statistically significant during the short squeeze period. After the short-squeeze period, tenure decreased. Lendable quantity decreased by 10.3 percentage points during the squeeze period, or 36% (relative to the average lendable quantity for that group of 28.4% before the short-squeeze period). Available quantity increased by 3.7 percentage points during the squeeze period, or 46% (relative to available quantity of 8.05% before the short-squeeze period). Finally, SAFs decreased by 513.5 basis points during the squeeze period, or 61% (relative to SAFs of 844.8 basis points before the short-squeeze period). This evidence indicates that, in addition to GameStop, the other six stocks also experienced short-squeeze events.

Panel B of Table 2 shows the results for the non-squeezed stocks. We find only a significant decrease in tenure during the short-squeeze window, with no change in the other variables. Overall, the evidence presented in this section suggests that there was a short squeeze in GameStop and six of the other meme stocks.

[Insert Table 1 here.]

[Insert Table 2 here.]

estimating standard errors clustered at the firm level. For example, Angrist and Pischke (2009) suggest that the cluster-firm adjustment for standard errors should not be performed with a small number of clusters (see Chapter 8.2.3 of Angrist and Pischke (2009) for more details). Therefore, in additional robustness tests for all regression estimations throughout, we also cluster standard errors only at the time level instead. The results are quantitatively and qualitatively very similar to the reported results (untabulated).

[42] We note that short interest in GameStop and other meme stocks was at elevated levels long before the short-squeeze period. For example, GameStop's short interest in percent of number of shares outstanding was above 50% since 2019, and above 70% since 2020.

[43] It is worth noting that the stock prices of the 13 meme stocks have stayed at elevated levels in the months following the short squeezes. For example, while volatile, GameStop's stock price has traded between USD 80 up to USD 250 after the short squeeze in early 2021. This can have several reasons. One is continued retail trader interest (see, e.g., "Swapping GameStop for ETFs, Retail Investors Ride Out Volatile Markets," Wall Street Journal, October 26, 2021, Link). Another reason is informational asymmetries. As a result of the elevated price levels some of the 13 companies have used their publicity to raise capital in seasoned equity offerings. For example, GameStop went through two offering rounds, raising USD 551 million on April 5, 2021, and USD 1,126 million on June 9, 2021. AMC also went through two capital offerings, raising USD 428 million on April 27, 2021, and USD 587.4 million on June 3, 2021. In general, elevated stock price levels following short squeezes are a well-documented pattern and do not necessarily speak to long-term changes from sentiment to fundamental trading. For example, Allen, Haas, Nowak, and Tengulov (2021) document that Volkswagen's stock price stayed at an elevated level for about a year following the short squeeze that was prompted by Porsche's takeover announcement. Eventually, however, the stock price returned to its pre-squeeze level. Further, Garleanu, Panageas, and Zheng (2021) provide a model that rationalizes why short sellers might choose to exit certain stocks even as mispricing widens when stock prices remain at elevated levels.

4.2. Conceptual framework

Brunnermeier and Pedersen (2005) and Pedersen (2022) present theoretical models that provide a motivation for our empirical short-squeeze analysis. However, these papers do not explicitly model the interaction between short sellers forced to close their positions because of margin calls due to increasing prices (or share recalls) and retail traders coordinating through social media networks. Therefore, below we discuss a framework that guides our empirical tests and interpretations.

First, suppose that there is a strategic player S that is large enough to affect prices. When this player purchases the asset, the price goes up. In turn, when this player sells the asset, the price goes down. In a simple version of this framework, one can assume that S is informed. Most importantly, S knows that there is a group of competitive short sellers who are short but have limited collateral capacity C or face recall risk R. If S wants to squeeze the shorts, they should buy enough stock to push the price up so that the shorts are forced to cover their positions. Since they run out of collateral or need to return the asset, the shorts have no alternative other than to close their position. When the short sellers cover their shorts, the price goes up further – this is the short squeeze. At this point S can sell at least some of its own position at a profit. The price will then fall.[44]

In Brunnermeier and Pedersen (2005) the strategic traders are "large, and hence, [their] trading [impacts] the equilibrium price." They therefore act "strategically and [take their] price impact into account when trading." The latter aspect of Brunnermeier and Pedersen (2005) does not apply to the January 2021 events. Here, the traders that profited off the large short sellers' need to liquidate were a mass of "small" traders that each by themselves would not have had any impact on the equilibrium price. If we translate this to the January 2021 events, the coordination through social media results in a wave of small, non-professional market participants, who exibited herding-like trading behaviour and were buying equivalent to S buying. These non-professional market participants are each not informed, but can become informed as a group (see Pedersen (2022)). They also each have negligible price impact, but can have substantial price impact if they trade in the same direction. Although this type of learning and trading resembles "sentiment" trading, in this short-squeeze framework the "sentiment" is a realization for the non-professional uninformed traders that coordinate through social media platforms that they can contribute to and be part of a short-squeeze event. Just like S, they can sell their

[44] The elements of this framework are based on the following model features from Brunnermeier and Pedersen (2005): i) there are large traders (i.e., short sellers) that try to minimize their (positive) price impact; ii) some of these large traders may experience financial difficulty, forcing them to liquidate their position (i.e., purchase the asset while the financial asset at issue experiences an upward-sloping demand curve); iii) the large traders' need to liquidate is known by other, strategic traders, who in turn trade in the same direction to profit from the price movement. In other words, the strategic traders withdraw liquidity instead of providing it, making the upward-sloping demand curve even steeper; iv) depending on how much the price of the financial asset moves, other large traders might become subject to financial distress as well, which reinforces this "vicious" circle and leads to an even steeper demand curve; v) it is only when most or all large traders have liquidated their positions, that prices return to "normal" levels.

holdings of the asset at the higher price when the shorts cover their position due to a lack of collateral or due to recalls. The price will then fall again.

In the conceptual framework outlined above a central component is coordination through social media platforms of retail traders to impact securities prices. In the next section we empirically analyze if social media platforms contributed to retail trading activity, and if retail trading contributed to the stock price movements of the stocks at issue during the short-squeeze period.

5. Social medial activity, retail trading, and stock returns

In this section, we analyze if there is evidence for retail trader coordination through social media platforms to impact securities prices. We hypothesize that if social media platforms were a medium for retail trader coordination we would observe a significant association between social media activity and retail trading activity. Further, if retail trading activity impacted securities prices we would observe a significant increase in the association between retail trading activity and stock returns during the short-squeeze window (over and above the documented association in normal times (Boehmer, Jones, Zhang, and Zhang, 2021)).

5.1. Did social media platforms contribute to the increase in retail trading volume?

We start by examining the association between social media activity (as proxied by the number of mentions on social media platforms) and retail trading volume during the short-squeeze period. To perform this analysis, we use the social media data described in Section 3, which includes time-stamped counts of posts and comments referencing the relevant stocks from the social media platforms Reddit, Twitter, and Stocktwits. We complement these data with market trading information on volume and prices from TAQ and Compustat.

To identify retail trading volume we follow Boehmer et al. (2021), who provide a methodology to identify retail order flow using publicly available equity transaction data. In particular, this methodology relies on the observation that a majority of marketable retail order flows in US equity markets are typically given a small fraction of a penny per share of price improvement relative to the national best bid or offer price, and are internalized or sold to wholesalers. Boehmer et al. (2021) report that (depending on the sample analyzed) between 60% and 99% of the trades reported on "retail venues" receive this price improvement and are therefore considered retail trades.

The two panels in Figure 4 show the average daily retail trading volume (following Boehmer et al. (2021)) and average daily social media activity. For the squeezed (non-squeezed) stocks it can be seen that average retail volume per day was around 30 (40) million contracts in the week before the short-squeeze period. During the short-squeeze period we see an increase in average retail volume with a peak of about 140 (130) million contracts around the day when retail brokers implemented trading restrictions, a relative increase of 370% (225%). Further, it can be seen that social media activity was on average around 7,000 (10,000) mentions per day in the week before the short-squeeze events. During the short-squeeze period we see an increase in average social media activity with a peak of about 230,000 (95,000) mentions on the day when retail brokers implemented trading restrictions, a relative increase of more than 3,000% (800%). This evidence suggests a strong association between social media activity and retail trading activity.[45]

[Insert Figure 4 here.]

Next, we examine whether intraday variation in social media activity predicts intraday variation in retail trading activity. Specifically, we estimate the following regression model:

$$\begin{aligned} Y_{i,t} = {} & \alpha + \beta_1 SSqueeze + \beta_2 Post\text{-}SSqueeze \\ & + \beta_3 ln(Mentions)_{i,t-1} + \beta_4 ln(Mentions)_{i,t-1} \times SSqueeze \\ & + \beta_5 ln(Mentions)_{i,t-1} \times Post\text{-}SSqueeze + \beta_6 Controls_{i,t-1} + \varepsilon_{i,t}, \end{aligned} \tag{2}$$

where $Y_{i,t}$ represents retail trading volume (measured as the sum of the number of shares of all trades signed as retail trades). The main independent variable is ln(Mentions), our proxy for social media activity, measured as the natural logarithm of one plus the total number of mentions of each of the 13 stocks. Both the dependent variables and the main independent variable are measured on an intraday basis over 30-second, 1-minute, and 2-minute intervals. To capture if social media activity predicts retail trading activity we lag ln(Mentions) by one period. This, in turn, mitigates reverse causality concerns. In line with Equation 1 we include companies' size (market capitalization), trading volume, price dispersion, as well as daily returns as control variables ($Controls_{i,t-1}$), all measured at the end of the previous day. The remaining variables are identical to Equation 1. Table 3 provides definitions and summary statistics for the variables used in this section. In this estimation, the coefficient of interest is β_4. If variation in social media activity predicted variation in retail trading volume during the short-squeeze period for the stocks concerned, we would expect to find that β_4 is positive and statistically significant.

[Insert Table 3 here.]

Table 4 presents the retail volume results. As before, Panel A presents the results for the squeezed stocks and Panel B for the non-squeezed stocks. We focus on column 1 for brevity. The results in both panels show that, on average, during the short-squeeze period retail volume was significantly higher for companies with relatively high social media activity compared to

[45] In Figure A17 and Figure A18 in the Internet Appendix we provide individual plots showing social media activity and retail trading activity for both the squeezed and the non-squeezed stocks, respectively. The evidence suggests that the majority of the stocks experienced similar patterns to the average patterns during the short-squeeze period described in this section.

companies with relatively low social media activity, as suggested by the positive and statistically significant coefficient β_4. More specifically, during the short-squeeze period, for every 1% increase in social media activity, relative to the respective group's pre-squeeze average, retail volume for the squeezed (non-squeezed) stocks increased by 0.21% (0.75%) in the following 30 seconds.[46] This evidence suggests that there is an economicaly significant association between social media activity and retail trading activity during the short-squeeze period, which in turn indicates that social media activity was a driver of retail trading activity. We interpret this as evidence that social media likely played a role as a coordination mechanism of retail trading activity and contributed to the herding-like retail trading behavior.[47]

[Insert Table 4 here.]

5.2. *Did retail trading activity in the equity market contribute to the price increases?*

To analyze if there is a significant increase in the association between retail trading activity and stock returns during the short-squeeze window we follow the approach of Boehmer et al. (2021) and measure retail traders' directional trades by computing a scaled order imbalance measure, which is based on the number of shares traded for each stock and period (*mroibvol*). As a robustness test, we also analyze a second scaled order imbalance measure suggested in Boehmer et al. (2021), which is based on the number of trades (*mroibtrd*). For institutional background and methodology we refer the reader to Boehmer et al. (2021).[48] We estimate the following regression model separately for the squeezed stocks and the non-squeezed stocks:

$$\begin{aligned} Y_{i,t} = {} & \alpha + \beta_1 SSqueeze + \beta_2 Post\text{-}SSqueeze + \beta_3 mroib_{i,t-1} \\ & + \beta_4 SSqueeze \times mroib_{i,t-1} + \beta_5 Post\text{-}SSqueeze \times mroib_{i,t-1} \\ & + \beta_6 Controls_{i,t-1} + \varepsilon_{i,t}, \end{aligned} \tag{3}$$

The dependent variable in Equation 3 is stock returns ($Y_{i,t}$). We follow the market microstructure literature and measure returns over intervals of 30 seconds, one minute, and two minutes. The key independent variable is $mroib_{i,t-1}$, which is referring to one of the two retail trading activity measures discussed above ($mroibvol_{i,t-1}$ and $mroibtrd_{i,t-1}$). These are lagged

[46]In additional tests we determine that the β_4 coefficient is statistically significantly larger for non-squeezed stocks compared to squeezed stocks (untabulated). The interpretation is that although we find a statistical and economic association between social media activity and retail trading activity during the short-squeeze period for both squeezed and non-squeezed stocks, the association had a larger magnitude for non-squeezed stocks.

[47]In Table A1 in the Internet Appendix we present robustness results by examining the association between social media activity and aggregate market trading activity, i.e., trading volume and number of trades. On average, during the short-squeeze period, we observe a significant increase in trading volume and number of trades for both squeezed and non-squeezed stocks. This evidence suggests that social media played a key role in the coordination of trading behavior for the stocks concerned.

[48]The results are robust to estimating the scaled order imbalance measures by following the approach in Barber, Huang, Jorion, Odean, and Schwarz (2022a). See Section A.7 in the Internet Appendix.

and measured at the same frequency as returns. In line with Equation 1 we include companies' size (market capitalization), trading volume, price dispersion, as well as daily returns as control variables ($Controls_{i,t-1}$), all measured at the end of the previous day. We also include the lagged intraday return to control for intraday reversal and momentum patterns in return predictability (see e.g., Lou, Polk, and Skouras (2019)). The remaining variables are identical to Equation 1. In this estimation, the coefficient of interest is β_4. If variation in retail trading activity predicted variation in stock returns during the short-squeeze period, over and above the association with stock returns in the period before the short-squeeze period, we would expect to find that β_4 is positive and statistically significant.

Panels A and B of Table 5 summarize the results of these estimations utilizing the *mroibvol* measure for the squeezed and non-squeezed stocks, respectively.[49] We find that β_4 is positive and statistically significant across all estimations. We focus on column 1 for brevity. The results show that for the squeezed (non-squeezed) stocks for every 1% increase in retail order imbalance stock returns in the following 30 seconds would be expected to increase by 4.5 bps (8.2 bps) during the short-squeeze period. This corresponds to a 35.1% (64%) price increase on a daily basis.[50] This evidence provides support that retail trading activity was a significant driver of stock returns of the stocks concerned during the short-squeeze period, over and above the association with stock returns in normal times. Overall, the evidence presented in this section combined with the evidence presented in Section 5.1 is consistent with the conjecture that retail traders coordinated on social media platforms to impact securities prices.[51]

[Insert Table 5 here.]

5.2.1. Placebo tests

To provide further support that social media was a medium for retail traders to coordinate and impact the prices of the meme stocks with high short interest we perform our tests on a control group of comparable stocks with high short interest but no or low social media activity. In particular, we hypothesize that if social media was a medium for retail traders to coordinate to impact prices of companies with high short interest, companies with no or low social media activity (but high short interest) should not experience a significant increase in the association between retail trading activity and stock returns during the short-squeeze window.

To select a sample of comparable companies with no or low social media activity but high

[49]Table A3 in the Internet Appendix confirms these results utilizing the *mroibtrd* measure.

[50]We also perform a test for differences between the estimates for the squeezed and non-squeezed stocks and find that they are not statistically different from each other (untabulated).

[51]In the Internet Appendix in Section A.8 we provide additional evidence about the association between social media sentiment and returns. In particular, we construct a social media sentiment score based on a text sentiment analysis of social media posts and test whether social media sentiment was a significant driver of stock return variation during the short-squeeze period for GameStop in particular, and all stocks at issue in general. After controlling for retail trading activity, the results suggest that social media sentiment was not a significant driver of stock price movements of the stocks concerned during the January 2021 events.

short interest, in a first step, we identify stocks that are in the same industries (utilizing Fama-French 49 industry classifications) as the seven squeezed meme stocks. Next, among these stocks, we select the sub-set of stocks with comparable short interest to the squeezed meme stocks. We observe that the squeezed meme stocks were in the 90^{th} percentile of the distribution of quantity on loan during the pre-squeeze window (ten trading days before the short squeeze window). Therefore, we select all stocks that are in the 90^{th} percentile of the distribution of quantity on loan during the same period. These selection criteria yield a control sample of 104 stocks. Finally, we collect social media activity data for the control sample from Reddit, Twitter, and Stocktwits and categorize the control sample into three groups based on a tercile split of the distribution of their social media activity during the pre-squeeze window. Compared to the squeezed meme stocks all three groups have a significantly lower average daily social media activity. For example, during the pre-squeeze window the average daily number of mentions on social media platforms for the squeezed meme stocks, the first tercile, second tercile, and third tercile of the control sample are 5095.6, 3.7, 12.9, and 135.3, respectively.[52]

We estimate Equation 3 separately for each of the three terciles. Panels A, B, and C of Table 6 summarize the results of these estimations utilizing the *mroibvol* measure for the three terciles.[53] We focus on column 1 for brevity. We find that β_4 (the coefficient of the interaction term *mroibvol* $\times$ *SSqueeze*) is not statistically different from zero for the first and the second tercile. Notably, for the third tercile, comprising the stocks with the highest social media activity within the control sample, β_4 is positive and statistically significant although the economic magnitude is low. Specifically, for every 1% increase in retail order imbalance stock returns in the following 30 seconds would be expected to increase by 0.4 bps during the short-squeeze period. This corresponds to a 3.12% price increase on a daily basis, significantly lower that the estimate of 35.1% for the squeezed meme stocks. We note that, when looking at 1-minute and 2-minute returns β_4 is not statistically significant for all three terciles.

[Insert Table 6 here.]

This evidence provides support for the hypothesis that comparable companies with no or low social media activity but high short interest would not experience a significant increase in the association between retail trading activity and stock returns during the short-squeeze window. We interpret this evidence as further support that social media was a medium for retail traders to coordinate and impact the prices of the meme stocks with high short interest.

[52]Table A5 in the Internet Appendix reports social media activity summary statistics for the squeezed meme stocks and the control sample split into terciles.

[53]Robustness utilizing marketable retail order imbalances based on the number of trades is presented in Table A6 in the Internet Appendix.

6. The role of the options market

In this section we analyze whether i) market participants increased the use of call options to circumvent the trading restrictions implemented by retail brokers and benefit from the positive price performance of the underlying stocks, ii) market participants increased the use of put options to bet on decreasing prices and circumvent the short squeezes in some of the stocks at issue, and iii) whether the change in stock and options market activity was associated with potential violations of the put-call parity relationship.

6.1. Did traders migrate to the options market?

We start by analyzing options open interest, separately for put and call options, for the periods before, during, and after the short-squeeze window.[54] The data set covers all stocks with options listed on them, i.e., ten out of the 13 meme stocks.[55] We follow Grundy, Lim, and Verwijmeren (2012) and Ofek, Richardson, and Whitelaw (2004) and exclude: i) options with zero open interest, ii) options that expire in less than 30 days and more than 365 days, and iii) options with ask prices that are smaller than bid prices.

The two panels in Figure 5 show the average call and put option open interest per day. For the squeezed stocks it can be seen that call (put) option open interest was on average approximately 220 (250) contracts in the week before the short-squeeze window. During the short-squeeze window we see an increase in average call and put option open interest to approximately 250 (450) contracts, a relative increase of 14% (80%). Open interest remained at elevated levels after the short-squeeze period. Similarly, for the non-squeezed stocks call (put) option open interest was on average approximately 400 (50) contracts in the week before the short-squeeze window. During the short-squeeze window we see an increase in average call and put option open interest to approximately 780 (200) contracts, a relative increase of 95% (300%). Open interest remained at elevated levels also for the non-squeezed stocks after the short-squeeze period.[56] This evidence is consistent with a migration towards call options, i.e., traders relied on call options during the January 2021 events to express their optimistic views on the stocks at issue and likely as a tool to circumvent the trading restrictions implemented by retail brokers.[57] Further, the evidence is consistent with some traders using put options to bet

[54]Open interest is the total number of contracts outstanding (long or short). Open interest is typically used as a measure of market activity. An increase in open interest indicates that traders have opened new options contracts and are participating in the market for a particular options contract, and vice versa for a decrease in open interest.

[55]The following companies did not have options coverage: Naked Brand Group, Koss, and Castor Maritime.

[56]In Figure A20 and Figure A21 in the Internet Appendix we provide individual call and put options open interest plots for both the squeezed and the non-squeezed stocks. The evidence suggests that the majority of the stocks with listed options experienced increases in open interest during the short-squeeze period.

[57]Posts on r/wallstreetbets encouraged traders to pursue options trading strategies in order to circumvent the trading limitations in the equity market imposed by retail brokers. See e.g., "How to Buy GME Above Broker Limits," (Link).

on reverting stock prices and to circumvent the short squeezes in some of the stocks at issue.

[Insert Figure 5 here.]

The increased usage of options for both squeezed and non-squeezed stocks likely caused options market makers and other professional market participants to increase their hedging activities by buying the underlying shares, which, in turn, was one potential factor that contributed to the upward price pressure on the stocks at issue.[58] To test this hypothesis, we examine the evolution of the share-equivalent options open interest, i.e., the amount of shares options market makers needed to trade to delta-hedge their positions. In particular, we calculate Delta-adjusted Open Interest (DOI) per stock as the sum of the open interest multiplied by the absolute value of the delta for each option *o* written on stock *i* on day *t*:

$$DOI_{i,t} = \sum_{o \in S} open\ interest_{o,t} \times |delta_{o,t}|. \tag{4}$$

Further, we differentiate between in-the-money (ITM), at-the-money (ATM), and out-of-the-money (OTM) options in order to examine which options category experienced a change in delta-adjusted open interest. We estimate the following regression model to compare the pre-squeeze period to the *SSqueeze* and the *Post-SSqueeze* periods:

$$Y_{i,t} = \alpha + \beta_1 SSqueeze + \beta_2 Post\text{-}SSqueeze + \beta_3 Controls_{i,t-1} + \varepsilon_{i,t}, \tag{5}$$

where $Y_{i,t}$ represents the natural log of $DOI_{i,t}$. We follow Grundy et al. (2012) and include the daily return, the daily trading volume, and the daily Chicago Board Options Exchange's Volatility Index (VIX) as additional control variables ($Controls_{i,t-1}$). The remaining variables are identical to Equation 1.

Table 7 presents the results. Panel A presents the results for the meme stocks that experienced a short squeeze. Panel B presents the results for the remaining meme stocks that did not experience a short squeeze.

[Insert Table 7 here.]

Panel A shows that, on average, we observe a statistically significant increase in delta-adjusted open interest for OTM put options during the short-squeeze period. Compared to before the short-squeeze period the increase persisted in the post short-squeeze period. In addition, we see

[58] This has been referred to as "a gamma squeeze" in the press. In particular, when a trader buys call options, this creates a risk for the counterparty that sold these options. In other words, if the underlying shares rise above the strike price, the options writer (seller) will have to acquire the shares in the open market, at a loss, to fulfill the contract obligation. Despite many ways to hedge this risk, in essence, somebody along the hedging chain has to buy the underlying shares, then the call options are converted into covered calls. In other words, if the options market maker has sold an option that goes up in value as the stock goes up, the more the stock goes up, the more the market maker loses. The market maker would typically hedge this exposure by buying, usually, the stock itself, which, in turn, exerts additional upward price pressure on the stock, in this particular set of events exacerbating the squeeze.

an increase in delta-adjusted open interest for ITM call options during the short-squeeze period. Compared to before the short-squeeze period there was an increase in the post-short-squeeze period in OTM call options.

Panel B reveals that, on average, there is a significant increase in delta-adjusted open interest for OTM put options. In addition, we see a significant increase in delta-adjusted open interest for ITM and OTM call options during the squeeze period.[59] This evidence is consistent with traders utilizing more call options during the short-squeeze period and as a result options market makers significantly increasing their hedging positions, which likely exerted upward price pressure on the underlying stocks. This evidence also provides support that these stocks attracted short sellers to the options market to exploit a potential price reversion after these stocks experienced sudden price increases around the broker bans.

6.2. *Put-call parity violations*

In this subsection, we provide an analysis of put-call parity. On the one hand a restriction on purchasing stocks might lead stock prices to be downward-biased. On the other hand the restrictions were implemented because the prices of these stocks increased rapidly, and as a result were already likely upward-biased. The short squeezes likely contributed further to upward-biased stock prices. Option prices reflect payoffs at future dates, by which the purchasing restrictions and short squeezes were likely to have ended and potential biases in stock prices likely to have been corrected. Therefore, the purchasing restrictions and shorts squeezes might have a lesser effect on option prices than on stock prices, which might lead to relative mispricings and market inefficiency from the resulting decoupling of these two markets.[60]

The put-call parity framework allows us to interpret the decoupling of a stock's market price from its price implied by the options market as a relative mispricing in the equity market and therefore a deterioration in market efficiency. We hypothesize that a potential put-call parity decoupling would be more pronounced for the squeezed stocks because the short squeezes likely contributed further to upward-biased stock prices of this set of stocks.

Under the no-arbitrage condition, for European options on non-dividend paying stocks put-call parity equates the value of a protective put (long positions in a put and a stock) and a fiduciary call (long positions in a call and the present value of the strike price). For American

[59]We also perform a test for differences between the statistically significant estimates for the squeezed and non-squeezed stocks during the squeeze period and find that they are not statistically different from each other (untabulated).

[60]One could argue that due to the increased demand for call and put options during the short-squeeze period the prices of these securities were also upward-biased. If this potential upward bias was asymmetric, e.g., there is a higher increase in put option implied volatilities compared to call options, this could be associated with put-call party violations (see e.g., Atmaz and Basak (2019)). In Section A.10 in the Internet Appendix we investigate whether there was a disproportionately larger increase in the pricing for call or put options. In particular, we follow the literature (e.g., Figlewski and Webb (1993)) and measure the implied volatility spread based on put-call option pairs on the same underlying stock with the same strike prices and time to expiration. We do not find significant changes in the implied volatility spread for options for the squeezed stocks and for the non-squeezed stocks, suggesting that the increased demand for these categories of options was somewhat similar.

options, however, the put-call parity relation is not a simple equality since we have to take into account the value of the early exercise premium (EEP) on the American put option (see, e.g., Ofek et al. (2004)). The estimation of the EEP assumes that the risk-neutral stock return process is characterized by a geometric Brownian motion. There is, however, no universally applicable formula for calculating the early exercise premium for American put options, despite the fact that many papers have provided analytical valuation formulas for American options under a geometric Brownian motion stock price process (see, e.g., Geske and Johnson (1984) and Barone-Adesi and Whaley (1987)). Further, the geometric Brownian motion assumption might not be a suitable choice for stocks that experience shorting constraints, such as high stock average fees or short squeezes, and are restricted from trading (see, e.g., Grundy et al. (2012)). We therefore utilize the following put-call parity relation for dividend paying stocks:[61]

$$S+P=PV(K)+C+PV(div) \tag{6}$$

where S is the closing stock price. PV(K) is the present value of the strike price. C and P are the call and put prices, respectively, on options with strike price K, underlying S and the same maturity, using the midpoints of the option quotes. PV(div) is the present value of the dividend, estimated by discounting the set of dividends with ex-dates prior to the option's maturity.

Following Ofek et al. (2004) we compute the ratio $R = 100 \times ln(S/S^*)$, where S is the stock price and S^* is the synthetic stock price derived from the options market by rearranging the terms in Equation 6, namely $S^* = PV(K)+C-P+PV(div)$. To test if a likely put-call parity decoupling is more pronounced for the squeezed stocks we estimate the following regression model:

$$\begin{aligned} Y_{i,t} = {} & \alpha + \beta_1 SSqueeze + \beta_2 Post\text{-}SSqueeze + \beta_3 Squeezed \\ & + \beta_4 Squeezed \times SSqueeze + \beta_5 Squeezed \times Post\text{-}SSqueeze \\ & + \beta_6 Controls_{i,t-1} + \varepsilon_{i,t}, \end{aligned} \tag{7}$$

Here the unit of observation is a put-call option pair, defined as a call and a put on the same stock with identical times to expiration and strike prices. $Y_{i,t}$ represents $R = 100 \times ln(S/S^*)$, *Squeezed* is an indicator variable that takes the value of one for squeezed stocks and zero for non-squeezed stocks. All other variables are identical to Equation 5.

Table 8 reports the results. We focus the results interpretations on column 1, the sub-sample of option pairs that are close to being at-the-money and therefore are expected to be relatively liquid. The squeezed stocks are having less expensive stock prices (relative to the synthetic price counterpart) compared to non-squeezed stocks during the pre-squeeze period (as indi-

[61] In robustness tests we explicitly accounting for the EEP as follows $S+P+EEP = PV(K)+C+PV(div)$. We apply the empirical EEP estimates provided by Ofek et al. (2004) in Table 1. In particular, we utilize the mean EEP (% of stock price) of 0.132. Further, as a conservative estimate we utilize the 95th percentile EEP estimate of 0.282. Our results are qualitatively and quantitatively similar to the results reported in the paper (untabulated).

cated by the *Squeezed* dummy). During the squeeze period the relative price of the stock compared to the synthetic stock increases significantly more for the squeezed stocks compared to the non-squeezed stocks (as indicated by the interaction term *Squeezed* $\times$ *SSqueeze*). In the post-squeeze period we do not see an increase in the relative price of the stock for the squeezed companies compared to the pre-squeeze period. We interpret this evidence as a potential decoupling of stock and option prices during the short-squeeze period for the squeezed stocks. This decoupling would have given rise to market inefficiency and possible arbitrage opportunities.[62]

[Insert Table 8 here.]

Overall, the findings of this section add to the literature that examines whether investors use equity options to circumvent restrictions in the underlying equity market. Early studies on the topic have argued that traders can build synthetic positions using options when trading in the equity market is either too costly or restricted through regulation (see, e.g., Diamond and Verrecchia (1987), Figlewski and Webb (1993), Easley, O'Hara, and Srinivas (1998)). Recent empirical evidence, however, provides mixed findings. On one hand, some studies argue that the 2008 US bans on equity short sales effectively acted as a restriction to options market trading (see e.g., Battalio and Schultz (2011) and Grundy, Lim, and Verwijmeren (2012)). On the other hand, recent research provides support for the trader migration hypothesis (see e.g., Chen, Chen, and Chou (2020), Jones, Reed, and Waller (2021), and Brand, Molnar, and Tengulov (2022)). We complement these studies by providing evidence that during the January 2021 events market participants used call options to likely circumvent the trading restrictions implemented by retail brokers and bet on increasing prices, and also used put options to likely circumvent the equity short-squeeze events. Further, we provide evidence of put-call parity violations for the squeezed stocks during the squeeze period, indicative of relative mispricings in the equity market and deterioration in market efficiency for the squeezed stocks.

7. The effect on market quality

In this section, we describe the extent to which the January 2021 events in general and the short squeezes in particular affected the stock market quality of the meme stocks and their product market competitors. To quantify the impact of these events we analyze (i) price metrics (spreads and volatility of returns) and (ii) volume metrics (trading volume and depth at the best bid and best offer (BBO)). To assess how market quality changed during the short-squeeze period, we examine the evolution of these metrics over time.[63]

[62] Although this potential put-call parity decoupling could be interpreted as an increase in arbitrage opportunities for the squeezed stocks, we note that one would need to take into account transaction costs associated with the arbitrage transactions (see, e.g., Ofek et al. (2004), Evans, Geczy, Musto, and Reed (2009), and Muravyev, Pearson, and Pollet (2022)).

[63] Higher quality markets often exhibit lower spreads and volatility as well as higher volumes and depth. Together these metrics provide measures of "market quality" (Harris, 2002). The following papers, among others,

The literature suggests that changes in the proportion of informed and liquidity traders lead to changes in spreads, volatility, and volume. First, Glosten and Milgrom (1985) demonstrated that bid-ask spreads are expected to be higher when informed trading is higher due to increased adverse selection risk. Second, volatility is expected to be higher when informed trading is higher because volatility is caused by an increase in information being incorporated into prices, which is mainly driven by an increased proportion of informed trading (Foster and Viswanathan, 1990; Holden and Subrahmanyam, 1992; Wang, 1998). While this process is ongoing, prices fluctuate between the previous fundamental value and the new fundamental value. Third, if informed traders are the reason for changes in volume the relation is expected to be positive, but if liquidity traders are the reason for changes in volume the relation is expected to be negative.

The January 2021 events and resulting short squeezes are unique because they were not triggered by a large informed trader, but by the coordinated efforts of a group of unsophisticated retail traders. Existing evidence on the effects of retail investors on financial markets is mixed. Retail traders are typically viewed as uninformed noise traders. Some papers have found that retail noise traders have a positive effect on market liquidity because they can counter-balance the effects of informed traders (e.g., Glosten and Milgrom (1985); Kyle (1985); Kaniel, Saar, and Titman (2008); Barrot, Kaniel, and Sraer (2016); and Boehmer and Song (2020)). Other papers have shown that momentum-oriented herding by retail noise traders can contribute to volatility and harm liquidity by creating inventory risk for market makers (e.g., Ho and Stoll (1981), Grossman and Miller (1988), Kumar and Lee (2006), Barber, Odean, and Zhu (2009), Hendershott and Menkveld (2014), and Eaton, Green, Roseman, and Wu (2022)).[64]

As shown in Section 5 there was an increase in retail trading that was coordinated through social media platforms and therefore exhibited herding-like behavior. We hypothesize that this might have created volatility and harmed liquidity resulting in deterioration in market quality. Further, we hypothesize that the January 2021 events changed the behavior of informed market participants. In particular, it might be that the January 2021 events induced more informed traders, who previously did not act on their information, to trade because they were worried that the value of their information would become obsolete in the future. This would have resulted in further deterioration in market quality. Alternatively, informed traders might have decided not to trade because the retail trading frenzy and discussions on social media platforms left them confused about the fundamental value of the stocks at issue. This would have resulted in an improvement in market quality. These contradicting hypotheses imply that whether market quality deteriorates or improves is an empirical question and depends on the

apply price and volume metrics to assess changes in market quality over time: Bessembinder (2003); Diether, Lee, and Werner (2009); Chordia, Roll, and Subrahmanyam (2011); and O'Hara and Ye (2011).

[64]Foucault, Sraer, and Thesmar (2011) study a legal reform in France that discouraged speculative and leveraged retail trading. The authors find that stock market liquidity increased after the reform. On the other hand, Peress and Schmidt (2020) use distracting US news stories to reflect the absence of noise traders and find that reduced retail trading is associated with lower stock market liquidity. Recent studies highlight that retail investors might exhibit different degrees of sophistication (Barber et al., 2022b; Eaton et al., 2022).

extent to which informed traders participated in the market and either reinforced or mitigated the adverse effect of the increased herding-like retail trading. This holds for all stocks at issue. For the subset of squeezed stocks, we expect an increase in informed trading in addition to an increase in herding-like retail trading. This is because short sellers, which are often considered informed institutional investors, had to cover their short positions and engage in trading. Thus, we hypothesize that the squeezed stocks experienced a deterioration in market quality.

To test the extent to which the short squeezes led to spillover effects on market quality more generally, we also examine changes in the market quality of the product market competitors of the stocks concerned. It is likely that the market quality of product market competitors was affected if the shares of these competitors were held in the same investor portfolios as the stocks concerned.[65]

7.1. Methodology and results

To test how market quality changed over time we compare the pre-squeeze period to the *SSqueeze* period and the *Post-SSqueeze* period. In particular, we estimate the following regression model:

$$Y_{i,t} = \alpha + \beta_1 SSqueeze + \beta_2 Post\text{-}SSqueeze + \beta_3 Controls_{i,t-1} + \varepsilon_{i,t} \tag{8}$$

where $Y_{i,t}$ represents one of the price and volume metrics of interest. Table 9 provides definitions and summary statistics for these variables. i is a firm index and t denotes time in minutes. Similar to Equation 1 we include size (market capitalization), trading volume, price dispersion, as well as returns, all measured on a daily basis at the end of the previous trading day ($Controls_{i,t-1}$). The model is estimated for all of the meme stocks, separated into squeezed stocks and non-squeezed stocks. Further, the model is estimated for the product market competitors of these two groups of stocks. The coefficient of interest is β_1, which measures the change in a given metric from the pre-squeeze period to the *SSqueeze* period. The coefficient β_2 measures the change in a given metric from the pre-squeeze period to the *Post-SSqueeze* period.

[Insert Table 9 here.]

The panels in Figure 6 show the evolution of average daily spreads (upper two panels) and average daily volatility (lower two panels) for the stocks that experienced a short squeeze, the

[65] While, to the best of our knowledge, data about the identities, exposures, and holdings of all the short sellers involved is not available, anecdotal evidence suggests that a number of hedge funds that liquidated their short positions during the January 2021 events also sold additional related portfolio holdings to reduce leverage and aggregate market exposure. For example, the public press claimed that during the January 2021 events "[f]unds have not only been covering their short positions — the bets they placed against individual shares — but also selling shares in companies to cut their leverage and reduce their gross exposure to the market," Financial Times, January 27, 2021, available at (Link). In other words, to the extent that the product market competitors were part of the sell-off of portfolio holdings, their market quality would have been affected by the January 2021 events.

stocks that did not experience a short squeeze, and their respective product market competitors. For the squeezed stocks it can be seen that the average daily spread (average daily volatility) was around 80 bps (0.36) in the week before the short-squeeze period. During the short-squeeze period, we see an increase in average daily spreads (average daily volatility) with a peak of about 160 bps (2.00) around the day when retail brokers implemented trading restrictions, a relative increase of 100% (450%). Further, for the competitors of the squeezed stocks, it can be seen that the average daily spread (average daily volatility) was around 170 bps (0.17) in the week before the short-squeeze events. During the short-squeeze period we see an increase in average daily spreads (average daily volatility) to about 250 bps (0.26) around the day when retail brokers implemented trading restrictions, a relative increase of about 47% (53%).

For the non-squeezed stocks we observe similar patterns. Average daily spreads (average daily volatility) were around 85 bps (0.32) in the week before the short-squeeze period. During the short-squeeze period we see an increase in average daily spreads (average daily volatility) with a peak of about 130 bps (1.30) around the day when retail brokers implemented trading restrictions, a relative increase of 53% (400%). Further, for the competitors of the non-squeezed stocks, it can be seen that average daily spreads (average daily volatility) were around 124 bps (0.15) in the week before the short-squeeze events. During the short-squeeze period we see an increase in average daily spreads (average daily volatility) to about 180 bps (0.25) around the day when retail brokers implemented trading restrictions, a relative increase of more than 45% (66%). This unconditional evidence suggests a deterioration in the market quality of the stocks at issue and their product market competitors.

[Insert Figure 6 here.]

Next, we discuss the estimation results of Equation 8. Panel A of Table 10 presents the results for the squeezed stocks. Panel B presents the results for the remaining non-squeezed stocks. The results in panel A indicate that, on average, during the short-squeeze period bid-ask spreads for the squeezed stocks increased by 34 bps, a relative increase of 38.7%. For the non-squeezed stocks we document a lower increase in bid-ask spreads of 6.1 bps, a relative increase of 5.6%. After the short-squeeze period, bid-ask spreads for squeezed and non-squeezed stocks remained elevated relative to the period before the squeeze.[66] Volatility during the short-squeeze period for the squeezed stocks increased by 0.190, a relative increase of 52.9%.[67] For the non-squeezed stocks, we observe a smaller increase in volatility of 0.136, or a relative increase of 42.2%. After the squeeze period, volatility for the squeezed stocks decreased, whereas volatility for the non-squeezed stocks decreased but remained at an elevated level compared to

[66]We also perform a test for differences between the estimates for the squeezed and non-squeezed stocks for all regression estimations in this section and find that they are statistically different from each other. See Table A11 in the Internet Appendix.

[67]We measure volatility as the rolling standard deviation of realized one-minute returns over 15 minutes. We also estimated all regression models with a measure for volatility over 30-minute non-overlapping windows. Results are qualitatively and quantitatively very similar (not tabulated).

the pre-squeeze period. Trading volume for the squeezed (non-squeezed) stocks increased by 196,776 (190,108) shares per minute during the short-squeeze period, a relative increase of 100% (55%). After the squeeze period, volume for the squeezed stocks decreased, whereas for the non-squeezed stocks it decreased compared to the squeeze period but remained at an elevated level compared to the pre-squeeze period. During the short-squeeze period, we do not observe an increase in the bid size but we observe an increase in the ask size for the squeezed stocks. For the non-squeezed stocks we observe an increase in both the bid and the ask size.

Overall, the evidence suggests that the January 2021 events distorted market quality of the stocks at issue. Importantly, we find a significantly larger increase in spreads and volatility for the squeezed stocks compared to the non-squeezed stocks. This indicates that the short squeezes distorted market quality over and above distortions in market quality introduced by other concurrent events, such as the introduction of trading restrictions by retail brokers and the retail trading hype on social media platforms.

[Insert Table 10 here.]

Panel C of Table 10 presents the results for the product market competitors of the squeezed stocks. Panel D presents the results for the product market competitors of the non-squeezed stocks. For the competitors of the squeezed stocks we observe that relative bid-ask spreads increased by 52.4 bps during the short-squeeze period, a relative increase of 29.8%. For the competitors of the non-squeezed stocks we observe an increase of 21.5 bps during the short-squeeze period, a relative increase of 16.5%. Spreads decreased for the competitors of the squeezed and non-squeezed stocks after the short-squeeze period compared to the period during the squeeze, but remained at elevated levels compared to the period before the short squeezes. Volatility for the competitors of the squeezed stocks increased during the short-squeeze period by 0.035, a relative increase of 21.1%. Volatility for the competitors of the non-squeezed stocks increased during the short-squeeze period by 0.029, a relative increase of 19%. After the squeeze period, volatility for the competitors of the squeezed and non-squeezed stocks decreased compared to the short-squeeze period, but remained at an elevated level compared to the period before. Trading volume increased for the competitors of the non-squeezed stocks only. Bid and ask quote sizes decreased during the short-squeeze period for the competitors of the squeezed stocks. Further, bid and ask quote sizes increased during the short-squeeze period for the competitors of the non-squeezed stocks.

Overall, the evidence is consistent with a deterioration in the market quality of the product market competitors of the stocks at issue during the short-squeeze period. Notably, we find a disproportionately larger increase in spreads and volatility for the product market competitors of the squeezed stocks compared to the non-squeezed stocks, which is consistent with negative spillover effects from the squeeze events.[68]

[68]We also perform a test for differences between the estimates for the competitors of the squeezed and non-

8. Conclusion

The events of January 2021, during which a group of stocks listed on US stock exchanges experienced sudden surges in their stock prices, are interesting and important. We show that these sudden price increases led to short squeezes in the restricted stocks with high short interest. We argue that these price increases were fueled by retail trader coordination on social media platforms. Using hand-collected data from Reddit, Twitter, and StockTwits we provide a detailed analysis of these events and show that they significantly impeded market quality not only of the stocks concerned but also of their product market competitors.

Understanding what happened during these events is important for the following reasons. First, while short squeezes did occur with some frequency historically, coordination among retail traders to target stocks with high short interest, as seen in these episodes, has not been seen before. The reason is that this type of coordination is a phenomenon made possible only in recent years through social media platforms. Importantly, these are not isolated events but rather a new regime in which retail traders have a new and effective mechanism to coordinate and potentially influence market outcomes. Therefore, it is important to understand whether retail traders can contribute to market-distorting events, such as the January 2021 events.

Second, the data available in modern markets allow us to study in detail the precise way in which short squeezes affect the operation of markets. This was not usually possible with historical manipulation events. This paper considers how the series of short squeezes in early 2021 impacted market quality and efficiency in a stock market in which information is in many circumstances incorporated quickly but in others, such as when there is asymmetric information, can take some time. We provide evidence that in the case of coordinated trading by a large crowd of retail traders that results in a short squeeze, market quality and market efficiency are subsequently reduced in these stocks despite real-time surveillance by market regulators and continuous information processing. In particular, the market for the stocks at issue becomes more illiquid (as indicated, for example, by increasing bid-ask spreads), and less efficient (as indicated by potential deviations from put-call parity).

Third, understanding how these events could occur in one of the most advanced countries in the world with arguably some of the most sophisticated financial market regulations, namely the US, is important for policy reasons. Since the development of social media platforms in the 1990s, their costs and benefits have been the topic of intense debates. While some financial researchers and regulators have repeatedly expressed concerns about social media platforms' potentially harmful effects on market efficiency and retail investors, others point to the benefits arguing that traders' discussions on social media provide investment value and make retail investors better informed. Still, information through social media is freely available and easily accessible to retail traders, which can potentially make the retail trader group a

squeezed stocks for all regression estimations in this section and find that they are statistically different from each other (untabulated).

powerful crowd that can move stock returns and volatility. It is difficult to establish what a potential new regulation of social media platforms, if any, with respect to what trading strategy discussions should look like. On the one hand, the First Amendment to the United States Constitution has been put in place to prevent the government from making laws that restrict free speech. On the other hand, regulators have expressed concern that the coordination among retail traders as evidenced in early 2021 constitutes market manipulation. Analyzing to what extent the First Amendment applies to trading discussions on social media platforms constitutes a fruitful avenue for future legal research. To prove manipulation, regulators would have to prove conspiracy and intent to impact the prices of the meme stocks to reach artificially high levels (GibsonDunn (2021)). Given the anonymity of social media platform users, it will be difficult to clearly establish or rule out market manipulation. What has become clear from the January 2021 events is that coordination through social media platforms to target stocks with high short interest has made short selling more risky. This has driven short sellers out of meme stocks, and, as a result, can have an adverse effect on the information intermediation role of short sellers in particular and on market quality more generally.

Tables and Figures

Fig. 1 Evolution of returns and social media activity of the meme stocks: January 01, 2021 – February 28, 2021: These figures depict the evolution of returns (lhs) and the evolution of social media activity, i.e., mentions on social media platforms (rhs) of the 13 stocks initially banned by Robinhood, among other retail brokers, on January 28. The start of the short squeeze is set to January 26, 2021. The end of the short squeeze is set to February 4, 2021. On January 28, 2021 Robinhood, among other brokers, implemented the trading limitations.

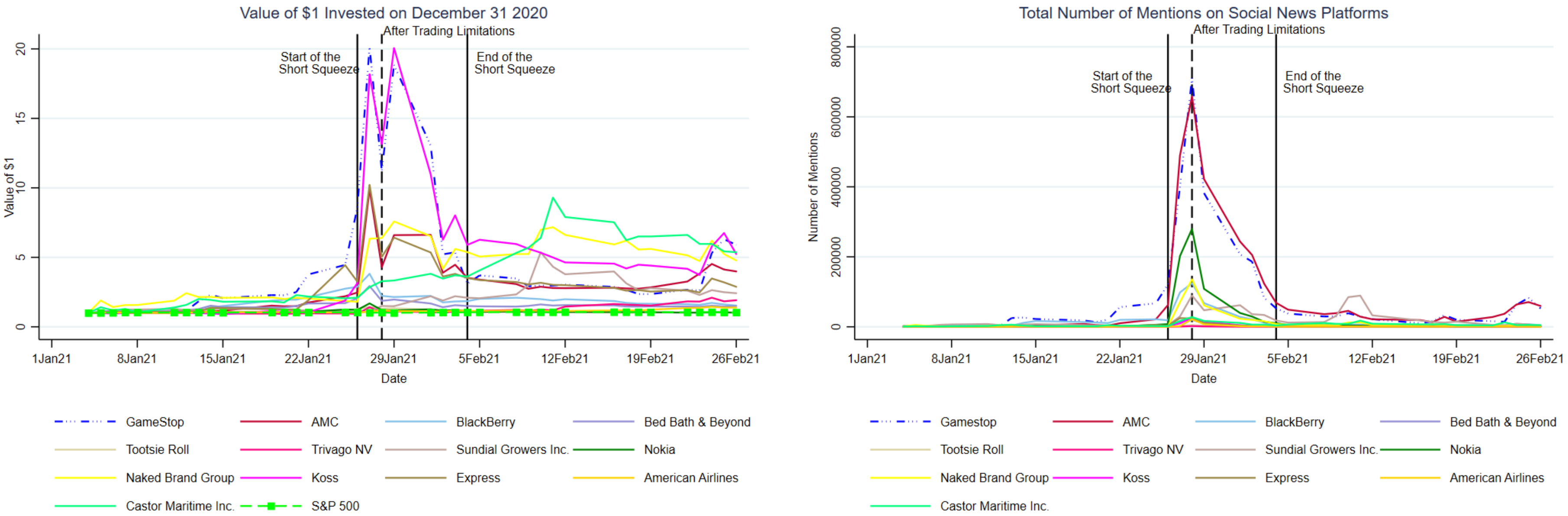


Fig. 2 Evolution of average quantity on loan and average returns of squeezed vs non-squeezed stocks: January 01, 2021 – February 28, 2021: These figures depict the evolution of average quantity on loan relative to shares outstanding (lhs) and the evolution of average returns (rhs) of the squeezed versus non-squeezed stocks. The start of the short-squeeze period is set to January 26, 2021. The end of the short-squeeze period is set to February 4, 2021. On January 28, 2021 Robinhood, among other brokers, implemented the trading limitations.

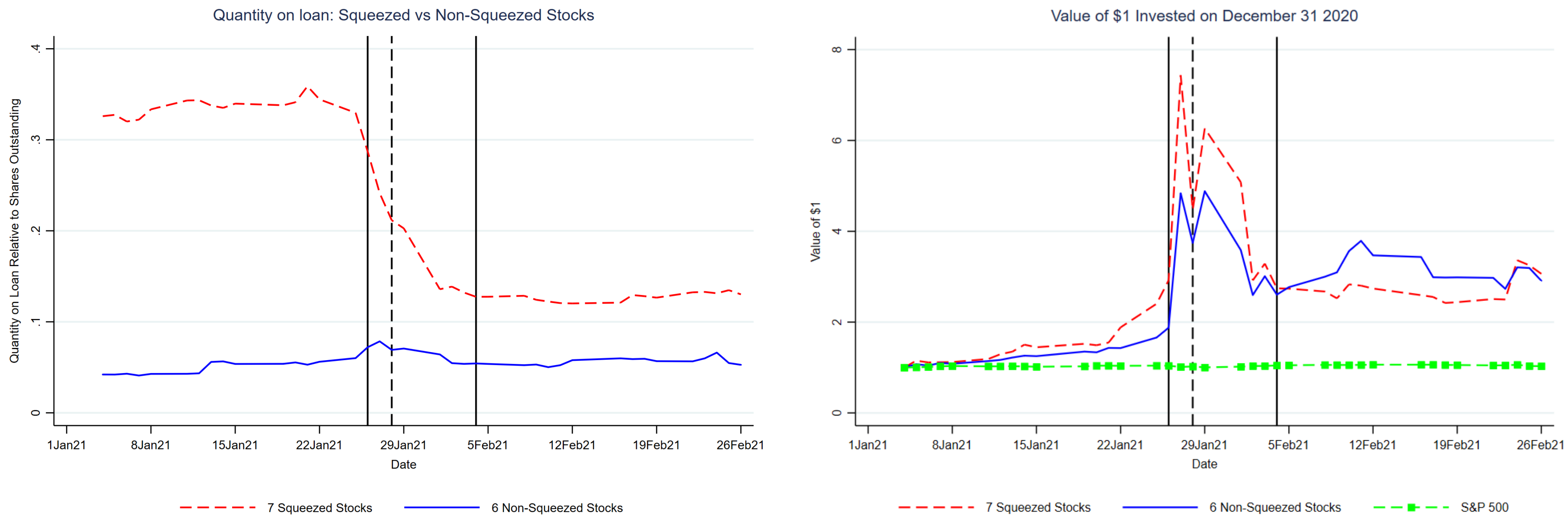


Fig. 3 Price and Quantity on loan: This graph shows GME's closing price (left y-axis in USD) and the quantity on loan for securities loans for GME relative to shares outstanding (right y-axis is in percent). **Tenure and Lendable quantity:** This graph shows tenure of securities loans outstanding for GME (left y-axis in number of days) and the quantity of shares available for lending for GME (right y-axis is in percent relative to shares outstanding). **Stock average fees (SAF) and active available quantity:** This graph shows stock average fees for GME (left y-axis in basis points) and the active available quantity of shares for lending for GME (right y-axis is in percent relative to shares outstanding).

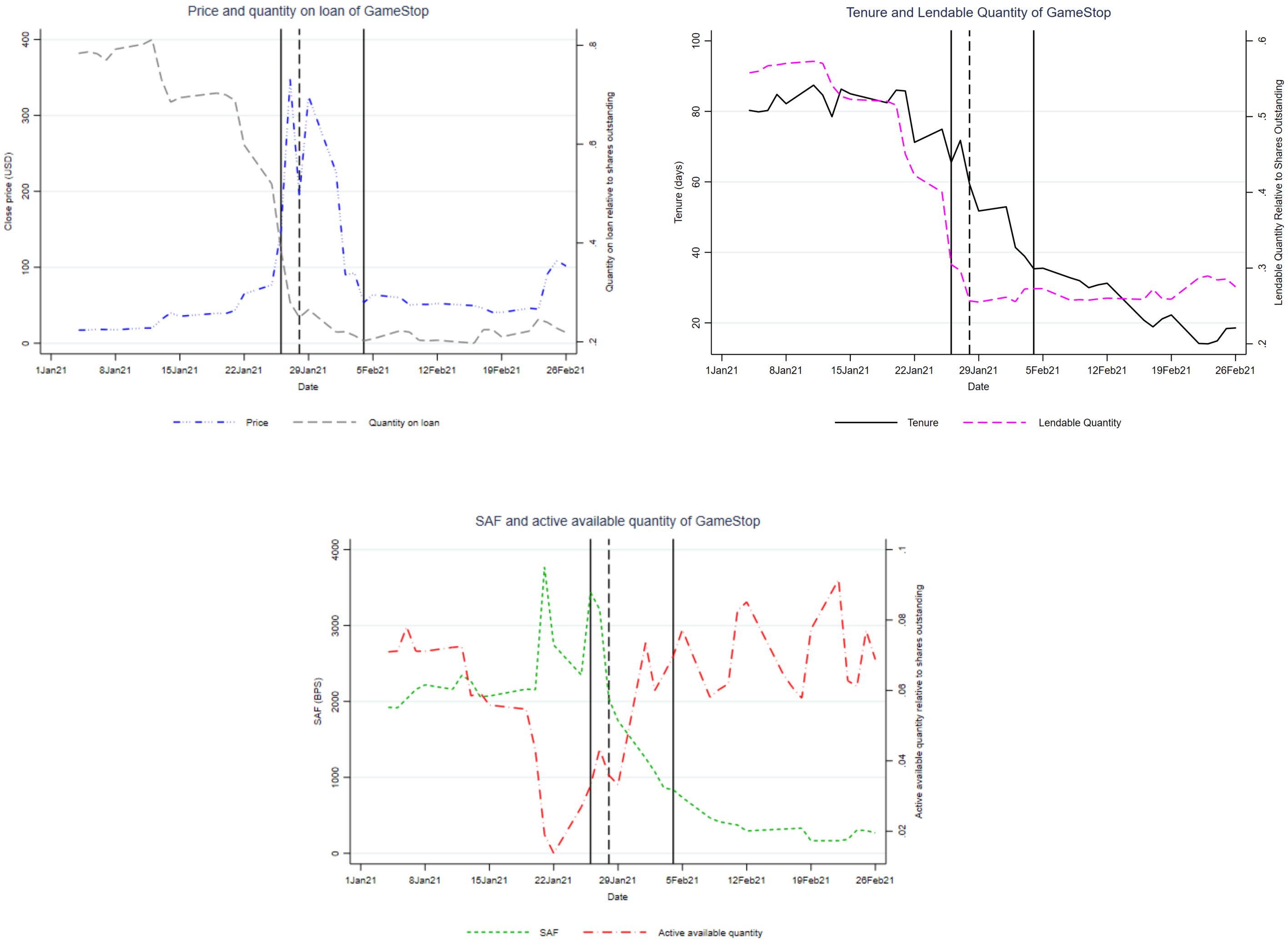


Table 1 Descriptive statistics for the securities lending market: This table presents descriptive statistics for the securities lending market measures for the 13 stocks impacted by the trading restrictions. Panel A presents information about the seven stocks that experienced a short-squeeze (GME, AMC, AAL, BBBY, EXP, NAKD, TR). Panel B presents information about the remaining six stocks that did not experience a short-squeeze (BB, CTRM, KOSS, NOK, SNDL, TRVG). We present descriptive statistics for the following variables: 1.) Quantity on Loan is the ratio of the total quantity of open securities loans relative to a company's shares outstanding; 2.) Tenure is the average number of days from start date to present for all loan transactions for a given security; 3.) Lendable Quantity is the active lendable quantity on stock available to lend adjusted to remove lendable which is not being actively made available for lending; 4.) Available Quantity is the quantity of actively lendable securities in lending programs not currently on loan/borrowed 5.) SAF is the average fees for stock borrow transactions in the respective security in basis points. The data cover the period January 11, 2021 through February 19, 2021, i.e., ten trading days before and ten trading days after the short-squeeze period (January 26 through February 04 included). The data frequency is daily. Data come from IHS Markit.

Panel A	Obs.	Mean	Stdev.	$Q_{0.01}$	$Q_{0.25}$	$Q_{0.50}$	$Q_{0.75}$	$Q_{0.99}$
Quantity on Loan	196	0.2192	0.1558	0.0697	0.1115	0.1657	0.2508	0.8021
Tenure	196	71.68	69.188	14.9193	24.7522	42.2474	84.7993	294.83
Lendable Quantity	196	0.2346	0.1239	0.0424	0.1461	0.2195	0.2794	0.5656
Available Quantity	196	0.1003	0.0873	0.0031	0.0353	0.0678	0.1291	0.3416
SAF	196	623.27	844.3288	33.1674	57.1694	148.87	804.1731	3437.95

Panel B	Obs.	Mean	Stdev.	$Q_{0.01}$	$Q_{0.25}$	$Q_{0.50}$	$Q_{0.75}$	$Q_{0.99}$
Quantity on Loan	168	0.0573	0.0381	0.001	0.0259	0.0464	0.0911	0.1412
Tenure	168	21.4745	20.6901	0.6939	7.6036	11.7354	33.3222	86.9208
Lendable Quantity	168	0.0807	0.0759	0.0009	0.0193	0.0362	0.1717	0.1996
Available Quantity	168	0.0554	0.0639	0	0.0068	0.0176	0.1242	0.184
SAF	168	1660.628	2572.62	36.5	60.9881	275.7125	2455.256	9950

Table 2 Securities lending market measures during and after the short-squeeze period: This table reports the results from the securities lending market regression estimation described in Equation 1. The dependent variables are defined in Table 1. We present results for the 13 stocks impacted by the trading restrictions. Panel A presents information about the seven stocks that experienced a short-squeeze (GME, AMC, AAL, BBBY, EXP, NAKD, TR). Panel B presents information about the remaining six stocks that did not experience a short-squeeze (BB, CTRM, KOSS, NOK, SNDL, TRVG). The data set covers the period January 11, 2021 through February 19, 2021. The data frequency is daily. We define the period before the short squeeze as the two weeks (ten trading days) preceding January 26, 2021. We define the short-squeeze period (SSqueeze) as January 26, 2021 through February 04, 2021. We define the period after the short squeeze (Post-SSqueeze) as the two weeks (ten trading days) after February 04, 2021. Controls include the daily return, daily size of the company (measured as the natural log of market capitalization), daily price dispersion, and daily trading volume, all measured at the end of the previous day. The t-statistics are reported in parentheses below the coefficient estimates and are based on robust standard errors clustered by firm and time (see Petersen (2009)). The symbols ***, ** and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Data come from IHS Markit.

	(1)	(2)	(3)	(4)	(5)
Panel A	Quantity on Loan	Tenure	Active Lendable Quantity	Active Available Quantity	SAF
SSqueeze	**-0.221*****	**21.547**	**-0.103*****	**0.037***	**-513.480****
	(-3.027)	**(0.861)**	**(-2.681)**	**(1.684)**	**(-2.076)**
Post-SSqueeze	-0.221***	-17.249***	-0.119***	0.019	-405.558
	(-3.944)	(-2.887)	(-3.271)	(0.750)	(-1.338)
Constant	0.191	118.927	-0.561***	-0.350**	2,763.296
	(0.485)	(0.652)	(-2.944)	(-2.522)	(0.852)
Observations	196	196	196	196	196
Controls	YES	YES	YES	YES	YES
Adjusted R^2	0.430	0.117	0.411	0.299	0.268

	(1)	(2)	(3)	(4)	(5)
Panel B	Quantity on Loan	Tenure	Active Lendable Quantity	Active Available Quantity	SAF
SSqueeze	**0.010**	**-18.330*****	**-0.001**	**-0.007**	**416.657**
	(0.617)	**(-2.800)**	**(-0.095)**	**(-1.082)**	**(0.537)**
Post-SSqueeze	-0.000	-15.998**	-0.017***	-0.014***	1,121.254
	(-0.029)	(-2.465)	(-4.686)	(-3.374)	(1.044)
Constant	0.006	-105.898**	-0.550***	-0.486***	10,216.764**
	(0.052)	(-2.455)	(-7.534)	(-8.493)	(2.028)
Observations	168	168	168	168	168
Controls	YES	YES	YES	YES	YES
Adjusted R^2	0.016	0.612	0.817	0.863	0.451

Table 3 Descriptive statistics for the trading and social media activity: This table presents descriptive statistics for trading in the equity and options markets and social media activity measures for the 13 stocks impacted by the trading restrictions. Panel A presents information about the seven stocks that experienced a short-squeeze (GME, AMC, AAL, BBBY, EXP, NAKD, TR). Panel B presents information about the remaining six stocks that did not experience a short-squeeze (BB, CTRM, KOSS, NOK, SNDL, TRVG). We present descriptive statistics for the following variables: 1.) Return is the simple return measured intra-daily; 2.) Volume is the total trading volume in number of shares; 3.) Num. Trades is the total number of trades; 4.) Retail Volume is the retail investors' volume in number of shares. To identify retail volume, we sum the number of shares of all trades signed as retail trades (Boehmer et al. (2021)); 5.) mroibvol and 6.) mroibtrd are two scaled marketable order imbalance measures based on the number of shares and on the number of trades, respectively (see Boehmer et al. (2021)). We do not compute mroibvol and mroibtrd if we have only buy or only sell retail trades during a particular intraday time interval; 7.) Mentions represents the total number of mentions of each of the 13 stocks on Reddit, Stocktwits, and Twitter. 8.) Sentiment is a score based on a text sentiment analysis of social media posts following Hutto and Gilbert (2014). All of these variables are measured at the 30-seconds frequency. We also present summary statistics for the following variables measured at the daily frequency: 8.) Daily Return is the daily simple return; 9.) Size is the natural log of daily market cap; 10.) Turnover is the daily turnover computed as shares traded divided by shares outstanding; 11.) Price Dispersion is measured as: $\frac{(High_{i,t}-Low_{i,t})}{m_{i,t}}$, where: $m_{i,t} = \frac{(High_{i,t}+Low_{i,t})}{2}$; 12.) Open Interest Call is total daily call options open interest; 13.) Open Interest Put is total daily put options open interest; 14.) $R = 100\ ln(S/S^{*})$ is a measure of put-call parity violations (see Ofek et al. (2004)). The data cover the period January 11, 2021 through February 19, 2021, i.e., ten trading days before and ten trading days after the short-squeeze period (January 26 through February 04 included). Data come from Reddit, Stocktwits, Twitter, TAQ, Compustat, and OptionMetrics.

Panel A	Obs.	Mean	Stdev.	$Q_{0.01}$	$Q_{0.25}$	$Q_{0.50}$	$Q_{0.75}$	$Q_{0.99}$
Return	141498	0	0.737	-1.991	-0.144	0	0.152	1.925
Volume	145580	124079.1	401655	3	5338	27216	94136.5	1581549
Num. Trades	145580	492.511	1286.074	1	39	126	371	6189
Retail Volume	122283	30467.86	79460.25	2	1311	7217	24576	352550
mroibvol	108223	0.001	0.512	-0.985	-0.365	0.005	0.362	0.986
mroibtrd	108223	0.067	0.311	-0.667	-0.137	0.062	0.283	0.75
Mentions	145580	18.823	60.652	0	0	1	10	331
Sentiment	145580	1.769	8.312	-6	0	0	1	31
Daily Return	196	6.35	38.579	-56.633	-4.107	-0.118	5.173	252.31
Size	196	20.955	1.639	17.446	19.875	21.173	22.022	23.844
Turnover	196	0.744	1.981	0.003	0.061	0.184	0.746	11.911
Price Dispersion	196	0.189	0.217	0.014	0.055	0.113	0.225	1.246
Open Interest Call	168	228255.4	251643.6	768	42812	133121	398052.5	835371
Open Interest Put	168	351409.2	422699.1	88	47979.5	117919	746914.5	1202537
R	26469	8.798	20.444	-2.817	1.630	3.988	8.856	82.092

Panel B	Obs.	Mean	Stdev.	$Q_{0.01}$	$Q_{0.25}$	$Q_{0.50}$	$Q_{0.75}$	$Q_{0.99}$
Return	117579	0.003	0.641	-1.806	-0.153	0	0.162	1.763
Volume	121097	280058.4	812487.1	5	6207	52603	229518	3421860
Num. Trades	121097	434.429	1151.52	1	33	140	394	4604
Retail Volume	87046	62443.54	190370.2	2	928	7357	40536	931047
mroibvol	74340	-0.021	0.534	-0.99	-0.428	-0.015	0.371	0.991
mroibtrd	74340	0.085	0.349	-0.676	-0.167	0.091	0.333	0.778
Mentions	121097	9.265	24.959	0	0	2	7	119
Sentiment	121097	1.247	5.67	-3	0	0	2	15
Daily Return	168	6.128	40.938	-42.857	-4.685	-0.468	7.005	79.641
Size	168	20.599	2.193	16.939	18.732	20.227	22.684	24.043
Turnover	168	0.405	0.617	0.004	0.025	0.155	0.529	3.318
Price Dispersion	168	0.175	0.199	0.017	0.062	0.112	0.211	1.324
Open Interest Call	112	585846.3	634488	6906	89195.5	391520.5	778148.5	2121459
Open Interest Put	112	134464.7	159218.8	1855	19259	62302.5	181321.5	522851
R	6566	3.877	6.379	-5.283	.930	2.224	5.344	25.970

Fig. 4 Evolution of average retail volume and social media activity of squeezed vs non-squeezed: January 01, 2021 – February 28, 2021: These graphs depict the evolution of average daily retail volume and average social media activity for the stocks that experienced a short-squeeze (GME, AMC, AAL, BBBY, EXP, NAKD, TR) and the stocks that did not experience a short-squeeze (BB, CTRM, KOSS, NOK, SNDL, TRVG). We compute daily retail trading volume by summing the number of shares of all the trades signed as retail trades (Boehmer, Jones, Zhang, and Zhang (2021)). To compute social media activity we use the social media data described in Section 3, which includes time-stamped counts of posts and comments referencing the relevant stocks from the social media platforms Reddit, Twitter, Stocktwits. We note that in the graph for the non-squeezed stocks we have trimmed outlier retail volume observations for the company SNDL during the morning 3 hours of trading on some days in the post-short squeeze period (February 10 and February 11, 2021). The start of the short-squeeze period is set to January 26, 2021. The end of the short-squeeze period is set to February 4, 2021. On January 28, 2021 Robinhood, among other brokers, implemented the trading limitations. We note that January 18 and February 15, 2021 were exchange holidays, see e.g., the NASDAQ trading calendar (Link).

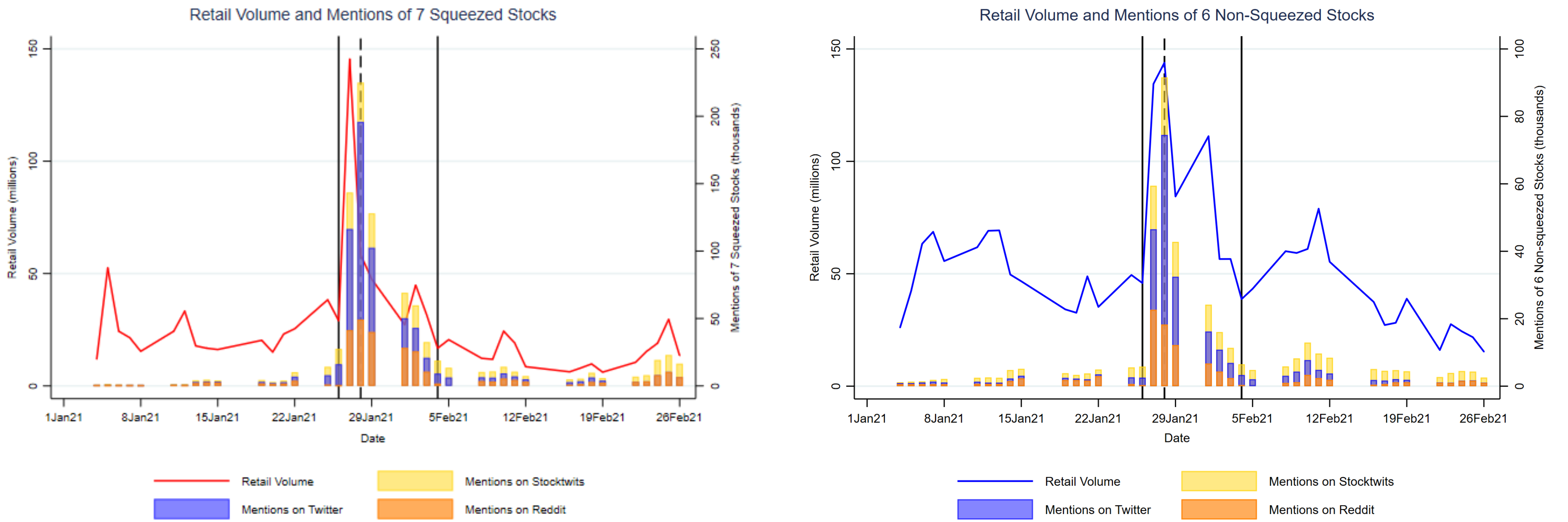


Table 4 Social media activity and retail trading activity: This table reports the results from the social media activity regression estimation described in Equation 2. Panel A presents information about the seven stocks that experienced a short-squeeze (GME, AMC, AAL, BBBY, EXP, NAKD, TR). Panel B presents information about the remaining six stocks that did not experience a short-squeeze (BB, CTRM, KOSS, NOK, SNDL, TRVG). The data set covers the period January 11, 2021 through February 19, 2021. The dependent variable is individual retail trading volume computed over different short-term periods (30-seconds, 1-minute, and 2-minute). We compute retail trading volume by summing the number of shares of all the trades signed as retail trades (Boehmer, Jones, Zhang, and Zhang (2021)). The main independent variable is ln(Mentions), where Mentions represents the total number of mentions of each of the 13 stocks on Reddit, Stocktwits, and Twitter. Controls include the daily return, daily size of the company (measured as the natural log of market capitalization), daily price dispersion, and daily trading volume, all measured at the end of the previous day. The t-statistics are reported in parentheses below the coefficient estimates and are based on robust standard errors clustered by firm and time (see Petersen (2009)). The symbols ***, ** and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Data come from Reddit, Stocktwits, Twitter, TAQ, and Compustat.

	(1)	(2)	(3)
Panel A	30-sec Retail Volume	1-min Retail Volume	2-min Retail Volume
SSqueeze	-4,459.481***	-3,468.171***	-11,567.841***
	(-10.535)	(-2.837)	(-3.255)
Post-SSqueeze	-1,816.205***	5,370.755***	15,797.005***
	(-6.062)	(3.669)	(4.501)
ln(Mentions)	9,498.986***	20,674.487***	30,768.270***
	(4.412)	(4.300)	(4.678)
ln(Mentions) x SSqueeze	**4,710.915*** **	**4,817.621*** **	**9,392.019*** **
	(7.469)	**(6.135)**	**(5.521)**
ln(Mentions) x Post-SSqueeze	-1,041.171	-4,115.454**	-7,253.212***
	(-1.406)	(-2.378)	(-2.665)
Constant	152,195.832***	375,476.552***	601,352.956***
	(6.117)	(5.285)	(6.264)
Controls	YES	YES	YES
Observations	120,942	52,539	27,470
Adjusted R^2	0.575	0.657	0.690

	(1)	(2)	(3)
Panel B	30-sec Retail Volume	1-min Retail Volume	2-min Retail Volume
SSqueeze	-24,565.254***	-36,446.312***	-52,103.794***
	(-9.190)	(-8.057)	(-5.384)
Post-SSqueeze	-49,255.788***	-76,822.971***	-132,294.344***
	(-10.361)	(-10.359)	(-8.816)
ln(Mentions)	9,168.337***	15,276.760***	27,815.693***
	(6.706)	(6.388)	(5.176)
ln(Mentions) x SSqueeze	**13,060.016*** **	**13,028.653*** **	**11,775.075*** **
	(7.112)	**(5.315)**	**(2.687)**
ln(Mentions) x Post-SSqueeze	58,443.242***	68,959.850***	94,666.546***
	(10.917)	(11.011)	(9.300)
Constant	168,432.750***	275,182.637***	455,065.679***
	(9.735)	(9.175)	(7.299)
Controls	YES	YES	YES
Observations	85,431	45,170	23,545
Adjusted R^2	0.681	0.744	0.745

Table 5 Explaining return variation during the short-squeeze period using marketable retail order imbalances: This table reports the results from the retail investors' trading activity regression estimation described in Equation 3. Panel A presents information about the seven stocks that experienced a short-squeeze (GME, AMC, AAL, BBBY, EXP, NAKD, TR). Panel B presents information about the remaining six stocks that did not experience a short-squeeze (BB, CTRM, KOSS, NOK, SNDL, TRVG). The data set covers the period January 11, 2021 through February 19, 2021. The dependent variable is individual stock returns in percent computed over different short-term periods (30-seconds, 1-minute, and 2-minute). The main independent variable is mroibvol, a scaled marketable retail order imbalance measure based on the number of shares traded (see Boehmer, Jones, Zhang, and Zhang (2021)). To capture the association of retail trading activity and returns during the different periods we interact this variable with corresponding dummies for the period during the short squeeze (SSqueeze) and the period after the short squeeze (Post-SSqueeze), as previously defined. Controls include the daily return, daily size of the company (measured as the natural log of market capitalization), daily price dispersion, and daily trading volume, all measured at the end of the previous day. We also include lagged intra-daily return, measured at the same frequency as the dependent variable, as an additional control. The t-statistics are reported in parentheses below the coefficient estimates and are based on robust standard errors clustered by firm and time (see Petersen (2009)). The symbols ***, ** and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Data come from TAQ and Compustat.

Panel A	(1) 30-second Return	(2) 1-minute Return	(3) 2-minute Return
SSqueeze	-0.007	-0.017	-0.024
	(-0.930)	(-1.163)	(-0.850)
Post-SSqueeze	-0.009*	-0.019**	-0.028*
	(-1.917)	(-2.294)	(-1.731)
mroibvol	0.017***	0.033***	0.060***
	(4.209)	(4.054)	(2.930)
mroibvol x SSqueeze	**0.045*** **	**0.066*** **	**0.139*** **
	(5.014)	**(3.760)**	**(3.382)**
mroibvol x Post-SSqueeze	0.008*	0.008	0.028
	(1.720)	(0.822)	(1.580)
Constant	0.029*	0.093	0.035
	(0.679)	(1.306)	(0.265)
Controls	YES	YES	YES
Observations	107,576	57,739	30,367
Adjusted R^2	0.002	0.003	0.020

Panel B	(1) 30-second Return	(2) 1-minute Return	(3) 2-minute Return
SSqueeze	-0.002	-0.007	-0.008
	(-0.252)	(-0.541)	(-0.317)
Post-SSqueeze	-0.005	-0.017*	-0.023
	(-0.995)	(-1.732)	(-1.266)
mroibvol	0.010**	0.022***	0.031*
	(2.465)	(2.942)	(1.725)
mroibvol x SSqueeze	**0.082*** **	**0.140*** **	**0.185*** **
	(5.036)	**(5.426)**	**(3.281)**
mroibvol x Post-SSqueeze	0.027***	0.041***	0.046*
	(4.547)	(3.526)	(1.896)
Constant	0.023	0.092	0.132
	(0.542)	(1.308)	(1.206)
Controls	YES	YES	YES
Observations	73,714	40,527	21,633
Adjusted R^2	0.014	0.012	0.008

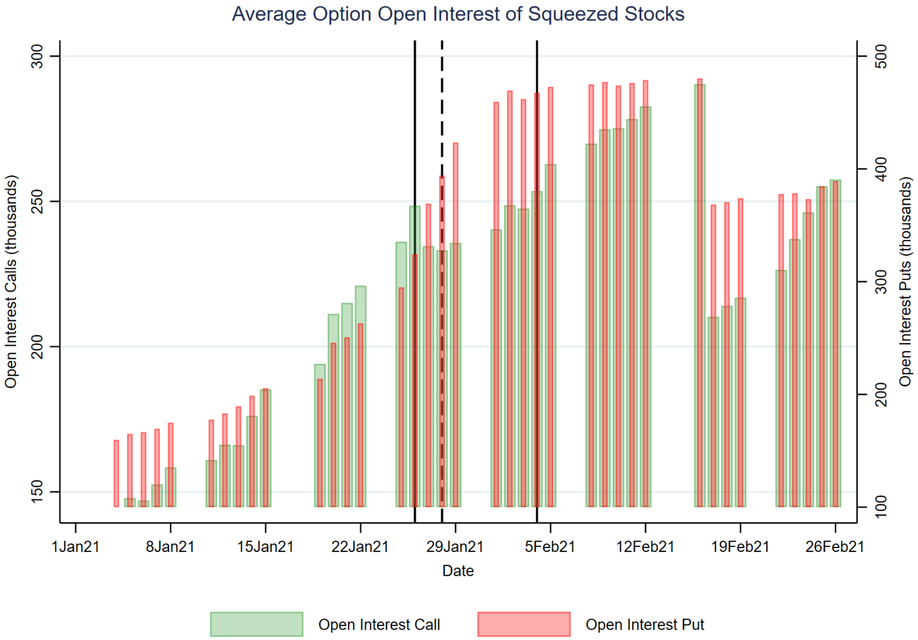
Table 6 Placebo test: Explaining return variation during the short-squeeze period using marketable retail order imbalances: This table reports results for the set of control companies for the retail investors' trading activity regression estimations described in Section 5.2.1. Panel A presents information about the first tercile of control companies. Panel B presents information about the second tercile of control companies. Panel C presents information for the third tercile of control companies. The data set covers the period January 11, 2021 through February 19, 2021. The dependent variable is individual stock returns in percent computed over different short-term periods (30-seconds, 1-minute, and 2-minute). The main independent variable is mroibvol, a scaled marketable retail order imbalance measure based on the number of shares traded (see Boehmer, Jones, Zhang, and Zhang (2021)). To capture the association of retail trading activity and returns during the different periods we interact this variable with corresponding dummies for the period during the short squeeze (SSqueeze) and the period after the short squeeze (Post-SSqueeze), as previously defined. Controls include the daily return, daily size of the company (measured as the natural log of market capitalization), daily price dispersion, and daily trading volume, all measured at the end of the previous day. We also include lagged intra-daily return, measured at the same frequency as the dependent variable, as an additional control. The t-statistics are reported in parentheses below the coefficient estimates and are based on robust standard errors clustered by firm and time (see Petersen (2009)). The symbols ***, ** and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Data come from TAQ and Compustat.

Panel A	(1) 30-second Return	(2) 1-minute Return	(3) 2-minute Return
SSqueeze	-0.001	-0.000	-0.003
	(-0.319)	(-0.085)	(-0.628)
Post-SSqueeze	-0.002	-0.007**	-0.001
	(-0.638)	(-2.067)	(-0.247)
mroibvol	0.012***	0.006*	0.012***
	(3.378)	(1.918)	(3.377)
mroibvol x SSqueeze	**-0.003**	**0.001**	**-0.001**
	(-0.498)	**(0.263)**	**(-0.094)**
mroibvol x Post-SSqueeze	-0.006	-0.004	-0.012**
	(-1.313)	(-0.987)	(-2.361)
Constant	0.087**	0.069	0.108**
	(2.113)	(1.597)	(2.240)
Controls	YES	YES	YES
Observations	27,085	37,871	43,036
Number of unique companies	35	35	35
Adjusted R^2	0.048	0.033	0.016

Panel B	(1) 30-second Return	(2) 1-minute Return	(3) 2-minute Return
SSqueeze	-0.002	-0.002	-0.005
	(-0.754)	(-0.703)	(-1.014)
Post-SSqueeze	-0.002	-0.003	-0.005
	(-1.251)	(-1.042)	(-1.369)
mroibvol	0.007***	0.003*	0.004
	(4.191)	(1.708)	(1.444)
mroibvol x SSqueeze	**0.004**	**0.005**	**-0.003**
	(1.281)	**(1.378)**	**(-0.657)**
mroibvol x Post-SSqueeze	-0.004	-0.002	-0.003
	(-1.585)	(-0.884)	(-0.941)
Constant	0.032	0.022	0.050*
	(1.528)	(0.981)	(1.726)
Controls	YES	YES	YES
Observations	97,382	104,892	91,434
Number of unique companies	34	34	34
Adjusted R^2	0.012	0.008	0.003

Panel C	(1) 30-second Return	(2) 1-minute Return	(3) 2-minute Return
SSqueeze	-0.000	-0.002	-0.005
	(-0.076)	(-0.753)	(-0.910)
Post-SSqueeze	-0.000	-0.001	-0.002
	(-0.108)	(-0.302)	(-0.388)
mroibvol	0.004***	0.006***	0.006**
	(4.245)	(4.510)	(2.487)
mroibvol x SSqueeze	**0.004****	**0.002**	**-0.001**
	(2.546)	**(0.666)**	**(-0.177)**
mroibvol x Post-SSqueeze	0.004***	0.001	0.003
	(2.755)	(0.568)	(1.088)
Constant	0.024*	0.037*	0.056*
	(1.794)	(1.947)	(1.883)
Controls	YES	YES	YES
Observations	350,382	247,932	154,336
Number of unique companies	35	35	35
Adjusted R^2	0.025	0.010	0.003

Fig. 5 Evolution of average open interest of squeezed vs non-squeezed stocks: January 01, 2021 – February 28, 2021: These graphs depict the evolution of the average open interest per day separately for call and put options for the stocks with listed options that experienced a short-squeeze (GME, AMC, AAL, BBBY, EXP, TR) and the stocks with listed options that did not experience a short-squeeze (BB, NOK, SNDL, TRVG). The start of the short-squeeze period is set to January 26, 2021. The end of the short-squeeze period is set to February 4, 2021. On January 28, 2021 Robinhood, among other brokers, implemented the trading limitations. We note that January 18 and February 15, 2021 were exchange holidays, see e.g., the NASDAQ trading calendar (Link).



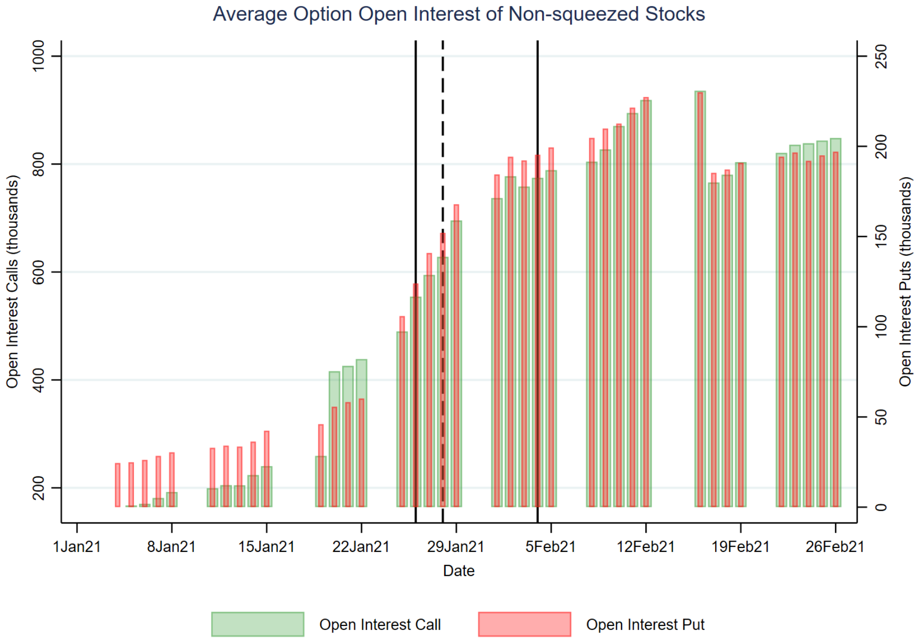


Table 7 Options delta-adjusted open interest during and after the short-squeeze period: This table reports the results from the open interest regression estimation described in Equation 5. The dependent variable in each regression is the natural log of total daily delta-adjusted options open interest per stock. We perform the estimation separately for call and put options. The data set covers all stocks with options listed on them from the 13 banned stocks. Panel A presents information about the stocks with listed options that experienced a short-squeeze (GME, AMC, AAL, BBBY, EXP, TR). Panel B presents information about the remaining stocks with listed options that did not experience a short-squeeze (BB, NOK, SNDL, TRVG). The period covered is January 11, 2021 through February 19, 2021. The data frequency is daily. We define the period before the short squeeze as the two weeks (ten trading days) preceding January 26, 2021. We define the short-squeeze period (SSqueeze) as January 26, 2021 through February 04, 2021. We define the period after the short squeeze (Post-SSqueeze) as the two weeks (ten trading days) after February 04, 2021. Options moneyness categories are defined as follows: i) at-the-money (ATM) options with S/X $\geq$ 0.95 and S/X $\leq$1.05; ii) in-the-money (ITM) options with S/X $>$ 1.05 for calls (reverse for puts); iii) out-of-the-money (OTM) options with S/X $<$ 0.95 for calls (reverse for puts), where S is the price of the underlying stock and X is the exercise price. Controls include the daily return, daily trading volume, and the VIX, all measured at the end of the previous day. The t-statistics are reported in parentheses below the coefficient estimates and are based on robust standard errors clustered by firm and time (see Petersen (2009)). The symbols ***, ** and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Data come from OptionMetrics.

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A	ATM Puts	ITM Puts	OTM Puts	ATM Calls	ITM Calls	OTM Calls
SSqueeze	**1.099**	**0.383**	**2.417*****	**-0.255**	**1.194*****	**1.507**
	(0.728)	**(0.209)**	**(4.788)**	**(-0.527)**	**(3.566)**	**(1.385)**
Post-SSqueeze	0.792	1.315	2.206***	-0.581	0.421	2.305***
	(0.686)	(1.060)	(3.264)	(-0.864)	(0.320)	(3.275)
Constant	4.337**	7.269***	9.873***	7.239***	12.434***	9.054***
	(1.962)	(2.856)	(6.518)	(2.670)	(8.770)	(2.788)
Observations	140	152	166	142	166	162
Controls	YES	YES	YES	YES	YES	YES
Adjusted R^2	0.071	0.099	0.250	0.090	0.179	0.276

	(1)	(2)	(3)	(4)	(5)	(6)
Panel B	ATM Puts	ITM Puts	OTM Puts	ATM Calls	ITM Calls	OTM Calls
SSqueeze	**0.257**	**1.114**	**2.933*****	**-0.149**	**2.108*****	**1.817*****
	(0.141)	**(1.127)**	**(13.808)**	**(-0.092)**	**(5.522)**	**(2.710)**
Post-SSqueeze	2.184***	1.267	1.232	0.432**	0.439	0.432
	(4.741)	(1.253)	(1.349)	(2.242)	(0.413)	(0.843)
Constant	5.685***	8.415***	8.891***	11.216***	12.989***	12.900***
	(2.594)	(4.647)	(11.630)	(7.167)	(7.980)	(4.840)
Observations	66	112	94	66	94	112
Controls	YES	YES	YES	YES	YES	YES
Adjusted R^2	0.297	0.253	0.433	0.288	0.377	0.440

Table 8 Put-call parity violations during and after the short-squeeze period: This table reports the results from the put-call parity decoupling regression estimation described in Equation 7. The dependent variable in each regression is $R = 100 \times ln(S/S^{*})$, where S is the stock price and S^{*} is the stock price derived from the options market using put–call parity as described in Equation 6. The data set covers all stocks with options listed on them from the 13 banned stocks. The period covered is January 11, 2021 through February 19, 2021. The data frequency is daily. We define the period before the short squeeze as the two weeks (ten trading days) preceding January 26, 2021. We define the short-squeeze period (SSqueeze) as January 26, 2021 through February 04, 2021. We define the period after the short squeeze (Post-SSqueeze) as the two weeks (ten trading days) after February 04, 2021. Option pairs moneyness categories are defined as follows: i) at-the-money (ATM) options with S/X $\geq$ 0.95 and S/X $\leq$1.05; ii) in-the-money (ITM) options with S/X $>$ 1.05; iii) out-of-the-money (OTM) options with S/X $<$ 0.95, where S is the price of the underlying stock and X is the exercise price. Controls include the daily return, daily trading volume, and the VIX, all measured at the end of the previous day. The t-statistics are reported in parentheses below the coefficient estimates and are based on robust standard errors clustered by firm and time (see Petersen (2009)). The symbols ***, ** and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Data come from OptionMetrics.

	(1) ATM	(2) ITM	(3) OTM
SSqueeze	-1.147*	0.783	1.897
	(-1.743)	(0.878)	(1.411)
Post-SSqueeze	-0.648	-0.633	-1.112
	(-1.340)	(-0.724)	(-0.998)
Squeezed	1.552	1.930	0.831
	(1.531)	(1.458)	(0.683)
Squeezed x SSqueeze	**2.232****	**1.650**	**8.405****
	(2.017)	**(1.625)**	**(2.141)**
Squeezed x Post-SSqueeze	-0.451	-0.768	9.817**
	(-0.600)	(-0.638)	(2.277)
Constant	0.538	6.479***	13.961***
	(0.323)	(2.742)	(2.811)
Observations	1,690	15,502	15,843
Controls	YES	YES	YES
Adjusted R^2	0.095	0.111	0.038

Table 9 Descriptive statistics for the market quality tests: This table presents descriptive statistics for the 13 stocks impacted by the trading restrictions and their product market competitors. Panels A and C present information about the seven stocks that experienced a short-squeeze (GME, AMC, AAL, BBBY, EXP, NAKD, TR) and their competitors, respectively. Panel B and D present information about the remaining six stocks that did not experience a short-squeeze (BB, CTRM, KOSS, NOK, SNDL, TRVG) and their competitors, respectively. 1.) Spread is the relative spread measured as: $\frac{(Ask_{i,t}-Bid_{i,t})}{m_{i,t}}$, where: $m_{i,t}=\frac{(Ask_{i,t}+Bid_{i,t})}{2}$. The relative spreads are multiplied by 100 for ease of interpretability, and also trimmed at the 1st and 99th percentile to remove outliers; 2.) Volatility is the rolling standard deviation of realized returns over a window of fifteen minutes; 3.) Volume is the total trading volume; 4.) Bid Size is the total number of shares quoted at the bid; 5.) Ask Size is the total number of shares quoted at the best ask. The data cover the period January 11, 2021 through February 19, 2021, i.e., ten trading days before and ten trading days after the short-squeeze period (January 26 through February 04). The data frequency is on the minute level. Data come from TAQ and Compustat.

Panel A: Squeezed Stocks

	Obs.	Mean	Stdev.	$Q_{0.01}$	$Q_{0.25}$	$Q_{0.50}$	$Q_{0.75}$	$Q_{0.99}$
Spread	74740	0.92	1.018	0.065	0.326	0.665	1.12	5.324
Volatility	76177	0.475	0.877	0.039	0.13	0.256	0.512	3.46
Volume	74923	242622.8	736275.1	6	10650	56880	187861	2998093
Bid Size	76294	94935.64	3222533	17	1943	9340.5	73497	844296
Ask Size	76294	75575.03	315306.1	16	1914	9311	70620	736570

Panel B: Non-Squeezed Stocks

	Obs.	Mean	Stdev.	$Q_{0.01}$	$Q_{0.25}$	$Q_{0.50}$	$Q_{0.75}$	$Q_{0.99}$
Spread	61547	1.041	1.65	0.091	0.242	0.491	0.89	8.841
Volatility	63068	0.447	0.621	0.043	0.15	0.267	0.496	3.044
Volume	62382	545443	1486636	9	11818	108206	457379	6603194
Bid Size	63643	459454.6	2017664	4	2154	32304	209270	6389726
Ask Size	63643	469694.3	3402850	4	2024	29931	192213	6596617

Panel C: Competitors of Squeezed Stocks

	Obs.	Mean	Stdev.	$Q_{0.01}$	$Q_{0.25}$	$Q_{0.50}$	$Q_{0.75}$	$Q_{0.99}$
Spread	385102	1.868	2.051	0.078	0.612	1.18	2.289	10.33
Volatility	386062	0.178	0.171	0.032	0.084	0.133	0.216	0.799
Volume	355690	5137.695	38205.36	1	127	675	2741	70159
Bid Size	391186	2283.246	8579.793	3	82	244	672	39048
Ask Size	391186	2302.377	8869.286	3	82	247	684	39350

Panel D: Competitors of Non-Squeezed Stocks

	Obs.	Mean	Stdev.	$Q_{0.01}$	$Q_{0.25}$	$Q_{0.50}$	$Q_{0.75}$	$Q_{0.99}$
Spread	384229	1.395	1.783	0.085	0.376	0.779	1.631	9.473
Volatility	373793	0.181	0.253	0.023	0.057	0.097	0.203	1.194
Volume	365747	17830.78	73395.85	2	536	2266	9364	263626
Bid Size	394296	7252.655	26812.93	2	187	550	2560	121868
Ask Size	394296	6791.418	25438.22	2	184	537	2324	116270

Fig. 6 Evolution of average spreads and volatility of squeezed (non-squeezed) stocks vs competitors: January 01, 2021 – February 28, 2021: These graphs depict the evolution of average daily spreads (upper two panels) and average daily volatility (lower two panels) for the stocks that experienced a short squeeze (GME, AMC, AAL, BBBY, EXP, NAKD, TR), the stocks that did not experience a short squeeze (BB, CTRM, KOSS, NOK, SNDL, TRVG), and their respective product market competitors. The variables are defined in Table 9. The start of the short-squeeze period is set to January 26, 2021. The end of the short-squeeze period is set to February 4, 2021. On January 28, 2021 Robinhood, among other brokers, implemented the trading limitations.

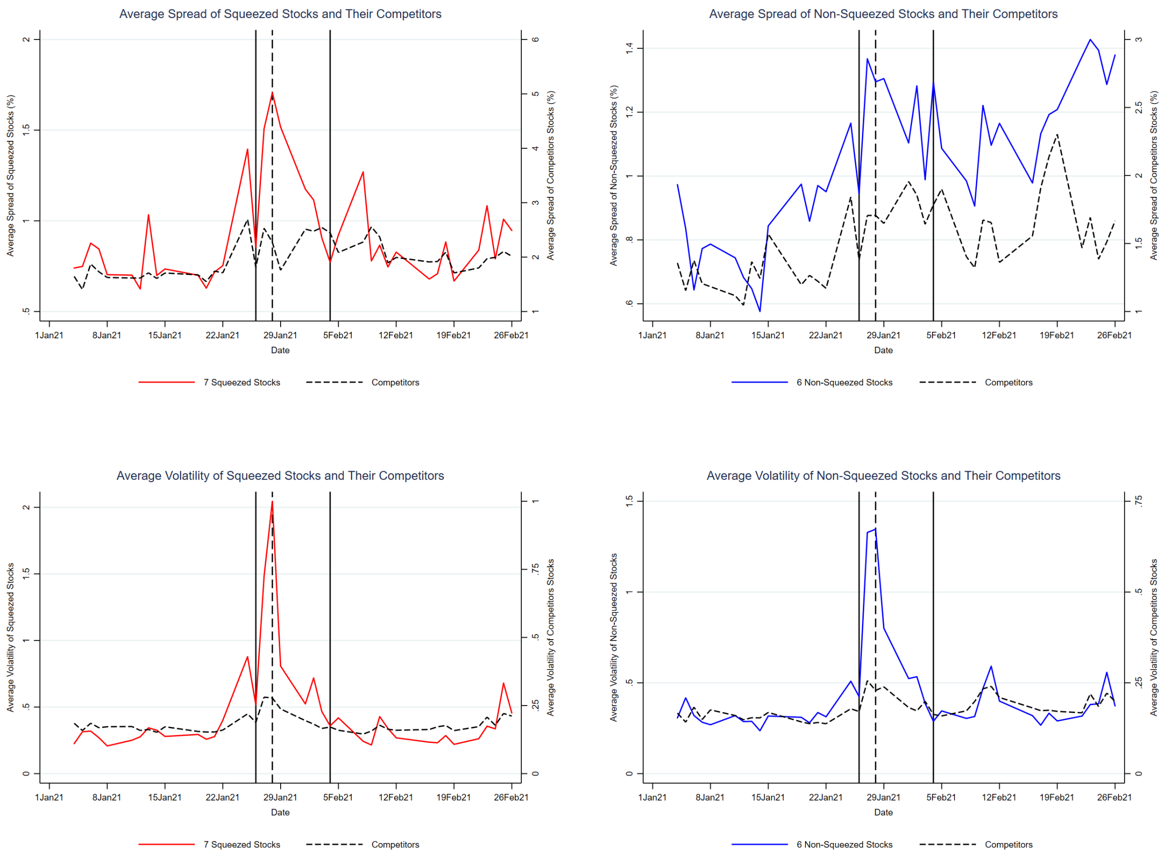


Table 10 Market quality tests for the meme stocks impacted by the trading restrictions and their competitors: The table reports the results from the market quality regression estimation described in Equation 8. We present results for the 13 stocks impacted by the trading restrictions and their product market competitors. Panel A and C present information about the seven stocks that experienced a short-squeeze (GME, AMC, AAL, BBBY, EXP, NAKD, TR) and their competitors, respectively. Panel B and D present information about the remaining six stocks that did not experience a short-squeeze (BB, CTRM, KOSS, NOK, SNDL, TRVG) and their competitors, respectively. The dependent variables are defined in Table 9. Controls include i) daily return, ii) natural log market cap, iii) daily price dispersion, and iv) daily volume, all measured at the end of the previous day. The data set covers the period January 11, 2021 through February 19, 2021. The data frequency is on the minute level. We define the period before the short squeeze (captured by the constant) as the two weeks (ten trading days) preceding January 26, 2021. We define the short-squeeze period (SSqueeze) as January 26, 2021 through February 04, 2021. We define the period after the short squeeze (Post-SSqueeze) as the two weeks (ten trading days) after February 04, 2021. The t-statistics are reported in parentheses below the coefficient estimates and are based on robust standard errors clustered by firm and time (see Petersen (2009)). The symbols ***, ** and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Data come from TAQ and Compustat.

Panel A: Squeezed Stocks

	(1) Spread	(2) Volatility	(3) Volume	(4) Bid Size	(5) Ask Size
SSqueeze	**0.340*****	**0.190*****	**196,776.056*****	**-3,895.790**	**26,424.214*****
	(29.490)	**(13.582)**	**(13.308)**	**(-0.116)**	**(5.531)**
Post-SSqueeze	0.112***	-0.011**	-25,111.945***	13,132.115	-3,962.421*
	(13.797)	(-2.217)	(-5.717)	(1.496)	(-1.897)
Constant	2.331***	0.608***	1140707.872***	-269,094.387***	-169,789.689***
	(75.333)	(12.497)	(19.023)	(-4.089)	(-7.559)
Controls	YES	YES	YES	YES	YES
Observations	74,740	76,177	74,923	76,294	76,294
Adjusted R^2	0.104	0.227	0.151	0.004	0.057

Panel B: Non-Squeezed Stocks

	(1) Spread	(2) Volatility	(3) Volume	(4) Bid Size	(5) Ask Size
SSqueeze	**0.061*****	**0.136*****	**190,108.266*****	**191,606.597*****	**296,988.697*****
	(4.460)	**(14.113)**	**(10.908)**	**(9.504)**	**(8.392)**
Post-SSqueeze	0.374***	0.020***	84,701.579***	330,262.896***	297,323.964***
	(34.617)	(4.618)	(8.416)	(27.019)	(15.327)
Constant	6.773***	1.344***	320,446.289***	-2107381.810***	-1957562.018***
	(112.720)	(58.009)	(9.497)	(-49.285)	(-40.467)
Controls	YES	YES	YES	YES	YES
Observations	61,547	63,068	62,382	63,643	63,643
Adjusted R^2	0.287	0.296	0.246	0.101	0.039

Panel C: Competitors of Squeezed Stocks

	(1) Spread	(2) Volatility	(3) Volume	(4) Bid Size	(5) Ask Size
SSqueeze	**0.524*****	**0.035*****	**547.838**	**-366.991*****	**-343.301*****
	(31.564)	**(13.567)**	**(1.605)**	**(-9.103)**	**(-8.102)**
Post-SSqueeze	0.169***	0.004**	-578.472**	-469.619***	-402.076***
	(11.339)	(2.022)	(-2.160)	(-12.440)	(-10.673)
Constant	4.309***	0.953***	-11,148.455***	7,527.229***	7,276.046***
	(71.598)	(163.890)	(-4.574)	(27.662)	(26.509)
Controls	YES	YES	YES	YES	YES
Observations	385,102	386,062	355,690	391,186	391,186
Adjusted R^2	0.091	0.129	0.046	0.286	0.265

Panel D: Competitors of Non-Squeezed Stocks

	(1) Spread	(2) Volatility	(3) Volume	(4) Bid Size	(5) Ask Size
SSqueeze	**0.215*****	**0.029*****	**1,708.763*****	**1,237.055*****	**904.787*****
	(22.203)	**(14.880)**	**(3.342)**	**(11.192)**	**(8.393)**
Post-SSqueeze	0.155***	0.024***	475.597	-581.586***	-1,171.608***
	(16.130)	(13.851)	(1.038)	(-5.740)	(-12.305)
Constant	2.744***	1.250***	11,134.111***	20,760.010***	22,919.754***
	(70.184)	(140.166)	(6.141)	(46.762)	(54.441)
Controls	YES	YES	YES	YES	YES
Observations	355,315	344,982	338,787	365,236	365,236
Adjusted R^2	0.091	0.341	0.194	0.139	0.142

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Internet Appendix
Squeezing Shorts Through Social Media Platforms

(*Not for Publication*)

Table of Contents

A.1. Were bots contributing to social media posts?

At the height of the short-squeeze period, the public press started to turn its focus to questions of fake postings on social media platforms.[1] Several news articles discussed the extent to which both positive and negative sentiment on meme stocks were seeded by automated social media accounts that were posting algorithmically by a computer (also known as "bots")[2] instead of manually through a human. In this section, we are interested in analyzing the posting behavior of users on social media platforms. In particular, we aim to answer the following questions: (1) Were bots contributing to social media posts? (2) If they were, did they try to influence market sentiment in a particular direction? (3) If bots did contribute to market sentiment, were they successful in impacting stock prices in the direction they wanted to?

The posting behavior of bots on social media platforms has been studied by the information technologies field. A prominent paper, which received wide coverage both among academics as well as the general public, is by Golbeck (2015). The author applies a quantitative tool known as Benford's Law to social and behavioral features of users in online social networks. Benford's Law is based on an observation that many naturally occurring datasets have specific patterns of digits that appear in them. In particular, Benford's Law states the likelihood of seeing the numbers 1, 2, and 3 in the leading digit. While intuition might suggest that each digit 1-9 is equally likely, Benford's Law states that in many naturally occurring datasets the first digit should be a 1 in approximately 30% of observations, while observations with a first digit of 2, 3, 4, and so on, should be increasingly unlikely.[3] Benford's Law further assigns specific probabilities to how unlikely these subsequent leading digits should be. In her study, Golbeck (2015) shows that the distribution of first significant digits of friends and follower counts for users in these systems follow Benford's Law. The author also discusses and shows how this tool can be applied to detect suspicious or fraudulent activity.

We apply Benford's Law analysis to social media platforms using the number of posts that a user submitted on a daily basis during the time periods before, during, and after the January 2021 short squeezes.[4] User posts have been scraped from Reddit, Twitter, and Stocktwits for

[1] "Traders Who Launched GameStop Frenzy Are Turning Against New Members," The Wall Street Journal, February 2, 2021, (Link); "Bots hyped up GameStop on major social media platforms, analysis finds," Reuters, February 26, 2021, (Link).

[2] "Bot or not? The facts about platform manipulation on Twitter," Twitter, May 18, 2020, (Link).

[3] E.g., a leading digit of 2 should appear in approximately 17.6% of observations. However, reasonable deviations from these precise probabilities are expected even in legitimate datasets. See, e.g., Aloosh and Li (2019), Figure 11 (showing an exchange found to have legitimate volume with a leading digit of 1 occurring in 40% of observations).

[4] The academic finance field has recently started to apply Benford's Law to measure the degree of "fake volume" in the cryptocurrency market. For example, two recent papers by Aloosh and Li (2019) and Cong, Li, Tang, and Yang (2023) study this question for the Bitcoin market by applying Benford's Law to trade sizes observed on exchanges. Aloosh and Li (2019) analyze the distribution of the leading digits from a data sample of all trade sizes. Specifically, this application of Benford's Law indicates that legitimate trades are more likely to occur in trade sizes that begin with the number one (e.g., 100 units, 15,000 units, or 120,000 units) than any other digit. Cong et al. (2023) apply this methodology as well and find exchanges with order size data that violates

the same periods and stocks analyzed in the main paper. Users are split into two groups: users that already had an account with one of the three platforms before January 26 (old users), and users that opened an account during the short-squeeze period after January 26 (new users). New users joined social media platforms with the hope to learn from and / or contribute to the discussions that were taking place on these platforms. If bots were among these new users, since they operate algorithmically, one would expect to see uniform posting patterns (e.g., same amount of posts each day at the same time).

We present our analyses at different levels of granularity. Figure A1, shows that for (i) the 13 impacted stocks in our sample, (ii) for both new and existing users combined, and (iii) across all three social media platforms analyzed, Benford's Law holds true for each of the three periods analyzed.[5] We observe leading digits of each value occurring with approximately the correct frequency for each of the three periods analyzed including the short-squeeze period. The findings shown in Figure A1 are confirmed when analyzing the sample more granularly. Figure A2 shows that for all stocks Benford's Law holds true when we differentiate between existing and new users and when we focus on the short-squeeze period for each of the three social media platforms separately. To summarize, among the user posts data from Reddit, Twitter, and Stocktwits, we do not find evidence of bot activity at any point in time over the sample period. This is not to say that bots did not exist or attempt to influence market participants' sentiment. Most social media platforms have committed themselves to screening for bot activity on a real-time basis, and to stop any such activity as it occurs.[6]

To corroborate the evidence presented above, we analyze the hourly posting patterns of users on Reddit, Twitter, and Stocktwits. If bots were among these users, since they operate algorithmically, one would expect to see uniform posting patterns also with respect to the time or frequency at which these new user accounts post (e.g., at the same time of the day, at regular frequencies) or posting patterns that are in line with time zones of foreign countries (outside of US business hours). As before, we present our analyses at different levels of granularity. Figure A3 shows that for (i) the 13 impacted stocks in our sample, (ii) for both new and existing users combined, and (iii) across all three social media platforms analyzed, hourly posting patterns of users did not change across all three periods analyzed. Most of the users' postings happen during US business hours, and we do not observe a change in this pattern from before to during to after the short-squeeze period. The findings shown in Figure A3 are confirmed when analyzing the sample more granularly. Figure A4 shows that for all stocks, the hourly posting pattern when a user posted a message did not change for old versus new users when focusing on the short-squeeze period and when analyzing each of the three platforms separately. The

Benford's Law.

[5]For brevity and because the results are the same across stocks, we discuss the results for all 13 stocks jointly instead of splitting them into squeezed and non-squeezed stocks (for a stock-by-stock analyses, see the charts in Figure A6 below.

[6]See, for example, "Bot or not? The facts about platform manipulation on Twitter," Twitter, May 18, 2020, (Link).

posting hour did not change when new users joined the platform and is similar across all three platforms. We perform the same analyses on a stock-by-stock basis and find that similar to the results from the Benford's Law analyses, also the hourly posting pattern analyses do not show any signs of bot activity for each stock in our sample during the short-squeeze period (see the charts in Figure A8 below).

Fig. A1 Benford's Law of count of social media mentions of the 13 stocks: January 11, 2021 – February 19, 2021: This figure shows the probability of the first digit of the count of social media mentions across the 13 stocks split into three time periods: before, during, and after the short squeezes. We define the period before the short squeeze as the ten trading days preceding January 26, 2021. We define the short-squeeze period as January 26, 2021 through February 4, 2021. We define the period after the short squeeze as the ten trading days after February 4, 2021. Mentions have been collected from posts and comments published on Reddit, Stocktwits, and Twitter.

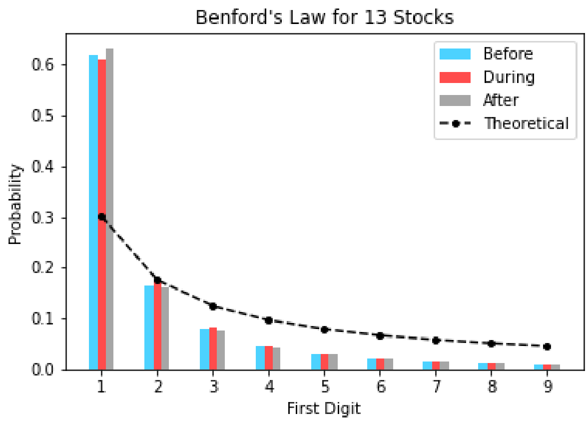


Fig. A2 Benford's Law of count of social media mentions of the 13 stocks for new and old users during the short-squeeze period: These figures show the probability of the first digit of the count of social media mentions for the short-squeeze period across the 13 stocks separately by social media platform. Users are split into two groups: users that already had an account with one of the three platforms before January 26 (old users), and users that opened an account during the short-squeeze period after January 26 (new users). The start of the short-squeeze period is set to January 26, 2021. The end of the short squeeze is set to February 4, 2021. On January 28, 2021 Robinhood, among other brokers, implemented the trading limitations. Mentions have been collected from posts and comments published on Reddit, Stocktwits, and Twitter.

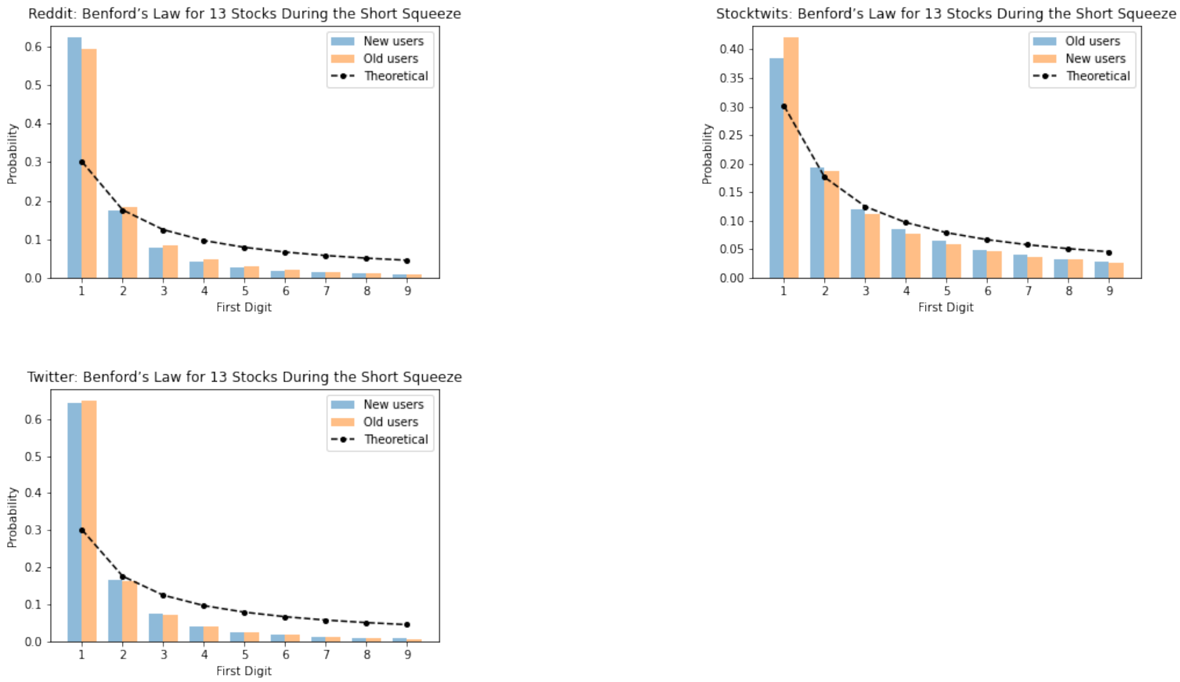


Fig. A3 Hourly posting patterns of social media mentions for the 13 stocks: January 11, 2021 – February 19, 2021: This figure shows the hourly posting pattern in NY time for social media mentions across the 13 stocks split into three time periods: before, during, and after the short squeezes. We define the period before the short squeeze as the ten trading days preceding January 26, 2021. We define the short-squeeze period as January 26, 2021 through February 4, 2021. We define the period after the short squeeze as the ten trading days after February 4, 2021. Mentions have been collected from posts and comments published on Reddit, Stocktwits, and Twitter.

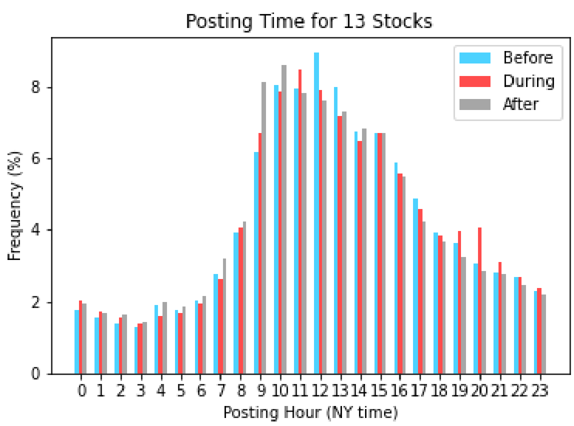
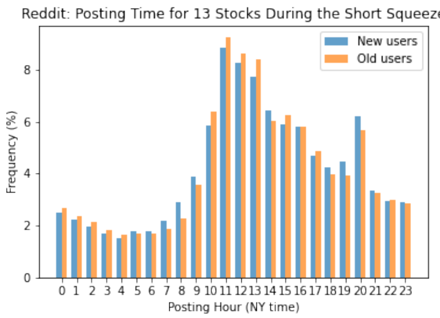
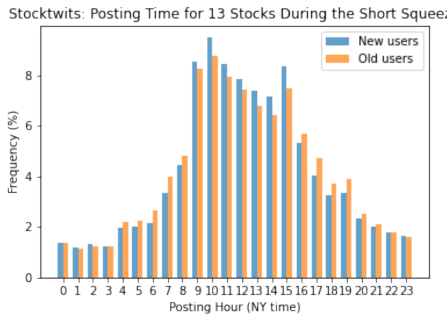


Fig. A4 Hourly posting patterns of social media mentions for the 13 stocks for new and old users during the short-squeeze period: These figures show the hourly posting pattern in NY time for social media mentions during the short-squeeze period across the 13 stocks separately by social media platform. Users are split into two groups: users that already had an account with one of the three platforms before January 26 (old users), and users that opened an account during the short-squeeze period after January 26 (new users). The start of the short-squeeze period is set to January 26, 2021. The end of the short squeeze is set to February 4, 2021. On January 28, 2021 Robinhood, among other brokers, implemented the trading limitations. Mentions have been collected from posts and comments published on Reddit, Stocktwits, and Twitter.





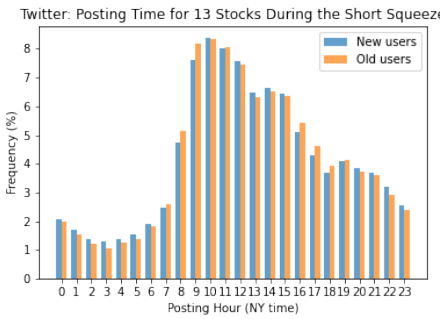


Fig. A5 Benford's Law of count of social media mentions of each of the 13 stocks for new and old users: Short-squeeze period: This figure shows the probability of the first digit of the count of social media mentions for each of the 13 stocks by social media platform and for just the short-squeeze period. The start of the short-squeeze period is set to January 26, 2021. Users are split into two groups: users that already had an account with one of the three platforms before January 26 (Old users), and users that opened an account during the short-squeeze period after January 26 (New users). The end of the short squeeze is set to February 4, 2021. On January 28, 2021 Robinhood, among other brokers, implemented the trading limitations. Mentions have been collected from posts and comments published on Reddit, Stocktwits, and Twitter.

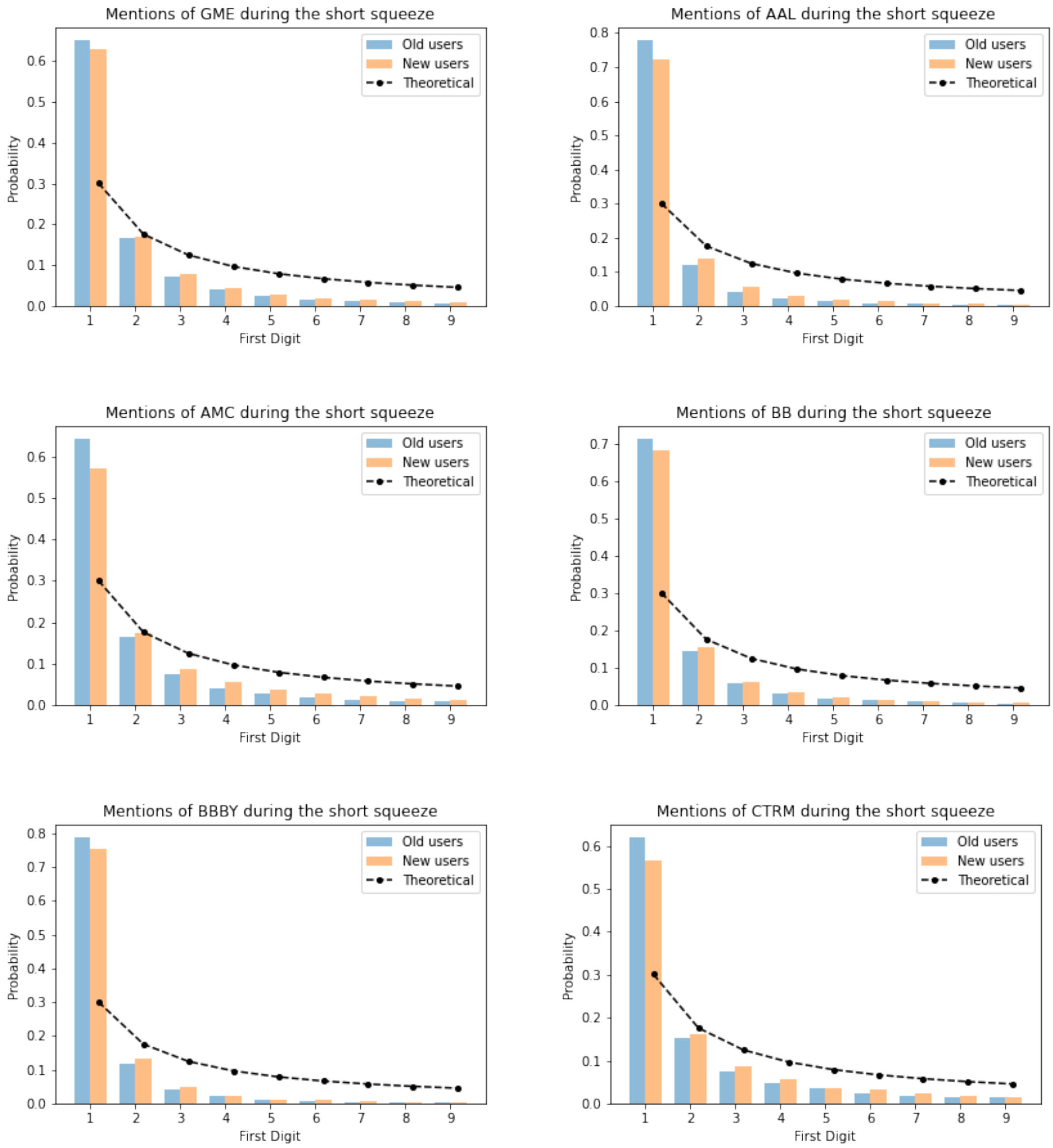


Fig. A6 Benford's Law of count of social media mentions of each of the 13 stocks for new and old users: Short-squeeze period(cont'd): This figure shows the probability of the first digit of the count of social media mentions for each of the 13 stocks by social media platform and for just the short-squeeze period. The start of the short-squeeze period is set to January 26, 2021. Users are split into two groups: users that already had an account with one of the three platforms before January 26 (Old users), and users that opened an account during the short-squeeze period after January 26 (New users). The end of the short squeeze is set to February 4, 2021. On January 28, 2021 Robinhood, among other brokers, implemented the trading limitations. Mentions have been collected from posts and comments published on Reddit, Stocktwits, and Twitter.

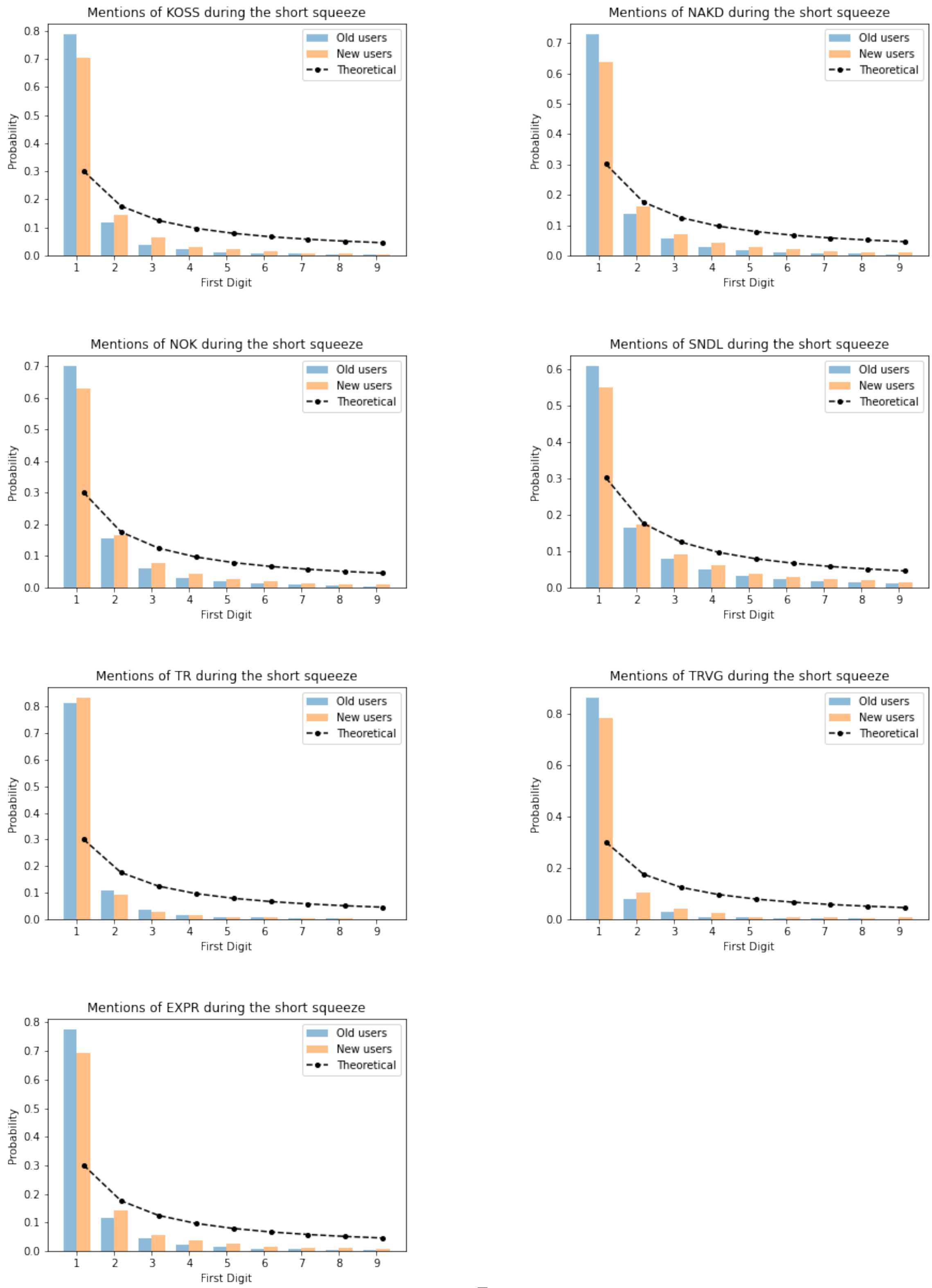


Fig. A7 Hourly posting patterns of social media mentions for the 13 stocks for new and experienced users: Short-squeeze period: This figure shows the hourly posting pattern in NY time for social media mentions for the 13 stocks by social media platform and for just the short-squeeze period. Users are split into two groups: users that already had an account with one of the three platforms before January 26 (Old users), and users that opened an account during the short-squeeze period after January 26 (New users). The start of the short-squeeze period is set to January 26, 2021. The end of the short squeeze is set to February 4, 2021. On January 28, 2021 Robinhood, among other brokers, implemented the trading limitations. Mentions have been collected from posts and comments published on Reddit, Stocktwits, and Twitter.

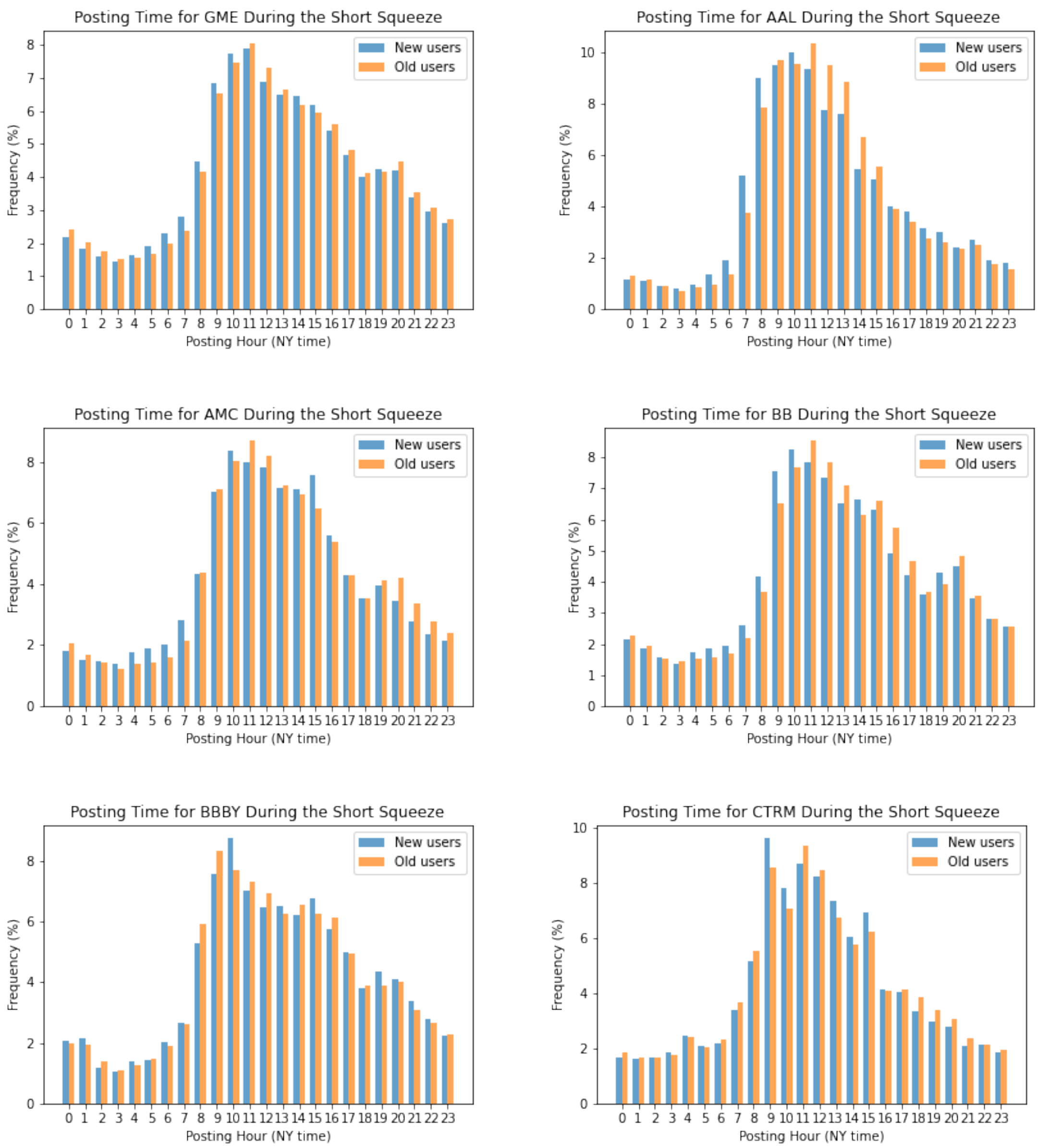
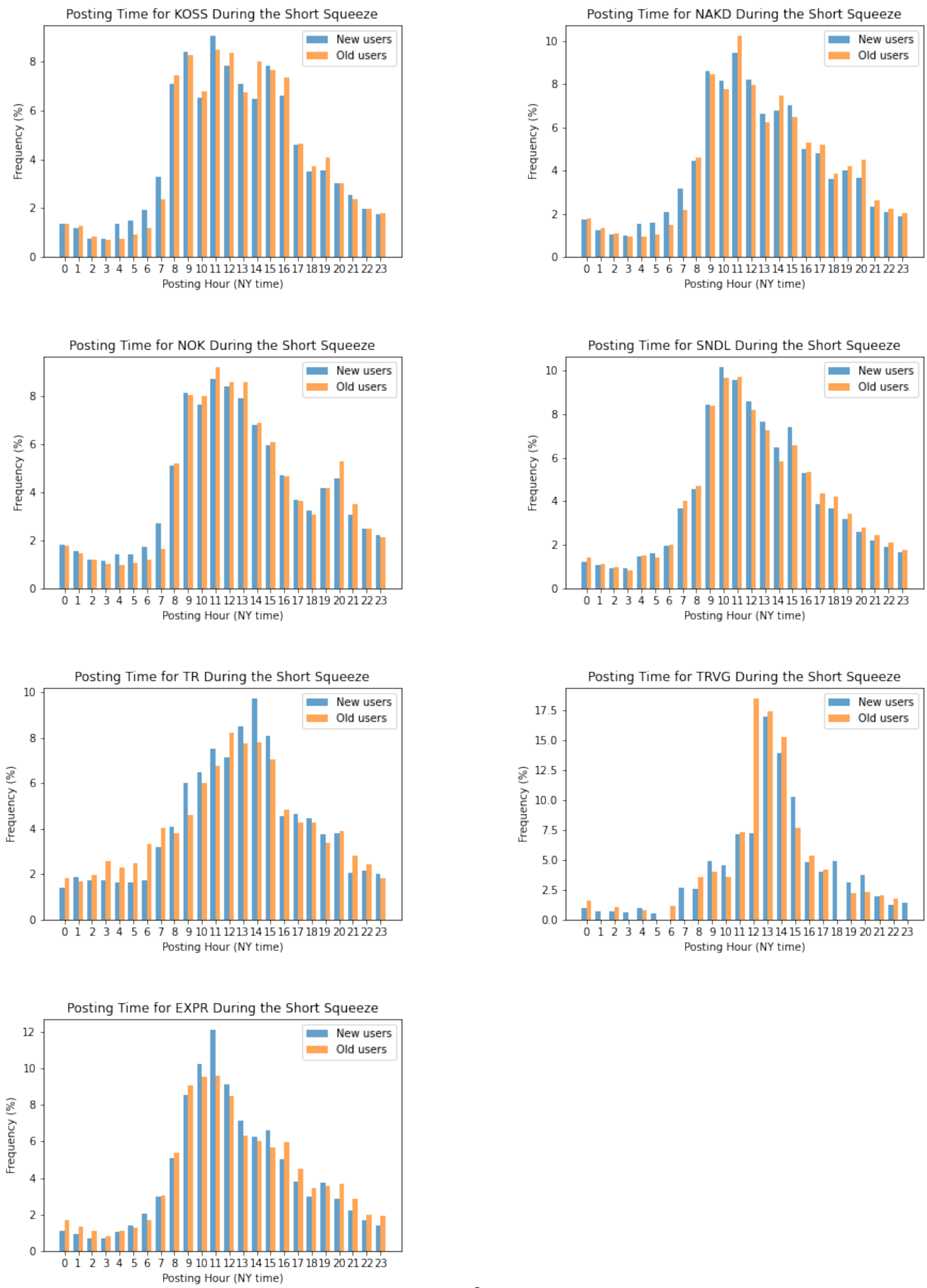


Fig. A8 Hourly posting patterns of social media mentions for the 13 stocks for new and experienced users: Short-squeeze period (cont'd): This figure shows the hourly posting pattern in NY time for social media mentions for the 13 stocks by social media platform and for just the short-squeeze period. Users are split into two groups: users that already had an account with one of the three platforms before January 26 (Old users), and users that opened an account during the short-squeeze period after January 26 (New users). The start of the short-squeeze period is set to January 26, 2021. The end of the short squeeze is set to February 4, 2021. On January 28, 2021 Robinhood, among other brokers, implemented the trading limitations. Mentions have been collected from posts and comments published on Reddit, Stocktwits, and Twitter.



A.2. Price and order imbalance charts.

This section describes the evolution of price and order imbalance for the 13 stocks initially banned by retail brokers (including Robinhood) for the period January 01, 2021 – February 19, 2021.

Fig. A9 Evolution of price and order imbalance: January 01, 2021 – February 19, 2021: This figure depicts the evolution of close price (lhs) and the evolution of order imbalances (rhs). The start of the short squeeze is set to January 26, 2021. The end of the short squeeze is set to February 4, 2021. On January 28, 2021 Robinhood, among other brokers, implemented the trading limitations.

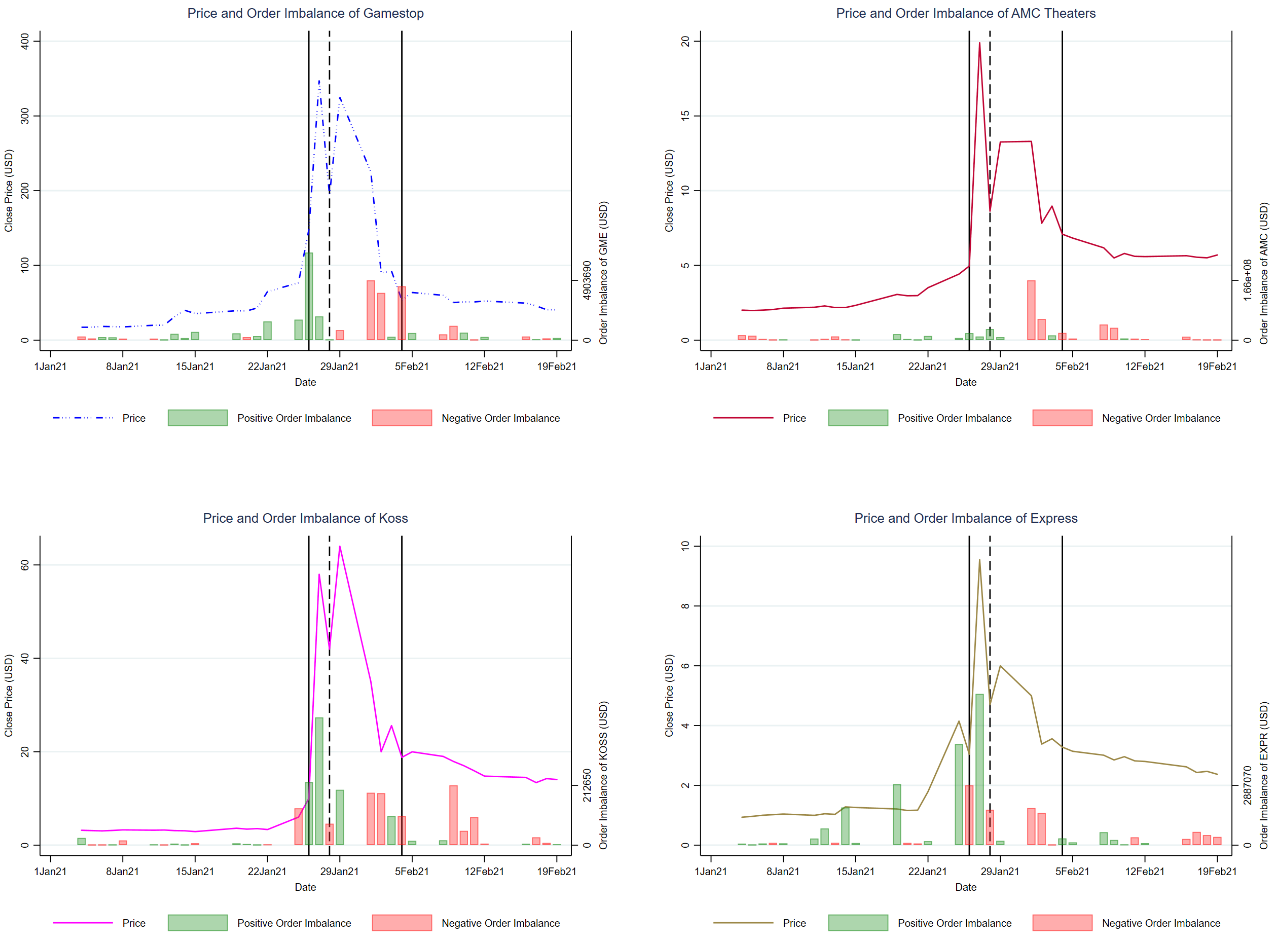


Fig. A10 Evolution of price and order imbalance: January 01, 2021 – February 19, 2021 (cont'd): This figure depicts the evolution of close price (lhs) and the evolution of order imbalances (rhs). The start of the short squeeze is set to January 26, 2021. The end of the short squeeze is set to February 4, 2021. On January 28, 2021 Robinhood, among other brokers, implemented the trading limitations.

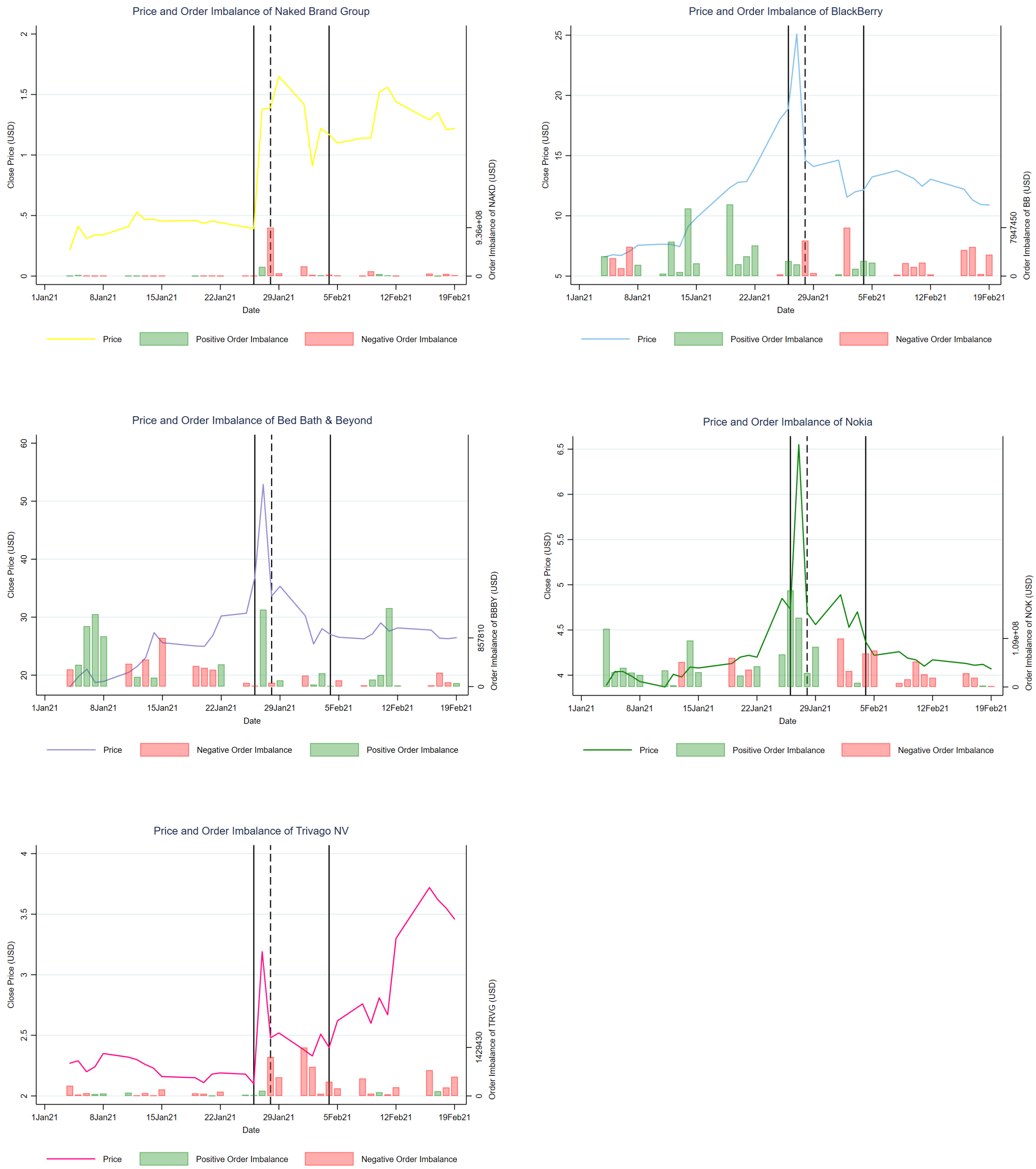
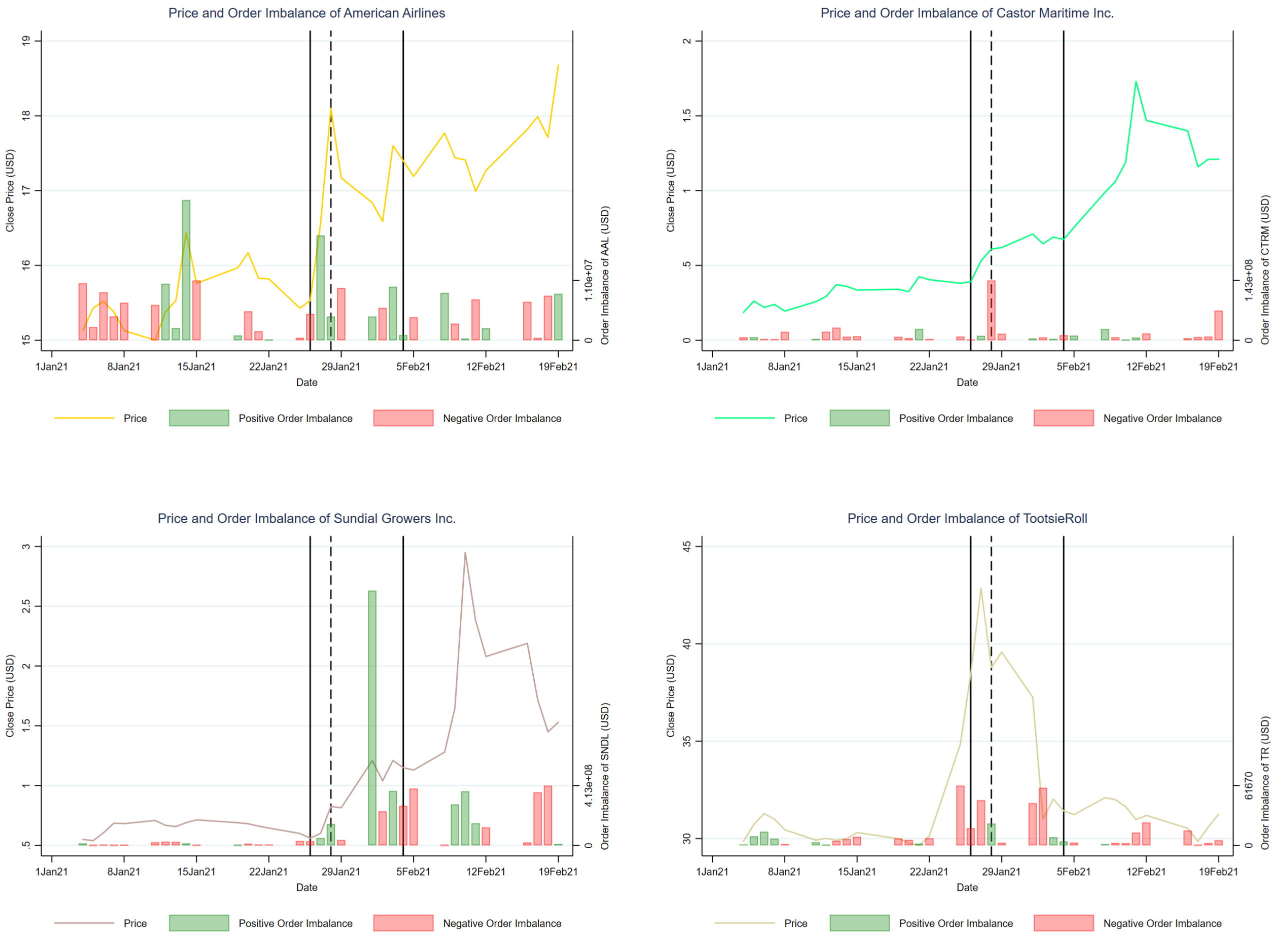


Fig. A11 Evolution of price and order imbalance: January 01, 2021 – February 19, 2021 (cont'd): This figure depicts the evolution of close price (lhs) and the evolution of order imbalances (rhs). The start of the short squeeze is set to January 26, 2021. The end of the short squeeze is set to February 4, 2021. On January 28, 2021 Robinhood, among other brokers, implemented the trading limitations.



A.3. Did professional stock market analysts expect the short squeezes?

By analyzing the time series evolution of mean and dispersion of stock analysts' price target estimates for the period around the short squeeze we aim to answer the following questions: (i) did analysts expect the prices of the stocks at issue to increase (or decrease) before the short-squeeze period, and (ii) did the trading restrictions make it difficult for analysts to determine a new price target estimate. Figures A12 and A13 present aggregate analyst price target forecasts for the 13 stocks. We note that I/B/E/S provides estimates only for nine of the 13 stocks. In general we observe two patterns: i) some of the stocks experience a gradual increase in their stock price estimates over time, e.g., GME, and ii) some of the stocks experienced a gradual decrease in their stock price estimates over time, e.g., AMC. For dispersion in price targets the patterns are similar. While the majority of the stocks at issue experienced an increase in price targets dispersion during and after the short-squeeze period, indicating an increase in disagreement and confusion among analysts, some stocks experienced no change. Overall, this evidence suggests that even professional market analysts were likely not anticipating the short-squeeze events and were confused about the true fundamental value of the stocks at issue.

Fig. A12 Evolution of price targets (in USD) for the initially banned stocks: January 2020 – March 2021: These figures plot the evolution of monthly average price target estimates of stock analysts. The shaded areas around the average price targets denote 95% confidence intervals. The vertical lines denote the start and the end of the short-squeeze period. We use data from the I/B/E/S Summary History file.

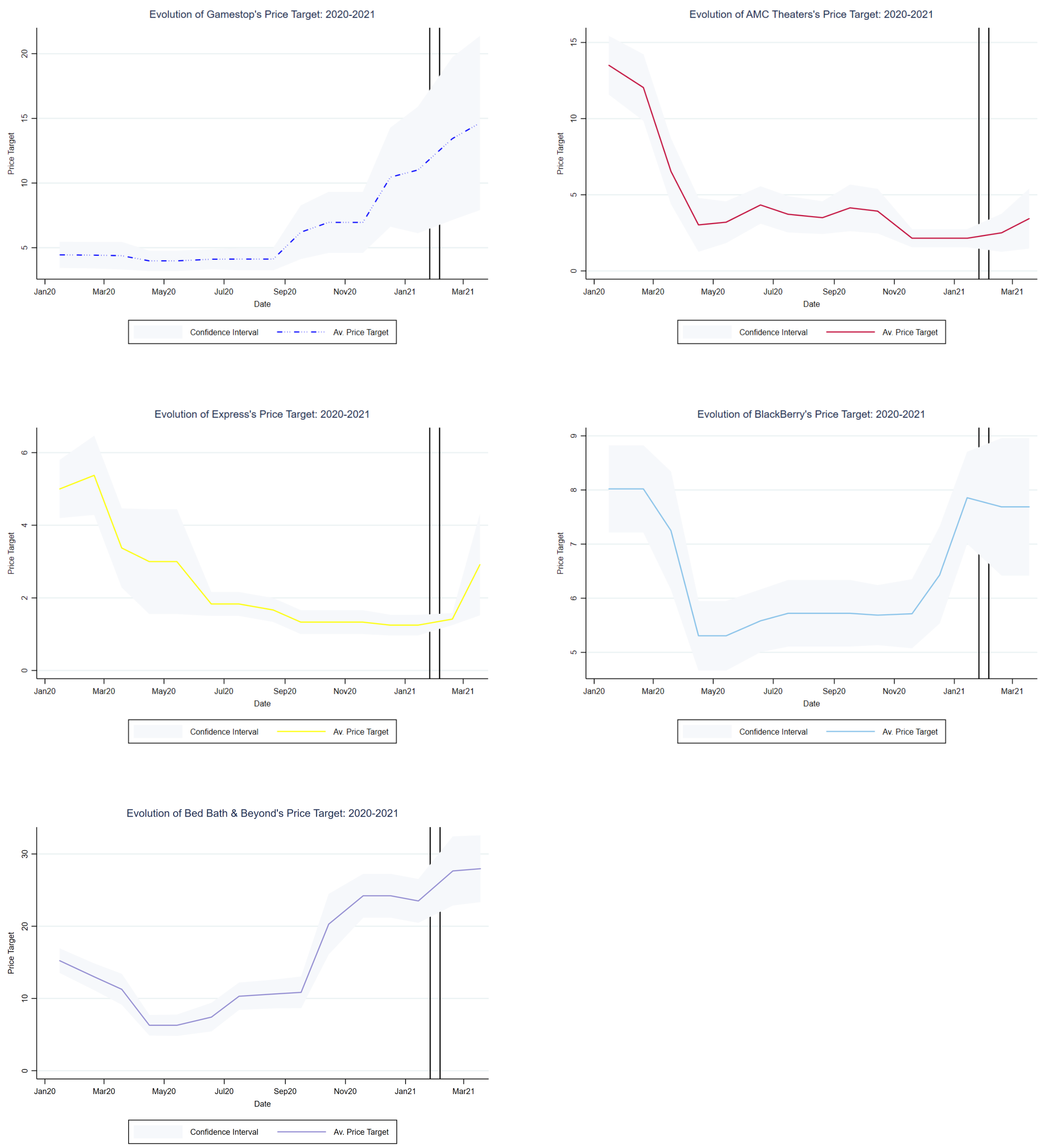
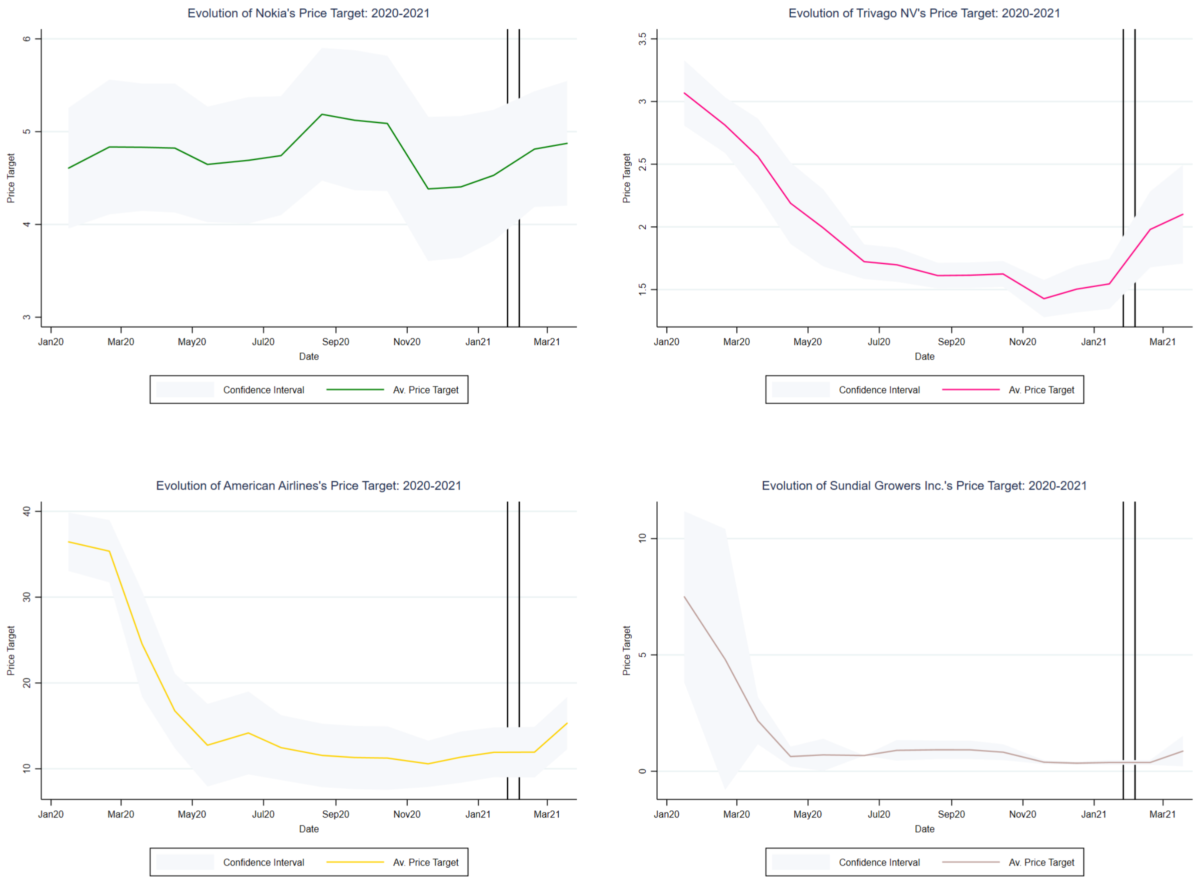


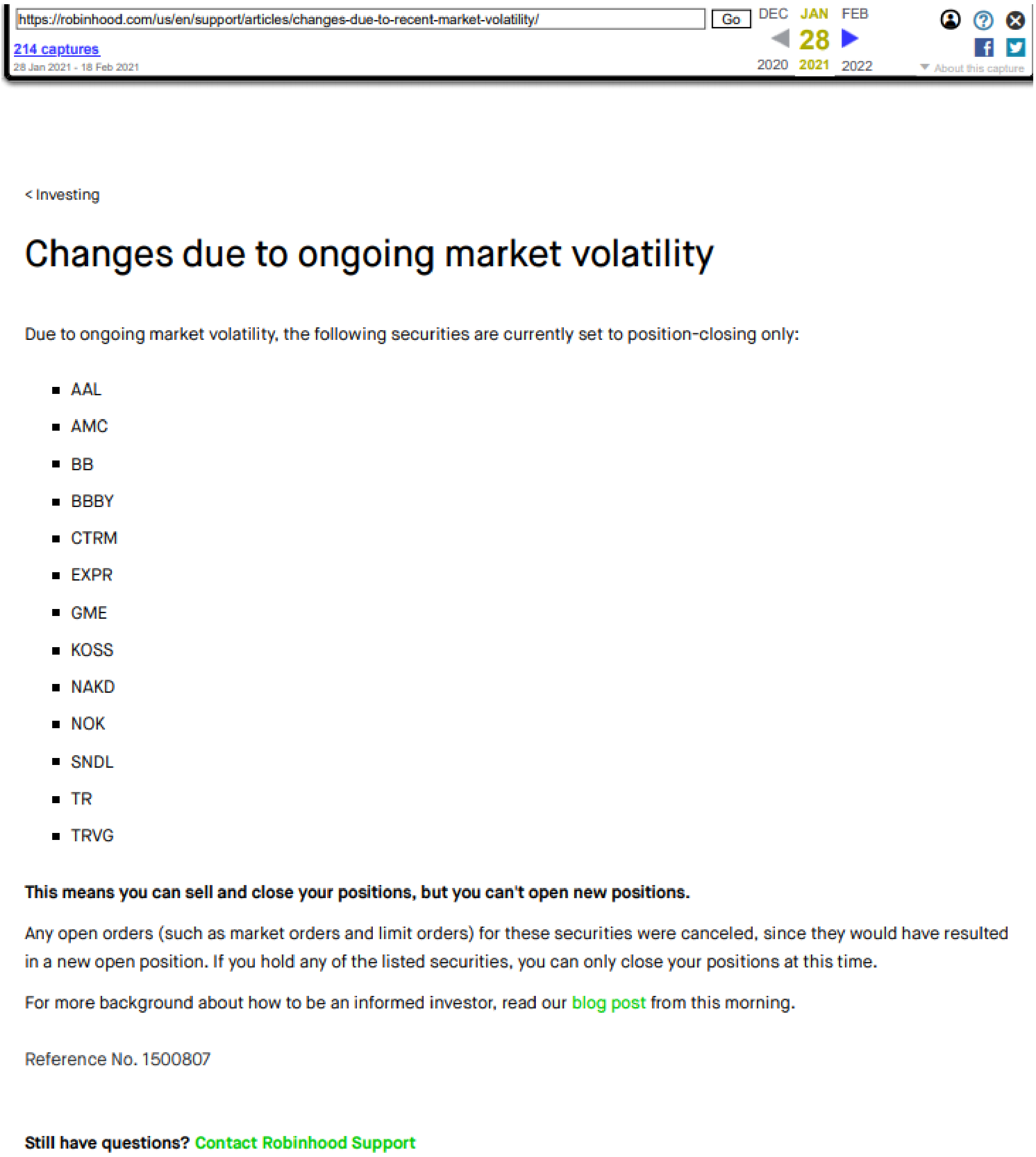
Fig. A13 Evolution of price targets (in USD) for the initially banned stocks (cont'd): January 2020 – March 2021: These figures plot the evolution of monthly average price target estimates of stock analysts. The shaded areas around the average price targets denote 95% confidence intervals. The vertical lines denote the start and the end of the short-squeeze period. We use data from the I/B/E/S Summary History file.



A.4. Relevant public announcements of brokers.

This section presents relevant public announcements made by Robinhood.

Fig. A14 Announcement made by Robinhood on January 28, 2021: This announcement illustrates that Robinhood, among other brokers, restricted 13 stocks from being purchased.


https://robinhood.com/us/en/support/articles/changes-due-to-recent-market-volatility/ Go DEC JAN FEB
214 captures 28 2020 2021 2022
28 Jan 2021 - 18 Feb 2021 About this capture

< Investing

Changes due to ongoing market volatility

Due to ongoing market volatility, the following securities are currently set to position-closing only:

- AAL
- AMC
- BB
- BBBY
- CTRM
- EXPR
- GME
- KOSS
- NAKD
- NOK
- SNDL
- TR
- TRVG

This means you can sell and close your positions, but you can't open new positions.

Any open orders (such as market orders and limit orders) for these securities were canceled, since they would have resulted in a new open position. If you hold any of the listed securities, you can only close your positions at this time.

For more background about how to be an informed investor, read our blog post from this morning.

Reference No. 1500807

Still have questions? Contact Robinhood Support

A.5. Quantity on loan charts for the remaining meme stocks.

This section presents quantity on loan and closing price for the remaining stocks at issue.

Fig. A15 Evolution of daily Quantity on Loan and Price for the remaining initially banned 12 stocks: January 01, 2021 – February 28, 2021: This figure depicts, for each of the stocks, the evolution of the respective closing price (left y-axis) and the evolution of the respective quantity on loan relative to shares outstanding (right y-axis). The start of the short squeeze is set to January 26, 2021. The end of the short squeeze is set to February 4, 2021. On January 28, 2021 Robinhood, among other brokers, started implementing trading limitations in GME and other stocks.

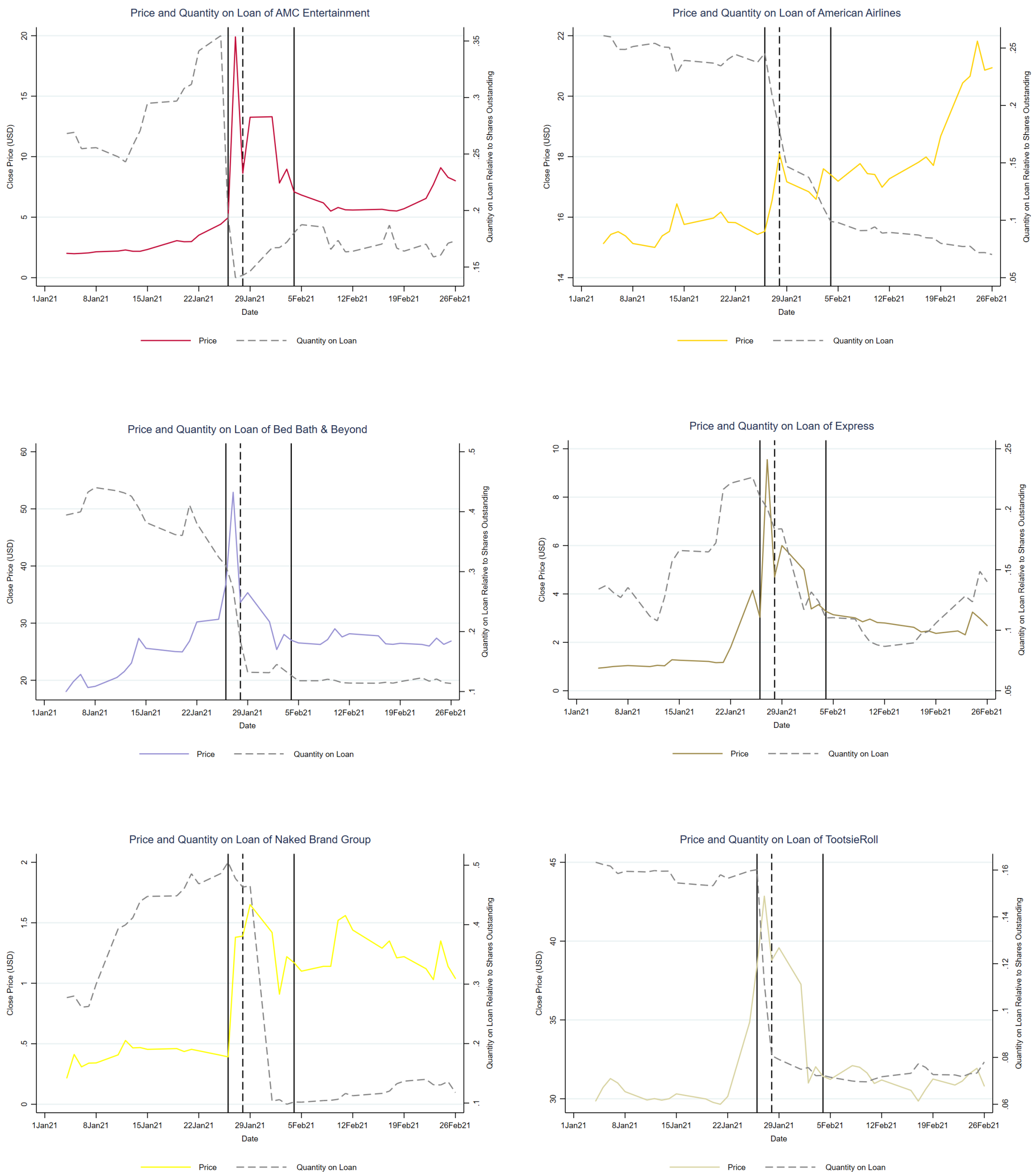
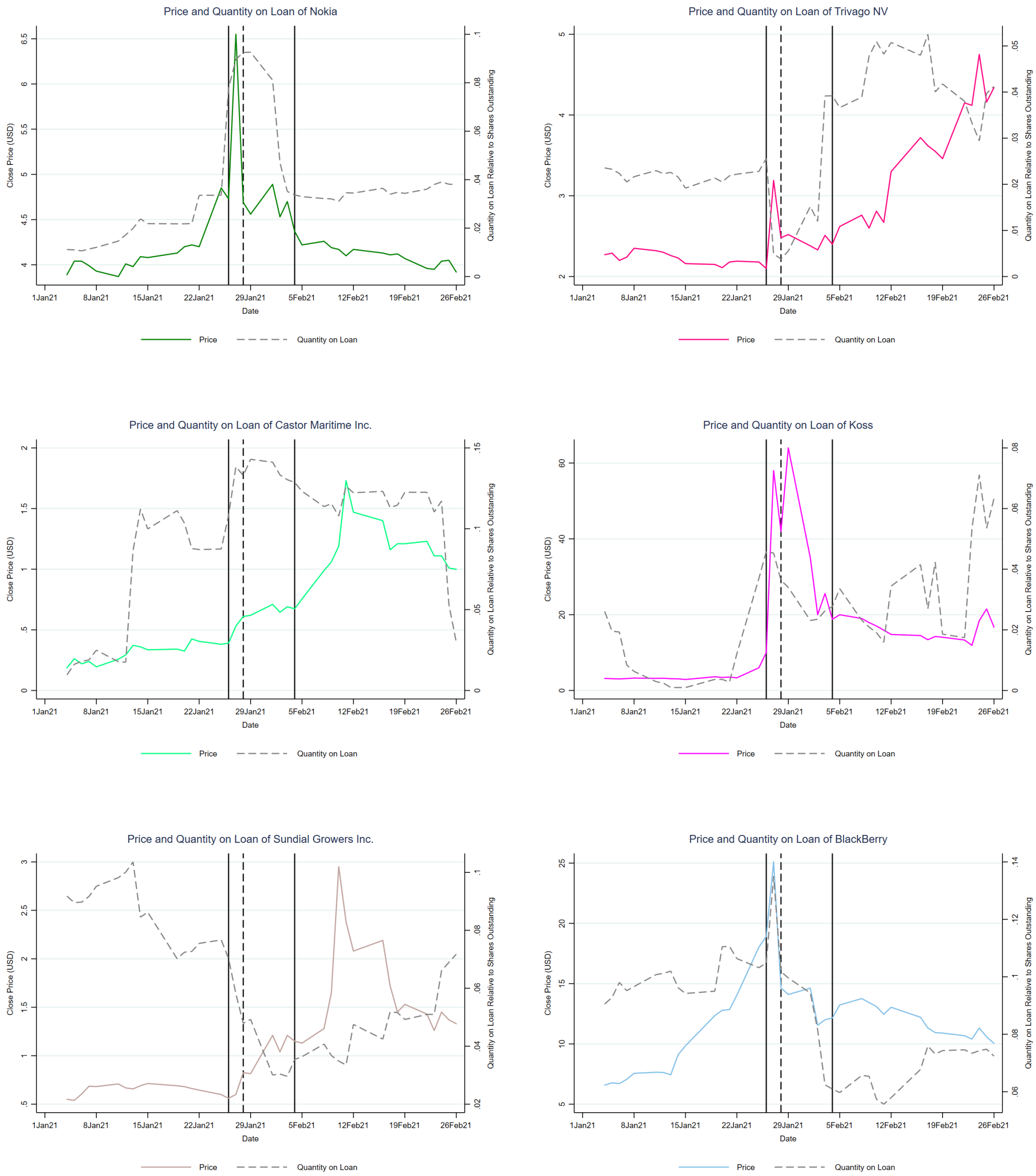


Fig. A16 Evolution of daily Quantity on Loan and Price for the remaining initially banned 12 stocks (cont'd): January 01, 2021 – February 28, 2021: This figure depicts, for each of the stocks, the evolution of the respective closing price (left y-axis) and the evolution of the respective quantity on loan relative to market capitalization (right y-axis). The start of the short squeeze is set to January 26, 2021. The end of the short squeeze is set to February 4, 2021. On January 28, 2021 Robinhood, among other brokers, started implementing trading limitations in GME and other stocks.



A.6. Evolution of social media activity and market activity charts.

This section presents individual retail volume and social media activity graphs for the impacted stocks.

Fig. A17 Evolution of average retail volume and social media activity of squeezed vs non-squeezed: January 01, 2021 – February 28, 2021: These graphs depict the evolution of average daily retail volume and average social media activity for the stocks at issue. The start of the short squeeze is set to January 26, 2021. The end of the short squeeze is set to February 4, 2021. On January 28, 2021 Robinhood, among other brokers, started implementing trading limitations in GME and other stocks.

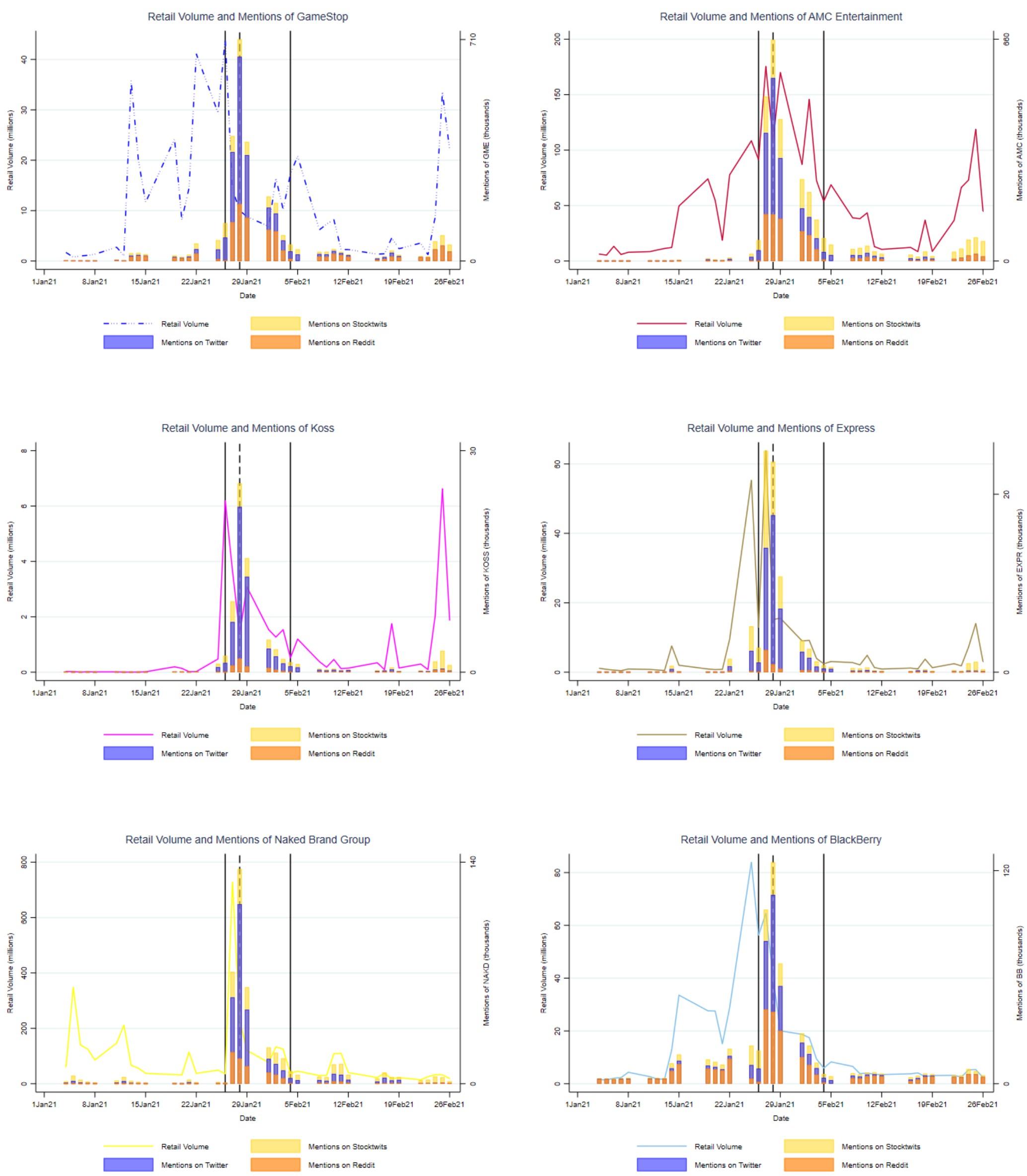
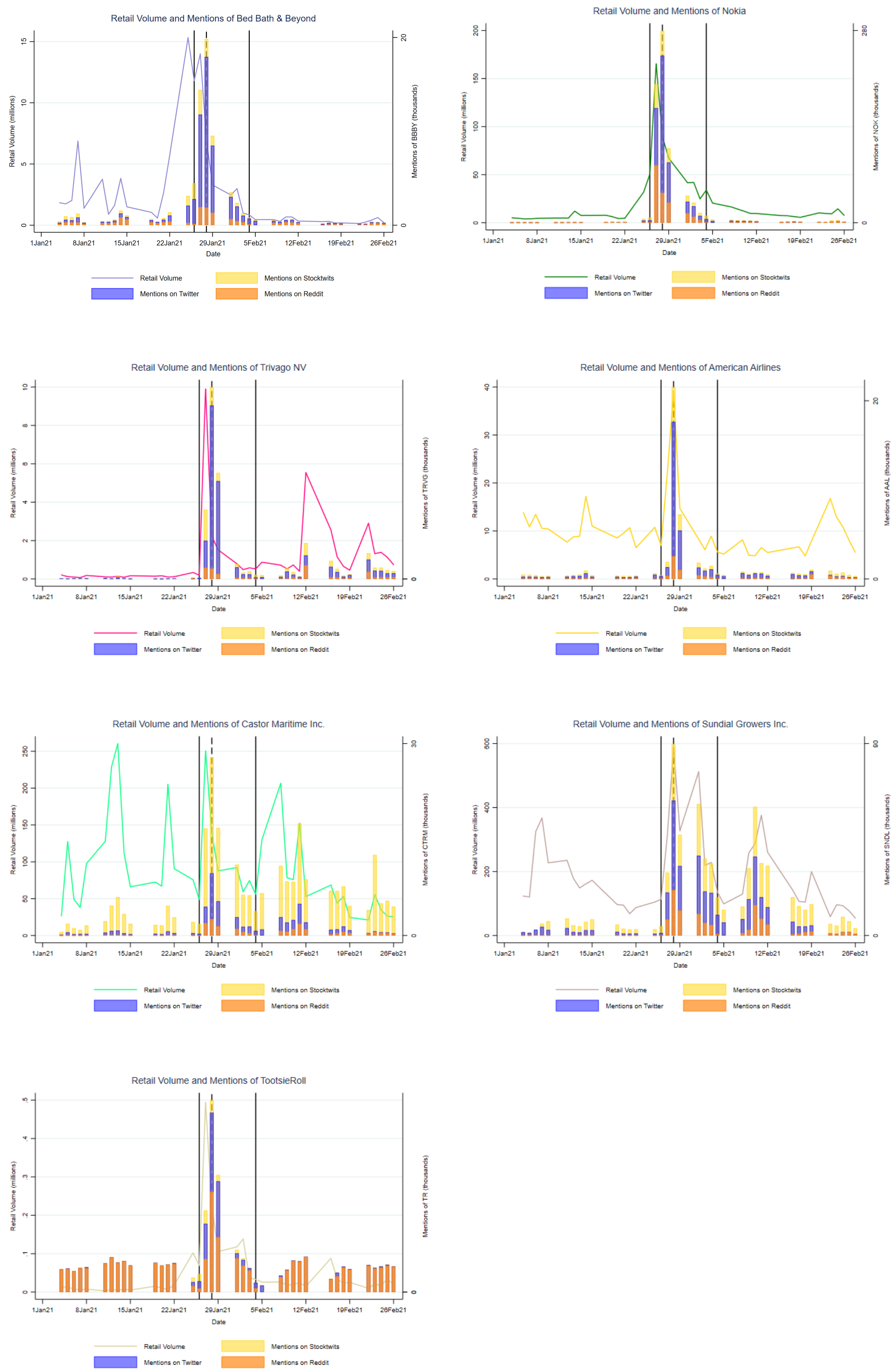


Fig. A18 Evolution of average retail volume and social media activity of squeezed vs non-squeezed (cont'd): January 01, 2021 – February 28, 2021: These graphs depict the evolution of average daily retail volume and average social media activity for the stocks at issue. We note that in the graph for SNDL we have trimmed outlier retail volume observations for the company SNDL during the morning 3 hours of trading on some days in the post-short squeeze period (February 10 and February 11, 2021) The start of the short squeeze is set to January 26, 2021. The end of the short squeeze is set to February 4, 2021. On January 28, 2021 Robinhood, among other brokers, started implementing trading limitations in GME and other stocks.



A.7. Additional social media activity and market trading tests.

This section presents robustness estimations for the social media activity and market trading activity.

Table A1 Social media activity and aggregate market activity: This table reports the results from the social media activity regression estimation described in Equation 2. The dependent variables are Volume (trading volume) and Trades (number of trades) computed over different short-term periods (30-seconds, 1-minute, and 2-minute) and defined in Table 3. Panel A presents information about the seven stocks that experienced a short-squeeze (GME, AMC, AAL, BBBY, EXP, NAKD, TR). Panel B presents information about the remaining six stocks that did not experience a short-squeeze (BB, CTRM, KOSS, NOK, SNDL, TRVG). The data set covers the period January 11, 2021 through February 19, 2021. We define the period before the short squeeze as the two weeks (ten trading days) preceding January 26, 2021. We define the short-squeeze period (SSqueeze) as January 26, 2021 through February 04, 2021. We define the period after the short squeeze (Post-SSqueeze) as the two weeks (ten trading days) after February 04, 2021. The main independent variable is ln(Mentions), where Mentions represents the total number of mentions of each of the 13 stocks on Reddit, Stocktwits, and Twitter. Controls include the daily return, daily size of the company (measured as the natural log of market capitalization), daily price dispersion, and daily trading volume, all measured at the end of the previous day. The t-statistics are reported in parentheses below the coefficient estimates and are based on robust standard errors clustered by firm and time (see Petersen (2009)). The symbols ***, ** and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Data come from Reddit, Stocktwits, Twitter, TAQ, and Compustat.

Panel A	(1) 30-sec Volume	(2) 30-sec Trades	(3) 1-min Volume	(4) 1-min Trades	(5) 2-min Volume	(6) 2-min Trades
SSqueeze	15,849.623***	-381.297***	34,741.933***	-1,215.609***	38,663.257***	-2,974.668***
	(3.848)	(-37.304)	(3.612)	(-34.061)	(2.900)	(-29.578)
Post-SSqueeze	7,735.279***	-45.336***	44,055.515***	-112.906***	83,941.410***	-174.208***
	(4.091)	(-10.161)	(4.447)	(-5.671)	(5.716)	(-3.992)
ln(Mentions)	37,859.295***	263.013***	70,572.916***	370.202***	101,378.343***	584.139***
	(4.148)	(18.127)	(4.122)	(12.030)	(5.245)	(12.753)
ln(Mentions) x SSqueeze	**6,151.309*****	**296.737*****	**3,712.056**	**634.606*****	**13,105.356****	**1,226.299*****
	(3.870)	**(33.696)**	**(1.572)**	**(30.739)**	**(2.216)**	**(24.751)**
ln(Mentions) x Post-SSqueeze	-15,952.445***	-112.065***	-29,988.570***	-157.129***	-43,665.325***	-243.577***
	(-3.966)	(-12.604)	(-3.971)	(-8.339)	(-4.685)	(-6.876)
Constant	445,926.070***	-1,570.110***	1,051,043.714***	-3,890.815***	1689122.107***	-8,281.850***
	(4.428)	(-10.611)	(4.470)	(-9.838)	(6.184)	(-14.183)
Controls	YES	YES	YES	YES	YES	YES
Observations	141,498	141,498	62,604	62,604	31,992	31,992
Adjusted R^2	0.661	0.521	0.738	0.549	0.761	0.564

Panel B	(1) 30-sec Volume	(2) 30-sec. Trades	(3) 1-min Volume	(4) 1-min. Trades	(5) 2-min Volume	(6) 2-min Trades
SSqueeze	-86,717.517***	-108.900***	-138,095.671***	-277.581***	-233,364.428***	-726.434***
	(-8.586)	(-9.055)	(-8.361)	(-8.764)	(-6.347)	(-7.956)
Post-SSqueeze	-122,545.217***	-36.663**	-175,548.819***	-29.980	-286,897.816***	-106.822
	(-9.322)	(-2.433)	(-9.812)	(-0.980)	(-9.073)	(-1.470)
ln(Mentions)	69,533.126***	112.879***	99,329.674***	110.769***	149,041.714***	104.625*
	(8.230)	(10.617)	(8.437)	(4.738)	(7.072)	(1.907)
ln(Mentions) x SSqueeze	**44,076.562*****	**138.918*****	**55,870.912*****	**257.527*****	**79,896.405*****	**496.050*****
	(8.000)	**(17.203)**	**(7.080)**	**(14.765)**	**(5.231)**	**(12.130)**
ln(Mentions) x Post-SSqueeze	127,010.768***	98.803***	139,095.784***	101.377***	180,302.016***	167.197***
	(9.391)	(6.202)	(9.535)	(4.126)	(8.521)	(3.633)
Constant	563,960.583***	-646.579***	851,733.632***	-1,535.265***	1375585.060***	-3,172.006***
	(8.588)	(-8.319)	(8.937)	(-8.502)	(7.605)	(-6.815)
Controls	YES	YES	YES	YES	YES	YES
Observations	117,579	117,579	60,790	60,790	31,093	31,093
Adjusted R^2	0.615	0.546	0.701	0.605	0.743	0.629

Table A2 Robustness: Explaining return variation during the short-squeeze period using marketable retail order imbalances following Barber, Huang, Jorion, Odean, and Schwarz (2022a): This table reports the robustness estimations for the results reported in Table 5. As an alternative robustness measure the main independent variable is mroibvol, a scaled marketable retail order imbalance measure computed following Barber, Huang, Jorion, Odean, and Schwarz (2022a). The procedure, variable definitions and data used are described in the caption of Table 5 and the corresponding section in the paper.

	(1)	(2)	(3)
Panel A	30-second Return	1-minute Return	2-minute Return
SSqueeze	-0.003	-0.034*	-0.049
	(-0.281)	(-1.845)	(-1.423)
Post-SSqueeze	-0.010*	-0.024**	-0.045***
	(-1.828)	(-2.547)	(-2.618)
mroibvol	0.022***	0.013	0.058**
	(3.522)	(0.932)	(2.236)
mroibvol x SSqueeze	**0.043*** **	**0.076*** **	**0.079* **
	(3.040)	**(3.281)**	**(1.740)**
mroibvol x Post-SSqueeze	-0.004	0.007	0.001
	(-0.511)	(0.526)	(0.051)
Constant	0.048	0.065	-0.047
	(0.948)	(0.782)	(-0.342)
Controls	YES	YES	YES
Observations	65,237	36,817	20,125
Adjusted R^2	0.003	0.003	0.011

	(1)	(2)	(3)
Panel B	30-second Return	1-minute Return	2-minute Return
SSqueeze	0.001	0.005	0.019
	(0.149)	(0.356)	(0.711)
Post-SSqueeze	-0.008	-0.018*	-0.006
	(-1.269)	(-1.703)	(-0.306)
mroibvol	0.007**	0.018***	0.008
	(2.018)	(2.630)	(0.564)
mroibvol x SSqueeze	**0.039*** **	**0.081*** **	**0.022**
	(3.351)	**(3.781)**	**(0.594)**
mroibvol x Post-SSqueeze	0.034***	0.024**	0.032
	(5.402)	(2.059)	(1.448)
Constant	-0.002	0.088	0.111
	(-0.037)	(1.060)	(0.894)
Controls	YES	YES	YES
Observations	52,619	28,196	14,723
Adjusted R^2	0.008	0.006	0.000

Table A3 Robustness: Explaining return variation during the short-squeeze period using marketable retail order imbalances based on the number of trades: This table reports the robustness estimations for the results reported in Table 5. As an alternative robustness measure the main independent variable is mroibtrd, a scaled marketable retail order imbalance measure based on the number of trades (see Boehmer, Jones, Zhang, and Zhang (2021)). The procedure, variable definitions and data used are described in the caption of Table 5 and the corresponding section in the paper.

Panel A	(1) 30-second Return	(2) 1-minute Return	(3) 2-minute Return
SSqueeze	-0.010	-0.022	-0.031
	(-1.291)	(-1.520)	(-1.092)
Post-SSqueeze	-0.007	-0.015*	-0.019
	(-1.420)	(-1.749)	(-1.171)
mroibtrd	0.022***	0.044***	0.089***
	(2.871)	(3.107)	(2.644)
mroibtrd x SSqueeze	**0.043****	**0.098****	**0.175****
	(2.228)	**(2.563)**	**(2.263)**
mroibtrd x Post-SSqueeze	0.009	0.011	0.020
	(0.894)	(0.613)	(0.567)
Constant	0.028	0.088	0.025
	(0.634)	(1.232)	(0.185)
Controls	YES	YES	YES
Observations	107,576	57,739	30,367
Adjusted R^2	0.002	0.003	0.019

Panel B	(1) 30-second Return	(2) 1-minute Return	(3) 2-minute Return
SSqueeze	-0.010	-0.020	-0.029
	(-1.309)	(-1.404)	(-1.091)
Post-SSqueeze	-0.005	-0.017	-0.024
	(-0.887)	(-1.600)	(-1.228)
mroibtrd	0.019**	0.032**	0.032
	(2.486)	(2.258)	(0.909)
mroibtrd x SSqueeze	**0.073*****	**0.116*****	**0.180****
	(3.843)	**(3.548)**	**(2.174)**
mroibtrd x Post-SSqueeze	0.002	0.002	-0.001
	(0.202)	(0.106)	(-0.025)
Constant	0.033	0.109	0.156
	(0.730)	(1.484)	(1.345)
Controls	YES	YES	YES
Observations	73,714	40,527	21,633
Adjusted R^2	0.013	0.010	0.007

Table A4 Robustness: Explaining return variation during the short-squeeze period using marketable retail order imbalances based on the number of trades following Barber, Huang, Jorion, Odean, and Schwarz (2022a): This table reports the robustness estimations for the results reported in Table A2. As an alternative robustness measure the main independent variable is mroibtrd, a scaled marketable retail order imbalance measure based on the number of trades is computed following Barber, Huang, Jorion, Odean, and Schwarz (2022a). The procedure, variable definitions and data used are described in the caption of Table 5 and the corresponding section in the paper.

Panel A	(1) 30-second Return	(2) 1-minute Return	(3) 2-minute Return
SSqueeze	-0.003	-0.035*	-0.049
	(-0.268)	(-1.935)	(-1.416)
Post-SSqueeze	-0.008	-0.024**	-0.043**
	(-1.500)	(-2.531)	(-2.511)
mroibtrd	0.028***	0.004	0.062**
	(3.217)	(0.209)	(2.054)
mroibtrd x SSqueeze	**0.030***	**0.079*****	**0.069**
	(1.806)	**(3.011)**	**(1.453)**
mroibtrd x Post-SSqueeze	-0.010	0.010	-0.016
	(-1.026)	(0.644)	(-0.614)
Constant	0.045	0.066	-0.057
	(0.884)	(0.786)	(-0.412)
Controls	YES	YES	YES
Observations	65,237	36,817	20,125
Adjusted R^2	0.003	0.003	0.011

Panel B	(1) 30-second Return	(2) 1-minute Return	(3) 2-minute Return
SSqueeze	-0.000	0.002	0.018
	(-0.021)	(0.177)	(0.666)
Post-SSqueeze	-0.008	-0.016	-0.008
	(-1.310)	(-1.507)	(-0.412)
mroibtrd	0.008	0.030***	-0.003
	(1.349)	(2.681)	(-0.163)
mroibtrd x SSqueeze	**0.028***	**0.062****	**0.003**
	(1.920)	**(2.386)**	**(0.074)**
mroibtrd x Post-SSqueeze	0.031***	0.004	0.032
	(2.996)	(0.225)	(1.071)
Constant	-0.021	0.075	0.109
	(-0.381)	(0.894)	(0.872)
Controls	YES	YES	YES
Observations	52,619	28,196	14,723
Adjusted R^2	0.007	0.005	0.000

Table A5 Placebo test: Descriptive statistics for social media activity: This table presents descriptive statistics for social media activity measures for the 13 stocks impacted by trading restrictions and the control stocks. Panel A presents information about the seven stocks that experienced a short-squeeze (GME, AMC, AAL, BBBY, EXP, NAKD, TR). Panel B presents information about the first tercile of control companies. Panel C presents information about the second tercile of control companies. Panel D presents information for the third tercile of control companies. We present descriptive statistics for combined daily Mentions on Reddit, Stocktwits, and Twitter. The data cover the period January 11, 2021 through January 26, 2021, i.e., ten trading days before the short-squeeze period (January 26 through February 04 included). Data come from Reddit, Stocktwits, Twitter.

Panel A: Squeezed Stocks

	Obs	Mean	Std. Dev.	Min	Max	P1	P25	P50	P75	P99
Mentions	70	5095.571	11690.79	35	67215	35	447	751.5	3122	67215

Panel B: First Tercile

	Obs	Mean	Std. Dev.	Min	Max	P1	P25	P50	P75	P99
Mentions	350	3.671	4.129	0	42	0	1	2	5	17

Panel C: Second Tercile

	Obs	Mean	Std. Dev.	Min	Max	P1	P25	P50	P75	P99
Mentions	339	12.929	11.17	1	69	1	6	10	16	58

Panel D: Third Tercile

	Obs	Mean	Std. Dev.	Min	Max	P1	P25	P50	P75	P99
Mentions	344	135.279	309.623	1	3538	4	32	62.5	116	1621

Table A6 Placebo test: Explaining return variation during the short-squeeze period using marketable retail order imbalances based on the number of trades: This table reports the robustness estimations for the results reported in Table 6. As an alternative robustness measure the main independent variable is mroibtrd, a scaled marketable retail order imbalance measure based on the number of trades (see Boehmer, Jones, Zhang, and Zhang (2021)). The procedure, variable definitions and data used are described in Section 5.2.1.

Panel A	(1) Return	(2) Return	(3) Return
SSqueeze	-0.001	-0.000	-0.004
	(-0.372)	(-0.117)	(-0.649)
Post-SSqueeze	-0.002	-0.007**	-0.001
	(-0.639)	(-2.055)	(-0.228)
mroibtrd	**0.019****	**0.006**	**0.004**
	(2.398)	**(0.969)**	**(0.635)**
mroibtrd x SSqueeze	0.006	0.008	0.013
	(0.471)	(0.746)	(1.208)
mroibtrd x Post-SSqueeze	-0.018*	-0.003	-0.003
	(-1.769)	(-0.326)	(-0.307)
Constant	0.084*	0.067	0.106**
	(2.032)	(1.554)	(2.210)
Observations	27,085	37,871	43,036
Number of unique companies	35	35	35
Adjusted R^2	0.048	0.033	0.016

Panel B	(1) Return	(2) Return	(3) Return
SSqueeze	-0.002	-0.003	-0.005
	(-0.811)	(-0.743)	(-1.012)
Post-SSqueeze	-0.002	-0.003	-0.005
	(-1.201)	(-1.009)	(-1.342)
mroibtrd	**0.004**	**0.002**	**0.001**
	(1.104)	**(0.543)**	**(0.145)**
mroibtrd x SSqueeze	0.010	0.007	-0.000
	(1.655)	(1.054)	(-0.015)
mroibtrd x Post-SSqueeze	0.000	-0.004	-0.003
	(0.044)	(-0.784)	(-0.575)
Constant	0.031	0.022	0.050*
	(1.516)	(0.990)	(1.723)
Observations	97,382	104,892	91,434
Number of unique companies	34	34	34
Adjusted R^2	0.012	0.007	0.003

Panel C	(1) Return	(2) Return	(3) Return
SSqueeze	-0.000	-0.002	-0.005
	(-0.190)	(-0.813)	(-0.915)
Post-SSqueeze	-0.000	-0.001	-0.002
	(-0.345)	(-0.371)	(-0.463)
mroibtrd	**0.006*****	**0.007*****	**0.006**
	(3.182)	**(2.793)**	**(1.334)**
mroibtrd x SSqueeze	0.004	0.004	0.001
	(1.314)	(0.874)	(0.187)
mroibtrd x Post-SSqueeze	0.006**	0.003	0.008
	(2.378)	(0.695)	(1.344)
Constant	0.021	0.035*	0.054*
	(1.570)	(1.811)	(1.799)
Observations	350,382	247,932	154,336
Number of unique companies	35	35	35
Adjusted R^2	0.025	0.010	0.003

A.8. Social media sentiment, marketable retail order imbalances, and returns.

In this section we examine whether social media sentiment was associated with returns of the stocks at issue during the short-squeeze period. To test this conjecture we perform statistical analyses in which we utilize our data on social media activity. We construct a social media sentiment score based on a text sentiment analysis of social media posts following Hutto and Gilbert (2014) and test for statistical association with returns.[7] Figure A19 depicts the evolution of positive and negative sentiment for the periods before, during, and after the short squeeze. It can be see that while social media activity increases during the short-squeeze period, the increase in positive and negative sentiment is largely balanced. We further perform a set of statistical analyses in order to test the conjecture that sentiment was a significant driver of stock price variation during the short-squeeze period. In particular, we estimate the following regression model:

$$\begin{aligned}
Y_{i,t} = {} & \alpha + \beta_1 SSqueeze + \beta_2 Post\text{-}SSqueeze + \beta_3 mroib_{i,t-1} + \beta_4 Sentiment_{i,t-1} \\
& + \beta_5 SSqueeze \times mroib_{i,t-1} + \beta_6 SSqueeze \times Sentiment_{i,t-1} \\
& + \beta_7 Post\text{-}SSqueeze \times mroib_{i,t-1} + \beta_8 Post\text{-}SSqueeze \times Sentiment_{i,t-1} \\
& + \beta_9 Controls_{i,t-1} + \varepsilon_{i,t},
\end{aligned} \tag{9}$$

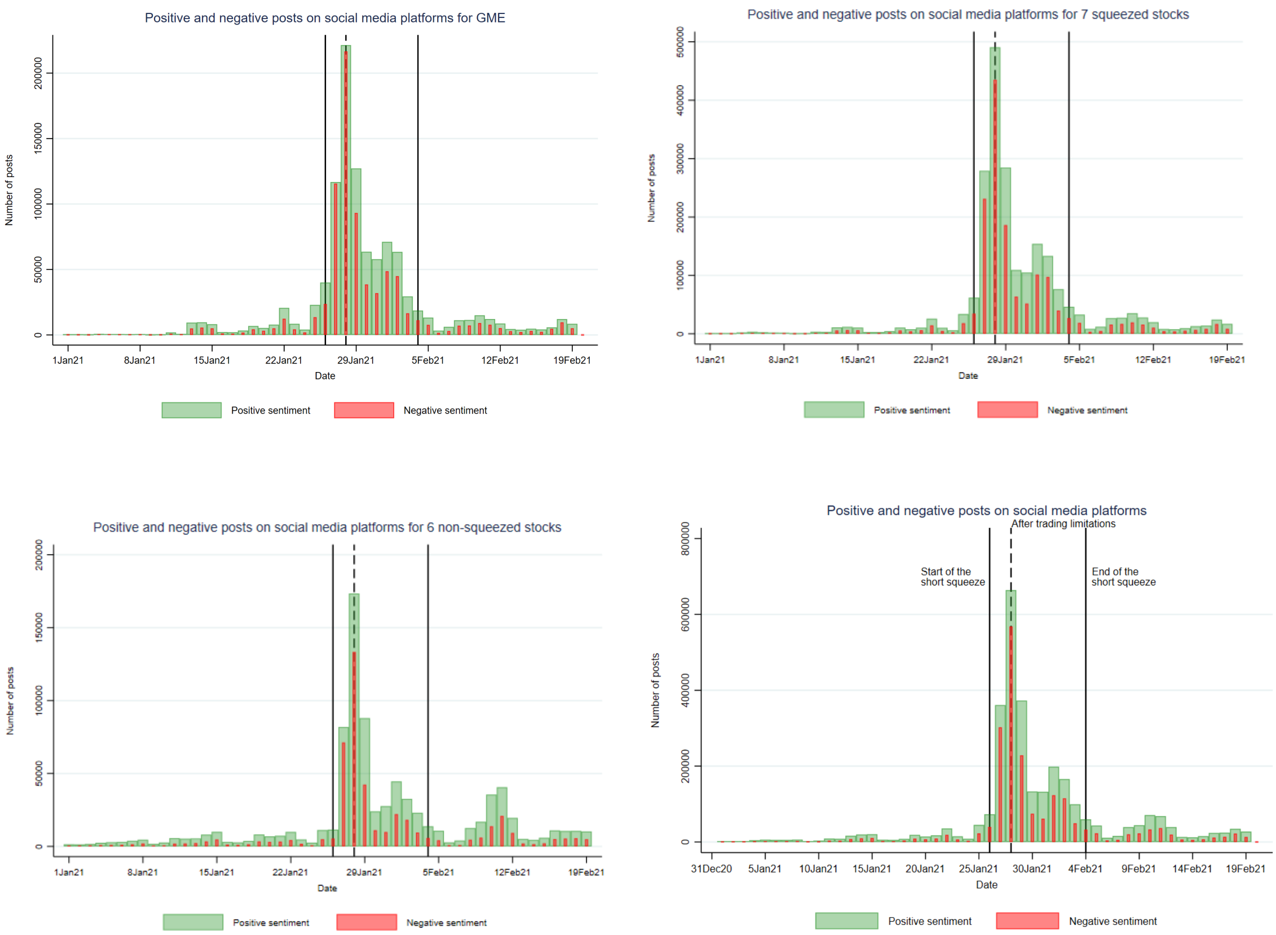
As before, this model is estimated for all of the 13 banned stocks separated into two groups: (i) a group of stocks that experienced short squeezes (the "squeezed stocks") and (ii) a group of stocks that did not experience short squeezes (the "non-squeezed stocks"). We include the sentiment score variable ($Sentiment_{i,t-1}$) as well as its interaction terms with the *SSqueeze* and *Post-SSqueeze* dummies. The remainder of the model specification is identical to Equation 3.

Table A7 presents the results of these regression estimations for squeezed (Panel A) and non-squeezed stocks (Panel B). In these estimations, the coefficient of interest is β_6. If variation in social media sentiment was associated with variation in stock returns during the short-squeeze period we would expect to find that β_6 is positive and statistically significant. The evidence suggests that β_6 is not significantly different from zero across all estimations. Further, the evidence suggests that β_4, the coefficient of the stand-alone sentiment measure, and β_8 the coefficient of the interaction term of the sentiment measure and the post-squeeze dummy are not significantly different from zero. On the whole, this evidence does not lend support to the conjecture that sentiment was a significant driver of stock price movements of the stocks at

[7] Our methodology relies on VADER, a widely used model specifically designed for text sentiment analyses of social media posts (see Hutto and Gilbert (2014)). VADER sentiment analysis maps the lexical features of a post to sentiment scores. First, a sentiment score is assigned to every word and emoticon of a post, considering also punctuation, capitalization and the basic context. Second, the sentiment score of the post can be obtained by summing up the sentiment score of each word and emoticon. This allows us to classify all the posts as positive or negative.

issue during the January 2021 events.[8]

Fig. A19 Evolution of social media sentiment for the stocks at issue: January 01, 2021 – February 19, 2021: This figure depicts the evolution of positive and negative posts on social media platforms for i) GameStop, ii) the seven stocks that experienced a short-squeeze (GME, AMC, AAL, BBBY, EXP, NAKD, TR), iii) the six stocks that did not experience a short-squeeze (BB, CTRM, KOSS, NOK, SNDL, TRVG), and iv) all the 13 stocks at issue combined. The start of the short squeeze is set to January 26, 2021. The end of the short squeeze is set to February 4, 2021. On January 28, 2021 Robinhood, among other brokers, started implementing trading limitations.



[8]Table A9 provides evidence from the estimation of Model 9 only for GME. In line with the results presented in this section the sentiment measure and its interactions with the *SSqueeze* and *Post-Squeeze* dummies are not significantly different from zero. Further, Table A7 provides robustness using the *mroibtrd* measure.

Table A7 Robustness: Explaining return variation during the short-squeeze period using marketable retail order imbalances and market sentiment: This table reports the robustness estimations for the results reported in Table A8. As an alternative robustness measure the main independent variable is mroibtrd, a scaled marketable retail order imbalance measure based on the number of trades (see Boehmer, Jones, Zhang, and Zhang (2021)). The procedure, variable definitions and data used are described in the caption of Table A8 and the corresponding section in the paper.

Panel A	(1) 30-second Return	(2) 1-minute Return	(3) 2-minute Return
SSqueeze	-0.004	-0.021	-0.020
	(-0.550)	(-1.499)	(-0.704)
Post-SSqueeze	-0.001	-0.014*	-0.009
	(-0.178)	(-1.702)	(-0.587)
mroibtrd	0.022***	0.044***	0.088***
	(2.859)	(3.125)	(2.592)
Sentiment	0.005	-0.001	0.004
	(1.211)	(-0.158)	(0.696)
mroibtrd x SSqueeze	0.048**	0.107***	0.170**
	(2.392)	(2.646)	(2.008)
Sentiment x SSqueeze	**-0.005**	**0.000**	**-0.003**
	(-1.361)	**(0.043)**	**(-0.647)**
mroibtrd x Post-SSqueeze	0.009	0.012	0.021
	(0.939)	(0.641)	(0.612)
Sentiment x Post-SSqueeze	-0.007	-0.000	-0.004
	(-1.573)	(-0.042)	(-0.663)
Lagged Return	-0.045***	-0.043*	-0.144**
	(-2.703)	(-1.949)	(-2.367)
Daily Return	0.000	-0.000	0.001
	(0.251)	(-0.154)	(1.326)
Size	-0.001	-0.003	-0.001
	(-0.308)	(-0.838)	(-0.208)
Turnover	-0.004	-0.009	-0.034*
	(-1.004)	(-1.180)	(-1.923)
Price Dispersion	-0.002	0.001	0.051
	(-0.085)	(0.027)	(0.531)
Constant	0.016	0.074	0.036
	(0.337)	(0.969)	(0.252)
Observations	107,576	57,739	30,367
Adjusted R^2	0.002	0.003	0.019

Panel B	(1) 30-second Return	(2) 1-minute Return	(3) 2-minute Return
SSqueeze	-0.012	-0.026*	-0.037
	(-1.570)	(-1.800)	(-1.325)
Post-SSqueeze	-0.004	-0.014	-0.014
	(-0.618)	(-1.214)	(-0.654)
mroibtrd	0.019**	0.033**	0.031
	(2.530)	(2.379)	(0.862)
Sentiment	-0.001	-0.003	-0.000
	(-0.478)	(-1.095)	(-0.098)
mroibtrd x SSqueeze	0.072***	0.113***	0.174**
	(3.746)	(3.475)	(2.096)
Sentiment x SSqueeze	**0.001**	**0.003**	**0.001**
	(0.680)	**(1.168)**	**(0.239)**
mroibtrd x Post-SSqueeze	0.006	0.014	0.024
	(0.497)	(0.631)	(0.511)
Sentiment x Post-SSqueeze	-0.001	-0.000	-0.003
	(-0.320)	(-0.075)	(-0.660)
Lagged Return	-0.105***	-0.095**	-0.075
	(-2.645)	(-2.143)	(-1.475)
Daily Return	0.000	0.000	-0.000
	(0.482)	(0.211)	(-0.369)
Size	-0.001	-0.003	-0.005
	(-0.538)	(-0.984)	(-0.881)
Turnover	0.042**	0.070**	0.120*
	(2.300)	(2.088)	(1.861)
Price Dispersion	-0.089**	-0.145*	-0.222
	(-2.129)	(-1.940)	(-1.610)
Constant	0.028	0.086	0.121
	(0.612)	(1.127)	(0.996)
Observations	73,714	40,527	21,633
Adjusted R^2	0.013	0.012	0.009

Table A8 Robustness: Explaining return variation during the short-squeeze period using marketable retail order imbalances and market sentiment: This table reports the results from the retail investors' trading activity regression estimation described in Equation 9. Panel A presents information about the seven stocks that experienced a short-squeeze (GME, AMC, AAL, BBBY, EXP, NAKD, TR). Panel B presents information about the remaining six stocks that did not experience a short-squeeze (BB, CTRM, KOSS, NOK, SNDL, TRVG). The data set covers the period January 11, 2021 through February 19, 2021. The dependent variable is individual stock returns in percent computed over different short-term periods (30-seconds, 1-minute, and 2-minute). The main independent variables are i) mroibvol, a scaled marketable retail order imbalance measure based on the number of shares traded (see Boehmer, Jones, Zhang, and Zhang (2021)), and ii) Sentiment, a score based on a text sentiment analysis of social media posts following Hutto and Gilbert (2014). To capture the association of retail trading activity and sentiment with returns during the different periods we interact these variables with corresponding dummies for the period during the short squeeze (SSqueeze) and the period after the short squeeze (Post-SSqueeze), as previously defined. Controls include i) daily return, ii) log market cap, iii) daily turnover, and iv) daily price dispersion, all measured at the end of the previous day. We also include v) a lagged intra-daily return as an additional control. The t-statistics are reported in parentheses below the coefficient estimates and are based on robust standard errors clustered by firm and time (see Petersen (2009)). The symbols ***, ** and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Data come from TAQ and Compustat.

Panel A	(1) 30-second Return	(2) 1-minute Return	(3) 2-minute Return
SSqueeze	-0.002	-0.017	-0.014
	(-0.204)	(-1.174)	(-0.510)
Post-SSqueeze	-0.003	-0.018**	-0.018
	(-0.645)	(-2.257)	(-1.179)
mroibvol	0.018***	0.033***	0.061***
	(4.313)	(4.054)	(2.967)
Sentiment	0.005	-0.001	0.004
	(1.217)	(-0.161)	(0.697)
mroibvol x SSqueeze	0.045***	0.066***	0.137***
	(5.032)	(3.801)	(3.334)
Sentiment x SSqueeze	**-0.005**	**0.000**	**-0.003**
	(-1.333)	**(0.084)**	**(-0.617)**
mroibvol x Post-SSqueeze	0.008	0.008	0.028
	(1.631)	(0.818)	(1.542)
Sentiment x Post-SSqueeze	-0.007	-0.000	-0.004
	(-1.569)	(-0.031)	(-0.648)
Constant	0.019	0.083	0.053
	(0.407)	(1.086)	(0.373)
Controls	YES	YES	YES
Observations	107,576	57,739	30,367
Adjusted R^2	0.003	0.003	0.020

Panel B	(1) 30-second Return	(2) 1-minute Return	(3) 2-minute Return
SSqueeze	-0.005	-0.015	-0.017
	(-0.628)	(-1.061)	(-0.653)
Post-SSqueeze	-0.004	-0.015	-0.012
	(-0.771)	(-1.447)	(-0.656)
mroibvol	0.010**	0.022***	0.031*
	(2.465)	(2.934)	(1.714)
Sentiment	-0.001	-0.002	0.000
	(-0.258)	(-0.874)	(0.047)
mroibvol x SSqueeze	0.081***	0.140***	0.183***
	(5.005)	(5.399)	(3.243)
Sentiment x SSqueeze	**0.001**	**0.003**	**0.000**
	(-1.333)	**(0.991)**	**(0.126)**
mroibvol x Post-SSqueeze	0.028***	0.042***	0.050**
	(4.626)	(3.686)	(2.052)
Sentiment x Post-SSqueeze	-0.001	-0.000	-0.003
	(-0.382)	(-0.129)	(-0.726)
Constant	0.024	0.083	0.113
	(0.534)	(1.119)	(0.999)
Controls	YES	YES	YES
Observations	73,714	40,527	21,633
Adjusted R^2	0.014	0.012	0.009

Table A9 Robustness: Explaining return variation during the short-squeeze period using marketable retail order imbalances and market sentiment for GME: This table reports the robustness estimations for the results reported in Table A8 and Table A7 for GME. This table reports the results from the retail investors' trading activity regression estimation described in Equation 3. Panel A presents information using mroibvol as main independent variable. Panel B presents information using mroibtrd as main independent variable. The procedure, variable definitions and data used are described in the caption of Table A8, Table A7 and the corresponding section in the paper.

	(1)	(2)	(3)
Panel A	30-second Return	1-minute Return	2-minute Return
SSqueeze	0.028	-0.005	-0.015
	(0.602)	(-0.061)	(-0.083)
Post-SSqueeze	-0.001	-0.025	-0.060
	(-0.050)	(-0.514)	(-0.616)
mroibvol	0.006	-0.000	0.151*
	(0.436)	(-0.003)	(1.817)
Sentiment	0.005	-0.003	0.003
	(1.024)	(-0.445)	(0.441)
mroibvol x SSqueeze	0.185**	0.385**	0.107
	(2.284)	(2.069)	(0.131)
Sentiment x SSqueeze	**-0.009**	**0.001**	**-0.005**
	(-1.595)	**(0.135)**	**(-0.653)**
mroibvol x Post-SSqueeze	0.050***	0.111***	0.084
	(3.284)	(3.268)	(1.002)
Sentiment x Post-SSqueeze	-0.007	0.002	-0.003
	(-1.261)	(0.227)	(-0.328)
Lagged Return	-0.051	-0.043	-0.159*
	(-1.573)	(-0.933)	(-1.800)
Daily Return	0.000	0.000	0.002
	(0.784)	(0.288)	(1.004)
Size	-0.025	-0.056	0.006
	(-0.864)	(-1.035)	(0.052)
Turnover	-0.030	-0.022	-0.086
	(-0.919)	(-0.382)	(-0.694)
Price Dispersion	0.121	0.167	0.271
	(1.524)	(1.165)	(0.951)
Constant	0.545	1.228	-0.099
	(0.866)	(1.060)	(-0.042
Observations	20,978	10,549	5,250
Adjusted R^2	0.003	0.002	0.023

	(1)	(2)	(3)
Panel B	30-second Return	1-minute Return	2-minute Return
SSqueeze	0.016	-0.034	0.072
	(0.335)	(-0.363)	(0.379)
Post-SSqueeze	0.003	-0.009	-0.009
	(0.130)	(-0.177)	(-0.086)
mroibtrd	0.015	0.080	0.321**
	(0.579)	(1.475)	(2.079)
Sentiment	0.005	-0.002	0.003
	(1.058)	(-0.369)	(0.437)
mroibtrd x SSqueeze	0.207	0.530	-1.277
	(1.191)	(1.308)	(-1.046)
Sentiment x SSqueeze	**-0.009**	**0.000**	**-0.005**
	(-1.629)	**(0.053)**	**(-0.640)**
mroibtrd x Post-SSqueeze	0.060	0.086	0.251
	(1.616)	(0.950)	(1.016)
Sentiment x Post-SSqueeze	-0.007	0.001	-0.003
	(-1.281)	(0.170)	(-0.351)
Lagged Return	-0.049	-0.041	-0.156*
	(-1.525)	(-0.915)	(-1.811)
Daily Return	0.000	0.000	0.003
	(0.799)	(0.302)	(1.063)
Size	-0.028	-0.064	0.019
	(-0.956)	(-1.182)	(0.165)
Turnover	-0.032	-0.028	-0.090
	(-0.981)	(-0.480)	(-0.731)
Price Dispersion	0.119	0.161	0.304
	(1.494)	(1.124)	(1.037)
Constant	0.604	1.388	-0.434
	(0.959)	(1.205)	(-0.174)
Observations	20,978	10,549	5,250
Adjusted R^2	0.003	0.002	0.024

A.9. Price and options open interest charts for the stocks at issue.

This section presents additional price and open interest graphs for the impacted stocks.

Fig. A20 Evolution of price and open interest: This figure depicts the evolution of close price (lhs) and the evolution of open interest separately for call and put options (rhs). The start of the short squeeze is set to January 26, 2021. The end of the short squeeze is set to February 4, 2021. On January 28, 2021 Robinhood, among other brokers, implemented the trading limitations. January 18 and February 15, 2021 were exchange holidays, see Link.

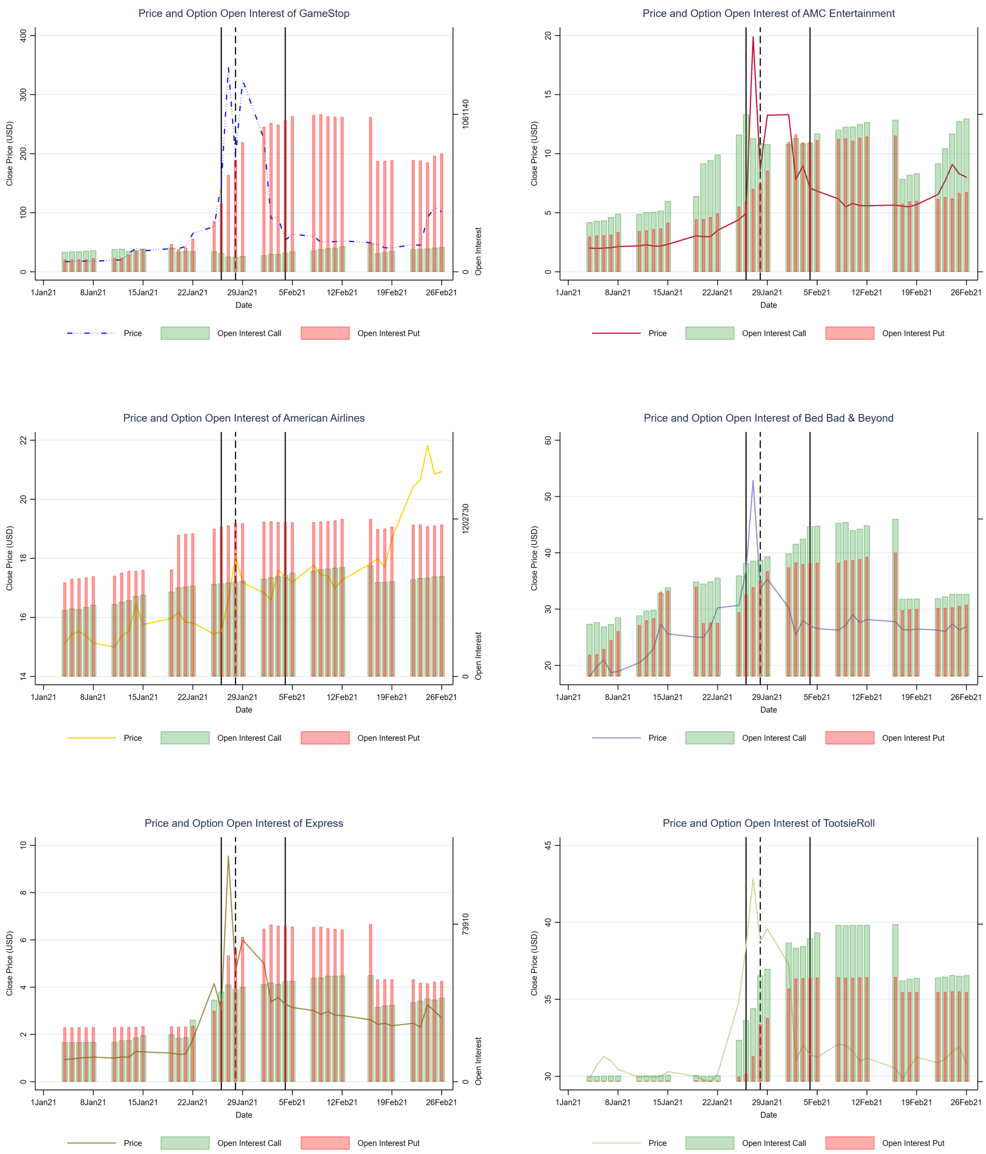
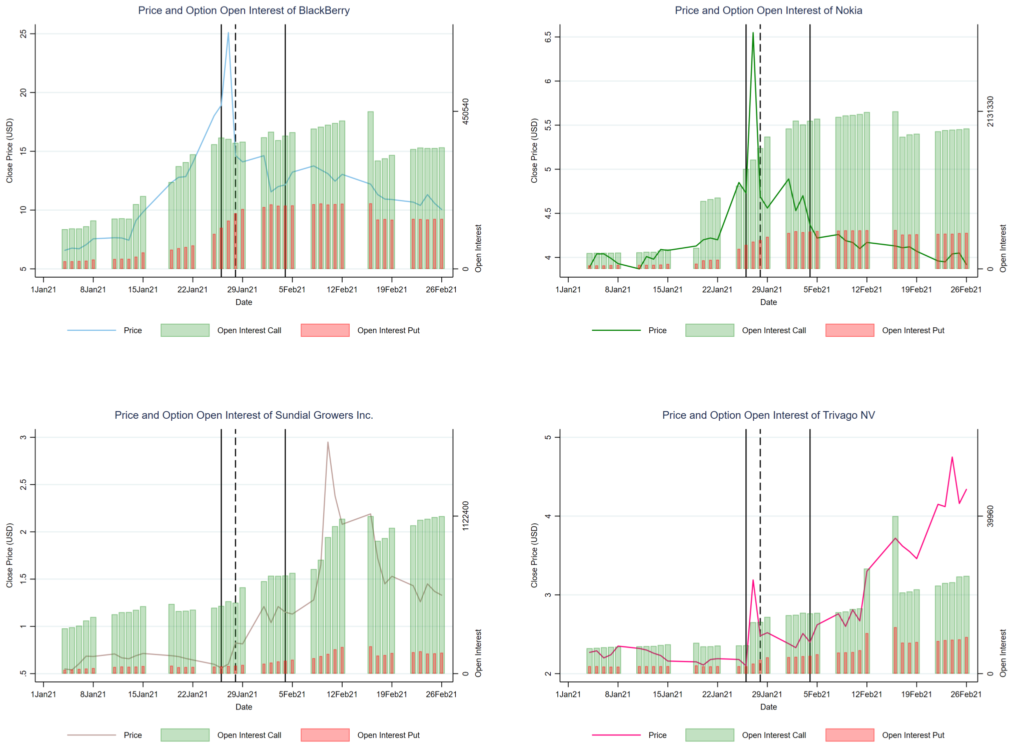


Fig. A21 Evolution of price and open interest (cont'd): This figure depicts the evolution of close price (lhs) and the evolution of open interest separately for call and put options (rhs). The start of the short squeeze is set to January 26, 2021. The end of the short squeeze is set to February 4, 2021. On January 28, 2021 Robinhood, among other brokers, implemented the trading limitations. January 18 and February 15, 2021 were exchange holidays, see Link.



A.10. Implied volatility spread tests.

This section presents additional implied volatility spread estimations. In particular, we investigate the effect of the January 2021 events on put and call option prices. Here, we are interested in examining whether there was a disproportionately larger increase in demand for call or put options during the short-squeeze period. We therefore apply a common options valuation metric, the implied volatility spread, which measures the difference in put and call options implied volatilities. We follow Figlewski and Webb (1993) and measure the implied volatility spread based on put-call option pairs on the same underlying stock with the same strike prices and time to expiration. We perform this analysis on ATM put-call option pairs, which are the most liquid options class and less susceptible to distortions from market frictions. Intuitively, a positive change in the implied volatility spread suggests that put options are relatively more expensive than the corresponding call options, i.e., the implied volatility of a put option is higher than the implied volatility of the corresponding call option counterparts. A negative change in the implied volatility spread suggests the opposite, namely that demand for call options is relatively higher than demand for the corresponding put options, therefore call options are more expensive.

To examine the effect of the January 2021 events on the implied volatility spread, similarly to before, we estimate the following regression model separately for squeezed and non-squeezed stocks:

$$Y_{i,t} = \alpha + \beta_1 SSqueeze + \beta_2 Post\text{-}SSqueeze + \beta_3 Controls_{i,t-1} + \varepsilon_{i,t}, \tag{10}$$

Here $Y_{i,t}$ represents the average implied volatility spread per stock. As before, we include the daily return, the daily trading volume, and the daily VIX as additional control variables ($Controls_{i,t-1}$).

Panels A and B in Table A10 present the results. We do not find significant changes in the implied volatility spread for both the squeezed stocks and the non-squeezed stocks, indicating that the change in demand for these options categories during the squeeze period was similar.

Table A10 Implied volatility spread during and after the short-squeeze period: This table reports the results from the implied volatility spread regression estimation described in Equation 10. The dependent variable in each regression is the average daily implied volatility spread per stock, measured as the difference in the implied volatility between ATM put and call options on the same underlying stock with the same strike prices and time to expiration (see e.g., Figlewski and Webb (1993)). The data set covers all stocks with options listed on them from the 13 banned stocks. Panels A presents information about the stocks with listed options that experienced a short-squeeze (GME, AMC, AAL, BBBY, EXP, TR). Panels B presents information about the remaining stocks with listed options that did not experience a short-squeeze (BB, NOK, SNDL, TRVG). The period covered is January 1, 2021 through February 19, 2021. The data frequency is daily. We define the period before the short squeeze (captured by the constant) as the two weeks (ten trading days) preceding January 26, 2021. We define the short-squeeze period (SSqueeze) as January 26, 2021 through February 4, 2021. We define the period after the short squeeze (Post-SSqueeze) as the two weeks (ten trading days) after February 4, 2021. We define at-the-money (ATM) as options with S/X $\geq$ 0.95 and S/X $\leq$1.05. Controls include the daily return, daily trading volume, and the VIX, all measured at the end of the previous day. The t-statistics are reported in parentheses below the coefficient estimates and are based on robust standard errors clustered by firm and time (see Petersen (2009)). The symbols ***, ** and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Data come from OptionMetrics.

	(1)
Panel A	ATM
SSqueeze	**-2.818**
	(-0.452)
Post-SSqueeze	-0.880
	(-0.641)
Constant	8.038
	(1.032)
Observations	139
Controls	YES
Adjusted R^2	0.168

	(1)
Panel B	ATM
SSqueeze	**0.663**
	(0.787)
Post-SSqueeze	-0.271
	(-0.655)
Constant	0.358
	(0.192)
Observations	65
Controls	YES
Adjusted R^2	0.112

A.11. Additional market quality tests: fully-interacted model.

Table A11 Robustness: Market quality. Fully interacted model:
To provide robustness of the results from Model 8 and to assess the statistical significance of changes between squeezed and non-squeezed stocks, we employ a regression model in which metrics for market quality are regressed on (1) a constant, (2) indicator variables for the short-squeeze and post short-squeeze periods, (3) an indicator variable for squeezed versus non-squeezed stocks, and (4) their interactions. This "fully-interacted" model, can be summarized by the following regression equation:

$$Y_{i,t} = \alpha + \beta_1 SSqueeze + \beta_2 Post\text{-}SSqueeze + \beta_3 Squeezed + \beta_4 Squeezed \times SSqueeze + \beta_5 Squeezed \times Post\text{-}SSqueeze + \beta_6 Controls_{i,t-1} + \varepsilon_{i,t}$$

where $Y_{i,t}$ represents one of the metrics defined in Table 9. i is a firm index and t denotes time in minutes. Controls include i) daily return, ii) log market cap, iii) daily price dispersion, and iv) daily volume, all measured at the end of the previous day. The data set covers the period January 11, 2021 through February 19, 2021. The data frequency is on the minute level. We define the period before the short squeeze as the two weeks (ten trading days) preceding January 26, 2021. We define the short-squeeze period (SSqueeze) as January 26, 2021 through February 4, 2021. We define the period after the short squeeze (Post-SSqueeze) as the two weeks (ten trading days) after February 4, 2021. The t-statistics are reported in parentheses below the coefficient estimates and are based on robust standard errors clustered by firm and time (see Petersen (2009)). The symbols ***, ** and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Data come from TAQ and Compustat.

	(1)	(2)	(3)	(4)	(5)
	Spread	Volatility	Volume	Bid Size	Ask Size
Post-SSqueeze	0.394***	0.016***	83,718.260***	336,916.514***	309,003.051***
	(36.717)	(3.585)	(8.070)	(22.089)	(15.296)
SSqueeze	0.245***	0.115***	186,306.539***	168,320.165***	296,864.795***
	(21.137)	(11.902)	(11.827)	(5.158)	(10.265)
Squeezed	-0.174***	-0.001	-10,373.176*	-15,102.439**	-9,227.751
	(-20.390)	(-0.221)	(-1.949)	(-2.322)	(-0.964)
SSqueeze x Squeezed	**0.041*** **	**0.109*** **	**-32,040.522** **	**-207,831.175*** **	**-346,493.532*** **
	(2.742)	**(10.330)**	**(-2.558)**	**(-4.952)**	**(-15.050)**
Post-SSqueeze x Squeezed	-0.197***	-0.023***	-123,052.393***	-365,937.346***	-355,460.237***
	(-16.295)	(-5.838)	(-13.175)	(-16.456)	(-18.470)
Constant	5.018***	0.973***	538,628.592***	-1445553.287***	-1463362.040***
	(128.563)	(34.619)	(16.085)	(-19.474)	(-34.770)
Observations	136,287	139,245	137,305	139,937	139,937
Adjusted R^2	0.184	0.240	0.232	0.031	0.043
Controls	YES	YES	YES	YES	YES