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Essays on Retail Investors, Short Selling, and Market Efficiency

PhD Thesis

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Chapter 1

Preface

1.1. Introduction

The central interest of my doctoral studies is to analyze market efficiency, with a particular emphasis on the role of retail traders and short sellers. My thesis consists of three chapters in the fields of asset pricing and corporate finance. Using unique datasets and empirical approaches I address several questions, including: "Can retail trader coordination lead to market-distorting events?", "How prevalent are short squeezes?", and "Can crowdfunding mitigate small firms' capital constraints?".

1.2. Summary of papers

Chapter 1, "Squeezing Shorts Through Social Media Platforms" (co-authored with Franklin Allen, Marlene Haas, Eric Nowak, and Angel Tengulov) analyzes the events of early 2021. In particular, 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 (Reddit, Twitter, and StockTwits) we provide a comprehensive account of these short squeezes and show that they significantly impeded market quality for the stocks at issue and their product market competitors. Thus, retail trader coordination can lead to market-distorting events and impair market efficiency. Understanding what happened during these events is important for several reasons. First, short-squeeze events are among the most important limits to arbitrage, the mechanism that ensures efficient market prices. The January 2021 events are unprecedented, since coordination of retail traders through social media to target stocks with high short interest has not been seen before. Second, we provide novel evidence regarding the interaction between social media and financial markets. Most of the prior literature argues that social media has a positive effect on financial markets. This, however, is not shared by all research. Our evidence suggests 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. Finally, US regulators are in the process of establishing the extend to which the January 2021 events have affected market quality and violated market regulations. We provide evidence that coordination through social media has driven short sellers out of meme stocks and made short selling more risky.

Chapter 2, "How prevalent are short squeezes? Evidence from the US and Europe" (co-authored with Franklin Allen, Marlene Haas, and Angel Tengulov) investigates more broadly the frequency of short squeezes. We propose a novel proxy for identifying short squeezes, which complements the measures provided by Schultz (2023). In particular, Schultz (2023) proposes measures that identify short-squeeze events when borrowed shares are recalled by the lender. However, short squeezes can also occur if prices increase drastically and, as a result, short sellers have to cover their positions. We call such a short-squeeze event a "market squeeze" and propose a new measure that allows us to capture this type of event. This measure can be applied to all types of financial markets including equity, commodities, and bond markets. The development of this measure was motivated by historical short-squeeze events described in the empirical literature on the topic, such as the January 2021 squeezes and the 2008 Volkswagen (VW) squeeze. Using IHS Markit data from 2006 to 2021, we find that stock-day short-squeeze events are rare and short-lived. While we find an uptick in the number of firms experiencing a squeeze in recent years in the US, squeezes are relatively constant across time in the EU. We also review the academic literature on the topic and provide directions for future research. This evidence is timely for regulatory reasons. In particular, the US SEC has proposed a new short-selling regulation that is intended to provide greater transparency through the publication of short-selling information. The regulatory proposal is somewhat similar to the short-sale disclosure requirements that the EU implemented in 2012. One of the goals of this US regulation is to allow the SEC and other regulators to more quickly identify potential short-squeeze events. At the same time, one concern related to the proposed regulation is that disclosing more short-sale information may also increase the risk of short squeezes.

Chapter 3, "Debt and Equity Crowdfunding in the Financial Growth Cycle" (co-authored with Markus Lithell, Davide Sinno, and Trang Q. Vu) investigates firms' choice between issuing crowdfunded debt and equity, and how this decision relates to their stage in the financial growth cycle and access to bank financing. In particular, we focus on crowdfunded equity and debt issued in the US under Regulation Crowdfunding (CF) of the JOBS Act. Since 2016 regulation CF allows firms to issue crowdfunded equity or debt to the investing public, including retail investors. Using EDGAR, we create a novel dataset of crowdfunding offerings from 2016 through 2021. We analyse firms' choices to issue crowdfunded debt and equity at different stages of the financial growth stage, a framework proposed by Berger and Udell

(1998). Berger and Udell (1998) suggest that the pecking order hierarchy depends on the size and stage of development of the firm, as there are different levels of information asymmetry and financial needs for each phase of growth. We categorize firms into three stages of the financial growth cycle that are appropriate for smaller entrepreneurial firms: a first stage where firms have assets in place but do not generate revenue, a second stage where firms have positive revenue but are unprofitable, and a third stage where firms achieve profitability to generate positive revenue and net income. We find that firms that are less profitable, are in an earlier developmental stage, and have stronger ties to the banking system are more likely to issue crowdfunded equity than debt. Using a matched diff-in-diff setting, we find that successful crowdfunding is associated with increases in firm size, revenue, and profitability for early-stage firms, but not for late-stage firms. Our findings are consistent with crowdfunding alleviating capital constraints and stimulating growth for early-stage startups, but having a negligible impact on established firms that are already profitable.

1.3. Additional work

In my second year solo-authored term paper **"ESG Scores and Fund Flows: A Measure of Price Pressures"**, I examined the impact of mutual fund ESG scores on fund flows and stock prices. Using US equity mutual funds data from CRSP and Refinitiv Eikon, I find evidence consistent with (i) ESG scores being one of the determinants of fund flows, and (ii) discrete ESG scores determining non-fundamental demand shocks. I am currently reviewing and updating this paper using Morningstar Direct data.

Finally, in the ongoing work **"REDD+ Projects Around the World"** (co-authored with Eric Nowak) we compiled a novel database of voluntary carbon credits retirements. REDD+ stands for "Reducing Emissions from Deforestation and Forest Degradation" and it is a program aimed at promoting projects to support forest protection and biodiversity around the world. The ultimate objective of the study is to assess how equity markets respond when public firms retire REDD+ carbon offsets.

Chapter 2

Squeezing Shorts Through Social Media Platforms*

Franklin Allen,† Marlene Haas,‡ Eric Nowak,§ Matteo Pirovano,¶ and Angel Tengulov‖

2.1. 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 ex-

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[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).

changes 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) decrease 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

[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 2.3 provides more details about our sample selection.

[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.9 in the Internet Appendix.

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 centers 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

[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)).

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 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

[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 2.3 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).

[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).

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 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]

[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).

[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)).

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 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 compa-

[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.

nies 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 2.2 reviews the background of the January 2021 events. Section 2.3 describes the underlying data. Section 2.4 analyzes the securities lending market. Section 2.5 investigates if retail traders contributed to the price increases and analyzes the interaction between social media platforms and retail trading activity.

[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.

Section 2.6 provides analyses related to the options market. Section 2.7 discusses the effects on market quality of the stocks at issue and their competitors. Section 2.8 concludes. The Internet Appendix provides further information and additional robustness tests.

2.2. 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 2.1 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 2.1 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 2.1 here.]

2.2.1. 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 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

[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.

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 2.1). 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 2.1.

2.2.2. 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 op-

[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.11 for details on price target dispersions among stock analysts.

[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).

tions. 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 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 2.1). Second, the majority of the 13 stocks also experienced sharp decreases in short interest on

[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).

[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).

January 26 (see e.g., Figure 2.3 for GameStop).[28] Third, the 13 stocks experienced a substantial increase in social media activity starting on January 26 (see Figure 2.1). 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]

2.3. 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 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.12 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).

[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)).

[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.

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.

2.4. 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.

2.4.1. 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 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 2.2 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

[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.

[34] See Figure 2.3 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.

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 2.2 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 2.2 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 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 2.3 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

[35] In the spirit of the theoretical framework of Pedersen (2022), Figure 2.2 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).

[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%.

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%, 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 2.3 here.]

To test more broadly if the findings for GameStop hold for the other stocks and how these

[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.

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:

$$Y_{i,t} = \alpha + \beta_1 SSqueeze + \beta_2 Post\text{-}SSqueeze + \beta_3 Controls_{i,t-1} + \varepsilon_{i,t}, \tag{2.1}$$

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 2.1 provides summary statistics and definitions of the dependent variables, and Table 2.2 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 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

[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 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,

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 2.2 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 2.1 here.]

[Insert Table 2.2 here.]

2.4.2. 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.

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.

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 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.

2.5. 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

[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.

in normal times (Boehmer, Jones, Zhang, and Zhang, 2021)).

2.5.1. 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 2.3, 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 2.4 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 2.4 here.]

Next, we examine whether intraday variation in social media activity predicts intraday vari-

[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.

ation in retail trading activity. Specifically, we estimate the following regression model:

$$\begin{aligned}Y_{i,t} = \alpha + \beta_1 SSqueeze + \beta_2 Post\text{-}SSqueeze \\ + \beta_3 ln(Mentions)_{i,t-1} + \beta_4 ln(Mentions)_{i,t-1} \times SSqueeze \\ + \beta_5 ln(Mentions)_{i,t-1} \times Post\text{-}SSqueeze + \beta_6 Controls_{i,t-1} + \varepsilon_{i,t},\end{aligned} \quad (2.2)$$

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 2.1 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 2.1. Table 2.3 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 2.3 here.]

Table 2.4 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 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

[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.

of retail trading activity and contributed to the herding-like retail trading behavior.[47]

[Insert Table 2.4 here.]

2.5.2. 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:

$$\begin{aligned} Y_{i,t} &= \alpha + \beta_1 SSqueeze + \beta_2 Post\text{-}SSqueeze + \beta_3 mroib_{i,t-1} \\ &+ \beta_4 SSqueeze \times mroib_{i,t-1} + \beta_5 Post\text{-}SSqueeze \times mroib_{i,t-1} \\ &+ \beta_6 Controls_{i,t-1} + \varepsilon_{i,t}, \end{aligned} \tag{2.3}$$

The dependent variable in Equation 2.3 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 and measured at the same frequency as returns. In line with Equation 2.1 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 2.1. 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 2.5 summarize the results of these estimations utilizing the *mroib-*

[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.15 in the Internet Appendix.

vol 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 2.5.1 is consistent with the conjecture that retail traders coordinated on social media platforms to impact securities prices.[51]

[Insert Table 2.5 here.]

2.5.3. 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 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

[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.16 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.

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 2.3 separately for each of the three terciles. Panels A, B, and C of Table 2.6 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 2.6 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.

2.6. 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.

[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.

2.6.1. 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 2.5 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 on reverting stock prices and to circumvent the short squeezes in some of the stocks at issue.

[Insert Figure 2.5 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

[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).

[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

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:

$$DOI_{i,t} = \sum_{o \in S} open\ interest_{o,t} \times |delta_{o,t}|. \tag{2.4}$$

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:

$$Y_{i,t} = \alpha + \beta_1 SSqueeze + \beta_2 Post\text{-}SSqueeze + \beta_3 Controls_{i,t-1} + \varepsilon_{i,t}, \tag{2.5}$$

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 2.1.

Table 2.7 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 2.7 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 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

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.

[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).

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.

2.6.2. 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 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)).

[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.18 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.

We therefore utilize the following put-call parity relation for dividend paying stocks:[61]

$$S + P = PV(K) + C + PV(div) \tag{2.6}$$

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 2.6, 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:

$$\begin{aligned} Y_{i,t} &= \alpha + \beta_1 SSqueeze + \beta_2 Post\text{-}SSqueeze + \beta_3 Squeezed \\ &+ \beta_4 Squeezed \times SSqueeze + \beta_5 Squeezed \times Post\text{-}SSqueeze \\ &+ \beta_6 Controls_{i,t-1} + \varepsilon_{i,t}, \end{aligned} \tag{2.7}$$

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 2.5.

Table 2.8 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 indicated 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

[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).

decoupling would have given rise to market inefficiency and possible arbitrage opportunities.[62]

[Insert Table 2.8 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.

2.7. 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]

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

[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, 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).

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 2.5 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 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,

[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).

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]

2.7.1. 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:

$$Y_{i,t} = \alpha + \beta_1 SSqueeze + \beta_2 Post\text{-}SSqueeze + \beta_3 Controls_{i,t-1} + \varepsilon_{i,t} \tag{2.8}$$

where $Y_{i,t}$ represents one of the price and volume metrics of interest. Table 2.9 provides definitions and summary statistics for these variables. i is a firm index and t denotes time in minutes. Similar to Equation 2.1 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 2.9 here.]

The panels in Figure 2.6 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 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

[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.

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 2.6 here.]

Next, we discuss the estimation results of Equation 2.8. Panel A of Table 2.10 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 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

[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).

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 2.10 here.]

Panel C of Table 2.10 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-squeezed stocks for all regression estimations in this section and find that they are statistically different from each other (untabulated).

2.8. 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 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. 2.1 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.

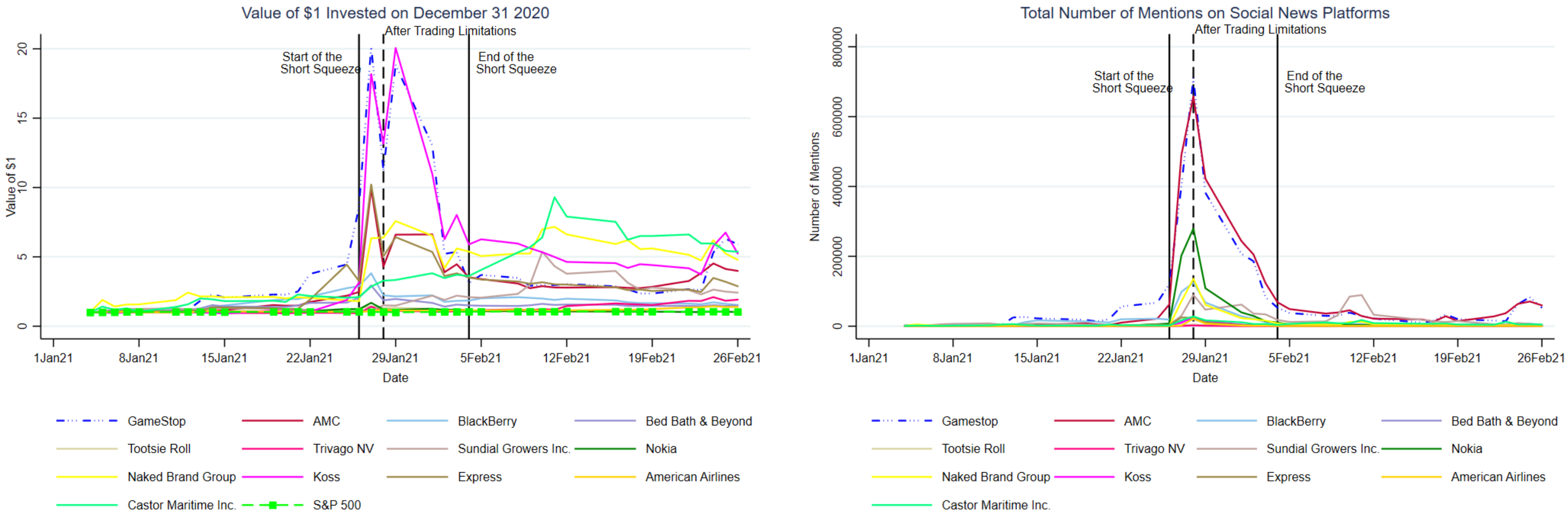


Fig. 2.2 Evolution of average quantity on loan and average returns of squeezed vs non-squeezed stocks: January 01, 2021 – February 28, 2021: These figures depict the evolution of average quantity on loan relative to shares outstanding (lhs) and the evolution of average returns (rhs) of the squeezed versus 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.

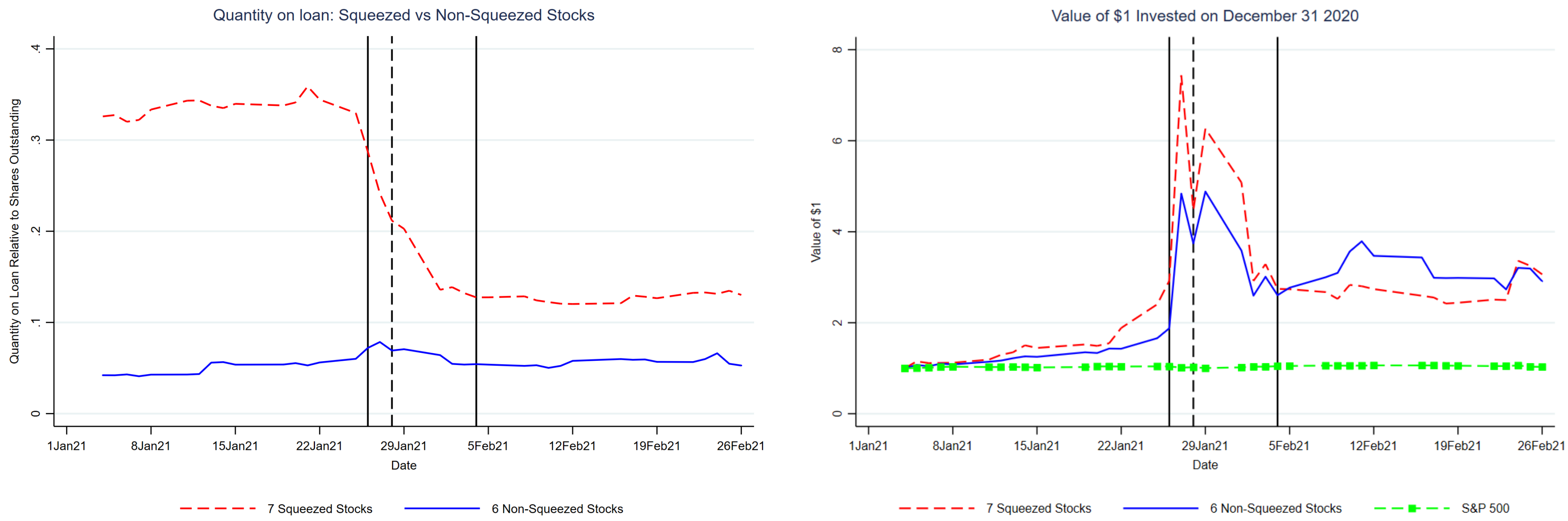


Fig. 2.3 Price and Quantity on loan: This graph shows GME's closing price (left y-axis in USD) and the quantity on loan for securities loans for GME relative to shares outstanding (right y-axis is in percent). **Tenure and Lendable quantity:** This graph shows tenure of securities loans outstanding for 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).

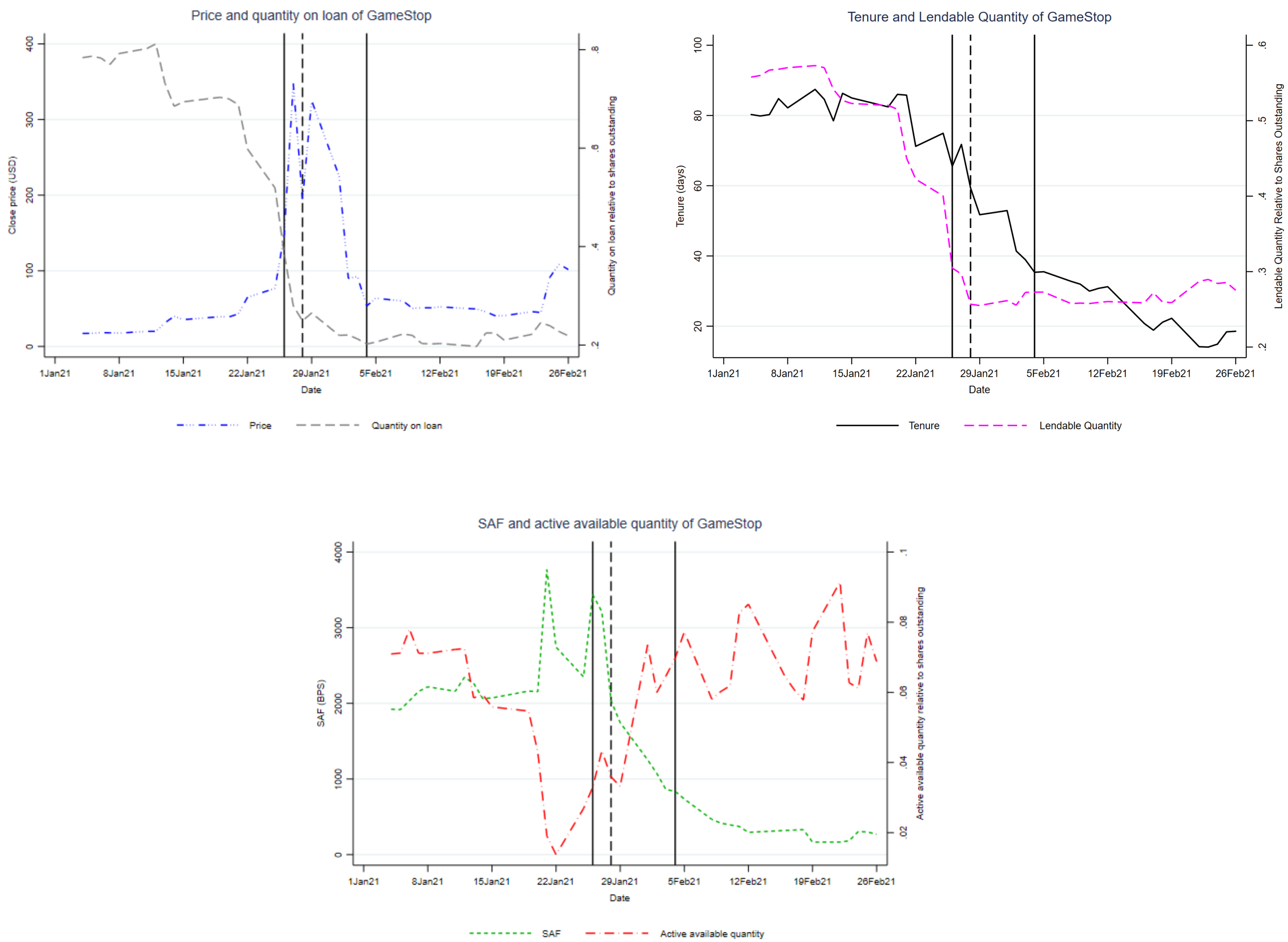


Table 2.1 Descriptive statistics for the securities lending market: This table presents descriptive statistics for the securities lending market measures for the 13 stocks impacted by the trading restrictions. Panel A presents information about the seven stocks that experienced a short-squeeze (GME, 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 2.2 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 2.1. The dependent variables are defined in Table 2.1. 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 2.3 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. 2.4 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 2.3, 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).

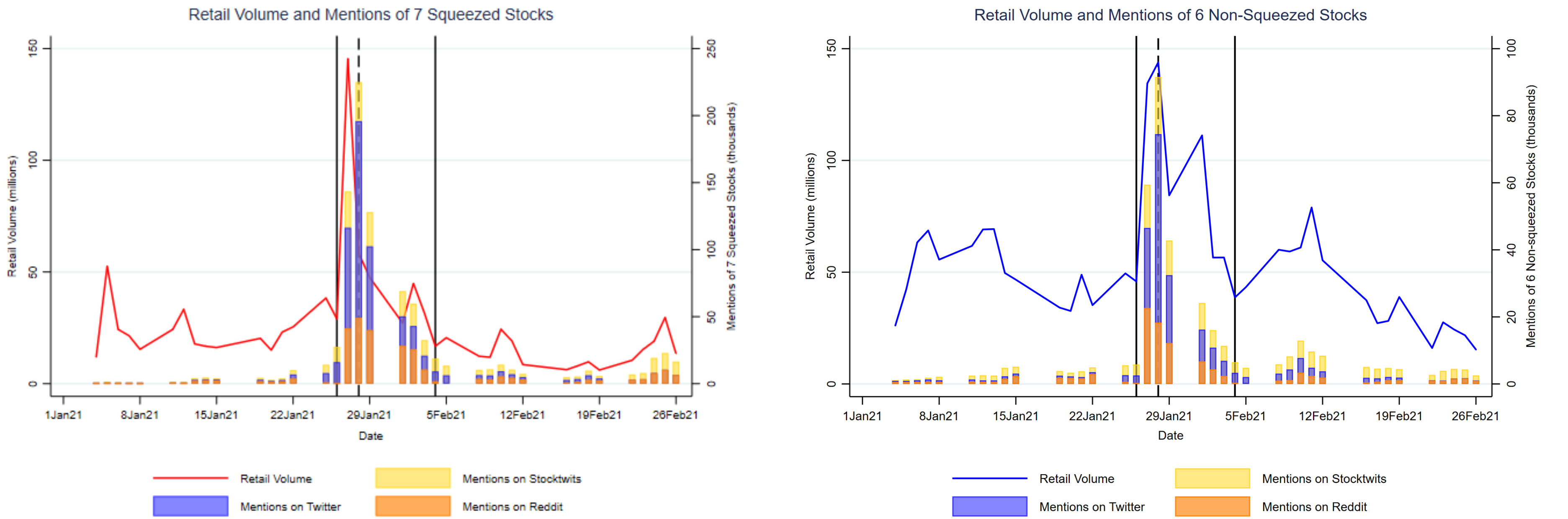


Table 2.4 Social media activity and retail trading activity: This table reports the results from the social media activity regression estimation described in Equation 2.2. Panel A presents information about the seven stocks that experienced a short-squeeze (GME, AMC, AAL, BBBY, EXP, NAKD, TR). Panel 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 2.5 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 2.3. 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.

	(1)	(2)	(3)
Panel A	30-second Return	1-minute Return	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

	(1)	(2)	(3)
Panel B	30-second Return	1-minute Return	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

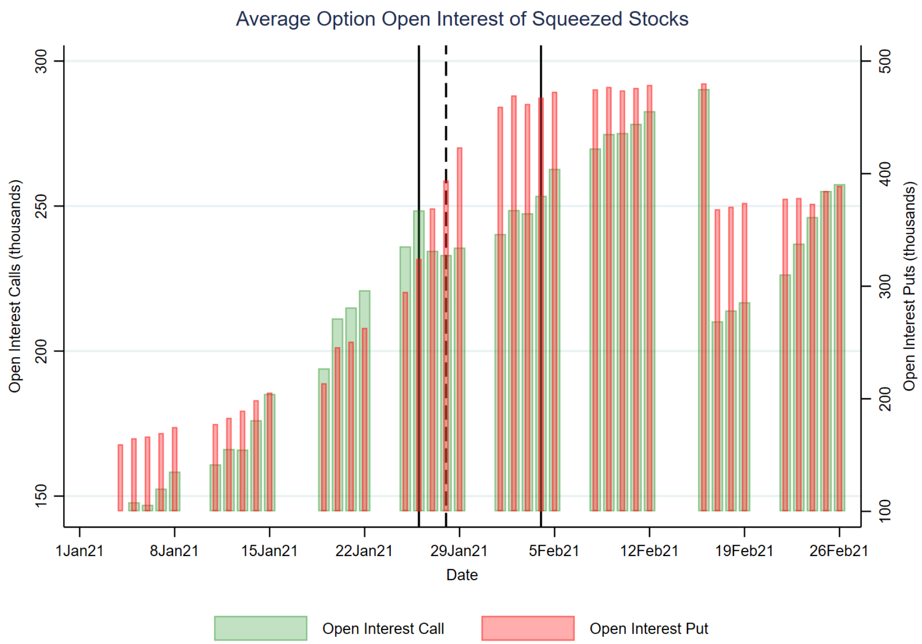
Table 2.6 Placebo test: Explaining return variation during the short-squeeze period using marketable retail order imbalances: This table reports results for the set of control companies for the retail investors' trading activity regression estimations described in Section 2.5.3. Panel A presents information 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.

	(1)	(2)	(3)
Panel A	30-second Return	1-minute Return	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

	(1)	(2)	(3)
Panel B	30-second Return	1-minute Return	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

	(1)	(2)	(3)
Panel C	30-second Return	1-minute Return	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. 2.5 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).



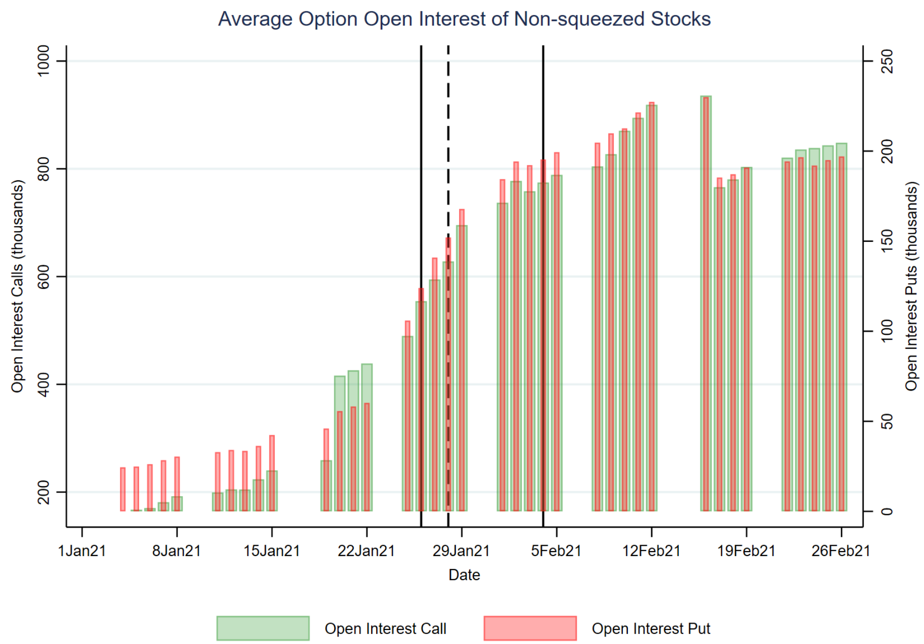


Table 2.7 Options delta-adjusted open interest during and after the short-squeeze period: This table reports the results from the open interest regression estimation described in Equation 2.5. The dependent variable in each regression is the natural log of total daily delta-adjusted options open interest 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.

Panel A	(1) ATM Puts	(2) ITM Puts	(3) OTM Puts	(4) ATM Calls	(5) ITM Calls	(6) 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

Panel B	(1) ATM Puts	(2) ITM Puts	(3) OTM Puts	(4) ATM Calls	(5) ITM Calls	(6) 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 2.8 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 2.7. 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 2.6. 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 2.9 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. 2.6 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 2.9. 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.

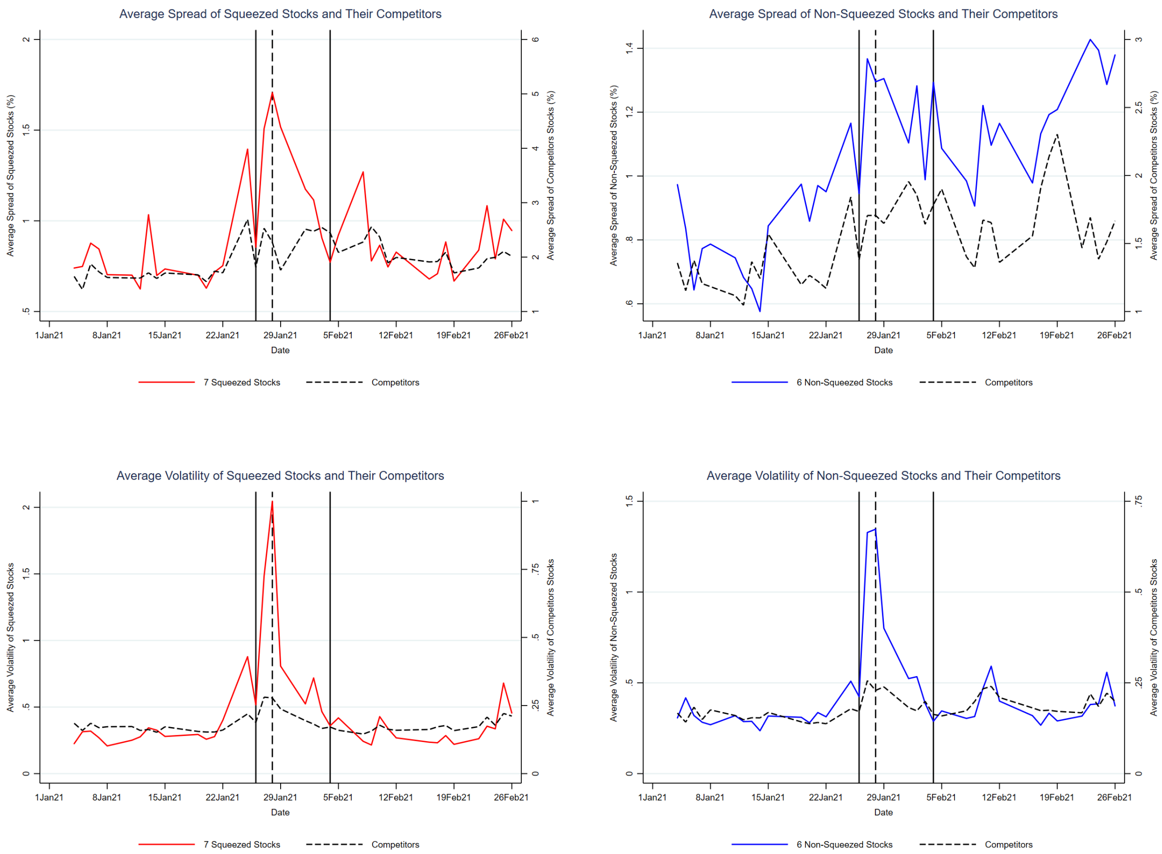


Table 2.10 Market quality tests for the meme stocks impacted by the trading restrictions and their competitors: The table reports the results from the market quality regression estimation described in Equation 2.8. We present results for the 13 stocks impacted by the trading restrictions and their product 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 2.9. 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

Internet Appendix

Squeezing Shorts Through Social Media Platforms

(*Not for Publication*)

A.9. 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.

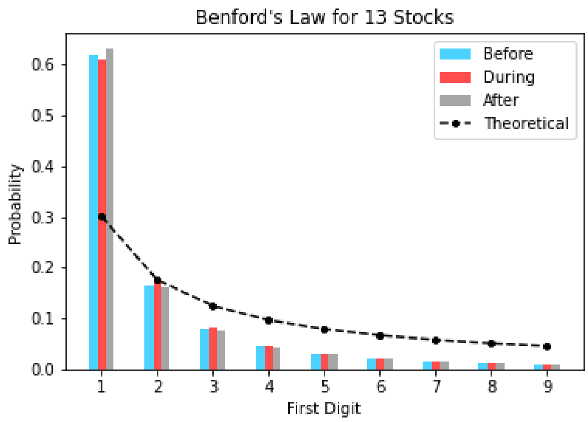


Fig. A2 Benford's Law of count of social media mentions of the 13 stocks for new and old users during the short-squeeze period: These figures show the probability of the first digit of the count of social media mentions for the short-squeeze period across the 13 stocks separately by social media platform. 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.

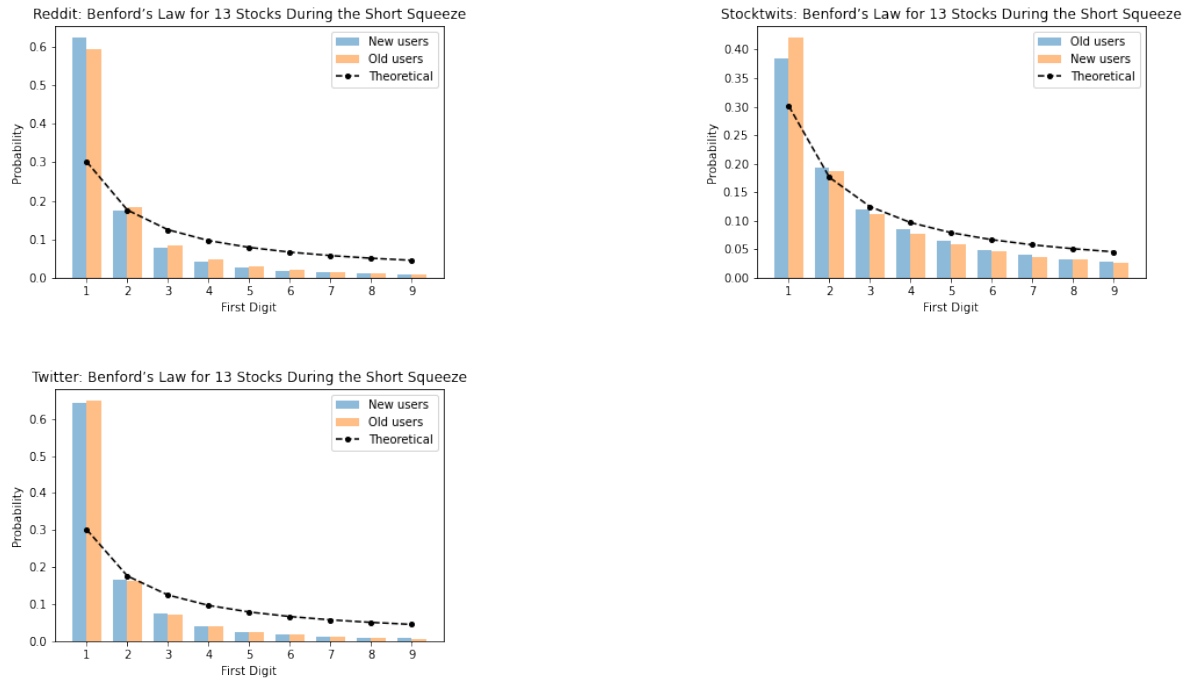


Fig. A3 Hourly posting patterns of social media mentions for the 13 stocks: January 11, 2021 – February 19, 2021: This figure shows the hourly posting pattern in NY time for social media mentions across the 13 stocks split into three time periods: before, during, and after the short squeezes. We define 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.

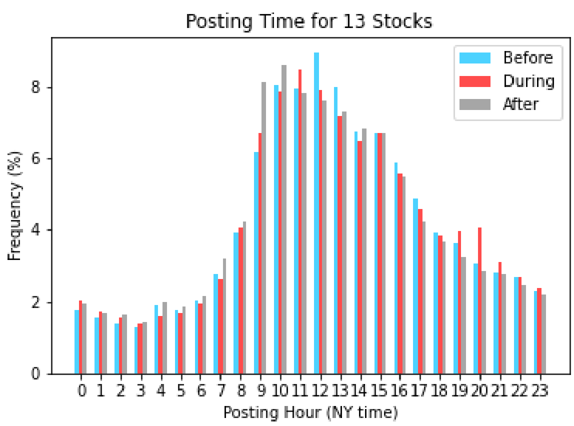
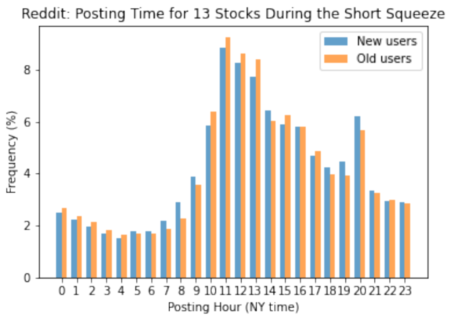
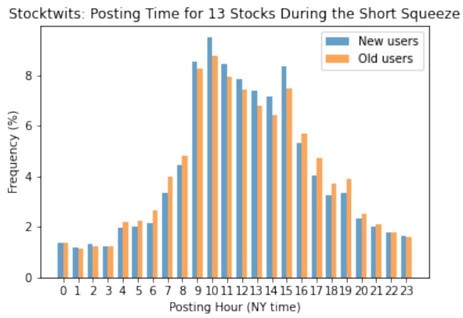


Fig. A4 Hourly posting patterns of social media mentions for the 13 stocks for new and old users during the short-squeeze period: These figures show the hourly posting pattern in NY time for social media mentions during the short-squeeze period across the 13 stocks separately by social media platform. 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.





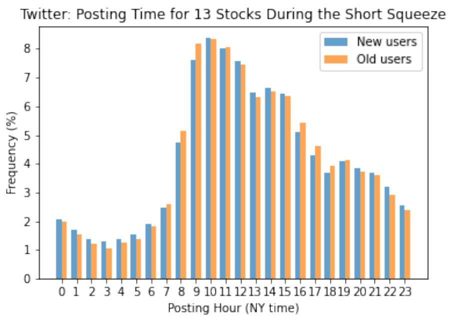


Fig. A5 Benford's Law of count of social media mentions of each of the 13 stocks for new and old users: Short-squeeze period: This figure shows the probability of the first digit of the count of social media mentions for each of the 13 stocks by social media platform and for just the short-squeeze period. 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.

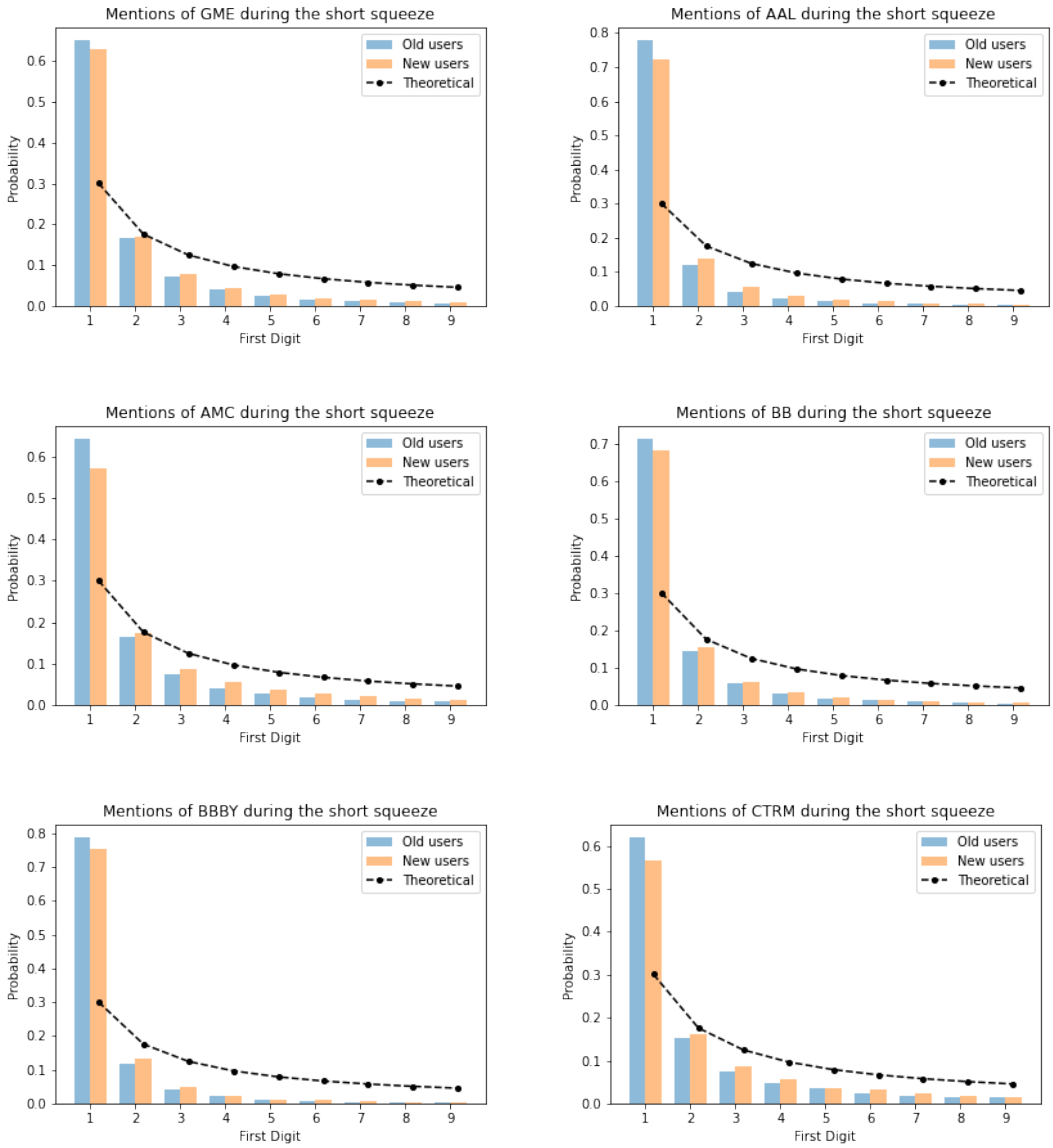


Fig. A6 Benford's Law of count of social media mentions of each of the 13 stocks for new and old users: Short-squeeze period(cont'd): This figure shows the probability of the first digit of the count of social media mentions for each of the 13 stocks by social media platform and for just the short-squeeze 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.

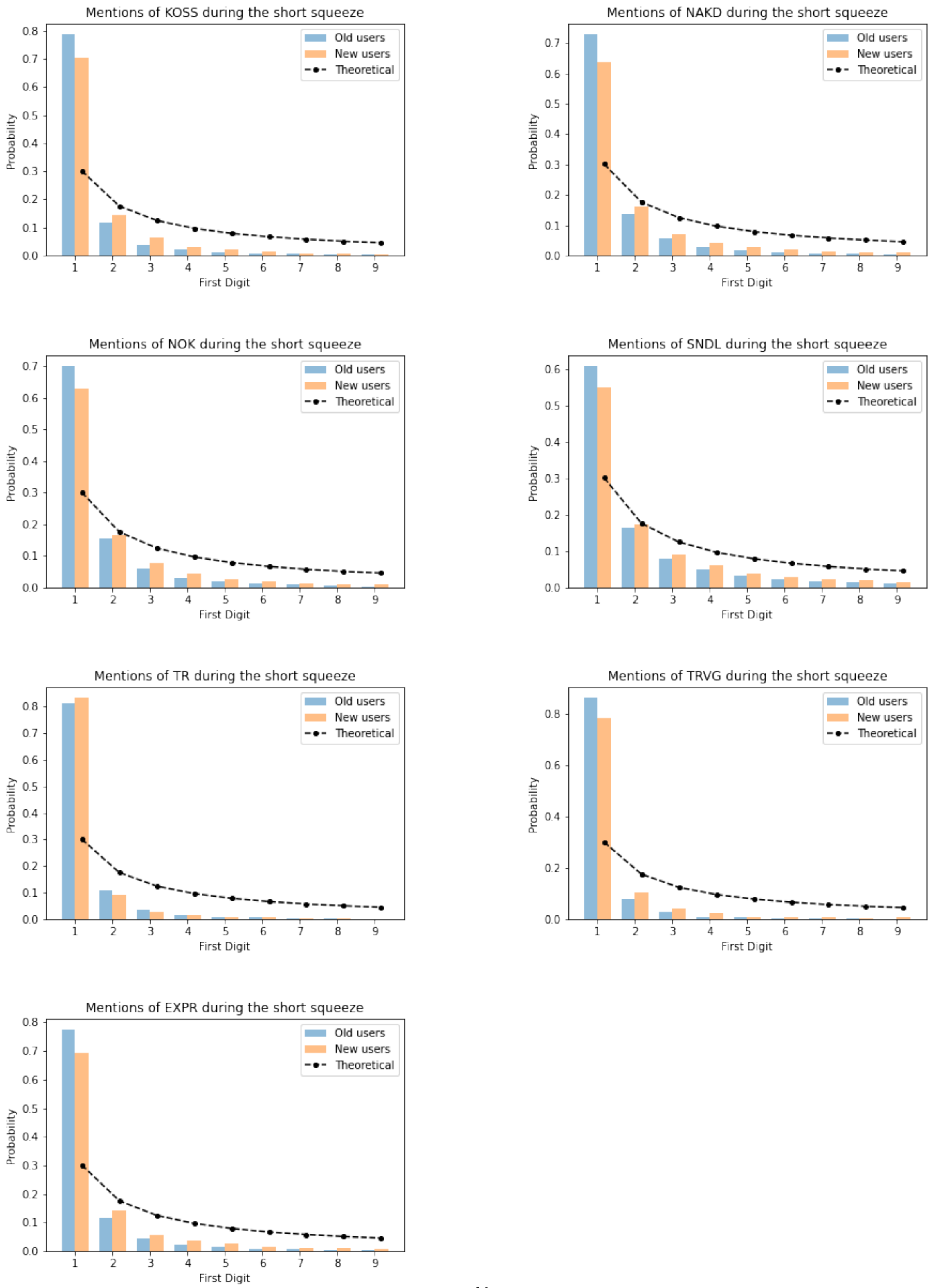


Fig. A7 Hourly posting patterns of social media mentions for the 13 stocks for new and experienced users: Short-squeeze period: This figure shows the hourly posting pattern in NY time for social media mentions for the 13 stocks by social media platform and for just the short-squeeze period. Users are 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.

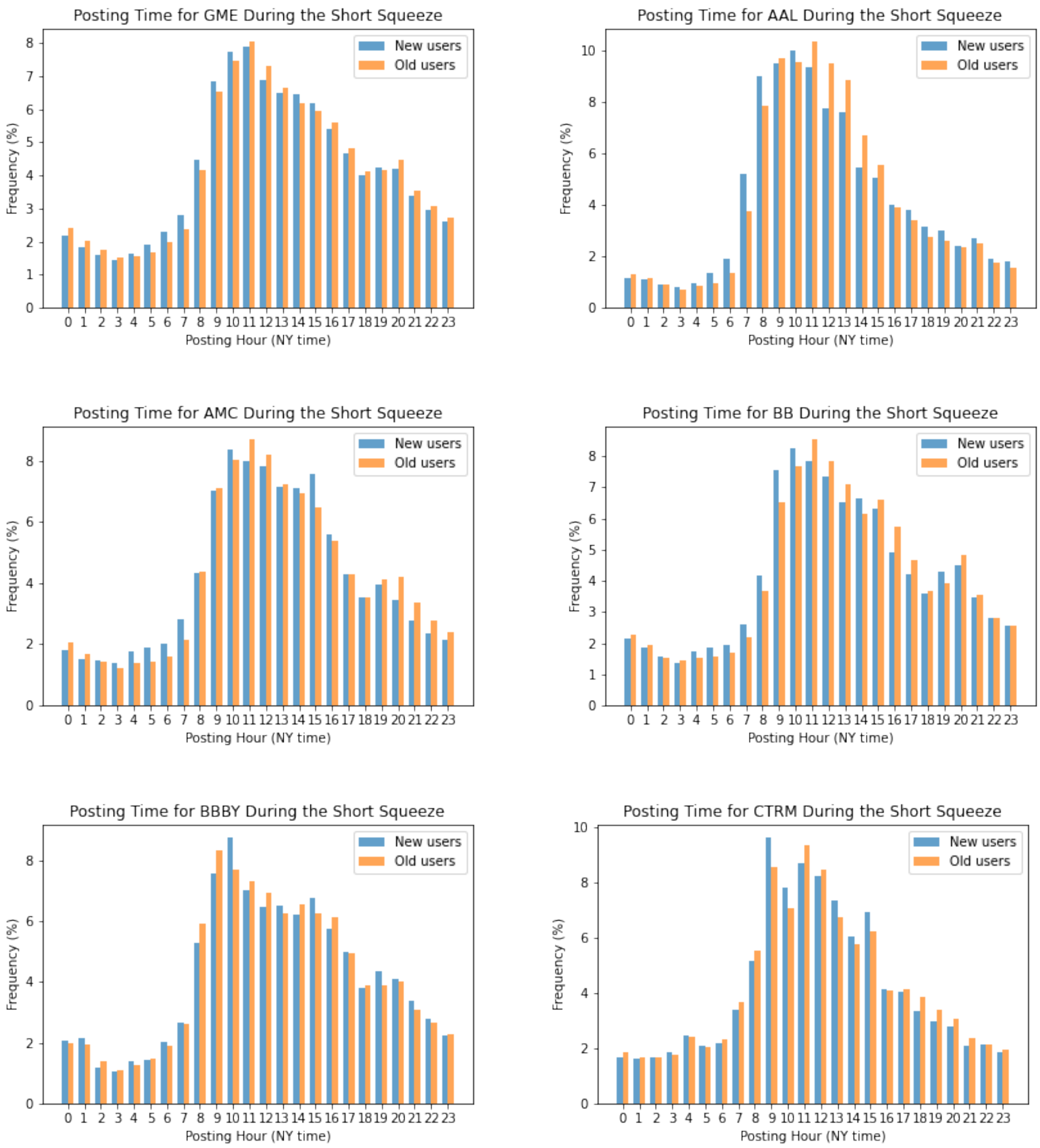
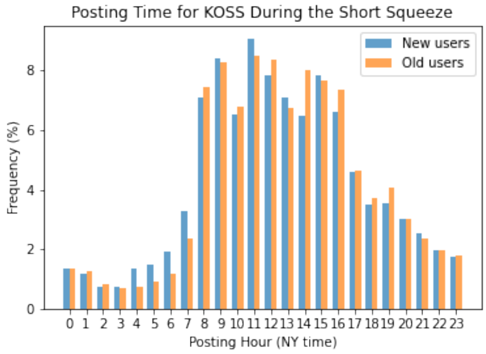
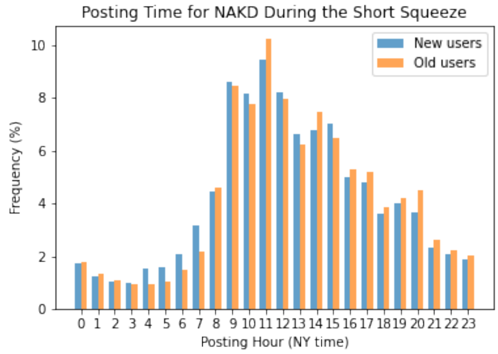
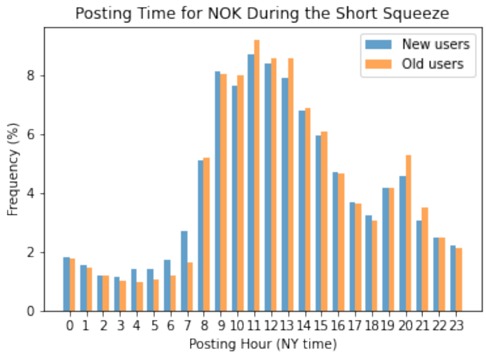
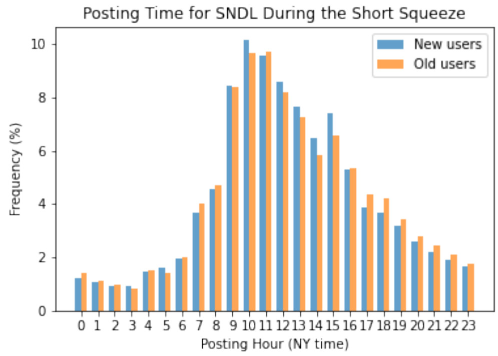


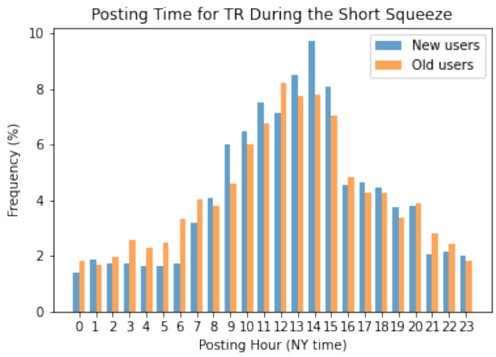
Fig. A8 Hourly posting patterns of social media mentions for the 13 stocks for new and experienced users: Short-squeeze period (cont'd): This figure shows the hourly posting pattern in NY time for social media mentions for the 13 stocks by social media platform and for just the short-squeeze period. 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.

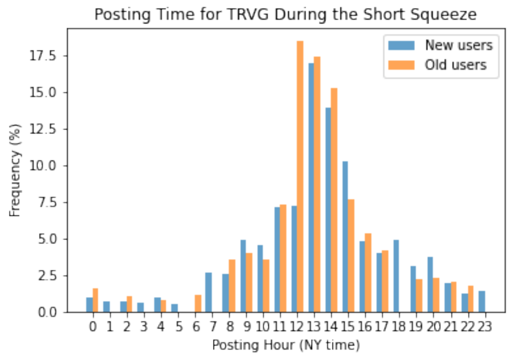


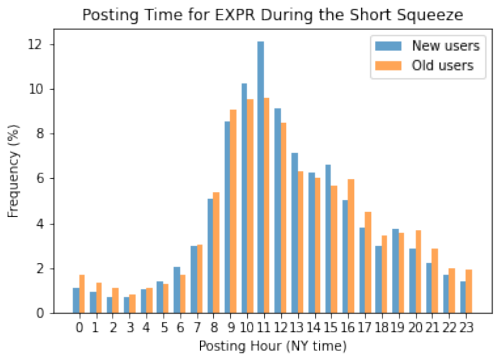












A.10. Price and order imbalance charts.

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.

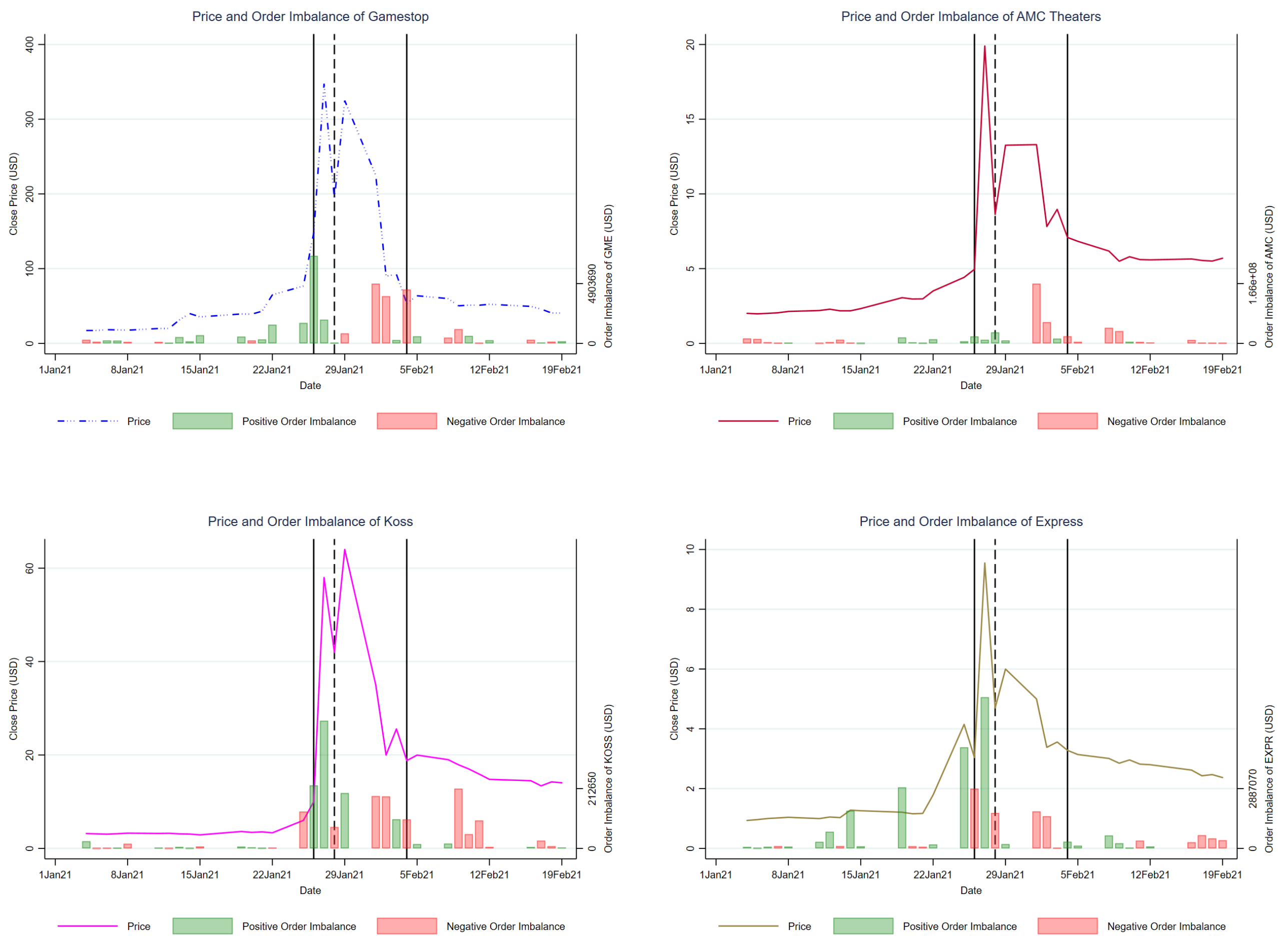


Fig. A10 Evolution of price and order imbalance: January 01, 2021 – February 19, 2021 (cont'd): This figure depicts the evolution of close price (lhs) and the evolution of order imbalances (rhs). The start of the short squeeze is set to January 26, 2021. The end of the short squeeze is set to February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

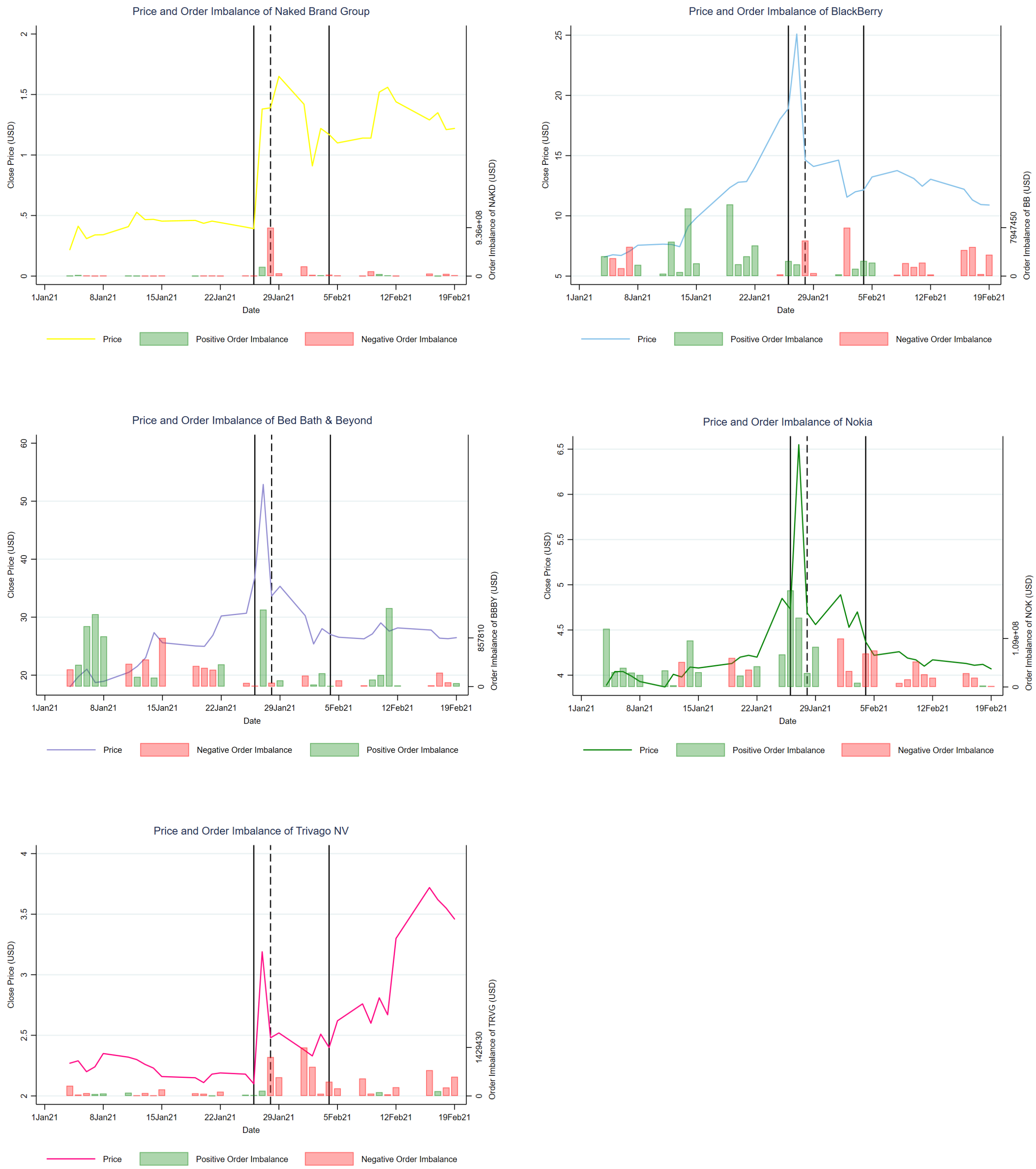
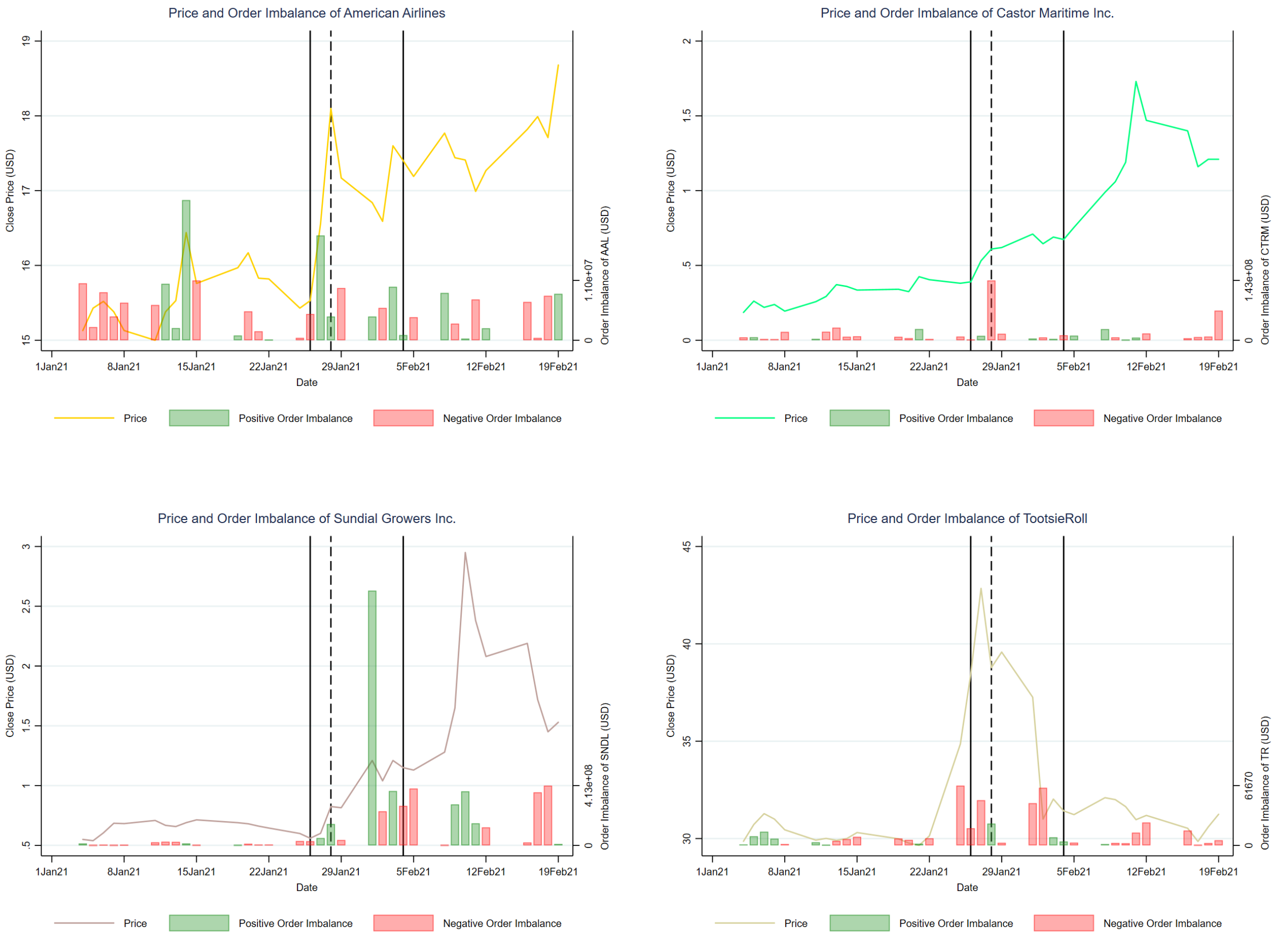


Fig. A11 Evolution of price and order imbalance: January 01, 2021 – February 19, 2021 (cont'd): This figure depicts the evolution of close price (lhs) and the evolution of order imbalances (rhs). The start of the short squeeze is set to January 26, 2021. The end of the short squeeze is set to February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



A.11. 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.

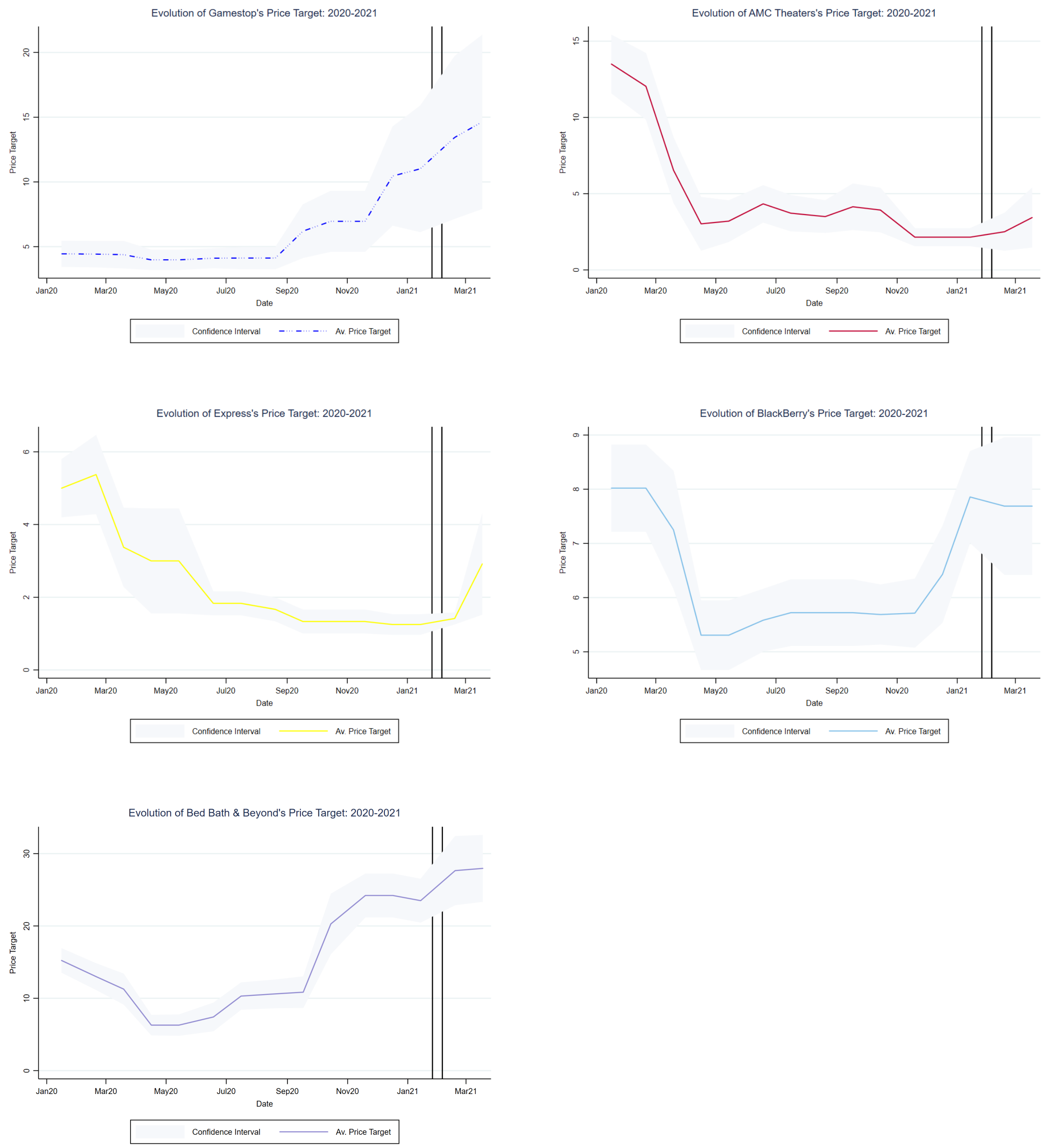
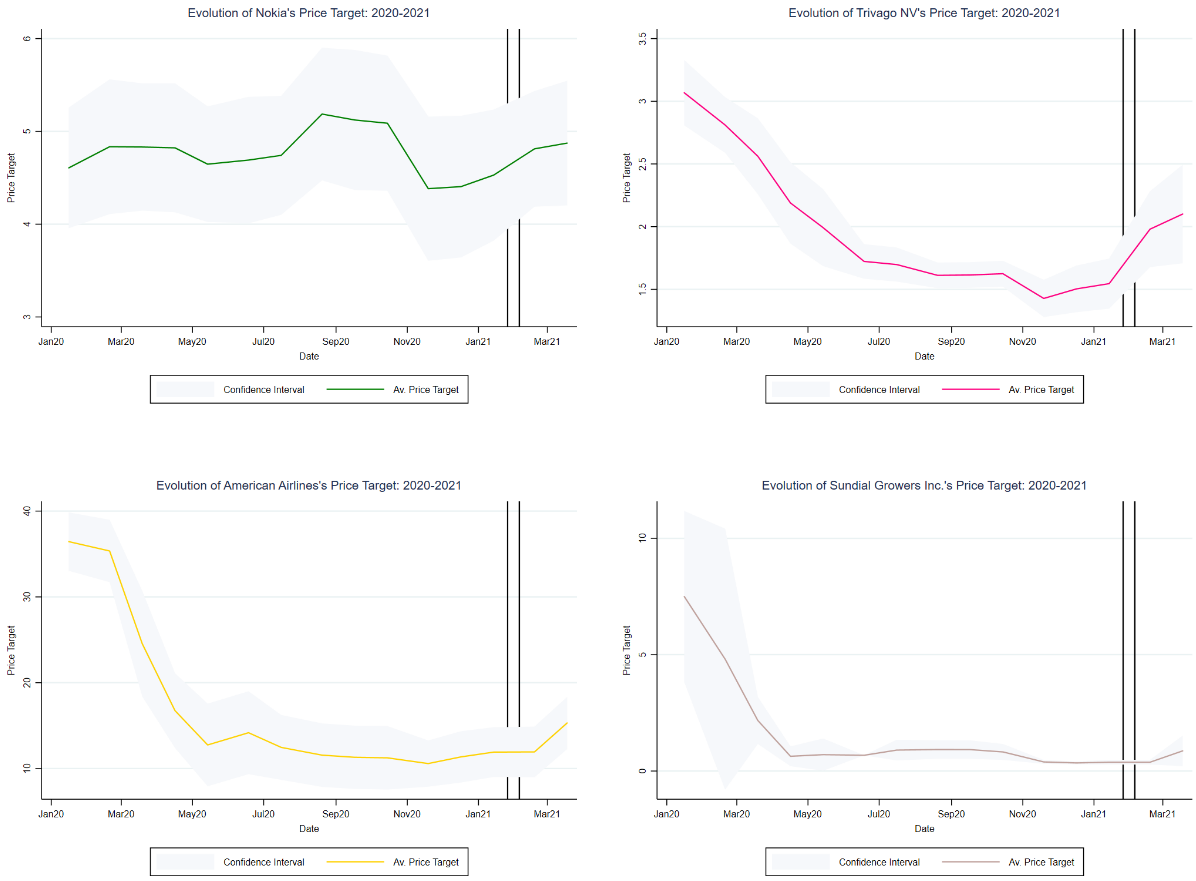


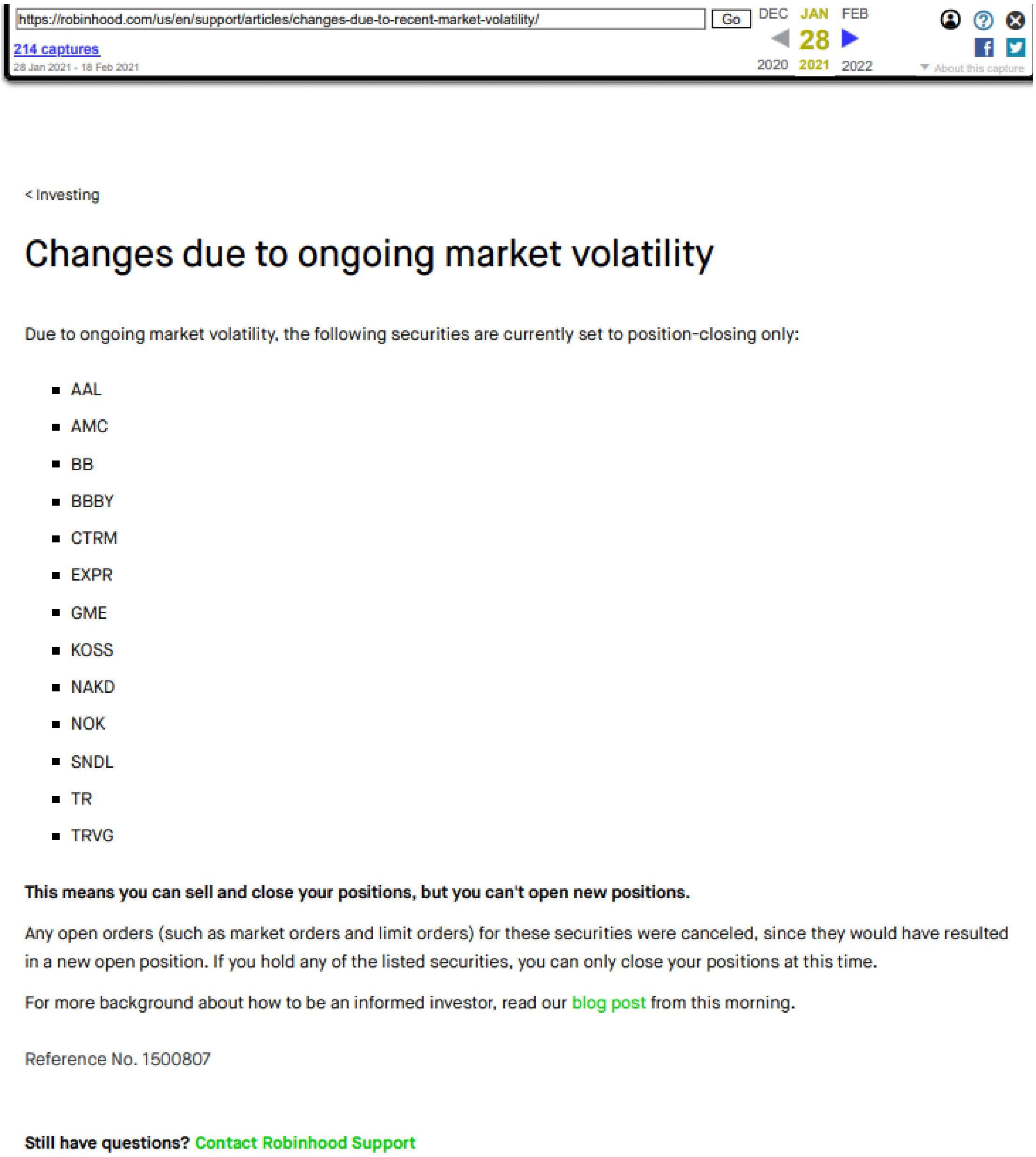
Fig. A13 Evolution of price targets (in USD) for the initially banned stocks (cont'd): January 2020 – March 2021: These figures plot the evolution of monthly average price target estimates of stock analysts. The shaded areas around the average price targets denote 95% confidence intervals. The vertical 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.12. 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 28 2020 2021 2022

214 captures

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.13. 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.

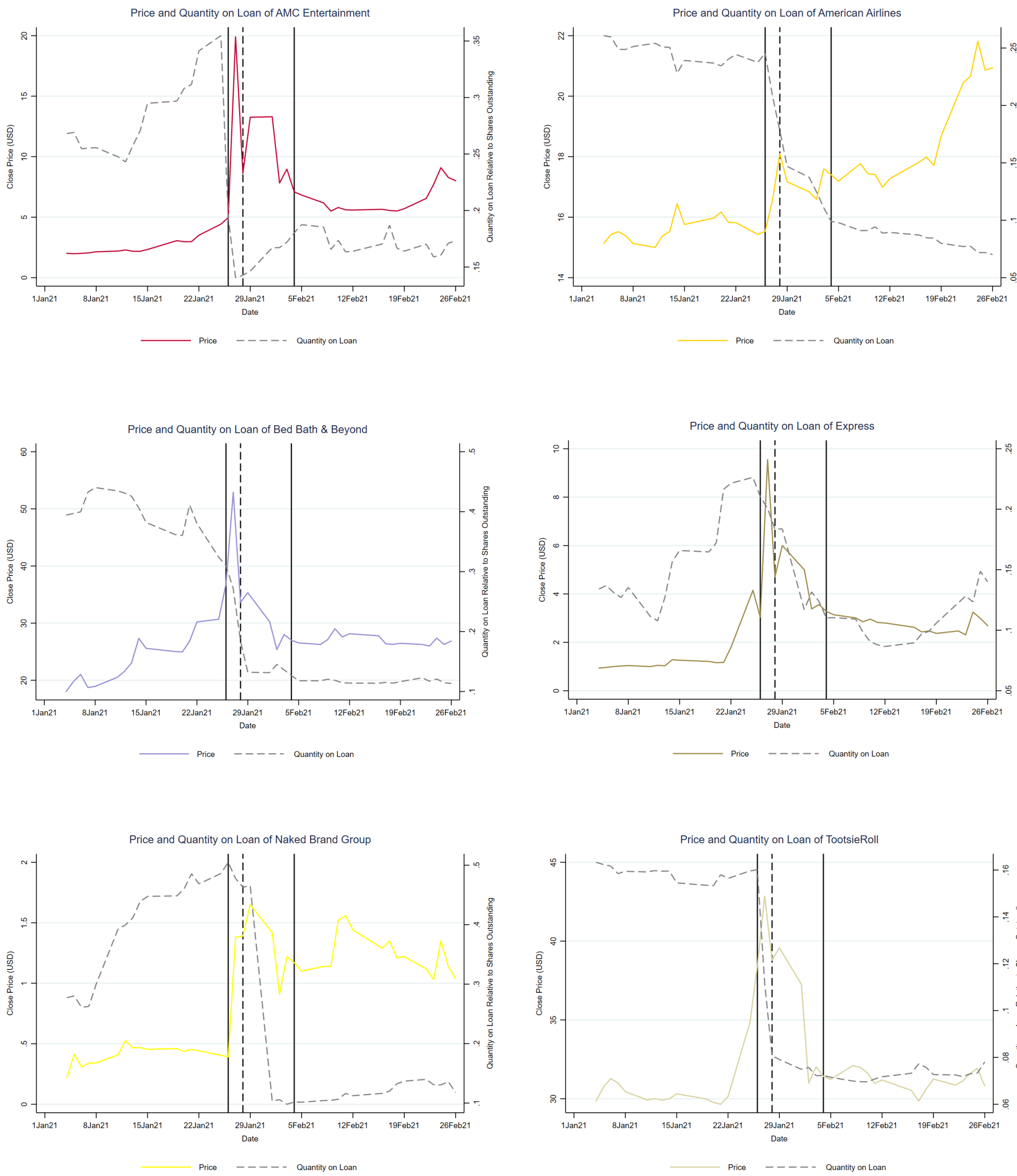
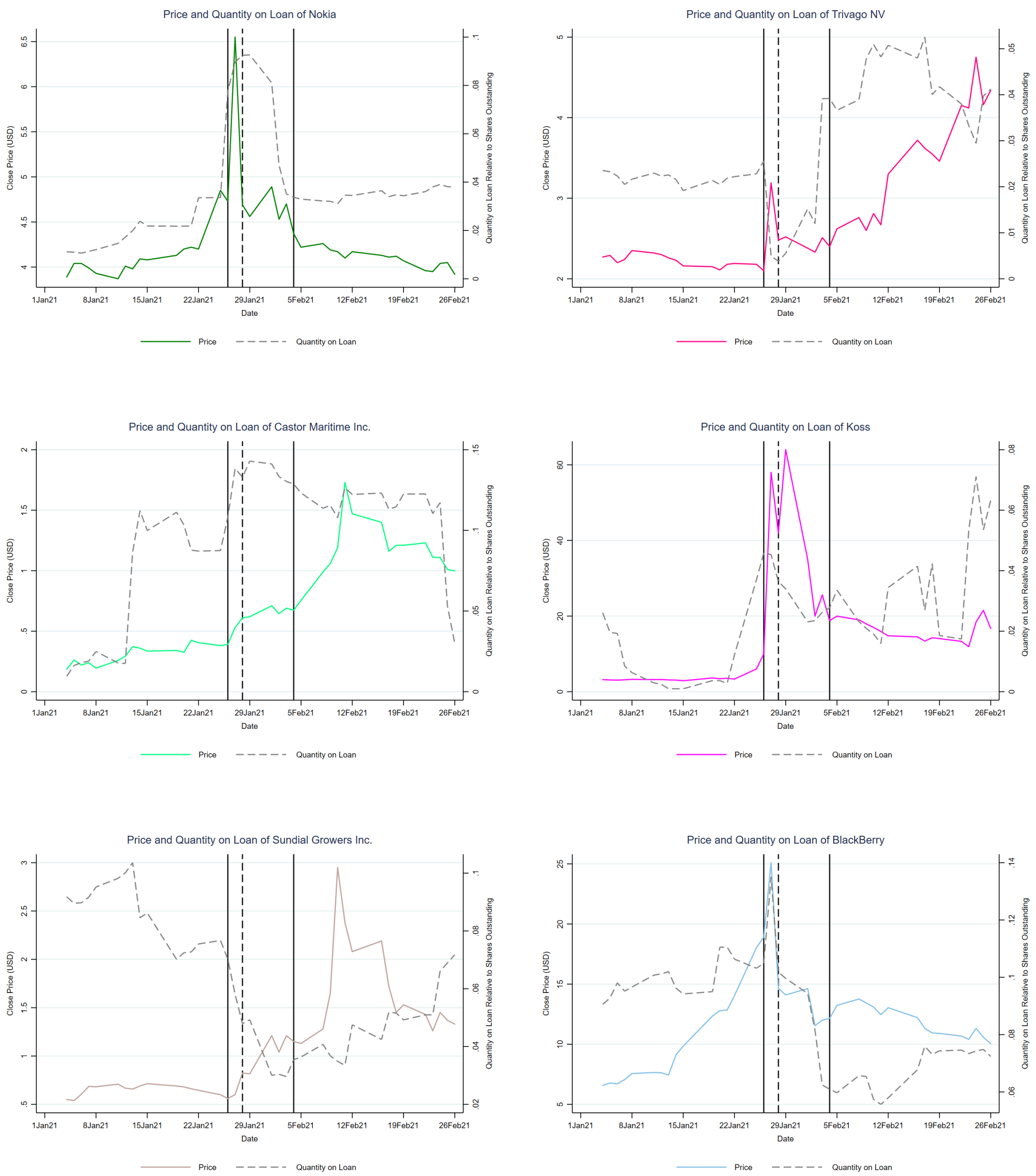


Fig. A16 Evolution of daily Quantity on Loan and Price for the remaining initially banned 12 stocks (cont'd): January 01, 2021 – February 28, 2021: This figure depicts, for each of the stocks, the evolution of the respective closing price (left y-axis) and the evolution of the respective quantity on 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.14. 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.

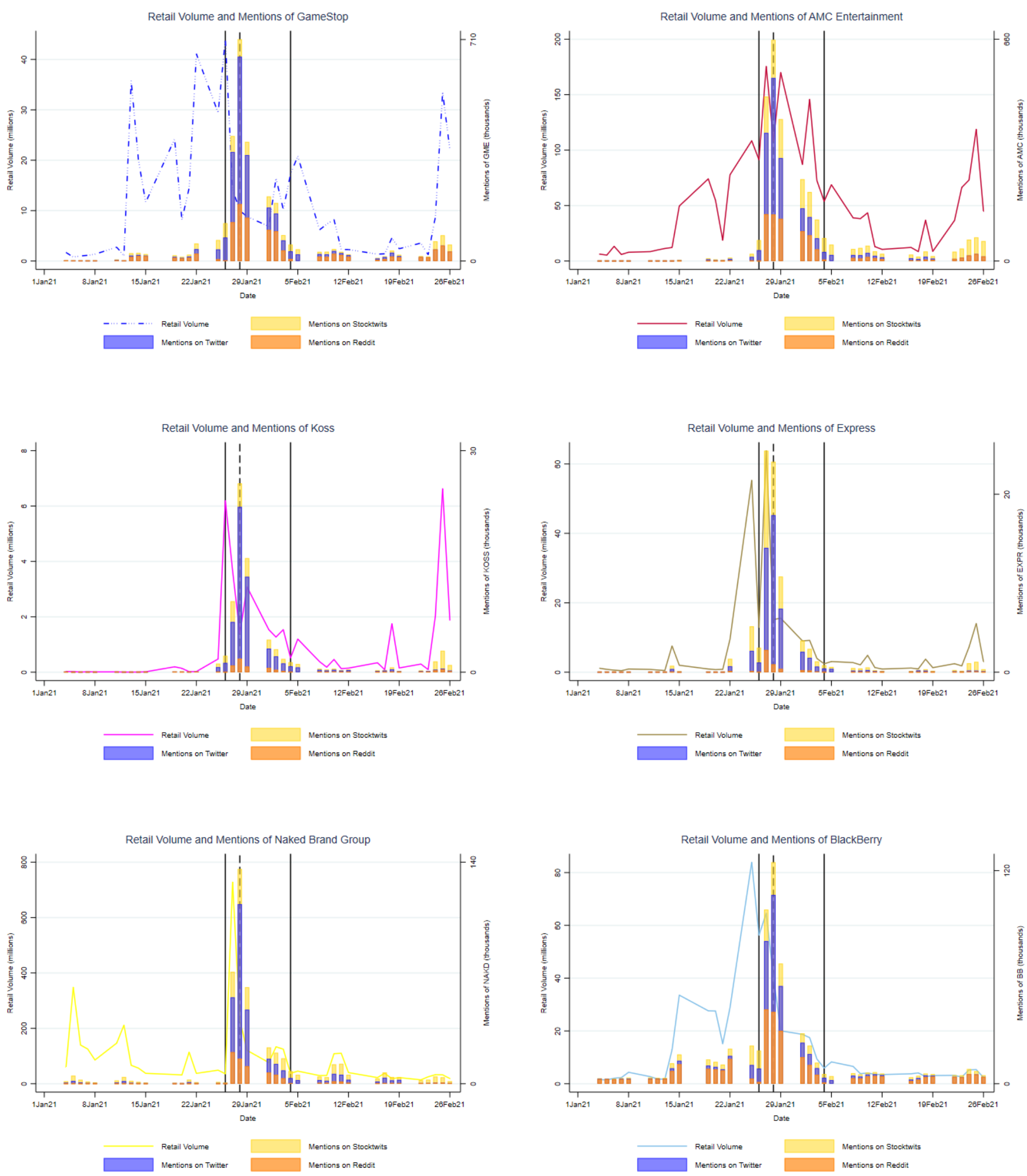
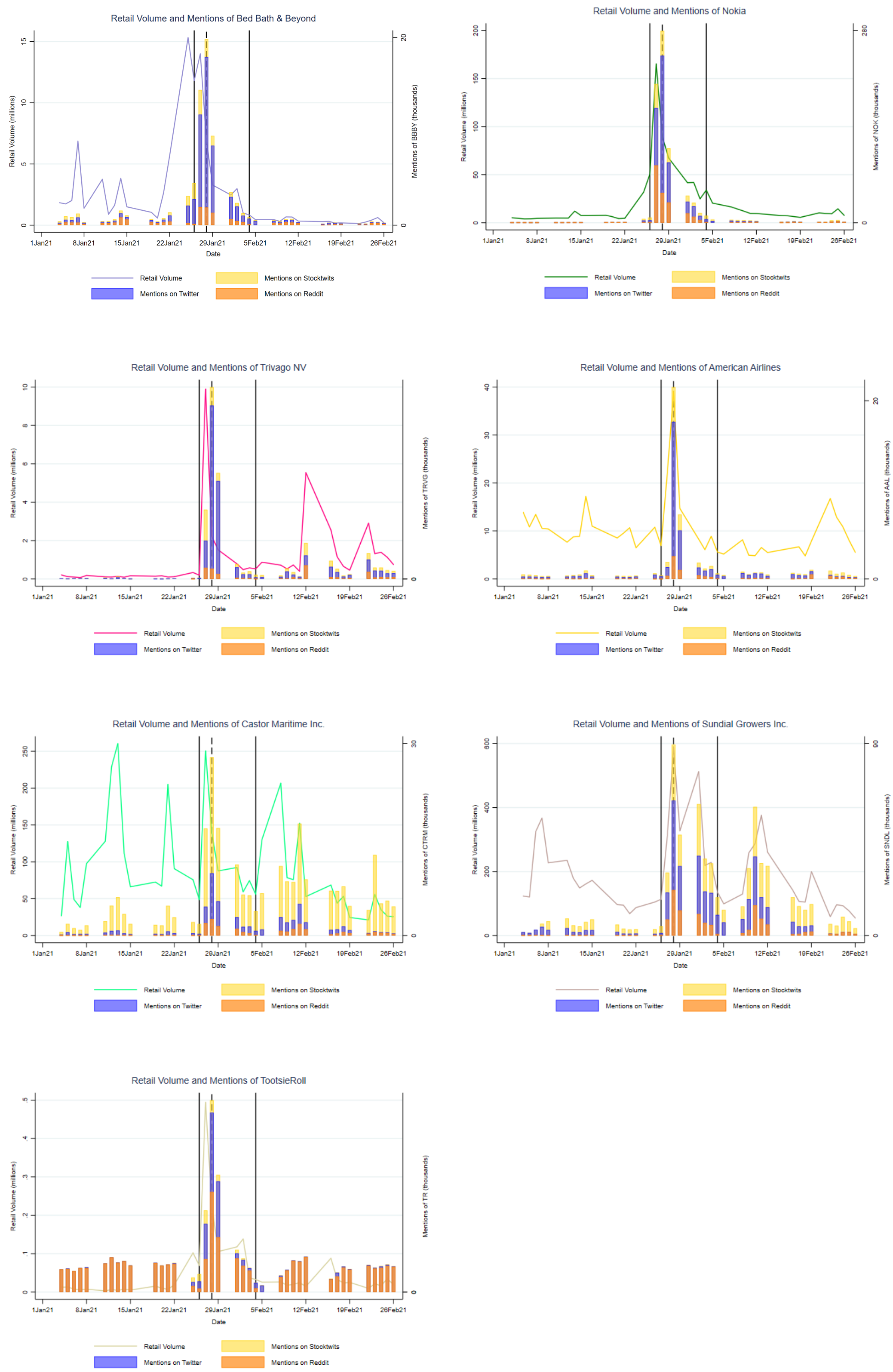


Fig. A18 Evolution of average retail volume and social media activity of squeezed vs non-squeezed (cont'd): January 01, 2021 – February 28, 2021: These graphs depict the evolution of average daily retail volume and average social media activity for the stocks at issue. We note that in the graph for SNDL 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.15. 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 2.2. 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 2.3. 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 2.5. 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 2.5 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 2.5. 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 2.5 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 2.5 and the corresponding section in the paper.

	(1)	(2)	(3)
Panel A	30-second Return	1-minute Return	2-minute Return
SSqueeze	-0.003	-0.035*	-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

	(1)	(2)	(3)
Panel B	30-second Return	1-minute Return	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 2.6. 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 2.5.3.

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.16. 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:

$$\begin{aligned} Y_{i,t} = \alpha &+ \beta_1 SSqueeze + \beta_2 Post\text{-}SSqueeze + \beta_3 mroib_{i,t-1} + \beta_4 Sentiment_{i,t-1} \\ &+ \beta_5 SSqueeze \times mroib_{i,t-1} + \beta_6 SSqueeze \times Sentiment_{i,t-1} \\ &+ \beta_7 Post\text{-}SSqueeze \times mroib_{i,t-1} + \beta_8 Post\text{-}SSqueeze \times Sentiment_{i,t-1} \\ &+ \beta_9 Controls_{i,t-1} + \varepsilon_{i,t}, \end{aligned} \tag{2.9}$$

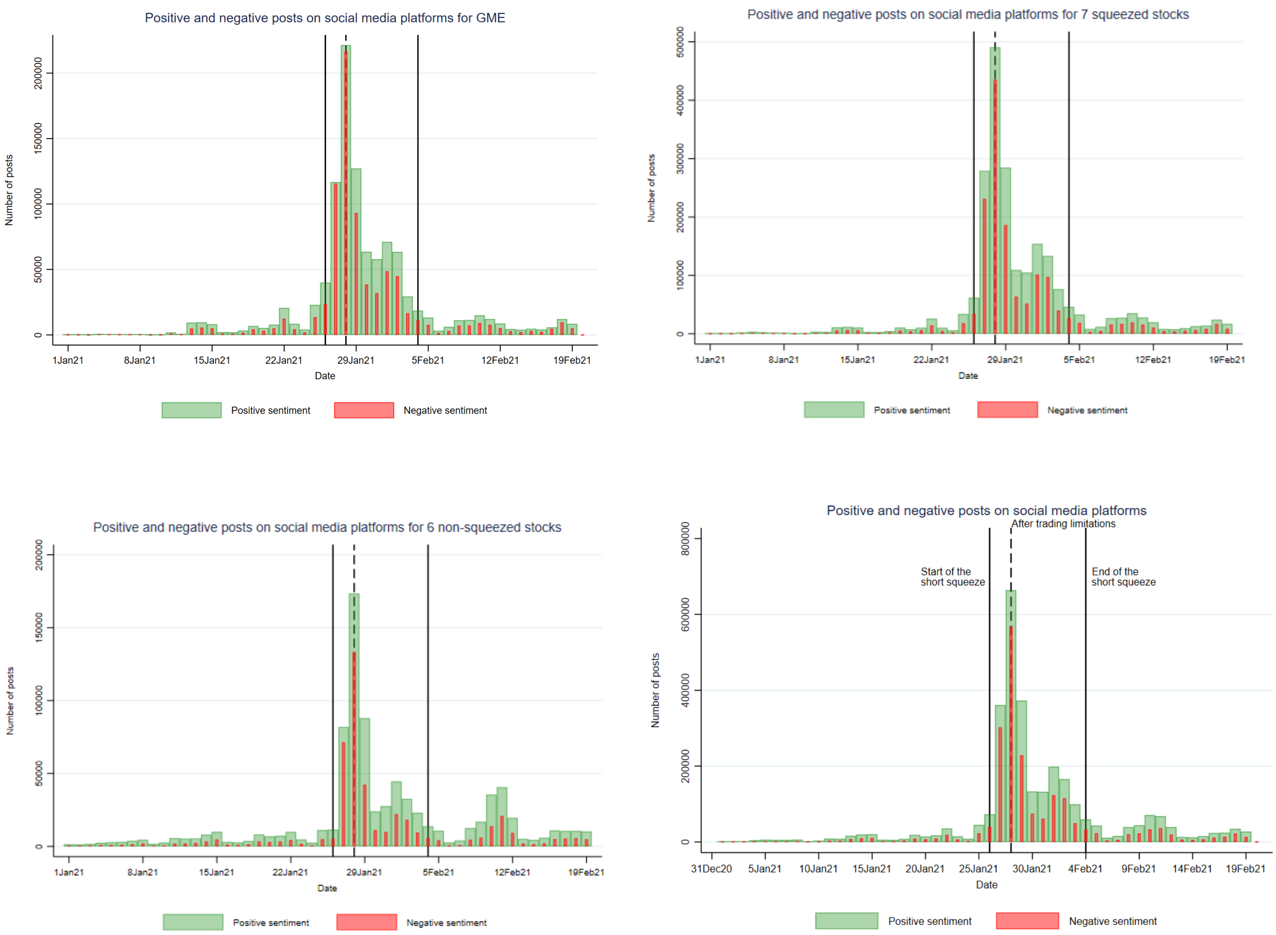
As before, this model is estimated for all of the 13 banned stocks separated into two groups: (i) a group of stocks that experienced short squeezes (the "squeezed stocks") and (ii) a group of stocks that did not experience short squeezes (the "non-squeezed stocks"). We include the sentiment score variable ($Sentiment_{i,t-1}$) as well as its interaction terms with the *SSqueeze* and *Post-SSqueeze* dummies. The remainder of the model specification is identical to Equation 2.3.

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 2.9 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 2.9. 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.

	(1)	(2)	(3)
Panel A	30-second Return	1-minute Return	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

	(1)	(2)	(3)
Panel B	30-second Return	1-minute Return	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 2.3. 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.

Panel A	(1) 30-second Return	(2) 1-minute Return	(3) 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

Panel B	(1) 30-second Return	(2) 1-minute Return	(3) 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.17. 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.

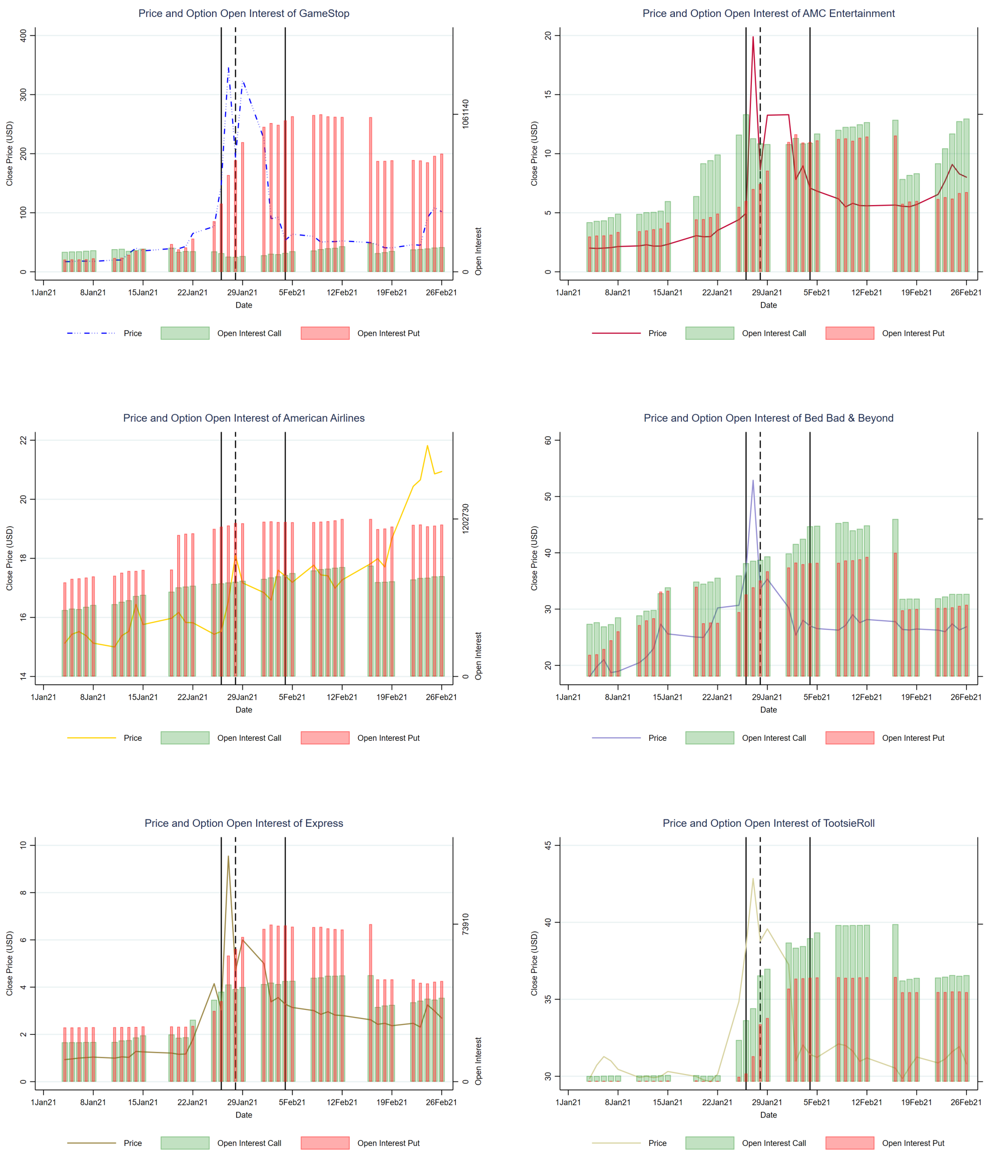
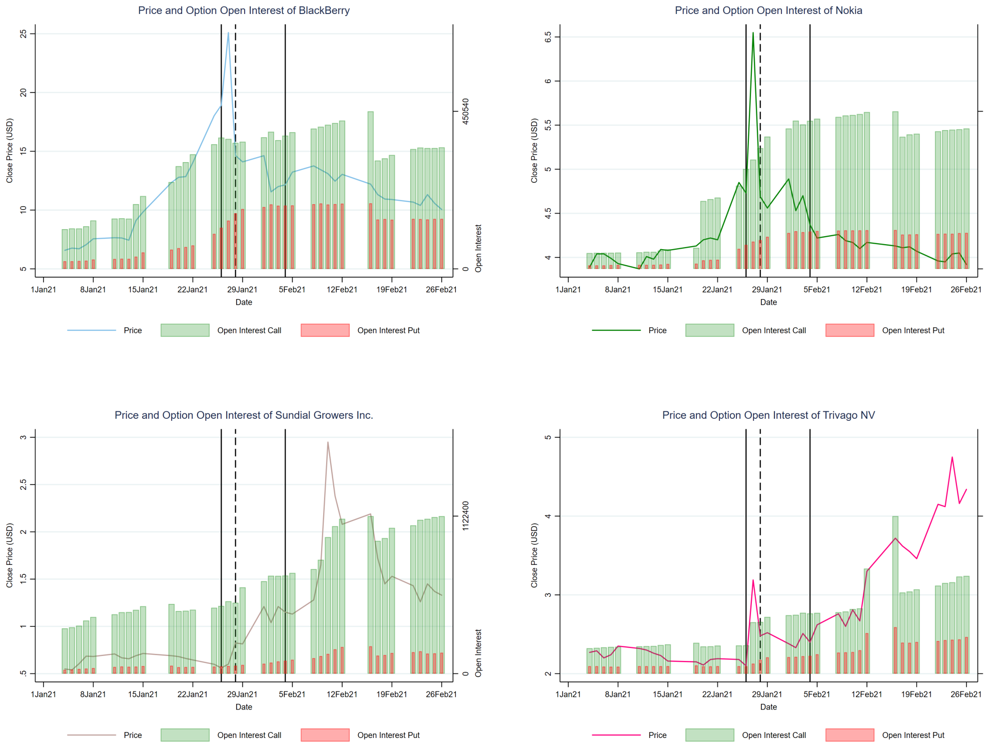


Fig. A21 Evolution of price and open interest (cont'd): This figure depicts the evolution of close price (lhs) and the evolution of open interest separately for call and put options (rhs). The start of the short squeeze is set to January 26, 2021. The end of the short squeeze is set to February 4, 2021.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



A.18. 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:

$$Y_{i,t} = \alpha + \beta_1 SSqueeze + \beta_2 Post\text{-}SSqueeze + \beta_3 Controls_{i,t-1} + \varepsilon_{i,t}, \quad (2.10)$$

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 2.10. 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.19. Additional market quality tests: fully-interacted model.

Table A11 Robustness: Market quality. Fully interacted model:
To provide robustness of the results from Model 2.8 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 2.9. 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

Chapter 3

How Prevalent Are Short Squeezes? Evidence From the US and Europe*

Franklin Allen†, Marlene Haas‡, Matteo Pirovano§, and Angel Tengulov¶

3.1. Introduction

The recent January 2021 short-squeeze events involving among others GameStop and AMC have attracted the attention of academics, investors, and regulators alike. Little is known, however, about the prevalence of short squeezes over time and across industries. The contribution of this article is twofold: First, using a novel proxy for identifying short-squeeze events, we document the time-series evolution and cross-industry dispersion of short squeezes across both the United States (US) and the European Union (EU). Second, we review the extent to which the academic literature has studied short squeezes and provide directions for future research. To put our findings into context, we also summarize the relevant regulatory regimes in the US and the EU.

There are several factors that represent risks to short sellers and that can contribute to the development of a short squeeze. First, the price can move adversely to the short seller's position, i.e., the price can increase resulting in a loss for the short seller. Theoretically, asset prices can increase to infinity, which implies that short-selling strategies have an unlimited loss potential. As a result, there is a risk of additional collateral requirements and related margin calls following such a price increase.[1] Second, the borrower can experience a recall of the shares by

*The views expressed in this article are solely those of the authors, who are responsible for the content, and do not represent the views of our employers. Any remaining errors are our own.

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[1]Collateral is usually set at 102%, meaning, when the borrower sells the securities short 100% of the proceeds have to be posted to the lender as collateral plus an additional 2%. 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

the lender. For example, if the price of the underlying security increases, lenders might decide to close their positions in order to realize the gains. To do so lenders have to recall the shares in order to sell them.[2] The materialization of any of these risks does not necessarily imply that a short squeeze is underway. Instead, a necessary condition for a short squeeze is the existence of relatively high short interest before a potential short-squeeze event. If then one of these risks materializes (e.g., a sharp price increase or a recall by the lender, or both) and short sellers find it difficult to acquire the securities they need to cover their short position because of a shortage of floating supply, the price of the asset rises as a result even further and a short squeeze has occurred.

We incorporate this logic into our empirical analyses. Our starting point are the proxies of lender short squeezes developed by Schultz (2023). In particular, Schultz (2023) proposes measures that identify if borrowed shares are recalled by the lender. However, as outlined above, short squeezes can also occur if prices increase drastically and, as a result, short sellers have to cover their positions.[3] We call such a short-squeeze event a "market squeeze" and propose a new measure that allows us to capture this type of event. This measure can be applied to all types of financial markets including equity, commodities, and bond markets. The development of this measure was motivated by historical short-squeeze events described in the extant empirical literature on the topic, such as the January 2021 squeezes and the 2008 Volkswagen (VW) squeeze (see e.g., Allen, Haas, Nowak, Pirovano, and Tengulov (2023) and Allen, Haas, Nowak, and Tengulov (2021)).

Specifically, the measure is a dummy variable that equals one when the following conditions are met for stock i on day t: (i) there is a pronounced positive return on day t, i.e., the daily stock return for stock i on day t falls within the 95^{th} percentile of the distribution of daily returns of companies within the same industry; (ii) there is a pronounced decrease on day t in quantity on loan, i.e., the daily decrease in quantity on loan for stock i on day t falls within the 95^{th} percentile of the distribution of decreases of quantity on loan of companies within the same industry; and (iii) on the day before event day t the stock has relatively high quantity on loan, i.e., quantity on loan for stock i on day $t-1$ falls within the 95^{th} percentile of quantity on loan of companies within the same industry. The January 27, 2021 AMC squeeze event provides an example. On January 26, 2021 there were 55,808,128 shares on loan or 34% relative to shares outstanding. This places AMC on that day in the 95^{th} percentile of quantity on loan of companies in the same industry. The next day, the company experienced a pronounced positive return of 301%, which places AMC on that day in the 95^{th} percentile

receives a margin call and is required to deposit additional funds.

[2]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. While an increase in the borrowing rate makes short selling less profitable, it does not result in an immediate need to close a position.

[3]According to the U.S. Securities and Exchange Commission (SEC), a short squeeze is created when there is "pressure on short sellers to cover their positions as a result of sharp price increases or difficulty in borrowing the security the sellers are short." "Key Points About Regulation SHO," SEC, available at https://www.sec.gov/investor/pubs/regsho.htm.

of daily returns of companies in the same industry. Concurrent with this price increase we observe a pronounced decrease in quantity on loan. Specifically, on January 27, 2021 quantity on loan fell to 40,390,072 or 24.5% relative to shares outstanding. This is an absolute decrease of 9.5% in short interest and places AMC in the 95^{th} percentile of the distribution of decreases of quantity on loan of companies within the same industry. In other words, there was a market squeeze because short sellers were likely forced to repurchase about 15,418,056 shares due to rising prices and increased margin calls. Further, we note that on January 27, 2021 AMC's shares available to borrow increased from the previous day, which indicates that there was no lender squeeze but only a market squeeze on that day.[4] For our empirical analyses, we not only present evidence for market squeezes and lender squeezes separately, but we also combine the two proxies into one short-squeeze measure. In particular, we define that a stock i has experienced a short squeeze on day t if either a market squeeze or a lender squeeze (or both) has occurred.

First, we examine the occurrence of short-squeeze events on a stock-day level. For the US market, we find evidence of a market squeeze and a lender squeeze in 0.14% and 0.83% of the stock-day observations, respectively. In other words, in about 99% of the stock-day observations we do not find evidence of a short squeeze. The proportion of days with a short-squeeze event in the EU is lower. Specifically, for the EU market we find evidence of a market squeeze and a lender squeeze in 0.27% and 0.17% of the stock-day observations, respectively. This evidence suggests that stock-day short-squeeze events of both types, market squeeze and lender squeeze, are rare across the US and the EU. We also find very little overlap between the market squeeze and the lender squeeze events for both geographic markets. This implies that our market squeeze proxy provides additional information and is complementary to the lender squeeze proxy developed by Schultz (2023).

Next, we examine the duration of short-squeeze events. We measure duration as the number of consecutive days with short-squeeze events for a particular stock. We find that short-squeeze events are short-lived. Specifically, more than 90% of the market and more than 70% of lender short-squeeze events across both the US and the EU do not last longer than one day. The longest duration we observe for market and lender short-squeeze events is 8 and 35 days, respectively.

Finally, we examine the time-series evolution and cross-industry dispersion of the number and proportion of unique stocks experiencing a short squeeze in a give year. For the US market we find that the annual average of stocks that experience a market squeeze or a lender squeeze is 302 (6.6%) and 860 (18.9%), respectively. While the first six years of our sample period do not show a clear trend in the number of unique stocks experiencing short squeezes, there is a clear uptick over the period from 2012 through 2018 with a peak in 2018. When examining the evidence across different industries in the US, we find that short squeezes are more frequently experienced by companies in the energy sector (coal and mining stocks) as well as the trans-

[4]Our market squeeze proxy successfully identifies the meme-stocks short squeeze events analyzed in detail in Allen et al. (2023).

portation and tobacco industries. For the EU market, we find that the annual average of unique firms that experience a market squeeze or a lender squeeze is 187 (11.4%) and 236 (13.9%), respectively. We do not find a clear trend in the number of unique stocks experiencing short squeezes. When examining the evidence across different industries, we find that short squeezes are more frequent in the tobacco and coal industries.

Providing international evidence about the prevalence of short squeezes is important for at least two reasons. First, while short squeezes did occur with some frequency historically (see e.g., Allen, Litov, and Mei (2006)) extreme examples such as the January 2021 events are almost unknown in recent times. The reason is that behavior precipitating short squeezes is illegal in most countries, which in turn helps to ensure capital market efficiency.[5] The latter relies to a large extent on the principle of arbitrage. If the price of an asset is too low relative to its discounted future cash flows then 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 squeezes and corners. In a squeeze, short sellers find it difficult to acquire the securities they need to cover their short position because of a shortage of floating supply and the price rises as a result. A corner is an extreme form of short squeeze, when the buy side has almost complete control of all floating shares. The January 2021 meme-stock short squeezes have been damaging to market efficiency (Allen et al. (2023)), therefore it is important to document the time-series evolution and cross-industry dispersion of short squeezes.

Second, this evidence is important for regulatory reasons. In particular, the US SEC has proposed a new short-selling regulation that is intended to provide greater transparency through the publication of short-selling information. The regulatory proposal is somewhat similar to the short-sale disclosure requirements that the EU implemented in 2012. One of the goals of this US regulation is to allow the SEC and other regulators to more quickly identify potential short-squeeze events. At the same time, one concern related to the proposed regulation is that disclosing more short-sale information may also increase the risk of short squeezes. Our data sample covers the period 2006 – 2021, i.e., a period before the EU implemented short-sale disclosure requirements and the period after. We do not find an increase in the short-squeeze frequency in the EU in the period after compared to before. This evidence might help inform US regulators by mitigating the concern that short squeezes might become more prevalent once the new short-sale disclosure requirements are implemented, as shown in the case of Europe.

The remainder of this article is organized as follows. In Section 3.2, we review the existing literature that has analyzed short squeezes. In Section 3.3, we explain the current regulatory short selling regimes in the EU and the US as well as the SEC's short selling disclosure proposal. In Section 3.4, we describe our proxy for market short squeezes and analyze these as well as lender short squeezes empirically for the US and the EU. In Section 3.5, we conclude.

[5] For an extensive discussion on the broader topic of manipulation and fraud in financial markets see Alexander and Cumming (2022).

3.2. Literature

While early literature on short squeezes focuses on either theoretical issues or empirical findings in the commodity, bond, and derivative markets, recent studies have branched out to examine squeezes and corners in equity markets.

Kyle (1984) shows, in the context of commodity futures markets, how short squeezes can arise even though all traders are fully rational. In his model the trading process is anonymous and a large trader, that possesses information about the trading of hedgers, can accumulate a large position to engineer a successful squeeze. This squeeze risk leads to increased hedging costs, reduction in the amount of hedging, and ultimately to misallocation of risk in the economy. 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. They conclude that manipulation has welfare implications since it hurts futures noise traders, but benefits spot noise traders and informed traders through increased spot liquidity. Jarrow (1992) theoretically examines market manipulation trading strategies, such as squeezes, by large traders in a securities market. He defines a large trader as any investor whose trades change prices. In his model, the manipulation strategies lead to price destabilization and a rational bubble in a finite horizon economy. Pirrong (1993) analyzes the delivery process in commodity futures markets and argues that increased marginal cost of delivery (e.g., transportation costs) allows the holder of a large long futures position to manipulate the market profitably. As a result, the liquidity and depth of the futures market are impaired prior to the delivery period. Cooper and Donaldson (1998) develop a model of a commodities futures market that allows to analyze the price dynamics of equilibrium trading strategies when prices can be manipulated by a corner or a squeeze. Their model accounts for the volatility in asset prices and price bubbles. They provide regulatory recommendations to prevent corners and squeezes, such as replacing delivery with cash settlement, decreasing individual position size, and imposing punitive costs on those who exercise corner power. Pirrong (2001) argues that the choice of settlement mechanism in futures markets depends on whether supply and demand conditions favor short or long manipulations. In his model it is always possible to design a delivery-settled futures contract that is less prone to cornering by a large long than a cash-settled contract. Therefore, cash settlement does not uniformly dominate delivery settlement as a means of reducing the frequency of market power manipulations in derivatives markets. Ben-Abdallah and Breton (2016) examine the CBOT T-bonds futures market for evidence of short squeezes. They concentrate on the period 1985 to 2014 and argue that low levels of interest rates and the composition of the delivery basket in this market represent very favorable conditions to the occurrence of short squeezes. The authors argue that a market squeeze leads to significant distortions in the behavior of futures prices. They also suggest ways to reduce the potential of market manipulation in this market, e.g., through reduction in the notional coupon level.

Researchers have also examined the market for Treasury securities. Jegadeesh (1993) examines the secondary market prices of notes issued in the May 1991 auction in which Salomon Brothers admitted to having violated auction regulations. The author provides evidence of a squeeze and argues that the price manipulation could potentially have an adverse effect on bond market liquidity. To deter potential squeezes the paper suggests standardizing the bond issues. Nyborg and Sundaresan (1996) analyze transaction data from Garban, one of the major interdealer brokers in the U.S. Treasury market at the time, in order to compare and contrast Treasury's uniform auctions as a mechanism to deter short squeezes. They provide evidence that uniform auctions increase pre-auction information and lower the short squeeze. Nyborg and Strebulaev (2004) analyze secondary market trading and the impact of potential short squeezes on bidding strategies. They discuss two types of auctions frequently used in practice, discriminatory and uniform auctions, and argue that discriminatory auctions lead to higher revenue than uniform auctions, but this revenue advantage comes at the cost of a higher incidence of short squeezes and consequently a more volatile secondary market. They argue that to alleviate a short squeeze one may attempt to release additional stock to the market and that uniform auctions might be beneficial. Merrick Jr, Naik, and Yadav (2005) investigate the strategic trading behavior, price distortion, and learning in a market manipulation setting of an attempted delivery squeeze in the long-term government bond futures contract traded in London. They estimate the profits of strategic traders during different phases of the squeeze and show that market prices and market depth were distorted. Their results suggest that the differences in the penalties for settlement failures in cash and futures markets create conditions that favor squeezes.

Recent studies have also examined short squeezes in the equity market. Brunnermeier and Pedersen (2005) present a theoretical model for "predatory trading,", i.e., when investors purposefully trade in the same direction as a large trader who has to liquidate a position, e.g., a short-seller that has to cover a position due to increasing prices or recalled shares (i.e., a "short squeeze"). They argue that this type of trading would withdraw liquidity from the market instead of providing it to the large trader, thereby making it more costly for the large trader to liquidate the position. Allen, Litov, and Mei (2006) present a model of squeezes and corners, in which squeezes can be the result of rational behavior. They argue that the possibility of a squeeze or a corner means that arbitrageurs might stay out of the market and, as a result, prices will not reflect values well, or arbitrageurs will only engage in a short position when the prospects of profits are high. In their setting, the presence of large investors makes it very risky for short sellers to engage in arbitrage. Using hand-collected data from the New York Times and Wall Street Journal from 1863–1980 they empirically investigate several well-known stock market and commodity corners and argue that large investors and corporate insiders possess market power that allows them to manipulate market prices. They show that market corners tend to increase market volatility and could have an adverse impact on other assets.[6] Lamont (2012) document that in order to hinder short selling in their own stock firms use various actions such as legal threats, investigations, lawsuits, and numerous technical actions intended to create a short squeeze. This, in turn, creates short sale constraints and might have contributed to the overall low short interest among large firms (see also D'Avolio (2002) for a discussion on the topic of low short interest among large firms). Riccò (2019) describes the dynamics of trade-based manipulation in the context of events surrounding the companies New Concept Energy and Avalon Holdings. In particular, he argues that during the summer of 2018 short squeezes developed in both companies. He further investigates the trading behavior of the alleged manipulator and the corresponding market impact. Allen, Haas, Nowak, and Tengulov (2021) describe the Porsche-VW short squeeze in 2008 as an example of the problems to which a lack of regulatory enforcement of securities laws in Europe can lead to. Using a unique hand-collected dataset from criminal proceedings against Porsche and its executives, the authors were able to reconstruct how Porsche managed to create one of the largest short squeezes in history and show that it significantly impeded market efficiency. The authors argue that preventing manipulation is important because without efficient securities markets, the EU's major project of the Capital Markets Union cannot be successful. Schultz (2023) examines recall risk and proposes an empirical proxy for lender short squeezes triggered by recalled share loans. He argues that for most stocks, the probability of a lender short squeeze is very low, however, hard-to-borrow stocks do experience lender short squeezes more frequently. Stice-Lawrence, Wong, and Zhao (2023) study public disclosures of negative information by short sellers. They find that many of the targeted firms initially experience positive returns that are likely to reverse. These reversals are concurrent with increased short covering, which the authors interpret as evidence consistent with short squeezes. Allen, Haas, Nowak, Pirovano, and Tengulov (2023) examine the January 2021 meme stock events. They provide evidence of short squeezes in some of the stocks at issue and argue that a major driver of these events was retail trading and coordination of investors on social media platforms. Further, the authors show that the short squeezes distorted market quality not only for the stocks at issue but also their product market competitors.

3.3. Regulatory Background

According to US regulators, in "recent years, market volatility associated with short selling has brought heightened attention to the difference in long and short position reporting requirements, and, more generally, the lack of transparency into the circumstances surrounding short

[6] More generally, impeding short selling can have an adverse impact on overall market quality, as short sellers provide many external benefits, such as uncovering misconduct and keeping prices closer to fundamental values (see, e.g., Karpoff and Lou (2010).)

sale transaction."[7] Contrary to the EU, US short selling regulation has not included any disclosure requirements. The US SEC is looking to change that. They have proposed a new rule pursuant to the Securities Exchange Act of 1934 that is "designed to provide greater transparency through the publication of short sale related data to investors and other market participants. Under the rule, institutional investment managers that meet or exceed a specified reporting threshold would be required to report, on a monthly basis using the proposed form, specified short position data and short activity data for equity securities."[8] While generally the SEC thinks that this disclosure requirement "may promote greater risk management [. . .] and may facilitate capital formation," its hope is that this "activity information will allow the [SEC] and other regulators to more quickly identify a potential 'short squeeze,' [. . .] and could perform further analysis regarding the squeeze. Increased risk of detection may deter some market participants seeking to orchestrate a short squeeze."[9] On the other hand, the SEC is aware that this type of information disclosure "may also increase the risk of short squeezes or other retaliatory actions in the case where there were very few reporters of Proposed Form SHO."[10] The EU's short selling regulatory design on the other hand already includes a disclosure requirement. In fact, the SEC is open to crafting its proposal to be "consistent with European disclosure requirements."[11] This difference between the US and the EU short sale regulations is not the only one. However, it has historically been thought of as a significant measure in a regulator's enforcement toolbox.[12] Below, we review key aspects of the regulatory frameworks governing short selling and manipulative short squeezes in the EU and the US.

3.3.1. US Regulation

Short sales are currently regulated under Regulation SHO, which took effect on January 3, 2005. It imposes four requirements to the short-selling market: (1) It requires broker-dealers to mark sale orders as "long," "short," or "short exempt;" (2) it requires broker-dealers, before effecting a short sale, to locate a source of shares for timely delivery on the day that delivery of shares is due; (3) it requires broker-dealers to close out failures to deliver that result from long or short sales; (4) and Regulation SHO imposes a short sale price test circuit breaker that is triggered if a price decline of at least 10 percent in one day is observed in a stock.[13] In addition, the SEC adopted Rule 10b-21 to address failures to deliver in securities that have been associated with "naked" short selling.[14]

Under the Dodd-Frank Act (DFA), the SEC has been required to adopt rules providing

[7] SEC, Release No. 34-94313; File No. S7-08-22.

[8] SEC, Release No. 34-94313; File No. S7-08-22.

[9] SEC, Release No. 34-94313; File No. S7-08-22.

[10] SEC, Release No. 34-94313; File No. S7-08-22.

[11] SEC, Release No. 34-94313; File No. S7-08-22.

[12] "Calls to Investigate Short Sellers Intensify as Bank Crisis Deepens," The New York Times, May 12, 2023, available at https://www.nytimes.com/2023/05/12/business/dealbook/jamie-dimon-short-sellers-banks.html.

[13] SEC, Release No. 34-94313; File No. S7-08-22.

[14] SEC, Release No. 34-94313; File No. S7-08-22.

for the public disclosure of short-sale information.[15] In February 2022, the SEC proposed such rules. New Exchange Act Rule 13f-2 and the corresponding Form SHO would require certain institutional investment managers to report short sale-related information to the SEC on a monthly basis. Based on this information, the SEC would make aggregate data about large short positions, including daily short sale activity data, available to the public for each individual security. In particular, the SEC has proposed to publish the following information one month after the end of each calendar month:[16] (i) The aggregate gross position as of the calendar month's last settlement date; (ii) the aggregate gross short position's dollar value; (iii) a summary of the managers' reported hedging information with respect to the reported equity security; (iv) the aggregate gross short position's percentage of the reported equity security that is being reported as being fully hedged, partially hedged or not hedged; and (v) the "net" activity in the reported equity security for each individual settlement date during the calendar month.

The delay between the data's publication and Form SHO's submission deadline is intended to reduce the risk of imitative trading activity by market participants and protect any managers' proprietary trading strategies. The proposal also suggests that the identity of the manager filing Form SHO is confidential to prevent retaliation against short sellers.

In the US, a short squeeze is considered manipulation if it involves defrauding or deceiving someone, including through the misrepresentation of material information and/or through other means such as trading, with respect to the sale or purchase of a security.[17] There are a couple of ways in which market manipulation can be prosecuted in the US: either criminally by the United States Department of Justice or through civil litigation brought by governmental institutions such as the SEC or private parties.[18] Civil litigation typically relies on Rule 10b-5, adopted by the SEC pursuant to the Securities Exchange Act of 1934, which generally prohibits all misrepresentations and deceptions in the trading of securities.[19]

Another route that regulators can take to prosecute manipulation is to allege "open-market manipulation." Transactions for which the regulator alleges open-market manipulation "may appear legitimate on their face because they are simply open market trades, but if their intent and effect is to artificially drive up a stock's closing price for the purposes of defrauding others, they may be actionable under Rule 10b-5."[20]

[15] SEC, Release No. 34-94313; File No. S7-08-22.

[16] SEC, Release No. 34-94313; File No. S7-08-22.

[17] Section 10(b) and 10b-5 of the Securities Exchange Act of 1934 (15 U.S. Code § 78j).

[18] " The GameStop Short Squeeze – Potential Regulatory and Litigation Fall Out and Considerations," Gibson Dunn, February 1, 2021, available at https://www.gibsondunn.com/the-gamestop-short-squeeze-potential-regulatory-and-litigation-fall-out-and-considerations/.

[19] " The GameStop Short Squeeze – Potential Regulatory and Litigation Fall Out and Considerations," Gibson Dunn, February 1, 2021, available at https://www.gibsondunn.com/the-gamestop-short-squeeze-potential-regulatory-and-litigation-fall-out-and-considerations/.

[20] " The GameStop Short Squeeze – Potential Regulatory and Litigation Fall Out and Considerations," Gibson Dunn, February 1, 2021, available at https://www.gibsondunn.com/the-gamestop-short-squeeze-potential-regulatory-and-litigation-fall-out-and-considerations/.

3.3.2. EU Regulation

In 2012, the European Parliament and the Council of the European Union implemented short selling regulations that were designed to standardize the reporting threshold for all EU member states. Under this regulatory framework, market participants need to report to the relevant member country regulator "when their net short position reaches the initial threshold of 0.2% of the share capital of the company, and in 0.1% up and down increments thereafter."[21] This threshold was recently lowered to 0.1%. Net short positions are computed taking into account relevant derivative positions such as options. If the net short position reaches 0.5% of the share capital of the company, then the reported short position is made public on a daily basis by the relevant countries' regulator, including with information about the identity of the short seller.

To the extent that short squeezes are the result of manipulation, they currently would fall under the EU's Market Abuse Regulation (MAR). MAR and the Directive 2014/57/EU of the European Parliament and of the Council of 16 April 2014 on criminal sanctions for market abuse (market abuse directive or CS MAD) were implemented in 2014 and came into effect in 2016. While market abuse can be sanctioned by administrative fines or criminal penalties, administrative fines are not imposed directly by the European equivalent to the SEC (European Securities and Markets Authority (ESMA)), but by the National Competent Authorities (NCAs) such as the German "Bundesanstalt für Finanzdienstleistungsaufsicht" (the BaFin). CS MAD requires market abuse to be sanctioned as a criminal offense. However, this puts the responsibility on the public prosecutors and courts where there is large EU-wide heterogeneity (e.g., Perrone, 2020).

For example, in Germany, any action to artificially create a short squeeze is considered a criminal offence. More specifically and as discussed in Allen et al. (2021), an intentionally false statement about a fact significant to the valuation of a security, as well as any other deliberately deceptive measure aimed at influencing the valuation of a security, is punishable as a criminal act according to Section 20a of German securities law.

3.4. Data, Empirical Approach, and Results

3.4.1. Data

The data for these analyses come from three sources. Daily data for the securities lending market are from IHS Markit. Data for daily stock prices, shares outstanding, and trading volume are from CRSP and Compustat. We analyze the period starting July 2006, which is when IHS Markit starts reporting their data, through March 2021. We restrict the sample to stocks listed on NYSE, NASDAQ, and AMEX for the US. We define the EU market as all market areas covered by IHS Markit EU and also part of the European Union (Austria, Belgium, Czech

[21] SEC, Release No. 34-94313; File No. S7-08-22.

Republic, Denmark, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Netherlands, Poland, Spain, and Sweden).[22] We drop missing observations and observations where the stock price is less than USD 1 or EUR 1. We remove observations with missing fees, utilization, stock price, and returns.[23]

Table 3.1, Panels A and B provide the distribution of key short-squeeze variables across all stock-day observations for the US and the EU, respectively. We note that the mean (median) short interest in the US during our sample period is 3.6% (1.49%). The corresponding mean (median) short interests for the EU is lower at 1.5% (0.49%). This evidence is consistent with the European equities securities lending market lagging behind US securities lending in terms of volume.[24]

[Insert Table 3.1 here.]

3.4.2. Empirical Analysis and Results

We start by describing the lender short squeeze measures proposed in Schultz (2023). Specifically, Schultz (2023) develops two proxies for the occurrence of lender short squeezes. The first proxy, which he calls "all lender squeeze," is a dummy variable that takes the value of one "when the shares available to lend are less than the shares on loan the previous day." The second proxy, which he calls "current lender squeeze," is a dummy variable that takes the value of one if "the total number of shares available to lend and the number of shares on loan fall by the same amount on the same day." We combine these two proxies to construct one measure that captures lender squeezes - a dummy variable that takes the value of one if a company experiences either an all lender squeeze or a current lender squeeze on a given day, and zero otherwise.

A disadvantage of the lender squeeze proxy is that it does not capture short squeezes that occur when prices increase drastically and, as a result, short sellers have to cover their positions. Therefore, we develop a new, complimentary proxy that captures short squeezes that occur due to price pressure in the market for the underlying security. We call this measure a "market squeeze." The development of this measure was motivated by short-squeeze events described

[22]We note that IHS Markit EU additionally includes the countries Norway, Russia, Switzerland, Turkey, and United Kingdom, which are currently not part of the European Union. In Table A1 and Figures A1 and A2 in the Internet Appendix we provide robustness evidence for the EU by including these additional countries. The proportion and duration of market and lender squeezes are comparable to the evidence presented in the main Appendix.

[23]IHS 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 in both the US (SEC Release No. 34-80295) and the EU (Article 5 of the European regulation on CSD). 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 the corresponding number of days.

[24]"Securities lending: year in review," S&P Global Market Intelligence, December 21, 2016, available at https://www.spglobal.com/marketintelligence/en/mi/research-analysis/21122016-Equities-Securities-lending-year-in-review.html.

in the extant empirical literature on the topic, such as the January 2021 squeezes and the 2008 VW squeeze (see e.g., Allen et al. (2023) and Allen et al. (2021)). Specifically, we construct an indicator that equals one when the following conditions are met for stock i on day t: (i) there is a pronounced positive return on day t, i.e., the positive daily stock return for stock i on day t falls within the 95^{th} percentile of the distribution of daily returns of companies within the same industry; (ii) there is a pronounced decrease on day t in quantity on loan, i.e., the daily decrease in quantity on loan for stock i on day t falls within the 95^{th} percentile of the distribution of decreases of quantity on loan of companies within the same industry; and (iii) on the day before event day t the stock has relatively high quantity on loan, i.e., quantity on loan for stock i on day $t-1$ falls within the 95^{th} percentile of quantity on loan of companies within the same industry. Industries are defined based on the two-digit standard industrial classification code (SIC2).

The October 27, 2008 VW squeeze event provides another example. On the previous trading day there were 39,368,440 shares on loan or 13.4% relative to shares outstanding. This places VW on that day in the 95^{th} percentile of quantity on loan of companies in the same industry. The next trading day, October 27, the company experienced a pronounced positive return of 123%, which places VW on that day in the 95^{th} percentile of daily returns of companies in the same industry. Concurrent with this price increase we observe a decrease in quantity on loan. Specifically, on October 27 quantity on loan fell to 37,919,968 or 12.9% relative to shares outstanding. This is an absolute decrease of 0.5% in relative quantity on loan and places VW in the 95^{th} percentile of the distribution of decreases of quantity on loan of companies within the same industry on that day. In other words, there was a market squeeze because short sellers were likely forced to repurchase at least 1,448,472 shares due to rising prices and increasing margin calls. Further, we note that on October 27, 2008 Volkswagen's shares available to borrow increased from the previous day, which indicates that there was no lender squeeze but only a market squeeze on that day.[25]

For our empirical analyses, we not only present evidence for market squeezes and lender squeezes separately, but we also combine the two proxies into one short squeeze measure. In particular, we define that a stock i has experienced a short squeeze on day t if either a market squeeze or a lender squeeze (or both) has occurred.

First, we examine the frequency of short-squeeze events on a stock-day level. Panels A and B in Table 3.2 show the proportion of sample stock days that are either market squeeze or lender squeeze and the proportion of stock days that are both for the US and the EU markets, respectively. The table further shows the proportion of stock days with no squeeze events of either type for both markets. In total, there are 13,993,006 stock-day observations for the US market and 4,804,849 stock-day observations for the EU market. On 19,015 stock-day observations, or 0.14% of the total event days, there is a market squeeze in the US market. On

[25]Our market squeeze proxy successfully identifies the meme-stocks short squeeze events analyzed in detail in Allen et al. (2023).

12,985 stock-day observations, or 0.27% of the total event days, there is a market squeeze in the EU market. Further, on 108,643 stock-day observations, or 0.83% of the total event days, there is a lender squeeze in the US market. On 7,962 stock-day observations, or 0.17% of the total stock days, there is a lender squeeze in the EU market. There are 229 event days, or 0% of the total, that are classified as having both a market squeeze and a lender squeeze for the US market and there are 46 event days, or 0% of the total for the EU market. The lender short squeeze statistics are in line with Schultz (2023). The results imply that short-squeeze events are rare in both the US and the EU.

[Insert Table 3.2 here.]

Next, we examine the duration of these events. The four panels in Figure 3.1 show the duration of short squeezes for the US and the EU by type of short squeeze. More than 90% of market and more than 70% of lender short squeezes in the US do not last longer than one day. The longest duration we observe for market (lender) short squeezes is 8 (33) days in the US, however, this is true only for very few stocks. In the EU, we observe that more than 90% of market and lender squeezes do not last longer than one day; the longest duration is 7 days for market squeezes and 7 days for lender squeezes. Similar to the US, these long squeeze durations are only true for a small number of stocks.

[Insert Figure 3.1 here.]

Finally, we examine the number of unique firms that experience a short squeeze event in any given year. Specifically, we examine the time-series evolution and cross-industry dispersion of the number and proportion of unique stocks experiencing a short squeeze in any given year. In the first panel of Figure 3.2, we show the total number of stocks and relative proportion of stocks experiencing short squeezes in the US over the period of July 2006 through March 2021. A unique short-squeezed stock is defined as a stock-year observation that experiences either a market and/or a lender short squeeze. The annual average of stocks that experience at least one of these two types of short squeezes is 25%. The proportion of unique stocks experiencing short squeezes has increased steadily over the entire sample period from approximately 13% in 2006 to approximately 26% in 2020. The largest increase happened over the years 2014 through 2018. Market commentators generally observed an elevated shorting activity during this time period "in the wake of market volatility."[26] An increase in market volatility and higher shorting demand can be one reason for the increase in the number of stocks experiencing short squeezes. In the second panel of Figure 3.2, we break down the total annual number of stocks experiencing a short squeeze into the respective short-squeeze type. The annual average of

[26] "Securities lending: year in review," S&P Global Market Intelligence, December 21, 2016, available at https://www.spglobal.com/marketintelligence/en/mi/research-analysis/21122016-Equities-Securities-lending-year-in-review.html.

firms that experience a market squeeze or a lender squeeze is 302 (6.6%) and 860 (18.8%), respectively. While market squeezes maintained a constant level throughout our sample period, lender squeezes have become more common in recent years.

[Insert Figure 3.2 here.]

In Figure 3.3, we show the corresponding statistics for the EU. In general, compared to the US we observe a lower number of unique firms experiencing short-squeeze events, however, the proportion is about the same (with an annual average of 25% of unique firms experiencing a short squeeze). We also do not find an upward trend in the number of short squeezes over time. Instead, the number of stocks experiencing short squeezes fluctuates relatively constantly between 400 (18%) and 700 (26%) over the course of the sample period. Further, for the EU market, we find that the annual average of unique firms that experience a market squeeze or a lender squeeze is 187 (11.4%) and 236 (13.9%), respectively (see the second panel of Figure 3.3).

[Insert Figure 3.3 here.]

In Figure 3.4, we provide an industry breakdown of the proportion of unique stocks experiencing a short squeeze aggregated over the entire sample period for both the US and the EU. In the first panel, we present the results for the US. The highest proportion of short-squeezed stocks in the US can be observed in the energy sector (coal and mining stocks) as well as the financial and tobacco industries. It is worth noting that the previous evidence of fewer market squeezes and relatively more lender squeezes also holds across industries, with the exception of the tobacco and coal industries. These industries show more market squeezes than lender squeezes over the time period analyzed.

In the second panel of Figure 3.4, we provide a breakdown of the proportion of stocks experiencing a short squeeze in the EU by industry. Similar to the US, the highest number of companies experiencing a short squeeze event can be observed in the tobacco and coal industries, followed by the textiles and games industries. Overall, the evidence for both geographic regions suggests that multiple stocks experience short squeeze events, which mitigate concerns that these events are concentrated in a few stocks.

[Insert Figure 3.4 here.]

One reason for the difference in the number of short squeezes in the EU versus the US could be the relative lack of securities lending activity in Europe. Market commentators have found that European equities securities lending has lagged behind US securities lending generally.[27]

[27] "Securities lending: year in review," S&P Global Market Intelligence, December 21, 2016, available at https://www.spglobal.com/marketintelligence/en/mi/research-analysis/21122016-Equities-Securities-lending-year-in-review.html; "Securities Finance Quarterly Review," IHS Markit, Q1 2017, available at

Given that there is overall fewer securities lending and shorting activity in the EU, we think it is reasonable to observe fewer short-squeeze events.

3.5. Conclusion

A short squeeze is triggered if there is pressure on short sellers to cover their positions because of a sharp price increase or a recall of borrowed shares. This drives short sellers to close their positions early. In this article, we construct a novel measure for identifying short-squeeze events triggered by sharp price increases, i.e., a market squeeze. This measure is distinct from and complimentary to existing lender squeeze measures, i.e., measures that identify short squeezes based on borrowed shares that are recalled by the lender. We document the time-series evolution and cross-industry dispersion of both market and lender short squeezes in the US and the EU. We find that short-squeeze events are rare and short-lived in nature. Further, the annual average of unique firms that experience a short-squeeze event (either a market or a lender squeeze) is 25% in both the US and the EU. This evidence implies that a non-trivial proportion of firms experience a short squeeze in a given year. The cross-industry analysis reveals that in the US short squeezes are more frequent in the energy sector (coal and mining stocks) as well as the financial and tobacco industries, whereas in the EU short squeezes are more frequent in the tobacco and coal industries.

The literature review reveals that while early literature on short squeezes focuses on either theoretical issues or empirical findings in the commodity, bond, and derivative markets, more and more recent studies have branched out to examine squeezes and corners in equity markets. We see the following fruitful avenues for future research: First, trading by retail investors has grown over the past years and is expected to stay. We need more research examining the impact of retail trading as a potential catalyst for short-squeeze events. Second, derivatives trading in general, and retail trading of options products in particular, has also gained momentum over the recent past. More needs to be done in examining how trading and hedging activities in the derivatives market might lead to price spikes and shortage of shares for borrowing in the equity lending market of the underlying assets. Finally, social media has become a primary tool for the exchange of ideas among retail and institutional investors. Social media coordination, however, can be another catalyst of short squeezes. Future work can examine the role of social media as a coordination device in short-squeeze attacks and their impact on market efficiency in general.

https://cdn.ihs.com/www/blog/commentary/pdf/Markit-Securities-Lending-Q1-2017-quarterly-review.pdf.

Appendix

Tables and Figures

Table 3.1 The distributions of key short-squeeze variables: This table presents descriptive statistics for the variables used to construct the market squeeze and the lender squeeze measures. Panel A presents information about the US market. Panel B presents information about the EU market. We present descriptive statistics for the following variables: 1.) Return is the simple return; 2.) Short Interest is the ratio of the total quantity of open securities loans relative to a company's shares outstanding; 3.) Quantity on Loan is the total quantity of open securities loans (in thousands of shares); 4.) Lendable Quantity is the active lendable quantity on stock available to lend adjusted to remove lendable quantity which is not being actively made available for lending (in thousands of shares). The data cover the period July 1, 2006 through March 31, 2021. Data come from IHS Markit, CRSP, and Compustat.

Panel A - US	Obs.	Mean	Stdev.	$Q_{0.01}$	$Q_{0.25}$	$Q_{0.50}$	$Q_{0.75}$	$Q_{0.99}$
Return	13993006	0.067	3.587	-9.012	-1.184	0	1.211	10.099
Short Interest	13993006	3.627	5.761	0.003	0.332	1.485	4.585	25.167
Quantity on Loan	13993006	3336.614	10279.22	0.3	111.925	782.993	3113.103	35034.7
Lendable Quantity	13993006	28391.31	97511.7	3.7	1418.657	7098.654	21484.58	363258.2

Panel B - EU	Obs.	Mean	Stdev.	$Q_{0.01}$	$Q_{0.25}$	$Q_{0.50}$	$Q_{0.75}$	$Q_{0.99}$
Return	4804849	0.029	2.537	-6.542	-0.982	0	0.964	7.218
Short Interest	4796635	1.531	3.178	0.001	0.096	0.494	1.752	12.619
Quantity on Loan	4804849	6010.191	31198.01	0.1	29.903	304.18	2441.123	100917.1
Lendable Quantity	4804849	34510.18	145328.9	3.165	447.066	3153.312	16997.46	571072.2

Table 3.2 The number and proportion of stock-day observations with market squeezes and lender squeezes: This table presents the number and proportion of stock-day observations with market squeezes and lender squeezes in the US and the EU. Panel A presents information about the US market. Panel B presents information about the EU market. Definitions of market squeeze and lender squeeze are provided in Section 3.4. The data cover the period July 01, 2006 through March 31, 2021. The data frequency is daily. Data come from IHS Markit, CRSP, and Compustat.

Panel A - US	No Market Squeeze	Market Squeeze	Total
No Lender Squeeze	13,865,577	18,786	13,884,363
	(99.09%)	(0.13%)	(99.22%)
Lender Squeeze	108,414	229	108,643
	(0.83%)	(0.00%)	(0.83%)
Total	13,973,991	19,015	13,993,006
	(99.86%)	(0.14%)	(100.00%)

Panel B - EU	No Market Squeeze	Market Squeeze	Total
No Lender Squeeze	4,783,948	12,939	4,796,887
	(99.57%)	(0.27%)	(99.83%)
Lender Squeeze	7,916	46	7,962
	(0.16%)	(0.00%)	(0.17%)
Total	4,791,864	12,985	4,804,849
	(99.73%)	(0.27%)	(100.00%)

Fig. 3.1 The duration of short-squeeze events for the period 2006 – 2021: These figures depict the duration (in number of days) of short-squeeze events in the US (upper row) and the EU (bottom row). The graphs on the left present the distribution of market squeeze duration, while the graphs on the right present the distribution of lender squeeze duration. Duration is defined as the number of consecutive stock-day short-squeeze events. Definitions of market squeeze and lender squeeze are provided in Section 3.4. The sample period is July 01, 2006 through March 31, 2021. Data come from IHS Markit, CRSP, and Compustat.

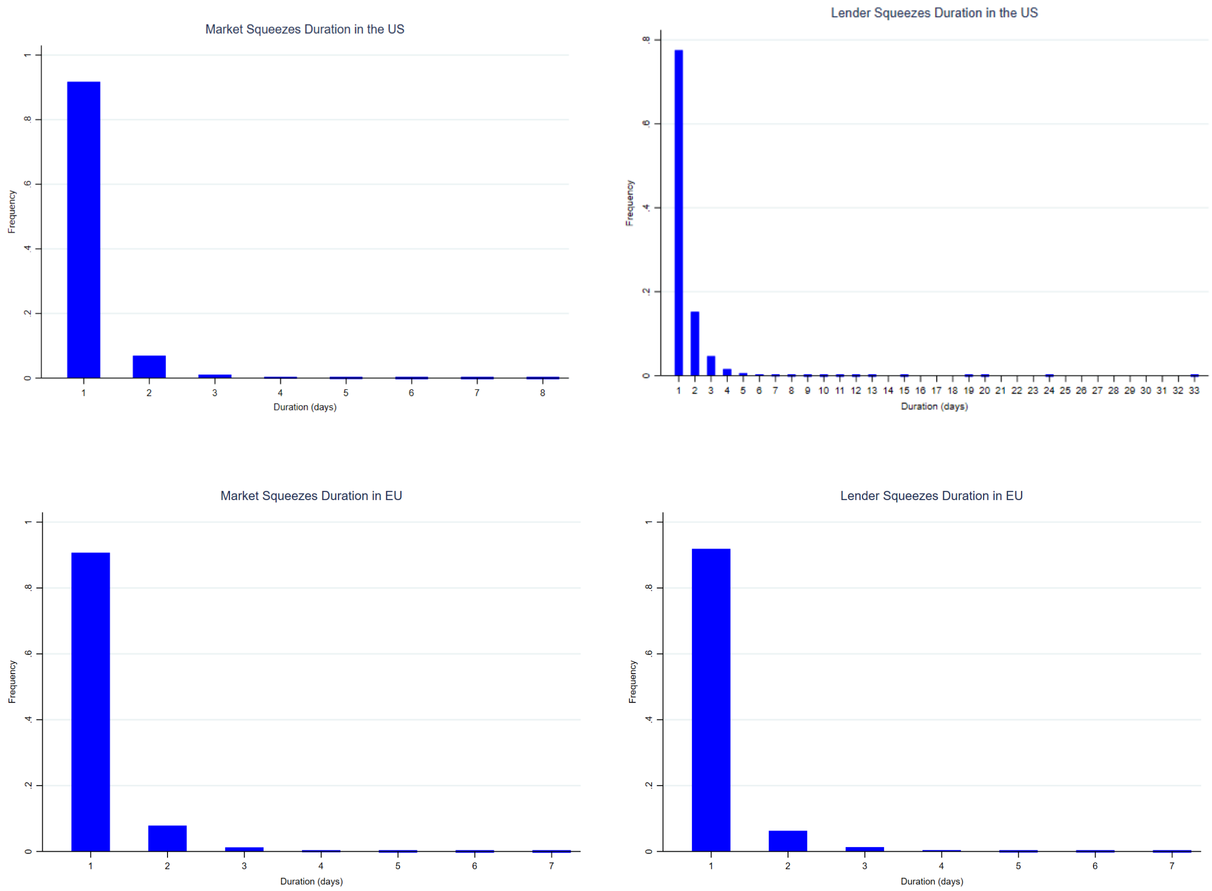


Fig. 3.2 The annual number and proportion of stocks experiencing a short squeeze in the US for the period 2006 – 2021: These figures depict the evolution of the number and proportion of unique stocks experiencing short squeeze events over time. The graph on the left presents the total number and relative proportion of short-squeezed stocks over time. The graph on the right presents a breakdown of the total number of short-squeezed stocks into lender squeeze and market squeeze. A unique short-squeezed stock is defined as a stock that experiences a market squeeze or a lender squeeze (or both) at least once in a given year. Definitions of market squeeze and lender squeeze are provided in Section 3.4. The sample period is July 01, 2006 through March 31, 2021. Data come from IHS Markit and CRSP.

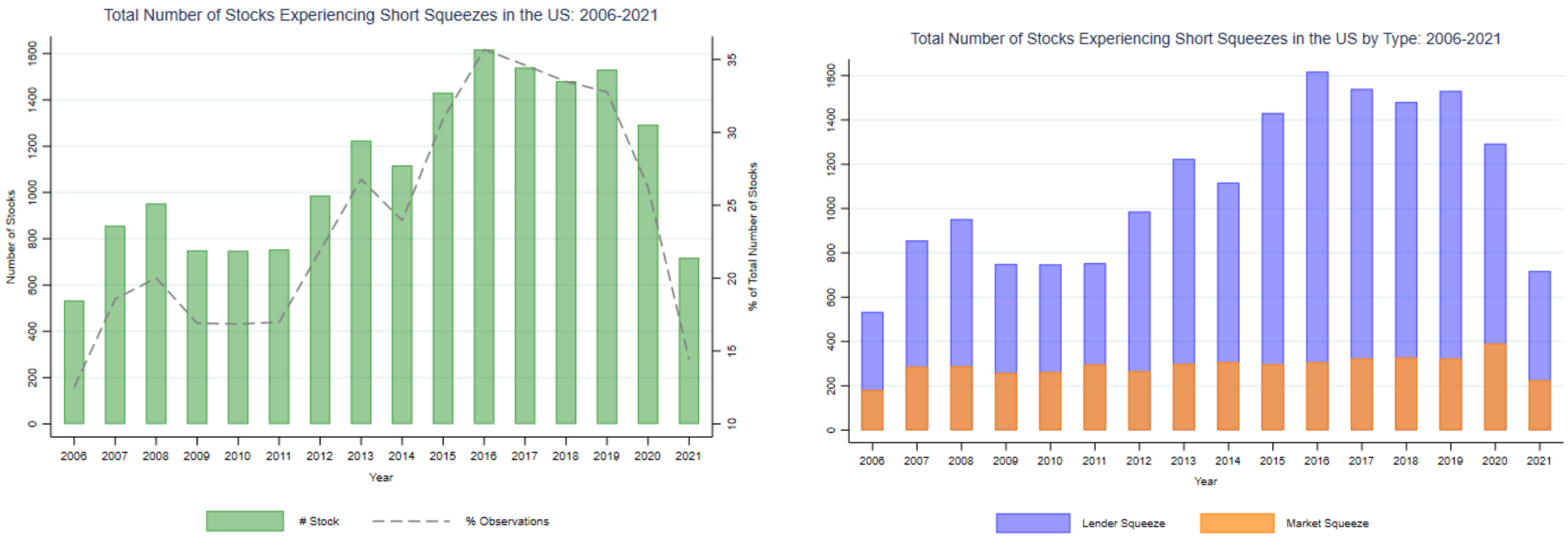
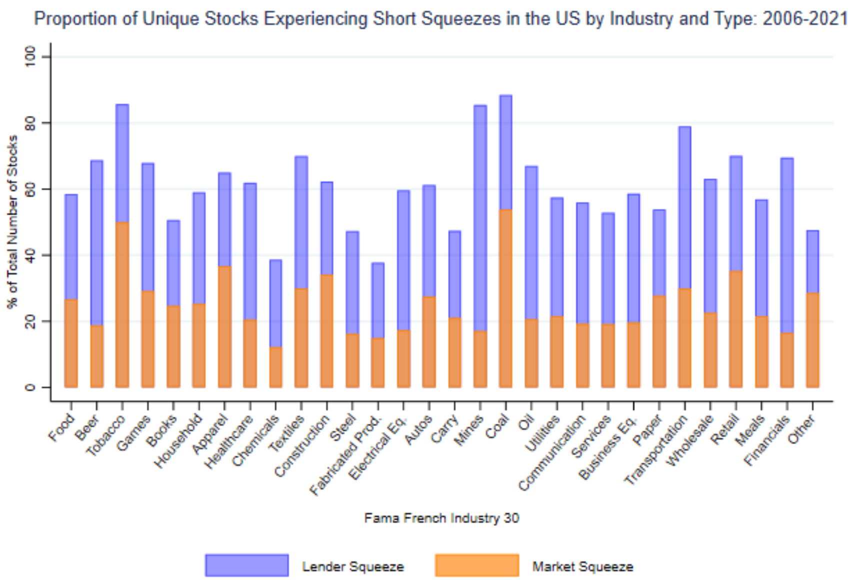
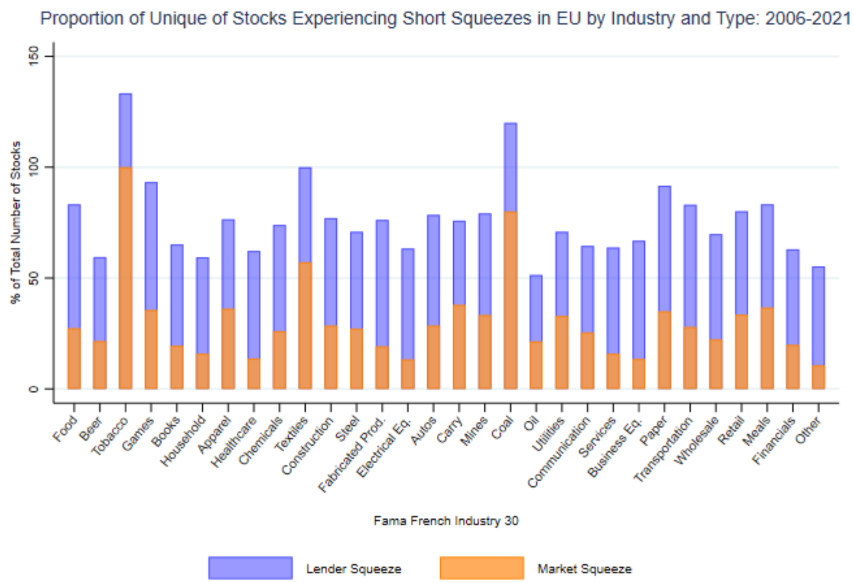


Fig. 3.3 The annual number and proportion of stocks experiencing a short squeeze in the EU for the period 2006 – 2021: These figures depict the evolution of the number and proportion of unique stocks experiencing short squeeze events over time. The graph on the left presents the total number and relative proportion of short-squeezed stocks over time. The graph on the right presents a breakdown of the total number of short-squeezed stocks into lender squeeze and market squeeze. A unique short-squeezed stock is defined as a stock that experiences a market squeeze or a lender squeeze (or both) at least once in a given year. Definitions of market squeeze and lender squeeze are provided in Section 3.4. The sample period is July 01, 2006 through March 31, 2021. Data come from IHS Markit and Compustat.

Fig. 3.4 The proportion of stocks experiencing a short squeeze by industry for the period 2006 – 2021: These figures depict the evolution of the number and proportion of unique stocks experiencing short squeeze events across industry, applying FF 30 industries. The graph on the left (right) presents a breakdown of the relative proportion of stocks experiencing squeezes into lender squeezes and market squeezes in the US (EU). Definitions of market squeeze and lender squeeze are provided in Section 3.4. Data come from IHS Markit, CRSP, and Compustat.





Internet Appendix to
How prevalent are short squeezes?
Evidence from the US and Europe

(*Not for Publication*)

Table A1 Robustness: The number and proportion of days with market squeezes and lender squeezes in the EU: This table presents the number and proportion of stock-day observations with market squeezes and lender squeezes in the EU market area, as defined by IHS Markit. We note that IHS Markit's EU definition includes the countries Norway, Russia, Switzerland, Turkey, and United Kingdom. These countries are not part of the European Union and therefore were excluded from the evidence presented in the main Appendix. Definitions of market squeeze and lender squeeze are provided in Section 3.4. The data cover the period July 01, 2006 through March 31, 2021. The data frequency is daily. Data come from IHS Markit and Compustat.

EU	No Market Squeeze	Market Squeeze	Total
No Lender Squeeze	8,312,038	16,985	8,329,023
	(99.66%)	(0.20%)	(99.87%)
Lender Squeeze	11,150	34	11,184
	(0.13%)	(0.00%)	(0.13%)
Total	8,323,188	17,019	8,340,207
	(99.80%)	(0.20%)	(100.00%)

Fig. A1 Robustness: The duration of short-squeeze events in the EU for the period 2006 – 2021: These figures depict the duration (in number of days) of short-squeeze events in the EU market area, as defined by IHS Markit. We note that IHS Markit's EU definition includes the countries Norway, Russia, Switzerland, Turkey, and United Kingdom. These countries are not part of the European Union and therefore were excluded from the evidence presented in the main Appendix. The graph on the left presents the distribution of market squeeze duration, while the graph on the right presents the distribution of lender squeeze duration. Duration is defined as the number of consecutive stock-day short-squeeze events. Definitions of market squeeze and lender squeeze are provided in Section 3.4. The sample period is July 01, 2006 through March 31, 2021. Data come from IHS Markit and Compustat.

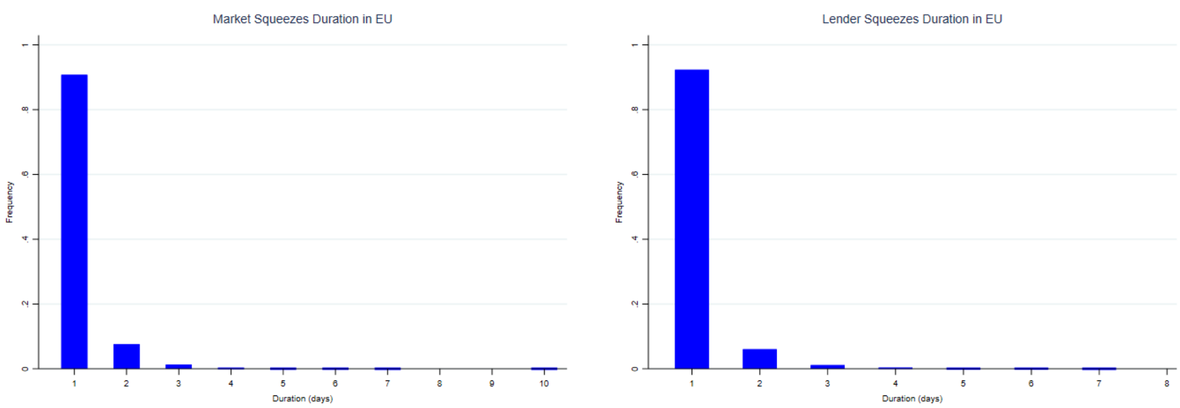
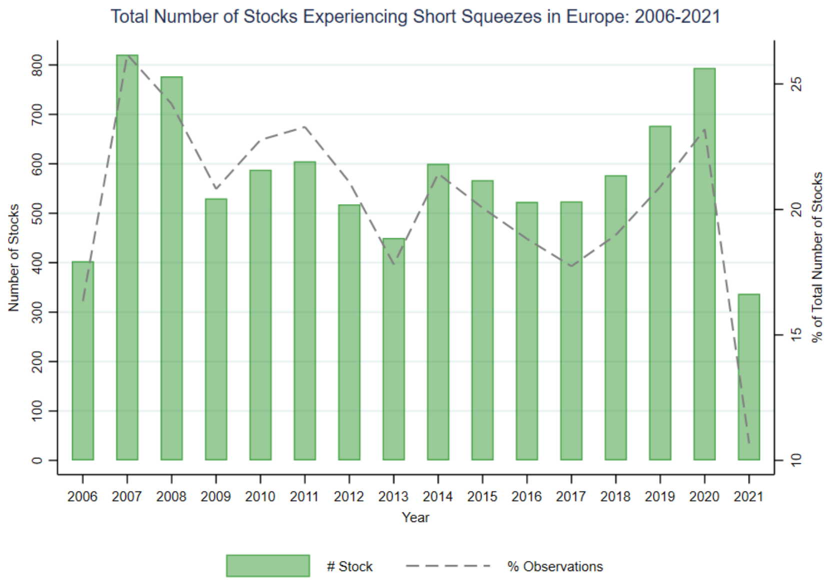
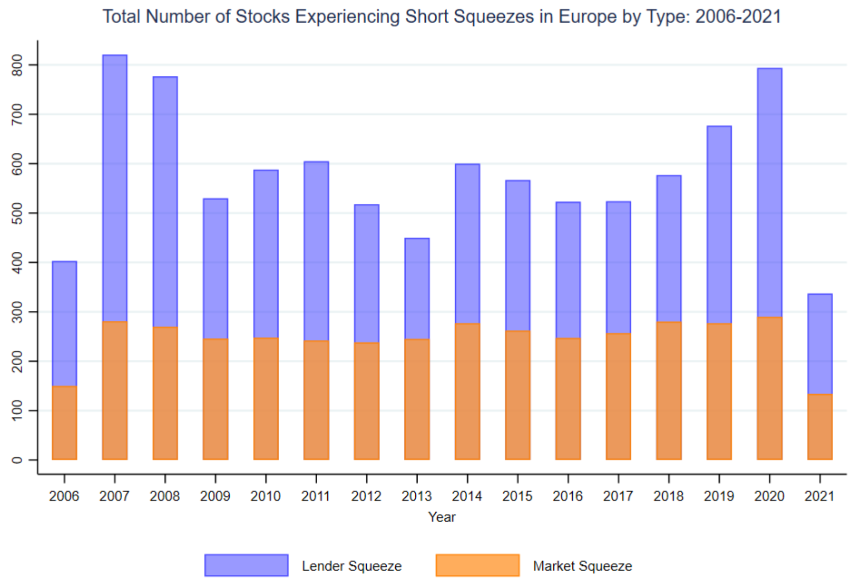


Fig. A2 Robustness: The annual number and proportion of stocks experiencing a short squeeze in the EU for the period 2006 – 2021: These figures depict the evolution of the number and proportion of unique stocks experiencing short squeeze events over time in the EU market area, as defined by IHS Markit. We note that IHS Markit's EU definition includes the countries Norway, Russia, Switzerland, Turkey, and United Kingdom. These countries are not part of the European Union and therefore were excluded from the evidence presented in the main Appendix. The graph on the left presents the total number and relative proportion of short-squeezed stocks over time. The graph on the right presents a breakdown of the total number of short-squeezed stocks into lender squeeze and market squeeze. A unique short-squeezed stock is defined as a stock that experiences a market squeeze or a lender squeeze (or both) at least once in a given year. Definitions of market squeeze and lender squeeze are provided in Section 3.4. The sample period is July 01, 2006 through March 31, 2021. Data come from IHS Markit and Compustat.





Chapter 4

Debt and Equity Crowdfunding in the Financial Growth Cycle*

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4.1. Introduction

It is becoming increasingly challenging for small businesses to take out loans. According to the Federal Reserve's April 2023 Senior Loan Officer Opinion Survey, a large fraction of banks reported tightening lending standards for firm loans, credit card loans, and home equity lines of credit — three of the most common sources of financing for startups — in the first quarter of 2023. This is particularly likely to impact small firms that do not qualify for public listing but are simultaneously unable to attract venture capital (VC) funding.[1] For these firms, alternative sources of capital are likely to become more important as catalysts of economic growth.

In this paper, we address two such alternatives: debt crowdfunding and equity crowdfunding. Since 2016, Regulation CF of the JOBS Act allows small businesses in the US to offer securities to individual investors via online crowdfunding platforms, with $530 million raised as of 2021. We investigate firms' decision to issue crowdfunded debt versus equity and how this choice relates to their stage in the financial growth cycle (Berger and Udell, 1998; Cole, Liang, and Zhang, 2020) as well as access to other sources of external financing. We find that firms that are less profitable, are in an earlier developmental stage, and have stronger ties to the

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[1]Nanda and Phillips (2022) report that only 0.5% (0.4%) of the firms in the US Survey of Business Owners use VC funding to start (expand) their business, while 22% (20%) use business loans from banks, 14% (18%) credit cards, and 7% (4%) home equity.

banking system are more likely to issue crowdfunded equity than debt. Successful crowdfunding is associated with increases in firm size, revenue, and profitability for early-stage firms, but not for late-stage firms. Our findings suggest that crowdfunding can alleviate capital constraints and foster growth for early-stage firms, but has a negligible impact on more mature firms that are already profitable.

In order to issue debt or equity via crowdfunding, an entrepreneur needs to file Form C with the Securities and Exchange Commission (SEC), disclosing information about the firms' financials, risk factors, business plan, leadership team and intended use of proceeds, as well as the type of security issued (debt or equity) and the crowdfunding goal (the amount that the entrepreneur intends to raise). The registrant also needs to select a crowdfunding platform (website) on which to issue securities, with platforms generally specializing in either equity or debt securities.[2] An important function of both Form C disclosure and platform due diligence (Cumming, Johan, and Zhang, 2019) is to reduce the information asymmetry that traditionally makes it difficult for entrepreneurs to secure external debt from providers other than banks (Diamond, 1984, 1991). If the entrepreneur manages to meet their crowdfunding goal, the campaign is considered successful and the securities are issued. If not, the funds are returned to the investors.[3]

We collect data from SEC Form C filings to construct a sample of 2,052 crowdfunding campaigns from 2016–2021, 1,697 of which are equity issuances and 355 debt. We supplement these data with firm-level characteristics from FactSet, SEC Form D filings on previous security issuances, and industry classifications from Capital IQ and web searches. We also include ZIP- and county-level data from the US Census Bureau, IPUMS (Manson et al., 2022), and the Federal Deposit Insurance Corporation (FDIC), among others.

We start by examining the factors associated with a firm's choice between debt and equity crowdfunding. The pecking order theory (Myers and Majluf, 1984) suggests that firms prefer debt over equity when seeking external capital due to lower information costs. Alternatively, the financial growth cycle framework proposed by Berger and Udell (1998) suggests that the hierarchy of financing options depends on firm size and development stage, as there are different levels of information asymmetry and financial needs for each phase of growth. Following

[2]Equity issuances most often consist of common stock or simple agreements for future equity (SAFE). SAFE contracts resemble warrants in that they give the investor rights to future shares when a priced investment round or liquidity event occurs, but do not immediately confer equity ownership unto the investor. Debt contracts vary; Some resemble traditional bonds with a predetermined yield and maturity, while others entitle investors to a percentage of the business's revenue each quarter until they reach a predetermined return on their investment or the note reaches maturity (thus resembling a royalty contract with maturity and capped payouts).

[3]The focus of our paper is securities crowdfunding (also referred to as return-based crowdfunding), which is distinct from project-based crowdfunding via platforms like Kickstarter. In the latter, individuals pledge capital in exchange for a specific product or service, whereas the former gives retail investors shares in the company itself (equity) or the right to pre-specified cash flows (debt). The incentives for entrepreneurs differ between these two types of crowdfunding; Project-based crowdfunding aims to deliver a specific product within a defined timeframe, while return-based crowdfunding is appropriate for investors with a long-run investment horizon due to the illiquidity of crowdfunded securities. Unless otherwise specified, "crowdfunding" in this paper refers to securities crowdfunding.

Cole, Liang, and Zhang (2020), we categorize firms into three stages of the financial growth cycle that are appropriate for smaller entrepreneurial firms: a first stage where firms have assets in place but do not generate revenue, a second stage where firms have positive revenue but are unprofitable, and a third stage where firms achieve profitability to generate positive revenue and net income. We find that the capital structure of crowdfunded firms tends to follow a growth cycle pattern. More specifically, early-stage startups are more likely than late-stage startups to fund themselves with equity crowdfunding. As firms move on from their introductory developmental phase, they tend to rely more on debt-based crowdfunding, consistent with improved financial stability and creditworthiness.

Next, we investigate how the availability of traditional bank financing is related to the firm's choice of crowdfunding offering. Previous studies in the banking literature document that banks are prone to establish lending relationships with borrowers located in close proximity to their branches and that lending to small businesses is usually restricted to local markets (Agarwal and Hauswald, 2010; Brevoort, Wolken, and Holmes, 2010; Nguyen, 2019). Likewise, the distance between entrepreneurs and offline early-stage investors, such as banks, venture capitalists, and angel investors, has been shown to be a barrier to small business financing (Stuart and Sorenson, 2003; Cumming and Dai, 2010). Since online funding platforms can reduce these distance-related costs, we hypothesize that debt crowdfunding can serve as a substitute for bank lending when the entrepreneur has limited access to traditional offline funding sources (Agrawal, Catalini, and Goldfarb, 2015; Vulkan, Åstebro, and Sierra, 2016).

Our results support the substitution hypothesis. We find that firms located in areas with access to a larger number of bank branches (proxying for access to bank loans) are more likely to issue crowdfunded equity. We also observe the same pattern for firms located in areas with higher house prices (proxying for access to home equity).

To conclude our analysis, we investigate whether successful crowdfunding is associated with realized gains in firm size and performance. Theoretically, it is ex-ante ambiguous whether to expect crowdfunding to result in positive firm outcomes, i.e., whether entrepreneurs are willing and able to put the funding to productive use. For example, due to high information asymmetry and moral hazard in crowdfunding markets, entrepreneurs may be less competent, take on riskier projects, and be more likely to commit fraud than entrepreneurs seeking traditional sources of funding (Agrawal, Catalini, and Goldfarb, 2014).

To analyze the relationship between crowdfunding and firm growth, we compare firms that successfully issue crowdfunded debt or equity to a sample of matched private firms from Factset in a matched diff-in-diff setting (as in Boucly, Sraer, and Thesmar (2011)). We find that crowdfunding firms increase their total assets, revenue, and profitability relative to the control sample. We also show that this difference is largest for first-stage firms, with the relationship weakening as firms mature. While the change in profitability associated with crowdfunding is positive and significant for both first- and second-stage firms, it is insignificant for third-stage firms. Our results suggest that crowdfunding can improve operational performance for firms that are not yet profitable but has a negligible impact on more mature, profitable, firms.

Related literature. Our paper primarily contributes to two strands of literature. First, we add to the literature on securities crowdfunding (see Mochkabadi and Volkmann (2020) and Bollaert, Lopez-de Silanes, and Schwienbacher (2021) for recent surveys) and Regulation Crowdfunding (CF) of the Jumpstart Our Business Startups (JOBS) Act. This paper is, to our knowledge, the first to investigate the choice between issuing crowdfunded debt or equity as well as how firm characteristics relate to this decision. While several papers explore either debt or equity crowdfunding in isolation, what motivates firms to choose between these two security types has not previously been documented. The only other paper addressing equity and debt crowdfunding simultaneously that we are aware of is Cumming, Johan, and Reardon (2022), who show that equity offerings are more likely to be successful and raise more capital than debt offerings.

Previous empirical evidence on whether securities crowdfunding facilitates firm growth is limited and mixed. Using a sample of UK firms, Eldridge, Nisar, and Torchia (2021) find that equity crowdfunding is associated with improved return on assets (ROA) but not increased innovation activity. Havrylchyk and Mahdavi Ardekani (2020) do not observe any relationship between debt crowdfunding and sales growth, investment, employment, or profitability for a sample of French firms. Hornuf, Schmitt, and Stenzhorn (2017), Butticè, Di Pietro, and Tenca (2020), and Dolatabadi, Fracassi, and Yang (2021) show that successful equity crowdfunding campaigns are associated with a higher likelihood of subsequent venture capital funding and higher survival rates. Our results show that post-crowdfunding growth is related to the firm's growth cycle stage, which may partially reconcile why prior papers have observed positive effects associated with equity (early-stage) crowdfunding, but not debt (late-stage) crowdfunding.[4]

Second, we contribute to prior work on the capital structure and growth of small entrepreneurial firms (see Ewens and Farre-Mensa (2022) and Nanda and Phillips (2022) for recent surveys). Due to data limitations, most studies on entrepreneurial financing decisions focus on small, privately held firms using data from surveys like the Federal Reserve Board's Surveys of Small Business Finances or the Kauffman Firm Surveys (Berger and Udell, 1998; Coleman, 2002; Robb and Robinson, 2012; Cole and Sokolyk, 2018). Berger and Udell (1998) find that small firms rely more on debt financing during their early growth stages but decrease their reliance on debt as they mature. Robb and Robinson (2012) show that young firms rely more on external debt financing and less on friends-and-family-based funding sources. More recently, Cole, Liang, and Zhang (2020) look at sources of debt financing for small firms that trade over-

[4]While this study focuses on existing firms' growth, other studies analyze whether crowdfunding is conducive to new business formation. Rashidi Ranjbar (2022) finds that the passage of both state-level crowdfunding legislation and Regulation CF increases the number of new business applications, but that only the former results in successful business formation. Lambert, Ralcheva, and Roosenboom (2022) show that project-based crowdfunding (Kickstarter) is positively associated with business formation and average establishment size at the county level.

the-counter (OTC). We contribute by providing the first evidence on the relationship between growth cycle patterns for startups and crowdfunding decisions, as well as showing that growth outcomes following crowdfunding are related to the firm's growth cycle stage.

The rest of this article proceeds as follows. In Section 2, we describe the institutional framework that motivates the article. In Section 3, we describe the data and provide summary statistics. Sections 4 through 5 present the empirical analysis, and Section 6 concludes.

4.2. Institutional background

The JOBS Act, signed into law on April 5, 2012, aims to facilitate capital raising for startups and small businesses by allowing them to offer securities to a wider pool of investors at lower costs. On October 30, 2015, the SEC adopted the final rules for Regulation CF, which became effective on May 16, 2016. Under Regulation CF, US private firms can raise up to $1.07 million in a 12-month period by issuing debt or equity securities. As of 2021, the maximum aggregated offering amount in a 12-month period is increased to $5 million.

Prior to Regulation CF, debt and equity crowdfunding was limited to accredited investors, typically high-income or high-net-worth individuals. Regulation CF expands investment opportunities to non-accredited (retail) investors, allowing them to purchase debt or equity securities issued through crowdfunding. To comply with SEC requirements, issuers must disclose both quantitative and qualitative information by filing Forms C, C-U, and C-AR, making this information publicly available at least 21 days before the securities are sold. Additionally, the offering must be conducted through a broker-dealer or a SEC-registered portal, which is a new type of intermediary introduced by the JOBS Act.

The disclosure requirements in Regulation CF are designed to protect investors from fraud and ensure the reliability of the information provided by businesses. To mitigate the risk of fraudulent activities, the JOBS Act introduces three additional measures. First, it sets limits on the amount that individuals can invest annually (up to 10% of their income or net worth), thereby limiting potential losses. Second, it enables civil actions against issuers, directors, and officers who provide false or misleading statements. Third, it grants the SEC authority over funding portals to enforce regulations and mandates for both issuers and intermediaries.

4.3. Data

4.3.1. Data sources

Our primary data source is the Electronic Data Gathering, Analysis, and Retrieval system (EDGAR) operated by the SEC. EDGAR serves as the primary system for companies and other entities submitting documents under various securities acts. We construct a sample of crowdfunding security offerings in the US under Regulation CF from July 2016 to the end of

2021. Regulation CF requires companies issuing securities through crowdfunding to disclose Forms C and C-U with the SEC, investors, and the intermediary facilitating the offering. These filings detail the firms' financials, risk factors, business plan, leadership team, and intended use of proceeds, as well as the type of security issued (debt or equity) and the crowdfunding goal (the amount that the entrepreneur intends to raise). These filings allow us to record information about the issuing firms' financial statements at the time of the offering, one year prior to the offering, and, if the offering is successful, one year after the crowdfunding campaign (Form C-AR).

Our main sample of analysis is a cross-section of 2,052 firms that launched a crowdfunding campaign in 2016–2021. To exclude firms that are crowdfunding but have not yet formed, we require firms to have non-zero assets. We winsorize all continuous variables at the 2% and 98% tails. Since industry codes are not specified in Form C filings, we collect SIC codes using Capital IQ and via manual web searches.

To get information about prior security issuances, we collect information from Form D filings in EDGAR. Firms that raise capital through private placement of securities under Regulation D are required to fill out Form D. These data allow us to get information about additional capital raised through institutional investors by firms in our sample. In particular, we are able to assess whether firms raise capital by issuing securities through other venues before and/or after the crowdfunding offering.

In order to investigate the relationship between crowdfunding and bank lending, we gather data on banks from the Board of Governors of the Federal Reserve System. These data provide information about the number of bank branches at the ZIP code or county level. We also collect the house price index (HPI) at the ZIP code level from Federal Housing Finance Agency).

To construct a control group of private firms, we rely on FactSet. FactSet allows us to access information about private firms in the US from 2015 to 2021. We construct a matched control sample by matching crowdfunding firms in the year before they issue crowdfunding securities to FactSet firms using propensity score matching on industry (SIC-2), ROA, and total assets.

Finally, we supplement our analysis with macroeconomic variables and Census data at the ZIP-code level from the IPUMS National Historical Geographic Information System (NHGIS) (Manson et al., 2022). IPUMS NHGIS offers easy access to summary tables and time series of population, housing, agriculture, and economic data for various levels of US census geography. In particular, we use data from the 2020 American Community Survey: 5-Year Data (2016-2020) for county-level control variables.

4.3.2. The US crowdfunding market

In this section, we describe the crowdfunding market governed by Regulation CF from 2016–2021. We start by presenting information about the number of total and successful offerings by year. Figure 4.1 shows that the number of security offerings increases from 192 in 2016 to

1,586 by 2021. The unconditional probability for a campaign to be successful remains fairly stable at around 40% during 2016–2020, but dips to 24% in 2021.

Figure 4.2 Panel A shows the quarterly amount successfully raised by crowdfunding firms in USD millions. Firms raised around $10 million in the third quarter of 2016, an amount which grows to $115 million by the fourth quarter of 2021, in part because Regulation CF was amended in 2021 to allow an increase in the maximum amount firms are allowed to raise via crowdfunding. In Panel B, we plot the average number of days that it takes a campaign to reach its goal. On average, it takes 150 days for a firm to meet its funding goal, but this figure starts to decline in 2021. The dramatic drop in the fourth quarter is mechanical: Since the sample ends in 2021, the closing date is recorded for only the fastest and most successful crowdfunding campaigns.

Next, we provide a more granular analysis of crowdfunding intermediaries. As of 2021, more than 100 internet portals are registered with the SEC. Figure 4.3 plots the number of internet portals acting as intermediaries from 2016–2021. However, more than 70% of the offerings are intermediated by only eight portals and the two most popular portals (Wefunder and StartEngine) manage as much as 45% of the offerings (see Figure 4.4). Thus, even though the number of registered portals is large, the intermediaries market is heavily concentrated, likely because network effects attract issuers to platforms that already have a large investor base.

Finally, we are interested in the location and legal status of issuing firms. Figure 4.5 shows the number of offerings per county in our sample period. Most of the issuers are headquartered in California, Florida, New York, and Oregon. Furthermore, 60% of the companies are corporations and 38% limited liabilities companies.

4.3.3. Summary statistics

Table 4.1 presents summary statistics for our sample of 2,052 crowdfunding firms. The table is divided into three panels: issuing firm characteristics (Panel A), offering characteristics (Panel B), and macro variables (Panel C). Table A1 provides detailed definitions for all variables.

Panel A displays firm characteristic sample statistics for several variables: profitability (ROA), the size of the firm measured as the natural log of total assets (Size), cash holdings (Cash), leverage measured as total debt over total assets (Leverage), sales measured as the natural log of total sales (Log sales), firm age in a number of years (Age), and the number of employees measured as the natural log of the total number of employees (Log employees). Issuers tend to be small firms both in terms of size (mean assets are $708,000 and median $103,000) and number of employees (mean 9 employees and median 4). Comparing firms issuing debt and equity reveals that the former is on median smaller but has a higher fraction of large issuers (resulting in a higher average), with average (median) assets of $1.07 million ($66,000) versus $632,000 ($114,000) for equity issuers. Equity issuers also tend to be younger, more levered, and less profitable than debt issuers.

Panel B summarizes offering campaign characteristics, with the amount of funding sought (Amount offered), price per security (Price security), type of security offered (Type of security, where 1 is debt and 0 equity), whether the campaign was successful (Success), and whether the firm had previously raised capital from institutional or accredited investors (Previous Institutional Funding). Firms seek to raise $63,000 on average ($25,000 median), with an average security price of $487 for debt and $92 for equity. 17% of the issuances are debt versus 83% equity, and 37% of campaigns are successful. Notably, around 25% of the sample has previous funding from institutional or accredited investors according to Form D filings, with a smaller fraction of debt issuers (14%) than equity (27%).

Panel C presents information regarding macro variables. Bank Density is the natural log of the total number of bank branches within 150 miles of the issuer's location. Top Bank is a dummy variable that takes the value of 1 if the issuer is located in an area that is in the top quartile of the Bank Density distribution, and 0 otherwise. Total population, Median Income, Frac. White, and Num. of Establishment are variables at the county level. A comparison of debt and equity issuers suggests that debt issuers are headquartered in areas with more access to banks and slightly lower median income.

Finally, Table 4.2 shows the industry distribution (classified by SIC-2 code) of our full sample as well as the subsamples of debt and equity issuers. Business services (in particular computer software) is the largest industry among equity issuers (19%) and second largest among debt issuers (15%). Food products (often breweries and distilleries) and eating and drinking places (mostly restaurants) also account for a large fraction of debt issuers (29%) and a smaller, but still significant, fraction of equity issuers (12%). Other represented industries among equity (debt) issuers include miscellaneous retail and wholesale trade at 8% (8%), engineering, research, and management services at 4% (5%), amusement and recreation services at 4% (3%), and chemicals and allied products at 3% (2%).

4.4. The Choice of Debt versus Equity Crowdfunding

4.4.1. Crowdfunding and the Financial Growth Cycle

How do firms choose between debt and equity crowdfunding? The pecking order theory, as developed by Myers and Majluf (1984), predicts that if capital is needed for new investment opportunities, firms have a preference for internal financing over external financing due to adverse selection. When outside funds are needed, firms prefer debt over equity because debt issues are associated with lower information costs. Equity is seldom issued. However, this theory does not account for several broad patterns of corporate finance. In particular, small high-growth firms are typically thought to have significant information asymmetries, making them particularly susceptible to adverse selection problems. Frank and Goyal (2009) find evidence that such firms generally do not act in accordance with the pecking order theory.

In Table 4.3, we run cross-sectional firm-level OLS regressions with security choice (1 if debt, 0 if equity) as the dependent variable. The control variables include a set of firm characteristics (profitability, size, cash holdings, long-term leverage, and short-term leverage) as well as year and industry fixed effects varying by column. Columns 1–3 contain the full sample of 2,052 firms, 4–5 the subsample of successful issuers, and 6–7 the subsample of failed issuers. The table shows that more profitable firms are more likely to issue debt, which is consistent with them being better able to service debt than less profitable firms. We also find that larger issuers are more likely to issue equity crowdfunding, although this relationship is not statistically significant for the subsample of successful crowdfunders. Finally, we note that firms with higher leverage are more likely to issue equity than debt. This could have several potential explanations, including levered firms (1) not needing to turn to crowdfunding for debt funding since they already have access to bank lending (which we explore further in Section 4.2), (2) being unable to issue further debt due to borrowing constraints, or (3) using crowdfunding to reduce their leverage and bankruptcy risk.

As noted by Berger and Udell (1998), the pecking order hierarchy depends on the size and stage of development of the firm, as there are different levels of information asymmetry and financial needs for each phase of growth. We next investigate whether the likelihood of issuing debt crowdfunding increases as the firm progresses through the financial growth cycle. We define three growth cycle stages appropriate for startups following Cole, Liang, and Zhang (2020): a first stage where firms are pre-revenue, a second stage where firms have positive revenue but are not yet profitable (negative or zero net income), and a third stage where firms achieve profitability to generate positive revenue and net income. Since businesses establish more solid track records (reducing information asymmetry) and start to generate steady revenue streams as they progress through these stages, we expect debt crowdfunding to become a more viable financing option for these firms as they mature.

In Table 4.4, we run the same set of regressions as in Table 4.3, but add two additional independent variables: a dummy designating that the firm is a second-stage firm (revenue-generating but not profitable) and a dummy for third-stage firms (revenue-generating and profitable). Our results indicate a monotonic and positive relationship between stage and the likelihood of issuing debt: As per Column 3, firms in the second stage are 4.6pp likelier to issue debt over equity, and firms in the third stage are 13.3pp likelier. In other words, more mature firms with positive cash flows are more likely to choose debt crowdfunding when available, allowing them to access funding without relinquishing ownership or control of their business. In contrast, early-stage firms that have not started generating revenues are the most likely to opt for equity issuance. These startups do not have a track record of stable cash flows and may be more informationally opaque for investors, which makes debt financing less attractive.

In Table A2 of the Appendix, we present consistent results when using age as an alternative measure for the firm's financial growth cycle. There are several reasons why we use age to proxy for growth cycle stage only for robustness. Faff, Kwok, Podolski, and Wong (2016) argue that firm age is not a reliable indicator of a firm's growth cycle stage, as the time it takes for a firm to transition across growth cycle stages can vary by industry, and firms of the same age can learn at different rates based on their feedback mechanisms. Furthermore, using age as a proxy for the growth cycle stage assumes that a firm progresses linearly through the cycle, which may not be the case (Dickinson, 2011).

4.4.2. Crowdfunding and Access to Bank Lending

Next, we ask whether debt crowdfunding can act as a substitute for bank lending for borrowers with limited access to capital through traditional banking channels. A large body of research in banking establishes that banks constrain their lending to areas surrounding their bank branches, and that lending to small businesses is usually restricted to local markets (Agarwal and Hauswald, 2010; Brevoort, Wolken, and Holmes, 2010; Nguyen, 2019). Accordingly, areas with a higher concentration of bank branches are known to have more competitive banking markets, resulting in improved credit access. In the same vein, the distance between entrepreneurs and offline early-stage investors, such as banks, venture capitalists, and angel investors, has been shown to be a barrier to small business financing (Stuart and Sorenson, 2003; Cumming and Dai, 2010). Since online funding platforms can reduce these distance-related costs, crowdfunding is anticipated to improve the odds for entrepreneurs located in areas underserved by traditional offline funding sources to secure outside capital (Agrawal, Catalini, and Goldfarb, 2015; Vulkan, Åstebro, and Sierra, 2016).

To distinguish between the effects of bank access and demographic differences in loan demand, we follow a similar approach as Erel and Liebersohn (2022) and control for county fixed effects. These capture systematic differences in the financial environment across counties (e.g., local business cycle or economic factors). In addition, we control for plausible demand-side factors by adding local demographic and income controls such as median income, the proportion of the white population, the total population, and the number of establishments within each ZIP code. Our baseline regression specification is as follows:

$$Equity_{i,t} = \beta BankAccess_{t-1} + Controls_{z,t} + \varphi_t + \gamma_s + \delta_c + \varepsilon_{i,t} \tag{4.1}$$

where i, s, z, c and t index crowdfunding campaign, industry sectors, ZIP codes, counties, and time, respectively. We are primarily interested in β, the coefficient on bank access measurements. It is difficult to measure a firm's access to bank lending directly, which makes it necessary to apply proxies instead. We proxy for bank access using two different measures. The first is the log local house price index (HPI) measured at the ZIP code level. Home equity is one of the most frequent sources of funding for startups (Nanda and Phillips, 2022), so we expect HPI to be positively correlated with greater access to bank lending. The second measure is the number of bank branches within 150 miles. We also use a dummy equal to one if the firm is located in the top quartile of ZIP codes by the number of bank branches within 150 miles.

To investigate whether debt crowdfunding can substitute for bank lending, Table 4.5 presents similar cross-sectional regressions as in Tables 4.3 and 4.4, but with the addition of the HPI variable, controls for ZIP-level economic and demographic conditions, and county fixed effects. We observe a negative and significant relationship between local house prices and a firm's likelihood of issuing debt instead of equity. In Column (5), which controls for year, industry, and county fixed effects, we estimate that a one standard deviation increase in HPI corresponds to a 2.9% lower likelihood for a firm to choose debt financing. This suggests that as home values increase — and entrepreneurs have more home equity to tap for funding — firms become more likely to seek equity crowdfunding instead of debt.

In Table 4.6, we again address the same question but with the second proxy for bank access: the number of bank branches within 150 miles of the firm's headquarters. Column 1 shows that firms located in areas with more bank branches (proxying for better access to bank loans) are less likely to issue crowdfunded debt. One log-point increase in bank branches within 150 miles is associated with a decrease in the likelihood of obtaining crowdfunded debt by about 0.62. The standard deviation of Log Bank Density is 0.69, so a one standard deviation increase in the log number of bank branches within 150 miles is associated with an approximately 42.9% decline in the odds of getting debt crowdfunding compared to the median. In Columns 2 and 3, year fixed effects are used to control for intertemporal variation in the crowdfunding choice, and industry fixed effects are used to control for unobservable, time-invariant differences across industries. The estimates obtained when including county fixed effects alone, as shown in Column 1, exhibit a similar magnitude to those obtained when incorporating year and industry effects, as presented in Columns 2 and 3. In Columns 4–6, we rerun our analysis with Top Bank Density (150 miles) as the alternative measure of bank access, showing consistent results across all specifications. As per Column 6, we estimate that a firm is 9.8pp less likely to choose debt financing if it is located in a ZIP code that is in the top quartile in terms of the number of nearby bank branches.

4.5. Crowdfunding and growth

In this section of the paper, we assess whether successful crowdfunding is associated with real growth outcomes, and how these outcomes relate to the firm's stage in the financial growth cycle. As discussed in Section 1, theory does not give a clear indication of whether to expect crowdfunding to result in improved performance due to issues of information asymmetry and moral hazard. Moreover, prior empirical evidence is ambiguous on whether crowdfunding fosters growth.

To analyze the relationship between crowdfunding and firm growth, we compare firms that successfully issued crowdfunded debt or equity to a sample of matched private firms from Factset in a matched diff-in-diff setting (as in Boucly, Sraer, and Thesmar (2011)). We create a matched set of control firms from the period 2016–2021 using propensity-score matching on the following variables, measured in the year before the treated firm launches its crowdfunding campaign: SIC-2 industry, ROA, and total assets. We additionally require matched firms to have non-missing data in the year after they are matched (i.e., the counterfactual year after crowdfunding). Due to data limitations, we are only able to analyze a two-period setting: one year before crowdfunding and one year after. Consequently, we can only evaluate short-term effects associated with crowdfunding.[5]

In Table 4.7, we run matched diff-in-diff panel regressions with two-way fixed effects (firm and year) for six different outcome variables: size (log total assets), log revenue, profitability (ROA), cash holdings, book leverage, short-term leverage, and long-term leverage. We include a post-period control dummy (equal to one if the observation represents the (matched) year after crowdfunding) and a post-period and treated interaction variable, which is our primary variable of interest and captures the estimated effect associated with crowdfunding after the campaign has concluded.

We find that crowdfunding firms increase their total assets, revenue, and ROA relative to similar firms that do not issue securities via crowdfunding. More specifically, successful crowdfunding is associated with a 42% increase in size, 46% increase in revenue, and a 0.96 higher ROA (for comparison, the pre-crowdfunding sample average ROA is 2.26). Short-term leverage is expected to decrease by 0.17, consistent with a majority of the offerings in the sample being equity. In other words, compared to similar firms that do not issue crowdfunded securities, issuers appear to grow in size while simultaneously improving their performance. This suggests that any information asymmetry and moral hazard problems present during crowdfunding do not fully disincentivize entrepreneurs from putting crowdfunded capital to good use.

In Section 4, we showed that the firm's choice of debt versus equity securities is related to its stage in the financial growth cycle. Next, we investigate whether the growth effects seen above also vary by developmental stage. To do so, we include controls in Table 4.8 for the growth stage as well as a pair of three-way interaction variables: post-period times treated times growth stages two and three, respectively. This allows us to estimate the relative growth effects associated with successful crowdfunding for startups in their first, second, and third stages of development.

Table 4.8 shows large increases in size (83%), revenue (90%), and ROA (1.25) for first-stage startups that successfully crowdfund versus similar firms that do not. Relative to first-stage firms, however, second- and third-stage firms see significantly lower gains in size (-71% and -50%) and revenue (-59% and -74%), with third-stage firms additionally seeing less of an increase in ROA (-1.19). Relative to control firms without crowdfunding, only second-

[5]Our sample is limited since firms that issue securities according to Regulation CF are only required to disclose financials once prior to crowdfunding and once after the campaign succeeds (no more than 120 days after fiscal year-end). Thus, we can only observe multiple post-crowdfunding years of data for a firm if it for some reason has to extend its filing period or if it makes subsequent Form C filings in conjunction with follow-on crowdfunding campaigns.

stage firms see gains in revenue (90%–59%=31%, significant at the 5% level) and profitability (1.25–0.21=1.04, significant at the 10% level). In contrast, third-stage firms that successfully crowdfund do not see significant gains in size, revenue, or profitability. In other words, the positive real economic effects associated with crowdfunding appear related to the firm's developmental stage, with startups that have yet to become profitable seeing significant operating gains while profitable, more mature, firms do not show signs of improvement.

Our findings may provide new context as to why prior empirical studies yield mixed predictions regarding the relationship between crowdfunding and growth. In particular, Eldridge, Nisar, and Torchia (2021) finds a positive relationship between equity crowdfunding and ROA for UK firms, while Havrylchyk and Mahdavi Ardekani (2020) do not observe any relationship between debt crowdfunding and sales growth or profitability for a sample of French firms. We document that both the firm's choice of security type — debt versus equity — and post-issuance gains in revenue and profitability are closely related to the firm's stage in the financial growth cycle.

4.6. Conclusion

Regulation CF of the JOBS Act allows small businesses in the US to offer crowdfunded debt and equity securities to individual investors. In this paper, we raise several questions regarding this recent source of startup capital: Which types of firms choose to issue crowdfunded debt, and which choose equity? How does this decision relate to the firm's stage in the financial growth cycle and access to bank lending? Is successful crowdfunding associated with realized improvements in firm size and profitability?

We start by examining the factors associated with a firm's choice between debt and equity crowdfunding. We find that larger, less profitable, and more levered firms are less likely to select debt when issuing securities via crowdfunding. We also find that the capital structure of crowdfunded firms tends to follow a growth cycle pattern. Specifically, early-stage startups are more likely than late-stage startups to finance their growth through equity crowdfunding. As firms develop, they tend to rely more on debt-based crowdfunding, potentially because improved financial stability and creditworthiness make debt financing less costly.

Next, we investigate how the availability of traditional bank financing is related to the firm's choice of crowdfunding security type. We find evidence consistent with debt crowdfunding serving as a substitute for bank lending. We show that firms located in areas with higher house prices (proxying for access to home equity, a frequent source of funding for startups) and a higher number of bank branches (proxying for access to bank loans) are more likely to issue crowdfunded equity.

To conclude our analysis, we investigate whether successful securities crowdfunding is associated with realized increases in firm size and performance. We compare firms that successfully issued crowdfunded debt or equity to a sample of matched private firms from Factset.

We find that crowdfunding firms increase their total assets, revenue, and ROA relative to the control sample. This difference is largest for first-stage firms, with the relationship weakening as firms mature. While the positive association between crowdfunding and ROA is positive and significant for both first- and second-stage firms, it is insignificant for third-stage firms. Our results suggest that crowdfunding can improve operational performance for firms that are not yet profitable but has a negligible impact on more mature, profitable, firms.

Fig. 4.1 Yearly offerings. This figure shows the total number of offerings and the number of successful offerings from 2016 through 2021. Data come from EDGAR.

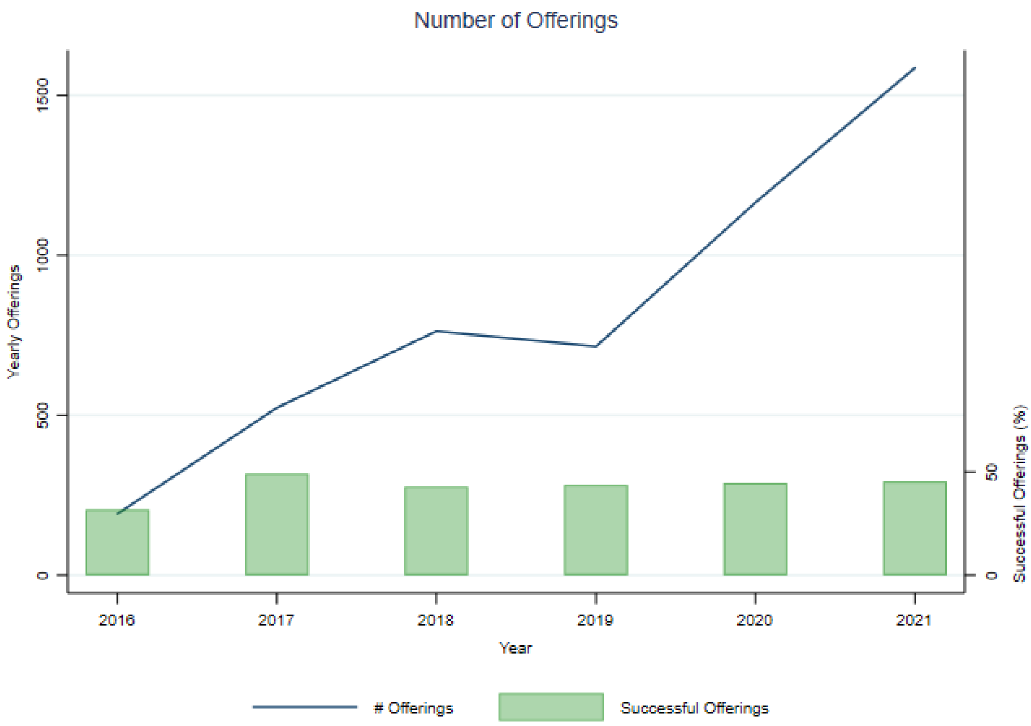


Fig. 4.2 Time required to meet the funding goal and total amount raised. These figures show respectively the total amount raised through crowdfunding (in millions USD) and the time required to raise the funds (in days). Data comes from EDGAR.

Fig. 4.3 Number of crowdfunding platforms. This figure shows the evolution of the total number crowdfunding from 2016 through 2021.

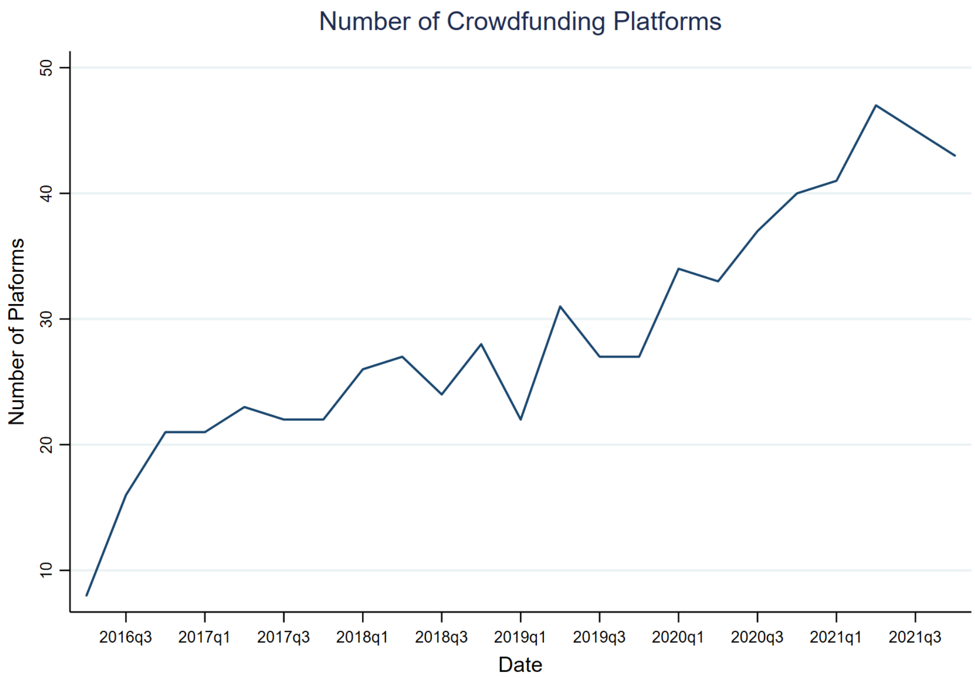


Fig. 4.4 Most popular crowdfunding platforms. This figure shows the percentage of the offerings managed by the most eight most popular crowdfunding portals. Data come from EDGAR.

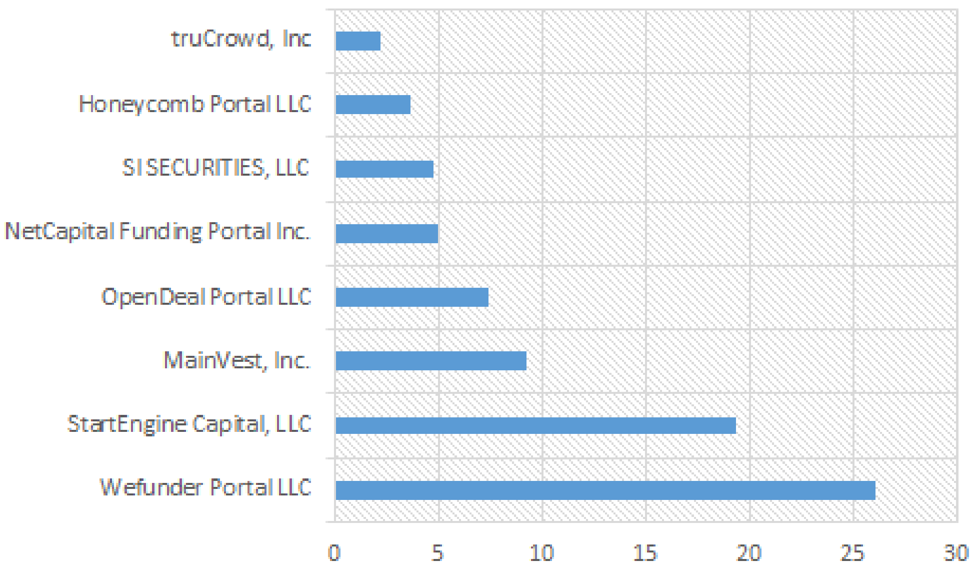


Fig. 4.5 Crowdfunding geography. This figure shows the country-level graph of the numbers of crowdfunding offerings across US Counties. Colors correspond to bins of the number of offerings. Data come from EDGAR.

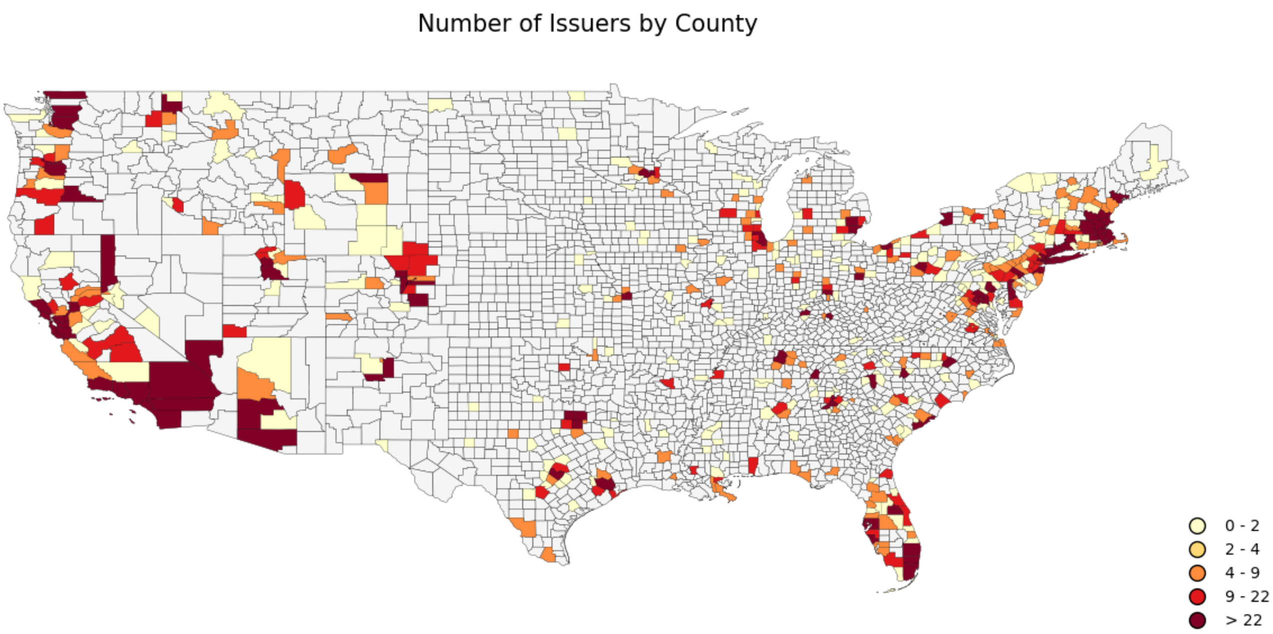


Table 4.1 Summary Statistics The table presents descriptive statistics for financial variables (Panel A), crowdfunding variables (Panel B), and macro variables (Panel C). The sample covers 2,052 US crowdfunded firms from June 2016 through December 2021. We require non-zero total assets and winsorize data at (2,98) level. All variables are defined in the Appendix (Table A1). Total Assets are in millions of dollars. Columns 4, 5 and 6, 7 show the subsamples of debt-based crowdfunding (CF) and equity-based CF, respectively. The p-value in column 9 is the significance of a t-test for the difference in mean between debt and equity crowdfunding. Data sources: EDGAR, FactSet, Board of Governors of the Federal Reserve System, IPUMS National Historical Geographic Information System.

	Full Sample (N = 2052)			Debt-based CF (N = 355)		Equity-based CF (N = 1657)		Difference	p-value of
	N	Mean	Median	Mean	Median	Mean	Median	in mean	difference
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: Firm Characteristics									
Total Assets	2052	708,164	103,416	1,070,204	65,549	632,428	113,741	437,776	0.236
Profitability	2052	2.36	0.35	3.75	1.33	2.07	0.25	1.68	0.000
Size	2052	11.28	11.55	11.02	11.09	11.33	11.64	-0.31	0.018
Cash holdings	2052	0.46	0.36	0.43	0.28	0.47	0.38	-0.03	0.135
Book Leverage	2052	5.07	0.92	3.35	0.85	5.43	0.94	-2.08	0.017
LT Leverage	2052	2.51	0.09	1.59	0.02	2.71	0.10	-1.11	0.019
ST Leverage	2052	1.51	0.18	1.21	0.15	1.57	0.18	-0.36	0.144
Log (Sales)	2052	11.61	11.87	11.56	11.81	11.63	11.88	-0.07	0.680
Age	2052	2.67	1.00	3.23	2.00	2.55	1.00	-0.68	0.004
Financial Growth Cycle	2052	1.86	2.00	2.07	2.00	1.81	2.00	-0.26	0.000
Log (Employees)	2052	8.98	4.00	6.96	4.00	9.43	4.00	-2.48	0.316
Panel B: Crowdfunding									
Amount Offered	2052	63631	25000	62734	25000	63834	25000	-1100	0.862
Price Security	2052	146	1	487	1	92	1	395	0.012
Type of Security	2052	0.17	0.00						
Success	2052	0.37	0.00	0.37	0.00	0.37	0.00	0.00	0.950
Previous Institutional Funding	2052	0.25	0.00	0.14	0.00	0.27	0.00	-0.12	0.000
Panel C: Macro variables									
Bank Density (150 miles)	2001	7.500	7.550	7.606	7.819	7.478	7.539	0.13	0.003
Top Bank	2001	0.25	0.00	0.33	0.00	0.23	0.00	0.09	0.001
Total population	2001	10.15	10.28	10.09	10.27	10.17	10.28	-0.08	0.130
Median Income	2001	82.74	78.07	78.80	72.16	83.58	79.27	-4.78	0.030
Frac. White	2001	21.82	20.02	21.35	18.79	21.91	20.04	-0.56	0.507
Num. of Establishment	2001	47.80	33.00	40.53	31.00	49.35	34.00	-8.82	0.007

Table 4.2 **Industry Distribution of Sample Crowdfunded Firms and Financing Choice** The table presents the distribution of sample firms based on their Standard Industrial Classification (SIC) 2-digit industry code, sorted by frequency. It also shows the number and percentage of firms that opt for debt-based crowdfunding (CF) and equity-based crowdfunding within each industry category. The sample contains 2,052 US crowdfunding campaigns, 2016–2021. All variables are defined in the Appendix (Table A1).

		All firms		Debt-based CF		Equity-based CF	
SIC2	Industry	Num.	Percent	Num.	Percent	Num.	Percent
73	Business Services	384	18.71	54	15.21	330	19.45
20	Food and Kindred Products	199	9.7	62	17.46	137	8.07
58	Eating and Drinking Places	111	5.41	42	11.83	69	4.07
87	Engineering, Accounting, Research, and Management Services	93	4.53	18	5.07	75	4.42
59	Miscellaneous Retail	87	4.24	14	3.94	73	4.3
51	Wholesale Trade - Nondurable Goods	80	3.9	15	4.23	65	3.83
79	Amusement and Recreation Services	76	3.7	11	3.1	65	3.83
28	Chemicals and Allied Products	56	2.73	7	1.97	49	2.89
54	Food Stores	50	2.44	15	4.23	35	2.06
80	Health Services	50	2.44	5	1.41	45	2.65
50	Wholesale Trade - Durable Goods	49	2.39	4	1.13	45	2.65
38	Measuring, Photographic, Medical, & Optical Goods, & Clocks	48	2.34	4	1.13	44	2.59
36	Electronic & Other Electrical Equipment & Components	47	2.29	2	0.56	45	2.65
72	Personal Services	46	2.24	8	2.25	38	2.24
48	Communications	42	2.05	5	1.41	37	2.18
35	Industrial and Commercial Machinery and Computer Equipment	38	1.85	3	0.85	35	2.06
82	Educational Services	38	1.85	7	1.97	31	1.83
27	Printing, Publishing and Allied Industries	30	1.46	2	0.56	28	1.65
78	Motion Pictures	30	1.46	2	0.56	28	1.65
37	Transportation Equipment	29	1.41	1	0.28	28	1.65
56	Apparel and Accessory Stores	28	1.36	6	1.69	22	1.3
39	Miscellaneous Manufacturing Industries	27	1.32	3	0.85	24	1.41
65	Real Estate	27	1.32	5	1.41	22	1.3
61	Nondepository Credit Institutions	26	1.27	3	0.85	23	1.36
62	Security & Commodity Brokers, Dealers, Exchanges & Services	24	1.17	5	1.41	19	1.12
67	Holding and Other Investment Offices	23	1.12	2	0.56	21	1.24
83	Social Services	23	1.12	5	1.41	18	1.06
47	Transportation Services	22	1.07	4	1.13	18	1.06
49	Electric, Gas and Sanitary Services	18	0.88	2	0.56	16	0.94
75	Automotive Repair, Services and Parking	17	0.83	4	1.13	13	0.77
89	Services, Not Elsewhere Classified	15	0.73	2	0.56	13	0.77
86	Membership Organizations	13	0.63	3	0.85	10	0.59
1	Agricultural Production - Crops	12	0.58	5	1.41	7	0.41
23	Apparel, Finished Products from Fabrics & Similar Materials	12	0.58	3	0.85	9	0.53
31	Leather and Leather Products	12	0.58	1	0.28	11	0.65
55	Automotive Dealers and Gasoline Service Stations	12	0.58	0	0	12	0.71
34	Fabricated Metal Products	11	0.54	0	0	11	0.65
15	Construction - General Contractors & Operative Builders	10	0.49	5	1.41	5	0.29
42	Motor Freight Transportation	10	0.49	1	0.28	9	0.53

Table 4.3 Financing Choice and Firm Characteristics The table presents the relationship between firm characteristics and the choice of security type in crowdfunding campaigns. The dependent variable is a dummy that takes the value of 1 when the issued security is in the form of debt, and 0 otherwise. Columns (1), (2), and (3) display the estimated coefficients for the full sample. Columns (4) and (5) present results for successful campaigns, while columns (6) and (7) report coefficients for failed campaigns. All variables are defined in the Appendix (Table A1). Firm-level variables are lagged by one year. The sample contains 2,052 US crowdfunding campaigns, 2016–2021. T-statistics are in parentheses and standard errors are clustered at the industry level. *, **, and *** indicate statistical significance at 10%, 5%, and 1%, respectively.

	Full Sample			Successful CF		Failed CF	
Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Profitability	0.009***	0.009***	0.008***	0.008**	0.007**	0.012***	0.010***
	(3.60)	(3.71)	(3.38)	(2.48)	(2.25)	(4.46)	(3.69)
Size	-0.013***	-0.012***	-0.011**	-0.006	-0.004	-0.022**	-0.022**
	(3.03)	(2.96)	(2.32)	(1.24)	(0.71)	(2.37)	(2.47)
Cash holdings	-0.056	-0.057	-0.027	-0.016	0.010	-0.113*	-0.082*
	(1.47)	(1.53)	(0.92)	(0.50)	(0.32)	(1.94)	(1.90)
LT Leverage	-0.003***	-0.003***	-0.003**	-0.003**	-0.002*	-0.003***	-0.003*
	(2.85)	(2.85)	(2.37)	(2.28)	(1.80)	(2.75)	(1.73)
ST Leverage	-0.005**	-0.004**	-0.003*	-0.002	-0.000	-0.010***	-0.008**
	(2.41)	(2.24)	(1.83)	(0.72)	(0.20)	(2.79)	(2.38)
Year FE		Y	Y	Y	Y	Y	Y
Industry FE			Y		Y		Y
Observations	2,052	2,052	2,045	1,292	1,286	760	741
Adjusted R-squared	0.024	0.025	0.057	0.025	0.049	0.041	0.084

Table 4.4 Financing Choice and Growth Stage The table presents the relationship between the stage of a firm's financial growth and the choice of security type in crowdfunding campaigns. The dependent variable is a dummy that takes the value of 1 when the issued security is in the form of debt, and 0 otherwise. Columns (1), (2), and (3) display the estimated coefficients for the full sample. Columns (4) and (5) present results for successful campaigns, while columns (6) and (7) report coefficients for failed campaigns. We categorize firms into three stages of the financial growth cycle: pre-revenue (Growth Stage 1), positive revenue but not yet profitable (Growth Stage 2), and profitable with positive revenue and net income (Growth Stage 3). All variables are defined in the Appendix (Table A1). Firm-level variables are lagged by one year. The sample contains 2,052 US crowdfunding campaigns, 2016–2021. T-statistics are in parentheses and standard errors are clustered at the industry level. *, **, and *** indicate statistical significance at 10%, 5%, and 1%, respectively.

	Full Sample			Successful CF		Failed CF	
Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Growth Stage 2	0.063***	0.065***	0.046*	0.092***	0.076**	0.022	0.013
	(3.69)	(3.15)	(1.97)	(3.39)	(2.44)	(0.82)	(0.38)
Growth Stage 3	0.179***	0.153***	0.133***	0.146***	0.130***	0.156***	0.122**
	(4.88)	(4.38)	(3.63)	(3.26)	(2.80)	(4.24)	(2.64)
Profitability		0.005*	0.004	0.003	0.003	0.007***	0.007**
		(1.80)	(1.62)	(0.95)	(0.87)	(2.67)	(2.46)
Size		-0.018***	-0.015***	-0.013**	-0.010	-0.024**	-0.024***
		(3.92)	(3.28)	(2.42)	(1.64)	(2.46)	(2.79)
Cash holdings		-0.041	-0.015	0.003	0.025	-0.097	-0.071
		(1.17)	(0.50)	(0.09)	(0.84)	(1.65)	(1.59)
LT Leverage		-0.003**	-0.002**	-0.003**	-0.002*	-0.003**	-0.002
		(2.61)	(2.14)	(2.14)	(1.69)	(2.55)	(1.65)
ST Leverage		-0.004*	-0.003	-0.001	-0.000	-0.009**	-0.007**
		(1.92)	(1.55)	(0.54)	(0.05)	(2.39)	(2.11)
Year FE		Y	Y	Y	Y	Y	Y
Industry FE			Y		Y		Y
Observations	2,032	2,032	2,025	1,280	1,274	752	733
Adjusted R-squared	0.023	0.037	0.064	0.037	0.056	0.054	0.092

Table 4.5 Housing Price Changes and Financing Choice of Crowdfunding The table presents the relationship between house prices and the choice of security type in crowdfunding campaigns. The dependent variable is a dummy that takes the value of 1 when the issued security is in the form of debt, and 0 otherwise. All variables are defined in the Appendix (Table A1). Firm-level variables and HPI are lagged by one year. HPI and the macro controls are at the ZIP code level. The sample contains 2,052 US crowdfunding campaigns, 2016–2021. T-statistics are in parentheses and standard errors are clustered at the industry level. *, **, and *** indicate statistical significance at 10%, 5%, and 1%, respectively.

Variables	(1)	(2)	(3)	(4)
log HPI	-0.049***	-0.052***	-0.040**	-0.041*
	(2.65)	(2.68)	(2.13)	(1.92)
log Med. Inc		0.004	0.001	0.015
		(0.13)	(0.02)	(0.44)
log Population		0.009	0.005	0.002
		(0.40)	(0.20)	(0.08)
Establishments Per Cap.		-0.002	-0.002	-0.002
		(0.30)	(0.36)	(0.28)
Firm Controls	Y	Y	Y	Y
County FE	Y	Y	Y	Y
Year FE			Y	Y
Industry FE				Y
Observations	1320	1180	1180	1166

Table 4.6 Bank-lending Availability and Crowdfunding Choice The table reports results from the bank-lending availability and the choice of security type in crowdfunding campaigns regression estimations. The dependent variable is a dummy that takes the value of 1 when the issued security is in the form of debt, and 0 otherwise. All variables are defined in the Appendix (Table A1). Firm-level variables are lagged by one year. The sample contains 2,052 US crowdfunding campaigns, 2016–2021. T-statistics are in parentheses and standard errors are clustered at the industry level. *, **, and *** indicate statistical significance at 10%, 5%, and 1%, respectively.

Variables	(1)	(2)	(3)	(5)	(6)	(8)
Log Bank Density (150 miles)	-0.622**	-0.588**	-0.551*			
	(2.41)	(2.27)	(1.88)			
Top Bank Density (150 miles)				-0.114***	-0.134***	-0.098*
				(2.96)	(3.47)	(1.85)
Log Med. Inc	0.000	0.000	0.000	0.000	0.000	0.000
	(0.32)	(0.41)	(0.39)	(0.31)	(0.40)	(0.39)
Frac. White	-0.036	-0.039	-0.023	-0.031	-0.034	-0.019
	(0.63)	(0.70)	(0.39)	(0.55)	(0.62)	(0.33)
Log Population	0.001	0.001	0.001	0.001	0.001	0.001
	(1.38)	(1.41)	(1.12)	(1.32)	(1.35)	(1.07)
Establishments Per Cap.	-0.000	-0.000*	-0.000*	-0.000*	-0.000*	-0.000*
	(1.67)	(1.71)	(1.70)	(1.78)	(1.82)	(1.78)
Firm Controls	Y	Y	Y	Y	Y	Y
County FE	Y	Y	Y	Y	Y	Y
Year FE		Y	Y		Y	Y
Industry FE			Y			Y
Observations	1,826	1,826	1,826	1,826	1,826	1,826
Adjusted R-squared	0.141	0.142	0.152	0.139	0.141	0.150

Table 4.7 Institutional Investors and Financing Choice The table provides regression results for the relationship between institutional funding and the choice of security type in crowdfunding campaigns. Columns (1), (2), and (3) display the estimated coefficients for the full sample. Columns (4) and (5) present results for successful campaigns, while columns (6) and (7) report coefficients for failed campaigns. The dependent variable is a dummy that takes the value of 1 when the issued security is in the form of debt, and 0 otherwise. All variables are defined in the Appendix (Table A1). Firm-level variables are lagged by one year. The sample contains 2,052 US crowdfunding campaigns, 2016-2021. T-statistics are in parentheses and standard errors are clustered at the industry level. *, **, and *** indicate statistical significance at 10%, 5%, and 1%, respectively.

	Full Sample			Successful CF		Failed CF	
Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Previous Institutional Funding	-0.094***	-0.075***	-0.065***	-0.059**	-0.040	-0.102***	-0.088**
	(5.03)	(4.07)	(3.95)	(2.14)	(1.51)	(3.01)	(2.48)
Profitability		0.009***	0.008***	0.008**	0.007**	0.011***	0.010***
		(3.66)	(3.35)	(2.41)	(2.23)	(4.23)	(3.47)
Size		-0.008*	-0.007	-0.003	-0.002	-0.015*	-0.016*
		(1.76)	(1.44)	(0.62)	(0.37)	(1.79)	(1.94)
Cash holdings		-0.046	-0.018	-0.009	0.014	-0.095*	-0.066
		(1.26)	(0.64)	(0.29)	(0.46)	(1.71)	(1.56)
LT Leverage		-0.003***	-0.003**	-0.003**	-0.002*	-0.003***	-0.003*
		(2.84)	(2.41)	(2.24)	(1.80)	(2.96)	(1.92)
ST Leverage		-0.003*	-0.003	-0.001	0.000	-0.009***	-0.008**
		(1.76)	(1.45)	(0.31)	(0.08)	(2.89)	(2.50)
Year FE		Y	Y	Y	Y	Y	Y
Industry FE			Y		Y		Y
Observations	2,052	2,052	2,045	1,292	1,286	760	741
Adjusted R-squared	0.011	0.031	0.061	0.029	0.050	0.053	0.092

Table 4.8 **Crowdfunding and Growth** The table presents results from the regression estimation of crowdfunding and growth. Post is a dummy variable that takes a value of 1 after the crowdfunding campaign, and 0 otherwise. Treated is a dummy variable that takes a value of 1 if the firm successfully concluded a crowdfunding campaign, and 0 otherwise. All variables are defined in the Appendix (Table A1). Firm-level variables are lagged by one year. The sample contains 349 US crowdfunding firms and their matched controls, 2016-2021. Data frequency is yearly. T-statistics are in parentheses and standard errors are clustered at the industry level. *, **, and *** indicate statistical significance at 10%, 5%, and 1%, respectively.

	(1) Size	(2) Log Revenue	(3) Profitability	(4) Cash holdings	(5) Book Leverage	(6) ST Leverage	(7) LT Leverage
Post	0.064	-0.065	-0.476	0.002	-0.861**	0.008	0.007
	(0.38)	(0.51)	(0.74)	(0.06)	(2.50)	(0.42)	(0.17)
Post x Treated	0.424***	0.464***	0.964*	0.044	0.274	-0.168***	-0.141
	(2.67)	(4.33)	(1.73)	(1.56)	(0.71)	(2.99)	(1.21)
Year FE	Y	Y	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y	Y	Y
Observations	1,359	1,113	1,352	1,349	1,241	1,363	1,241
Adjusted R-squared	0.700	0.871	0.673	0.693	0.494	0.511	0.619

Table 4.9 Crowdfunding, Growth, and Financial Growth Cycle The table presents the relationship between crowdfunding, growth, and the financial growth cycle. Post is a dummy variable that takes a value of 1 after the crowdfunding campaign, and 0 otherwise. Treated is a dummy variable that takes a value of 1 if the firm successfully concluded a crowdfunding campaign, and 0 otherwise. We categorize firms into three stages of the financial growth cycle: pre-revenue (Growth Stage 1), positive revenue but not yet profitable (Growth Stage 2), and profitable with positive revenue and net income (Growth Stage 3). All variables are defined in the Appendix (Table A1). Firm-level variables are lagged by one year. The sample contains 349 US crowdfunding firms and their matched controls, 2016-2021. Data frequency is yearly. T-statistics are in parentheses and standard errors are clustered at the industry level. *, **, and *** indicate statistical significance at 10%, 5%, and 1%, respectively.

	(1) Size	(2) Revenue	(3) Profitability	(4) Cash holdings	(5) Book Leverage	(6) ST Leverage	(7) LT Leverage
Post	-0.027	-0.079	-0.526	0.019	-0.361	0.005	0.009
	(0.17)	(0.66)	(0.82)	(0.57)	(1.21)	(0.24)	(0.23)
Post x Treated	0.829***	0.899***	1.248**	0.028	-0.468	-0.162*	-0.338*
	(4.54)	(5.43)	(2.23)	(0.81)	(1.18)	(1.93)	(1.79)
Post x Treated x Growth Stage 2	-0.705***	-0.588***	-0.212	0.023	0.214	-0.092	0.369
	(4.80)	(3.02)	(1.07)	(0.63)	(0.51)	(0.73)	(1.42)
Post x Treated x Growth Stage 3	-0.498***	-0.738***	-1.190***	-0.075	0.697*	0.221*	0.450*
	(2.70)	(4.05)	(3.02)	(1.40)	(1.82)	(1.83)	(1.87)
Growth Stage 2	0.748	-0.351**	3.525**	-0.265	0.112	0.332	-0.054
	(1.59)	(2.31)	(2.28)	(1.10)	(0.21)	(1.14)	(0.37)
Growth Stage 3	1.184**		1.662	-0.252	0.130	0.306	-0.070
	(2.53)		(0.99)	(1.04)	(0.21)	(1.04)	(0.45)
Year FE	Y	Y	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y	Y	Y
Observations	1,339	1,109	1,336	1,329	1,221	1,343	1,221
Adjusted R-squared	0.719	0.876	0.683	0.709	0.558	0.502	0.620

Table A1 Variable Definition

Variables	Source	Description
A. Firm Characteristics (measured at the most recent fiscal year (t-1))		
Profitability	Edgar Form C	Revenue/Total Assets
Total Assets	Edgar Form C	Total Assets (in $ million)
Size	Edgar Form C	Natural log of total assets
Cash holdings	Edgar Form C	Cash and cash equivalents/Total Assets
Book Leverage	Edgar Form C	Total Debt/Total Assets
LT Leverage	Edgar Form C	Long-term Debt/Total Assets
ST Leverage	Edgar Form C	Short-term Debt/Total Assets
Log (Sales)	Edgar Form C	Natural log of total revenues
Age	Edgar Form C	First form C filing date - Date in corporation
Financial Growth Cycle	Edgar Form C	Growth stage = 1 if Revenue = 0 & Net Income <= 0 Growth stage = 2 if Revenue > 0 & Net Income <= 0 Growth stage = 3 if Revenue > 0 & Net Income > 0
Log (Employees)	Edgar Form C	Natural log of current employees
B. Crowdfunding		
Amount Offered	Edgar Form C	Amount offered
Price Security	Edgar Form C	Price security
Num. of Securities	Edgar Form C	Number of securities issued
Time to raise funds	Edgar Form C	First form C Filing date - Filing date form C/U (signaling the success of the crowdfunding campaign)
Interest Rate	Edgar Form C	Interest rate that the issuer pays to the intermediary
Type of Security	Edgar Form C	Dummy that takes the value of 1 when the issued security is in the form of debt, and 0 if equity. Equity definition includes common stock, preferred stock, and other securities
Success	Edgar Form C	Dummy that takes the value of 1 when firms raise the crowdfunding campaign target amount and 0 otherwise
Previous Institutional Funding	Edgar Form D	The variable takes a binary value of 1 if a firm filed Form D prior to the crowdfunding campaign, indicating that the firm received financing from Private Equity, Venture Capital, or Hedge Funds. Otherwise, it takes a value of 0 if the firm did not file Form D, indicating no such financing.
C. Macro variables		
Num. Bank Branches	FDIC Summary of Deposits Database	Number of bank branches per ZIP code
Bank Density (100 miles)	FDIC Summary of Deposits Database	Log of the total number of bank branches within 100 miles from the issuer's location
Bank Density (150 miles)	FDIC Summary of Deposits Database	Log of the total number of bank branches within 150 miles from the issuer's location
Total population	American Community Survey, 2016–2020	Total population per ZIP code
Median Income	American Community Survey, 2016–2020	Median income per ZIP code
Num. of Establishment	American Community Survey, 2016–2020	Number of establishment per ZIP code

Fig. A1 Example of a crowdfunding offering. This figure shows the example of a crowdfunding offering from StartEngine.

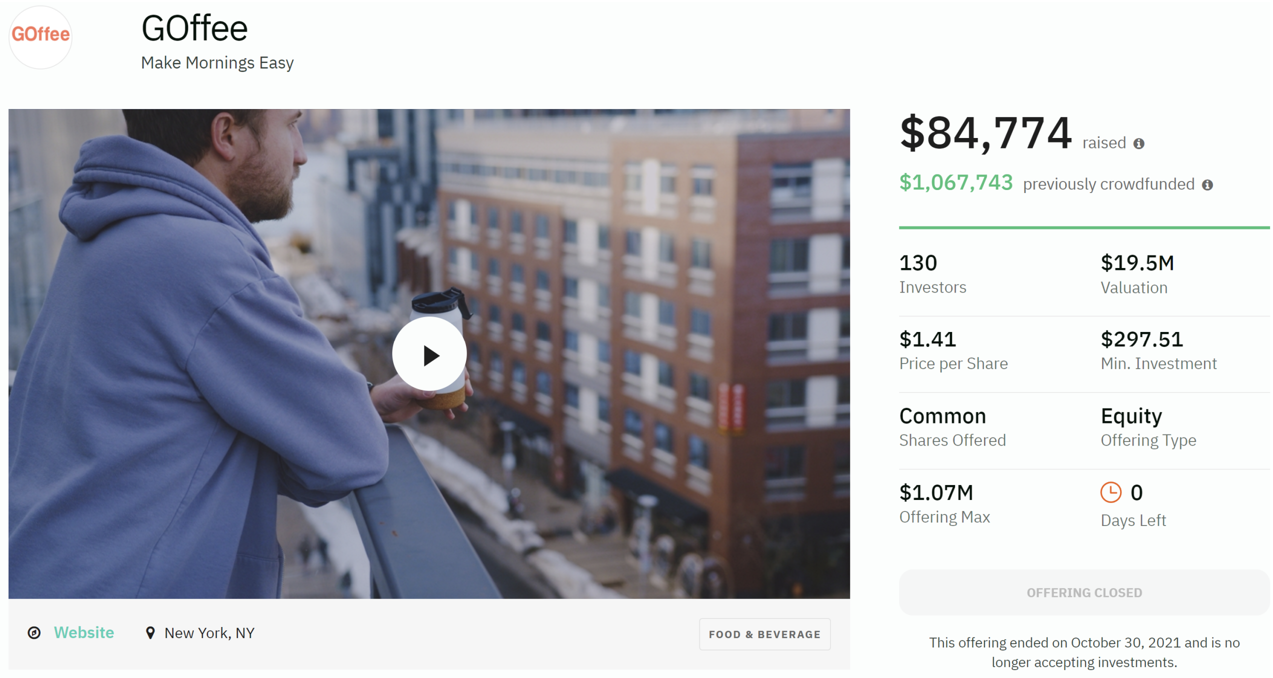


Fig. A2 **Number of bank branches New York Metropolitan Area.** This figure shows data from New York County, Bronx County, Queens County, Kings County, and Richmond County (New York Metropolitan Area) ZIP Codes. Colors correspond to bins of the number bank branches per establishment per ZIP code.

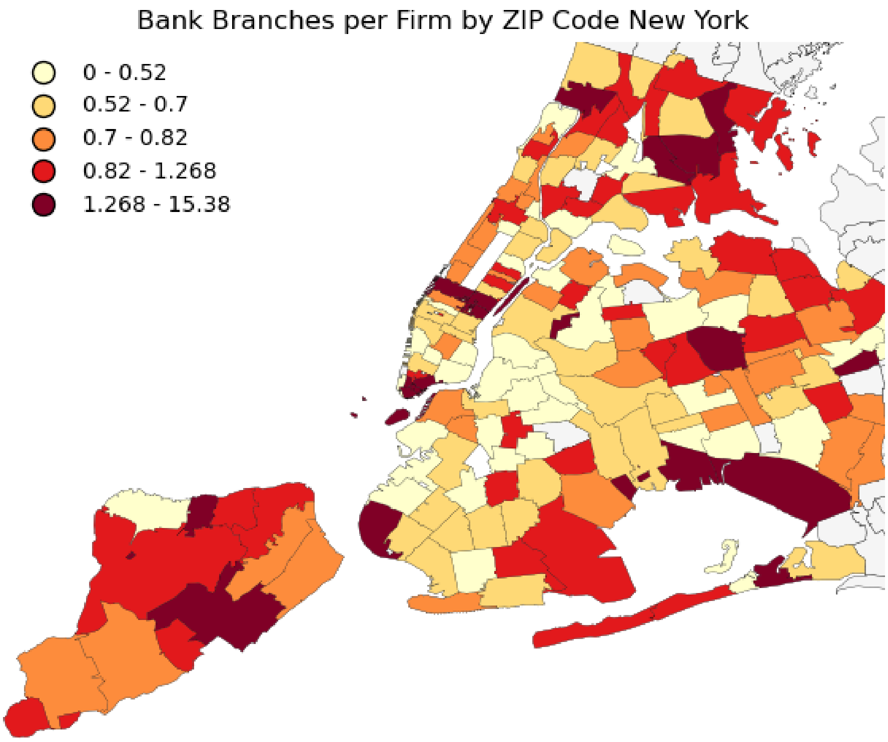
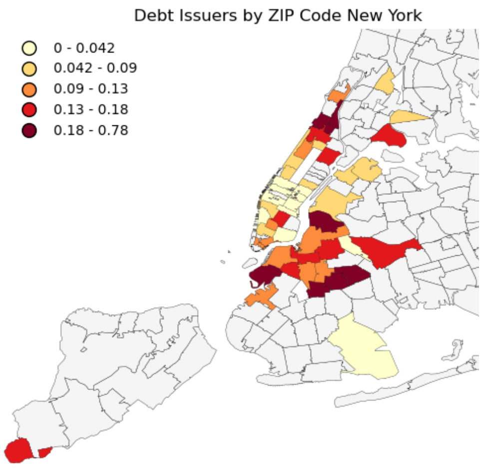


Fig. A3 Number of debt and issuers New York Metropolitan Area: This figure shows data from New York County, Bronx County, Queens County, Kings County, and Richmond County (New York Metropolitan Area) ZIP Codes. The left panel colors correspond to bins of the percentage of establishments that issued debt securities through crowdfunding. The right panel colors correspond to bins of the percentage of establishments that issued equity securities through crowdfunding.



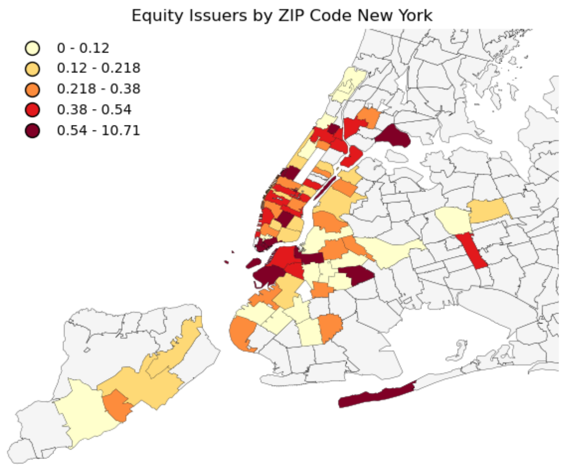


Table A2 Financing Choice and Growth Stage (proxied by Age) The table presents the relationship between the choice of security type in crowdfunding campaigns and age. All variables are defined in the Appendix (Table A1). Firm-level variables are lagged by one year. The sample contains 2,052 US crowdfunding campaigns, 2016–2021. T-statistics are in parentheses and standard errors are clustered at the industry level. *, **, and *** indicate statistical significance at 10%, 5%, and 1%, respectively.

	Full Sample			Successful CF		Failed CF	
Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Age	0.006*	0.006**	0.007**	0.005	0.005	0.009**	0.011***
	(1.69)	(2.07)	(2.22)	(1.46)	(1.38)	(2.33)	(2.81)
Profitability		0.009***	0.008***	0.008**	0.007**	0.011***	0.010***
		(3.67)	(3.30)	(2.40)	(2.19)	(4.56)	(3.60)
Size		-0.015***	-0.014***	-0.008**	-0.007	-0.026**	-0.027**
		(3.35)	(2.93)	(2.00)	(1.39)	(2.56)	(2.68)
Cash holdings		-0.048	-0.020	-0.006	0.019	-0.105*	-0.075*
		(1.31)	(0.68)	(0.18)	(0.59)	(1.87)	(1.81)
LT Leverage		-0.003***	-0.003**	-0.003**	-0.003**	-0.003***	-0.003*
		(3.12)	(2.51)	(2.49)	(2.03)	(2.73)	(1.74)
ST Leverage		-0.005**	-0.004*	-0.002	-0.001	-0.011***	-0.010**
		(2.29)	(1.81)	(0.80)	(0.31)	(2.88)	(2.53)
Year FE		Y	Y	Y	Y	Y	Y
Industry FE			Y		Y		Y
Observations	2,011	2,011	2,002	1,258	1,253	753	735
Adjusted R-squared	0.004	0.029	0.062	0.028	0.055	0.050	0.094

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