How Can Bad News Increase Price? Short Squeezes After Short-Selling Attacks

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Abstract

We examine market returns following short-selling attacks, where short sellers publicly disclose the negative information that led them to short their targets. Counterintuitively, we find that for a significant proportion of these attacks (about 30%), the initial market reactions are positive. Consistent with short squeezes being a major driver of these positive returns, we demonstrate that about half of initially positive returns fully reverse over the following quarter, relative to about a third of initially negative returns, and this asymmetric reversal pattern cannot be explained by short sellers profitably covering their positions, by misleading disclosures, or by market attention. Further, short covering levels are high for target firms with initially positive returns that reverse, further suggesting that price pressure from short sellers forced to close their positions explains some of these positive returns. We find that short squeezes are difficult to predict ahead of time but may be triggered by conditions on the day of the attack, including insider purchases, highlighting the difficulty short sellers face in avoiding this risk. Lastly, short squeezes impose substantial costs on short sellers, leading to an average loss of $70 million per suspected squeezed campaign relative to estimated profits of $35 million per successful campaign.

Keywords: short squeezes, short attacks, short selling, financial disclosure

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I. Introduction

Recent and highly visible short squeezes, such as that of Gamestop, have drawn immense attention to what previously was a relatively obscure aspect of capital markets. Short squeezes occur when a shortage of shares relative to demand from short sellers seeking to cover their positions pushes a stock's price higher, thereby creating a feedback loop that forces short sellers to cover more positions. Short squeezes are often triggered by positive news events. However, in this paper we document the existence of short squeezes in a counterintuitive setting—when short sellers release *negative* information about the firm as part of a short-selling "attack"—and demonstrate that short sellers face a significant risk of costly short squeezes when publicly revealing their negative information. Our results expand our understanding of short squeezes in particular, which have received relatively little attention in the academic literature, and contribute to our understanding of the costs faced by short sellers more generally. These issues are especially timely as short sellers face calls for yet tighter restrictions, which can further add to the costs that we document (Cohodes, 2020).

Short selling occurs when an investor borrows a stock and then sells it with the intent to repurchase it later at a lower price. They pay a lending fee to maintain their short position until they close out or "cover" the position by repurchasing the stock and returning it to their lender. Short sellers make money when the price of the stock decreases between the time when they initially sell the stock and when they buy it back. As a result, investors short stock when they believe its price is likely to fall. When short sellers' need to cover is strong relative to the limited shares available for them to purchase, this covering demand can drive up the price of a stock, in turn triggering a greater number of short sellers to scramble to purchase the stock to cover their positions and perpetuating the cycle. This phenomenon is referred to as a short squeeze.

Short squeezes are triggered by rapid price increases often caused by positive news events (Kumar, 2015) such as positive earnings announcements (Hong et al., 2012; Lasser et al., 2010). This is because short sellers may voluntarily reduce their positions as prices increase in order to limit the amount they might have to pay at the time they close their short positions.[1] Further, short sellers may be forced to reduce their short positions if their brokers, fearing they may be unable to cover their short positions if prices continue to rise, initiate margin calls. A margin call requires short sellers to either deposit more money in their brokerage accounts or liquidate some of their positions in order to increase their relative amount of collateral.[2] Another factor that contributes to short squeezes is a relative shortage of shares that are available for short sellers to buy to cover their positions (Bhojraj and Zhao, 2021). While prominent short squeezes of Gamestop in 2021 or Volkswagen in 2008 have been highly visible events that highlight potential market distortions, there has been relatively little systematic study of short squeezes in the academic literature.

In this study, we examine short squeezes in the setting of short-selling attacks, where there is disclosure of negative rather than positive news. Short attacks, also known as short-selling campaigns, occur when short sellers publicly disclose reports that provide research about a company, often combining both public information and original evidence, with the express intent of lowering a firm's stock price. These reports may relate to a variety of topics, from operational failures to poor governance to fraud, but all have the shared purpose of explaining why a company is overvalued. Short sellers release these reports in order to precipitate a stock price decline so that they can close their short positions at a profit. As discussed in Ljungqvist and Qian (2016), short

[1] For example, according to the renowned short seller James Chanos, "Even if we love a position, if it's going against us, we will trim it back" (Pedersen, 2019; page 131).

[2] It is worth noting the following details relating to short sales. Short sellers need to put up collateral when borrowing, which is usually 102-105% of the borrowed value. As a result, when the price of the shorted stock increases, so does the collateral requirement. Further, when stock price volatility increases, the prime broker may even increase the percentage of margin requirement (i.e., reduce the leverage it offers to the hedge fund), which requires further funding into the margin account (Pedersen, 2019; page 118).

attacks are a way for short sellers to mitigate short-selling constraints by increasing the speed of price discovery and therefore reducing short sellers' risk. Short sellers have an incentive to make sure that their disclosures, known as short theses, are credible because they will forgo trading profits if the market fails to fully incorporate their negative information. Consistent with short theses generally conveying accurate negative information and correctly identifying problematic firms, prior research has shown that firms that are subject to short attacks are more likely to experience a variety of negative outcomes such as auditor changes, delistings, restatements, and AAERs (Brendel and Ryans, 2020; Ljungqvist and Qian, 2016). However, using a sample of 1,427 short attacks initiated by prominent short sellers between 2006 and 2020, we document that a surprisingly large number of short attacks—roughly 30% in our sample—are followed by *positive* returns. This finding is puzzling given that short reports contain unambiguously negative news and that short sellers have strong incentives to avoid any circumstances that might lead to positive returns at the time of the short attack. We propose that a major cause of these positive returns are short squeezes.

Conditions around short attacks are especially ripe for short squeezes because short sellers are likely to have large, unhedged positions in targeted firms. Short sellers initiating attacks certainly have unhedged short positions in target firms, but, importantly, they often also work with other short sellers holding more substantial positions (Celarier, 2020).[3] Short sellers with large positions are disproportionately exposed to the risk of short squeezes because as price increases, short positions become a larger proportion of their total portfolios, posing a risk of substantial

[3] Based on our conversations with activist short sellers, sometimes they buy out-of-money call options to hedge the risk caused by precisely the topic of this paper – short squeezes. However, it is worth noting that any hedging activities would reduce the returns to the short sellers. This is why they usually do not hedge the high-conviction ideas based on which they launch public short attacks. Thus, although we say "unhedged" throughout the paper, it would perhaps be more accurate to say that these short sellers are *under*hedged.

losses to short sellers with large positions (Xu and Zheng, 2016). As a result, the presence of one or more short sellers with large positions in the target firm in the period surrounding a short attack makes the potential for a short squeeze especially high. In addition, although market participants can observe the total short interest in a stock, they cannot observe the size of individual positions, how concentrated they are, or the reasons for the positions. As a result, when short sellers initiate short attacks, their public signal alerts other market participants, including corporate insiders, to the fact that conditions are ripe for a short squeeze and potentially inviting predatory trading which might further increase this risk (Brunnermeier and Pedersen, 2005).[4]

We perform a variety of empirical tests to determine whether the positive returns that we observe around short attacks are the result of short squeezes. First, we document that about half of attacked firms that experience positive returns following short attacks experience full return reversals over the subsequent three months compared to only about a third of attacked firms with initial negative returns.[5] Such reversals should occur if positive returns are the result of short squeezes, which lead to a short-term artificial inflation in prices (Hong et al., 2012; Liu and Xu, 2016). On the other hand, if positive returns following short attacks are driven by factors other than short squeezes, then there is no reason to expect that these returns would be more likely to reverse. For example, short attack returns may be positive if the market interprets the information in the report positively, possibly because they anticipate that short sellers are negatively biased or if the firm's management issues a response that discredits the report. Alternatively, the market may

[4] There is no love lost between firms and the short sellers that hold positions in their stock. For example, Tesla CEO Elon Musk publicly taunted short sellers after Tesla's stock hit a record high in April 2017 with the tweet "Stormy weather in Shortville…" Further, Lamont (2012) and Ljungqvist and Qian (2016) identified a few cases where corporate insiders appeared to deliberately try to prompt a squeeze by urging investors not to lend out their shares (e.g., Harbin Electric, 2011).

[5] For example, on December 11, 2017, Hindenburg Research issued a short-selling report on Riot Blockchain that is included in our sample. The report listed various red flags in Riot's business model, acquisitions, and insider self-dealing. Riot's price increased 46% on the report date and a total of 130% by the end of *t+5* before subsequently decreasing 49% by the end of the quarter, completely reversing the initial-day return.

have anticipated the short attack, for example because of an increase in short interest, and already impounded the negative news into price; the positive return after the attack could be a market correction if the actual report is not as negative as anticipated. Lastly, the short attack may coincide with unrelated positive news events. Although each of these alternative scenarios may contribute to positive returns after short attacks, none should be incrementally associated with return reversals. As a result, the fact that we find strong evidence of disproportionate reversals for positive returns after short attacks indicates that short squeezes may play a significant role in driving these positive market reactions.

We next investigate and rule out several alternative explanations for this asymmetric pattern of return reversals. First, we demonstrate that it is unlikely that the temporary increase in price that we observe is caused by short sellers profitably closing out their short positions after initial *negative* returns. We also find no evidence that firms themselves cause temporary price increases by issuing 8-Ks or press releases with potentially misleading positive news in response to short attacks. In fact, our evidence indicates that firms with positive returns and subsequent reversals are less likely to issue press releases than other short attack targets. Further, it does not appear to be the case that temporary increases in price after short attacks are driven by increased attention from unsophisticated investors (Barber and Odean, 2008). We also find no evidence that positive return reversals are driven mechanically by these firms having returns of a smaller initial magnitude than those of positive returns that do not reverse.

Next, we examine short covering (i.e., short sellers closing out their positions) for the targeted stocks in our sample. Because short covering is a major component of short squeezes, we expect to find unusually high short covering in suspected short squeeze cases. Consistent with this, we find that positive/reversal target firms tend to experience similar and even slightly higher levels of short covering around short-selling attacks relative to positive/no reversal firms or those with initially negative returns.[6] We further compare the short covering in our sample with that of a sample of highly shorted firms with positive earnings shocks. Prior literature has shown that short sellers' buy-to-cover demand is sufficiently high in this setting to temporarily increase price, making it an ideal comparison group to determine whether the short covering in our sample is sufficient to cause the price pressure that we propose (Hong et al., 2012; Lasser et al., 2010). We find that our set of suspected short squeeze firms has significantly higher levels of short covering relative to this benchmark, suggesting that this is indeed the case. Overall, these results are highly consistent with the presence of short squeezes.

We next examine factors that contribute to the probability of a potential short squeeze, as identified empirically by cases with positive returns and a subsequent reversal. We find very little cross-sectional evidence that allows us to predict the occurrence of a short squeeze based on characteristics or events preceding the short attack. This result is intuitive because if short sellers, who are highly sophisticated, could anticipate conditions ripe for a short attack, then they would avoid initiating a short attack in the first place. However, we do find evidence that conditions on the day of the short attack, in particular market-wide returns and online media sentiment, are significantly associated with short squeezes. Further, suspected short squeeze firms tend to have higher levels of insider buying, consistent with anecdotal evidence that insiders may try to trigger squeezes by purchasing shares in response to short attacks (Ljungqvist and Qian, 2016). This evidence highlights one of the major risks that short sellers face when initiating short attacks: while they may be able to plan around and avoid short squeezes based on known conditions leading up to the short attack, they have no control over conditions on the day of the attack itself.

[6] This is in spite of the fact that both benchmark sets are also settings in which we would expect unusually high short covering given the high levels of short interest leading up to the attacks.

We next quantify the costs that short sellers face as a result of short squeezes following short attacks, assuming that short sellers are forced to close their positions at the highest price in a short window after the attacks. Using closing prices after three months as an estimate of the fundamental value, as in Ljungqvist and Qian (2016), we estimate that short sellers lose approximately $68 – $83 million in each of the 204 squeezed cases (or $13.8 – $16.8 billion in total) as a result of temporary price increases immediately following short attacks. These losses are substantial, especially when compared with the similarly estimated $27 – $39 million in average trading profits for the 1,018 cases that witness immediate price declines after the short attacks, or $27 – $40 billion in total.

Our results provide a significant contribution to our understanding of the risks faced by short sellers. While prior studies have documented that the presence of short selling has positive market benefits by increasing price efficiency and curbing fraud and mismanagement (Engelberg et al., 2018; Fang et al., 2016; Karpoff and Lou, 2010), researchers have long been puzzled by the relatively low level of short selling (Lamont and Stein, 2004). We contribute to this literature by documenting that short squeezes pose a significant risk to short sellers, even when they release negative news to the market. The short attack setting is particularly well suited to examining short squeezes because it allows us to identify a set of firms at a higher risk of short squeezes due to the presence of traders with large short positions and public disclosure which might attract predatory trading. This allows us to identify short squeezes and systematically study and quantify the costs of short squeezes to short sellers. Although this market phenomenon has been relatively overlooked in the past academic literature, our results suggest the costs associated with short squeezes are substantial, thus helping to explain the low-short-interest-puzzle in the prior literature and providing an explanation for why short sellers appear to be exiting the market, such as the prominent example of Citron Research in 2021 (Sen et al., 2021). Thus while research such as Engelberg et al. (2018) has studied the risk associated with lending fees in general, we examine the risk associated with short squeezes in particular, which are material tail events. Surprisingly, we show that they appear to occur relatively frequently in our setting. While short attacks are a nonrandom subset of short-selling activities, we believe that the forces that we document in this paper are generalizable to the risks faced by short sellers in general.

Our paper is especially timely in the face of calls to impose additional regulations on short sellers in general and on those initiating short attacks in particular. For example, Cohodes (2020) proposes “a ten-day minimum holding period that would apply to any stock promoter or short seller who opens a large position and disseminates market-moving information.” At first glance, this proposal appears to impose equally restrictive constraints on activists taking both long and short positions. However, it fails to recognize that short sellers will be forced to cover their positions as prices move up in order to avoid runaway losses, whereas investors with long positions, who risk only the amount of their original investment, do not have such urgency as prices move down. As a result, in addition to the high risk and costs already faced by short sellers, such a measure would subject short sellers to even higher costs in the form of margin calls if price were to increase as the result of a short squeeze, with no ability for them to reduce their positions and cut their losses once they see that a squeeze is occurring. Moreover, such a rule would be a perfect invitation for predatory traders who know that short sellers cannot cover voluntarily within 10 days, therefore further increasing the risk of short squeezes. We believe that our results can help regulators more accurately weigh the pros and cons of future regulations by more fully understanding the costs already faced by short sellers.

II. Related Literature and Research Question

We build our paper around one central research question: How prevalent are short squeezes after short attacks? This section describes the relevant prior literature that helps motivate our tests. First we note that the academic literature on short squeezes is underdeveloped, with a few published papers dealing with market distortions in general (Allen et al., 2006; Brunnermeier and Pedersen, 2005; Hong et al., 2012; Richardson et al., 2017), but only a handful of working papers relating specifically to short squeezes (Bhojraj and Zhao, 2021; Blocher and Ringgenberg, 2019; Liu and Xu, 2016; Xu and Zheng, 2016; Hong et al., 2016). As a whole, these papers point to two major factors that contribute to squeezes: a lack of liquidity relative to the amount of short interest, which prevents short sellers from covering their positions without driving up price; and a positive shock to price, which often precipitates short sellers' need to cover their positions in the first place. Our setting fulfils the first condition, as the presence of a short attack is likely to indicate that one or more short sellers have large, unhedged short positions in the firm, making their need to cover much more sensitive to price changes. Brunnermeier and Pederson (2005) further point out that traders with a need to reduce large positions are targets ripe for predatory trading by others in the market, which further increases the probability of a short squeeze. While our short attack setting is similar in some respects to the conditions pointed out in prior studies, it is unique in that short attacks, rather than precipitating price *increases*, are explicitly designed to lead to price *decreases.*[7]

Short attacks occur when short sellers publicly talk down securities by disseminating evidence supporting their positions in the form of a report or "short thesis." These "activist short

[7] Richardson et al. (2017) show that a trading strategy of buying low short-interest firms and shorting high short-interest firms has a negative alpha in the days after market-wide funding shocks, possibly because leveraged investors such as short sellers rush to deleverage and cover positions at a loss. Their paper therefore implies that there are positive returns to highly-shorted firms after market-wide negative news. Our paper is different because we focus on firm-level negative news announced by short sellers that have the clear intention of lowering stock prices.

sellers," as they are frequently referred to, tend to target opaque firms (Zhao, 2020) or non-U.S. firms with financial reporting red flags (Brendel and Ryans, 2020; Chen, 2016) and utilize short attacks as a way to overcome short-selling constraints (Ljungqvist and Qian, 2016). Most importantly, these short attacks attract a significant amount of attention and generally do a good job of identifying overvalued firms, with many targets subsequently issuing restatements, experiencing auditor turnover, delisting, or receiving an AAER (Brendel and Ryans, 2020). These results are consistent with the general literature on short selling showing that short sellers are sophisticated market participants who anticipate price declines and accurately identify fraud (Christophe et al., 2004; Dechow et al., 2001; Karpoff and Lou, 2010) and as a result contribute to price discovery and market efficiency (Boehmer and Wu, 2013; Engelberg et al., 2018). While there has been some evidence that anonymous short sellers sometimes launch short attacks on the crowdsourced platform *SeekingAlpha* to manipulate stock price by disseminating inaccurate reports (Mitts, 2020), our sample includes only short attacks tied to known short sellers. Further, although only 30% of fraud allegations by short sellers are eventually confirmed, short seller allegations are the strongest predictor of fraud when compared to other commonly used fraud indicators (Kartapanis, 2019). Overall, the existing evidence suggests that short attacks are credible negative signals and as a result are expected to be associated with negative returns. This is especially likely to be the case because short sellers have flexibility to time their attacks when they are least likely to coincide with other events (such as scheduled earnings announcements) that have the potential to increase price. However, in spite of this planning, a market distortion arising from a short squeeze may still lead prices to increase after a short attack.

Firms that are the targets of short attacks may be particularly susceptible to short squeezes because there are likely one or more short sellers with large, unhedged short positions in these stocks. The presence of these large positions increases the relative demand for liquidity in these stocks when short sellers cover their positions. The short seller initiating the attack usually has a significant position in the firm, but, importantly, they often work with other short sellers holding much larger positions. These "balance sheet partners" have substantial short interest but rely on activist short sellers to publicize short theses, often paying them a commission in return. Sometimes they even share research that contributes to the short thesis so that they can benefit from its public disclosure without attaching their name to the attack (Celarier, 2020).[8] However, in contrast to an investor buying a stock long who can lose only up to the amount that they originally invested, short sellers face unlimited losses if prices rise. When prices go against investors' positions, losing long positions automatically become a smaller part of their portfolio, but short positions become a larger part, triggering risk management concerns. Given this unbounded risk, short sellers with larger positions are likely to be especially sensitive to price increases and more proactive in trying to limit their losses by covering their positions. As a result, they may disproportionately contribute to price increases in the event of a short squeeze.

In addition, the disclosure of a short thesis alerts the market to the fact that there are traders with material, unhedged short positions in the target firm. In contrast, available information on short interest does not usually allow outsiders to observe the size of the short positions held by individual short sellers or the reason for the positions.[9] However, both factors are important in

[8] Here are examples of these two types. First, in August 2019, Harry Markopolos posted a negative report on General Electric disclosing in the report that his research firm "entered into an agreement with a third-party entity to review an advanced copy of the Report in exchange for compensation" and that "Those positions taken by the third-party entity are designed to generate profits should the price of GE securities decrease." See: https://fm.cnbc.com/applications/cnbc.com/resources/editorialfiles/2019/8/15/2019_08_15_GE_Whistleblower_Report.pdf. Second, in January 2020, Muddy Waters Research posted a report on Luckin Coffee they received from an anonymous source, which was later confirmed to be Snow Lake Capital, a hedge fund in China. See: https://www.wsj.com/articles/coffees-for-closers-how-a-short-sellers-warning-helped-take-down-luckin-coffee-11593423002.

[9] Since 2012, all EU countries have required disclosure of large short positions (e.g., Jones et al., 2016).

determining the risk of a short squeeze. For example, many institutions hold short positions for hedging and tax purposes (Brent et al., 1990), and such traders would be insensitive to price changes because they hold corresponding long positions. Moreover, when short interest is spread evenly across many short sellers, each short seller would be more tolerant of price increases and less motivated to cover their positions, making it harder to trigger a short squeeze. However, short attacks are high visibility events in which the short seller publicly announces they have a material short position in a specific company for non-hedging purposes. Such visibility could attract the attention of other traders. Brunnermeier and Pedersen (2005) predict that market participants who become aware of the need for an investor to close out a large position may engage in predatory trading by trading in the same direction, thus leading to price distortions.[10] Consistent with this, Li et al. (2021) find that in the EU, where the disclosure of large short positions is mandatory, firms are more likely to be subject to an attack by activist *long* investors seeking to increase stock price when there is at least one large disclosed short position in the stock, even after controlling for total short interest. Further, anecdotal evidence has shown that target firms sometimes take actions to restrict short sellers' ability to borrow shares by publicly calling on their shareholders to stop lending out shares, by repurchasing stock, and by having insiders purchase shares (Ljungqvist and Qian, 2016; Harbin Electric, 2011).[11] As a result, at the time of the short attack, other market participants may purposefully restrict the shares available for short sellers to buy, further increasing the possibility of a short squeeze.

[10] For this reason, when short interest becomes extremely high, public attention could also contribute to short squeezes, similar to the role of short attacks in alerting the market. For example, a FactSet data error briefly made it appear that short interest in Clover Health on April 16, 2021 exceeded 140% of total shares outstanding, leading to a sharp increase in price as long investors attempted to squeeze short sellers, although actual short interest was a less extreme (although still high) value of 35% (Durden, 2021).

[11] For example, in our sample, Richard Pearson shorted Synageva on April 22, 2014. The next day, Synageva experienced seven insider purchases, driving price up by more than 10% before reversing fully over the next quarter.

While this paper focuses on investigating short squeezes as the driving force behind positive stock reactions after short attacks, there could be several other reasons why firms might experience positive returns. First, market participants may interpret short theses favorably if they expect they are negatively biased (Mitts, 2020). Further, firms often directly respond to short attacks by denying the claims and sometimes threatening litigation (Lamont 2012; Brendel and Ryans, 2020). Second, if market participants anticipated the existence of bad news, for example by observing a run-up in short interest, there might be no stock reaction or a positive reaction if the news contained in the report is not as negative as expected. Lastly, short attacks may potentially occur on the same day as unrelated positive news. Although all of these alternative explanations might lead to positive returns after short attacks, short squeezes differ in one very important way from each of these events: short squeezes lead to only *temporary* increases in prices (Hong et al., 2012; Liu and Xu, 2016; Bhojraj and Zhao, 2021). As a result, if positive returns after short attacks are driven *solely* by the factors above, with no additional price pressure induced by short squeezes, then we would expect these price increases to be fairly persistent, with a similar rate of reversal as initial negative returns.[12] However, a short squeeze by definition will lead to a subsequent price reversal after the alleviation of extreme market conditions allows a firm's price to return to its fundamental level.

[12] There are at least two reasons why reversals could actually be more prevalent for attacks with *negative* initial returns. First, stock prices generally go up in the long term, especially during our sample period which overlaps with the longest bull market in U.S. history. Second, to the extent that short sellers launch short-and-distort campaigns as frequently alleged by managers (e.g., MiMedx, 2017) and charged by the SEC in rare cases (SEC, 2018), the prices of targets with initial negative returns would likely reverse after short sellers take their profits.

III. Empirical Setting and Data

3.1 Short Attacks Sample

We collect activist short-selling cases from Activists Shorts Research (ASR) (now part of Activist Insight) for cases from 2006 to 2015 and from BreakOut Point (BOP) from 2015 to 2020. Both ASR and BOP are independent data providers that track short-selling campaigns waged by prominent traders. ASR has been used in prior research such as Kartapanis (2019), Zhao (2020) and Bushman et al. (2021). BOP is a fintech startup located in Germany providing data on global activist short campaigns, EU regulatory short disclosure, and retail popularity starting in 2015. It has gained recognition by being quoted by mainstream media such as Bloomberg, Financial Times, and the Wall Street Journal. Both ASR and BOP identify and track activist campaigns in which short sellers publicly talk down stocks by either publishing detailed reports on their websites or presenting their short theses at investing conferences or through mainstream media. While both of them cover the most prominent short sellers, ASR has a slightly broader coverage and includes some relatively newer and less influential short sellers; this is the reason why the sample drops from 2015 to 2016, when we only have access to BOP data. Table 1 presents the sample distribution by year. Overall, we have 1,427 short attacks against 992 unique U.S.-listed companies by 181 short sellers from 2006 to 2020.

3.2 Other Data Sources

We also use data from various other sources. Specifically, we collect market-based data from CRSP, financial accounting and short interest data from Compustat, analyst information from I/B/E/S, media data from RavenPack, 8-K filings from the EDGAR database, shares-on-loan data from Markit, short trading volume data from the FINRA website, and data on insider trades disclosed in Form 4 filings from the WRDS SEC Insider database.

3.3 Descriptive Statistics on Raw Returns after Short-Selling Attacks

Table 2 Panel A tabulates the distribution of raw returns in various windows around and after short attacks. We follow Shumway (1997) and adjust for delisting returns and use the delisting price as a replacement for closing price if it is missing. Consistent with prior papers on short-selling attacks (e.g., Ljungqvist and Qian, 2016), the immediate returns to these campaigns are on average overwhelming negative, with mean (median) return ranging from -4.7% (-3.0%) on the attack day to -6.3% (-4.8%) in the window of [0, 5]. When we focus on returns over the subsequent period (e.g., [1,63]), we find that prices continue to be negative for the overall sample, indicating further downward price drift after short attacks on average.

Table 2 Panel B tabulates summary statistics of variables used in our later regression analyses. Of particular note is the fact that average short interest (*SIR*) is 11% among short attack targets prior to the attack, which is much higher than that of a typical firm (around 3-4% according to Bhojraj and Zhao, 2021). Further, this short interest is increasing for our sample firms on average, as reflected in the mean *Chg_SIR* of 0.5%. Thus, as discussed earlier, our setting has the benefit of having particularly high levels of short-selling activity, making it a particularly relevant setting in which to study short squeezes. However, this comes with the caveat that our results may not necessarily generalize to other less extreme settings.

IV. Empirical Results

4.1 Positive Returns After Short Attacks

One of the main motivations of this paper is the observed frequency with which short attacks are followed by positive returns. We document this empirically in Table 3. Panel A uses closing prices to sort firms into categories based on the sign and magnitude of their raw stock return over the period following the short attack, ranging from just the returns on the day of the short attack itself ([0,0]) to the returns over the five-day period starting on the day of the short attack ([0.5]).[13] Just examining the day of the short attack itself, we see that 407 observations, or 29% of our sample, experience positive returns. This increases to 442 (31%) if we include the entire 5-day period. Not surprisingly, both of these proportions decrease when we restrict ourselves to looking just at those firms with larger positive returns. For example, 100 observations (7%) have returns greater than 5% on the day of the short attack and 226 (16%) over the full 5-day period. For comparison, on the right side of the panel, we also tabulate the percentages of targets witnessing *negative* returns after short attacks. For example, 539 observations (38%) have returns lower than -5% on the day of the short attack and 701 (49%) over the full 5-day period. Overall, the numbers on the right side are much larger than their counterparts on the left side, consistent with the overall return statistics in Table 2 and the prior research that, on average, there are substantial negative returns after short attacks (Ljungqvist and Qian, 2016).

Panel B categorizes the returns of short attack targets slightly differently, by identifying positive (negative) return observations based on their maximum (minimum) price over the relevant window. Because prices can fluctuate within a window, a given target may be categorized as having both a positive or negative return, and therefore these categories are not mutually exclusive. Examining the maximum (minimum) return within a window allows us to have an upper bound on the potential loss (profit) of short sellers following a short attack. In particular, the maximum positive returns are particularly relevant because when prices rise far enough at any given point, internal risk management measures or margin calls from prime brokers may force short sellers to cover their positions at a loss, regardless of whether price subsequently drops. Based on maximum

[13] We focus on raw, rather than abnormal, stock return in this and subsequent tables because raw returns are most relevant from the perspective of short sellers, who profit from price declines and lose from price increases in an individual stock, regardless of the performance of the rest of the market or the relative risk profile of that company.

prices, 1,081 (1,185) targets have positive returns at some point over the day of (5-day window following) the short attack, with 236 (524) having returns greater than 5%. As in Panel A, the right side of Panel B describes the short attacks with initial negative returns. Based on minimum prices, 1,363 (1,399) targets have negative returns at some point over the day of (5-day window following) the short attack, with 841 (1,114) having returns lower than -5%. In short, the descriptive evidence in Table 3 provides evidence that a substantial portion of targets experience positive returns immediately following negative disclosures of short attacks.[14]

4.2 Asymmetric Return Reversals After Short Attacks

As discussed above, there are multiple reasons in addition to short squeezes that might lead a stock's price to increase in the period immediately following a short attack such as company responses to the attack and unrelated positive news. However, in the absence of a short squeeze, none of these alternative drivers are expected to increase the probability that these positive returns subsequently reverse. In other words, if factors other than short squeezes are the primary drivers of positive returns, then they should have the same probability of experiencing a reversal as negative returns after short attacks.

In Table 4, we provide descriptive evidence of the relative frequency of return reversals for targets experiencing positive and negative returns following short attacks, respectively. Panel A of Table 4 corresponds to Panel A of Table 3 and shows the proportion of targets falling within each group that experience a return reversal, defined as a return over the post-event period which fully negates the return during the event period, with returns calculated using closing prices. As before, we provide multiple event periods ranging from just the day of ([0,0]) to the 5-day period

[14] While it is difficult to know exactly how to benchmark these proportions, roughly 30% of firms experiencing positive returns seems high, particularly given short sellers' incentives and the fact that they have flexibility to time their reports to avoid coinciding with potential positive news events, for example earnings announcements.

following the short attack ([0,5]). The post-event period begins immediately after the event period and ends 63 trading days (approximately one quarter) following the short attack. We use price at the end of the post-event period as an estimate of long-run fundamental price after all information from the short attack and company responses have been incorporated into price and after any temporary mispricing has been corrected (Liu and Xu, 2016). As seen in Panel A, 53% (50%) of targets with positive returns on the day of (5-day period starting at) the short attack experience a full reversal over the post period compared to only 34% (31%) of those with negative returns. The differences in reversal rates are statistically significant at the 1% level for all windows, with t-statistics ranging from 4.4 to 6.9. Interestingly, targets with initially negative returns are substantially less likely to experience reversals as return magnitude increases. This is consistent with negative returns being less likely to reverse if the short attack is both highly credible and highly damaging. While 34% of overall negative returns on the day of the short attack reverse, only 19% of negative returns greater than 10% subsequently reverse. In contrast, large positive returns have relatively similar rates of reversal compared to small positive returns, and in some cases are even *more* likely to reverse. Thus, unlike negative returns, the magnitude of positive returns does not appear to impound information about the quality of the signal that drove the return in the first place.

Panel B is similar to Panel A, but documents the frequency of reversals when observations are categorized based on returns defined using maximum and minimum prices over the event window, corresponding to Panel B of Table 3. Because the initial returns in this panel are based on maximum and minimum returns during the event period, the closing price at the end of the post-event period is compared to the maximum (minimum) price during the event period for positive (negative) return observations. The event and post-event periods are defined as in Panel A.[15] The inferences from Panel B are very similar to those from Panel A and show that observations with positive returns following short attacks experience more reversals than those with negative returns. The disproportionate rate of reversals provides strong evidence that short squeezes are at play.

Figure 1 depicts the results of Table 4 in graphical form by splitting targets by the sign of their raw returns in the [0, 1] window and then tracking their mean cumulative returns over the subsequent quarter. We use shaded areas to indicate 95% confidence intervals. Figure 1 shows that both the positive return group (top) and the negative return group (bottom) experience some reversal after short attacks. However, the positive return group has a relatively larger reversal, going from a maximum of 5.3% in returns to 4.0% at the end of the period, or about a 25% reversal. In contrast, the returns of the negative return group go from a low of -11.7% to -10.0%, or a 15% reversal. In fact, by the end of the period, the average returns of the positive return group are insignificantly different from 0, while those of the negative return group are still significantly negative. We investigate the asymmetric reversal of positive returns following short attacks more rigorously using a regression framework that estimates the following equation:

$$Ret[j+1,63]_i = \alpha + \beta_1 Ret[0,j]_i + \beta_2 Positive[0,j]_i + \beta_3 Ret[0,j]_i \times Positive[0,j]_i + \varepsilon_i \quad (1)$$

Ret[j+1,63] is the raw returns of the target firm over the post period, starting the day after the event period and ending 63 trading days after the attack, and *Ret[0,j]* is the return of the target firm over the event period. We provide multiple event periods ranging from just the day of ([0,0]) to the 5-day period following the short attack ([0,5]). *Positive[0,j]* is an indicator variable set to 1 if *Ret[0,j] > 0*. If positive returns after short attacks are significantly more likely to reverse relative

[15] Although the event period returns are calculated based on maximum and minimum prices to get a sense of the potential gains and losses faced by short sellers, we continue to use closing price at the end of the post-event period as the benchmark for reversals because it is intended to capture "fundamental" price, which would not be the case if we instead calculated reversals based on the maximum or minimum price during the post-event period.

to negative returns (consistent with the presence of short squeezes), then β_3 should be significantly less than 0. $\beta_1 > 0$ would be evidence of momentum on average, and $\beta_1 < 0$ would be evidence of mean reversion on average. The standard errors in this table are clustered by firm. Columns 1-4 include no fixed effects and columns 5-8 include year-quarter fixed effects.[16]

Table 5 provides evidence that β_3 is significantly negative in our sample regardless of the specification, confirming that positive initial returns are significantly more likely to reverse. Interestingly, β_3 is close to -1 and highly significant when we focus on the event window of [0,0], implying that targets with positive returns on the attack day fully reverse on average. Overall, the results of Tables 4 and 5 and Figure 1 indicate that positive returns after short attacks are significantly more likely to reverse than negative returns on average. These asymmetric reversals would be unlikely to occur if the positive returns were driven by other positive information events, but are consistent with the presence of short squeezes.

4.3 Alternative Explanations for Asymmetric Return Reversals

Although asymmetry in the frequency with which positive and negative returns reverse after short attacks allows us to rule out other information events as the major drivers of the unusually frequent positive returns, it is possible that factors other than short squeezes drive these reversals. We explore such alternative explanations in this section.

First, it is possible that temporary positive price pressure occurs when short sellers profitably close their positions. This would lead initially negative returns after the attack to be followed immediately by price increases caused by short covering. If this is the case, mechanical increases in price as the result of profitable short covering, not short squeezes, would explain the positive returns that we observe. Nevertheless, in order to examine this possibility, Table 6 Panel

[16] Our results remain similar when we include both year-quarter and short seller fixed effects.

A identifies the lowest possible return for each observation based on the minimum price of the firm over several windows following the attack. If profitable short covering contributes both to the positive returns and to the reversals that we observe, then firms that have positive returns (based on closing prices) and subsequent reversals should have negative returns at some point over the period examined. We first compare positive/reversal firms with all other observations in the sample and find that their minimum returns are significantly higher than those of all other observations on average. Thus, if short sellers are trying to cover their positions in these firms at a profit, they are not doing so successfully compared to the rest of the short attacks in our sample. Further, if we restrict the comparison to just the set of firms which experienced positive initial returns but did *not* have subsequent reversals (positive/no reversal targets), we find no significant difference in returns. If returns for the positive/reversal firms were low enough to prompt short sellers to close their positions at a profit, then the nearly identical returns for the positive/no reversal firms would also have induced short sellers to close their positions. However, we do not observe a mechanical return reversal for the positive/no reversal firms. As a result, it does not appear that profitable short covering mechanically drives our results.

Another potential explanation for the disproportionate reversal of positive returns after short attacks is that they are driven by management disclosures that temporarily increase price. If management disclosures after short attacks are particularly likely to lead to positive returns, and if these disclosures are misleading or inaccurate, then this could explain why positive returns after short attacks are particularly likely to reverse. In order to examine this, Table 6 Panel B examines whether the presence of 8-Ks (*8K*) or press releases (*RavenPack_PR_#Article*) issued by firms immediately following short attacks is associated with the presence of positive returns which subsequently reverse (*Pos_Reversal)*. Although the issuance of 8-Ks is unrelated to the presence of positive reversals, press releases are *negatively* associated with positive reversals, the opposite of what we would expect if managers use disclosures to temporarily push price up following a short attack. Instead, it appears that firms may actually be *less* likely to disclose when they experience positive returns following short attacks, probably because they see less of a need to respond to short seller allegations if the initial market reaction is favorable. As a result, it does not appear that misleading responses by managers drive the patterns that we document.

Next, we examine whether positive returns and subsequent reversals after short attacks are driven by heightened attention by unsophisticated investors (Barber and Odean, 2008). It could be the case that short attacks draw the attention of unsophisticated investors through media coverage of the attack. An increase in attention by such traders could lead to an increase in non-fundamentals-driven trading which could temporarily push price up, only to revert later once attention decreased. We examine this possibility in Table 6 Panel C by examining whether attention to the firm, as measured by media coverage, is associated with whether firms experience a positive return reversal (*Pos_Reversal*). In columns 1-4 we examine overall media coverage (*RavenPack_Full_#Article)* and find no evidence that attention leads to more reversals. In columns 5-8, we focus specifically on media coverage by online sources (*RavenPack_Web_#Article)*, as online media outlets may be a better proxy for the attention of retail investors. We find no significant link with *Pos_Reversal*. Overall, this test provides no evidence that positive return reversals after short attacks are driven by attention.

Lastly, we compare the magnitude of returns immediately following short attacks between firms with initially positive returns that experience a reversal with those that do not. The purpose of this test is to see if the way that we partition firms actually identifies meaningful differences between positive/reversal firms and positive/no reversal firms. Specifically, we examine whether it is mechanically easier for our set of positive/reversal firms to experience full return reversals; if these firms experienced smaller initial positive returns, it would take smaller subsequent negative returns to fully reverse. When we compare the magnitude of the positive returns between the positive/reversal and positive/no reversal firms, we find that they are insignificantly different. This suggests that the reversals we identify are not simply because these firms had smaller initial returns. In sum, although these results are indirect and somewhat circumstantial, they are consistent with what we would expect if positive/reversal firms are especially likely to have undergone a short squeeze, and inconsistent with mechanical effects driving our results.

Overall, Table 6 explores alternative explanations for the asymmetric reversal of positive returns that we observe following short-selling attacks and finds no evidence of these other stories. As a result, it appears very likely that short squeezes are a major contributor to the relatively high incidence of positive returns after short attacks. Although it is possible that additional alternative explanations exist, such explanations would have to explain both the presence of positive returns, as well as why such positive returns would be disproportionately likely to reverse.

4.4 Short Covering

Next, we examine short covering activities after short attacks. As explained earlier, a key feature of short squeezes is that short sellers buy-to-cover their positions, creating buying pressure that then triggers a greater need to cover. As a result, we would expect to see significant short covering in the event of a squeeze. As short covering volume is unobservable, we follow Blocher and Ringgenberg (2019) and infer daily short covering from daily changes in shares-on-loan in Markit and daily short trading volume available from FINRA.[17] Specifically, we construct *Daily*

[17] A short-seller who sells short on day t can borrow the shares on $t+3$ for delivery to buyers and minimize the borrowing costs, as equity transactions are settled in a $T+3$ cycle ($T+2$ after September 5, 2017) (Geczy et al., 2002). In this case, the shares-on-loan recorded in Markit on day t reflects short sales that had been initiated by t-3. So we

Short Covering at day t as the net decrease of shares-on-loan relative to day t-1 plus the newly opened short trades on day t, scaled by shares outstanding. We multiply this number by 100 to facilitate interpretation. We lose 321 attacks because the short volume data are available only starting in August 2009 and our Markit data end in December 2018.

We tabulate the mean *Daily Short Covering* from day 0 (the attack day) to 10 trading days afterwards for three groups of targets separately: positive/reversal targets (i.e., potential short squeezes), positive/no reversal targets, and negative initial return targets. These means are provided in columns 1-3. Consistent with short squeezes being tied to significant covering activities, we find that positive/reversal targets experience significant covering for 8 out of the 10 days examined. Further, covering by positive/reversal targets is larger in magnitude than that of positive/no reversal and negative return targets over every window shown except negative return targets on day 0, although the large amount of variation in covering for positive/reversal firms means that this difference is only statistically significant in one case. However, comparing covering activities of our potential short squeeze firms with the other targets in our sample is not necessarily a fair comparison. Although we expect greater than usual covering around short squeezes, we also expect particularly high levels of covering after short attacks when short sellers close out large positions at a profit (in the case of initial negative returns) or scramble to cut their losses by covering after fundamentals-driven price increases (in the case of the positive/no reversal targets). Thus the magnitude of covering for the positive/reversal firms may appear somewhat understated in comparison to these other benchmarks.[18]

use shares-on-loan observed on *t+3* (*t+2* after September 5, 2017) to measure shares that have already sold short on day *t* (Richardson et al. 2017).

[18] One thing to keep in mind when comparing the two sets of positive return firms is that the subsequent presence or lack of a reversal serves as a signal of the accuracy of the price following the short attack. Because the positive/no reversal firms do not subsequently experience reversals, the positive returns appear to be fundamentals-driven. If short sellers are indeed sophisticated, one would expect them to recognize this, at least partially, and cover their positions because price would be unlikely to go back down. On the other hand, if they recognized that positive/reversal targets

To give a better sense of the magnitude of the short covering that we observe for the positive/reversal targets in our sample, and to show why other targets of short attacks are somewhat biased benchmarks in this regard, in column 4 we provide another benchmark. Specifically, Hong et al. (2012) show that highly shorted firms with large positive earnings surprises are much more likely to experience positive price pressure as a result of covering by short sellers. We therefore use these firms as a benchmark for magnitudes of short covering that can lead to the type of price pressures that can cause a short squeeze. We follow Hong et al. (2012) and sort quarterly earnings surprises and the shares-on-loan (scaled by shares outstanding) into quarterly terciles and focus on firms that are in the top tercile for both. Overall we have 14,063 quarterly earnings announcements with non-missing short covering data from August 2009 to December 2018 in this sample. We then calculate the short covering each day starting from the earnings announcement date and report it in column 4. We find that these firms have significant short covering every day following their earnings announcements. Importantly, the short covering in this sample is significantly lower than the short covering in the positive/reversal sample for all ten days examined (1% level).

Lastly, we confirm these results visually by plotting the daily mean short covering for the four comparison groups in Figure 2. We find that the positive/reversal group (solid red line) has higher short covering almost every day in the first 20 days after the short-selling attack. However, after this period, short covering largely converges across all four groups, indicating that the observed differences around the short attack are attributable to the events surrounding the short attack, not inherent differences across firms. Overall, the results in Table 7 and Figure 2 provide additional evidence that short squeezes occur after short-selling attacks.

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were overvalued, they would be more likely to hold their positions and wait for prices to drop again. If that were the case, we would actually expect *greater* short covering for positive/no reversal targets relative to positive/reversal targets. The fact that we actually find the opposite is more consistent with the presence of a short squeeze forcing short sellers to cover their positions, even when price increases are temporary.

4.5 Leading Indicators of Short Squeezes

Now that we have ruled out alternative explanations for the positive returns and subsequent reversals that we observe after short attacks, and provided circumstantial evidence that these positive/reversal firms likely experienced short squeezes, we are now interested in investigating factors that may contribute to the occurrence of these potential squeezes. In particular, we examine leading indicators that short sellers might anticipate ahead of time. We examine multiple leading indicators that have been shown to be associated with short squeezes in the concurrent literature (Bhojraj and Zhao, 2021; Blocher and Ringgenberg, 2019; Xu and Zheng, 2016). These indicators include: short-selling dynamics such as the level (*SIR)* and change (*Chg_SIR)* in short interest;[19] ownership structure variables such as total percentage (*IOR_Total)* and concentration (*IOR_HHI*) of institutional ownership (Prado et al., 2016); the information environment such as analyst following (*Numest)* and the presence of management guidance (*Guidance*); market-based variables including the bid-ask spread (*BASpread)* and momentum (*Momentum***)** prior to the attack; media sentiment before the attack from traditional (*RavenPack_DJ_Pre)* and web (*RavenPack_Web_Pre)* sources; and an indicator for whether the allegations involve fraud or accounting issues (*Fraud_Accounting*).[20]

We focus on trying to predict those cases that are most likely to be short squeezes after short attacks, which we define (albeit with noise) as all cases in which a target firm experiences a positive event period return and then a subsequent full reversal over the period up to 63 trading

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[19] Our tests use the last short interest reported by the stock exchange, but our results remain similar when we use the level and change of daily shares-on-loan from Markit.

[20] In untabulated results, we examine whether Chinese companies are more or less susceptible to short squeezes as they are frequently targeted for short attacks (Chen, 2016). We find no evidence that the incidence of short squeezes differs for Chinese firms.

days after the short attack (*Pos_Reversal).* We estimate the following regression to see which observable factors before the attack are associated with this indicator of short squeezes:

$$Pos\_Reversal_i = \propto + \beta_1 Ex\ Ante\ Predictors_i + Controls + \varepsilon_i \quad (2)$$

Table 8 shows that, for the most part, the comprehensive list of leading indicators that we examine provides very little ability to anticipate short squeezes in our sample. Although *Fraud_Accounting* is negative and significant in 6 of the 8 specifications, the overall adjusted R-squared in the regression analyses before adding in fixed effects is very low, ranging from -0.1% to -0.5%. Further, in untabulated results, we examine each of the determinants included in Table 8 separately and find that none of the insignificant coefficients become significant and the adjusted R^2s of the resulting regression analyses are negative, indicating that none of these attributes individually appear to be useful predictors of short squeezes after short attacks.

While at first surprising, these results are intuitive in the sense that if short sellers could anticipate that their short attacks would lead to short squeezes, they would avoid instigating the attacks, either by avoiding the types of firms that would be likely to experience short squeezes, or by timing the publication of the report to occur when market conditions are more favorable. This highlights one of the key risks faced by short sellers engaging in short attacks: although short squeezes appear to occur with alarming frequency, it is very difficult for short sellers to predict ex ante which short attacks will set off short squeezes. Our conversations with prominent short sellers confirm that they view the first few hours after the release of a short thesis as a period of high uncertainty as they wait to see how the market and the firm will react to the report.

4.6 Conditions Immediately After Short Attacks that Contribute to Short Squeezes

Table 9 further examines whether conditions on the day of the short attack itself can explain under what circumstances potential short squeezes occur. Although conditions leading up to the short attack cannot predict the incidence of short squeezes in equilibrium because short sellers anticipate and respond to these factors, market conditions and events immediately following the short attack are out of the control of the short seller. We therefore estimate determinants of *Pos_Reversal*, our indicator for likely cases of short squeezes, this time using only independent variables that describe conditions immediately following the attack.

$$Pos\_Reversal_i = \propto + \beta_1 Market\ Conditions_i + \varepsilon_i \quad (3)$$

We examine four types of conditions: media sentiment; the sentiment of firm-initiated disclosures; overall market sentiment; and insider trading. We measure media sentiment in two ways. First, we calculate the tone of articles in traditional news media sources using the average tone of articles captured by the RavenPack Dow Jones Edition (*RavenPack_DJ_Sentiment*). We also calculate the tone of articles in online media sources using the average tone of articles captured in the RavenPack Web Edition (*RavenPack_Web_Sentiment*). While we expect that the tone of traditional media sources captured by the RavenPack Dow Jones Edition (such as the Wall Street Journal) is likely to reflect the market's assessment of the fundamentals for the target firm, incremental variation in the tone of online media sources is more likely to pick up short-term or myopic sentiment of traders which might be more linked with non-fundamentals-based trading on the day of the short attack. We next measure the sentiment of firm-initiated disclosures as the average tone of 8-K disclosures (*8-K_Tone*) and firm press releases tracked by RavenPack (*RavenPack_PR_Sentiment)* over the event period. Ljungqvist and Qian (2016) provide anecdotal evidence that some firms attempt to issue retaliatory statements in response to short attacks in an effort to squeeze short sellers. Further, they found reports that some firm insiders appeared to instigate stock purchases following short-selling attacks with the intent of triggering a price increase and subsequent squeeze. As a result, we also examine whether net insider purchases

(*Insider_BuySellImb*) are associated with potential short squeezes. Last, we measure overall market conditions and sentiment during the short-attack as the value-weighted market return on the attack day (*MktRet*). Because short squeezes require an increase in price to precipitate the squeeze, days of high market returns for the overall market may have the spillover effect of lifting prices of short attack firms and triggering a squeeze. As in previous tables, we measure all of these variables, as well as our dependent variable, *Pos_Reversal,* over multiple windows.

The results in Table 9 show that the sentiment of online media (*RavenPack_Web_Sentiment)* and market-wide returns (*MktRet)* are significantly associated with the presence of positive returns that subsequently reverse (*Pos_Reversal*) in three out of four columns. This suggests that positive sentiment, in particular on online sources, can lead to positive returns followed by a reversal. We point out that this is not mechanical (i.e., it is not just the case that positive firm-level returns are associated with positive web and market sentiment) because our dependent variable also incorporates the reversal, meaning that these sentiment measures do not lead to *persistent* price increases. These results suggest that concurrent sentiment may contribute to short squeezes, but that the traditional news media do not appear to play a role. In addition, we find significant evidence in all four specifications that insider trades are significantly associated with potential short squeezes, with firms more likely to experience a positive return followed by a reversal if firm insiders are net buyers of the firm's shares. This suggests firm insiders may try to use stock purchases to squeeze short sellers. Overall, these results highlight the risk faced by short sellers, who may try to optimally time their short attacks but can never perfectly anticipate market conditions on the day of the short attack, nor how online media or the firm itself may respond.

4.7 Quantifying the Cost of Short Squeezes

If short squeezes are relatively frequent following short attacks, a natural question is whether this constitutes an economically significant phenomenon. We answer this question by examining the magnitude of the costs that short sellers bear as a result of short squeezes.

There is a large literature on various types of costs and constraints to short sellers. These costs include regulatory obstacles such as uptick rules (i.e., no short sales at decreasing prices; Diether et al., 2009) and outright short-selling bans (e.g., Beber and Pagano, 2013). They also include transaction costs such as lending fees (Nagel, 2005; Schultz, 2020). However, although practitioners have long recognized short squeezes as arguably the biggest risk to short sellers (e.g., Kumar, 2015), only a few academic papers discuss short squeezes as a potential cost of short selling, and most of this evidence is inferred indirectly by examining actions short sellers take to *avoid* short squeezes (Liu and Xu, 2016; Xu and Zheng, 2016; Bhojraj and Zhao, 2021). We add to this literature by providing evidence on the *ex post* magnitude of realized short squeeze costs in our setting. While these short squeezes are undoubtedly different from the counterfactual short squeezes that short sellers are able to avoid, we believe it is still useful to add actual dollar amounts to the discussion. Further, as shown previously, it is difficult to predict ex ante which short attacks will be followed by short squeezes, indicating that it may not be possible for short sellers to completely anticipate this risk.

We begin by estimating the trading profits that short sellers forfeit as a result of non-fundamentals-driven increases in stock prices following potential short attacks (identified as attacks with initially positive returns which fully reverse). We make two assumptions in order to estimate these forfeited profits: (1) prices settle at their fundamental level after three months, and (2) short sellers are forced to cover their positions at the highest price reached in the short period after the attacks. Intuitively, the profits a short seller should theoretically have made is the number of shares shorted prior to the attack (N) multiplied by the price difference between the closing price prior to the attack (P0) and the "fair" price, proxied by the closing price three months later (PF). However, if the short seller was forced to cover their position at the highest price (PH) due to a short squeeze, the forfeited profits would be N * (PH – PF). That is, estimated forfeited profits equal the difference between the price at which the short seller is assumed to settle minus the fair price at which the short seller *should* have settled, multiplied by the number of shares.[21] We use the exchange-disclosed short interest at the settlement date prior to the attack to measure the short positions accumulated by short sellers.[22]

As we are unsure when short sellers are forced to cover their positions, we provide estimates based on the highest prices in four windows: [0, 1], [0, 3], [0, 5], and [0, 10]. Mechanically, the estimate is higher when we use the highest price in a wider window. Table 10 Panel A presents the results. For the 204 cases where price increased in the first two days after the short attack but fully reversed by the end of three months, we find that short sellers on average forfeit $67.8 million if they are forced to cover at the highest price in the first two days. This number increases to $73.7 million, $78.5 million, and $82.5 million if they cover at the highest

[21] Let's again use the case of Hindenburg Research shorting Riot Blockchain to illustrate. There were 0.88 million shares shorted prior to the short attack. The highest price in the [0, 5] window was $45.99, while the closing price after 63 trading days was $8.15. If short sellers were forced to cover their positions at the highest price in [0, 5], they would have forfeited profits of approximately 0.88 * ($45.99 - $8.15), or $33.3 million.

[22] One drawback is that the exchanges only announce short interest twice a month. In other words, the disclosed short interest at the settlement date might not reflect the latest short interest prior to the short attacks. The benefit of exchange-disclosed numbers is that they are available for all campaigns in our sample. We have two other sources of daily short interest that cover parts of the sample that we use in robustness tests. First, for 2015 to 2020, we use daily short-interest from S3 Partners (available through Bloomberg terminals) and find that the average forfeited profit is $61.8 million if short sellers are forced to cover at the highest price in [0,1]. Second, for 2006 to 2018, we use daily shares-on-loan data from Markit and find that the average forfeited profit is $48.1 million. Markit short interest is known to be lower than exchange-disclosed short interest because it is based on net rather than gross short interest, and Markit only reports loans when brokers borrow from other agents.

price in the windows of [0, 3], [0, 5], and [0, 10], respectively. Summed over all 204 short attacks in this subsample, this amounts to \$13.8 – \$16.8 billion in forfeited profits.

To put these numbers into perspective, we also estimate the potential profits short sellers could potentially have realized on those campaigns that witnessed initially negative returns, assuming that they could have covered their short positions at the *lowest* price in the four windows after the attack. Table 10 Panel B presents the results. For the 1,018 cases where price decreased in the first two days following the short attack, we find that short sellers could have realized \$27.5 million on average if they had been lucky enough to cover at the lowest price in the first two days. This number increases to \$32.6 million, \$34.9 million, and \$39.4 million if they cover at the lowest price in the windows of [0, 3], [0, 5], and [0, 10], respectively. Overall, this amounts to \$28.0 – \$40.1 billion in potential profits for the 1,018 successful campaigns. In other words, successful campaigns occur with five times the frequency of potential squeezes but have only twice the profit. This comparison highlights the enormous risk short squeezes impose on short sellers.

Overall, the evidence presented in Table 10 suggests that short squeezes after short attacks may impose significant costs on short sellers. These costs are in addition to prior studies documenting the constraints, risks, and other implicit costs faced by short sellers in general (Engelberg et al. 2018; Richardson et al., 2017; Schultz, 2020).

V. Conclusion

In this paper we study market returns of firms facing short attacks, where short sellers publicly reveal their negative information to the market. Counterintuitively, we find that a large proportion of these attacks, roughly 30%, are followed by positive market returns. We investigate these positive returns and find that they are disproportionately likely to reverse in the long run relative to negative returns, consistent with them being temporary price increases driven by short squeezes. We investigate and rule out several alternative explanations for this asymmetric reversal pattern and also document high levels of short covering for positive/reversal firms after short attacks, further providing evidence consistent with short squeezes. While we find very little evidence that suspected short squeezes can be predicted prior to short attacks, we find that short squeezes are more likely to occur when there are high market returns and online sentiment immediately after the disclosure of short theses. Further, firm insiders appear to use stock trades to retaliate against short sellers by inducing a squeeze. Lastly, we document that short squeezes impose significant costs on short sellers with an estimated $70 million in forfeited profits per suspected short squeeze case.

Our results provide important evidence on the risks and costs faced by short sellers. While short sellers have been shown to increase price efficiency on average (Nagel, 2005), their activities are substantially hampered by the risks that they face (Engelberg et al., 2018). We show that short squeezes constitute a significant risk to short sellers, even in the setting when they are revealing negative information to the market. These results are especially timely in informing policy debates on the regulation of short selling, especially proposals calling for further restrictions on short sellers which might further compound the risks that we document here (Cohodes, 2020).

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Appendix: Variable Definitions

Variables	Definitions
Ret[i, j]	The cumulative raw return from trading date i to trading date j, where date 0 is the date of short attack
Pos[i, j]	Indicator. One if the Ret[i, j] is positive and zero otherwise
Pos_Reversal[0, j]	Indicator of short squeeze. One if the *Ret[i, j]* is positive but *Ret[0, 63]* is negative, and zero otherwise. In other words, the positive return in [i, j] fully reverses within the first three months.
8K [0,j]	Indicator. One if an 8k was filed between date of short attack and date j
RavenPack_Full_#Article[i,j]	The number of media articles captured by Ravenpack Full edition from date i to date j, where date 0 is the date of short attack. Only full articles with a relevant score of 50 or more are included
RavenPack_PR_#Article[i,j]	The number of press releases captured by Ravenpack Press Release edition from date i to date j, where date 0 is the date of short attack. Only full articles with a relevant score of 50 or more are included
RavenPack_Web_#Article[i,j]	The number of web-based articles captured by Ravenpack Web edition from date i to date j, where date 0 is the date of short attack. Only full articles with a relevant score of 50 or more are included
Chg_SIR (in percent)	The change in *SIR* reported by the stock exchanges prior to the short attack relative to the prior announcement
SIR	The last reported short interest by the stock exchanges prior to the short attack scaled by total shares outstanding
IOR_Total	Total percentage of institutional ownership, measured by the last available reported number prior to the short attack in the Thomson Reuters 13F database
IOR_HHI	The concentration of institutional ownership as measured by the Herfindahl–Hirschman Index, measured by the last available reported number at or prior to the short attack
Numest	The number of analysts providing one-year ahead earnings forecast in the consensus prior to the short attack
BASpread (in percent)	The average bid-ask spread in the 63 trading days prior to the short attack
RavenPack_DJ_Pre	The average composite sentiment score of all traditional media articles captured by Ravenpack Dow Jones edition in the 63 trading days prior to the short attack. Only full articles with a relevant score of 50 or more are included
RavenPack_PR_Pre	The average composite sentiment score of all press releases captured by Ravenpack Press Release edition in the 63 trading days prior to the short attack. Only full articles with a relevant score of 50 or more are included
RavenPack_Web_Pre	The average composite sentiment score of all web-based media articles captured by RavenPack Web edition in the 63 trading days prior to the short attack. Only full articles with a relevant score of 50 or more are included.
Momentum (in percent)	The cumulated raw return 10 trading days prior to and ending 1 trading day prior to the short attack

Guidance	Indicator. One if management guidance was provided in the previous quarter, and zero otherwise
Fraud or Accounting	Indicator. One if the primary allegation as coded by the data providers involves fraud or accounting issues
RavenPack_DJ_Sentiment[i,j]	The average composite sentiment score of traditional media articles captured by RavenPack Dow Jones edition from date i to date j, where date 0 is the date of short attack. Only full articles with a relevant score of 50 or more are included
RavenPack_PR_Sentiment[i,j]	The average composite sentiment score of press releases captured by RavenPack Press Release edition from date i to date j, where date 0 is the date of short attack. Only full articles with a relevant score of 50 or more are included
RavenPack_Web_Sentiment[i,j]	The average composite sentiment score of all web-based media articles captured by RavenPack Web edition from date i to date j, where date 0 is the date of short attack. Only full articles with a relevant score of 50 or more are included
8-K_Tone (in percent)	The average sentiment of the 8-K disclosures issued starting on the day of the short attack and ending one day after the short attack. Calculated as the difference between the percentage of Loughran-McDonald positive words and negative words
MktRet[i,j] (in percent)	The cumulated value weighted market return from date i to date j, where date 0 is the date of short attack
Insider_BuySellImb[0,j]	The amount of cumulated net insider buy as a percentage of shares outstanding starting from date 0 to date j, where date 0 is the date of short attack

Table 1: Sample Selection and Distribution

Year	Frequency	Percent	Cumulative Frequency	Cumulative Percent
2006	23	1.61%	23	1.61%
2007	13	0.91%	36	2.52%
2008	22	1.54%	58	4.06%
2009	37	2.59%	95	6.66%
2010	49	3.43%	144	10.09%
2011	110	7.71%	254	17.80%
2012	77	5.40%	331	23.20%
2013	134	9.39%	465	32.59%
2014	161	11.28%	626	43.87%
2015	205	14.37%	831	58.23%
2016	118	8.27%	949	66.50%
2017	127	8.90%	1,076	75.40%
2018	112	7.85%	1,188	83.25%
2019	130	9.11%	1,318	92.36%
2020	109	7.64%	1,427	100%

This table presents the yearly distribution of our sample of short-selling attacks.

Table 2. Descriptive Statistics

Panel A: Descriptive Statistics for Returns after Short Attacks

	N	Mean	Q1	Median	Q3	Std
Ret[0,0]	1,427	-0.047	-0.080	-0.030	0.004	0.097
Ret[0,1]	1,427	-0.056	-0.098	-0.040	0.007	0.116
Ret[0,3]	1,427	-0.058	-0.115	-0.040	0.011	0.138
Ret[0,5]	1,427	-0.063	-0.133	-0.048	0.018	0.155
Pos[0,0]	1,427	0.285	0.000	0.000	1.000	0.452
Pos[0,1]	1,427	0.287	0.000	0.000	1.000	0.452
Pos[0,3]	1,427	0.294	0.000	0.000	1.000	0.456
Pos[0,5]	1,427	0.310	0.000	0.000	1.000	0.463
Ret[1,63]	1,427	-0.013	-0.213	-0.034	0.139	0.352
Ret[2,63]	1,427	-0.012	-0.209	-0.026	0.134	0.349
Ret[4,63]	1,427	-0.008	-0.197	-0.024	0.125	0.340
Ret[6,63]	1,427	-0.004	-0.184	-0.023	0.129	0.340
Pos_Reversal[0,0]	1,427	0.152	0.000	0.000	0.000	0.359
Pos_Reversal[0,1]	1,427	0.146	0.000	0.000	0.000	0.353
Pos_Reversal[0,3]	1,427	0.143	0.000	0.000	0.000	0.350
Pos_Reversal[0,5]	1,427	0.144	0.000	0.000	0.000	0.351

Panel B: Descriptive Statistics for Other Variables Employed in Regression Analyses

	N	Mean	Q1	Median	Q3	Std
8K [0,0]	1,427	0.028	0.000	0.000	0.000	0.165
8K [0,1]	1,427	0.055	0.000	0.000	0.000	0.227
8K [0,3]	1,427	0.106	0.000	0.000	0.000	0.308
8K [0,5]	1,427	0.130	0.000	0.000	0.000	0.336
RavenPack_PR_#Article[0,0]	1,427	0.546	0.000	0.000	0.000	1.488
RavenPack_PR_#Article[0,1]	1,427	2.840	0.000	0.000	3.000	7.712
RavenPack_PR_#Article[0,3]	1,427	1.514	0.000	0.000	2.000	3.549
RavenPack_PR_#Article[0,5]	1,427	2.001	0.000	0.000	2.000	4.409
RavenPack_Full_#Article[0,0]	1,427	16.525	0.000	2.000	8.000	111.629
RavenPack_Full_#Article[0,1]	1,427	35.333	0.000	2.000	12.000	221.477
RavenPack_Full_#Article[0,3]	1,427	43.687	0.000	5.000	19.000	335.119
RavenPack_Full_#Article[0,5]	1,427	54.996	0.000	7.000	26.000	404.972
RavenPack_Web_#Article[0,0]	1,427	15.392	0.000	2.000	8.000	102.804
RavenPack_Web_#Article[0,1]	1,427	27.313	0.000	3.000	14.000	183.410
RavenPack_Web_#Article[0,3]	1,427	41.080	0.000	5.000	19.000	321.050
RavenPack_Web_#Article[0,5]	1,427	51.889	0.000	7.000	25.000	390.705
Chg_SIR (in percent)	1,427	0.501	-0.172	0.114	0.742	1.751
SIR	1,427	0.112	0.025	0.072	0.156	0.126
IOR_Total	1,427	0.494	0.101	0.449	0.840	0.422
IOR_HHI	1,427	0.135	0.041	0.071	0.145	0.183
Numest	1,427	5.779	1.000	4.000	8.000	6.401
BASpread (in percent)	1,427	0.268	0.049	0.117	0.310	0.399
Ravenpack_DJ_Pre	1,427	50.588	50.341	50.201	51.184	1.005
Ravenpack_PR_Pre	1,427	50.976	50.000	50.750	51.714	1.301

Ravenpack_Web_Pre	1,427	50.674	50.329	50.429	51.769	1.506
Momentum (in percent)	1,427	0.036	-0.096	-0.014	0.072	0.370
Guidance	1,427	0.515	0.000	1.000	1.000	0.500
Fraud or Accounting	1,427	0.166	0.000	0.000	0.000	0.372
Ravenpack_DJ_Sentiment[0,0]	1,427	49.777	50.000	50.000	50.000	1.666
Ravenpack_DJ_Sentiment[0,1]	1,427	49.766	50.000	50.000	50.000	1.768
Ravenpack_DJ_Sentiment[0,3]	1,427	49.749	50.000	50.000	50.000	1.932
Ravenpack_DJ_Sentiment[0,5]	1,427	49.755	50.000	50.000	50.000	1.980
Ravenpack_PR_Sentiment[0,0]	1,427	50.007	50.000	50.000	50.000	1.432
Ravenpack_PR_Sentiment[0,1]	1,427	50.160	50.000	50.000	50.000	1.384
Ravenpack_PR_Sentiment[0,3]	1,427	50.179	50.000	50.000	50.000	1.491
Ravenpack_PR_Sentiment[0,5]	1,427	50.273	50.000	50.000	50.000	1.831
Ravenpack_Web_Sentiment[0,0]	1,427	49.518	49.667	50.000	50.000	2.791
Ravenpack_Web_Sentiment[0,1]	1,427	49.771	49.625	50.000	50.429	2.342
Ravenpack_Web_Sentiment[0,3]	1,427	49.957	49.724	50.000	50.677	2.074
Ravenpack_Web_Sentiment[0,5]	1,427	50.092	49.844	50.000	50.750	2.372
8-K_Tone[0,0]	1,427	0.006	0.000	0.000	0.000	0.113
8-K_Tone[0,1]	1,427	0.021	0.000	0.000	0.000	0.174
8-K_Tone[0,3]	1,427	0.020	0.000	0.000	0.000	0.171
8-K_Tone[0,5]	1,427	0.020	0.000	0.000	0.000	0.171
MktRet[0,0]	1,427	0.035	-0.356	0.070	0.545	0.916
MktRet[0,1]	1,427	0.008	-0.380	0.068	0.495	1.112
MktRet[0,3]	1,427	0.016	-0.374	0.069	0.497	1.112
MktRet[0,5]	1,427	0.039	-0.372	0.079	0.538	1.104
Insider_BuySellImb[0,0]	1,427	-0.003	0.000	0.000	0.000	0.124
Insider_BuySellImb[0,1]	1,427	-0.016	0.000	0.000	0.000	0.450
Insider_BuySellImb[0,3]	1,427	-0.055	0.000	0.000	0.000	1.105
Insider_BuySellImb[0,5]	1,427	-0.102	0.000	0.000	0.000	1.968

This panel presents descriptive statistics for variables used in this paper. Panel A presents descriptive statistics for raw returns in windows around and after short attacks. Specifically, Ret[i, j] is the cumulative raw return from trading date i to trading date j, where date 0 is the date of short attack. Pos[i,j] is an indicator for positive return in the event window date i to date j. Pos_Reversal[0,j] is an indicator for a positive return in the initial event window date until date j and a subsequent reversal from date j to trading date 63. Panel B presents descriptive statistics for all remaining variables employed in our regression analyses, defined in detail in the Variable Appendix. All continuous variables are winsorized at the 1st and 99th percentiles, except for stock returns.

Table 3. Frequency of Positive and Negative Returns After Short-Selling Attacks

Panel A. Returns Calculated Using Closing Price

	Positive Returns							*Negative Returns*						
	Raw ret using close t-1 and close t+i							*Raw ret using close t-1 and close t+i*						
Event Window	>0	>1%	>2%	>3%	>4%	>5%	>10%	<= 0%	<-1%	<-2%	<-3%	<-4%	<-5%	<-10%
[0,0]	407	286	210	163	127	100	28	1,020	917	806	717	638	539	283
[0,1]	409	338	270	215	165	135	48	1,018	950	865	788	710	629	351
[0,3]	419	362	311	268	234	206	93	1,008	937	868	786	715	656	417
[0,5]	442	397	344	293	263	226	118	985	927	856	809	751	701	464

Panel B. Returns Calculated Using Maximum/Minimum Price

	Positive Returns							*Negative Returns*						
	Raw ret using close t-1 and highest price in window							*Raw ret using close t-1 and lowest price in window*						
Event Window	>0	>1%	>2%	>3%	>4%	>5%	>10%	<=0%	<-1%	<-2%	<-3%	<-4%	<-5%	<-10%
[0,0]	1,081	807	573	440	331	236	90	1,363	1,272	1,152	1,048	952	841	495
[0,1]	1,123	889	678	544	433	333	149	1,381	1,319	1,230	1,154	1,070	975	639
[0,3]	1,167	971	783	653	537	458	234	1,393	1,348	1,276	1,217	1,150	1,063	743
[0,5]	1,185	1,006	835	729	609	524	291	1,399	1,361	1,301	1,258	1,189	1,114	810

This table demonstrates the frequency of positive and negative raw returns in response to short-selling campaigns. In Panel A, returns are calculated by comparing the closing price at time t-1 with the closing price at the end of the event window. Hence, campaigns that fall into the positive and negative return categories are mutually exclusive. In Panel B, positive (negative) returns are calculated by comparing the closing price at time t-1 with the highest price (lowest price) in the event window. Because the highest price in the window can be above the closing price at t-1 *and* the lowest price can be below the closing price at t-1, campaigns that fall into the positive and negative return categories are not mutually exclusive in this panel.

Table 4. Frequency of Full Return Reversals After Short-Selling Attacks

A. Returns Calculated Using Closing Price

	Positive Initial Returns							*Negative Initial Returns*						
Event Window	>0	>1%	>2%	>3%	>4%	>5%	>10%	<=0%	<-1%	<-2%	<-3%	<-4%	<-5%	<-10%
[0,0]	0.53	0.54	0.51	0.48	0.47	0.51	0.64	0.34	0.32	0.3	0.28	0.28	0.25	0.19
[0,1]	0.51	0.5	0.51	0.49	0.48	0.46	0.5	0.33	0.32	0.31	0.29	0.27	0.25	0.19
[0,3]	0.49	0.49	0.49	0.49	0.47	0.46	0.46	0.32	0.31	0.3	0.27	0.26	0.24	0.19
[0,5]	0.5	0.5	0.5	0.49	0.46	0.49	0.43	0.31	0.29	0.27	0.26	0.24	0.23	0.17

B. Returns Calculated Using Maximum/Minimum Price

	Positive Initial Returns							*Negative Initial Returns*						
Event Window	>0	>1%	>2%	>3%	>4%	>5%	>10%	<=0%	<-1%	<-2%	<-3%	<-4%	<-5%	<-10%
[0,0]	0.61	0.6	0.61	0.6	0.6	0.61	0.61	0.4	0.39	0.39	0.38	0.38	0.36	0.35
[0,1]	0.6	0.59	0.59	0.59	0.57	0.56	0.56	0.39	0.39	0.38	0.38	0.37	0.36	0.33
[0,3]	0.6	0.58	0.57	0.57	0.55	0.53	0.5	0.39	0.39	0.39	0.38	0.37	0.36	0.32
[0,5]	0.6	0.58	0.56	0.55	0.54	0.52	0.47	0.39	0.39	0.39	0.38	0.38	0.36	0.32

This table demonstrates the frequency of full return reversals for initial positive and negative raw returns after short-selling campaigns, where the set of initial positive and negative return observations corresponds to Table 3. Each cell shows the proportion of targets falling within each group that experienced a return reversal, defined as a return measured at the closing price of the post-event period which fully negates the amount of the return during the event period. In Panel A, the initial event window return is sorted based on the closing price at the end of the event window. In Panel B, the initial event window return is sorted based on the highest (lowest) price within the event windows for positive (negative) returns.

Table 5. Return Reversals

	Dependent Variable= Ret [j+1,63]							
Where j=	*0*	*1*	*3*	*5*	*0*	*1*	*3*	*5*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Positive[0,j]	0.006	0.011	-0.026	-0.002	0.010	0.011	-0.033	-0.013
	(0.27)	(0.45)	(-1.05)	(-0.06)	(0.42)	(0.40)	(-1.40)	(-0.44)
Ret[0,j]	0.129	0.123	0.020	0.094	0.022	0.076	0.012	0.070
	(1.24)	(1.21)	(0.20)	(1.40)	(0.19)	(0.62)	(0.12)	(0.86)
Positive[0,j]×Ret[0,j]	-1.152***	-0.741***	-0.317*	-0.645*	-0.992***	-0.682**	-0.317*	-0.574
	(-3.91)	(-3.01)	(-1.74)	(-1.87)	(-3.17)	(-2.46)	(-1.69)	(-1.59)
Constant	0.004	0.003	0.005	0.020				
	(0.25)	(0.16)	(0.33)	(1.37)				
Fixed Effects	None	None	None	None	Year-Qtr	Year-Qtr	Year-Qtr	Year-Qtr
Std Dev	Firm	Firm	Firm	Firm	Firm	Firm	Firm	Firm
Observations	1,427	1,427	1,427	1,427	1,427	1,427	1,427	1,427
Adjusted R-squared	0.010	0.005	0.004	0.012	0.108	0.104	0.110	0.114

This table demonstrates the association between the sign of the event window stock return and the subsequent reversal. Campaign-level regressions estimate the association between *Ret* during the event window and subsequent *Ret*, depending on whether the sign of *Ret* was positive or negative (*Positive).* We include year-quarter fixed effects in Columns 5 – 8. Robust t-statistics clustered by firm in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 6. Alternative Explanations for Asymmetric Reversal of Positive Returns

Panel A: Stock Returns Based on Minimum Price Following the Short Attack

Event Window	N	Positive Initial Return **With** Reversal	N	Everything Else	dif
[0,0]	217	-0.028	1,210	-0.106	-0.078***
[0,1]	209	-0.042	1,218	-0.132	-0.090***
[0,3]	204	-0.056	1,223	-0.151	-0.095***
[0,5]	219	-0.057	1,208	-0.194	-0.137***

Event Window	N	Positive Initial Return **With** Reversal	N	Positive Initial Return **Without** Reversal	dif
[0,0]	217	-0.028	190	-0.027	0.001
[0,1]	209	-0.042	200	-0.036	0.006
[0,3]	204	-0.056	215	-0.047	0.009
[0,5]	219	-0.057	223	-0.053	0.003

Panel B: Management Responses to Short Attacks

	Dependent Variable= Pos_Reversal			
Window:	*[0,0]*	*[0,1]*	*[0,3]*	*[0,5]*
	(1)	(2)	(3)	(4)
8K	0.029	0.091	0.041	0.058
	(0.41)	(1.45)	(0.90)	(1.20)
RavenPack_PR_#Article	-0.028***	-0.005***	-0.009**	-0.006**
	(-4.11)	(-4.80)	(-2.54)	(-2.00)
Fixed Effects	Year-Qtr	Year-Qtr	Year-Qtr	Year-Qtr
Observations	1,427	1,427	1,427	1,427
Adjusted R-squared	0.021	0.024	0.014	0.010

Panel C: Investor Attention and Positive Return Reversals

	Dependent Variable: Pos_Reversal							
Window:	*[0,0]*	*[0,1]*	*[0,3]*	*[0,5]*	*[0,0]*	*[0,1]*	*[0,3]*	*[0,5]*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
RavenPack_Full_#Article	-0.000	-0.000	0.000	0.000				
	(-0.83)	(-0.28)	(0.67)	(0.61)				
RavenPack_Web_#Article					-0.000	-0.000	0.000	0.000
					(-0.74)	(-0.26)	(0.60)	(0.56)
Fixed Effects	Year-Qtr	Year-Qtr	Year-Qtr	Year-Qtr	Year-Qtr	Year-Qtr	Year-Qtr	Year-Qtr
Observations	1,427	1,427	1,427	1,427	1,427	1,427	1,427	1,427
Adjusted R-squared	0.006	0.007	0.004	0.003	0.006	0.007	0.004	0.003

Panel D: Magnitude of Returns

	Positive Return With Reversal		Positive Return Without Reversal			
Window	**N**	**Mean Return**	**N**	**Mean Return**	**Dif**	**t-stat**
[0,0]	217	0.040	190	0.038	-0.002	-0.260
[0,1]	209	0.050	200	0.054	0.004	0.460
[0,3]	204	0.068	215	0.081	0.013	1.320
[0,5]	219	0.078	223	0.089	0.012	1.080

This table reports four sets of analyses that rule out alternative explanations for the asymmetric reversal of positive returns following short attacks. Panel A examines whether positive stock price reversals are driven by short sellers profitably closing their positions within the event window. Panel B demonstrates the association between the issuance of 8-Ks and press releases immediately following short attacks with positive stock price reversals. Panel C estimates the association between media attention following short-selling attacks and positive stock price reversals. Columns 1 – 4 calculate attention using the number of articles captured by the Ravenpack Full Edition within the event window. Columns 5 – 8 calculate attention using the number of articles captured just by the Ravenpack Web Edition. Panel D compares the magnitude of positive returns between reversal and no-reversal firms to see if the magnitude of returns is mechanically smaller for reversal firms. All continuous non-return independent variables are winsorized at the 1st and 99th percentiles. Robust t-statistics clustered by firm in parentheses for regression analyses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 7. Short Covering Around Short Attacks

Date	Positive Reversal (N = 160)	Positive No-Reversal (N = 150)	Negative Return (N = 796)	EA Benchmark Group (N = 14,063)	Difference in Means		
	(1)	(2)	(3)	(4)	(1) – (2)	(1) – (3)	(1) – (4)
0	1.317***	0.797***	1.586***	0.837***	0.52	-0.269	0.481***
1	1.351**	0.581***	0.850***	0.446***	0.77	0.501	0.905***
2	0.918***	0.373***	0.769***	0.347***	0.545*	0.15	0.571***
3	0.673***	0.492***	0.659***	0.324***	0.181	0.014	0.349***
4	0.631***	0.361***	0.566***	0.299***	0.269	0.065	0.332***
5	0.819	0.345***	0.430***	0.281***	0.474	0.389	0.538***
6	0.971*	0.426***	0.509***	0.263***	0.545	0.462	0.708***
7	0.558**	0.255***	0.489***	0.255***	0.304	0.069	0.303***
8	0.636***	0.327***	0.414***	0.278***	0.309	0.222	0.358***
9	0.712***	0.330***	0.414***	0.247***	0.382	0.298	0.465***
10	1.648	0.292***	0.532***	0.262***	1.356	1.116	1.386***

This table reports average daily short covering as a percentage of total shares outstanding in the [0,10] window following either short-selling attacks or earnings announcements (only for the EA Benchmark group). We report the daily averages for four samples: targets with positive initial returns and reversals (Column 1), targets with positive initial returns without reversals (Column 2), targets with negative initial returns (Column 3), and the earnings announcements (EA) benchmark group (Column 4). We also report the differences in means between Column 1 and remaining columns. Short covering at day t is calculated as the net decrease of shares-on-loan relative to day t-1 plus the newly opened short trades on day t, scaled by shares outstanding. We multiply this number by 100 to facilitate interpretation. The EA Benchmark Group is identified following the approach in Hong et al. (2012) as firms with top tercile earnings surprises and short interest, examined in the period starting at the earnings announcement date. *** p<0.01, ** p<0.05, * p<0.1

Table 8. Leading Indicators of Short Squeezes

	Dependent Variable= Pos_Reversal							
Window:	*[0,0]*	*[0,1]*	*[0,3]*	*[0,5]*	*[0,0]*	*[0,1]*	*[0,3]*	*[0,5]*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Chg_SIR	0.767	0.408	0.847	0.226	0.772	0.187	0.827	0.228
	(1.25)	(0.71)	(1.40)	(0.39)	(1.20)	(0.32)	(1.36)	(0.39)
SIR	-0.064	-0.005	-0.083	-0.100	-0.080	-0.029	-0.087	-0.114*
	(-0.91)	(-0.07)	(-1.27)	(-1.58)	(-1.05)	(-0.40)	(-1.26)	(-1.68)
IOR_Total	-0.003	-0.016	-0.012	0.010	-0.005	-0.005	-0.006	0.009
	(-0.09)	(-0.58)	(-0.47)	(0.39)	(-0.17)	(-0.16)	(-0.22)	(0.36)
IOR_HHI	0.016	-0.047	-0.022	-0.050	-0.017	-0.061	-0.024	-0.062
	(0.26)	(-0.86)	(-0.39)	(-0.95)	(-0.28)	(-1.11)	(-0.42)	(-1.10)
Numest	0.001	0.001	0.002	0.000	0.001	0.001	0.003	0.000
	(0.83)	(0.74)	(1.25)	(0.08)	(0.47)	(0.60)	(1.28)	(0.24)
BASpread	-1.121	-0.674	4.277	2.371	-1.196	-0.941	4.014	2.342
	(-0.43)	(-0.26)	(1.43)	(0.80)	(-0.43)	(-0.33)	(1.27)	(0.73)
Momentum	-0.015	-0.008	-0.006	0.007	-0.022	-0.015	-0.008	0.004
	(-0.95)	(-0.53)	(-0.46)	(0.46)	(-1.37)	(-0.94)	(-0.60)	(0.25)
Guidance	0.002	0.000	-0.005	-0.003	0.005	0.005	-0.003	-0.000
	(0.20)	(0.05)	(-0.51)	(-0.31)	(0.48)	(0.53)	(-0.30)	(-0.04)
RavenPack_DJ_Pre	0.000	-0.001	0.004	0.002	0.003	0.001	0.003	0.002
	(0.06)	(-0.17)	(0.72)	(0.41)	(0.45)	(0.17)	(0.50)	(0.41)
RavenPack_PR_Pre	0.001	-0.035*	-0.021	-0.051**	-0.006	-0.034	-0.020	-0.056***
	(0.05)	(-1.74)	(-0.82)	(-2.31)	(-0.22)	(-1.52)	(-0.82)	(-2.69)
RavenPack_Web_Pre	-0.005	0.006	0.032	0.016	-0.004	0.003	0.033	0.010
	(-0.22)	(0.28)	(1.51)	(0.73)	(-0.18)	(0.13)	(1.45)	(0.44)
Fraud or Accounting	-0.049*	-0.028	-0.033	-0.062***	-0.079***	-0.060**	-0.058**	-0.082***
	(-1.94)	(-1.11)	(-1.33)	(-2.71)	(-3.20)	(-2.28)	(-2.25)	(-3.21)
Constant	0.777	0.603	0.470	-0.153				
	(1.44)	(1.21)	(1.01)	(-0.32)				
Fixed Effects	None	None	None	None	Year-Qtr	Year-Qtr	Year-Qtr	Year-Qtr
Observations	1,427	1,427	1,427	1,427	1,427	1,427	1,427	1,427
Adjusted R-squared	-0.002	-0.004	0.000	0.001	0.007	0.007	0.006	0.006

This table examines leading indicators of short squeezes. Campaign-level regressions estimate the association between *Pos_Reversal*, an indicator for whether firms experience positive initial event returns followed by a full reversal, and leading indicators. *Pos_Reversal* is defined using various event windows surrounding the short attack. All continuous non-return independent variables are winsorized at the 1st and 99th percentiles. We exclude year-quarter fixed effects in Columns 1 – 4 but include them in Columns 5 – 8. Robust t-statistics clustered by firm in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 9. Conditions on the Day of the Short Attack

	Dependent Variable= Pos_Reversal			
Window:	*[0,0]*	*[0,1]*	*[0,3]*	*[0,5]*
	(1)	(2)	(3)	(4)
RavenPack_DJ_Sentiment	-0.001	0.002	0.001	0.004
	(-1.20)	(0.51)	(0.18)	(1.26)
RavenPack_Web_Sentiment	0.014***	0.014***	0.007	0.016***
	(4.53)	(3.73)	(1.45)	(3.25)
RavenPack_PR_Sentiment	-0.002	-0.007	-0.007	-0.007
	(-0.31)	(-1.01)	(-0.97)	(-1.02)
8-K_Tone	0.056	0.115	0.055	0.034
	(0.75)	(1.59)	(0.74)	(0.46)
Insider_BuySellImb	0.084***	0.019***	0.007**	0.003**
	(4.13)	(4.30)	(2.44)	(2.44)
MktRet	5.848***	3.669***	2.066***	-0.001
	(6.22)	(5.28)	(4.24)	(-0.00)
Fixed Effects	Year-Qtr	Year-Qtr	Year-Qtr	Year-Qtr
Observations	1,427	1,427	1,427	1,427
Adjusted R-squared	0.039	0.037	0.017	0.009

This table examines conditions at the time of the short attack that are associated with short squeezes, identified with *Pos_Reversal*, an indicator for whether firms experience positive initial event returns followed by a full reversal. All continuous non-return independent variables are winsorized at 1st and 99th percentiles. Robust t-statistics clustered by firm in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 10: The Costs of Short Squeezes to Short Sellers

Panel A: Estimated Profits (in million USD) Short Sellers Forfeited Had They Been Forced to Cover at the Highest Price (for firms with initial positive returns and a subsequent full reversal, N = 204)

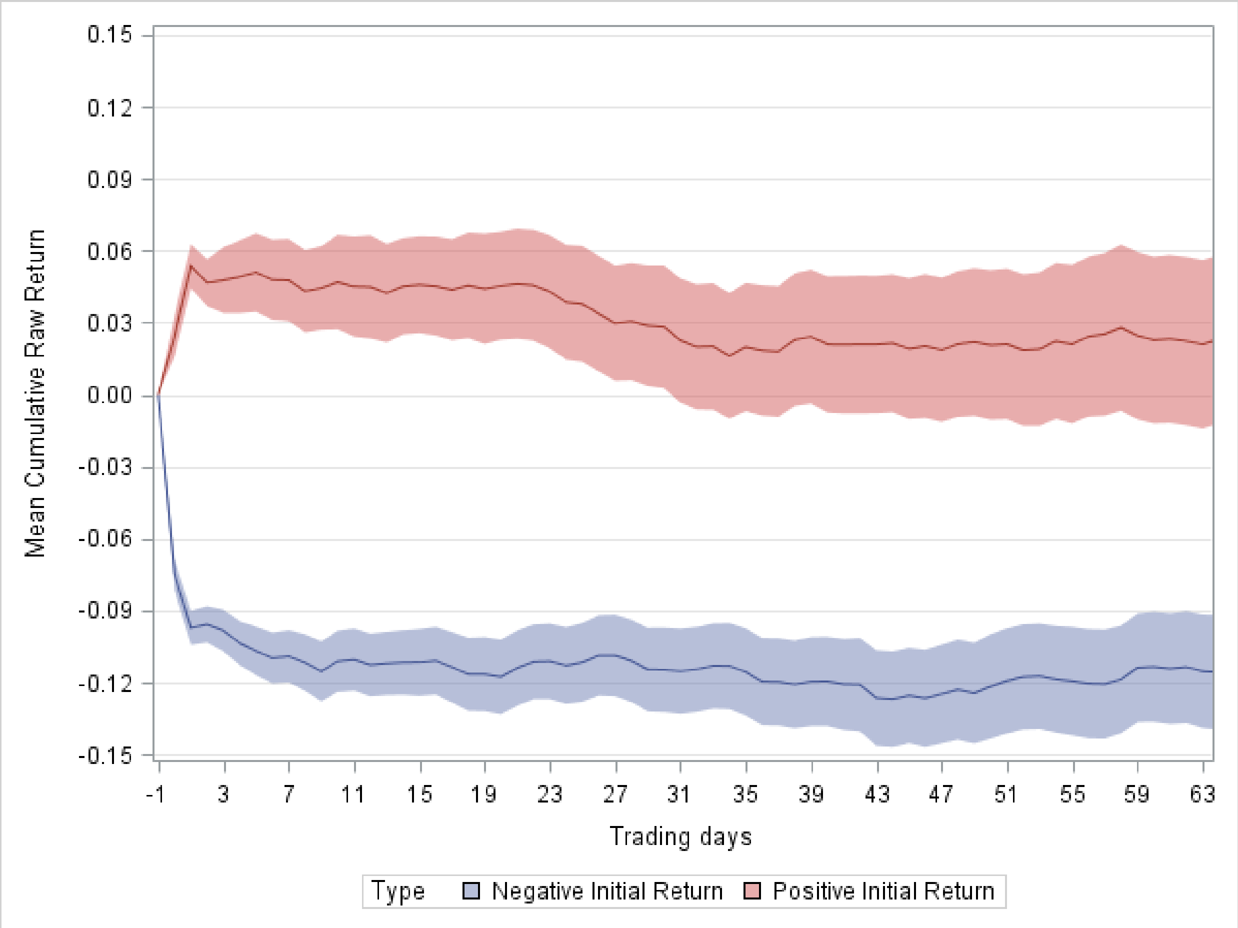
Highest Price in	Mean	Std Dev	Min	P5	P25	Median	P75	P95	Max	Total
[0, 1]	67.78	157.19	0.04	0.37	5.1	22.62	65.1	277.81	1,656.84	13,827.74
[0, 3]	73.73	172.93	0.05	0.37	5.7	26.03	69.87	277.91	1,824.97	15,041.47
[0, 5]	78.51	187.26	0.07	0.38	6.01	27.17	71.1	277.91	1,824.97	16,015.34
[0, 10]	82.54	192.42	0.11	0.52	6.08	28.56	74.81	277.91	1,824.97	16,838.60

Panel B: Estimated profits (in million USD) of Short Sellers Had They Been Forced to Cover at the Lowest Price (for firms with initial negative returns, N = 1,018)

Lowest Price in	Mean	Std Dev	Min	P5	P25	Median	P75	P95	Max	Total
[0, 1]	27.47	66.18	0	0.09	1.95	7.95	24.52	115.41	1,037.15	27,964.35
[0, 3]	32.56	82.07	0	0.11	2.3	9.23	28.51	135.78	1,281.44	33,151.16
[0, 5]	34.88	84.93	0	0.13	2.58	10.39	30.68	145.19	1,281.44	35,510.27
[0, 10]	39.42	91.23	0	0.15	3.05	11.58	37.11	170.69	1,281.44	40,131.63

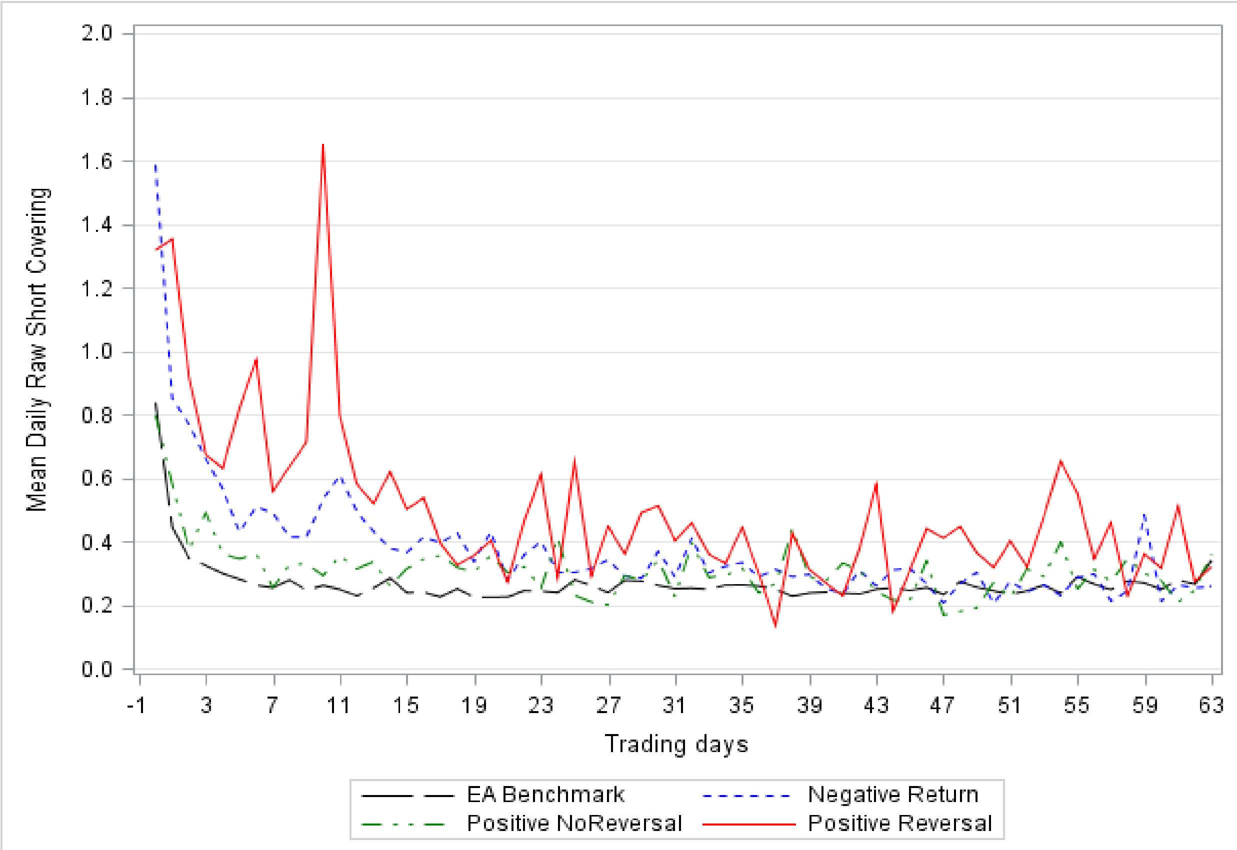
This table presents descriptive statistics for estimates of the forfeited profits (Panel A) and potential profits (Panel B) that short sellers could have gotten by taking short positions in target firms. In Panel A we focus on firms with returns that are initially positive (in the [0,1] window) but then fully reverse by the end of 63 trading days. Forfeited profits are calculated as the product of the short interest before the short attack and the difference between the highest price in the specified window and the closing price 63 trading days after the short attack. In Panel B we focus on short attack cases with negative returns over the [0,1] window. Potential profits are calculated as the product of the short interest before the short attack and the difference between the closing price prior to the short attack and the lowest price during the specified window.

Figure 1: Post-Attack Returns After Splitting on Initial Returns



This figure plots the mean cumulative raw returns for targets with initial positive returns in the [0, 1] window following the short-selling attack and those with negative returns in the 63 trading days following the attack date. The shaded area represents the 95% confidence interval of the average returns.

Figure 2: Daily Raw Short Covering



This figure plots the mean daily short covering as a percentage of total shares outstanding in the [0,63] window following either short-selling attacks or earnings announcements (only for the EA Benchmark group). We examine four samples separately: the EA benchmark group, targets with negative initial returns in [0,1], targets with positive initial return without reversals, and targets with positive initial return and reversals. Short covering at day t is calculated as the net decrease of shares-on-loan relative to day t-1 plus newly opened short trades on day t, scaled by shares outstanding. We multiply this number by 100 to facilitate interpretation.