Aggressive Short Selling and Price Reversals*

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ABSTRACT

We show that short selling may, occasionally, cause excessive price pressure. We study large negative price reversals that occur on no-news days and find that short selling during such reversals is abnormally aggressive and substantially increases the magnitude of price declines. This negative effect on prices extends beyond a mere selling pressure from aggressive sell orders. Consistent with extant theories of predatory trading, price reversals are also accompanied by aggressive non-short selling. Large price reversals are more likely to occur in the stocks for which short selling restrictions are lifted; however, even when restrictions apply, traders often successfully circumvent them.

Introduction

Short selling is currently the focus of intense industry debate triggered by the rapid decline in stock prices in the second half of 2008. Industry observers argue that, during this period, short selling in certain stocks was abusive and that abuses should be curtailed by bringing back short selling restrictions.[1] The SEC seems to take these arguments seriously, having instituted temporary short selling bans and having introduced a requirement for hedge funds to disclose their short positions.[2] Supported by a recent proposal of the four major U.S. exchanges, the SEC is currently considering bringing back a modified tick rule that will activate in cases of unusually precipitous price declines.[3]

In contrast, academic research argues that there is no evidence of abusive short selling. A number of empirical studies (e.g., Alexander and Peterson, 2008; Diether, Lee, and Werner, 2009; SEC, 2006; and Boehmer and Wu, 2009) search short selling data for evidence of excesses and reach the conclusion that short selling is not systematically abusive. These studies conclude that short selling enhances price discovery, improves market efficiency and, hence, should be unrestricted.

In this paper, we present evidence of *occasional* excesses in short selling. We do not dispute the academic consensus that short selling typically enhances market efficiency and price discovery. However, we show that short sellers may occasionally create unwarranted pressure on prices. In particular, we find that short sellers are abnormally active at the beginning of large negative intraday price reversals – periods during which prices fall

[1] "There's a Better Way to Prevent 'Bear Raids'" by R. Pozen and Y. Bar-Yam, The Wall Street Journal, November 18, 2008; "Anatomy of the Morgan Stanley Panic" by S. Pulliam et al., The Wall Street Journal, November 24, 2008; "Restore the Uptick Rule, Restore Confidence" by C. Schwab, The Wall Street Journal, December 9, 2008.
[2] Emergency Orders Pursuant to Section 12(k)(2) of the Securities and Exchange Act of 1934: Release No. 58166, July 15, 2008, Release No. 34-58592, September 18, 2008, and Release No. 58591, September 21, 2008.
[3] "Exchanges Try to Limit Shorts Ban" by Jacob Bunge, The Wall Street Journal, March 25, 2009.

substantially but then quickly rebound.[4] Short selling at the beginning of such periods is aggressive and has a significant causal effect on the magnitude of price declines.

Our focus on price reversals relies on the theoretical argument that, in the absence of news, price declines that are followed by quick rebounds suggest undue pre-rebound price pressure. Brunnermeier and Pedersen (2005) theorize that markets are susceptible to episodic liquidity crises caused by the weakening capital positions of large institutional investors. In particular, an ailing institution (or a group of institutions) may be compelled to sell out of a large stock position, creating downward pressure on the stock price. Market-watchers with predatory intentions may then exacerbate the price decline by short selling along with the institution. As the selling pressure subsides, the price quickly rebounds. Thus, after the episode, a reversal price pattern emerges.

We use this theoretical argument as a basis for our identification procedure and study large intraday price reversals that are not accompanied by informational events. Figure 1 contains an example of a reversal pattern that we use for identification. The details of the identification procedure are described in a later section. As we focus exclusively on no-news, we believe that the price reversals in our sample are not due to the workings of price discovery. We identify large reversals for NASDAQ stocks during a one-year period from May 2005 to May 2006 and inquire whether short selling contributes to the magnitude of the pre-rebound price declines.

Our analysis requires merging of the intraday short sale (Regulation SHO[5]) datasets with the TAQ trade files. We use only NASDAQ stocks, as the intraday short sale data for

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[4] In the remainder of the paper, we refer to negative price reversals as *price reversals*.

[5] Regulation SHO was adopted by the SEC in June, 2004. According to rule 202T of the Regulation, the SEC established a Pilot Program to study the effects of elimination of short sale restrictions. The Pilot Program

the NYSE stocks contain multiple inconsistencies and do not merge well with TAQ. While we are able to find TAQ matches for 97% of short sales in NASDAQ stocks, the match rate for the NYSE stocks is only about 70%.

The data confirm that short selling exerts substantial price pressure during the early stages of large price reversals. Specifically, we show that the magnitude of pre-rebound price declines is a function of short volume and its aggressiveness. Although our data do not allow us to argue that short selling triggers price declines, we definitively show that it contributes to their development. As prices fall, short sellers actively consume liquidity and tend to route their orders to venues that do not restrict short selling (e.g., do not comply with the bid test[6]) or sufficiently expedite it. In addition, we show that the bid test is partly circumvented by frequent submission of small fleeting up-bid quotes.

As prices decline, the effect of short volume is beyond that of order imbalances created by aggressive short selling. In particular, when we model price changes as a function of, simultaneously, short volume and order imbalances created by short volume, short volume retains its causal effect on price changes. We hypothesize that this effect may be ascribed to psychological pressures fueled by aggressive short selling.

Short selling is not the only activity that creates pressure on prices during large price reversals. Aggressive short selling is usually accompanied by the even more aggressive *non-short selling*. Since our sample is free of informational events, we suggest, consistent with Brunnermeier and Pedersen (2005), that aggressive non-short selling is likely to be

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required that self-regulatory organizations make trade-by-trade short selling data publicly available. We use these intraday short sale datasets to identify short sales on the intraday basis in TAQ.

[6] The bid test is the NASD's adaptation of the tick rule. During our sample period, the bid test on NASDAQ's SuperMontage prohibits short sale executions at the bid or below-bid prices on down-bid quotes (i.e., when the bid quote is lower than the previous bid quote).

performed by ailing institutions. Together, non-short selling and short selling contribute to price declines, although only short selling has a lasting effect on prices.

We also inquire whether any characteristics distinguish the stocks prone to reversals from the matched stocks that do not undergo reversals during our sample period. We propose that (i) the probability that an institution finds itself in need of a large-scale position reduction is a function of institutional ownership; (ii) stocks that are to be sold out of such institutional positions are likely to have higher short interest; and (iii) aggressive short selling is more likely in stocks, for which short selling restrictions are lifted by the Reg. SHO pilot. The data fully confirm our expectations, as the reversal-prone stocks have (i) higher institutional ownership shares, (ii) higher short interest, and (iii) are often on the Reg. SHO pilot list of securities.

Ours is not the first study to look at price reversals in conjunction with short selling. Before eliminating short selling restrictions, the SEC conducted a study (SEC, 2006) that investigated the impact of short selling on the frequency of intraday price reversals. The study found that elimination of short selling restrictions increased the frequency of 5-minute reversals, but diminished the frequency of 30-minute reversals. The SEC concluded that there was no decisive evidence of abusive short selling. Our study differs from that of the SEC, as we investigate return reversals that are large and take much longer than 30 minutes to unfold. The advantage of this approach is that it allows us to detect occurrences during which short selling has an opportunity to affect prices.

Our contribution to the literature is threefold. First, we expose an undocumented kind of short selling; the kind that, instead of enhancing market efficiency and price discovery, occasionally increases price pressures. Second, we provide a detailed analysis of price reversals and of the role that aggressive short selling plays in their development. Third, we identify common characteristics among stocks that are susceptible to price reversals. In particular, we show that the reversal occurrence is higher in stocks for which short sales are unrestricted. We do not suggest that short selling is systematically abusive. During our sample period, large price reversals occur only in a few stocks on an average no-news day. The sole purpose of our study is to provide support to the claims that short selling may *occasionally* put unwarranted pressure on prices.

The remainder of the paper is organized as follows. Section 1 summarizes theoretical and empirical evidence on short selling and speculative/predatory trading. Section 2 introduces data sources and describes the identification procedure. Section 3 examines the relation between short selling and price reversals, the mechanics of such reversals, the role of non-shorted order flow, and the determinants of pre- and post-rebound returns. Section 4 focuses on the cross-sectional properties of reversal-prone stocks. Section 5 concludes.

1. Background

Short sellers are usually viewed as informed traders. Initially modeled by Diamond and Verrecchia (1987), short sellers' informedness is extensively tested. Dechow et al. (2001) discover that short sellers are able to identify firms that are overvalued based on their book-to-market ratios and short stock in these firms with subsequent covering after the ratios mean-revert. Desai et al. (2002) find that future returns of heavily shorted firms are negative, and the absolute value of these negative returns increases in short interest. Diether et al. (2009) suggest that, in addition to the ability to predict future stock performance, investors who choose to sell short are able to recognize transient market overreactions.

In a theoretical model, Brunnermeier and Pedersen (2005) define *predatory trading* as "trading that induces and/or exploits the need of other investors to reduce their positions." If one or more traders need to sell, others may also engage in selling (or short selling) and then profit by buying the stock back at a lower price. As such sellers aggressively open new positions at the beginning of a predatory episode; they drain liquidity and temporarily push prices below equilibrium levels. Prices rebound after predatory activity ceases.

Attari, Mello, and Ruckes (2005) postulate that traders may manipulate prices to exploit financially constrained arbitrageurs. Undercapitalization makes arbitrageurs' actions predictable and allows speculators to profitably trade against them. Carlin, Lobo, and Viswanathan (2007) describe a market in which traders usually cooperate and provide each other with apparent liquidity. In their model, cooperation sometimes breaks down, leading to transitory illiquidity and predatory trading. Similar to Brunnermeier and Pedersen's model, Carlin et al. analysis suggests that predation may lead to negative return reversals.[7]

In summary, theoretical studies suggest that a predatory episode may be triggered by an institution's attempt to unload a sizeable stock position. Such a scenario may seem somewhat unrealistic, as a financially healthy institution is unlikely to subject itself to the possibility of predation by attempting to quickly sell out of a large position. In fact, Lipson and Puckett (2006) show that institutions habitually spread their sales and purchases over several consecutive days. Nonetheless, if an institution is financially constrained, it may have to sell quickly. Since it is estimated that nearly 600 hedge funds failed in 2005 alone,[8]

[7] These theoretical models are supplemented by abundant anecdotal evidence of skillful manipulators trading against other market participants. Examples include Flynn (1934), Huebner (1934), Brady et al. (1988), Lowenstein (2000), and Cramer (2002).

[8] "Hedge Fund Realities," *The Wall Street Journal*, February 26, 2007.

predatory episodes triggered by rushed institutional selling may be relatively abundant during our sample period.

Theoretical models of predation discount the fact that large orders may be routed to the upstairs market to mitigate, or entirely avoid, manipulative trading. Meanwhile, studies of block trading provide evidence that upstairs markets periodically facilitate executions of large blocks. Grossman (1992) suggests that many large investors do not express their trading interests publicly, and upstairs brokers collect information on such interests, occasionally drawing on this information to provide additional liquidity to block orders. Bessembinder and Venkataraman (2004) confirm Grossman's suggestion and show that upstairs brokers on the Paris Bourse are able to tap into pools of unexpressed liquidity. Nonetheless, only 67% of block volume on the Bourse executes upstairs. Similarly, Madhavan and Cheng (1997) investigate upstairs trading in the 30 Dow Jones stocks and discover that as much as 80% of block dollar volume executes downstairs. Thus, although upstairs markets regularly facilitate large executions, there may still exist sufficient opportunities for price pressures in the downstairs market.

Two studies of mutual fund flows shed some light on the possibility and the profitability of trading against constrained institutions. Coval and Stafford (2007) show that selling pressure originated by distressed mutual funds may create profitable front-running opportunities. Chen et al. (2008) link such opportunities to hedge fund profits and discover that hedge fund returns increase when the number of distressed mutual funds is high. Although our data do not allow us to identify hedge funds as active participants in the development of price reversals, we are able to describe the mechanics of such reversals and define the role of short sales in their development.

2. Sample selection and identification of reversals

2.1. Data

The main sample consists of all trades and quotes in NASDAQ securities from May 2005 to May 2006.[9] Trades that involve shorted shares are identified by merging TAQ (all trades) and the Reg. SHO database (short sale trades). The merged files allow us to identify short sales in the TAQ data.

We apply conventional filters to the TAQ data and exclude trades and quotes that are reported out of time sequence and are coded as involving an error or a correction. We also exclude trades with a nonstandard settlement. Quotes are omitted if either ask or bid price is non-positive. We also exclude quotes with bids equal to or greater than asks as well as quotes (trades) with zero depths (sizes).

Merging TAQ and Reg. SHO data involves matching trades from the two datasets that satisfy the following four conditions: (i) both trades are in the same stock and are executed on the same day, (ii) both are executed by the same market center, (iii) at the same price, and (iv) have matching timestamps. The fourth condition is used sparingly, due to reporting lags in the two datasets.[10] We are able to find TAQ matches for 97% of short sales using 1- to 5-second lags where appropriate. We examine the unmatched 3% of short sales for sample selection bias and do not find any notable differences between the matched and unmatched transactions.[11]

[9] A control sample used for the estimation of abnormal short selling statistics includes additional three months: from February 2005 until May 2005.
[10] We do not match records by trade size, because trades reported in TAQ occasionally include shorted and non-shorted shares.
[11] In particular, we check for differences in trade sizes and price impacts of matched and unmatched short sales as well as clustering of such trades in certain stocks.

The files that result from merging TAQ trades and Reg. SHO short sales are then merged with TAQ quote files. We follow Bessembinder (2003) and do not lag quote time stamps when merging quotes and trades. If a quote has the same time stamp as a trade, we assume that the quote was posted before the trade. We restrict the analysis to regular trading hours (9:30 a.m. to 4:00 p.m.) and divide each trading day into seventy-eight 5-minute intervals j. For each interval, we use volume-weighted within-interval prices to compute continuously compounded 5-minute returns, ret_j. Securities with prices lower than \$1 per share and those with fewer than 60 intervals with at least one trade per interval on a given day are omitted.[12]

2.2. Identification of large price reversals

To identify a trading day d in a stock i as a day with a large price reversal (hereafter, an *event day*), we first assess stock i's historical intraday volatility by computing the average standard deviation of its 5-minute cumulative returns during twenty trading days preceding day d, $\sigma_{i,j}$. Subsequently, we define a day d as an event day, if stock i's cumulative intraday return decreases by two or more $\sigma_{i,j}$s and subsequently rebounds by 90% to 110% of the initial decline by the end of the day. For instance, for a stock with $\sigma_{i,j}$ = 1%, a day d is identified as an event day if the minimum cumulative intraday return is -2%, and the cumulative return at the end of the day is higher than or equal to -0.2% (= [1-0.9]× [-2%]) and lower than or equal to 0.2% (= [1-1.1] ×[-2%]). An illustration of event day identification is provided in Figure 1.

[12] We check for robustness of the sample selection procedure by restricting the sample to stock-days with (a) 50 and (b) 70 identifiable intervals j. Qualitatively, the main findings do not change when these checks are performed.

We set the recovery range to 90-110% in an attempt to filter out the reversals that may be triggered by arrival of new information. As new information is likely to result in a new price level at the end of the day, we restrict the sample to days when prices almost fully recover. To further eliminate the possibility of informational influences, we search LexisNexis for corporate announcements that occur on and around price reversal days and restrict the sample to the reversals with no announcements occurring on days *d-1*, *d*, and *d+1*.

Next, we divide each event day *d* into two stages: (i) [$ret_{max,pre}$; ret_{min}] and (ii) (ret_{min}; $ret_{max,post}$], where $ret_{max,pre}$ is the maximum ret_j during the pre-rebound stage; $ret_{max,post}$ is the maximum ret_j during the post-rebound stage; and ret_{min} is the minimum ret_j. Each of the two stages is further divided into 10 periods, for a total of twenty time periods per event day.[13] This adjustment benefits subsequent analysis, as it allows for standardization of price reversals that, naturally, vary in length; however, it restricts the sample to event days with pre- and post-rebound stages lasting at least 50 minutes each. This restriction does not significantly reduce the number of event days, as the vast majority of large reversals take longer than 50 minutes to unfold.

The sample selection procedure identifies 7,470 no-news days that satisfy the price reversal criteria outlined above. To provide sufficient detail on the level of price fluctuations, we subdivide event days into four groups by the magnitude of the pre-rebound price decline. In particular, we allow *m* in $-m \times \sigma_{i,j}$ to alternate among the following intervals: [2; 3); [3; 4); [4; 5); and [5; ∞). Table 1 shows that the largest pre-rebound price declines of

[13] For instance, if the [$ret_{max,pre}$; ret_{min}] stage consists of twenty 5-minute intervals, and the (ret_{min}; $ret_{max,post}$] stage consists of fifty 5-minute intervals, then the pre-rebound stage is divided into ten 10-minute periods, and the post-rebound stage is divided into ten 25-minute periods. If the number of 5-minute intervals in either stage is not evenly divisible by ten, we retain the quantity of pre- and post-rebound periods, but adjust their length to accommodate the extra intervals. For instance, if the (ret_{min}; $ret_{max,post}$] stage in the example above consisted of fifty-five 5-minute intervals, the odd post-rebound periods (1^{st}, 3^{rd}, 5^{th}, etc.) would last 25 minutes and the even periods – 30 minutes.

five or more $\sigma_{i,j}$s (we identify 995 reversals with such declines) lead to an average cumulative return of -3.52%.

3. Short selling during price reversals

3.1. Abnormal short selling

We start by computing a standardized measure of abnormal short selling for every 5-minute interval j on each event day d:

$$ashvol_{i,d,j} = \frac{shvol_{i,j,d} - \overline{shvol_{i,j,d\in[-20;-1]}}}{st.dev.(shvol_{i,j,d\in[-20;-1]})} , \quad (1)$$

where $shvol_{i,j,d}$ is short volume (quantity of shorted shares) in stock i during a 5-minute interval j on event day d; and $\overline{shvol_{i,j,d\in[-20;-1]}}$ and $st.dev.(shvol_{i,j,d\in[-20;-1]})$ are, respectively, the mean and the standard deviation of short volume computed during 20 trading days preceding day d.[14] We match each 5-minute event-day measure to a respective 5-minute mean and a 5-minute standard deviation to account for intraday volume patterns.

Table 2 contains the *ashvol* estimates grouped into the pre- and post-rebound stages (Panel A) and into 20 intraday periods (Panel B). All estimates are statistically different from zero at the 1% level; therefore we omit the asterisks. Overall, *ashvol* gradually increases early in the pre-rebound stage and then begins to decline mid-stage. The magnitude of abnormal short volume increases, as we move to the larger reversals. For instance, for the [5; ∞) reversals, *ashvol* reaches a maximum of 3.71 during period -5 and averages at 2.96 standard deviations above the mean during the pre-rebound stage.

[14] Results do not qualitatively change if we use the number of trades instead of volume.

In summary, short volume is abnormally high during the pre-rebound stage. It is, however, notable that the post-rebound short volume is also high. In particular, the statistics in Panel A suggest that, for the [5; ∞) reversals, the post-rebound *ashvol* averages at 1.30 standard deviations above the mean. Although this figure is not as large as that estimated for the pre-reversal stage, it is significantly different from zero. Generally, positive *ashvol* during the post-rebound stages is consistent with Diether et al. (2009) who show that short sellers open most of their positions during periods of positive returns. Thus, whereas aggressive activities may cease by the time prices reach a reversal point, a contrarian activity may replace it.

Next, to account for the fact that short selling is contingent on contemporaneous returns (e.g., Diether et al., 2009), we modify the *ashvol* metric as follows:

$$mashvol_{i,j,d,m} = ashvol_{i,j,d,m} - ashvol\_nonrev_{i,j,d,m} \;, \tag{2}$$

where $mashvol_{i,j,d,m}$ is the modified abnormal short selling measure, computed separately for the four magnitudes of the pre-rebound price declines, $-m\times\sigma_{i,j}$, and post-rebound price increases, $m\times\sigma_{i,j}$; and $ashvol\_nonrev_{i,j,d,m}$ is the abnormal short selling measure computed on days with negative and positive price changes of $-m\times\sigma_{i,j}$ and $m\times\sigma_{i,j}$ magnitudes that are not followed by reversals. The *ashvol_nonrev* statistics are computed during the three rolling months preceding day *d*.

A positive *mashvol* indicates that short selling activity is (i) higher than its 20-day historical average and (ii) higher than shorting activity during a price decline of a similar magnitude that was not followed by a reversal. A robustness check that adjusts the statistic in Equation (2) for the level of market short selling produces qualitatively similar results.

The modified metric in Equation (2) allows us to compare short selling during price reversals to short selling during similarly significant price declines that do not reverse. Such comparison is warranted, as Brunnermeier and Pedersen (2005) and the SEC (2006) suggest that, in the absence of news, a quick price rebound is a litmus test for predatory/abusive trading. Thus, incremental short selling obtained by differencing short volume during reversals and short volume during non-reversals may be deemed excessive.

Figure 2 provides an illustration of modified abnormal short volume, *mashvol*, computed for the reversals of different magnitudes. The results are also presented in Table 2. The data confirm that price declines are accompanied by substantial increases in shorting activity during all but the smallest reversals. In particular, for the reversals of [3; 4), [4; 5), and [5; ∞) magnitudes, pre-rebound *mashvol* averages 0.16, 0.90, and 1.33 standard deviations away from the respective historical return-adjusted means. In the meantime, *mashvol* is significantly negative during the post-rebound stages across reversals of all magnitudes.

Although our findings in Table 2 suggest a positive relation between the magnitude of price reversals and abnormal short selling, they do not identify the causality of this relation. We address the issue of causality in the subsequent sections.

3.2. Order aggressiveness

As the price reversals in our sample are relatively fast-paced, we expect short sellers to be particularly aggressive and heavily rely on market orders. Aggressive short orders should actively consume bid-side liquidity and should be often classified by trade identification algorithms as seller-initiated.[15] To measure short sale aggressiveness, we compute, similar to Chordia and Subrahmanayam (2004), an order imbalance metric, *shimb*, as the difference between the buyer- and the seller-initiated short volume scaled by total short volume.[16] In Table 3, order imbalances are presented separately for the pre- and post-rebound stages and for the four reversal magnitudes.

The results in Panel A of Table 3 show that, as reversals unfold, sellers dominate. In particular, pre-rebound *shimb* averages -21% for the smallest reversals and -28% for the largest. During the largest reversals, short order imbalance falls to a low of -38% during the peak shorting period -5 (not tabulated), corresponding to the heaviest short selling period as reported in Table 2. During the post-rebound stages, *shimb* is, as expected, positive.

In the control sub-samples of non-reversals (e.g., significant price declines that are not followed by reversals), short sales are also predominantly seller-initiated; however to a lesser degree than those in the main sub-samples. All differences between the sub-samples of reversals and non-reversals are significant at the 0.01 level.

Thus far, we have looked only at the aggressiveness of short sales. Non-shorted order flow is, however, an integral part of the theoretical models of speculation and predation. For instance, Brunnermeier and Pedersen (2005) and Attari et al. (2005) imply that predatory trading is triggered by institutional non-short sales. In both models, selling by institutions causes negative order imbalances that are subsequently worsened by predators.

[15] We use the Chakrabarty et al. (2007) algorithm to classify short sales into buyer- and seller-initiated. In the modern environment of electronic limit order book trading, this algorithm is shown to perform better than the conventional algorithms of Lee and Ready (1991) and Ellis et al. (2000).

[16] A buyer-initiated short sale may sound as an oxymoron. Nevertheless, Diether et al. (2009) imply that most short sales are, in fact, buyer-initiated, in a sense that short orders are submitted as liquidity-providing limit orders. We however anticipate that, during the unusual events that we study, short sellers switch from providing liquidity to demanding it.

We report statistics on non-short order imbalances, *nonshimb*, in Panel B of Table 3. Non-short selling is far more aggressive than short selling, as non-short volume imbalances during the pre-rebound stages range from -32% to -36% depending on the reversal magnitude. For the largest reversals, the lowest non-short imbalances coincide with the lowest short imbalances during period -5 when the non-short imbalances reach -42% (not tabulated). Post-rebound non-short imbalances are, as expected, positive. Non-short selling in non-reversal sub-samples is noticeably less aggressive.

Although suggestive of a link between short and non-short selling, the results in Table 3 do not provide any evidence on the temporal relation between the two processes. We examine this relation in a subsequent section.

3.3. The bid test and execution locations

During our sample period, the bid test on NASDAQ's SuperMontage prohibits short sale executions at the bid or below-bid prices on down-bid quotes (i.e., when the bid quote is lower than the previous bid quote). Reg. SHO pilot stocks are exempt from this restriction. Consequently, a market order to sell short may not immediately execute and may have to remain dormant until the bid moves up, or until a market order to buy is submitted. Meanwhile, Table 3 implies that most of pre-rebound short sales execute via market orders. We therefore inquire how short sellers manage to bypass the requirements of the bid test.

At the time of this study, NASDAQ securities trade via six different market centers: the American Stock Exchange (AMEX), ArcaEx, the Chicago Stock Exchange (CSE), the NASD Alternative Display Facility (ADF), INET, and NASDAQ's SuperMontage. AMEX, CSE, and ADF volumes comprise, in total, less than 1% of the sample volume. We therefore focus on short sales executed on SuperMontage, INET, and ArcaEx. In 2003, ArcaEx acquired an exchange status and stopped complying with the NASD regulations, including the bid test. As a result, the orders to short sell NASDAQ stocks on ArcaEx were virtually unrestricted.[17] Meanwhile, INET was automatically up-pricing short sale orders that violated the bid test to the lowest legal short sale price.[18] We suggest that aggressive pre-rebound short sales could be routed to these two venues in search of timely and less restrictive executions.

Table 4 indicates that, during the reversals of magnitudes [3; 4) and higher, short selling switches to ArcaEx and INET as compared to non-reversals. For instance, during the [5; ∞) reversals, 66.31% of the pre-rebound short volume is executed on one of the two ECNs. Meanwhile, the ECN share of executions is significantly lower during comparable non-reversals, when only 51.90% of short sales are routed away from SuperMontage.

Table 5 continues with a detailed analysis of the relation between short sale execution locations and quotes. For the sake of brevity, we present only the results for the reversals of [5; ∞) magnitude.[19] Panel A shows that, during large reversals in non-pilot stocks, 49% of short volume is executed on down-bids. Although this figure is considerably lower than the 77% obtained for pilot stocks, it is nontrivial.

In Panel B, we report short sale execution locations contingent on quotes and execution prices. Our main goal is to see which venues short sellers use when they execute on down-bids and how down-bid executions are priced. Note that short sales that execute on

[17] Orders in NASDAQ stocks that were routed to ArcaEx and subsequently sent to other market centers by the venue's smart router were still subject to the bid test. A short seller could, however, choose to assign her order a "non-proactive" status. The order with such status would not be routed out, and hence would not be subject to the bid test.
[18] https://infocenter.inetats.com/subscriber/shortsales.jsp
[19] The results for reversals of other magnitudes are qualitatively similar and are available upon request.

down-bids at prices above the prevailing bid do not violate the bid test. Thus, for non-pilot stocks, we are only interested in execution locations at bid or below-bid prices that occur on down-bids (the highlighted column in Panel B). Consistent with our expectations as to the effect of the bid test, short sale executions switch to ArcaEx during such quote-price combinations, with the ECN executing 54% of short volume. Nevertheless, a significant portion of remaining short sales still execute on INET or SuperMontage, respectively, 32% and 14%.

The question that arises next is: How is the bid test circumvented on the two venues? We suggest that, since our analysis only uses the most recent quotes before each trade, it may fail to account for the fleeting small up-bid quotes that may be submitted and quickly withdrawn prior to short sale executions. Thus, whereas a short sale may originate following an up-bid, it may be reported in TAQ as executed on a down-bid. With the widespread use of algorithmic trading, submission of such fleeting quotes is technologically straightforward.

To provide evidence on the existence of such quotes, we compute the percentage of up-bid quotes as a share of all quotes during the pre-rebound stage. The results are reported in Panel C separately for pilot and non-pilot stocks. Consistent with our expectations, the share of up-bids for non-pilot stocks is 47% as compared to only 26% for pilot stocks. Although abundant, up-bid quotes in non-pilot stocks have significantly smaller depths (the highlighted column in Panel D) as compared to up-bid quotes in pilot stocks. In particular, up-bid quotes in non-pilot stocks average 232 shares; whereas up-bid quotes in pilot stocks average 460 shares. Thus, the evidence is consistent with frequent small up-bid quotes being used to circumvent the bid test.

3.4. Liquidity and trading costs

Madrigal (1996) and Brunnermeier and Pedersen (2005) posit that predatory traders reduce liquidity in the marketplace. Indeed, for a substantial no-news price decline to occur, liquidity on the buy side should be limited. To assess liquidity, we examine percentage time-weighted quoted spreads, *qsp*, and percentage trade-weighted effective spreads, *esp*.[20] Percentage quoted spreads are computed as the difference between the best ask and the best bid quotes scaled by the midpoint of these quotes. Percentage effective spreads are computed as twice the signed difference between the transaction price and the corresponding midpoint scaled by the midpoint.

Table 6 shows that, for the three larger groups of reversals, both quoted and effective spreads widen during the pre-rebound stages, indicating lower liquidity and higher trading costs. In particular, for the [5; ∞) reversals, quoted spreads are, 0.27 bps or 22.7% (= 0.27/0.22) higher than their non-reversal counterparts. Effective spreads, for the [5; ∞) reversals, average 0.16 bps and are higher than the non-reversal controls by 33.33% (= 0.16/0.12). Although depleted during the price decline stages, liquidity notably improves during the post-rebound stages.

Effective spread estimates allow us to speculate on the potential profitability of pre-rebound short selling. In particular, for every short position opened during the pre-rebound stage, we can estimate the cost of opening the position, e.g., percentage effective half-spread. Unfortunately, we may only hypothesize when such a position is closed, as our data do not provide information on short covering. For the sake of illustration, we assume that a short position may be closed in any of the remaining pre- or post-rebound periods throughout the

[20] We acknowledge that quoted and effective spreads may not capture liquidity in all of its dimensions. The length of our observation periods, however, constrains our ability to estimate other liquidity metrics, for instance that of Amihud (2002).

event day. Consequently, the return from the position is the difference between the opening price and the covering price scaled by the opening price. The difference between this return and the costs of opening and closing the position represents the profit.

The results of this estimation (not tabulated) show the highest average profit of 2.94%. Although the figure is quite sizeable, we reiterate that it is hypothetical due to our inability to observe short covering.

3.5. Temporal relations among price declines, short selling, and non-short selling

The results so far suggest that sharp pre-rebound price declines are accompanied by aggressive short and non-short selling. The event study results do not, however, identify a temporal relation among these processes.

To shed some light on this issue, we test for Granger causality between the following variables computed on a 5-minute basis during the pre-rebound stage: (i) $ashvol_j$, abnormal short volume from equation (1); (ii) $avol_j$, a similarly computed measure of abnormal non-short volume; and (iii) ret_j, returns. To establish whether variable Y Granger-causes variable X, we estimate the following two models:

$$x_j = c_1 + \sum_{i=1}^{p} a_i x_{j-i} + \sum_{i=1}^{p} \beta_i y_{j-i} + u_j \text{ and} \tag{3}$$

$$x_j = c_1 + \sum_{i=1}^{p} \gamma_i x_{j-i} + e_j , \tag{4}$$

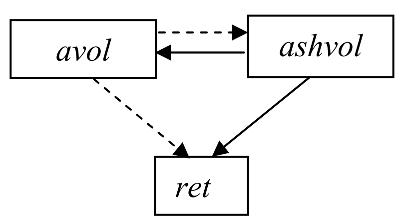
where the subscript j indicates a 5-minute value of one of the three variables of interest, i is the number of lagged observations of Y and X, and $p = 3$. The sums of squared residuals from the two models, $RSS_u = \sum_{j=1}^{J} \hat{u}_j^2$ and $RSS_r = \sum_{j=1}^{J} \hat{e}_j^2$, are then included in a test statistic $S = \dfrac{(RSS_r - RSS_u)/p}{RSS_u/(J-2p-1)} \sim F_{p,J-2p-1}$. If the statistic is greater than the specified critical value, we reject the null hypothesis that Y does not Granger-cause X, H_0: $\beta_1 = \beta_2 = \ldots = \beta_p = 0$. We estimate the models in (3) and (4) separately for the four sub-groups of reversals (namely, [2; 3); [3; 4); [4; 5); and [5; ∞)) and report the p-values corresponding to the estimated test statistics S in Table 7. A p-value lower than 0.1 indicates that we can reject the corresponding null hypothesis.

The results of Granger causality testing compiled in Table 7 can be summarized by the following three statements:

1. Abnormal short volume Granger-causes (i) abnormal non-short volume and (ii) price declines;

2. Abnormal non-short volume Granger-causes (i) abnormal short volume and (ii) price declines, but only for the reversals of [4; 5) and [5; ∞) magnitudes.

3. Price declines do not Granger-cause changes in either short or non-short volume. The figure below portrays these relations graphically:



What follows, is a more econometrically precise description of the results in Table 7. First, the p-values of zero indicate that the data reject the hypothesis that abnormal short volume does not Granger-cause abnormal non-short volume (H_0: $ashvol_j \not\Rightarrow avol_j$). This result holds for the reversals of all magnitudes and for all three lags. The opposite hypothesis (H_0: $avol_j \not\Rightarrow ashvol_j$) is rejected only for the two largest reversal sub-groups. Second, the data reject the hypothesis that abnormal short volume does not Granger-cause price changes (H_0: $ashvol_j \not\Rightarrow ret_j$); whereas they do not reject the opposing hypothesis (H_0: $ret_j \not\Rightarrow ashvol_j$).

This finding mitigates the endogeneity concerns in the model of intraday price changes that we will introduce in the next sub-section. Finally, abnormal non-short volume Granger-causes price changes during the reversals of magnitudes [4; 5) and [5; ∞) (H_0: $avol_j \not=> ret_j$), but not vice versa (H_0: $ret_j \not=> avol_j$).

3.6. Determinants of the pre-rebound price changes

Although the Granger causality tests imply that aggressive short selling precedes price declines, they also suggest that non-short selling may contribute to these declines, especially for the largest reversals. In addition, negative order imbalances and low liquidity that we document in the previous sub-sections also may have an effect on pre-rebound price changes. We therefore test for a causal relation between short selling and returns in a multivariate model that controls for non-short volume, order imbalances, and liquidity.

We recognize that, if short selling has a causal effect on pre-rebound price changes, the nature of this effect may be merely mechanical. Chordia and Subrahmanyam (2004) show that order imbalances originated by seller-initiated trades have a negative effect on prices. Since short selling in our sample is aggressive, the downward price pressure from it may be attributable solely to the negative order imbalances it generates. Alternatively, if short sales contribute to price declines via non-mechanical channels (e.g., stirring panic among traders), short selling may have a more profound effect on intraday returns.

To gain insight into the nature of short sellers' ability to influence prices, we estimate several specifications of the following model:

$$ret_{i,j} = \alpha + \beta_k \sum_{k=0}^{1} ashvol_{i,j-k} + \gamma_k \sum_{k=0}^{1} avol_{i,j-k} + \theta_k \sum_{k=0}^{1} shimb_{i,j-k} + \lambda_k \sum_{k=0}^{1} nonshimb_{i,j-k} + \delta\, qsp_{i,j} + \nu\, ret_{i,j-1} + \varepsilon_i, \quad (5)$$

where $ret_{i,j}$ is the pre-rebound (in specifications [1]-[3]) or post-rebound (in specification [5]) 5-minute percentage return for stock i from the main sample; or the 5-minute percentage return from the control sample of non-reversals (specification [4]); $ashvol_{i,j}$ is the abnormal short volume from equation (1);[21] $avol_{i,j}$ is the abnormal non-short volume computed similarly to the short volume measure; $(non)shimb_{i,j}$ are (non-)short order imbalances in stock i computed in a manner similar to the measures in Table 3 and, subsequently, standardized; $qsp_{i,j}$ is the quoted spread computed similarly to the measure in Table 6 and, subsequently, standardized; and $ret_{i,j-1}$ is a lagged return. Thus, all independent variables aside from the lagged return are standardized at the stock level.

The model includes lags of all variables to verify the causality of relations. Fitting the model on two or three lags of volume and order imbalance variables produces qualitatively similar results. All models include intraday indicator variables (not tabulated) to account for intraday patterns in returns and volume. In Table 8, we present the coefficients from the models estimated for return reversals of [5; ∞) magnitudes. Results for the reversals of other magnitudes follow in Table 9.

Our earlier suggestion of a causal relation between pre-rebound short selling and returns is confirmed in the multivariate setting by the negative coefficients of $ashvol_{j-1}$ in specification [1] of Table 8. Particularly, the coefficient indicates that if abnormal short volume is one standard deviation above the mean during a period $j-1$, return in the following 5-minute period is -0.005% (0.5 bps). The causal effect is not attributable to short volume causing more short or non-short volume and, subsequently, more price pressure, because

[21] We run similar regressions with *mashvol* – the modified measure from equation (2) – instead of *ashvol*. Coefficients from this alternative specification are qualitatively similar to the ones reported in Table 8. We opt for the more straightforward *ashvol* measure to simplify the interpretation of the results.

contemporaneous short and non-short volumes are controlled for via $ashvol_j$ and $avol_j$ variables.

The coefficient of $ashvol_j$ in specification [1] indicates that a one standard deviation increase in abnormal short volume accompanies a 5-minute return of -0.6 bps. We refrain from claiming a causal link between this negative return and contemporaneous short selling, as the direction of the relation is not obvious. It is, however, important to note that the negative estimated coefficient of $ashvol_j$ implies that, during steep price declines, short sellers become momentum traders or, in other words, pile on the ailing stock. This finding appends that of Diether et al. (2009) who argue that short sellers are contrarian. Notably, momentum traits in short selling are unique to the pre-rebound stages, as short selling is contrarian post-rebounds (specification [5]) and during the non-reversal price declines (specification [4]). This result supports our suggestion that pre-rebound short selling is a previously unexplored type of shorting activity.

We next examine the economic effect of pre-rebound short selling on returns. From Panel A of Table 2, the average 5-minute pre-rebound $ashvol_j$ for the reversals of $[5; \infty)$ magnitude is 2.96 standard deviations above the mean. Thus, ceteris paribus, the 5-minute causal effect of short volume on returns is -0.015% ($\approx -0.005\times2.96$). Consequently, in every hour of the pre-rebound stage, prices fall by 0.178% ($\approx -0.015\times60/5$) only due to the causal effect of short volume. Although economically significant, this figure implies that negative pre-rebound returns cannot be attributed solely to short sellers. Even if we were to assume the longest possible pre-rebound period allowed by the sampling procedure,[22] the maximum causal effect of short selling on returns is only -1.01%, a figure that is lower than the minimum cumulative intraday return of -3.52% identified in Table 1. The effect is still not

[22] Such a pre-rebound period would last 340 minutes, allowing for a 50-minute post-rebound stage.

large enough even if we account for the effect of contemporaneous short selling. Thus, corroborating the Granger causality results, the negative pre-rebound returns cannot be ascribed to short selling alone.

Non-short selling, *avol*, and liquidity, *qsp*, do not have significant lagged effects on returns. Meanwhile, the contemporaneous coefficients of *avol* and *qsp* are negative, indicating that a one standard deviation increase in abnormal non-short volume (quoted spread) is accompanied by a -0.011% (-0.053%) return.

If short selling affects prices via a purely mechanical channel, introduction of order imbalances into the model should significantly decrease, or even eliminate, the negative effect of *ashvol*. Alternatively, if the effect of short sales is more complex than pure selling pressure, we should continue observing the negative coefficients on *ashvol*.

In specification [2], once we introduce order imbalances, the coefficients of $ashvol_{j-1}$ and $ashvol_{j}$ remain significant and only marginally decrease. The order imbalance coefficients are positive, as expected, indicating that negative imbalances lead to or accompany negative returns and vice versa. The mechanical effect of non-short sales is almost twice as large as that of short sales. The economic significance of this effect is compounded by the fact that, according to Table 3, non-short order imbalances during pre-rebound stages are larger than short order imbalances.

In specification [3], we separate abnormal short volume by the venue of execution. As previously discussed, we expect that impatient short sellers will prefer routing to ArcaEx and INET, leading to larger price impacts of these orders. The results in specification [3] confirm this expectation.

Overall, the examination of pre-rebound price changes in a multivariate setting confirms that short sales have a causal negative effect on returns and that this effect surpasses the effect of order imbalances. In addition, the data show that a significant portion of price changes can be ascribed to the mechanical effect of non-short volume.

In Table 9, we present the results of running specification [2] of model (5) on the reversals of all four magnitudes. We copy the results for the [5; ∞) reversals and the non-reversal controls from Table 8 to facilitate comparison. We anticipate that short selling has a greater effect on prices during the reversals of larger magnitudes. The results in Table 9 support this expectation, as the coefficients of both lagged and contemporaneous *ashvol* variables are significant only for the reversals of [4; 5) and [5; ∞) magnitudes and are larger for the latter. For the reversals of [2; 3) and [3; 4) magnitudes, short volume does not have either a lagged or a contemporaneous non-mechanical effect on prices.

The lagged mechanical effects of short volume represented by the *shimb* variable are, however, significant for the reversals of all magnitudes. Conversely, the mechanical effect of the lagged non-short volume, represented by the *nonshimb* variable is significant only for the largest reversals, corroborating the Granger causality results in Table 7.

Overall, the results in Table 9 show that, whereas the pre-rebound price declines may be attributed to negative order imbalances created by aggressive short selling for all reversal magnitudes, the short selling effect that surpasses that of order imbalances is observed only for the largest reversals.

3.7. Alternative identification procedure

Our sample selection is based on the theoretical argument of Brunnermeier and Pedersen (2005) that predatory events lead to large price reversals. We confirm this argument by finding a causal relation between short selling and pre-rebound price declines. Although these results hold in a multivariate setting; by construction, our identification procedure limits the sample to instances of aggressive short selling that result in reversals. Meanwhile, these episodes could constitute only a subset in a larger set of aggressive short selling events, not all of which result in significant price fluctuations.

Ideally, we would focus our identification procedure on reversals in short selling instead of price reversals. Such a procedure however proves prohibitively cumbersome, as the intraday time series of the *ashvol* variable often do not contain an easily identifiable inflection point. Meanwhile, the estimation of the *mashvol* variable is impossible without conditioning on the magnitude of the price decline.

Having acknowledged these difficulties, we conduct a full-sample robustness check (not tabulated, but available upon request) that is based on identifying intraday switches in short selling regimes as opposed to intraday price reversals. As expected, not all of the event days identified in our main sample are captured by this alternative procedure. The analysis however confirms that significant changes in short selling magnitude are associated with increases in intraday price volatility. Further, an intraday switch from relatively active to relatively passive shorting regimes is usually accompanied by negative price reversals.

4. Cross section

Having shed light on the reversal mechanics, we next turn our attention to identifying the cross-sectional characteristics that are notably different between the stocks that are prone to reversals and those that are not. First, we hypothesize that the reversal-prone stocks may have high institutional ownership, *inst*, as it may proxy for an eventual need of large position reductions. The more institutions that own a stock, the more likely one of them may find itself in a fire sale situation that may encourage aggressive short selling. For each sample stock i in every quarter q, we define *inst* as the number of shares owned by institutions scaled by the number of shares outstanding.[23]

In addition, we anticipate more reversals to occur in stocks with high relative short interest, *si*. High short interest is usually associated with negative subsequent returns and, therefore, may point to the stocks likely to be unloaded from institutional portfolios. The relative short interest measure is defined, for each sample stock i, in every month m, as the number of shorted shares scaled by the number of shares outstanding.[24]

Finally, we expect that the elimination of the bid test by the Reg. SHO pilot may make aggressive short selling easier and reversals more frequent. We therefore inquire whether pilot stocks are more prone to price reversals. All of our expectations are confirmed by the data, as we discuss below.

By construction, the reversal-prone sample consists of relatively active stocks. To facilitate proper comparison, we match the reversal-prone stocks with the control group

[23] We are restricted to quarterly observations, because Thomson Financial institutional ownership statistics are only available on a quarterly basis.

[24] Institutional ownership and short interest metrics are both related to the supply of shortable shares. Institutional ownership is often used to proxy for the supply (e.g., Asquith et al., 2005), whereas short interest is a function of such supply. Since intraday short sellers may not have to borrow shares, as their positions are very short-lived, we refrain from emphasizing the supply issue.

chosen (without replacement) from a sample of securities that do not experience price reversals during our sample period. As suggested by Davies and Kim (2009), we match the stocks by market capitalization, *mcap*, and price.[25] For each possible pair of reversal (main) and non-reversal (control) event days, we calculate the following score:

$$\sum_{i=1}^{2}\left[\frac{2\left(Y_i^C - Y_i^M\right)}{Y_i^C + Y_i^M}\right]^2, \tag{6}$$

where Y_i represents one of the two matching criteria, and C and M identify, respectively, control and main samples. For each of the main sample stocks, we then retain the control match with the lowest score. Panel A of Table 10 contains full sample means of the matching variables and variables of interest.

Although the procedure identifies non-reversal stock-days that are the best matches to the stock-days from the reversal sample, results in Table 10 indicate that only the market capitalizations match well, whereas prices for the smaller (namely, [2; 3) and [3; 4)) reversals remain statistically different. A detailed examination of these smaller reversal stock-days suggests that the differences are driven by a few large outliers. Davies and Kim (2008) show that eliminating such outliers may reduce the power of the subsequent tests. We, therefore, choose to retain the outliers.

With *mcap* and *price* controlled for in Panels B through E, the reversal-prone stocks are the ones with the higher percentage of institutional ownership: 67-69% vs. 8-10% for the matches. Short interest in the reversal-prone stocks averages 7%, whereas it is only 3% for the control stocks. Finally, pilot stocks are more likely to become subject to reversals, as 26-

[25] We test the robustness of the matching procedure to replacing price with book-to-market ratio along the lines of Diether et al. (2009). The results are robust to this alternative procedure.

29% of all reversal-prone stocks are pilot stocks, with a similar statistic for the control stocks being only 6-8%.

Overall, the results confirm our expectations that high institutional ownership, high short interest, and the lack of short selling restrictions are associated with higher incidence of reversals. Notably however, the statistics of interest do not substantially vary among price reversals of different magnitudes.

5. Conclusions

In this paper, we present evidence of occasional excesses in short selling. In particular, we find that short sellers are abnormally active at the beginning of large negative intraday price reversals that are not accompanied by news. Short selling at the beginning of such reversals is aggressive and has a significant effect on the magnitude of price declines.

As prices fall, short sellers actively consume liquidity and tend to route their orders to venues that do not restrict short selling (e.g., do not comply with the bid test) or sufficiently expedite it. In addition, the bid test is partly circumvented by frequent submission of small fleeting up-bid quotes. The effect of short volume on prices is beyond that of order imbalances created by aggressive short selling. In particular, when we model price changes as a function of, simultaneously, short volume and order imbalances created by short volume, short volume retains its causal effect on price changes.

We also show that short selling is not the only activity that creates pressure on prices during large reversals. Aggressive short selling is usually accompanied by the even more aggressive non-short selling. Together, non-short selling and short selling contribute to price declines, although only short selling has a lasting effect on prices.

We also inquire whether any characteristics distinguish the stocks prone to reversals from the matched stocks that do not undergo reversals during our sample period. We suggest that (i) the probability that an institution finds itself in need of a large-scale position reduction is a function of institutional ownership; (ii) stocks that are to be sold out of such institutional positions are likely to have higher short interest; and (iii) aggressive short selling is more likely in stocks for which short selling restrictions are lifted by the Reg. SHO pilot. The data confirm our expectations, as the reversal-prone stocks have (i) larger institutional holdings, (ii) higher short interest, and (iii) are often on the Reg. SHO pilot list of securities.

Our contribution to the literature is threefold. First, we expose an undocumented, kind of short selling; the kind that, instead of enhancing market efficiency and price discovery, occasionally creates undue pressure on prices. Second, we provide a detailed analysis of price reversals and of the role that aggressive short selling plays in their development. Third, we identify common characteristics among stocks that are susceptible to price reversals.

The rapid decline in stock prices in the second half of 2008 caused some industry observers to suggest that the elimination of short selling restrictions in 2007 may have been premature. The SEC is currently considering reinstituting the tick rule in a circuit breaker form – the rule will be invoked if a stock price decline is abnormally precipitous. Although our results generally support implementation of such rule, we caution that, in contemporary markets, traders may attempt to evade price restrictions. In particular, similar to circumventing the bid test by frequently posting small up-bids, traders may attempt to dodge the tick rule by frequently executing small trades on up-ticks. The SEC should take this possibility into account when and if they devise the new restrictions.

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Table 1

Large price reversals

The table contains cumulative intraday percent returns for a sample of large price reversals. A day d is identified as an event day for stock i, if the stock's price declines by two or more standard deviations of the stock's historical intraday returns measured over the preceding 20 trading days, $\sigma_{i,j}$, and subsequently rebounds by more than 90% to 110% of the initial decline by the end of the day. Each event day d is divided into two stages: [$ret_{max,pre}$; ret_{min}] and (ret_{min}; $ret_{max,post}$], where $ret_{max,pre}$ is the maximum ret_j during the pre-rebound stage; $ret_{max,post}$ is the maximum ret_j during the post-rebound stage; and ret_{min} is the minimum ret_j. Each stage is further divided into 10 periods, for a total of twenty time periods per event day. Event days are divided into four groups according to the pre-rebound price decline magnitude. In particular, we distinguish between the days, during which prices fall by (i) 2 to 3, (ii) 3 to 4, (iii) 4 to 5, and (iv) 5 and more $\sigma_{i,j}$s. Panel A contains pre- and post-rebound cumulative returns; Panel B contains period-by-period cumulative returns. Panel C displays the number of event days in each of the groups. Statistical significance is indicated by the asterisks: ***, **, *, respectively, for 0.01, 0.05, and 0.10 significance levels.

	[1]	[2]	[3]	[4]
	[2; 3)	[3; 4)	[4; 5)	[5; ∞)
Panel A: Pre- and post-rebound cumulative return				
pre-	-1.33***	-1.86***	-2.32***	-3.52***
post-	-0.27**	-0.33*	-0.36**	-0.57**
Panel B: Pre- and post-rebound statistics, by period				
-10	-0.01	-0.03*	-0.01	-0.04
-9	-0.07**	-0.43***	-0.53**	-0.81***
-8	-0.26**	-0.62***	-0.77***	-1.16***
-7	-0.46***	-0.79***	-0.98***	-1.42***
-6	-0.63***	-0.93***	-1.17***	-1.69***
-5	-0.71***	-1.06***	-1.32***	-1.96***
-4	-0.82***	-1.19***	-1.50***	-2.24***
-3	-0.96***	-1.38***	-1.76***	-2.58***
-2	-1.12***	-1.59***	-2.06***	-2.97***
-1	-1.33***	-1.86***	-2.32***	-3.52***
1	-0.89***	-1.44***	-1.81***	-2.48***
2	-0.72***	-1.16***	-1.46***	-2.00***
3	-0.63***	-1.02***	-1.25***	-1.73***
4	-0.56***	-0.91***	-1.09***	-1.51***
5	-0.51***	-0.80***	-0.93***	-1.30***
6	-0.45***	-0.69***	-0.80***	-1.11***
7	-0.39***	-0.59***	-0.65***	-0.92***
8	-0.32**	-0.45***	-0.48***	-0.71***
9	-0.22*	-0.27*	-0.26*	-0.44**
10	-0.27**	-0.33*	-0.36**	-0.57**
Panel C: Number of events				
	3,481	1,894	1,100	995

Table 2
Short selling during large price reversals
The table contains abnormal short volume, *ashvol*, and modified short volume, *mashvol*, computed, respectively, via equations (1) and (2) during large price reversals. Each event day *d* is divided into two stages: [$ret_{max,pre}$; ret_{min}] and (ret_{min}; $ret_{max,post}$], where $ret_{max,pre}$ is the maximum ret_j during the pre-rebound stage; $ret_{max,post}$ is the maximum ret_j during the post-rebound stage; and ret_{min} is the minimum ret_j on day *d*. Each stage is further divided into 10 periods, for a total of twenty time periods per an event day. Event days are divided into groups by the pre-rebound price decline magnitude. We distinguish between the days, during which returns fall by (i) 2 to 3, (ii) 3 to 4, (iii) 4 to 5, and (iv) 5 and more $\sigma_{i,j}$s. Panel A contains averages of *ashvol* and *mashvol* statistics during pre- and post-rebound stages; whereas Panel B contains period-by-period statistics. Statistical significance is indicated by the asterisks: ***, **, *, respectively, for 0.01, 0.05, and 0.10 significance levels. All *ashvol* statistics are significantly different from zero at the 0.01 level, therefore we omit the asterisks.

	ashvol†				*mashvol*			
	[2; 3)	[3; 4)	[4; 5)	[5; ∞)	[2; 3)	[3; 4)	[4; 5)	[5; ∞)
Panel A: Pre- and post-rebound aggregate statistics								
pre-	0.68	0.73	1.68	2.96	-0.01	0.16**	0.90***	1.33***
post-	0.60	0.61	0.86	1.30	-0.19***	-0.37***	-0.31***	-0.65***
Panel B: Pre- and post-rebound statistics, by period								
-10	0.79	0.85	0.83	2.07	-0.04	-0.06	0.20**	0.49***
-9	0.71	0.45	0.87	2.25	-0.07	-0.34***	0.30**	0.69***
-8	0.57	0.57	1.67	2.90	-0.19**	-0.38***	0.44**	1.30***
-7	0.53	0.68	1.74	3.07	-0.32***	0.15	1.23***	1.46***
-6	0.69	0.69	2.19	3.19	-0.14*	0.29***	1.44***	1.77***
-5	0.63	1.22	2.54	3.71	-0.07	0.56***	1.69***	2.15***
-4	0.49	0.83	2.48	3.58	-0.09	0.51***	1.65***	1.99***
-3	0.59	0.79	1.81	3.10	-0.04	0.44***	0.99***	1.47***
-2	0.72	0.67	1.45	3.03	0.10	0.30***	0.59***	1.24***
-1	1.13	0.56	1.22	2.69	0.51***	0.25***	0.51***	0.75***
1	0.60	0.57	1.05	1.31	-0.35***	-0.56***	0.15*	-0.76***
2	0.39	0.57	1.04	1.26	-0.48***	-0.56***	0.22*	-0.60***
3	0.79	0.61	0.72	1.17	-0.10*	-0.53***	-0.34***	-0.80***
4	0.70	0.60	0.63	1.06	-0.18*	-0.46***	-0.71***	-0.91***
5	0.39	0.50	0.87	1.37	-0.26***	-0.37***	-0.44***	-0.63***
6	0.56	0.53	0.68	1.26	-0.19***	-0.38***	-0.69***	-0.75***
7	0.39	0.61	0.85	1.31	-0.40***	-0.33**	-0.35***	-0.86***
8	0.54	0.56	0.70	1.57	-0.14***	-0.33***	-0.60***	-0.59***
9	0.79	0.54	0.77	1.39	-0.11	-0.13*	-0.42***	-0.43***
10	0.82	0.95	1.26	1.36	0.17**	0.07	0.13*	-0.21**

† All *ashvol* statistics are significantly different from zero at the 0.01 level.

Table 3
Order imbalances
The table contains short (Panel A) and non-short (Panel B) order imbalances during the large intraday price reversals. The reversals are separated into four sub-groups by magnitude (namely, [2; 3); [3; 4); [4; 5); and [5; ∞)) and into pre- and post-rebound stages. We also define a control sample of non-reversals, viz. price declines of similar magnitudes that do not reverse. Order imbalance is computed as the difference between the buyer- and the seller-initiated short (non-short) volume divided by total short (non-short) volume. Order direction is identified by the Chakrabarty et al. (2007) algorithm. Results are tested for statistical significance of differences between the pre-rebound stage of the reversals and the non-reversals. Significance levels of 0.01are identified, with ***.

		Panel A: shimb		*Panel B: nonshimb*	
		reversals	non-reversals	reversals	non-reversals
[2; 3)	pre	-0.21***	-0.11	-0.32***	-0.21
	post	0.20		0.10	
[3; 4)	pre	-0.23***	-0.15	-0.34***	-0.22
	post	0.18		0.12	
[4; 5)	pre	-0.26***	-0.15	-0.35***	-0.23
	post	0.18		0.11	
[5; ∞)	pre	-0.28***	-0.16	-0.36***	-0.23
	post	0.20		0.12	

Table 4
Percent of short volume executed on ArcaEx and INET
The table contains statistics on the percentage short volume executed via ArcaEx and INET during the pre-rebound stages of reversals and the matching non-reversals. The reversals are separated into four sub-groups by magnitude (namely, [2; 3); [3; 4); [4; 5); and [5; ∞)) and into pre- and post-rebound stages. Non-reversals are matched to the reversals by the magnitude of price decline. Results are tested for statistical significance between the pre-rebound reversal statistics and the non-reversal statistics. Significance levels of 0.01 are identified with ***.

		reversals	non-reversals
[2; 3)	pre	51.26	52.87
	post	51.91	
[3; 4)	pre	55.40***	52.83
	post	52.75	
[4; 5)	pre	60.02***	51.77
	post	54.99	
[5; ∞)	pre	66.31***	51.90
	post	54.44	

Table 5

Compliance with the bid test

The table contains statistics on short volume and quote submissions during the pre-rebound stages of price reversals of [5; ∞) magnitude. Throughout the table, the results are reported separately for non-pilot and pilot stocks. Pilot stocks are those temporarily exempt from short selling restrictions by the Reg. SHO pilot. Panel A contains the percent share of short volume executed on down-bids. Panel B contains percent shares of short volume executed on INET, ArcaEx, and SuperMontage contingent on the prevailing quote and the execution price. We distinguish between the up-bid (the current bid quote is greater than the previous bid quote) and down-bid (the current bid is lower than the previous bid) quotes, as well as between short sales executed at above-bid, bid, or below-bid prices. In Panel C, we report the frequency of up-bid quotes. In Panel D, we report up-bid and down-bid quote depths. The differences between the figures for pilot and non-pilot stocks in Panels A and C are statistically significant. In Panel B, the highlighted figures for ArcaEx and SuperMontage are statistically different from the other same-venue figures in the Panel. In Panel D, the highlighted figure is statistically different from all other figures in the Panel.

	non-pilot				pilot			
Panel A: Percent of short volume executed on down-bids								
	49				77			
Panel B: Quote-contingent percent of short volume, by venue								
	up-bid		down-bid		up-bid		down-bid	
	above-bid	bid/below-bid	above-bid	bid/below-bid	above-bid	bid/below-bid	above-bid	bid/below-bid
INET	33	32	33	**32**	33	32	32	27
ArcaEx	31	32	32	**54**	33	32	29	24
SuperMontage	36	36	35	**14**	34	36	39	49
Panel C: Percent share of up-bid quotes								
	47				26			
Panel D: Bid quote depth, share 100s								
	up-bid		down-bid		up-bid		down-bid	
	2.32		5.18		4.60		5.47	

Table 6

Liquidity and trading costs

The table contains statistics on the quoted and effective spreads during the pre- and post-rebound stages of reversals and the matching non-reversals. The reversals are separated into four sub-groups by magnitude (namely, [2; 3); [3; 4); [4; 5); and [5; ∞)) and into pre- and post-rebound stages. Percentage quoted spread, *qsp*, is time-weighed and is defined as the difference between the inside ask and the inside bid divided by the corresponding quote midpoint. Percentage effective spread, *esp*, is volume-weighed and is defined as twice the signed difference between the exercise price and the corresponding quote midpoint, scaled by the midpoint. Trade direction is determined using the Chakrabarty et al. (2007) algorithm. Results are tested for statistical significance of differences between the pre-rebound and the non-reversal samples. Significance levels of 0.01, 0.05, and 0.01 are identified, respectively, with ***, **, and *.

		% *qsp*, bps		% *esp*, bps	
		reversals	non-reversals	reversals	non-reversals
[2; 3)	pre	0.20	0.21	0.11	0.10
	post	0.19		0.10	
[3; 4)	pre	0.22*	0.21	0.13**	0.10
	post	0.19		0.11	
[4; 5)	pre	0.26***	0.22	0.14***	0.11
	post	0.23		0.11	
[5; ∞)	pre	0.27***	0.22	0.16***	0.12
	post	0.22		0.12	

Table 7
Granger causality
The table contains p-values from testing Granger causality between the following variables computed on the 5-minute basis during the pre-rebound stages of return reversals: $ashvol_j$, abnormal short volume; $avol_j$, abnormal non-short volume, and, ret_j, returns. The Granger causality tests from variable Y to X with p lags first estimate the unrestricted model: $x_j = c_1 + \sum_{i=1}^{p} a_i x_{j-i} + \sum_{i=1}^{p} \beta_i y_{j-i} + u_j$ and then estimate the restricted model: $x_j = c_1 + \sum_{i=1}^{p} \gamma_i x_{j-i} + e_j$. Next, the sums of squared residuals from these two models, $RSS_u = \sum_{j=1}^{J} \hat{u}_j^2$ and $RSS_r = \sum_{j=1}^{J} \hat{e}_j^2$, are included in a test statistic $S = \frac{(RSS_r - RSS_u)/p}{RSS_u/(J-2p-1)} \sim F_{p,J-2p-1}$. If the statistic is greater than the specified critical value (e.g., the corresponding p-value is lower than 0.1), the null hypothesis H_0: $\beta_1 = \beta_2 = \ldots = \beta_p = 0$ is rejected. Each hypothesis is estimated separately for four reversal sub-groups by magnitude (namely, [2; 3); [3; 4); [4; 5); and [5; ∞)). For each hypothesis, we report p-values for three lags.

		p-value		
		lag1	*lag2*	*lag3*
H_0: $ashvol_j \not\Rightarrow avol_j$	[2; 3)	0.00	0.00	0.00
	[3; 4)	0.00	0.00	0.00
	[4; 5)	0.00	0.00	0.00
	[5; ∞)	0.00	0.00	0.00
H_0: $avol_j \not\Rightarrow ashvol_j$	[2; 3)	0.99	0.49	0.22
	[3; 4)	0.73	0.72	0.37
	[4; 5)	0.06	0.01	0.00
	[5; ∞)	0.00	0.00	0.00
H_0: $ashvol_j \not\Rightarrow ret_j$	[2; 3)	0.00	0.00	0.00
	[3; 4)	0.00	0.00	0.00
	[4; 5)	0.00	0.00	0.00
	[5; ∞)	0.00	0.00	0.00
H_0: $ret_j \not\Rightarrow ashvol_j$	[2; 3)	0.97	0.83	0.88
	[3; 4)	0.60	0.28	0.23
	[4; 5)	0.49	0.19	0.18
	[5; ∞)	0.25	0.14	0.14
H_0: $avol_j \not\Rightarrow ret_j$	[2; 3)	0.74	0.75	0.71
	[3; 4)	0.49	0.43	0.33
	[4; 5)	0.02	0.00	0.00
	[5; ∞)	0.00	0.00	0.00
H_0: $ret_j \not\Rightarrow avol_j$	[2; 3)	0.98	0.83	0.83
	[3; 4)	0.91	0.75	0.77
	[4; 5)	0.79	0.60	0.51
	[5; ∞)	0.22	0.24	0.15

Table 8

Determinants of intraday returns: largest reversals

The table contains coefficients from a regression model outlined in equation (5) with (i) pre-rebound 5-minute returns, (ii) 5-minute returns during control non-reversal days, and (iii) post-rebound returns as dependent variables. The vector of independent variables includes $ashvol_{i,j}$ – the abnormal short selling measure from equation (1); $avol_{i,j}$ – similarly computed abnormal non-short volume measure; $(non)shimb_{i,j}$ – (non-)short order imbalances computed similarly to the measures in Table 3 and, subsequently, standardized; $qsp_{i,j}$ – percentage quoted spread computed similarly to the measure in Table 6 and, subsequently, standardized; and $ret_{i,j-1}$ – lagged returns. The model includes one lag for all volume and order imbalance variables. Fitting the model on two or three lags of volume and order imbalance variables produces qualitatively similar results. All independent variables, excluding lagged returns, are standardized at the stock level. All models are de-trended on the intraday level. *p*-Values are in parentheses. Statistical significance at 0.01 and 0.05 levels is denoted with *** and **.

	$ret_{i,j}$				
	pre-rebound			*non-reversal*	*post-rebound*
	[1]	[2]	[3]	[4]	[5]
$ashvol_{j-1}$	-0.005***	-0.004***		0.002	0.000
	(0.00)	(0.00)		(0.24)	(0.39)
$ashvol_j$	-0.006***	-0.005***	-0.006***	0.002***	0.002***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
$avol_{j-1}$	0.000	0.000	0.000	0.000	0.001**
	(0.38)	(0.12)	(0.12)	(0.55)	(0.02)
$avol_j$	-0.011***	-0.010***	-0.010***	0.001	0.002***
	(0.00)	(0.00)	(0.00)	(0.63)	(0.00)
$shimb_{j-1}$		0.002**	0.002**	0.001	0.008***
		(0.04)	(0.03)	(0.47)	(0.00)
$shimb_j$		0.062***	0.061***	0.063***	0.051***
		(0.00)	(0.00)	(0.00)	(0.00)
$nonshimb_{j-1}$		0.013***	0.013***	0.001	0.006***
		(0.00)	(0.00)	(0.25)	(0.00)
$nonshimb_j$		0.104***	0.104***	0.040***	0.042***
		(0.00)	(0.00)	(0.00)	(0.00)
$arca\_ashvol_{j-1}$			-0.021***		
			(0.00)		
$inet\_ashvol_{j-1}$			-0.015**		
			(0.01)		
sm_ashvol_{j-1}			-0.004		
			(0.64)		
qsp_{j-1}	-0.010	-0.004	-0.004	-0.001	0.001
	(0.11)	(0.21)	(0.24)	(0.59)	(0.14)
qsp_j	-0.053***	-0.054***	-0.054***	-0.006***	0.020***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
ret_{j-1}	0.108***	0.097***	0.097***	0.061***	0.077***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Intercept	-0.206***	-0.131***	-0.132***	-0.012**	0.018***
	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)
Adj. R^2, %	10.14	19.24	19.31	5.41	9.44

Table 9

Determinants of intraday returns: reversals of all magnitudes

The table contains coefficients from a regression model (5) with pre-rebound 5-minute returns as dependent variables. We run the model for the four sub-groups of price reversals (namely, [2; 3); [3; 4); [4; 5); and [5; ∞)) and for a control sample of non-reversals. The vector of independent variables includes $ashvol_{i,j}$ – the abnormal short selling measure from equation (1); $avol_{i,j}$ – similarly computed abnormal non-short volume measure; $(non)shimb_{i,j}$ – (non-)short order imbalances computed similarly to the measures in Table 3 and, subsequently, standardized; $qsp_{i,j}$ – percentage quoted spread computed similarly to the measure in Table 6 and, subsequently, standardized; and $ret_{i,j-1}$ – lagged returns. The models include one lag for all volume and order imbalance variables. All independent variables, excluding lagged return, are standardized at the stock level. All models are de-trended on the intraday level. *p*-Values are in parentheses. Statistical significance at 0.01 and 0.05 levels is denoted with *** and **.

	$ret_{i,j}$				
	[2; 3)	[3; 4)	[4; 5)	[5; ∞)	*non-reversal*
$ashvol_{j-1}$	-0.001	-0.002	-0.003***	-0.004***	0.002
	(0.35)	(0.18)	(0.00)	(0.00)	(0.24)
$ashvol_j$	0.002	0.004	-0.003***	-0.005***	0.002***
	(0.28)	(0.13)	(0.00)	(0.00)	(0.00)
$avol_{j-1}$	0.000	0.001	0.000	0.000	0.000
	(0.55)	(0.29)	(0.14)	(0.12)	(0.55)
$avol_j$	-0.014***	-0.015***	-0.010***	-0.010***	0.001
	(0.00)	(0.00)	(0.00)	(0.00)	(0.63)
$shimb_{j-1}$	0.001*	0.003**	0.003***	0.002**	0.001
	(0.07)	(0.04)	(0.00)	(0.04)	(0.47)
$shimb_j$	0.043***	0.060***	0.065***	0.062***	0.063***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
$nonshimb_{j-1}$	0.001	0.001	0.008**	0.013***	0.001
	(0.30)	(0.11)	(0.02)	(0.00)	(0.25)
$nonshimb_j$	0.057***	0.061***	0.070***	0.104***	0.040***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
qsp_{j-1}	0.000	-0.001	-0.002	-0.004	-0.001
	(0.74)	(0.68)	(0.35)	(0.21)	(0.59)
qsp_j	-0.002*	-0.004**	-0.038***	-0.054***	-0.006***
	(0.07)	(0.03)	(0.00)	(0.00)	(0.00)
ret_{j-1}	-0.013	0.042***	0.066***	0.097***	0.061***
	(0.22)	(0.00)	(0.00)	(0.00)	(0.00)
Intercept	-0.217***	-0.204***	-0.174***	-0.131***	-0.012***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)
Adj. R^2, %	9.48	10.65	16.04	19.24	5.41

Table 10
Characteristics of reversal-prone stocks
The table contains the cross-sectional characteristics of two groups of stocks: (1) stocks that become subject to large reversals and (2) the rest of the NASDAQ stocks. In Panel A, we report the means of the following characteristics: (i) *mcap* – market capitalization (in $ millions); (ii) *price* – stock price; (iii) *inst* – institutional ownership as a percent of shares outstanding; (iv) *si* – short interest as a percent of shares outstanding; and (v) *pilot* – an indicator that equals to one if the stock belongs to the list of Reg. SHO pilot securities and equals to zero otherwise. Panels B through E compare the abovementioned characteristics for stock-days with reversals, *rev*, with those of stocks that do not undergo reversals, *non-rev*. The panels contain statistics for the reversals of, respectively, [2; 3) through [5; ∞) magnitudes. To eliminate the influence of size and price differences, the *non-rev* group is matched to the *rev* group by market capitalization and price. *p*-Values in parentheses represent the results of the difference in means testing between the reversal and non-reversal sub-samples in each panel. Statistics that are statistically different at the 0.01 and 0.05 levels are indicated with, respectively, *** and ** asterisks.

	Matching variables		*Variables of interest*		
	mcap (M)	*price*	*inst*	*si*	*pilot*
Panel A: Full sample means					
	1,143	17.82	0.42	0.04	0.15
Panel B: Matched samples, $m \in [2; 3)$					
rev	2,358	24.10***	0.67***	0.07***	0.26***
non-rev	1,916	22.66	0.09	0.03	0.06
p-value	(0.12)	(0.00)	(0.00)	(0.00)	(0.00)
Panel C: Matched samples, $m \in [3; 4)$					
rev	2,110	23.38***	0.68***	0.07***	0.26***
non-rev	1,784	22.27	0.08	0.03	0.06
p-value	(0.11)	(0.00)	(0.00)	(0.00)	(0.00)
Panel D: Matched samples, $m \in [4; 5)$					
rev	2,294	23.95	0.68***	0.06***	0.27***
non-rev	1,766	22.65	0.10	0.03	0.07
p-value	(0.08)	(0.07)	(0.00)	(0.00)	(0.00)
Panel E: Matched samples, $m \in [5; \infty)$					
rev	2,451	23.09	0.69***	0.07***	0.29***
non-rev	1,696	21.96	0.10	0.03	0.08
p-value	(0.12)	(0.08)	(0.00)	(0.00)	(0.00)

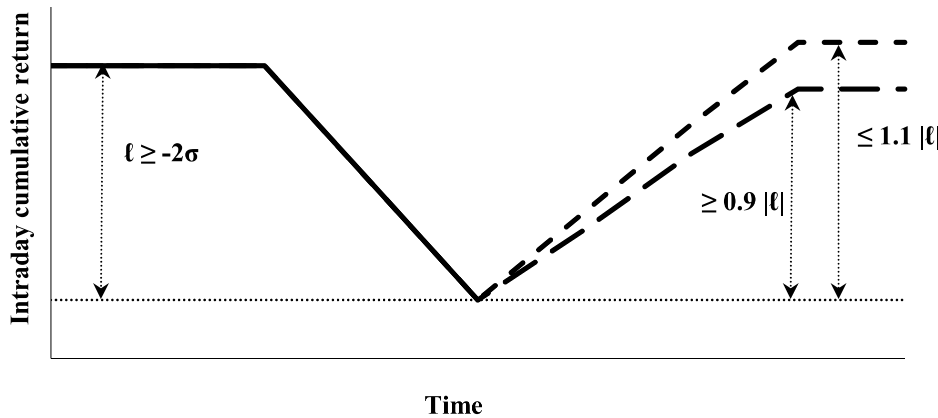

Figure 1
Event day identification
A day during which stock price declines to a level equal to or lower than two standard deviations of historical intraday cumulative returns, $\sigma_{i,j}$, and then rebounds by 90% to 110% of the initial decline is identified as an event day. Standard deviations of historical intraday cumulative returns are computed during twenty trading days preceding the event day.

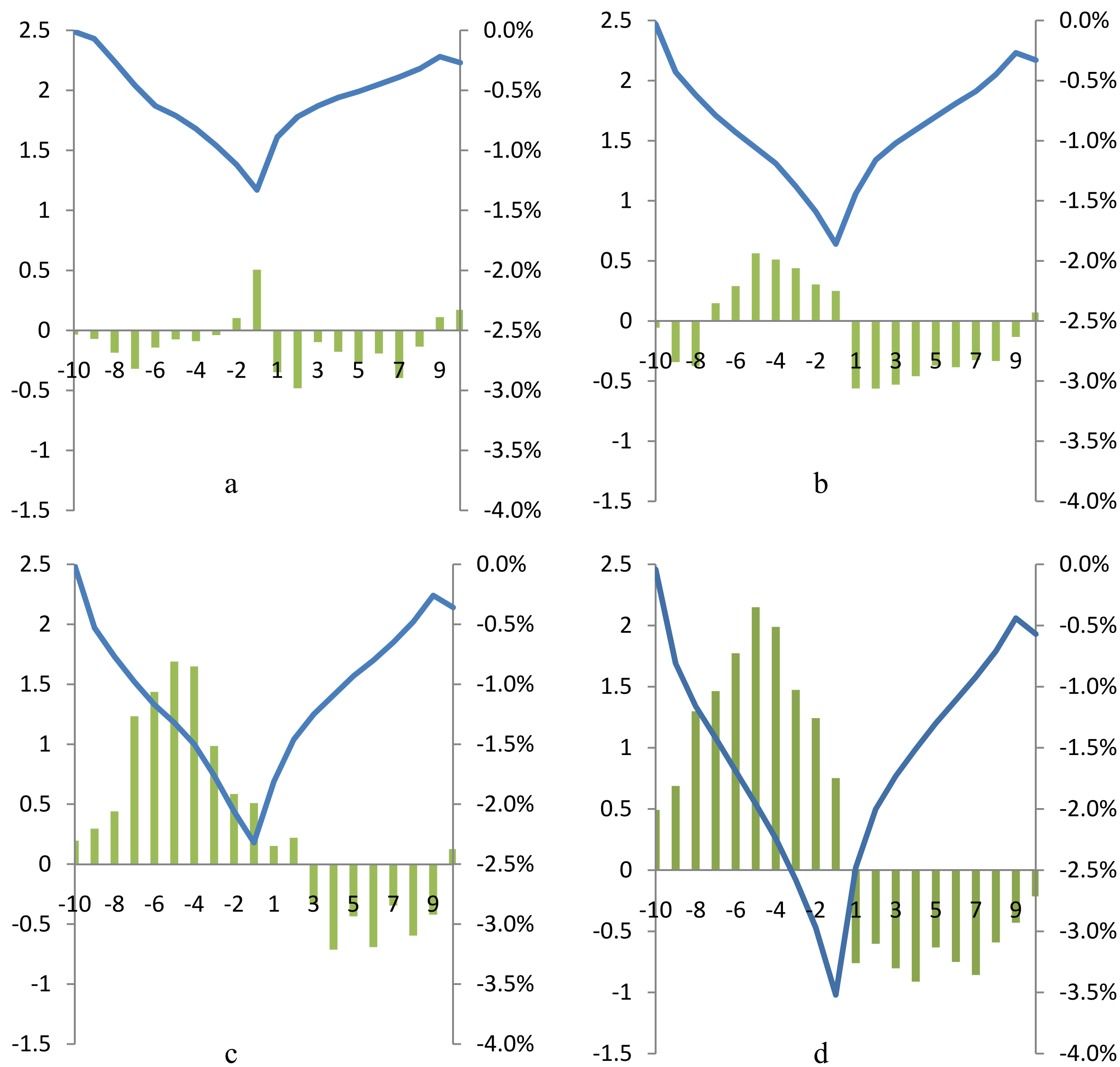

Figure 2
Short selling and price reversals
The figure displays modified abnormal short volume, *mashvol*, (bars, with the values plotted on the left vertical axis) during intraday price reversals (cumulative returns are plotted on the right vertical axis). Figures 2a, 2b, 2c, and 2d contain patterns for reversals with the pre-rebound price declines of $-m\times\sigma_{i,j}$ magnitudes, where m belongs to one of the following intervals: [2; 3); [3; 4); [4; 5); and [5; ∞).