Concentrated short-selling activity: bear raids or contrarian trading?

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Abstract

Purpose – The purpose of this paper is to investigate what is denoted as episodes of concentrated short-selling activity, or consecutive days of abnormal short-sale activity in a particular stock. The motivation to do so is two fold. First, US regulators and regulators in other countries have restricted short selling in order to protect the integrity of markets. Second, there is some conflicting academic research determining whether short sellers are manipulative in nature.

Design/methodology/approach – After defining these episodes by concentrated short selling, the paper examines returns before and after to determine whether these episodes target struggling stocks and whether these episodes predict negative returns.

Findings – Contrary to the argument that episodes of concentrated shorting activity target struggling stocks, it is found that these episodes follow periods of positive returns. Further, it is found that abnormal volatility and high trading volume also predict the occurrence of these episodes. These results suggest that concentrated shorting occurs in stocks that are increasing in price during periods of heterogeneity among investors expectations (Berkman *et al.*). It is also found that short sellers during bear raids are able to predict when prices reverse as returns become negative the day after the last day of the raid. Combined, the results suggest that bear raids by short sellers are important for the efficiency of markets.

Originality/value – The results from this study have important regulatory implications as well as implications regarding the informational efficiency of stock prices.

Keywords Short selling, Informed trading, Insider trading, Selling, Trade

Paper type Research paper

Introduction

An ongoing debate between academicians and regulators has intensified during the recent financial crisis. While prior research shows that short-sale constraints can lead to overvalued stocks and that short sellers assist in making markets more efficient (Miller, 1977; Diamond and Verrecchia, 1987; Senchack and Starks, 1993; Aitken *et al.*, 1998; Dechow *et al.*, 2001; Desai *et al.*, 2002; Bris *et al.*, 2007; Chang *et al.*, 2007; Boehmer *et al.*, 2008), recent regulation by the Securities and Exchange Commission (SEC) implies that short sellers, if unconstrained, will target struggling stocks and attempt to profit by pushing prices lower. These types of "bear raids" threaten the integrity of markets and can potentially affect the economy by putting downward pressure on stock prices. During the 2008 financial crisis in the USA, the SEC took a temporary and emergency action to protect struggling financial companies from short sellers who might be further driving down stock prices. The SEC released the following statement:

> The Commission is committed to using every weapon in its arsenal to combat market manipulation that threatens investors and capital markets. The emergency order temporarily banning short selling of financial stocks will restore equilibrium to markets[1],[2].

Motivated by this continuing debate, this study examines consecutive days of abnormally high short selling in a particular stock. For brevity, we denote these

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episodes as concentrated short-selling activity. In particular, we attempt to determine whether consecutive days with abnormally high shorting activity represents bear raids by short sellers who attempt to push the prices of struggling stocks even lower. We examine the returns of individual stocks surrounding these concentrated shorting episodes. If short sellers truly target struggling stocks, then we expect concentrated shorting activity to occur after periods of negative returns. On the other hand, if short sellers add the informational efficiency of individual stock prices by targeting stocks that become out-of-line with their fundamental value (Diether *et al.*, 2009a), then we expect that concentrated shorting activity will occur in stocks that have experienced recent price run-ups.

Results in this study show that concentrated shorting activity occurs after periods of positive returns rather than periods of negative returns. This finding suggests that these multi-day episodes of abnormally high short-selling target stocks that are performing well instead of performing poorly. While Diether *et al.* (2009a) and Boehmer and Wu (2010) show that short sellers add to the efficiency of stock prices, recent evidence by Henry and Koski (2010) and Blocher *et al.* (2011) indicates that short sellers attempt to manipulate prices. Our findings are more consistent with Diether *et al.* (2009a) and suggest that concentrated short-selling activity reflects episodes of contrarian trading.

In addition to finding that these short-selling episodes follow periods of positive returns, we also show strong evidence that concentrated short selling occurs after periods of abnormally high volatility. This finding is important in light of theory in Miller (1977) that argues that, in the presence of heterogeneous beliefs by investors, short-sale constraints lead to overvaluation. While Miller does not necessarily assert that short sellers will target stocks that experience heterogeneity *per se*, if short-sale constraints are not binding, then Miller's theory implies that short sellers will not only target stocks that are increasing in price, but short sellers will also target stocks that are increasing in heterogeneity. Given that volatility is often used as a proxy for heterogeneous beliefs among investors (Xu, 2007; Berkman *et al.*, 2009), our finding that abnormal volatility precedes episodes of concentrated short selling is consistent with implications in Miller's theory.

In our final set of tests, we examine the relation between concentrated short selling and future returns. Interestingly, we find that returns become significantly negative the day after the last day of the episode. Combined with early findings that these episodes are positively related to both contemporaneous and past returns, this result indicates that short sellers that establish short positions during these episodes are informed about future price movements (Diamond and Verrecchia, 1987; Boehmer *et al.*, 2008; Diether *et al.*, 2009a). In multivariate tests, we find that after controlling for a variety of factors that influence future daily returns, including current short activity, returns become negative shortly after the concentrated shorting episodes end.

In general, the findings in this paper support implications in Miller (1977) which suggest that unconstrained short selling can mitigate possible overvaluation caused by binding constraints and investor uncertainty. If anything, our findings show that concentrated short selling does not represent bear raids; rather, short sellers target stocks that are increasing in price during periods of investor uncertainty and are able to establish short positions prior to declining stock prices.

Subsequent sections of this paper will provide a brief review of the literature and develop our hypotheses, describe the data, present the empirical results, and offer concluding remarks.

Background and hypotheses development

In addition to the 2008 US short-sale ban, regulators in the USA and in other countries have attempted to restrict manipulative short-selling practices. As part of the 1934 Securities and Exchange Act, SEC Rule 10a-1 (the uptick rule) restricted the execution of short sales on downticks. The uptick rule was repealed in 2007 after studies by Alexander and Peterson (2008) and Diether *et al.* (2009b) showed that the uptick rule had little effect on the trading behavior of short sellers. Shortly after the repeal, and during the 2008 financial crisis, calls for reinstatement of the uptick rule by policy makers and legislators lead to the adoption of an alternative uptick rule "designed to restrict short selling from further driving down the price of a stock that has dropped more than 10 percent in one day"[3].

In other countries, short selling is also heavily regulated. For instance, the Hong Kong stock exchange establishes which stocks can and cannot be sold short (Chang *et al.*, 2007). Bris *et al.* (2007) examine 46 countries and find that short sales were, at some point, completely restricted in 23 of the 46 countries. According to their study, which used data up to 2001, ten of the 23 countries that imposed restrictions on shorting still had binding regulatory short-sale constraints.

While much of this regulation attempts to combat manipulative short-selling activity, the academic literature suggests that short sellers can improve the efficiency of markets. In fact, results in both Chang *et al.* (2007) and Bris *et al.* (2007) show that international regulations that restrict short selling lead to overvaluation or mispricing. These findings are consistent with theory in Miller (1977) that suggests that short-sale constraints lead to overvaluation. These studies imply that, absent short-sale constraints, short sellers will likely target stocks that begin to become overvalued.

In a rational expectations framework, Diamond and Verrecchia (1987) show that the possibility of constraint-induced overvaluation is already priced into securities. Further, Diamond and Verrecchia show that unanticipated increases in short activity lead to negative price adjustments. This finding implies that short sellers are informed about future stock price movements. Empirical evidence tends to support the conjecture in Diamond and Verrecchia, as short activity is negatively related to future returns (Senchack and Starks, 1993; Aitken *et al.*, 1998; Dechow *et al.*, 2001; Desai *et al.*, 2002; Christophe *et al.*, 2004; Boehmer *et al.*, 2008; Diether *et al.*, 2009a)[4]. In addition, Boehmer and Wu (2010) show that short activity reduces mispricing at the daily level, indicating that short sellers add to market efficiency. These results imply that short sellers provide an important informational benefit to the market and that regulatory constraints may inadvertently affect the efficiency of prices. In fact, Beber and Pagano (2010) show that the regulatory constraints imposed during the recent financial crisis lead to less price discovery.

While there appears to be a consensus in the literature regarding the informational role of short sellers, recent studies show some evidence that short sellers attempt to manipulate prices. In particular, Henry and Koski (2010) observe abnormal shorting around seasoned equity offerings, and that pre-issue short activity is related to larger issue discounts, which supports the idea that short sellers can manipulate stock prices around SEOs. Further, Blocher *et al.* (2011) show that short sellers attempt to manipulate end-of-year prices[5].

Combined with regulators' inclination to restrict short sellers from pushing prices of struggling stocks even lower, these latter findings indicate that short sellers may indeed manipulate prices. In the framework of our study, we test two competing hypotheses:

H1a. Concentrated short-selling activity will follow periods of negative returns.

Observing supportive evidence of *H1a* suggests that episodes of abnormally high short-selling targets stocks that are decreasing in price and represents an attempt by short sellers to profit from pushing prices even lower. To the contrary, short sellers may indeed add to the efficiency of stock prices by targeting stocks that become out-of-line with their fundamental value. Diether *et al.* (2009a) show that short sellers are contrarian in both contemporaneous and past returns and argue that short sellers target overvalued stocks in attempt to correct mispricing. Similar conclusions are drawn in Boehmer and Wu (2010):

H1b. Concentrated short-selling activity will follow periods of positive returns.

Consistency with *H1b* suggests that concentrated short selling does not represent bear raids and instead represents short sellers' attempts to correct temporary mispricing (Diether *et al.*, 2009a). Distinguishing between these competing hypotheses will have important regulatory implications and will provide a greater understanding of the role short sellers play in financial markets.

Data description

The data consists of short-sale transactions that were made available in response to Regulation SHO. The data contain time-stamped executions of short sales on various exchanges, which we aggregate to the daily level. To obtain a broad cross-sectional sample, data from the Center for Research in Security Prices (CRSP) are used to determine which stocks trade each trading day of 2006 and have a stock price greater than $5. Similar to Diether *et al.* (2009a), the sample is restricted to ordinary common stocks (CRSP share code of 10 or 11) listed on the NYSE and NASDAQ during the calendar year 2006. The number of stocks in the sample is 2,624, of which 1,229 are NYSE-listed stocks and 1,395 are NASDAQ-listed stocks.

From CRSP, we include the number of shares outstanding, market capitalization, daily returns, daily volume, and daily prices. We calculate return volatility by estimating the standard deviation in daily returns from day $t-10$ to t, where day t is the current trading day. Following Diether *et al.* (2009a), we measure price volatility by taking the difference between the daily high price and the daily low price (both from CRSP) and dividing the difference by the daily high price. Table I reports statistics that describe the sample. Panel A reports the results for NYSE stocks, while panel B shows the results for NASDAQ stocks. The average stock in the NYSE sample has a price of $38.56 and a market capitalization of $9.2 billion. Further, the mean daily return volatility is 1.81 percent while the mean daily price volatility is 2.36 percent. The average stock has a daily volume of 1.4 million shares. We follow prior research and calculate two different measures of short activity. Short turnover is the short volume as a percentage of shares outstanding (Asquith *et al.*, 2005; Christophe *et al.*, 2010) while the short ratio is the ratio of daily short volume to daily trade volume (Boehmer *et al.*, 2008; Diether *et al.*, 2009a). The average short turnover for the NYSE sample is 0.1713 while the average short ratio is 0.2214. These values are similar to those reported in previous studies. Panel B shows that the average NASDAQ stock has a price of $25.23,

	Price (1)	Market cap (2)	Return volatility (3)	Price volatility (4)	Volume (5)	Short turnover (6)	Short ratio (7)
Panel A: NYSE short selling							
Mean	38.56	9.231	0.0081	0.0236	1,418,790	0.1713	0.2214
SD	33.97	26.081	0.0029	0.0076	2,799,579	0.2157	0.1039
Minimum	5.05	0.065	0.0000	0.0000	100	0.0000	0.0000
Maximum	813.02	459.190	0.0397	0.3889	338,334,200	4.6471	0.6854
n	1,229	1,229	1,229	1,229	1,229	1,229	1,229
Panel B: NASDAQ short selling							
Mean	25.23	2.081	0.0210	0.0319	854,233	0.1874	0.2651
SD	19.38	10.264	0.0041	0.0091	3,760,478	0.3701	0.1624
Minimum	5.09	0.0009	0.0000	0.0000	100	0.0000	0.0000
Maximum	509.65	296.781	0.0390	0.6216	592,924,962	5.8501	0.8054
n	1,395	1,396	1,396	1,396	1,396	1,396	1,396

Notes: The table presents statistics that describe the sample of stocks used in the analysis. The sample includes ordinary common stocks (share code 10 or 11) that are listed on NASDAQ or the NYSE, that trade every day of 2006, and have a price $>$ \$5. The total number of stocks in the sample 2,624 (1,395 NASDAQ stocks and 1,229 NYSE stocks). Panel A shows the statistics for the daily ending CRSP price, daily CRSP raw return, daily CRSP market capitalization, daily CRSP volume, and short volume obtained from the Regulation SHO data. Return volatility is the standard deviation in daily returns from day $t-10$ to t, where day t is the current trading day. Price volatility is the difference between the daily high price and the daily low price divided by the daily high price. Short turnover is the percentage of shares outstanding that are shorted on a particular day, while short ratio is the fraction of daily trade volume that is made up from short-sale volume. Panel B shows the same statistics for NASDAQ stocks

Table I.
Summary statistics

a market cap of $2.1 billion, a daily return volatility of 2.1 percent, and a daily price volatility of 3.2 percent. Further, the daily trading volume for the average NASDAQ stock is approximately 854,000, while short turnover (short ratio) is 0.1874 (0.2651).

Empirical results

Correlation in daily short-selling activity

Before we test our competing hypotheses, we present correlation coefficients for the two measures of daily short-selling activity in Table II. The correlation between the short-selling measure for the current day and the short-selling measure for previous days is reported along with corresponding p-values. Panel A reports the correlation for NYSE-listed stocks, while panel B shows the correlation for NASDAQ-listed stocks. As mentioned previously, we include short turnover (*sh_turn*) and the short ratio (*sh_rat*) as measures of short-selling activity[6]. The results reported in the table show strong, positive correlation between trading days for each short measure for both NYSE-listed stocks and NASDAQ-listed stocks. A possible explanation for greater serial correlation in NASDAQ-listed stocks is that NASDAQ stocks suffer from greater inefficiency. In fact, Theissen (2000) shows that dealer markets (e.g. NASDAQ) are less informationally efficient than auction markets (e.g. NYSE). Perhaps short sellers are more likely to attempt to correct temporary mispricing in NASDAQ stocks, creating greater serial correlation in short-sale volume. In fact, this possibility might also explain the higher levels of short selling in NASDAQ stocks than in NYSE stocks documented in Diether *et al.* (2009a). Short activity on day t is positively and strongly correlated with short activity on day

	t−1 (1)	t−2 (2)	t−3 (3)	t−4 (4)	t−5 (5)	t−10 (6)
Panel A: NYSE stocks (n = 1,229)						
$sh\_turn_{i,t}$	0.49330**	0.45033**	0.42622**	0.40369**	0.36401**	0.34744**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$sh\_rat_{i,t}$	0.49215**	0.42123**	0.38049**	0.35184**	0.32414**	0.28330**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Panel B: NASDAQ stocks (n = 1,395)						
$sh\_turn_{i,t}$	0.76940**	0.72030**	0.68148**	0.65247**	0.61776**	0.46527**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$sh\_rat_{i,t}$	0.53577**	0.46329**	0.42515**	0.40855**	0.39116**	0.26297**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Notes: The table reports the Spearman correlation coefficients between our short-selling measures (short turnover and short ratio) on day t and short-selling measures on day $t-j$, where $j = 1, 2, 3, 4, 5, 10$. We include the *sh_turn*, short turnover series and the *sh_rat*, short ratio. Panel A shows the results for NYSE sample while panel B shows the results for NASDAQ stocks, respectively. p-values are reported in parentheses. *, **Statistical significance at 0.05, 0.01 levels, respectively

Table II.
Correlation in daily short-selling activity

$t-10$, suggesting that the autocorrelation in daily short volume is much stronger than the first-order autocorrelation documented in Blau (2011). This positive serial correlation makes the case for examining concentrated shorting activity more compelling.

Concentrated short selling and the relationship to past returns

In this subsection, we examine consecutive days of significantly high (at the 0.05 level) short-selling activity, which we denote as episodes of concentrated shorting activity[7]. The relation between these episodes and past daily returns are examined to provide tests of our competing hypotheses. This analysis is motivated by the common regulatory notion that short sellers target poor-performing firms, pushing their stock prices even lower, and thus harming the integrity of the market. Examining returns around concentrated short selling can provide insight into the behavior of short sellers and test for the presence of bear raids by short sellers.

Three different episodes are defined. After identifying the days in which short-selling activity is significantly positive for each stock, an episode of concentrated shorting activity is defined as a period of three days, five days, or ten days of significant short activity followed by a period of ten days with insignificant short-sale activity[8]. By allowing a ten-day period of insignificant short activity after an episode, we can isolate the true effect of the episode on prices. If, after a three-day period of significant short activity, returns begin to adjust downward and short selling increases significantly again a few days after the original episode ends, then returns may be affected.

Table III reports statistics that describe these episodes. For brevity, we only report episodes of concentrated shorting activity when using the short ratio, although similar results are found when defining episodes using short turnover. In panel A, we report the level of short selling during three-day episodes, while panels B and C report the results from five-day and ten-day episodes. As expected, we find that both short

	Mean (1)	SD (2)	Minimum (3)	Maximum (4)	N (5)
Panel A: three-day episodes					
$sh\_turn_{i,t}$	0.3250	0.4679	0.1481	3.5378	2,985
$sh\_rat_{i,t}$	0.3013	0.0963	0.1134	1.0000	2,985
Panel B: five-day episodes					
$sh\_turn_{i,t}$	0.3315	0.4828	0.1173	2.9935	1,463
$sh\_rat_{i,t}$	0.3158	0.1022	0.0842	1.0000	1,463
Panel C: ten-day episodes					
$sh\_turn_{i,t}$	0.4533	0.5314	0.1357	2.7048	381
$sh\_rat_{i,t}$	0.3537	0.1204	0.1263	0.7749	381

Notes: The table reports summary statistics for both short turnover and short ratio for three-day episodes (panel A), five-day episodes (panel B), and ten-day episodes (panel C). We define the K-day episode as K consecutive days with an abnormally high short ratio (at the 0.05 level). We report the mean measure for short turnover (*sh_turn*) and the short ratio (*sh_rat*), as well as other statistics

Table III. Short-selling levels during concentrated short-selling episodes

turnover and the short ratio are markedly higher during the concentrated shorting episodes. For instance, panel A shows that the mean short turnover is 0.3250 during a three-day episode. In unreported results, we find that the mean short turnover during non-event times is approximately 0.18. Similar results are found when examining the short ratio[9]. We also note that there are 2,985 unique three-day episodes; 1,463 five-day episodes, and 381 ten-day episodes.

We begin by examining daily returns around three-day, five-day, and ten-day episodes. Table IV shows the results of the event study. We report CRSP raw returns as well as two different types of risk-adjusted returns. First, we estimate the CAPM using daily returns, the daily risk-free rate, and the daily market risk premium. From this estimation, we obtain the residual returns, which we denote as CAPM residual returns. Second, we obtain risk-adjusted returns by estimating the daily Fama-French Three-Factor Model. We report the five-day pre-event cumulative return, along with the K-day event cumulative returns, where $K = \{3, 5, \text{or } 10\}$. We also present the ten-day post-event cumulative return in the table. Again, Table IV reports the results when using the short ratio to define concentrated short selling. Similar results are obtained when using short turnover as our short-selling measure.

The table shows that three-day episodes follow periods of positive returns, as returns are significantly positive in the pre-event period. This finding is robust to using different types of risk-adjusted returns. We also find that returns are generally positive during the episode. Combined, these findings reject *H1a* in favor of *H1b* and provide consistency with the contrarian trading behavior of short sellers documented by Diether *et al.* (2009a). Further, our results suggest that concentrated short-selling episodes do not appear to be "piling on" downward pressure to already struggling stocks. Interestingly, returns are significantly negative during the ten days after the episode ends, suggesting that short sellers are informed about future price movements (Diamond and Verrecchia, 1987; Boehmer *et al.*, 2008; Diether *et al.*, 2009a). The results for five-day and ten-day episodes are generally similar. In unreported tests, we also examine five-day post-event returns. We note that five-day post-event returns are only significantly negative after ten consecutive days of a significant short ratio – not a short turnover.

	Three-day episode			Five-day episode			Ten-day episode		
	Raw returns (1)	CAPM residual returns (2)	Three-factor residual returns (3)	Raw returns (4)	CAPM residual returns (5)	Three-factor residual returns (6)	Raw returns (7)	CAPM residual returns (8)	Three-factor residual returns (9)
$ret_{t-5,t-1}$	0.0111**	0.0061**	0.0056**	0.0069**	0.0051**	0.0056**	0.0026	0.0044*	0.0061**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.368)	(0.048)	(0.009)
$ret_{t0,t+2}$	0.0089**	0.0025**	0.0031**						
	(0.000)	(0.000)	(0.000)						
$ret_{t+3,t+12}$	−0.0141**	−0.0063**	−0.0054**						
	(0.000)	(0.000)	(0.000)						
$ret_{t0,t+4}$				0.0197**	0.0116**	0.0044**			
				(0.000)	(0.000)	(0.001)			
$ret_{t+5,t+14}$				−0.0194**	−0.0161**	−0.0131**			
				(0.000)	(0.000)	(0.000)			
$ret_{t0,t+9}$							0.0340**	0.0342**	0.0358**
							(0.000)	(0.000)	(0.000)
$ret_{t+10,t+19}$							−0.0354**	−0.0378**	−0.0331**
							(0.000)	(0.000)	(0.000)

Notes: The table presents different types of returns around concentrated short-selling episodes. Event day 0 is the first day of K consecutive days of a significantly high short ratio. Columns (1) through (3) report the results of three consecutive days, while columns (4) through (6) and (7) through (9) report the results of five- and ten-day episodes. In columns (1), (4), and (7), we use cumulative CRSP raw returns which are summed across the days denoted in the subscripts. In columns (2), (5), and (8), we report the CAPM risk-adjusted returns, which are calculated as the residual from daily CAPM regressions. Similarly, columns (3), (6), and (9) report Fama-French Three-Factor risk-adjusted returns. p-values are reported in parentheses and are obtained from t-statistics testing the difference between the reported returns and zero. *, **Statistical significance at 0.05, 0.01 levels, respectively

Table IV.
Event study of returns around concentrated short-selling episodes

Other factors that influence concentrated short-selling episodes

This subsection explores other factors (other than returns) that may precede episodes of concentrated shorting activity. We begin by using an event study method with the following standardization procedure for several variables, similar to Lakonishok and Vermaelen (1986), Koski and Scruggs (1998), and Sias (2004):

$$Std\_measure_{i,t} = \frac{Measure_{i,t} - \overline{Measure_i}}{\sigma(Measure_i)} \tag{1}$$

The difference between the variable for stock i on day t and the time-series mean for the stock is divided by the standard deviation across the sample time period. The standardization procedure allows each stock to have a standardized variable that is similarly distributed with a zero mean and a unit variance.

Possible factors influencing concentrated shorting episodes are volume, return volatility, and price volatility. Diether *et al.* (2009a) find that trading activity affects the behavior of short sellers; therefore, volume is included as a possible factor. He and Wang (1995) argue that information flow produces serially correlated trades. Ross (1989) shows that return volatility is an appropriate approximation for information flow, while Clark (1973) and Lamoureux and Lastrapes (1990) establish a theoretical relation between price volatility and information flow. Therefore, return volatility and price volatility are also included as possible predictors of concentrated shorting episodes. The volatility measures may also approximate investors' uncertainty (Berkman *et al.*, 2009). This latter interpretation of the approximation of these variables may have important theoretical implications. Miller (1977) argues that, in the presence of heterogeneity among investors' opinions about the true value of stocks, short-sale constraints can result in overvaluation. Combined with the contrarian-type trading observed in Table IV, the finding that concentrated shorting occurs after periods of high heterogeneity suggests that short sellers attempt to correct potential overvaluation by targeting these stocks that are increasing in price.

Table V reports the results of the event study around concentrated shorting episodes. As before, we only report the results when the shorting episodes are defined using the short ratio, although similar results are found when using short turnover. The table reports abnormal price and return volatility in the pre-event period. The table documents slight abnormal volatility prior to three-day episodes, and greater abnormal volatility prior to five-day episodes. When examining the ten-day episode, price volatility and return volatility are positive and significant during the five days

		Episode(3)			Episode(5)			Episode(10)	
	Volume	*P_volt*	*R_volt*	Volume	*P_volt*	*R_volt*	Volume	*P_volt*	*R_volt*
Event day	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
−5	−0.0050	−0.0020	0.0183	0.1086**	0.0707**	0.0800**	−0.0180	0.2003**	0.1620**
−4	−0.0300*	0.0125	0.0224	−0.0004	0.0569*	0.0861**	0.0330	0.2998**	0.1440**
−3	−0.0460**	−0.0420**	0.0123	−0.0250	0.0083	0.0652**	0.1374**	0.3974**	0.1695**
−2	−0.0170	0.0230	0.0291*	−0.0150	0.0537**	0.0837**	0.0942**	0.2900**	0.2184**
−1	−0.0190	0.0421**	0.0434**	−0.0190	0.0236	0.0822**	0.0695	0.2359**	0.2966**
First day	−0.0330*	0.0928**	0.0558**	−0.0170	0.0921**	0.1093**	0.2916**	0.2667**	0.3068**
+1	−0.0540**	0.0325*	0.0449**	−0.0810**	0.0329	0.1040**	−0.0110	0.1387**	0.2873**
+2	−0.0170	0.1103**	0.0665**	−0.0650**	0.0670**	0.1062**	−0.1210**	0.0503	0.2437**
+3				−0.0830**	0.0618**	0.0879**	−0.1080**	0.1238*	0.2616**
+4				0.0399	0.2209**	0.1208**	−0.1690**	−0.0650	0.2274**
+5							−0.0850	0.0722	0.2324**
+6							−0.1410**	−0.0240	0.1922**
+7							−0.1200**	0.0818	0.1522**
+8							−0.1120**	0.1103*	0.1130*
+9							0.1637**	0.4094**	0.1874**

Notes: The table presents different trading characteristics prior to a concentrated short-selling episode. The trading variables are standardized using the following procedure: we divide the difference between the variable on a particular day during the event window and the mean of that variable during the sample time period by the standard deviation of the variable during the sample time period for each stock. This standardization procedure allows each stock to have a standardized variable that is similarly distributed with a 0 mean and a unit variance. Event days are specified as the first day of K consecutive days of significant high short ratio, where $K = 3, 5$, or 10. That is, *Episode*(K) describes the number of K days that a stock experienced significantly (at the 0.05 level) high short volume relative to total trade volume. Event day 0 is the first day of a K-day episode. The results of a t-test that determines whether volume, return volatility, or price volatility is significantly different from 0 are given by the reported mean return. *, **Statistical significance at 0.05, 0.01 levels, respectively

Table V. Other indicators of concentrated short-selling episodes prior to the event. The table shows mixed results when examining volume prior to episodes. Results from Table V therefore suggest that concentrated shorting episodes occur after periods of abnormal volatility. This finding is consistent with the idea that greater heterogeneity among investors results in a greater likelihood of concentrated short selling. Combined with findings in Table IV, our results are consistent with implications in Miller (1977) that suggest that, absent constraints, short sellers will target stocks that have been increasing in price during periods of heterogeneity among other investors.

We recognize the need to control for other independent factors so we estimate the following model using pooled data:

$$
\begin{aligned}
Episode(K)_{i,t} = {} & \beta_0 + \beta_1 ret_{i,t-j,t-1} + \beta_2 vol_{i,t-j,t-1} + \beta_3 rvolt_{i,t-j,t-1} \\
& + \beta_4 pvolt_{i,t-j,t-1} + \beta_5 sh\_vol_{i,t-j,t-1} + \beta_6 \ln cap_{i,t} + \varepsilon_{i,t}
\end{aligned}
\tag{2}
$$

The dependent variable is binary and equal to unity if day t for stock i is the first day of a K-day concentrated shorting episode, where K is defined as before. The independent variables are the lagged three-factor risk-adjusted returns (*ret*), volume (*vol*), return volatility (*rvolt*), price volatility (*pvolt*), and short volume (*sh_vol*)[10]. These independent variables are lagged from day $t-j$ to $t-1$, where $j = \{1 \text{ or } 5\}$. The natural log of the stocks' market cap is also included as an independent variable.

Table VI reports the results from estimating Equation (2) using a logistic regression[11],[12]. For brevity, we only report the results when concentrated shorting episodes are defined using the short ratio. Similar results are found when using the short turnover to define the shorting episodes. We control for fixed effects across both stocks and days and find that larger stocks (in terms of market capitalization) increase the likelihood of a ten-day episode although market cap produces insignificant estimates in columns (1) through –(4). Lagged returns consistently produce positive and significant estimates in each column. Further, these results are robust to different lagged time periods ($t-5$ to $t-1$). We also find that lagged price volatility produces positive and significant estimates in four of the six columns while lagged return volatility produces only one significant estimate across the six columns. Interestingly, lagged volume is negatively related to the likelihood of concentrated shorting episodes as the estimates for β_2 are negative.

The results in Tables IV-VI support *H1b* rather than *H1a* and suggest that short sellers are indeed contrarian traders who target stocks that are both increasing in price and volatility. If volatility properly approximates investor uncertainty (Berkman *et al.*, 2009), then our results tend to support the implications in Miller's (1977) theory, which suggest that short sellers will attempt to correct overvaluation in the presence of heterogeneity among investors' beliefs.

Return predictability of concentrated short-selling episodes

In this subsection, we conduct our final set of tests. In Table IV we find that returns become negative shortly after concentrated shorting episodes end. Both Boehmer *et al.* (2008) and Diether *et al.* (2009a) argue that short sellers can predict negative returns. A natural extension to our tests is to examine the relation between concentrated shorting episodes and future returns. The purpose in doing so is to determine whether

Table VI. Pooled logistic regression results

	Episode(3)		Episode(5)		Episode(10)	
	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	5.9176**	5.6114**	7.0383**	6.7432**	8.3414**	8.8245**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ret_{t-1}	11.6285**		8.4404**		3.0968*	
	(0.000)		(0.000)		(0.047)	
vol_{t-1}	−0.1092**		−0.1502**		−0.7237**	
	(0.000)		(0.000)		(0.000)	
$rvolt_{t-1}$	0.4903*		0.2986		0.6553	
	(0.044)		(0.318)		(0.257)	
$pvolt_{t-1}$	3.8358**		−1.1710		3.5845	
	(0.003)		(0.469)		(0.124)	
sh_vol_{t-1}	0.0474**		0.0312		0.1770**	
	(0.000)		(0.070)		(0.000)	
$ret_{t-5,t-1}$		6.6535**		7.6569**		4.0984**
		(0.000)		(0.000)		(0.000)
$vol_{t-5,t-1}$		−0.1779**		−0.2316**		−0.7017**
		(0.000)		(0.000)		(0.000)
$rvolt_{t-5,t-1}$		−0.1595		−0.1153		0.6303
		(0.475)		(0.684)		(0.317)
$pvolt_{t-5,t-1}$		13.7938**		12.6901**		9.0197*
		(0.000)		(0.000)		(0.037)
$sh\_vol_{t-5,t-1}$		0.1499**		0.1600**		0.2856**
		(0.000)		(0.000)		(0.000)
cap_t	0.0160	0.0092	0.0454	0.0287	0.4542**	0.3562**
	(0.469)	(0.700)	(0.140)	(0.397)	(0.000)	(0.000)
Wald statistics	272.62**	517.95**	150.36**	402.05**	224.24**	400.55**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Frequency	2,985	2,985	1,463	1,463	381	381
Stock FE	Yes	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The table reports the results of a logistic regression where the data is pooled. The following equation is estimated:

$$\begin{aligned} Episode(K) = {} & \beta_0 + \beta_1 ret_{i,t-1} + \beta_2 rvol_{i,t-1} + \beta_3 rvolt_{i,t-1} + \beta_4 pvolt_{i,t-1} + \beta_5 sh\_vol_{i,t-1} + \beta_6 ret_{i,t-1,t-5} \\ & + \beta_7 vol_{i,t-1,t-5} + \beta_8 rvolt_{i,t-1,t-5} + \beta_9 pvolt_{i,t-1,t-5} + \beta_{10} sh\_vol_{i,t-1,t-5} + \varepsilon_{i,t} \end{aligned}$$

The dependent variable is equal to 1 if day t is the first day of a K-day concentrated short-selling episode where $K = 3, 5$, or 10. The independent variables are lagged measures of three-factor risk-adjusted returns (*ret*), volume (*vol*), return volatility (*rvolt*), price volatility (*pvolt*), and short-sale volume (*sh_vol*). We lagged the values from day $t-1$ to $t-j$, where $j = 1$ or 5. We also include market capitalization on day t (cap_t). We include both stock and day fixed effects in the estimation. p-values are reported in parentheses. *, **Statistical significance at 0.05, 0.01 levels, respectively

these concentrated shorting episodes contain information about future stock price movements. Using pooled data, the following equation is estimated:

$$\begin{aligned} ret_{i,t+2-t+s} = {} & \beta_0 + \beta_1 \ln vol_{i,t} + \beta_2 rvolt_{i,t} + \beta_3 pvolt_{i,t} \\ & + \beta_4 \ln cap_{i,t} + \beta_5 sh\_rat_{i,t} + \beta_6 Episode(K^L)_{i,t} + \varepsilon_{i,t+1} \end{aligned} \quad (3)$$

The dependent variable is the cumulative three-factor risk-adjusted return for stock i from day $t+2$ to $t+s$ where $s=\{2 \text{ or } 5\}$. We follow Diether *et al.* (2009a) and exclude returns on day $t+1$ to avoid the possibility of microstructural bias such as bid-ask bounce. Further, we follow Diether *et al.* (2009a), who also examine returns from day $t+2$ to $t+5$ in their analysis. The independent variables include the natural log of volume for stock i on day t, the return volatility (*rvolt*), the price volatility (*pvolt*), the short ratio (*sh_rat*), and three dummy variables. *Episode*(K^L) is equal to one if day t is the last day of a K-day episode for stock i, where $K=\{3, 5, \text{or } 10\}$[13].

Karpoff (1987) surveys the literature and finds a positive relation between volume and price changes; therefore, a positive relation between volume and future returns is expected. We use three-factor risk-adjusted returns to control for the size and value premiums discussed in Fama and French (1992, 1996). The volatility measures are expected to be positive. Diether *et al.* (2009a) estimate an equation similar to Equation (3) and find that relative short-sale volume is inversely related to future returns. Therefore, the estimate for β_5 is expected to be negative. If concentrated shorting episodes contain information about future price movements, then the dummy variables should produce negative estimates. Negative dummy variable estimates suggest that, after controlling for other factors that influence future returns, including relative short activity, these episodes relate negatively to subsequent returns, indicating that these concentrated shorting episodes contain information about future stock price movements.

Table VII presents the results from estimating Equation (3) for the entire sample. A Hausman test rejects the presence of random effects. However, an F-test finds observed differences across stocks and days so we control for stock and day fixed effects. The results show a positive estimate for volume, which is consistent with past literature. Further, mixed signs for the volatility estimates are shown in the table. Consistent with Diether *et al.* (2009a), the short ratio predicts negative returns as the estimate for β_5 is negative and significant in each column. In economic terms, a 1 standard deviation increase in the short ratio in say, column (1), can reduce returns on day $t+2$ by approximately 0.02 percent. When annualizing 0.02 percent, this daily estimate results in 5 percent lower returns per year after controlling for other factors that influence future daily returns. After controlling for the information contained in relative short activity, episodes of concentrated shorting activity also contain information, as returns become negative shortly after the last day of the episode. In column (1), the economic implication from the estimate β_6 is that returns are 0.33 percent lower on day $t+2$ after the last day of a concentrated shorting episode. In annual terms, 0.33 percent is more than 82 percent per year. In column (4), the estimate for β_6 is -0.91 percent. In economic terms, the negative return during this four-day (from day $t+2$ to $t+5$) period is more than -57 percent when annualized. Combined with findings in Tables IV and VI, results in Table VII suggest that traders who establish short positions during periods of concentrated shorting activity are generally informed.

Robustness

In this subsection, we discuss other sensitivity tests that we conduct to assure that our results are robust. First, we partition the sample of stocks into NYSE- and NASDAQ-listed stocks and perform the entire analysis separately. In general, we find that the conclusions that we draw for our entire sample hold when examining these subsamples separately.

Table VII. Regression results

	$Ret_{i,t+2}$			$Ret_{i,t+2,t+5}$		
	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	0.0026	0.0026	0.0026	0.0098**	0.0097**	0.0096**
	(0.079)	(0.083)	(0.085)	(0.001)	(0.001)	(0.001)
$ln\ vol_t$	−0.0002**	−0.0002**	−0.0002**	−0.0005**	−0.0005**	−0.0005**
	(0.003)	(0.003)	(0.003)	(0.000)	(0.000)	(0.000)
$rvolt_t$	0.0008*	0.0008*	0.0008*	0.0014*	0.0014*	0.0014*
	(0.015)	(0.015)	(0.016)	(0.031)	(0.032)	(0.034)
$pvolt_t$	0.0007	0.0007	0.0007	0.0140**	0.0140**	0.0139**
	(0.717)	(0.715)	(0.734)	(0.000)	(0.000)	(0.000)
sh_rat_t	−0.0015**	−0.0016**	−0.0017**	−0.0032**	−0.0034**	−0.0036**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$Episode(3^L)$	−0.0033**			−0.0091**		
	(0.000)			(0.000)		
$Episode(5^L)$		−0.0038**			−0.0114**	
		(0.000)			(0.000)	
$Episode(10^L)$			−0.0027**			−0.0105**
			(0.006)			(0.000)
R^2	0.0131	0.0130	0.0129	0.0157	0.0156	0.0154
Stock FE	Yes	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The table reports the results of estimating the following equation:

$$ret_{i,t+2,t+s} = \beta_0 + \beta_1 \ln vol_{i,t} + \beta_2 rvolt_{i,t} + \beta_3 pvolt_{i,t} + \beta_4 \ln cap_{i,t} + \beta_5 sh\_rat_{i,t} + \beta_6 Episode(K^L)_{i,t} + \varepsilon_{i,t+1}$$

where the dependent variable is the three-factor risk-adjusted cumulative return for stock i from day $t+2$ to $t+s$ where $s=2$ or 5. Columns (1) through (3) report the results when $s=2$, while columns (4) through (6) show the results when $s=5$. This dependent variable is similar to those used in Diether *et al.* (2009b). We include the following independent variables: $Ln\ vol_{i,t}$ is the natural log of volume on day t; $rvolt_{i,t}$ the return volatility; $pvolt_{i,t}$ the price volatility; and $sh\_rat_{i,t}$ the volume ratio (short volume divided by trade volume) measured for each stock on day t. $Episode(K^L)_{i,t}$ is a dummy variable equal to 1 if day t is the last day of a K-day episode for stock i. In response to Hausman tests and F-tests, we report two-way fixed effects estimates. p-values are reported in parentheses. *, **Statistical significance at 0.05, 0.01 levels, respectively

In other unreported multivariate tests, we control for conditional heteroskedasticity and clustering in the error terms of each regression in Table VII. Again we find that the results reported in this paper are robust to alternative econometric specifications. Further, our results are robust to four-day, six-day, seven-day, eight-day, and nine-day episodes. That is, we perform the analysis for different K-day episodes, where $K = \{4, 6, 7, 8, \text{or } 9\}$. These results are qualitatively similar to the findings reported in this paper.

In our regression analysis, we also control for option volume. After replicating Table VI and including lagged trading activity in both call options and put options, we do not find that option activity predicts concentrated shorting episodes, nor do we find that including lagged option activity affects the conclusions we draw in Table VI. We also find that our results in Table VII are robust to including option activity as independent variables.

In addition to controlling for option trading activity, we also control for the possibility that concentrated shorting episodes occur in conjunction with other corporate announcements. Specifically, we control for two dummy variables. The first variable is equal to 1 if there is an earnings announcement during the shorting episode, or during the five days prior to, or during the five days after the episode; 0 otherwise. The second variable is similar to the first except instead of earnings announcements, we control for analyst recommendations. We find the results in Tables VI and VII are robust after controlling for these dummy variables.

Finally, we conduct the analysis when we define a concentrated shorting episode as consecutive days of abnormally high raw short-sale volume and find that this alternative definition of a concentrated shorting produces results that are similar to those reported in this paper. In Tables IV-VII, we also conduct the analysis using short turnover instead of the short ratio when defining shorting episodes. Again, the results are similar to those reported in this study.

Conclusion

While recent regulatory action around the world attempts to protect the integrity of financial markets from short sellers who may be targeting struggling stocks and pushing their prices even lower, some academic research finds that short sellers can play an important informational role in financial markets. Miller (1977) argues, for example, that in the presence of heterogeneity among investors' opinions, short-sale constraints can lead to overvaluation. Further, other research shows that short sellers are informed investors as current short-selling activity is negative related to future returns (Diamond and Verrecchia, 1987; Senchack and Starks, 1993; Aitken *et al.*, 1998; Desai *et al.*, 2002; Christophe *et al.*, 2004; Boehmer *et al.*, 2008; Diether *et al.*, 2009a). While most empirical research suggests that short selling makes markets more efficient, some studies show that short sellers may attempt to manipulate prices (Blocher *et al.*, 2011; Henry and Koski, 2010). Motivated by these latter studies and the regulatory implications about manipulative short selling, we examine consecutive days of abnormally high shorting activity, which we denote as concentrated shorting episodes, to determine whether these episodes are indeed an attempt by short sellers to push prices lower in stocks that are already underperforming.

Contrary to this theory, results in this study show that concentrated shorting episodes occur after periods of positive returns rather than periods of negative returns. These findings are consistent with the notion that short sellers are contrarian traders (Diether *et al.*, 2009b) instead of momentum traders (Christophe *et al.*, 2010). Further, our tests reveal that concentrated shorting episodes occur after periods of abnormal volatility. If volatility properly approximates investors' uncertainty (Berkman *et al.*, 2009), then these results are consistent with theoretical inferences made in Miller (1977) that suggest that short sellers will target stocks that are increasing in price during periods of high investor uncertainty in an attempt to correct overvaluation.

While concentrated shorting episodes generally follow periods of positive returns, we find strong evidence that returns become negative shortly after the last day of the episode. This finding suggests that, during these episodes, short sellers are informed about future price movements, which supports prior work that explores the information contained in short sales (Diamond and Verrecchia, 1987; Dechow *et al.*, 2001; Desai *et al.*, 2002; Boehmer *et al.*, 2008; Diether *et al.*, 2009a).

Notes

1. See www.sec.gov/news/digest/2008/dig091908.htm
2. Beber and Pagano (2010) show that short-selling restrictions during the recent financial crisis reduced both liquidity and price discovery. Further, Battalio and Schultz (2011) report that option market liquidity worsened during the imposed short-sale restrictions because option market makers were no longer allowed to short underlying stocks to hedge against increased bearish option volume.
3. See www.sec.gov/news/press/2010/2010-26.htm
4. Senchack and Starks (1993) and Desai *et al.* (2002) find significant negative returns follow increases in monthly short interest. Aitken *et al.* (1998) find that short sales predict negative returns within 15 minutes on the Australian Stock Exchange. Christophe *et al.* (2004) find that short-selling activity increases for stocks with unfavorable earnings announcements during the pre-announcement period. More recently, Boehmer *et al.* (2008) and Diether *et al.* (2009a, b) find that short sellers are able to predict negative next day returns.
5. In other studies, Christophe *et al.* (2010) find evidence of short selling prior to analyst downgrade recommendations. Results from their tests suggest that short sellers are beneficiaries of leaked information obtained directly from analysts prior to the public announcement of the recommendation. In addition, Shkilko *et al.* (2010) find that when large intraday price reversals are accompanied by abnormal short selling, prices will decrease. This finding supports theory in Brunnermeier and Pedersen (2005) that examines predatory trading.
6. In unreported results, we also include raw daily short volume. We include this variable as a short activity measure throughout the analysis and find that our results are robust to this additional shorting measure.
7. We determine statistical significance by standardizing short selling so that each stock has a standardized measure than similarly distributed with a zero mean and a unit variance. In particular, for each stock on each day, we subtract the mean short-selling measure (across the time series) from the daily short-selling measure. We then divide this difference by the standard deviation of the short-selling measure (across the time series). After adjusting this standardized measure of short selling for the square root of the number of observations in the time series, we use a standard normal table to determine statistical significance at the daily level. For robustness, we obtain the distribution of the short-selling measure for each stock and find uniformly that the statistical significance determined by our methods represents days with short-selling activity above the 95 percentile.
8. Our results are robust to when we do not impose the post-event ten-day insignificant short-selling restriction. That is, when we examine returns around three consecutive days of short selling, our results are similar to those reported in this paper. The same is true when we examine five- and ten-day episodes without the post-event restriction.
9. The difference is statistically significant at the 0.01 level.
10. Similar results are found when using other CRSP raw returns or CAPM risk-adjusted returns.
11. Similar results are found when we use a probit regression.
12. Augmented Dickey-Fuller test statistics reject the presence of unit roots.
13. We define concentrated shorting episodes using the short ratio although similar results are found using short turnover.

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