Short Selling during Extreme Market Movements

Benjamin M. Blau
Utah State University

Bonnie F. Van Ness
University of Mississippi

Robert A. Van Ness
University of Mississippi

Robert A. Wood
University of Memphis

Current Version: August 14th, 2009

Short Selling during Extreme Market Movements

Abstract

This study examines short selling of NYSE stocks contained in the S&P 500 on days with extreme increases (up days) and extreme decreases (down days) in the index. While Diether, Lee, and Werner (2009) show that short sellers are generally contrarian in contemporaneous returns, we find that short selling increases on large down days and decreases on large up days suggesting that during extreme market movements, short sellers tend to follow the crowd. Further, our results indicate that short sellers do not anticipate down days indicating that these event days are largely unforeseen. When examining the return predictability of short sellers on event days, we observe that short sellers on up days are significantly better at predicting negative next-day returns than short sellers on down days indicating that contrarian short selling is more profitable than momentum short selling.

I. Introduction

Research showing that short sellers are informed about future stock returns is robust (Diamond and Verrecchia, 1987; Senchack and Starks, 1993; Aitken et al., 1998; Desai et al., 2002; Christophe, Ferri, and Angel, 2004; and Boehmer, Jones, and Zhang, 2008). Diether, Lee, and Werner (2009) argue that informed investors are able to short stocks that become overvalued or out of line with their fundamental value while documenting the short sellers are contrarian in contemporaneous and past returns. Boehmer and Wu (2008) show that the contrarian behavior of short sellers assists in the informational efficiency of stock prices. In particular, Boehmer and Wu find that short selling at the daily level reduces pricing errors suggesting that when stocks become temporarily overvalued, informed investors short these stocks thus reducing any further overvaluation.

Similarly, Boehmer and Kelly (2008) show that trading by institutions adds to stock price efficiency, which is consistent with the idea that institutional investors are informed (Lo and MacKinlay, 1990; Meulbroek , 1992; Cornell and Sirri, 1992; Chakravarty and McConnell, 1997; Koski and Scruggs, 1998; and Chakravarty, 2001). While empirical evidence supports the idea that institutional investors are informed and improve price efficiency, some studies show that institutions engage in less sophisticated behavior, such as positive feedback trading and herding (Nofsinger and Sias, 1999; and Sias, 2004). Dennis and Strickland (2002), document that institutional investors generally trade in the direction that markets move on days with extreme market movements and suggest that institutions tend to "blink in volatile markets".

Since short sellers are deemed sophisticated and are shown to be consistently contrarian traders, we examinewhether short sellers blink during extreme market movements. Two competing expectations can be inferred from our tests. First, if short sellers add to the informational efficiency of stock prices, then when markets substantially increase the contrarian behavior of short sellers will assist in monitoring the price inefficiencies caused by positive feedback trading by other investors. Second, and contrary to the first, if short sellers blink during extreme market movements, then short sellers will forego their usual contrarian role, and instead trade in the direction that markets move.

The results from our tests favorably support the latter contention. After controlling for factors that influence the amount of short selling at the daily level, we find abnormal short activity in stocks contained in the S&P 500 index on days when the index substantially declines (extreme down days). Further, we observe unusually low short selling for these stocks on days when the index substantially increases (extreme up days). Combined, these findings indicate that while short sellers are generally contrarian in contemporaneous daily returns, they tend to become momentum traders on days when markets experience extreme price movements.

Additional tests show that short sellers do not anticipate extreme down days. If anything, we show that short selling is abnormally low during the days prior to the down day. This observation becomes important in our interpretation of the earlier results. The lack of abnormal short selling indicates that short sellers are caught off guard by the extreme market movement and respond by following the crowd.

Consistent with the idea that short sellers do not anticipate days with extreme price movements, we find some evidence that short selling increases during the few days prior to extreme up days. Even so, short selling becomes abnormally low on the event day indicating that short sellers' usual contrarian behavior in contemporaneous returns changes due to unusual increases in market prices.

We continue our analysis by examining the common negative relation between current short selling and future returns. Diamond and Verrecchia (1987) propose that unanticipated increases in short selling will be followed by a price decline. Consistent with the proposition of Diamond and Verrecchia, Senchack and Starks (1993) and Desai et al. (2002) show that monthly short interest predicts negative returns for NYSE stocks and NASDAQ stocks, respectively. Diether, Lee, and Werner (2009) and Boehmer, Jones, and Zhang (2008) show that short sellers are able to predict negative returns using daily data. Aitken et al. (1998) show that returns become negative within 15 minutes after a short sales on the Australian Stock Exchange, suggesting that short sellers are informed about intraday price movements. Previous research supports the notion that short sellers are informed at the monthly, daily, and intradaily levels. Our final test is to compare the ability of short sellers to predict future negative returns on down days and up days. Our comparison shows first, that short selling on down days does not predict negative next-day returns. On the contrary, we show favorable evidence that short selling on up days is able to predict future negative returns. Together, these results indicate that trading in the direction that markets move decreases the ability of short sellers to capture short-term profits. Instead, remaining contrarian on days with extreme price increases is more likely to produce short-term trading profits.

To summarize, this study suggests that short sellers tend to follow the crowd during volatile markets, which is contrary to their usual behavior. Diether, Lee, and Werner (2009) and Boehmer and Wu (2008) document that short sellers, who are contrarian in contemporaneous returns, add to the informational efficiency in stock prices by targeting stocks that become overvalued. Our general results show consistency with this idea. However, contrarian trading is more likely to occur on days without extreme price movements. Theory regarding herding behavior suggests that traders may rationally decide to focus on short-term information and inevitably ignore valuable information, which may take longer to impact prices (Froot et al., 2002). Additionally, Delong et al. (1990) show that when positive feedback trading (positive correlation between herding and lagged returns) exists, prices deviate from their fundamental value. Determining whether short sellers that trade in the direction that markets move destabilize prices is outside the scope of this paper. However, we can infer that daily short selling, which is found to add to price efficiency, resembles positive feedback trading on days when markets move the most.

The rest of this paper follows. Section II describes the data used and the event day selection method. In Section III we describe and present the results from our tests of abnormal short selling on event days. We also examine the return predictability of short sales in Section III. Section IV summarizes our findings and concludes.

II. Data

In our analyses, we use data that is made available by the Securities and Exchange Commission's Regulation SHO and trade transactions from the Trade and Quotes (TAQ) data base. We merge short sales from the SHO data with trades from TAQ for NYSE stocks that are part of the S&P 500.[1] We are able to match approximately 99 percent of short sales and trades. We obtain the shares outstanding, market capitalization, daily returns, and prices (to calculate various measures of volatility) from the Center of Research on Security Prices (CRSP). Using CRSP shares outstanding, we calculate two measures of turnover. First, volume turnover is calculated by dividing daily volume by the number of shares outstanding. Second, short turnover is the number of outstanding shares that are shorted on a particular

[1] We also require our sample of stocks to be traded every day of the sample time period, which is 2005 and 2006.

day. Since research shows that short selling is related to information flow about future stock prices, we include two measures of volatility.[2] Using CRSP prices, we calculate a measure of price volatility following Diether, Lee, and Werner (2009), which is the difference between the daily high price and the daily low price divided by the daily high price.[3] From CRSP returns, we calculate return volatility, which is the standard deviation of daily returns from day *t-10* to day *t*, where day *t* is the current trading day.

In order to determine the event days for the analysis, we calculate close-to-close returns and open-to-close returns of the S&P 500 for the period of January 2005 to December of 2006.[4] After calculating the mean of daily returns, we select days that the S&P 500 moves two standard deviations above or below the mean. Table 1 reports the dates and the returns for days that meet the event selection criteria. We are able to define 12 extreme down days and 12 extreme up days during our sample time period. These 24 days result in slightly less than five percent of all of the trading days during 2005 and 2006 and represent days when prices move the most. We note that close-to-close and open-to-close returns yield the same event days with the exception of one down day, 5/11/2006.[5] Our method of selecting days is similar to Dennis and Strickland (2002) and Lipson and Puckett (2007).[6]

Table 2 presents statistics that describe our sample. Panel A contains the stock characteristics during non-event days while Panel B (Panel C) contains the same characteristics

[2] Ross (1989) shows the variance in asset returns is directly related to the arrival of information while Clark (1973) and Lamoureux and Lastrapes (1990) derive a theoretical relation between price volatility and information flow.
[3] This volatility measure follows Diether, Lee, and Werner (2007).
[4] Our time period is restricted to 2005 and 2006 because of Reg SHO data limitations.
[5] We perform preliminary analysis with and without this date, 5/11/2006, and the results are qualitatively similar. We focus our analysis on close-to-close returns.
[6] Dennis and Strickland (2002) report their results for event days that are three standard deviations away from the mean although they report that their results are qualitatively similar for days that are two standard deviations away from the mean. We examine days that are two standard deviations away from the mean instead of days that are three standard deviations in order to obtain enough observations to avoid any collinearity problems in our regression analysis.

on extreme down (up) days. We report in Table 2 the market capitalization in dollars (*size*) as well as the price (*price*) reported on the Center of Research on Security Prices (CRSP). Using daily CRSP returns and prices we report two measures of volatility. The first is the return volatility (*r_volt*), which is defined as the standard deviation in daily returns from day *t-10* to day *t*, where day *t* is the current trading day. The second measure of volatility is the price volatility (*p_volt*), which is calculated by dividing the difference between the daily high price and the daily low price by the daily high price (Diether, Lee, and Werner, 2009). We also report two measure of trading activity. *Volume* is obtained from TAQ and is aggregated to the daily level while share turnover (*turn*) is defined previously. On non-event days the average stock in our sample has market cap of $22.4 billion and a price of $46.88. The average return volatility on these days is 1.49 percent while the average price volatility is 2.04 percent. Nearly 2.3 million shares are traded on the average non-event day which equates to approximately 0.6 percent of shares outstanding. Interestingly, down days and up days appear to occur in smaller cap stocks as the size reported in Panels B and C ($22.1 million and 22.16 million, respectively) is less than the reported market cap in Panel A. Volatility and trading activity is also higher on these event days, which is somewhat expected.

III. Empirical Results

In this section we describe our empirical tests. We first examine and compare short selling on event days and non-event days. Second, we use an event study method to determine whether short sellers anticipate extreme market movements. Third, we compare the ability of short sellers to predict negative returns on event days.

III.a Short Selling during Extreme Market Movements

Table 3 presents preliminary tests of short selling on event days. We report means of daily returns, daily short volume, and the daily short turnover.[7] The means are equally weighted by NYSE component stocks that are part of the S&P 500. Panel A reports the returns and short activity for days where the S&P 500 returns are within 2 standard deviations of the mean during the sample time period. Panels B and C show the returns and short activity for down days and the difference in means between Panels A and B. In Panel C, we observe significantly higher short volume and short turnover on down days. Panel D reports the results for up days and Panel E reports the difference in means between non-event days and up days. By construction, returns are greater on up days than on non-event days. We also show that short selling is significantly higher on up days than on non-event days.

Combined, the results in Panel E are consistent with the notion that short sellers are contrarian in contemporaneous returns (Diether, Lee, and Werner, 2009). However, the findings in Panel C suggest that short sellers trade in the direction the market moves.

Table 2 revealed that trading activity and volatility increase on event days. Both of these variables are found to affect the amount of short selling at the daily level (Diether, Lee, and Werner, 2009). Further, Boehmer, Jones, and Zhang (2008) document that short selling is related to firm size. Therefore, we recognize the need to control for factors that influence the level of short selling in a multivariate framework. We estimate the following equation using pooled data:

---

[7] This short-selling measure is similar to the measures used in Asquith, Pathak, and Ritter (2005) and Christophe, Ferri, and Hseih (2008). Further, short turnover is similar to the measure of short interest used in several studies. Short interest is usually defined as the uncovered amount of short volume on a particular day (usually called the settlement day) scaled by the number of shares outstanding.

$$Sh\_turn_{i,t} = \beta_0 + \beta_1 size_{i,t} + \beta_2 turn_{i,t} + \beta_3 p\_volt_{i,t} + \beta_4 r\_volt_{,t} + \beta_5 sh\_turn_{i,t} + \beta_6 ret_{i,t} + \beta_7 ret_{i,t-5,t-1} + \beta_8 DN_t + \beta_9 UP_t + \varepsilon_{i,t} \quad (1)$$

The dependent variable is the daily short turnover. We include as independent variables, market capitalization in billions (*size*), share turnover (*turn*), price volatility (*p_volt*), return volatility (*r_volt*), a lagged dependent variable ($sh\_turn_{t-5,t-1}$) to control for serial correlation in daily short activity, daily returns (*ret*), and the cumulative return from day *t-5* to day *t-1* ($ret_{t-5,t-1}$). Others find that similar variables influence the level of short selling in a particular stock.[8] In order to test whether the level of short selling is abnormal on event days, we include two dummy variables: *DN* is equal to unity if the S&P 500 experiences a two-standard deviation decrease on day *t*. *UP* is equal to one on up days.

A Hausman test shows evidence of fixed effects by stock and day, so we estimate equation (1) using a fixed effects regression.[9] Table 3 reports the regression results for both dependent variable specifications. Consistent with previous research, we find that short activity is positively related to price volatility and negatively related to market capitalization and return volatility. We also document that volume turnover is positively related to short turnover. Further, we show that short sellers are contrarian in contemporaneous and past returns as short activity is positively related to daily returns and lagged cumulative returns; a result consistent with Diether, Lee, and Werner (2009). The estimates for the dummy variables in columns (2) and (3) show that short activity is abnormally high on down days (estimate = 0.0002, *p*-value = 0.000) and abnormally low on up days (estimate = -0.0001, p-value = -0.0001). The latter result

[8] For example, see Diether, Lee, and Werner, 2009; and Boehmer, Jones, and Zhang, 2008

[9] We also estimate equation (1) using tobit model to control for the censoring of the dependent variable and pooled OLS controlling for conditional heteroskedasticity (White, 1980) and clustering of errors. The results are qualitatively similar.

differs from our univariate findings in Table 3. Initially, we found that short volume and short turnover where significantly higher on extreme up days (Table 3, Panels D and E). Here, we observe that, after controlling for other factors that influence the level of short-selling activity, short selling is abnormally low on extreme up days. To ascertain the economic magnitude of these results, we compare the dummy variable estimates to non-event day short turnover reported in Table 3 Panel A. After controlling for independent factors, we find, on average, that short selling increases 15.4 percent (0.0002 divided by 0.0013) on extreme down days and decreases 7.7 percent on extreme up days (-0.0001 divided by 0.0013).

These findings indicate that while short sellers are generally contrarian in contemporaneous returns, they tend to trade in the direction the market moves on days with extreme price changes. In unreported results, we estimate equation (1) and include an interaction estimate where we multipy the dummy variables and the contemporaneous returns. Results reveal that on extreme up days, short sellers become less contrarian as the interaction estimate is negative (estimate = -0.0032, p-value = 0.000). On extreme down days, the interaction estimate is insignificant (p-value = 0.522). Combined with our findings in Table 3, these results are consistent with the notion that short sellers, who generally add to the informational efficiency in stock prices by targeting stocks that are temporarily overvalued, are more prone to follow the crowd during periods of extreme price movements.

III.b Short Selling Surrounding Extreme Market Movements

In this subsection, we examine short-selling activity around event days using standard event study methods. We report short turnover during a 21-day event window where the event day is defined as an extreme down day and an extreme up day. To determine statistical significance, we calculate two additional measures of short turnover. The abnormal short turnover (*ab_sh_turn*) is the short turnover for stock *i* on day *t* less a benchmark, which defined as the average short turnover during the period [*t-30* to *t-11*].[10] If short selling is abnormally high, then abnormal short turnover will be significantly greater than zero. For robustness, we follow Lakonishok and Vermaelen (1986) and Koski and Scruggs (1998) and standardize short turnover (*stand_sh_turn*) by calculating the difference between short turnover for stock *i* on day *t* and the average short turnover for stock *i* during the entire sample time period. We then divide this difference by the standard deviation of short turnover for stock *i* during the time period. This type of standardization procedure allows *stand_sh_turn* for each stock on each day to be similarly distributed with a zero mean and a unit variance.

The results from the event study are reported in Table 5. The results for extreme down days are reported in columns (1) through (3) while the results for up days are presented in columns (4) through (6). In column (1), we find that pre-event short selling appears relatively normal with only slight variation. On the event day we observe a surge in short turnover that continues during the post-event period. In columns (2) and (3), we find that short turnover is abnormally low prior to the event day and significantly increases and remains abnormally high throughout the rest of the event window. Observing abnormally low short selling prior to the extreme down days indicates that short sellers do not anticipate the market decrease. The results in columns (2) and (3) appear to suggest that short sellers are caught off guard by the extreme price decline.

On the contrary we find some evidence of abnormal short selling prior to extreme up days. If short sellers anticipated such an event, we expect that short selling would be abnormally

[10] We use several different benchmarks such as [*t-40* to *t-21*] and [*t-20* to *t-11*]. Results using these other benchmarks are qualitatively similar.

low prior to the event. The non-negative abnormal short turnover prior to the up day indicates that short sellers do not anticipate extreme up days either. These univariate results also show that short selling is significantly high on the event day, which is consistent with our earlier univariate results in Table 3. However, when controlling for other factors that influence short selling, Table 4 shows that short selling is abnormally low on extreme up days. Therefore, results in Table 5 must be interpreted with caution.

We attempt to control for these other factors in a limited dependent variable framework by estimate the following equations using pooled data.

$$DownDay_{i,t} = \upsilon_0 + \upsilon_1 size_{i,t} + \upsilon_2 price_{i,t} + \upsilon_3 turn_{i,t} + \upsilon_4 turn_{i,t-5,t-1} + \upsilon_5 r\_volt_{i,t} + \upsilon_6 r\_volt_{i,t-5,t-1} + \upsilon_7 p\_volt_{i,t} + \upsilon_8 p\_volt_{i,t-5,t-1} + \upsilon_9 sh\_turn_{i,t} + \upsilon_{10} sh\_turn_{i,t-5,t-1} + \varepsilon_{i,t} \quad (2)$$

$$UpDay_{i,t} = \upsilon_0 + \upsilon_1 size_{i,t} + \upsilon_2 price_{i,t} + \upsilon_3 turn_{i,t} + \upsilon_4 turn_{i,t-5,t-1} + \upsilon_5 r\_volt_{i,t} + \upsilon_6 r\_volt_{i,t-5,t-1} + \upsilon_7 p\_volt_{i,t} + \upsilon_8 p\_volt_{i,t-5,t-1} + \upsilon_9 sh\_turn_{i,t} + \upsilon_{10} sh\_turn_{i,t-5,t-1} + \varepsilon_{i,t} \quad (3)$$

The dependent variable is equal to unity if day *t* is a down day in equation (2) or an up day in equation (3). The independent variables include contemporaneous and lagged stock characteristics that have been defined previously. If the estimate for lagged short turnover is significantly positive in equation (2), then short sellers are able to anticipate extreme price declines, this after controlling for other factors that likely affect short selling. Likewise, if the estimate for lagged short turnover is negative in equation (3) then short sellers are able to anticipate extreme price increases.

Results from estimating equations (2) and (3) are reported in Table 6. Columns (1) and (2) contain the estimates from equation (2) while columns (3) and (4) show that results from equation (3). In column (2), we show that the estimates for the lagged return and price volatility are positive and significant indicating that volatility predicts the occurrence of an extreme down day. Consistent with the findings in Tables 2 and 3, we find that contemporaneous short turnover is positive indicating that on down days, short turnover is abnormally high. Further, we find consistency with the results in Table 5 as the estimate for lagged short turnover is negative in both columns (1) and (2).

Next, we discuss the results from estimating equation (3). We find that return volatility predicts extreme up days as the estimate for lagged return volatility is positive. However, the estimate for lagged price volatility is negative and significant. The contemporaneous short turnover is negative and significant in columns (3) and (4) which is consistent with our multivariate results in Table 4 and suggests that short turnover is abnormally low on extreme up days. Again, this findings is consistent with the idea that short sellers forego their usual contrarian behavior and tend to trade in the direction the market moves. Further, we show that the estimates for the lagged short turnover are positive and significant, which is consistent with the univariate results in Table 5.

To summarize, we find that short selling is abnormally low prior to extreme down days and abnormally high prior to extreme up days. These results run counter to the argument that short sellers anticipate extreme price movements. If anything, our results suggest that short sellers are caught off guard by these dramatic market changes and react by following the crowd.

III.c Return Predictability of Short Sales in Volatile Markets

Thus far, we show that in spite of the general contrarian behavior of short sellers, abnormally high levels of short activity occur on days when the market substantially decreases and abnormally low levels of short activity occur on days when market moves upward. In this section we attempt to determine whether short sellers are better off following the crowd or remaining contrarian in contemporaneous returns on event days by examining the negative relation between current short selling and future returns at the daily level. Specifically, we test whether short sellers are able to predict negative returns after the event day. Several studies document that short selling at the daily level contains information about future stock price declines (Diether, Lee, and Werner, 2009; Boehmer, Jones, and Zhang, 2008; and Boehmer and Wu, 2008). The objective our tests is to determine whether short sellers that trade in the direction that markets move are less concerned with the price of stocks in the next few days and instead are attempting to capitalize on the price decrease on down days. Under this assumption, we expect that short sellers on down days are not going to be able to predict negative returns in the days after the event day. Similarly, short sellers on up days are likely more concerned with the price movements over the next few days instead of the event-day price movements. We anticipate that short sellers on up days will be able to predict negative returns after the event day.

Following Diether, Lee, and Werner (2009) and Christophe, Ferri, and Angel (2004), we regress post-event day cumulative returns on several independent variables including our different measures of short selling. The following equation is estimated after controlling for fixed effects by stock and by day.

$$Ret_{i,t+1,t+s} = \beta_0 + \beta_1 size_{i,t} + \beta_2 turn_{i,t} + \beta_3 r\_volt_{i,t} + \beta_4 p\_volt_{i,t} + \beta_5 ret_{i,t} + \beta_6 sh\_turn_{i,t} + \varepsilon_{i,t+1,t+s} \tag{4}$$

The dependent variable is the cumulative return from day $t+1$ to $t+s$, where s = {1,2, and 3}. The regressors are defined similar to those in equation (1).

Table 7 reports the results of estimating equation (4). Consistent with the previous research, we find that size is negatively related to future returns (Banz, 1981; Fama and French, 1992; and Fama and French, 1996). When examining the return predictability of short selling at the daily level, we find evidence of our expectation as the estimate for β_6, the coefficient for short turnover, is not significantly different from zero on down days and negative and significant on up days. We compare the magnitude of the estimates on up days and down days and the F-test reveals that the estimates are more negative (significant at the 5 percent level) on up days than on down days. These results indicate that following the crowd on days with extreme market movements is less profitable than remaining contrarian on these days. Dennis and Strickland (2002) argue that institutional investors, who are generally considered informed traders, tend to blink in volatile markets by trading in the direction that markets move. The case of short sellers is particularly appealing because short sellers are shown to be contrarian in contemporaneous returns. Not only do we find that that short sellers become less sophisticated by following the crowd, but here, we also show that doing so decreases their ability to predict negative returns.

IV. Summary and Conclusion

While Diether, Lee, and Werner (2009) find that short sellers are contrarian in contemporaneous returns, we investigate whether the general contrarian behavior of short sellers changes in volatile markets. We examine the short selling of S&P 500 stocks on days when the index moves two standard deviations away from its mean. We denote days when the index decreases as extreme down days and days when the index increases as extreme up days.

First, we document abnormally high levels of short selling on extreme down days and unusually low levels of short selling on up days. These combined results suggest that while short sellers are typically contrarian, some short sellers appear to trade in the direction the market moves indicating that short sellers become less sophisticated on these event days (Dennis and Strickland, 2002).

Christophe, Ferri, and Angel (2004) show that pre-earnings announcement short selling relates inversely with post-earnings announcement returns and argue that short sellers are able to anticipate negative news events, such as unfavorable earnings announcements. Under this assertion, we test whether short sellers are able to anticipate these days with extreme market movements. Contrary to this argument, we find abnormally low short selling prior to extreme down days and abnormally high short selling prior to extreme up days. Our results suggest that, if anything, short sellers are caught off guard during extreme market movements and respond by following the crowd.

Observing this type of positive feedback trading by short sellers on event days is not tantamount to findings that short sellers are unsophisticated. There still exists the possibility that short selling in the direction the market moves provides unusually high profits. To explore this possibility, we examine the common negative relation between current short selling and future returns at the daily level. Interestingly, we do not find evidence that short selling on down days is able to predict negative next-day returns. However, the opposite is true on up days. Statistical comparisons reveal that the return predictability of short sellers is greater on up days than on down days.

The implications of our study suggest that while short sellers are generally contrarian, some tend to trade in the direction the market moves on extremely volatile days. Those short sellers who follow the crowd are less able to predict negative returns than those who remain contrarian in contemporaneous returns.

References

Aitken, M.; A. Frino; M. McCorry; and P. Swan, 1998, "Short Sales are Almost Instantaneously Bad News: Evidence from the Australian Stock Exchange." *Journal of Finance* 53, 2205-2223.

Asquith, P., P.A. Pathak, and J.R. Ritter, 2005, Short interest, institutional ownership, and stock returns, *Journal of Financial Economics* 78, 243-277.

Banz, R.W., 1981, "The Relationship Between Return and Market Value of Common Stocks." *Journal of Financial Economics* 9, 3-18.

Boehmer E., C.M. Jones, and X. Zhang, 2008, "Which Shorts are Informed?" *Journal of Finance* 63, 491-527.

Boehmer, E. and J. Wu, 2008, "Short Selling and the Informational Efficiency of Prices." Working paper, University of Georgia.

Chakravarty, S., 2001, "Stealth Trading: Which Trader's Trades Move Prices?" *Journal of Financial Economics*, 61, 289-307.

Chakravarty, S. and J.J. McConnell, 1997, "An Analysis of Prices, Bid/Ask Spreads and Bid/Ask Depths Surrounding Ivan Boesky's Illegal Trading in Carnation's Stock." *Financial Management*, 26, 18-34.

Christophe, S.; M. Ferri; and J. Angel, 2004, "Short selling Prior to Earnings Announcements." *Journal of Finance* 59, 1845-1875.

Christophe, S.; M. Ferri; and J. Hsieh, 2008, Informed Trading Before Analyst Downgrades: Evidence from Short Sellers. Forthcoming, *Journal of Financial Economics*.

Clark, P.K., 1973, "A Subordinate Stochastic Process Model with Finite Variance for Speculative Prices." *Econometrica* 41, 135-155.

Cornell, B. and E. Sirri, 1992, "The Reaction of Investors and Stock Prices to Insider Trading." *Journal of Finance* 47, 1031-1059.

Delong, J.B. A. Shleifer, L.H. Summers, and R.J. Waldmann, 1990, "Positive Feedback Investment Strategies and Destabilizing Rational Speculation." *Journal of Finance* 45, 379-395.

Dennis, P.J. and D. Strickland, 2002, "Who Blinks in Volatile Markets, Individuals or Institutions?" *Journal of Finance* 57, 1923-1949.

Desai, H., K. Ramesh, S. Thiagarajan, and B. Balachandran, (2002). "An Investigation of the Information Role of Short Interest in the NASDAQ Market." *Journal of Finance* 52, 2263-2287.

Diamond, D. and R. Verrecchia, 1987, "Constraints on Short Selling and Asset Price Adjustment to Private Information." *Journal of Financial Economics* 18, 277-312.

Diether, K.B., K. Lee, and I.M. Werner, 2009, Short-Selling Strategies and Return Predictability, *Review of Financial Studies* 22, 575-607.

Fama, E. and K. French, 1992, "The Cross-Section of Expected Stock Returns." *Journal of Finance*, 47, 427-465.

Fama, E. and K. French, 1996, "Multifactor Explanations of Asset Pricing Anomalies." *Journal of Finance* 51, 55-84.

Froot, K.A, D.S. Scharfstein, and J.C. Stein, 1992, "Herd on the Street: Informational Inefficiencies in a Market with Short-Term Speculation." *Journal of Finance* 47, 1461-1484.

Koski, J.L. and J.T. Scruggs, 1998. Who Trades Around the Ex-Dividend Day? Evidence from NYSE Audit File Data. *Financial Management* 27, 58-72.

Lakonishok, J. and T. Vermaelen, 1986, Tax-Induced Trading Around Ex-dividend Days. *Journal of Financial Economics* 3, 287-319.

Lamoureux, C.G., and W.D. Lastrapes, 1990, "Heteroskedasticity in Stock Return Data: Volume vs. GARCH Effects." *Journal of Finance* 45, 487-498.

Lipson, M.L., and A. Puckett, 2007, Institutional Trading During Extreme Market Movements." Working paper, University of Virginia.

Lo, A. W. and A.C. MacKinlay, 1990, "When are Contrarian Profits Due to Stock Market Overreaction?" *Review of Financial Studies* 3, 175-206.

Meulbroek, L., 1992, "An Empirical Analysis of Illegal Insider Trading." *Journal of Finance*, 47, 1661-1699.

Nofsinger, J.R., and R.W. Sias, 1999, "Herding and Feedback Trading by Institutional and Individual Investors." *Journal of Finance* 54, 2263-2295.

Ross, S.A., 1989, "Information and Volatility: The No-Arbitrage Martingale Approach to Timing and Resolution Irrelevancy." *Journal of Finance* 44, 1-17.

Senchak, A. J., and L.T. Starks, 1993, "Short-sale Restrictions and Market Reaction to Short-Interest Announcements." *Journal of Financial and Quantitative Analysis* 28, 177-194.

White, H., 1980, "A Heteroscedasticity-Consistent Covariance Matrix Estimator and a Direct Test for Heteroscedasticity." *Econometrica*, 48, 817-838.

Table 1

S&P 500 Returns

The table reports S&P 500 close-to-close returns days when the S&P moves two standard deviations above (Up-Days) and below (Down-Days) from its mean. The sample time period is from January 2005 to December 2006. The results for the close-to-close returns and open-to-close returns are similar.

Down Days		Up Days	
Date	Close to Close Returns	Date	Close to Close Returns
2/22/2005	-0.01451	3/30/2005	0.01377
4/15/2005	-0.01672	4/21/2005	0.01974
4/20/2005	-0.01326	10/19/2005	0.01496
10/5/2005	-0.01489	10/24/2005	0.01678
10/20/2005	-0.01502	10/28/2005	0.01655
1/20/2006	-0.01833	1/3/2006	0.01643
5/11/2006	-0.01280	4/18/2006	0.01708
5/17/2006	-0.01684	6/15/2006	0.02124
5/30/2006	-0.01585	6/29/2006	0.02157
6/5/2006	-0.01780	7/19/2006	0.01856
7/13/2006	-0.01297	7/24/2006	0.01663
11/27/2006	-0.01356	8/15/2006	0.01369

Table 2
Summary Statistics
The table presents characteristics of the sample on non-event days (Panel A), extreme down days (Panel B), and extreme up days (Panel C). We report the average *size* (the market capitalization in dollars), the daily ending *price*, *r_volt* (return volatility), *p_volt* (price volatility), *volume*, and *turn* (share turnover). *R_volt* is the standard deviation of daily returns from day *t-10* to *t*, where day *t* is the current trading day. *P_volt* is the difference between the daily high price and the daily low price divided by the daily high price. *Turn* is the daily volume scaled by the shares outstanding.

	Size	*Price*	*R_volt*	*P_volt*	*Volume*	*Turn*
Panel A. Non-Event Days						
Mean	$22,439,625,620	$46.88	0.0149	0.0204	2,266,260.96	0.0062
Std. Deviation	$38,855,028,150	$27.49	0.0052	0.0070	2,642,615.34	0.0050
Panel B. Down Days						
Mean	$22,089,849,640	$46.19	0.0149	0.0250	2,567,745.08	0.0069
Std. Deviation	$38,248,964,890	$26.74	0.0054	0.0087	3,245,191.48	0.0056
Panel C. Up Days						
Mean	$22,158,246,460	$46.99	0.0163	0.0257	2,713,406.21	0.0072
Std. Deviation	$38,270,283,280	$27.37	0.0061	0.0089	3,094,563.98	0.0052

Table 3

Raw Returns and Short-Selling Activity on Down Days and Up Days

The table reports the mean returns, equally-weighted by NYSE-listed stocks that are part of the S&P 500. We exclude NYSE stocks that are listed on the S&P 500 if the stocks do not trade every day of the sample time period, which consists of the calendar years 2005 and 2006. The table reports the mean raw return from CRSP; the average daily short volume; the average daily short turnover, which is measured as the daily number of shares that are shorted divided by the number of shares outstanding; the average daily short ratio, which is calculated by dividing the daily short volume by the daily total trade volume. Panel A shows the returns and short-selling measures for days that are not considered down days or up days, non-event days. Panel B reports the returns and short activity for days that the S&P 500 are two standard deviations below the mean. Panel C gives the difference between returns and short activity for non-event and down days. Panels D and E report the variables for days that the S&P 500 are two standard deviations above the mean and the difference in the variables between non-event days and up days. P-values obtained from t-tests in the differences are reported in parentheses.

Panel A. Non-event Days (Close to Close Returns)			
	Returns	*Short Volume*	*Short Turnover*
Mean	0.0001	417,992.32	0.0013
St. Deviation	0.0016	418,708.62	0.0014
Panel B. Down Days (Close to Close Returns)			
Mean	-0.0154	472,619.44	0.0015
St. Deviation	0.0062	465,346.17	0.0015
Panel C. Difference (Non-event days – Down days)			
Difference	0.0155**	-54,627.12*	-0.0002*
p-value	(0.000)	(0.034)	(0.023)
Panel D. Up Days (Close to Close Returns)			
Mean	0.0175	20,282.57	0.0016
St. Deviation	0.0083	537,821.85	0.0016
Panel E. Difference (Non-event days – Up days)			
Difference	-0.0174**	-102,290.25**	-0.0003**
p-value	(0.000)	(0.002)	(0.004)

*,** Statistically significant at the 0.01, 0.05 levels

Table 4
Short Selling Regression Results
The table reports the results from estimating the following pooled equation:

$$Sh\_turn_{i,t} = \beta_0 + \beta_1 size_{i,t} + \beta_2 turn_{i,t} + \beta_3 p\_volt_{i,t} + \beta_4 r\_volt_{,t} + \beta_5 sh\_turn_{i,t} + \beta_6 ret_{i,t} + \beta_7 ret_{i,t\text{-}5,t\text{-}1} + \beta_8 DN_t + \beta_9 UP_t + \varepsilon_{i,t}$$

The dependent variable is the daily short turnover (*sh_turn*). The independent variables include *size* (the daily market capitalization in 000,000,000s), turnover, (*turn* is the number of shares that are traded divided by the number of outstanding shares), price volatility (*p_volt* is the difference between the daily high price and the daily low price divided by the daily high price), return volatility (*r_volt*), a lagged dependent variable ($sh\_turn_{t\text{-}5,t\text{-}1}$), the contemporaneous returns (r*et*), and the lagged cumulative return from day t-5 to day t-1 ($ret_{t\text{-}5,t\text{-}1}$). *DN* (*UP*) is a dummy variable that is equal to unity if day t is a day when the S&P 500 is two standard deviations below (above) it mean. A Hausman test reveals preference for fixed effects , therefore we report the estimates after controlling for stock fixed effects and day fixed effects (in columns 1 and 4). We also use a pooled tobit model to control for the censoring of the dependent variables and the results are qualitatively similar. P-values are reported in parentheses.

	[1]	[2]	[3]
intercept	-0.0003**	-0.0001*	-0.0001*
	(0.002)	(0.025)	(0.033)
$size_t$	-0.0005	-0.0047**	-0.0048**
	(0.510)	(0.000)	(0.000)
$turn_t$	0.1261**	0.1263**	0.1262**
	(0.000)	(0.000)	(0.000)
p_volt_t	0.0175**	0.0166**	0.0172**
	(0.000)	(0.000)	(0.000)
r_volt_t	-0.0058**	-0.0054**	-0.0056**
	(0.000)	(0.000)	(0.000)
$sh\_turn_{t\text{-}5,t\text{-}1}$	0.2799**	0.2806**	0.2806**
	(0.000)	(0.000)	(0.000)
ret_t	0.0109**	0.0093**	0.0092**
	(0.000)	(0.000)	(0.000)
$ret_{t\text{-}5,t\text{-}1}$	0.0023**	0.0021**	0.0021**
	(0.000)	(0.000)	(0.000)
DN_t		0.0002**	
		(0.000)	
UP_t			-0.0001**
			(0.000)
R-squared	0.7718	0.7611	0.7608
Stock FE	Yes	Yes	Yes
Day FE	Yes	No	No

*,** Statistically significant at the 0.01, 0.05 levels

Table 5

Event Study around Extreme Market Movements

The table reports an event study examining short selling around extreme down days and extreme up days. Short turnover (*sh_turn*) is reported in columns (1) and (4) around down days and up days, respectively. To test for statistical significance, we calculate the abnormal short turnover (*ab_sh_turn*), which is the difference between *sh_turn* on day *t* and a non-event benchmark [*t-30* to *t-11*]. For robustness, we also report the standardized short turnover (*stand_sh_turn*), which is the difference between sh_turn for stock *i* on day *t* and the mean *sh_turn* for stock *i* divided by the standard deviation of *sh_turn* for stock *i*. The standardization procedure allows the short turnover measure to be similarly distributed with the zero mean and a unit variance.

	Down Days			*Up Days*		
	Sh_turn [1]	*Ab_sh_turn* [2]	*Stand_sh_turn* [3]	*Sh_turn* [4]	*Ab_sh_turn* [5]	*Stand_sh_turn* [6]
t-10	0.0014	-0.00003	-0.0520**	0.0013	-0.00015**	-0.1256**
t-9	0.0014	0.00003	0.0481**	0.0013	-0.00015**	-0.1108**
t-8	0.0013	-0.00006*	-0.0486**	0.0013	-0.00018**	-0.1587**
t-7	0.0013	-0.00008*	-0.0911**	0.0014	-0.00004	0.0153
t-6	0.0014	-0.00002	-0.0212	0.0014	-0.00009**	-0.0462**
t-5	0.0013	-0.00008**	-0.0965**	0.0015	-0.00006*	-0.0082
t-4	0.0014	-0.00002	-0.0397**	0.0015	0.00008*	0.1278**
t-3	0.0014	-0.00000	-0.0261*	0.0015	0.00002	0.0727**
t-2	0.0013	-0.00005*	-0.0521**	0.0016	0.00008	0.0471**
t-1	0.0014	-0.00002	-0.0240	0.0017	0.00019*	0.1677**
Event Day	0.0016	0.00020**	0.1888**	0.0017	0.00020**	0.3102**
t+1	0.0015	0.00015**	0.1451**	0.0016	0.00010**	0.2135**
t+2	0.0015	0.00013**	0.1002**	0.0015	0.00001	0.1117**
t+3	0.0016	0.00017**	0.1256**	0.0016	0.00011**	0.1806**
t+4	0.0016	0.00018**	0.1539**	0.0015	0.00005	0.1435**
t+5	0.0016	0.00019**	0.1865**	0.0015	0.00007	0.1133**
t+6	0.0016	0.00018**	0.1841**	0.0015	0.0003	0.0875**
t+7	0.0015	0.00016**	0.1585**	0.0013	-0.00016**	-0.1057**
t+8	0.0015	0.00012**	0.1289**	0.0015	0.00001	0.0953**
t+9	0.0015	0.00014**	0.1427**	0.0015	0.00004	0.0929**
t+10	0.0015	0.00014**	0.1594**	0.0015	0.00000	0.0296*

*,** Statistically significant at the 0.01, 0.05 levels

Table 6
Logistic Regression Results
The table reports the logistic regression results from the estimating the following equation.

$$DownDay_{i,t} = \upsilon_0 + \upsilon_1 size_{i,t} + \upsilon_2 price_{i,t} + \upsilon_3 turn_{i,t} + \upsilon_4 turn_{i,t-5,t-1} + \upsilon_5 r\_volt_{i,t} + \upsilon_6 r\_volt_{i,t-5,t-1} + \upsilon_7 p\_volt_{i,t} + \upsilon_8 p\_volt_{i,t-5,t-1} + \upsilon_9 sh\_turn_{i,t} + \upsilon_{10} sh\_turn_{i,t-5,t-1} + \varepsilon_{i,t}$$

$$UpDay_{i,t} = \upsilon_0 + \upsilon_1 size_{i,t} + \upsilon_2 price_{i,t} + \upsilon_3 turn_{i,t} + \upsilon_4 turn_{i,t-5,t-1} + \upsilon_5 r\_volt_{i,t} + \upsilon_6 r\_volt_{i,t-5,t-1} + \upsilon_7 p\_volt_{i,t} + \upsilon_8 p\_volt_{i,t-5,t-1} + \upsilon_9 sh\_turn_{i,t} + \upsilon_{10} sh\_turn_{i,t-5,t-1} + \varepsilon_{i,t}$$

The dependent variable is the logs odd ratio that day t is a day with extreme market movement. Columns (1) and (2) report the results with the dependent variable specified as a down day while columns (3) and (4) present our findings for up days. The independent variables include the contemporaneous size ($size_t$), price ($price_t$), turnover ($turn_t$), return volatility (r_volt_t), price volatility (p_volt_t), and short turnover (sh_turn_t). We also include lagged variables to determine whether these factors predict the occurrence on a day with extreme market movements. *P*-values are reported in parentheses.

	$Down_t$		Up_t	
	[1]	[2]	[3]	[4]
intercept	3.3279**	3.0962**	3.4916**	3.3567**
	(0.000)	(0.000)	(0.000)	(0.000)
$size_t$	-0.3080	-0.0245	-0.6686	-0.4284
	(0.416)	(0.949)	(0.074)	(0.258)
$price_t$	0.0001	0.0004	0.0000	-0.0001
	(0.761)	(0.406)	(0.997)	(0.899)
$turn_t$	3.0550	2.8182	2.7546	6.7523
	(0.054)	(0.139)	(0.070)	(0.001)
$turn_{t-5,t-1}$		2.4780		-2.7595
		(0.375)		(0.206)
r_volt_t	31.7248**	3.2537	5.8916**	-35.7951**
	(0.000)	(0.394)	(0.003)	(0.000)
$r\_volt_{t-5,t-1}$		13.2386**		62.7761**
		(0.001)		(0.000)
p_volt_t	-28.7657**	-30.0316**	-23.1332**	-20.2843**
	(0.000)	(0.000)	(0.000)	(0.000)
$p\_volt_{t-5,t-1}$		22.8500**		-9.9583**
		(0.000)		(0.000)
sh_turn_t	0.4911**	0.5148**	-1.0148**	-0.9695**
	(0.008)	(0.005)	(0.000)	(0.000)
$sh\_turn_{t-5,t-1}$	-1.3309**	-1.4326**	0.7232**	0.5893*
	(0.000)	(0.000)	(0.003)	(0.013)
Wald Stat	702.2169**	848.9669**	641.7937	894.8138
	(0.000)	(0.000)	(0.000)	(0.000)
Stock FE	Yes	Yes	Yes	Yes

*,** Statistically significant at the 0.01, 0.05 levels

Table 7
Next Day Returns Regressions
The table reports the results of estimating the following equation on down days and up days.

$$Ret_{i,t+1,t+s} = \beta_0 + \beta_1 size_{i,t} + \beta_2 turn_{i,t} + \beta_3 r\_volt_{i,t} + \beta_4 p\_volt_{i,t} + \beta_5 ret_{i,t} + \beta_6 sh\_turn_{i,t} + \varepsilon_{i,t+1,t+s}$$

The dependent variables are the cumulative returns from day $t+1$ to day $t+s$, where $s = \{0,1,2\}$. The independent variables are similarly defined as before. The short selling measures include the contemporaneous daily short turnover. We control for stock and day fixed effects and test whether the estimated coefficients, β_6, for down days are equal to the estimates when using up days. *P*-values are reported in parentheses.

Panel A. Short Turnover

	Ret_{t+1}		$Ret_{t+1,t+2}$		$Ret_{t+1,t+3}$	
	Down Days	*Up Days*	*Down Days*	*Up Days*	*Down Days*	*Up Days*
Intercept	0.0045	0.0134**	0.0248**	0.0212**	0.0301**	0.0223**
	(0.297)	(0.009)	(0.000)	(0.004)	(0.000)	(0.009)
$size_t$	-0.2001**	-0.2394**	-0.4572**	-0.4500**	-0.6497**	-0.4742**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$turn_t$	-0.0509	0.1004	-0.0244	0.0944	-0.0968	0.1837
	(0.493)	(0.149)	(0.831)	(0.342)	(0.506)	(0.110)
r_volt_t	0.0745	-0.0352	-0.0596	-0.0819	0.0460	-0.1603*
	(0.054)	(0.428)	(0.318)	(0.196)	(0.544)	(0.029)
p_volt_t	-0.0655*	-0.0589*	-0.1305**	-0.0161	-0.2505**	-0.0061
	(0.012)	(0.032)	(0.001)	(0.680)	(0.000)	(0.893)
Ret_t	-0.0001	0.0242	-0.0659*	-0.0035	-0.0877**	-0.0567
	(0.994)	(0.169)	(0.012)	(0.889)	(0.009)	(0.052)
Sh_turn_t	0.1657	-0.4006	0.2431	-0.6592*	0.2467	-0.8863*
	(0.271)	(0.067)	(0.563)	(0.042)	(0.644)	(0.022)
$F\text{-}stat_{\beta 6^{dn} = \beta 6^{up}}$	4.45*		5.55*		6.52*	
p-value	(0.035)		(0.018)		(0.011)	
R-squared	0.3228	0.2417	0.2956	0.2086	0.3010	0.2234
Stock FE	Yes	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes	Yes

*,** Statistically significant at the 0.01, 0.05 levels