Are short sellers manipulating the market?

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Abstract

We examine the informativeness of short sellers by directly measuring the abnormal returns earned on individual short sales on the New York Stock Exchange. We find that short sellers correctly predict permanent negative future returns and improve market efficiency by trading against instances of overpricing. Their informational advantage is greater in small stocks, stocks with low book-to-market ratios and stocks with low analyst coverage; but smaller in the 2008 bear market than the 2006 bull market. Short sellers are less likely than non-short sellers to be associated with large negative return reversals indicative of predatory trading or bear raid manipulation. However, our results indicate that some naked short sellers may be involved in manipulation. Our findings suggest regulators should not restrict short selling in general because such actions are likely to impair market efficiency. However, restrictions on naked short selling may enhance market integrity.

JEL classification: G14, G19

Keywords: short selling, naked short selling, informed trades, manipulation

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1. Introduction

Short sellers are at the center of an intense debate that is in progress between regulators, politicians, the media and academics. The key questions in this debate concern the role of short sellers in markets. In particular, are short sellers informed traders that improve market efficiency? Do short sellers manipulate the market by exploiting fear to drive prices below fundamental values? This study contributes theoretical and empirical evidence on these questions.

On one side of the debate, industry observers, issuers, and much of the popular media argue that short sellers employ abusive trading strategies, manipulate stock prices and amplify price declines beyond fundamentals.[1] Company directors, shareholders and the media have even gone so far as to blame short sellers for the sharp price declines or collapses of companies such as Bear Stearns, Halifax Bank of Scotland, Lehman Brothers and Merrill Lynch.[2] Several instances of legal action have been initiated by the US Securities and Exchange Commission (SEC) and investor groups alleging manipulation by short sellers.[3] Regulators, such as the SEC, have responded with a frenzy of new rules and temporary bans including weekly reporting of short positions by large investment managers, requirements to locate shares before short selling and temporary bans of all short sales in financial stocks. In explaining the reason for recently banning short selling in financial stocks the SEC stated "unbridled short selling is contributing to the recent, sudden price declines in the securities of financial institutions unrelated to true price valuation".[4]

On the other hand, most academic research argues that short sellers are relatively informed, improve market efficiency and therefore should be unrestricted.[5] This view is not unanimous and some studies argue short sellers follow manipulative or predatory trading strategies (e.g., Gerard and Nanda (1993), Brunnermeier and Pedersen (2005), Goldstein and Guembel (2008)). We contribute to this debate by

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[1] For examples see "There's a Better Way to Prevent 'Bear Raids'" by R. Pozen and Y. Bar-Yam, The Wall Street Journal, 18 November 2008, "Anatomy of the Morgan Stanley Panic" by S. Pulliam et al., The Wall Street Journal, 24 November 2008.

[2] For example, Richard Fuld Jr., the former CEO of Lehman Brothers, during hearings on the bankruptcy filing by Lehman Brothers and bailout of AIG alleged that a host of factors including naked short selling attacks followed by false rumors contributed to both the collapse of Bear Stearns and Lehman Brothers (http://oversight.house.gov/documents/20081006125839.pdf).

[3] For example, SEC v. Paul Berliner (Civil Action No. 08-CV-3859), the Overstock and NovaStar Financial lawsuits against ten of the largest US prime brokers, and the Biovail lawsuit against Stephen Cohen, Gradient and others.

[4] SEC press release 2008-211 (http://www.sec.gov/news/press/2008/2008-211.htm).

[5] See, for example, Dechow et al. (2001), Abreu and Brunnermeier (2002), Alexander and Peterson (2008), Boehmer et al. (2008), Boehmer and Wu (2009) and Diether et al. (2009).

providing direct evidence on: (i) the informativeness of short sales over a finer time scale than previously studied; and (ii) to what extent short sellers are associated with abnormal return patterns indicative of manipulation. We do this using trade-level information on all short sales conducted on the NYSE in a sample of 350 stocks during 2006 and 2008 (a bull market and a bear market).

Much of the existing literature on the informativeness of short sales analyzes returns on portfolios of stocks grouped by various measures of short selling activity. As the available information on short selling activity has become more detailed, from monthly short interest to daily short follows, the estimates of short sellers' informational advantage have become more accurate. Our main contribution to this literature is to take one further step and analyze risk-adjusted abnormal returns on individual *trades*.

The high level of granularity in our analysis is important in capturing the full extent of short sellers' abnormal returns, particularly in light of the evidence that short sellers employ rapid trading strategies to profit from short lived information or predatory trading.[6] To illustrate, consider the two scenarios: (i) a trader learns of a large pending trade package of sales, immediately short sells the stock without borrowing, waits for the trade package to depress the stock price, buys the stock at the depressed price covering his position before the end of the day so that he does not have to borrow the stock; (ii) a trader is informed about a pending company announcement of negative news, short sells the stock, waits for the announcement and covers his position the following day. While short interest and daily short flow data will not accurately capture the short seller's abnormal returns in these scenarios, returns on individual short sales will.

We examine the variation in magnitude and duration of short sellers' information in cross-section and compare their informational advantage in bull and bear markets. We also decompose short sellers' informational advantage into stock-selection and timing abilities. This enhances our understanding of the sources of short sellers' information.

[6] For example, Jones (2004) finds that "in-and-out shorting" (short selling and covering the position before the end of the day as in the first scenario) represented about 5% of total daily volume (and a much bigger, but unknown, fraction of short selling activity) in the early 1930s. It is reasonable to expect this fraction to be higher in today's markets given the increases in automation, algorithmic trading, statistical arbitrage and turnover. The argument that short sellers employ rapid trading strategies is also consistent with the finding of Diether et al (2009) that short sales represent on average 23.9% of NYSE and 31.3% of Nasdaq volume.

Despite the short selling restrictions and bans introduced in 2008, we find a very high prevalence of short selling during the 2008 bear market. During 2008, short sales on the NYSE correspond to 38% of total volume, compared to 26% during the 2006 bull market. Whereas Boehmer et al (2008) estimate the average time between opening and closing a short position in NYSE stocks during 2004 is 37 trading days, we estimate it is 16 trading days in 2006 and 2008. The average holding period of long positions is much higher but does not change substantially between 2004, 2006 and 2008. Therefore, the increase in short sellers' share of trading volume is partly due to the increased rate at which they turn over their positions.

We find that individual short sales earn a risk-adjusted average abnormal return of -0.207% and -0.152% relative to other trades over the average holding period of 16 trading days during 2006 and 2008, respectively. Annualized, short sellers' informational advantage equates to excess abnormal returns of 3.26% and 2.40% and excess information ratios of 1.18 and 0.34 during 2006 and 2008, respectively. This is a more direct estimate of the actual abnormal returns earned by short sellers than in previous studies. The substantially greater information advantage during the 2006 bear market (more than three times greater information ratio) is consistent with the evidence that short sellers trade against temporarily overpriced stocks (e.g. Dechow et al. (2001)) and overpricing is less frequent during a bear market. Short sellers' informational advantage is substantial in both stock selection and timing abnormal price changes in stocks.

Short sellers' informational advantage is greater in small stocks, stocks with low book-to-market ratios and stocks with low analyst coverage. Short sales in stocks subject to the uptick rule are more informed on average than short sales in exempt stocks because the uptick rule constrains the ability for short sellers to trade aggressively, thereby slowing the rate at which their information is incorporated into prices. We find that while short interest captures a component of short sellers' information, short sales have substantial information not contained in short interest, as evidenced by the large excess abnormal returns earned on short sales relative to other trades in stocks with low short interest.

Our second contribution is in providing evidence on the involvement of short sellers in market manipulation. We construct a simple theoretical model of manipulation by short sellers based on Allen and Gale (1992) to provide predictions about the price paths under informed and manipulative short selling. We then empirically test the extent to which short selling is associated with abnormal return patterns indicative of informed and manipulative trading, while controlling for characteristics related to the likelihood of manipulation.

We find that short sellers are primarily informed traders that correctly predict abnormal returns. They trade at heightened levels prior to large negative return continuations indicative of negative informed trading. They tend to trade against instances of overpricing that are subsequently reversed and are less likely than non-short sellers to be associated with negative return reversals indicative of predatory trading or bear raid manipulation. This evidence suggests that short sellers as a group do not have a greater involvement in possible episodes of market manipulation than non-short sellers. Analyzing subsets of short selling activity under various characteristics, we find some evidence that a particular subgroup of short sellers, naked short sellers, trade at heightened levels prior to negative return reversals. This suggests some naked short sellers may be involved in manipulating prices.

Overall, these results suggest that short sellers as a group are beneficial for markets because by trading on information, rather than with manipulative intent, they enhance the informational efficiency of prices. Therefore, regulators should not restrict short selling in general (as the SEC and a number of other regulators did during 2008) because such actions are likely to impair market efficiency. However, restrictions on naked short selling may enhance market integrity.

2. Related literature

2.1. The informativeness of short sales

There are theoretical reasons to expect short sellers are relatively informed. Diamond and Verrecchia (1987) model short sellers as rational and informed traders that take advantage of mispricings, and note that market participants do not short sell for liquidity reasons because they do not have use of the sale proceeds. Theory also predicts that prices diverge from fundamental values when short selling is constrained (e.g., Miller (1977), Duffie et al. (2002), Hong et al. (2006)). This prediction is supported by empirical evidence that finds overpricing is reduced when short selling constraints are relaxed (e.g., Danielsen and Sorescu (2001), Jones and Lamont (2002), Cohen et al. (2007)).

Evidence on the relation between short selling and future returns is not uniform, but is increasingly moving towards the consensus that short sellers predict future returns. This trend is particularly true in the more recent work that uses data on short flows.

Several empirical studies use monthly short interest data (number of shares sold short at a particular point in time each month) and find mixed results. For example, Brent et al. (1990) and Lamont and Stein (2004) find that short interest is positively related to past returns but does not predict future returns in cross-section or time-series. Asquith et al. (2005) find return predictability only in the smallest stocks and report that the effect is stronger in low institutional ownership stocks. In contrast, Desai et al. (2002) find that high short interest predicts negative returns in Nasdaq stocks, and Dechow et al. (2001) find that short sellers target firms that are overpriced according to fundamental ratios. Boehmer et al. (2009) find that although high short interest predicts future negative abnormal returns, this effect can be transient and of debatable economic significance.

Three recent studies use more granular data. Christophe et al. (2004) find that daily flows of short sales are concentrated prior to disappointing earnings announcements, which suggests short sellers have access to private information. Boehmer et al. (2008) and Diether et al. (2009) construct portfolios of stocks with high and low daily short flows. They measure the informativeness of short sales by comparing the risk adjusted performance of the portfolios over five (Diether et al., 2009) and 20 (Boehmer et al., 2008) days, after omitting a day between constructing the portfolios and measuring their returns. Boehmer et al. find that heavily shorted stocks underperform lightly shorted stocks in the following 20 days and that institutional non-program short sales are the most informative. Diether et al. (2009) find that short sellers increase their trading following positive returns and they correctly predict future negative returns.

2.2. Short selling as a tool for market manipulation

Evidence on the involvement of short sellers in market manipulation or predatory trading is scarce. Goldstein and Geumbel (2008) model short sellers that target companies with aggressive short selling to depress their share prices. The depressed prices distort companies' investment decisions, thereby harming fundamentals and allowing the short sellers to cover their positions at depressed prices. Brunnermeier and Pedersen (2005), Carlin et al. (2007) and Attari et al. (2005) model predatory trading involving sellers (including short sellers) profitably exploiting investors that have a need to exit long positions, or undercapitalized arbitrageurs. Such trading leads to negative return reversals.

Allen and Gale (1992) and Aggarwal and Wu (2006) present theoretical and empirical evidence of "pump-and-dump" manipulation. This type of manipulation involves taking a position in a stock, inflating the price with techniques such as wash trades or rumor mongering, at the same time attracting liquidity to the stock, and finally reversing the original position at a profitable price. Although the documented evidence of this strategy involves stock price inflation, i.e. profiting from long initial positions, it is not difficult to imagine a similar strategy involving initially short selling the stock and then manipulating the price downwards. Such trading strategies, commonly known as "bear raids", were widespread in the 1930s and prompted the introduction of the "uptick rule", which has governed short selling in the US since 1938. Anecdotal evidence suggests such strategies have been used recently by market manipulators exploiting the environment of fear and uncertainty to profit from attacks on vulnerable companies.

Three recent papers empirically examine short selling in relation to particular manipulative or abusive trading strategies. Shkilko et al. (2009) examine short selling during intra-day liquidity crises and find that short sellers have de-stabilizing effects on prices. Short sellers amplify intra-day price decreases that appear to be unrelated to information. Shkilko et al. (2009) suggest that their findings are consistent with short sellers occasionally engaging in predatory trading. Fotak et al. (2009) investigate the effects of naked short selling on markets using the level of fails to deliver during settlement as a proxy for naked short selling. They find that naked short sellers have positive effects on market quality, such as reducing price error and volatility. They also examine the levels of naked short selling surrounding four high profile cases of financial firms that experienced dramatic stock price declines during 2008. Fotak et al. (2009) conclude that the level of short selling prior to the price declines was too low to reasonably "cause" the price declines and naked short selling only become abnormally heavy *after* the price declines, not *before*. Blocher et al. (2009) examine whether fund managers holding short positions manipulate prices down with short selling on the last trading day of the year. They find increased levels of short selling in the last hour of the last trading day of the year for stocks that have large short interest. The short selling is accompanied by poor returns and subsequent reversals at the beginning of the year. All of these results are consistent with end of year manipulation by fund managers holding short positions.

3. Data and summary statistics

We obtain data on all short sales executed at the NYSE in a sample of 350 stocks. We obtain these data from the NYSE during two sample periods: the full years of 2006 and 2008. The year 2006, with little doubt, exemplifies a bull market; the global financial crisis had not yet impacted stock markets and the NYSE Composite index rose 17.9% in the year. In 2007 the market turned, and 2008 with little doubt exemplifies a bear market with the NYSE Composite index falling 40.9% in the year. We examine a sample of 350 stocks which are selected by sorting all NYSE listed common stocks (Center for Research in Securities Prices (CRSP) share codes 10 and 11) into deciles based on their market capitalization as at 1 July 2007 and then randomly sampling 35 stocks from each size decile. As part of Regulation SHO, in January 2005 the SEC introduced a pilot program whereby it suspended the uptick rule for a sample of stocks known as the "pilot group".[7,8] Of our 350 stocks, 103 stocks are in the pilot group. The uptick rule was subsequently abandoned in July 2007 and therefore none of our stocks are subject to the uptick rule in 2008.

We couple the short sales data with all NYSE trades and quotes during the same period, obtained from a Reuters database maintained by the Securities Industry Research Centre of Asia-Pacific.[9] We add company level variables, including book-to-market ratio, market capitalization, number of shares on issue, analyst coverage and short interest from the CRSP database, Compustat and Thomson's Datastream. We obtain daily data on the amount of fails to deliver (FTD) in each stock during our sample period from the US Securities and Exchange Commission (SEC).[10]

[7] The uptick rule, formally known as rule 10a-1, only allows short sales to be made at a price above that of the immediately preceding sale or at the last sale price if it is higher than the last different price.
[8] The pilot stocks are every third stock by market capitalization from the Russell 3000 index. See http://www.sec.gov/rules/other/34-50104.htm.
[9] We match short sales to trades by exchange, symbol, date, price, size and time. To correct for occasional small differences in the timestamps recorded in each of the databases, we allow a two second window around a given trade for the purpose of matching. For our sample, 98.2% of the short sales match to trades and we discard the remaining 1.8%.
[10] The FTD data record the number of FTDs in the Continuous Net Settlement system (consisting of new fails on the reporting day and existing fails), for each stock with an FTD balance of 10,000 shares or more. Because the number of FTDs for stocks with an FTD balance less than 10,000 shares are not recorded, our FTD measure is a lower bound for the actual number of FTDs at any point in time.

< TABLE 1 HERE >

Table 1 reports summary statistics about the number, volume and size of short sales relative to non-short sales during both of our sample periods, as well as the pooled sample. Short sales constitute approximately 26% and 38% of total dollar volume in 2006 and 2008, respectively. Short sales account for a marginally higher proportion of trades (29% and 39%), consistent with the fact that short sales in both sample periods tend to be slightly smaller than non-short sales. This equates to a mean of 530 and 1,124 shorts sales (worth \$9.1 million and \$10.1 million) per stock per day in 2006 and 2008. The proportion of short selling in our 2006 sample is consistent with Diether et al. (2009) who report that on average short selling represents 24% of share volume on the NYSE in 2005. However, the increase in short selling to 38% of dollar volume and 39% of trades in 2008 is large. We do not exclude the periods in 2008 in which the SEC banned short selling in certain stocks such as financials. Had these bans not been made, it is likely that short selling in 2008 would have accounted for an even larger proportion of total volume. In the next table we examine if this increase is due to the removal of the uptick rule in 2007.

One of the reasons why the proportion of volume made up by short selling may seem surprisingly high is that short positions are on average shorter lived than long positions. Boehmer et al. (2008) estimate that the average short position on the NYSE in 2004 lasts 37 trading days, whereas the average long position lasts 1.2 years. Their estimates are based on the relation $D_i = 1/T_i$, where D_i is the length of time between opening and closing a position in stock *i* and T_i is the turnover (shares traded / shares outstanding) in stocks *i*. Using the same approach we estimate the average short position in our sample of NYSE stocks lasts 16 trading days in both 2006 and 2008, whereas the average long position lasts 0.91 years in 2006 and 1.06 years in 2008. While the rate at which long positions are turned over increases slightly from 2004 to 2006 and 2008, the rate at which short positions are turned over more than doubles.

The mean size of short sales decreases from \$11,377 in 2006 to \$6,034 in 2008, but at the same time the size of non-short sales decrease by approximately the same amount from \$12,543 to \$5,994. The general decrease in trade size is likely to reflect the global trend of increased algorithmic trading and order splitting strategies.

In total, our sample contains 348 million trades (148 million in 2006 and 236 million in 2008) of which 133 million are short sales (42 million in 2006 and 91 million in 2008).

< TABLE 2 HERE >

Table 2 reports how average short selling activity varies with firm characteristics. We sort stock-days into quintiles based on each of the firm characteristics and then calculate the mean daily dollar volume of short sales per stock and the proportion of total dollar volume made up by short sales. The relation between average short selling activity and firm characteristics is similar in our two sample periods and therefore we only report the pooled results (except for Panel C where we report 2006 only). There is weak tendency for proportionally more short selling in small stocks and stocks with high book-to-market ratios. Boehmer et al. (2008) and Diether et al. (2009) similarly find only weak relations. The amount of FTDs and short interest, on the other hand, have larger positive correlations with the proportion of short selling.

In Panel C, which examines the variation in short selling activity by the level of analyst coverage and whether or not the stock is in the RegSHO pilot group, we only report data from 2006 because during that year pilot stocks are exempt from the uptick rule and non-pilot stocks are not. This allows us to examine the effect of the uptick rule on the level of short selling. Although the amount of short selling in pilot stocks is greater than in non-pilot stocks, the difference in short selling activity as a proportion of total trading is not large (26.5% for pilot stocks compared to 24.9% for non-pilot stocks). This result suggests that the removal of the uptick rule in 2007 may not be responsible for the increased level of short selling activity in 2008.

4. The informativeness of short sales

4.1 The magnitude of short sellers' information

We examine the informativeness of short sales relative to other trades by computing cumulative abnormal returns for every trade in our sample.[11] We calculate

[11] For comparisons of the informativeness of short sales relative to other trades, such as ordinary sales, within a stock, differencing cumulative returns for the trade categories would be sufficient. Such analysis would estimate the abnormal returns from the timing of trades but not include the abnormal

returns at one-hour intervals from the time of the trade to 20 trading days after. Abnormal return for a trade in stock *i* in the one-hour interval *t* is the difference between the midquote return (thereby minimizing microstructure effects such as bid-ask bounce) on stock *i* in interval *t*, r_{it}, and the expected return from a four factor return model (three Fama and French (1993) factors and the Carhart (1997) momentum factor):

$$AR_{it} = r_{it} - r_{ft} - \beta_{i1}(r_{mt} - r_{ft}) - \beta_{i2}SMB_t - \beta_{i3}HML_t - \beta_{i4}UMD_t \tag{1}$$

In the equation above, r_{ft}, r_{mt}, SMB_t, HML_t and UMD_t are returns on one-month T-bills, the value weighted index of all NYSE stocks, the size factor, the value factor and the momentum factor, respectively, over interval *t*, and the β_i are estimates of the sensitivities of stock *i* to each of the risk factors.[12] We calculate cumulative abnormal returns to each trade by summing the abnormal returns from the interval immediately following a trade:

$$CAR_{it} = \sum_{j=1}^{t} AR_{ij} \tag{2}$$

We use information ratio, the metric commonly used to gauge the skill of active fund managers, as an alternative measure of the informativeness of short sales. We calculate the information ratio at the trade level as:

$$IR_{it} = \frac{CAR_{it}}{\sigma_{AR_{it}}} \tag{3}$$

where $\sigma_{AR_{it}}$ is the standard deviation of the stock *i* abnormal returns from the time of a trade to t^{th} hourly interval after the trade. This is very similar to the standard definition of the information ratio because CAR_{it} is the cumulative alpha from a factor model of returns. While CAR_{it} controls for much of the cross-sectional differences in risk, it does not take into account time series differences in risk. For example, short sales may be used to hedge or speculate around earnings

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returns from the short sellers' stock selection. We use alphas from Fama and French (1993) regressions to allow comparisons of the returns for different trade types across multiple stocks controlling for the cross-sectional differences in risk.

[12] We estimate the β_i using the high frequency approach shown by Bollerslev and Zhang (2003) to provide more accurate estimates of systematic risk than conventional lower frequency approaches. Specifically, our estimation is conducted on hourly observations during the full sample period using the infrequent trading adjustments adapted by Bollerslev and Zhang (2003) from the procedures proposed by Scholes and Williams (1977). We construct the four factors using the methodology in Fama and French (1993) and Carhart (1997).

announcements and because these periods are associated with higher idiosyncratic risk, they tend to have higher average returns than other periods. The information ratio controls for these types of differences in risk.

Most of the analysis that follows is conducted at the trade level. In calculating means and estimating regressions, to give a direct measure of the abnormal returns earned on short sales, we weight trades by their dollar volume. To avoid the estimates being dominated by a small proportion of extremely high turnover stocks, we normalize the weights such that the sum of weights in each stock is equal. In robustness tests we consider alternative weights such as dollar volume without normalization and equal weights on trades and find similar results.

< FIGURE 1 HERE >

Figure 1 plots the dollar volume weighted mean CAR for short and non-short sales over the 20 days following each trade. In both 2006 and 2008 mean CAR in our sample of stocks is decreasing for short and non-short sales in the 20 days following a trade.[13] In both years the magnitude of the negative CAR is larger for short sales than for non-short sales, indicating that short sales tend to be more informative about future prices than the average trade. Panels B and C plot the informational advantage of short sellers in terms of the mean and median CAR and IR that they earn in excess of non-short sellers. The mean and median differences tend to increase steadily in magnitude for the first 100 (70) hourly intervals following a trade in 2006 (2008) and then stabilize. This trend is most apparent in IRs.

In the previous section we estimated the mean time between opening and closing a short position is 16 trading days in both 2006 and 2008. The mean 16-day excess CAR (CAR of short sales less CAR of non-short sales) is -0.207% and -0.152% in 2006 and 2008, respectively. Annualized, short sellers informational advantage measured by excess CAR is 3.26% and 2.40% in 2006 and 2008. Short sellers' mean 16-day excess IR is -0.298 and -0.087, which equates to an annualized

[13] The negative average CARs may appear unusual given that CAR should on average be zero if the model for risk adjustment is correctly specified. There are two reasons why the average CAR in this implementation need not be zero. First, our random sample of 350 stocks may by chance include more underperforming stocks. Second, consistent with Fama and French (1993) and Carhart (1997), returns in the market risk factor are value (market capitalization) weighted across all NYSE stocks and returns on the size, value and momentum factors are equal weighted across the relevant stocks. We weight CARs by the dollar volume of each *trade* rather than stock-level weights.

excess IR of 1.18 and 0.34 in 2006 and 2008. This informational advantage is economically meaningful, particularly in 2006.[14]

The results indicate that short sellers' informational advantage is larger in the 2006 bull market than the 2008 bear market (one third larger excess CAR and more than three times greater IR). This finding is consistent with previous studies that show short sellers trade against overpriced firms and profit when prices revert towards fundamental values (e.g. Dechow et al. (2001)). In a bear market, where market sentiment is predominantly negative, overpricing is less likely to occur and therefore short sellers may have fewer opportunities to earn abnormal returns. Short sellers' mean excess IR is disproportionately smaller in 2008 than in 2006, relative to the differences in excess CAR. This is likely to be due to the high level of volatility in 2008 compared to 2006, and suggests that the additional volatility did not increase profit opportunities for short sellers.

There are several limitations to these estimates. First, since we do not observe when short positions are covered and instead approximate this time with the average holding period, our abnormal return estimates could under or over estimate the returns to any particular trade. Second, our analysis only extends 20 trading days (approximately one calendar month) from the time of the trade. Any information that short sellers have which takes longer than one calendar month to be impounded into prices is missed in our analysis. Third, to say short sellers earn rates of return annualized from holding period returns assumes they can repeatedly make informed trades by opening a new short position immediately after closing out an existing short position.

< TABLE 3 HERE >

Table 3 reports short sellers' mean excess CAR (short sellers' CAR less non-short sellers' CAR), similar to Figure 1 Panel B, as well as short sellers' excess CAR attributable to stock selection and timing abilities. We obtain these estimates from trade-level OLS regressions of CAR on an intercept and an indicator variable for short sales. To gauge short sellers' stock selection ability, we include fixed effects for each of the hourly intervals such that the excess CAR earned by short sellers is estimated using only cross-sectional variation. To gauge short sellers' timing ability we include

[14] Grinold and Kahn (1995) assert that in the context of fund managers an IR of 0.5 is "good", 0.75 is "very good" and 1.0 is "exceptional".

fixed effects for each stock such that the excess CAR earned by short sellers is estimated using only time-series variation.

Consistent with Figure 1, at each interval, short sellers earn more negative abnormal returns (favorable for short sellers) that are highly statistically significant. The annualized informational advantage of short sellers corresponding to the 2 hour, 1 trading day, 5 trading day and 20 trading day returns is 13.2%, 11.1%, 5.3% and 2.8%, highlighting the limitation of not observing the covering trades. The excess CAR estimates in Panel C using only time-series variation in CAR are larger than those in Panel B using only cross-sectional variation. This suggests short sellers' informational advantage is greater from their ability to anticipate price increases and decreases within a stock than their ability to pick over- or under-priced stocks at any particular point in time. However, short sellers' stock selection ability is also significant.

Our findings can only be indirectly compared to previous studies due to significant differences in the measure used to gauge the informativeness of short selling. Boehmer et al. (2008), using NYSE stocks during 2000-2004, report that heavily shorted stocks underperform lightly shorted stocks by an average of 1.16% over 20 days (15.6% annualized). Using a similar approach, Diether et al. (2009) report that in NYSE non-RegSHO pilot stocks during 2005 heavily shorted stocks underperform lightly shorted stocks by an average of 1.39% per month (16.7% annualized). Both of these sets of returns represent abnormal returns that an investor could earn by going long a portfolio of stocks in the lowest quintile of daily short selling flow and going short a portfolio of stocks in the highest quintile, rebalancing the portfolios daily. While this provides an indication of how well short sellers predict future returns it is not a direct measure of the abnormal returns earned by short sellers. In contrast, we report value weighted abnormal returns averaged across each individual short sale. This includes short sales in each of the quintiles by daily short selling flow and is a direct measure of short sellers' aggregate abnormal returns.

< FIGURE 2 HERE >

To examine the proportion of short sellers that earn abnormal returns and the extent to which the mean differences may be driven by a small proportion of highly informed short sellers, we compare the distributions of CAR for short and non-short sellers. Figure 2 illustrates that overall the distributions for short and non-short sellers are similar. The distributions of CAR are more dispersed at intervals further from the time of the trade. The distributions for short sales are less peaked indicating that short sales less frequently have CAR values close to zero compared to non-short sales. Short sales also have less observations in the extreme tails (beyond +/-30%) than non-short sales. This suggests that the differences in mean CAR between short and non-short sales are not driven by a small number of extremely informed short sales.

4.2 The duration of short sellers' information

The analysis so far provides an indication of the magnitude of short sellers' information. The duration of information, i.e. the time it takes information to be impounded into prices, cannot be adequately gauged from plots of average CAR (such as Figure 1) due to the effect of averaging on duration. To illustrate this, consider the plots of the cumulative abnormal returns to three trades with different information durations (Figure 3). The seller in each of the trades is informed about a 1% overpricing that is incorporated into the price linearly over the periods of 1 day, 4 days and 8 days, with no noise from the trading process. Averaging over many trades, the mean cumulative abnormal return only allows us to infer the duration of the information that takes the longest to be incorporated into price. This motivates the need to define a measure of information duration to be used in cross-sectional analysis

< FIGURE 3 HERE >

A simple measure of duration is simply the time at which the maximum CAR ($CAR_{it}^{\max}$) occurs in the 20 trading days following a trade which has positive information. For trades with negative information, duration is the time at which the minimum CAR ($CAR_{it}^{\min}$) occurs. We define positive information using the indicator variable,

$$I_{it}^{PosInfo} = \begin{cases} 1 & \text{if } \quad (CAR_{\max} + CAR_{\min})/2 > 0 \\ 0 & \text{otherwise} \end{cases} \tag{4}$$

In essence, if $CAR_{it}^{\max}$ is further above zero than $CAR_{it}^{\min}$ is below zero then the trade is classified as having positive information (and vice versa). In the example above, the durations of trades 1, 2 and 3 would be 1, 4 and 8 days respectively. While this measure has the appeal of being simple, price shocks and microstructure noise associated with the trading process cause CAR_{it} to fluctuate around the (unobservable) true CAR, and therefore $CAR_{\max}$ on average overestimates duration. To overcome this problem we define our primary duration measure as the time at which the maximum (minimum) value of IR_{it} occurs for trades that have positive (negative) information. Because the denominator of IR_{it} is the standard deviation of the trade's abnormal returns, once all of the information contained in a trade is impounded into the price, shocks and microstructure noise that are unrelated to the trade's information will on average reduce IR_{it}, thus providing a more accurate measure of information duration. In robustness tests we find that the duration measure based on CAR produces similar results.

< FIGURE 4 HERE >

Figure 4 plots the cumulative distribution of information duration for short and non-short sales. The distributions are very similar (the two lines in the plot appear as one), suggesting that the time taken for short sellers' information to be impounded into prices is not substantially different from that of other traders. Approximately 30% of trades have duration less than 10 trading days, and 60% have duration less than 16 trading days, the average holding period of short positions. This evidence is consistent with short sellers trading to maximize their IR by holding their positions for approximately the time it takes for their information to be impounded into prices.

4.3 Short sellers' information in cross-section

Table 4 reports how the informational advantage of short sellers differs across the two years in our sample and across high and low quintiles of a number of stock characteristics. Although the 20-day excess CAR earned by short sellers in 2006 is greater than in 2008, the difference between the two years in the 5-day CAR is not large (0.108% compared to 0.099%). This suggests that while the magnitude of short sellers' information may be greater in 2006, the rate at which it is impounded into prices over the first five days is greater in 2008.

< TABLE 4 HERE >

Short sellers' informational advantage (measured by their 20-day CAR) is greater in small stocks (0.348% compared to 0.274% for big stocks), stocks with low book-to-market ratios (0.403% compared to 0.306% for high B/M) and stocks with low analyst coverage (0.569% compared to 0.137% for high analyst coverage). These cross-sectional differences are not driven by the CAR anomalies documented in the literature because they represent the difference in CAR to short and non-short sales within the same group of stocks. The greater informational advantage in small stocks and stocks with low analyst coverage makes sense because mispricing is more likely to occur in these stocks, thereby creating more opportunities for informed traders such as short sellers to profit. The difference in informational advantage for high and low book-to-market ratios is consistent with the findings of Boehmer et al. (2008) and Diether et al. (2009). Boehmer et al. (2008) provide the explanation that low book-to-market might be a necessary but not sufficient condition for a stock to be overpriced. Therefore, short sellers identify overpriced stocks from this group, short sell them and profit from the eventual negative returns.

Interestingly, short sellers do not have an informational advantage in stocks with a high level of short interest (none of the CARs are statistically significant at the 5% level) but do have a substantial informational advantage in stocks with low short interest. This is not to say that short sellers do not earn abnormal returns in stocks with a high level of short interest (most research finds such stocks tend to underperform), but rather that they do not earn abnormal returns any different than other trades. An explanation for this result is that short interest captures a component of short sellers' informational advantage. Conditional on being in the group of stocks identified by short sellers as likely to experience negative abnormal returns (the high short interest group), short sales earn the same negative abnormal returns as non-short sales. Further, the fact that conditional on high short interest short sales and non-short sales earn the same abnormal returns is evidence that our results are not driven by microstructure effects (such as bid ask bounce, for example).

While short interest captures a component of short sellers' information it certainly does not capture all of their information because short sales in low short interest stocks earn large excess CARs (0.414%). The excess CARs in low short interest stocks are likely to be due to less widely exploited information such that the short selling does not increase the level of short interest. This is consistent with the differences in duration that indicate that the duration short sellers' information is less than that other sellers' duration in high short interest stocks, but greater in low short interest stocks.

The difference in informational advantage in stocks with high and low levels of fails to deliver (FTDs) is not large (0.208% compared to 0.232%). In 2006, a subset of the stocks in our sample (RegSHO pilot group) was exempt from the uptick rule, while the rest were not. The results indicate that short sellers' informational advantage is greater in non-exempt stocks (0.270% compared to 0.153% for exempt stocks). An explanation for this result is that by constraining the ability for short sellers to trade aggressively, the uptick rule reduces the rate at which short sellers' information is eroded through competition amongst short sellers, thereby increasing the retention of short sellers' informational advantage and making short sales on average more informative. This explanation is supported by the information duration measure which indicates that the duration of short sellers' information is greater than non-short sellers' in the presence of the uptick rule, but less in the stocks exempt from the rule.

5. Are short sellers manipulating the market?

Our approach to examining the extent of short sellers' involvement in market manipulation involves: (i) establishing the difference in abnormal return paths for informed short selling and manipulative short selling; (ii) identifying likely episodes of informed trading and manipulation based on abnormal return paths; (iii) identifying stock- and time-specific characteristics that affect the likelihood of manipulation; and (iv) testing whether increased short selling activity is associated with episodes of informed trading or manipulation, while controlling for factors that affect the likelihood of manipulation.

5.1 Price paths under informed and manipulative short selling

There is a large amount of theoretical support and some empirical evidence that manipulation leads to reversals in prices. Examples of theoretical models in which the manipulator causes price reversals include Vila (1989), Allen and Gale (1992), Allen and Gorton (1992), Jarrow (1992), Benabou and Laroque (1992), Gerard and Nanda (1993), Bagnoli and Lipman (1996), Van Bommel (2003), Chakraborty and Yilmaz (2004a, 2004b), Aggarwal and Wu (2006) and Allen, Litov and Mei (2006). In an empirical study of 51 cases of manipulation prosecuted by the

US Securities and Exchange Commission (SEC) during 1990-2001, Aggarwal and Wu (2006) find that manipulation is associated with price reversals. Two theoretical studies, Khanna and Sonti (2004) and Goldstein and Geumbel (2008), differ from the general consensus in the literature in that the price changes brought about by the manipulator do not subsequently reverse to their full extent. This occurs because the initial price changes affect firms' investment decisions, which influence fundamental values. The feedback of prices to fundamental values is likely to take months or years. Our focus is on shorter term manipulation strategies (lasting up to one month) and therefore the evidence supporting price reversals is more relevant in our case.

Nearly all of the theoretical studies model manipulation using long positions: a manipulator buys the stock, inflates its prices and then sells the stock. To illustrate how short sellers might profitably manipulate prices, and how price paths would differ between informed trading and manipulation involving short positions, we construct a simple theoretical model. Our model has the same set-up and assumptions as Allen and Gale (1992). It differs in the information structure, which we have reversed, producing the result that manipulators use short sales in their trading strategies.

In our model, like in Allen and Gale (1992), there are three types of agent: a continuum of small risk-averse uninformed investors, a risk-neutral informed trader and a risk-neutral manipulator. Agents trade cash (assumed to be risk free and have zero return) and a stock that pays a final dividend that is either a high or a low value, $v \in \{V_H, V_L\}$. Initially the uninformed investors hold all of the stock, and without loss of generality, the agents' holdings of cash (the numeraire) are normalized to zero. Trading takes place at three dates indexed by t=1,2,3. With probability α an informed trader enters the market and an announcement is made about the value of the stock. With probability π the announcement is bad news ($v = V_L$) and with probability (1- π) it is good news ($v = V_H$). If no announcement is made $v = V_H$, in other words, no news is good news. This information structure is illustrated in Figure 5.

< FIGURE 5 HERE >

As an example of how such an information structure may arise consider the circumstances of financial firms as the 2007-2009 financial turmoil was unfolding.

Some firms in this period suffered large losses due to bad debt ($v = V_L$), while others did not ($v = V_H$). If a firm had no exposure to bad debt, it would not be required to make an announcement and the firm's value would be $v = V_H$. If a firm made an announcement it could announce that it has no or low exposure to bad debt ($v = V_H$), or that it has substantial exposure to bad debt ($v = V_L$).

The informed trader's informational advantage is knowledge of whether an announcement will be made, but not the nature of the announcement. This imprecise information is advantageous because the expected value of the stock is lower when an announcement is forthcoming. The equilibrium strategy of the informed trader is to short sell the stock at t=1 and then cover his short position at t=2. The manipulator profits by mimicking the informed trader, i.e. short selling at t=1 and covering at t=2. The profitability of this strategy hinges on information asymmetry. When a large trader heavily short sells the stock at t=1, investors cannot tell whether this is because the informed trader knows an announcement is forthcoming or because the manipulator is trying to fool the market. More details about the model, its assumptions and a characterization of the equilibrium are provided in the appendix.

< FIGURE 6 HERE >

Figure 6 illustrates the price paths in the model under informed trading and manipulation. Informed trading moves prices gradually towards fundamental value. Manipulation, however, moves prices away from fundamental value, and then once the manipulator exits the market, prices spring back to fundamental value creating a reversal in returns.

5.2 Proxies for informed trading, manipulation and short sale clustering

The previous subsection establishes that reversals in cumulative abnormal returns are indicative of manipulation, whereas abnormal return continuations are associated with informed trading. We define a measure of reversal as:

$$Reversal_{it} = \begin{cases} \arg\min\left[(CAR_{it}^{\max} - CAR_{i0}),(CAR_{it}^{\max} - CAR_{i140})\right] & \text{if} \quad I_{it}^{PosInfo} = 1 \\ \arg\max\left[(CAR_{it}^{\min} - CAR_{i0}),(CAR_{it}^{\min} - CAR_{i140})\right] & \text{if} \quad I_{it}^{PosInfo} = 0 \end{cases} \tag{5}$$

This measure recognizes that for a positive reversal, CAR must increase and subsequently decrease such that $CAR_{it}^{\max}$ is above both the CAR at the time of the trade ($CAR_{i0} = 0$) and the CAR at the end of the measurement window (CAR_{i140}, where 140 hourly intervals are equivalent to 20 trading days or approximately one calendar month). If CAR increases and remains high, we have a continuation of abnormal returns rather than a reversal and our reversal measure gives a value of zero. In Figure 6, assuming the expected return on the stock from systematic risk factors is zero, $Reversal_{i0} = 0$ for the price path with informed trading and $Reversal_{i0} = -12.9\%$ for the price path with manipulation (representing the return from the time of the trade, \$11.43, to the low of \$10.05).

To minimize the tendency for volatile stocks to have large return reversals by virtue of their volatility, we standardize $Reversal_{it}$ to have a mean of zero and standard deviation of one in each stock. Our proxy for negative manipulation, the type that may be undertaken by a short seller, is the sample of trades with cumulative abnormal return paths for which $Reversal_{it}$ is more than two standard deviations below its mean. Similarly our proxy for positive manipulation is the sample for which $Reversal_{it}$ is more than two standard deviations above its mean.

Informed trading is characterized by abnormal return continuations. Our proxy for negatively informed trading, the type of trading that may be undertaken by a short seller, is the sample of trades that earn a 20-day CAR more than one standard deviation below the stock's mean CAR. We use CAR from the previous section derived from a four factor return model. Similarly, our proxy for positively informed trading is the sample of trades with CAR more than one standard deviation above the stock's mean CAR. As an alternative proxy for informed trading we add the condition that as well as having CAR more than one standard deviation above the mean, $Reversal_{it}$ must also be zero. We find similar results using both proxies. The classification threshold for informed trading (one standard deviation) is lower than that for manipulation (two standard deviations) because we expect informed trading to be more prevalent than manipulation.

To quantify the intensity of short selling prior to an informed trading or manipulation episode, relative to total volume, we calculate the following variable:

$$ShortVol_{it} = \frac{\dfrac{Vol_{it}^{SS}}{Vol_i^{TOTAL}} - \overline{\left(\dfrac{Vol_{it}^{SS}}{Vol_i^{TOTAL}}\right)}}{\sigma} \tag{6}$$

where Vol_{it}^{SS} is the dollar volume (alternatively, the number) of short sales in stock i in interval t, Vol_i^{TOTAL} is the mean total dollar volume per interval in stock i, $\overline{\left(\frac{Vol_{it}^{SS}}{Vol_i^{TOTAL}}\right)}$ and σ are the mean and standard deviation, respectively, of the fraction of volume made up by short sales in stock i, $\frac{Vol_{it}^{SS}}{Vol_i^{TOTAL}}$. This measure of the concentration of short selling, $ShortVol_{it}$, is a standardized form of main short selling metric used by Diether et al. (2009) and Boehmer et al. (2009).

5.3 Determinants of manipulation

In testing the extent of short sellers' involvement in market manipulation it is important to control for characteristics that affect the likelihood of manipulation. In our theoretical model, as well as many of the existing models cited above, information asymmetry is critical for manipulation to be successful. If all market participants have the same information, a potential manipulator cannot lead others to believe he is more informed about the value of a stock. We use the number of analyst forecasts of earnings as a proxy for information asymmetry.

Market conditions are another important determinant of the prevalence and type of manipulation. Anecdotal evidence suggests that short sellers have exploited the fear and uncertainty that has prevailed through the 2007-2009 financial turmoil to manipulate prices.[15] The existence of such an effect is related to the perceived information structure. For example, in our theoretical model the value of a stock is high unless bad news is announced about the stock. Investors fear the bad news and the manipulator exploits this fear by short selling the stock to give the impression that an announcement is forthcoming, thereby causing the price to fall. On the other hand, in Allen and Gale (1992) the value of the stock is low unless good news is announced. Investors hope for the good news and the manipulator exploits investor hope by buying the stock to give the impression that an announcement is forthcoming, thereby

[15] See, for example, "There's a Better Way to Prevent 'Bear Raids'" by R. Pozen and Y. Bar-Yam, The Wall Street Journal, 18 November 2008, "Anatomy of the Morgan Stanley Panic" by S. Pulliam et al., The Wall Street Journal, 24 November 2008.

causing the price to increase. The information structure in our model more accurately reflects investor sentiment during a bear market and Allen and Gale's reflects a bull market. Therefore, consistent with the anecdotal evidence, we expect manipulation by short sellers to be more prevalent in 2008 (bear market) than in 2006 (bull market).

In a similar line of reasoning, the short interest in a stock may be an indicator of market sentiment towards that stock and therefore determine how easily short sales can be used to drive down the stock's price. High levels of short interest are likely to indicate pessimistic views about a stock. Such an environment is conducive to manipulation by short sellers because the higher probability of bad news amplifies the market's negative reaction to short selling when the market is unsure whether the short selling is informed or not.

Naked short selling (short selling without borrowing or making arrangements to borrow the stock) has recently been widely criticized for helping facilitate market manipulation. One of the reasons for this criticism is that in a manipulative raid on a stock, non-naked short sellers are limited by the amount of stock they can locate to borrow, which in many stocks can constrain a manipulator. Naked short selling, however, allows a manipulator to make virtually unlimited short sales regardless of the supply of the stock.

Typically, naked short sales result in fails to deliver (FTD) on T+3. The SEC have on several occasions expressed their concern about the use of naked short selling in manipulation schemes and introduced a number of new rules during 2008 and 2009 to combat the problem. For example, in the SEC's July 27, 2009, announcement about "making permanent a rule to curtail naked sort selling", the SEC states "Sellers sometimes intentionally fail to deliver securities as part of a scheme to manipulate the price of a security … We have been concerned about reducing fails to deliver and addressing "naked" short selling, in particular, abusive "naked" short selling for some time."[16] Therefore, we use the number of fails (lagged three trading days to correspond to the originating trades) as a proportion of shares on issue, interacted with $ShortVol_{it}$, as a proxy for naked short selling. We expect manipulation to be more likely in the presence of naked short selling.

Finally, the removal of the uptick rule may be associated with a higher likelihood of manipulation. The uptick rule was enacted in 1938 to reduce the

[16] http://www.sec.gov/news/press/2009/2009-172.htm

prevalence of “bear raids”, which were widespread at the time. Since the uptick rule was abandoned in July 2007, the SEC has received criticism from some market participants claiming that abandoning this rule has created new opportunities for abusive and manipulative short selling. This criticism has prompted the SEC to consider reinstating a modified uptick rule.[17] Therefore, manipulation by short sellers may be more likely in 2008 and in the RegSHO pilot group of stocks in 2006.

< FIGURE 7 HERE >

Figure 7 plots the distributions of $Reversal_{it}$ comparing short and non-short sales (Panel A) and high and low quintiles of manipulation-related characteristics (Panels B-D). Reversals in excess of +/-20% are pooled at the corresponding endpoint. The distributions have a spike at zero reflecting trades that have a continuation of CAR rather than a positive or negative reversal of CAR. The distributions for short and non-short sales in the pooled sample are very similar, indicating there is no obvious evidence of manipulation by short sellers in aggregate. Stocks with high information asymmetry (lowest quintile of analyst coverage) have a higher incidence of large CAR reversals (reversals in excess of +/-20%) than stocks with low information asymmetry. Similarly, stocks with high levels of short interest and FTDs have a substantially increased incidence of large CAR reversals, in particular, large negative reversals. These results are consistent with our expectations about the determinants of manipulation and the role of reversals as indicators of manipulation.

5.4 Is short selling associated with informed trading or manipulation?

We use regression to test the extent of short sellers’ involvement in episodes of informed trading and manipulation. We run OLS regressions of the continuous variables *Reversal* and *CAR* and logistic regressions of the binary variables that classify observations as preceding negative manipulation, positive manipulation, negative informed trading or positive informed trading (*NegManip*, *PosManip*, *NegInfo* and *PosInfo*). The unit of observation is a stock in an hourly interval.

[17] See, for example, SEC press release 2009-185 “SEC seeks comment on alternative uptick rule”.

The key independent variable that indicates short sellers' involvement in the various types of trading is $ShortVol_{it}$, the proportion of dollar volume made up by short sales. Other independent variables include the factors hypothesized in the previous subsection to affect the likelihood of manipulation. These are important in the tests of involvement in manipulative trading and, for consistency, we also include them in the informed trading regressions. In an alternative specification we include interactions between $ShortVol_{it}$ and the manipulation determinants. In all regressions we include the control variables market capitalization, book-to-market ratio, volatility and turnover.

< TABLE 5 HERE >

Table 5 reports the regression coefficients for the tests of involvement in manipulative trading. Short selling is associated with more negative reversals (*ShortVol* coefficient of -0.009). This is consistent with the earlier findings that short selling precedes negative CARs and does not in itself indicate involvement in manipulation. The second specification, with interaction terms, reveals that a large part of the negative effect of short selling on reversals is due to short selling that occurs concurrently with delivery failures, i.e. naked shot selling (*Fails*ShortVol* coefficient of -0.020).

In the logistic regressions of the proxies of manipulation (*NegManip* and *PosManip*) the coefficients of *ShortVol* reveal a key result: heightened levels of short selling do not increase the probability of negative manipulation. The opposite is true. Conditional on a high level of short selling, abnormal return patterns indicative of negative manipulation are less likely and return patterns indicative of positive manipulation are more likely (*ShortVol* coefficients of -0.013 and 0.005). An explanation for this result is that short sellers as a group are dominated by informed traders rather than manipulators. When short sellers take a position in a stock expecting prices to fall, on average prices do fall and stay down, such that large negative reversals are unlikely when short sellers are active. Further, when prices are manipulated upwards or they simply overshoot fundamental values due to overreaction and subsequently undergo a large positive reversal, short sellers tend to trade against the overpricing and therefore positive reversals are more likely to be preceded by increased short selling.

While the explanations of why increased short selling might precede large positive reversals but not large negative ones is consistent with evidence on the informativeness of short selling, the magnitudes of the marginal effects are not large. A 10% increase in short selling activity relative to total volume is estimated to decrease the probability of a return pattern indicative of negative manipulation by 0.4% and increase the probability of a positive manipulation return pattern by 0.1%.

Interactions between short selling activity and other determinants of manipulation reveal interesting effects. The effect of short selling concurrent with delivery failures (a proxy for naked short selling) on large price reversals is opposite to that for short selling in general. Increased naked short selling is associated with price patterns indicative of negative manipulation and unlikely to occur preceding large positive reversals (*Fails*ShortVol* coefficients of 0.023 and -0.107). In contrast to short selling in general, these results suggest naked short sellers do not trade against overpricing as frequently as non-naked short sellers, and naked short sellers are more likely to be associated with return patterns indicative of bear raid manipulation.

Short selling is more likely to be associated with large positive and negative price reversals when it occurs in stocks with high information asymmetry (*Analysts*ShortVol* coefficients of -0.004 and -0.012) and stocks with high short interest (*ShortInt*ShortVol* coefficients of 0.005 and 0.002). Stocks with high information asymmetry are more likely to experience large positive reversals (*Analysts* coefficient of -0.029) and short interest has a similar effect to the amount of short selling activity measured by *ShortVol* in that it decreases the likelihood of large negative reversals (*ShortInt* coefficient of -0.013). Large reversals are much more likely to occur in 2008 than in 2006. Although theory predicts negative manipulation by short sellers is more likely in a bear market than a bull market, the interaction of *ShortVol* and the 2008 indicator variable is negative for the dependent variable *NegManip* (-0.033). This supports the evidence that short sellers are not often involved in negative manipulation.

Of the control variables, volatility and turnover have the largest effects on the probability of a large return reversal. Unsurprisingly, the probability of a large reversal increases with high volatility and low liquidity.

< TABLE 6 HERE >

Table 6 reports the regression coefficients for the informed trading dependent variables. Short selling is associated with more negative CARs (*ShortVol* coefficient of -0.028). This highly statistically significant result suggesting short sellers on average predict future negative returns after controlling for a number of factors is consistent with our findings in the previous section as well as studies such as Boehmer et al. (2008) and Diether et al (2009). The relation between short selling and negative returns is also reflected in the logistic regressions. A 10% increase in the amount of short selling relative to total volume is estimated to increase the probability of a large negative 20-day CAR by 1.8% and decrease the probability of a large negative 20-day CAR by 10.2%.

In the bear market of 2008 average CARs are more negative than in the bull market of 2006 (*I_2008* coefficient of -0.042). The ability for short sellers to predict large positive and negative CARs is decreased in the 2008 bear market, consistent with earlier results. Higher information asymmetry increases the ability of short sellers to correctly predict large negative CARs (*Analysts**ShortVol* coefficient of -0.007), but decreases their ability to correctly predict large positive CARs (*Analysts**ShortVol* coefficient of -0.003). Fails to deliver in themselves are associated with a higher probability of a large positive CAR (*Fails* coefficient of 0.275), a lower probability of a large negative CAR (*Fails* coefficient of -0.414), and therefore more positive CARs on average (*Fails* coefficient of 0.124). However, fails in conjunction with short selling, a proxy for naked short selling, increase the probability of large negative returns (*Fails**ShortVol* coefficient of 0.004) and decrease the probability of large positive returns (*Fails**ShortVol* coefficient of -0.027). High levels of short interest increase (decrease) the probability that heightened short selling activity is followed by a large negative (positive) return (*ShortInt**ShortVol* coefficients of 0.006 and -0.001).

Of the control variables, volatility and turnover have the largest effects on the probability of a large CAR. The probability of a large positive or negative CAR increases with high volatility and lower liquidity.

Considering the relations between short selling and both the manipulation proxy and the informed trading proxy gives a consistent picture of short selling. Short sellers are primarily informed traders that correctly predict abnormal returns. They trade at heightened levels prior to large negative return continuations indicative of negative informed trading. They tend to trade against instances of overpricing that are subsequently reversed and are less likely than non-short sellers to be associated with negative return reversals indicative of predatory trading or bear raid manipulation.

A particular subgroup of short sellers, naked short sellers, trade at heightened levels prior to negative return reversals, suggesting some naked short sellers may be involved in manipulating prices. Overall, these results suggest that short sellers as a group are beneficial for markets because by trading on information rather than manipulative intent they enhance the informational efficiency of prices.

6. Conclusions

We characterize the informativeness of short selling using trade-level data from the NYSE during a bull and a bear market. Overall our results indicate that short sellers as a group are informed traders that correctly predict permanent negative future returns and improve market efficiency by trading against instances of overpricing. We find that short sellers' informational advantage is smaller in the 2008 bear market than the 2006 bull market consistent with less frequent overpricing in bear markets. Their informational advantage is greater in small stocks, stocks with low book-to-market ratios and stocks with low analyst coverage. The magnitude of short sellers' informational advantage is economically meaningful.

We estimate their annualized excess cumulative abnormal returns are 3.26% and 2.40% and their excess information ratios are 1.18 and 0.34 in 2006 and 2008, respectively. These estimates are obtained from individual trades and therefore are a direct measure of the abnormal returns earned by short sellers before considering costs.

We find that short sellers are less likely than non-short sellers to be associated with large negative return reversals indicative of predatory trading or bear raid manipulation. This evidence suggests that short sellers as a group do not have a greater involvement in market manipulation than do non-short sellers. We find some evidence that a subgroup of short sellers, naked short sellers, trade at heightened levels prior to negative return reversals that are indicative of manipulation.

Our findings have implications for the current debate over the role of short sellers in markets and for determining the appropriate regulatory response. While manipulation may occur in markets and may even contribute to sharp price declines in targeted companies, our results suggest that short sellers as a group, perhaps with the exception of naked short sellers, are not the culprits. Further, short sellers are beneficial to market efficiency. Therefore, regulators should not restrict short selling in general (as the SEC and a number of other regulators did during 2008) because such actions are likely to impair market efficiency. Our results also suggest that regulators' current actions of restricting naked short selling may be justified. Such restrictions should target occasions where naked short selling is most likely to be used as a tool for market manipulation. Further research focused on this particular type of manipulation would benefit this purpose.

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Appendix: Characterization of pooling equilibrium

A.1 Additional details and model assumptions

All traders maximize the utility of their final wealth (wealth at t=2 for informed traders and manipulators and wealth at t=3 for investors). The utility function of the risk averse investors, $U(W)$, are assumed to be continuously differentiable, strictly increasing and strictly concave. Consistent with Allen and Gale (1992) the stochastic and information structures of this model assume the manipulator enters only if no information is expected, and bad news is revealed after good news. See Allen and Gale (1992) for a discussion on the role of these assumptions and possibility of relaxing them. In the following subsections we characterize the equilibrium by backward induction.

A.2 Equilibrium at *t*=2

A.2.1 Large trader did not enter at t=1

No trade occurs at t=1 and therefore investors know that a large trader did not enter. Investors therefore know that $v=V_H$ and therefore set $P_2=V_H$.

A.2.2 Large trader entered at t=1

The large trader short sells S>0 shares at t=1 and therefore investors know that a large trader entered. Given this knowledge, the investors' belief about the probability that the large trader is informed is:

$$Q_1 = \Pr(\text{informed} \mid \text{large}) = \gamma = \frac{\alpha}{\alpha + \beta} \tag{A1}$$

Two further scenarios are possible. In the first scenario, where news is released at t=2, the equilibrium is trivial. The news reveals that $v=V_H$ and therefore investors set $P_2=V_H$. Because there is no uncertainty, investors are willing to trade any amount at this price, so the informed trader buys B at P_2 to close out his short position.

In the second scenario, where no news is released at t=2, the equilibriums is non-trivial. Investors do not know if the large investor is informed (in which case $v=V_L$) or a manipulator (in which case $v=V_H$). The probability of no news at t=2 given that an informed trader has entered is:

$$\Pr(\text{no news} \mid \text{informed}) = \pi \tag{A2}$$

Therefore, upon observing that no news is released, investors update their posterior belief that the large investor is informed:

$$\Pr(\text{informed} \mid \text{large and no news}) = \frac{\gamma\pi}{\gamma\pi + 1 - \gamma} \tag{A3}$$

The large trader buys B at P_2 to close out his short position. In equilibrium, the investors must sell B shares to the large trader, giving the investors (E+S-B) stock and ($-SP_1+BP_2(B)$) cash. The investors' final wealth will be:

$$W_H(B) = (E + S - B)V_H - SP_1 + BP_2(B) \quad \text{if } v{=}V_H \tag{A4}$$

$$W_L(B) = (E + S - B)V_L - SP_1 + BP_2(B) \quad \text{if } v{=}V_L \tag{A5}$$

Investors know $v=V_L$ if the large trader is informed, which they believe occurs with probability Q_2. The investors' expected utility at t=3 is therefore:

$$E[U(B)] = Q_2 U[W_L(B)] + (1 - Q_2)U[W_H(B)] \tag{A6}$$

The investors' are price takers in that a change in their holdings at t=2 is assumed to leave P_2 unchanged, although in equilibrium P_2 does depend on B. In equilibrium investors' beliefs must be consistent with the strategy of the large trader and the investors' prior beliefs,

$$Q_2 = \frac{Q_1\pi}{Q_1\pi + 1 - Q_1} \tag{A7}$$

and the market must clear at a price P_2 consistent with investors' first order conditions,

$$P_2(B) = \frac{Q_2 V_L U[W_L(B)] + (1 - Q_2)V_H U[W_H(B)]}{Q_2 U[W_L(B)] + (1 - Q_2)U[W_H(B)]} \tag{A8}$$

We have characterized a plausible equilibrium outcome at t=2 as a well defined function of the initial conditions (S, P_1, Q_1).

A.3 Equilibrium at t=1

A.3.1 Large trader does not enter

No trade occurs at t=1 and therefore investors know that a large trader is not in the market. Investors therefore know that $v=V_H$ and therefore set $P_1=V_H$.

A.3.2 Large trader enters

Suppose the manipulator enters at *t*=1. Since he pools with the informed trader he short sells S at *t*=1 and buys back B=S at t=2 to cover his position. His equilibrium profit is therefore:

$$W^M(S) = S(P_1(S) - P_2(S)) \tag{A9}$$

The informed trader's equilibrium profit depends on the probability of an announcement:

$$W^I(S) = S(P_1(S) - \pi P_2(S) - (1-\pi)V_H) \tag{A10}$$

The investors' equilibrium profit depends on whether: (i) the large trader is the manipulator; (ii) the large trader is informed and $v=V_H$; or (iii) the large trader is informed and $v=V_L$:

$$W_M(S) = EV_H + S(P_2(S) - P_1(S)) \text{ with probability } (1-Q_1) \tag{A11}$$

$$W_H(S) = EV_H + S(V_H - P_1(S)) \text{ with probability } Q_1(1-\pi) \tag{A12}$$

$$W_L(S) = EV_L + S(P_2(S) - P_1(S)) \text{ with probability } Q_1\pi \tag{A13}$$

The investors' expected utility at *t*=3 is therefore:

$$E[U(S)] = (1-Q_1)U[W_M(S)] + Q_1(1-\pi)U[W_H(S)] + Q_1\pi U[W_L(S)] \tag{A14}$$

The investors' are price takers in that changes in their holdings are assumed to leave P_1 and P_2 unchanged, although in equilibrium P_1 and P_2 depend on *S*. In equilibrium investors' beliefs must be consistent with the probability that a large trader is informed,

$$Q_1 = \gamma \tag{A15}$$

and the market must clear at a price P_1 consistent with investors' first order conditions,

$$P_1(S) = \frac{(1-Q_1)U[W_M(S)]P_2(S) + Q_1(1-\pi)U[W_H(S)]V_H + Q_1\pi U[W_L(S)]P_2(S)}{(1-Q_1)U[W_M(S)] + Q_1(1-\pi)U[W_H(S)] + Q_1\pi U[W_L(S)]} \tag{A16}$$

We have characterized a plausible equilibrium outcome at *t*=1.

Table 1
Summary statistics

This table reports summary statistics on the number, volume and size of short sales relative to non-short sales during 2006 (Panel A), 2008 (Panel B) and the pooled sample consisting of 2006 and 2008. *25%*, *50%* and *75%* refer to distribution quartiles, *n* refers to the total number of short sales and non-short sales in the sample. To calculate daily number of trades and dollar volume per stock, we first sum the number of trades and dollar volume for each stock-day and then calculate the mean and quartiles for the stock-days in the sample. To calculate short and non-short trade sizes, we first find the mean (median) short and non-short trade sizes for each stock-day and then calculate the mean (quartiles) for the stock-days in the sample.

	Daily number of short sales per stock	Shorting share of trades	Daily dollar volume of short sales per stock ($‘000)	Shorting share of dollar volume	Size of a short sale ($)	Size of non-short sale ($)
Panel A: Year 2006						
Mean	530	28.6%	9,067	25.6%	11,377	12,543
25%	158	26.9%	903	25.8%	2,793	2,943
50%	351	27.7%	3,074	26.8%	4,500	4,750
75%	692	28.3%	9,098	26.6%	7,723	8,274
n					41,837,337	105,751,093
Panel B: Year 2008						
Mean	1,124	39.0%	10,133	37.9%	6,034	5,994
25%	263	38.4%	796	39.0%	1,494	1,503
50%	678	39.6%	3,050	40.0%	2,741	2,750
75%	1,436	39.4%	9,601	39.3%	4,469	4,477
n					91,213,295	144,790,741
Panel C: Pooled sample						
Mean	831	35.0%	9,608	31.0%	8,668	9,220
25%	195	31.5%	850	32.8%	2,004	2,056
50%	473	32.8%	3,064	33.0%	3,590	3,668
75%	1,029	34.3%	9,362	32.3%	5,819	6,017
n					133,050,632	250,541,834

Table 2
Dollar volume of short sales

This table reports mean daily dollar volumes ($ '000s) of short sales per stock and the percentage of total daily dollar volume per stock made up by short sales. The dollar volumes and percentages are reported for stock-days grouped in quintiles of five variables: book-to-market ratio (*B/M*), market capitalization (*Size*), the number of fails to deliver as a percentage of total shares on issue (*FTD*), the open short interest as a percentage of total shares on issue (S*hort Interest*) and the number of analyst forecasts of earnings (*Analyst coverage*). In Panel C stocks are also grouped by whether they are in the RegSHO pilot group. *Pooled* indicates results not grouped by quintiles of the corresponding variable. The sample consists of years 2006 and 2008, except Panel C which consists of the year 2006 only.

Panel A: Size and book-to-market quintiles

	Size					
B/M	Small	2	3	4	Big	Pooled
Low	465	1,660	5,856	10,027	34,158	14,161
	33.0%	34.1%	33.7%	31.5%	29.5%	30.2%
2	546	1,915	4,570	8,727	29,715	11,126
	36.2%	31.7%	33.0%	31.7%	27.9%	29.4%
3	608	1,720	4,527	8,538	29,772	8,647
	32.0%	34.1%	33.2%	32.3%	30.6%	31.7%
4	466	1,824	4,264	8,673	30,169	8,692
	35.6%	34.9%	34.0%	34.8%	30.0%	31.5%
High	490	1,974	3,878	8,654	39,322	5,304
	36.6%	36.8%	35.1%	35.1%	33.1%	34.2%
Pooled	504	1,813	4,624	8,956	31,854	9,584
	35.0%	34.6%	33.6%	32.6%	29.7%	30.9%

Panel B: Fail to deliver and short interest quintiles

	Short Interest					
FTD	Low	2	3	4	High	Pooled
Low	3,078	3,267	2,415	2,264	2,471	2,718
	24.4%	30.1%	30.1%	35.1%	42.5%	30.1%
2	26,212	12,613	10,540	5,189	4,199	17,961
	24.0%	30.0%	30.3%	31.1%	37.0%	25.6%
3	25,761	14,316	10,735	4,988	5,916	14,330
	26.8%	32.2%	34.2%	34.6%	36.8%	29.8%
4	22,360	15,268	18,123	9,588	6,161	13,775
	26.7%	32.6%	36.9%	36.3%	37.9%	32.9%
High	9,416	8,722	12,770	9,750	6,441	8,329
	26.0%	31.4%	35.1%	36.5%	38.7%	35.8%
Pooled	16,722	9,997	9,440	6,039	5,658	9,584
	25.7%	31.7%	34.8%	35.8%	38.9%	30.9%

Panel C: Pilot group stocks and analyst coverage quintiles (year 2006 only)

	Analyst coverage					
Pilot group	Low	2	3	4	High	Pooled
No	1,252	2,458	4,650	10,354	20,954	7,403
	26.7%	27.3%	27.4%	24.0%	24.5%	24.9%
Yes	1,279	3,636	6,163	10,093	33,742	12,651
	32.2%	27.9%	29.6%	26.8%	25.4%	26.5%
Pooled	1,258	2,851	5,131	10,276	26,161	9,038
	27.8%	27.6%	28.2%	24.8%	25.0%	25.6%

Table 3

Excess cumulative abnormal returns of short sales

This table reports mean cumulative abnormal returns (CAR) for short sales less the mean CAR for non-short sales over periods of 2 hours, 1 trading day, 5 trading days and 20 trading days following a trade. We obtain these estimates from trade-level OLS regressions of CAR (in %) on an intercept and an indicator variable for short sales (*I_short*). Trades are weighted by their dollar volume. In Panel B we include fixed effects for each of the hourly intervals such that the excess CAR earned by short sellers is estimated using only cross-sectional variation. In Panel C we include fixed effects for each stock such that the excess CAR earned by short sellers is estimated using only time-series variation. The sample consists of years 2006 and 2008.

	CAR (2hr)	CAR (1day)	CAR (5day)	CAR (20day)
Panel A: Total abnormal returns				
I_short	-0.015***	-0.044***	-0.106***	-0.218***
t-Statistic	(-2.83)	(-5.45)	(-7.62)	(-8.24)
Panel B: Abnormal returns from stock selection				
I_short	-0.014***	-0.038***	-0.078***	-0.158***
t-Statistic	(-2.63)	(-5.17)	(-5.72)	(-6.11)
Panel C: Abnormal returns from market timing				
I_short	-0.016***	-0.047***	-0.109***	-0.234***
t-Statistic	(-3.02)	(-6.36)	(-8.04)	(-9.03)

Table 4
Magnitude and duration of short sellers' information in cross-section

This table reports dollar volume weighted mean cumulative abnormal returns (in %) calculated at the trade level for short sales less the returns to non-short sales over periods of 2 hours, 1 trading day, 5 trading days and 20 trading days following a trade. *Duration* measures the time taken for a trade's information to be impounded in the price and is calculated as the number of one-hour intervals before the trade's maximum information ratio (for net positive information, and vice versa for net negative information). *n* refers to the number of trades. *Pooled* contains the full sample. The categories *Big/Small/High/Low* correspond the first and fifth quintiles of the variables: market capitalization, book-to-market ratio, the number of analyst forecasts of earnings, the short interest as a percentage of total shares on issue and the number of fails to deliver as a percentage of total shares on issue. In Panel H stocks are grouped by whether they are in the RegSHO pilot group. T-statistics are reported in parentheses. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels. The sample consists of years 2006 and 2008, except Panel H which consists of the year 2006 only.

	CAR (2hr)	CAR (1day)	CAR (5day)	CAR (20day)	Duration
Panel A: Pooled					
	0.015***	0.044***	0.106***	0.218***	0.00
	(5.31)	(10.17)	(12.41)	(13.14)	(0.02)
Panel B: By year					
2006	0.016***	0.034***	0.108***	0.226***	0.17*
	(6.06)	(7.64)	(12.16)	(12.79)	(1.72)
2008	0.008	0.054***	0.099***	0.175***	-0.14
	(1.56)	(7.14)	(6.63)	(6.13)	(-1.52)
Panel C: By stock size					
Big	0.011**	0.032***	0.112***	0.274***	-0.07
	(2.23)	(4.44)	(8.19)	(10.70)	(-0.49)
Small	0.018**	0.077***	0.103***	0.348***	-0.12
	(2.06)	(5.84)	(3.76)	(6.55)	(-0.77)
Panel D: By B/M					
High	0.019**	0.063***	0.062**	0.306***	-0.44***
	(2.37)	(5.16)	(2.57)	(6.65)	(-2.88)
Low	0.015**	0.051***	0.202***	0.403***	0.17
	(2.58)	(5.63)	(10.95)	(11.44)	(1.12)
Panel E: By analyst coverage					
Low	0.015**	0.065***	0.124***	0.569***	-0.20
	(2.05)	(5.74)	(5.34)	(12.76)	(-1.24)
High	0.010*	0.028***	0.088***	0.137***	-0.02
	(1.90)	(3.60)	(5.86)	(4.77)	(-0.10)
Panel F: By short interest					
High	0.009	0.012	0.019	-0.082*	-0.72***
	(1.13)	(0.98)	(0.79)	(-1.74)	(-4.90)
Low	0.010*	0.047***	0.135***	0.414***	0.76***
	(1.96)	(5.76)	(8.39)	(13.38)	(4.71)
Panel G: By fail rate					
High	0.015*	0.050***	0.154***	0.208***	-0.15
	(1.91)	(3.97)	(6.24)	(4.52)	(-1.03)
Low	0.016***	0.046***	0.076***	0.232***	-0.05
	(3.29)	(6.32)	(5.18)	(7.95)	(-0.42)
Panel H: By RegSHO pilot group (2006 only)					
Yes	0.013***	0.025***	0.080***	0.153***	-0.32*
	(2.79)	(3.25)	(5.39)	(4.90)	(-1.77)
No	0.018***	0.037***	0.123***	0.270***	0.44***
	(5.37)	(6.86)	(11.11)	(12.58)	(3.53)

Table 5
Regressions of manipulation proxy

This table reports results from OLS regression (with the continuous dependent variable *Reversal*) and logistic regression (with the binary dependent variables *NegManip* and *PosManip*). *Reversal* is the magnitude of positive or negative CAR reversals following a trade (standardized to a mean of zero, standard deviation of one). *NegManip* (*PosManip*) equals one if *Reversal* is more than two standard deviations below (above) its mean and zero otherwise. *ShortVol* is the proportion of dollar volume made up by short sales (per stock per one-hour interval). *I_2008* is an indicator variable for the year 2008. *Analysts* is the number of analyst forecasts of earnings. *Fails* and *ShortInt* are the number of fails to deliver and short interest in a stock as a percentage of shares outstanding. *Volatility* is the standard deviation of a stock's hourly midquote returns during the last 10 trading days. *Turnover* is the dollar volume of trades in a stock during the last 10 trading days. Numbers in parentheses are t-statistics for the OLS regressions and marginal effects (in percent) for the logistic regressions. *, ** and *** denote significance at the 10%, 5% and 1% levels.

	Reversal		NegManip		PosManip	
Intercept	0.059***	0.060***	-7.079***	-7.074***	-7.782***	-7.762***
	(6.37)	(6.51)	(-22.73)	(-22.71)	(-18.83)	(-18.78)
ShortVol	-0.009***	-0.001**	-0.013**	-0.001**	0.005**	0.022**
	(-7.78)	(-0.66)	(-0.04)	(0.00)	(0.01)	(0.05)
I_2008*ShortVol		0.009***		-0.033**		0.038**
		(3.99)		(-0.11)		(0.09)
Analysts*ShortVol		-0.001***		-0.004***		-0.012***
		(-8.01)		(-0.01)		(-0.03)
Fails*ShortVol		-0.020***		0.023**		-0.107**
		(-2.72)		(0.07)		(-0.26)
ShortInt*ShortVol		0.000**		0.005***		0.002**
		(-0.47)		(0.02)		(0.01)
I_2008	-0.032***	-0.033***	2.151***	2.150***	2.418***	2.420***
	(-13.30)	(-13.45)	(6.91)	(6.90)	(5.85)	(5.85)
Analysts	0.001***	0.001***	-0.002**	-0.002**	-0.029***	-0.030***
	(5.62)	(5.81)	(-0.01)	(-0.01)	(-0.07)	(-0.07)
Fails	0.035***	0.035***	0.024**	-0.012**	-0.255***	-0.257***
	(6.87)	(7.02)	(0.08)	(-0.04)	(-0.62)	(-0.62)
ShortInt	0.001***	0.001***	-0.013***	-0.012***	0.000**	0.001**
	(3.05)	(3.18)	(-0.04)	(-0.04)	(0.00)	(0.00)
Market cap.	-0.009***	-0.009***	0.108***	0.108***	0.162***	0.161***
	(-8.15)	(-8.39)	(0.35)	(0.35)	(0.39)	(0.39)
B/M ratio	0.027***	0.027***	-0.112***	-0.111***	-0.095***	-0.093***
	(9.48)	(9.57)	(-0.36)	(-0.36)	(-0.23)	(-0.23)
Volatility	-0.030***	-0.029***	0.510***	0.509***	0.501***	0.501***
	(-12.83)	(-12.64)	(1.64)	(1.63)	(1.21)	(1.21)
Turnover	-0.021***	-0.021***	-0.478***	-0.473***	-0.402***	-0.392***
	(-7.57)	(-7.53)	(-1.53)	(-1.52)	(-0.97)	(-0.95)

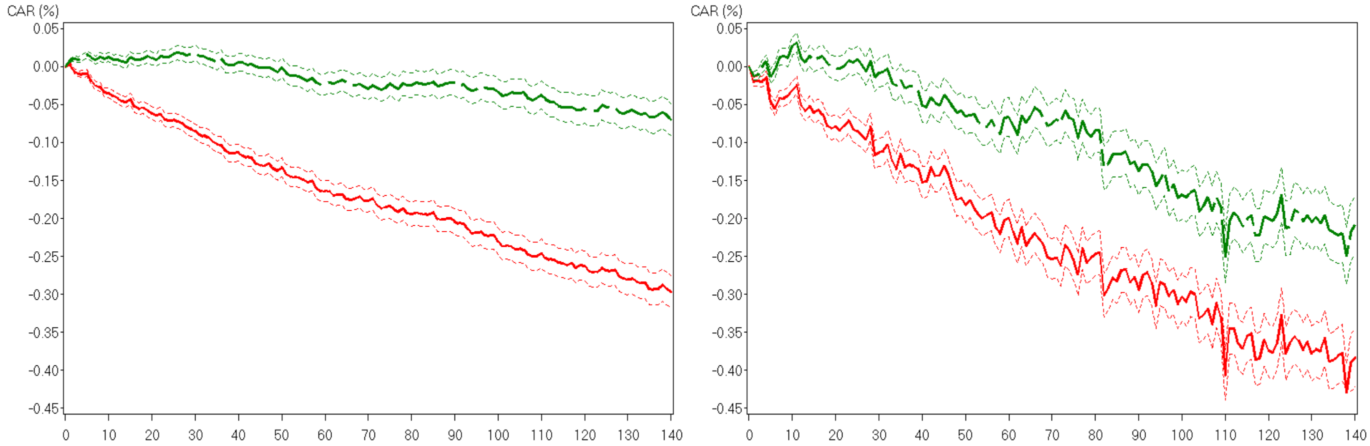
Table 6
Regressions of information proxy

This table reports results from OLS regression (with the continuous dependent variable *CAR*) and logistic regression (with the binary dependent variables *NegInfo* and *PosInfo*). *CAR* is the cumulative abnormal return for a stock from a four factor model over the following 20 trading days (standardized to a mean of zero, standard deviation of one). *NegInfo* (*PosInfo*) equals one if *CAR* is more than one standard deviation below (above) its mean and zero otherwise. *ShortVol* is the proportion of dollar volume made up by short sales (per stock per one-hour interval). *I_2008* is an indicator variable for the year 2008. *Analysts* is the number of analyst forecasts of earnings. *Fails* and *ShortInt* are the number of fails to deliver and short interest in a stock as a percentage of shares outstanding. *Volatility* is the standard deviation of a stock's hourly midquote returns during the last 10 trading days. *Turnover* is the dollar volume of trades in a stock during the last 10 trading days. Numbers in parentheses are t-statistics for the OLS regressions and marginal effects (in percent) for the logistic regressions. *, ** and *** denote significance at the 10%, 5% and 1% levels.

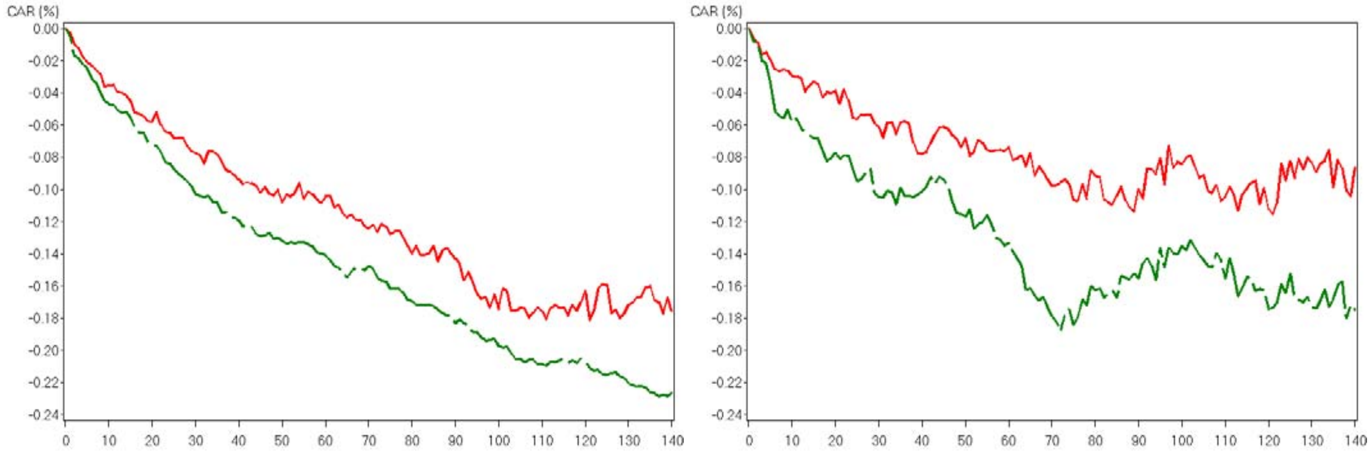
	CAR		NegInfo		PosInfo	
Intercept	-0.245***	-0.242***	-2.471***	-2.469***	-3.431***	-3.436***
	(-25.28)	(-24.95)	(-39.67)	(-39.63)	(-36.53)	(-36.58)
ShortVol	-0.028***	-0.017***	0.011***	0.059***	-0.096***	-0.145***
	(-23.54)	(-7.51)	(0.18)	(0.95)	(-1.02)	(-1.54)
I_2008*ShortVol		-0.003**		-0.077***		0.114***
		(-1.23)		(-1.24)		(1.21)
Analysts*ShortVol		-0.001***		-0.007***		-0.003***
		(-6.13)		(-0.12)		(-0.03)
Fails*ShortVol		0.007***		0.004**		-0.027**
		(2.63)		(0.06)		(-0.28)
ShortInt*ShortVol		0.000**		0.006***		-0.001**
		(-1.60)		(0.10)		(-0.01)
I_2008	-0.042***	-0.042***	0.130***	0.129***	0.742***	0.749***
	(-16.69)	(-16.61)	(2.08)	(2.07)	(7.90)	(7.97)
Analysts	0.004***	0.004***	0.010***	0.009***	0.000**	0.000**
	(16.50)	(16.74)	(0.15)	(0.15)	(0.00)	(0.00)
Fails	0.124***	0.124***	-0.414***	-0.441***	0.275***	0.273***
	(26.38)	(26.41)	(-6.65)	(-7.09)	(2.93)	(2.91)
ShortInt	-0.001***	-0.001***	-0.012***	-0.011***	0.004***	0.004***
	(-3.99)	(-4.01)	(-0.19)	(-0.17)	(0.05)	(0.05)
Market cap.	-0.012***	-0.012***	0.003**	0.002**	0.035***	0.034***
	(-10.14)	(-10.44)	(0.04)	(0.04)	(0.37)	(0.36)
B/M ratio	0.065***	0.065***	0.014***	0.015***	-0.095***	-0.093***
	(19.74)	(19.71)	(0.23)	(0.24)	(-1.01)	(-0.99)
Volatility	0.044***	0.044***	0.286***	0.283***	0.192***	0.195***
	(19.19)	(19.16)	(4.60)	(4.54)	(2.05)	(2.08)
Turnover	-0.196***	-0.195***	-0.516***	-0.514***	-0.389***	-0.391***
	(-60.66)	(-60.41)	(-8.28)	(-8.26)	(-4.15)	(-4.16)

Year 2006 Year 2008

Panel A: Mean CARs for short and non-short sales



Panel B: Means and medians of differences in CARs (shorts minus non-shorts)



Panel C: Means and medians of differences in information ratios (shorts minus non-shorts)

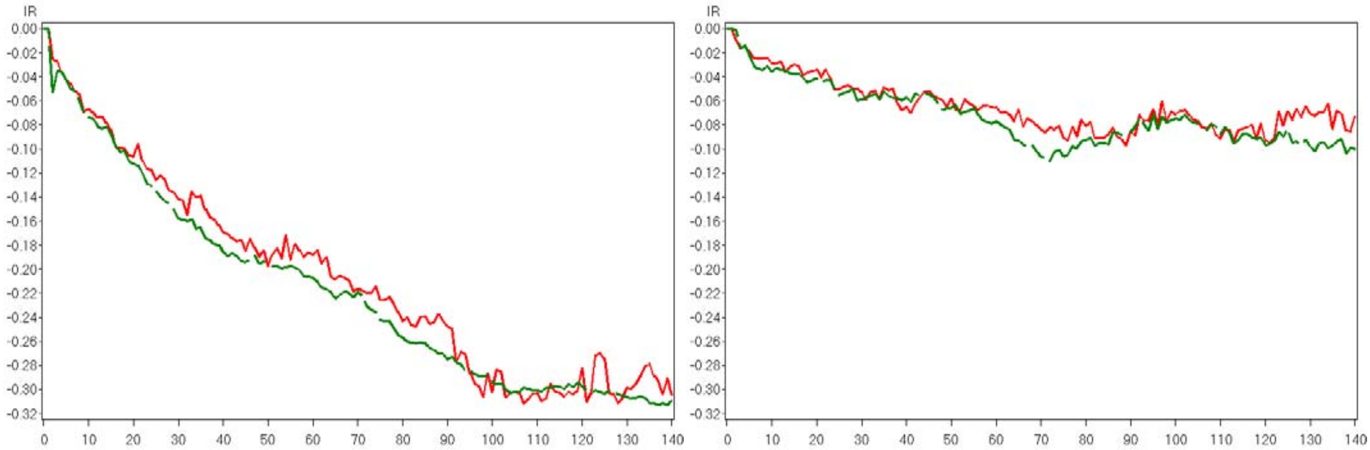
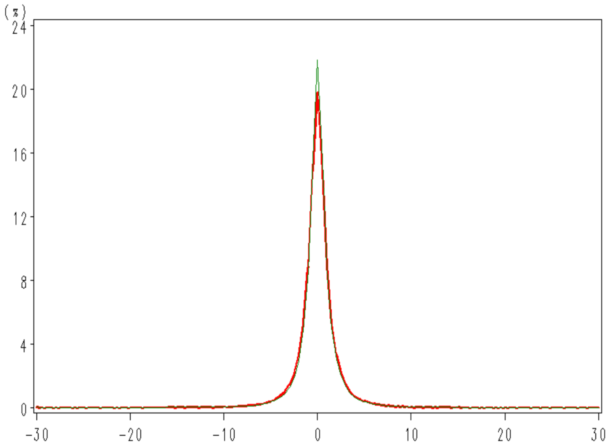
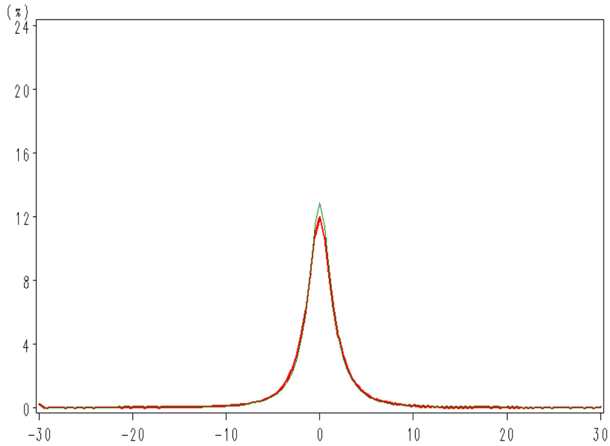


Figure 1. Panel A plots the dollar volume weighted mean cumulative abnormal returns (CAR) and 95% confidence bands for short sales (red solid line) and non-short sales (green broken line), from the time of the trade to 20 days after in one-hour intervals. Panel B plots the mean (green broken line) and median (red solid line) difference in the CAR for short and non-sales (short minus non-short). Panel C plots the mean (green broken line) and median (red solid line) difference in the information ratios for short and non-sales (short minus non-short). In all plots the horizontal axis is in trade hours from the time of the trade (0 trade hours) to 20 trading days after (140 trade hours).

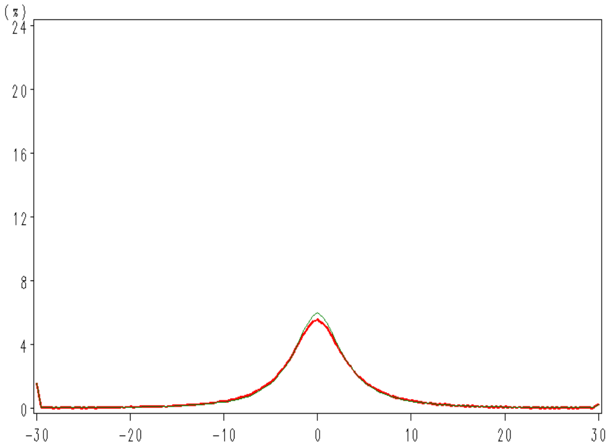
Panel A: CAR at 2 hours



Panel B: CAR at 1 day



Panel C: CAR at 5 days



Panel D: CAR at 20 days

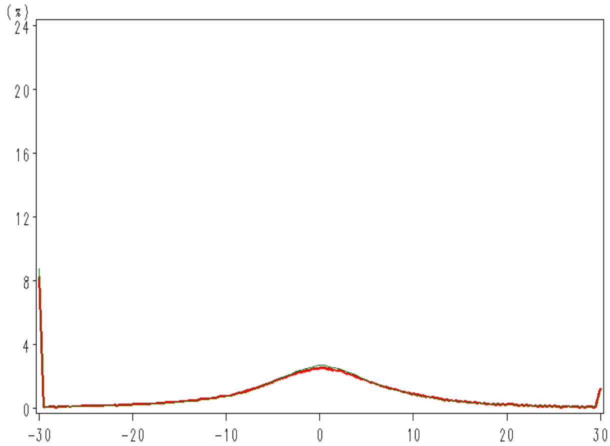


Figure 2. This figure plots the distributions of the cumulative abnormal returns for short sales (red thick line) and non-short sales (green thin line) at times of 2 hours, 1 day, 5 days and 20 days after the trade. The horizontal axis (measuring CAR in %) is restricted to the range +/-30% and observations outside that range are pooled at the corresponding endpoints. The vertical axis measures percentage of observations. The sample consists of years 2006 and 2008

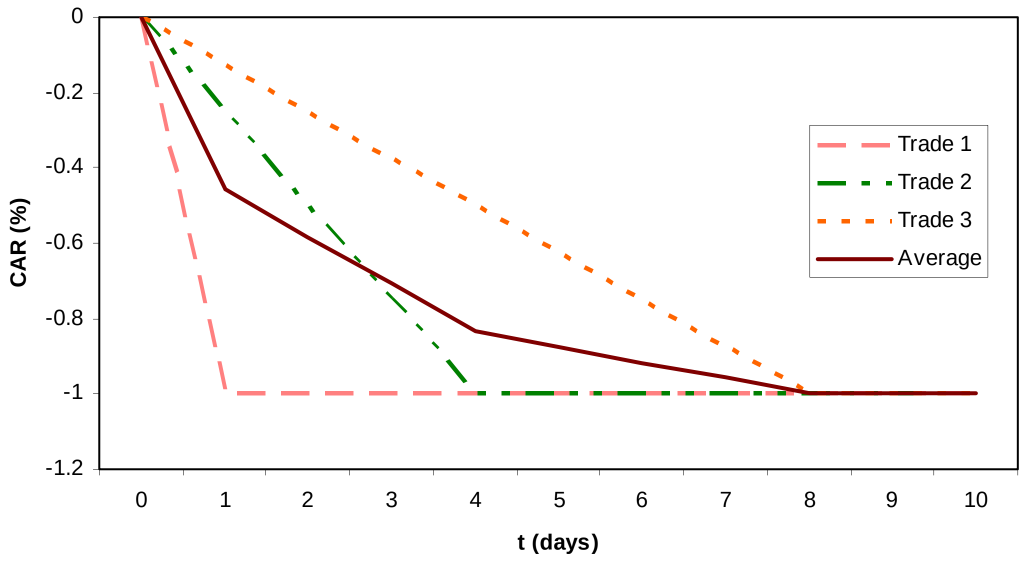


Figure 3. This figure illustrates the effects of averaging the cumulative abnormal returns of trades with different information duration (time taken for information to be impounded into the price). Trades 1, 2 and 3 are each informed about a 1% overpricing, which takes 1, 4 and 8 days, respectively, to be impounded into the price.

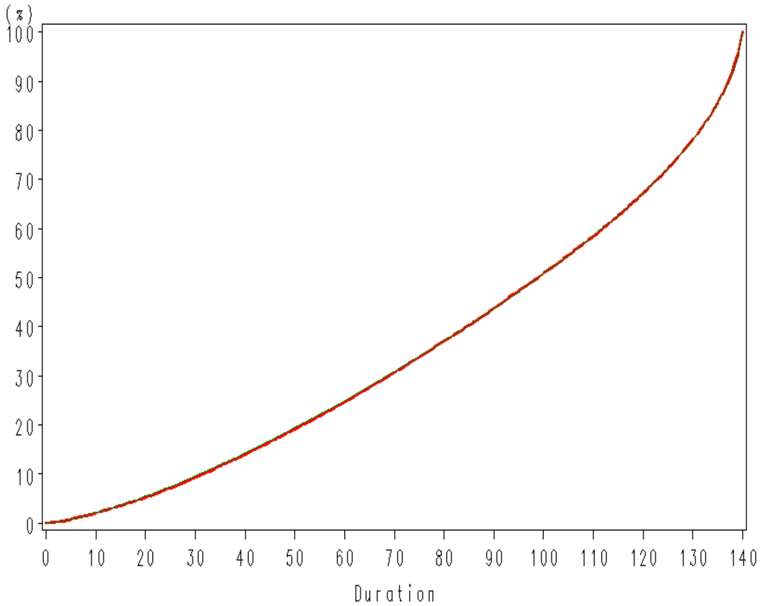


Figure 4. This figure plots the cumulative distribution of the time taken for a trade's information to be impounded in the price (*Duration*) for short sales (red thick line) and non-short sales (green thin line). The lines almost perfectly coincide. We calculate duration as the number of one-hour intervals before the trade's maximum information ratio (for net positive information, and vice versa for net negative information). The sample consists of years 2006 and 2008

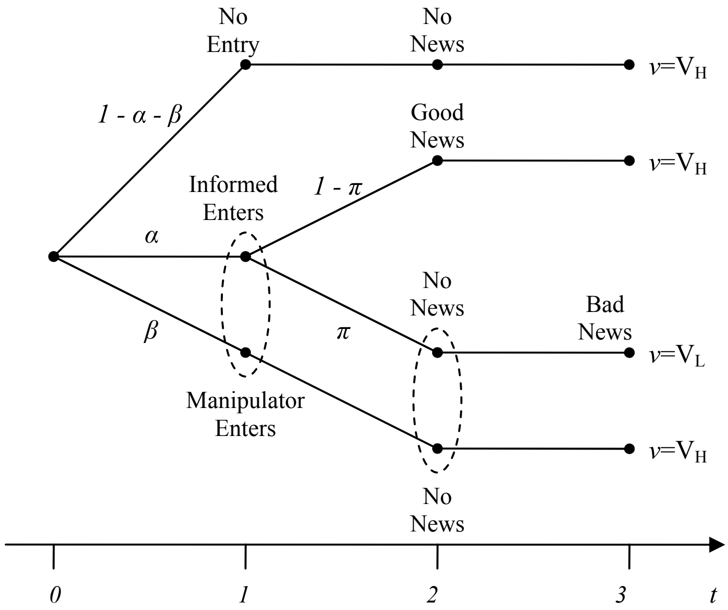


Figure 5. This figure illustrates the stochastic structure and information structure of our theoretical model. With probability α an informed trader enters the market because he knows a company announcement is forthcoming. With probability π the announcement is bad news and with probability (1- π) it is good news. If an announcement is not forthcoming the manipulator may enter (with unconditional probability β) and mimic the behavior of the informed trader (pooling indicated with dashed ovals), or there may be no entry by a large trader (with unconditional probability 1- α -β).

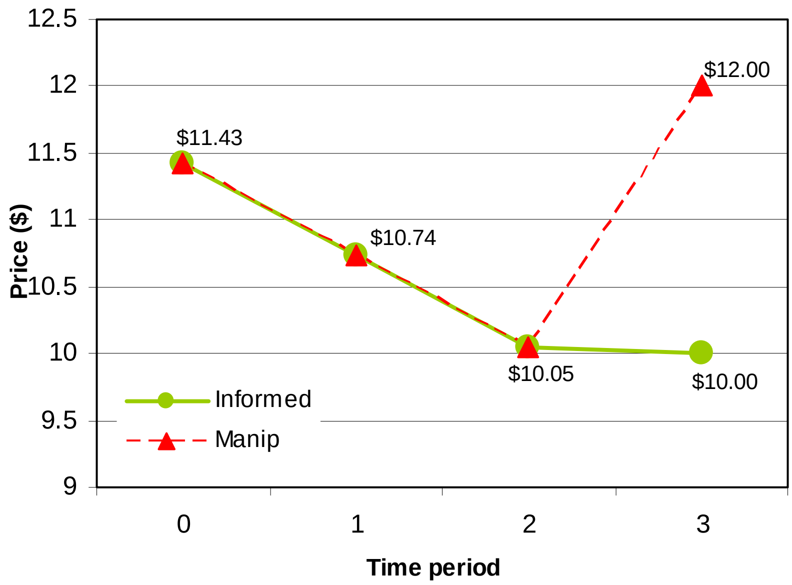


Figure 6. This figure illustrates the price paths under informed trading and manipulation in our theoretical model of manipulation. In this example investors have a constant absolute risk aversion (CARA) utility function (risk aversion parameter of 0.2) and the model parameters are: V_H=12, V_L=10, α=0.5, π =0.5, E=1, S=0.45, probability of manipulation (1-γ)=0.02.

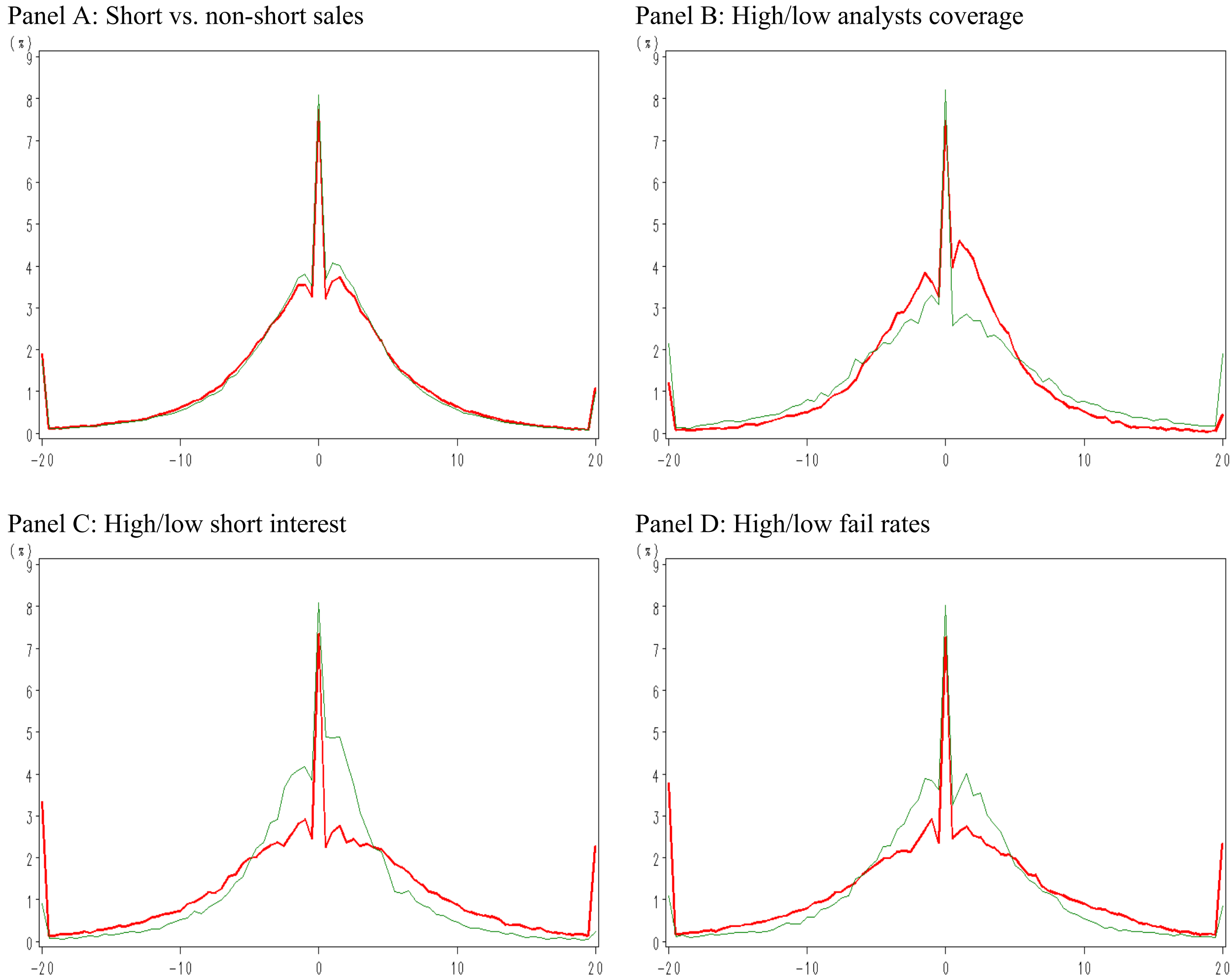


Figure 7. This figure plots the distributions of positive and negative reversals in cumulative abnormal returns following a trade (in %). The horizontal axis (measuring reversal in %) is restricted to the range +/-20% and observations outside that range are pooled at the corresponding endpoints. The vertical axis measures percentage of observations. Panel A compares short sales (red thick line) and non-short sales (green thin line). Panels B, C and D compare the highest quintile (red thick line) to the lowest quintile (green thin line) in the following variables: the number of analyst forecasts of earnings (*Analyst coverage*), the open short interest as a percentage of total shares on issue (S*hort Interest*) and the number of fails to deliver as a percentage of total shares on issue (*Fail rate*). The sample consists of years 2006 and 2008.