Can Short-sellers Predict Returns? Daily Evidence

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This Version: July 14, 2005
First Version: June 17, 2005
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Abstract

We test whether short-sellers in Nasdaq-listed stocks are able to predict future returns based on new SEC-mandated data for the first quarter of 2005. There is a tremendous amount of short-term trading strategies involving short-sales during the sample: Short-sales represent 25 percent of Nasdaq share volume while monthly short-interest is 3.3 percent of shares outstanding (4.7 days to cover). Short-sellers are on average contrarian - they sell short following positive returns. Increasing short-sales predict future negative returns, and the predictive power comes primarily from small trades. A trading strategy based on daily short-selling activity generates significant returns, but incurs costs large enough to wipe out any profits. More binding short-sale constraints result in reduced short-selling, but there is only a significant effect on future returns among low priced stocks.

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Many market observers accuse short-sellers of destabilizing markets by selling stocks (they do not even own) when prices are already trending downward, exacerbating the negative momentum. Issuers and journalists often characterize short-sellers' activities as immoral, unethical and downright un-American.[1] Academics and traders instead argue that short-sellers stabilize security prices by selling stocks when prices exceed fundamental values, thus helping correct market over-reaction. Short-term over-reaction could be caused by impediments to short-selling, as high costs of executing short-sales may result in stock prices reflecting the opinions of optimistic investors only (Miller (1977)).[2] Some researchers have even argued that costly short-selling was one of the culprits behind the stock market bubble of the late 1990s (e.g., Ofek and Richardson (2003)).

In this study, we use the SEC mandated tick-by-tick short-sale data for 2,815 Nasdaq-listed stocks for the period January 2, 2005 to March 31, 2005 to test whether short-sellers are contrarian or momentum traders and whether they are able to predict future returns. We test these hypotheses by studying the link between short-selling activity and future returns and how short-sellers react to past returns on a daily level.

The literature on short-selling is growing rapidly. Most of the previous studies have used monthly stock-specific short interest data (e.g., Figlewski and Webb (1993), Figlewski (1981), Dechow, Hutton, Meulbroek, and Sloan (2001), Asquith, Pathak, and Ritter (2005), and Singal and Xu (2005)). There are three important problems with using monthly short interest data. First, the monthly reporting frequency does not permit researchers to study short-term trading strategies. Second, monthly short interest data does not distinguish between the short interest of dealers (who are exempt from short-sale restrictions) from that of customers. Third, the monthly short interest data does not permit a researcher to discern whether a high level of short interest means that short-selling is more expensive.

More recently, several authors have relied on proxies for short-sale restrictions (Chen, Hong, and Stein (2002) - breath of ownership, Nagel (2004) - institutional ownership, Lamont (2004) - firm's actions to impede short-selling), and even the actual cost of borrowing stock (D'Avolio (2002), Cohen, Diether, and Malloy (2005a), Jones and Lamont (2002), Geczy, Musto, and Reed (2002), Ofek and Richardson (2003), Reed (2002), Ofek, Richardson, and Whitelaw (2003),

[1] For example, John Rothchild in the *Bear Book* said, "Known short sellers suffer the same reputation as the detested bat. They are reviled as odious pests, smudges on Wall Street, pecuniary vampires."

[2] See also Harrison and Kreps (1978), Hong and Stein (2002), Duffie, Garleanu, and Pedersen (2002).

Mitchell, Pulvino, and Stafford (2002)) to investigate if short-sale constraints contribute to short-term over-reaction in stock prices, and if short sellers are informed. The general conclusion reached by this literature is that short-sale costs are higher and short-sale constraints are more binding among stocks with low market capitalization and stocks with low institutional ownership. The literature also finds that high shorting demand predicts abnormally low future returns both at the weekly and monthly frequency. To our knowledge, no one has examined whether short-sellers are contrarian or momentum traders.

Our data has several advantages compared to the previous literature. We are able to distinguish short-selling by investors who are subject to short-sale rules from market makers that are exempt. Our study focuses on short-selling by non-exempt traders. This is important since market makers will tend to be contrarian investors due to their role as intermediaries. We can identify trade size, and hence can use the dollar size of trades to proxy for short-selling by institutional investors. Moreover, the data allows us to study daily (and even intradaily) shorting activity. Hence, we can capture patterns of short-selling which would never appear in the monthly short interest data. The main drawback with the data is that we cannot capture the ultimate covering of short-sale trades.

We find a tremendous amount of short-selling in our sample. Short-sales represent on average 25.1 percent of Nasdaq reported share volume! By comparison, monthly short interest data for the same period reveal short-interest of 3.3 percent of shares outstanding (4.7 days to cover). Hence, we conjecture that the high fraction of short-sales in daily volume is caused by short-term, perhaps even intradaily, trading strategies. This extensive amount of short-term short-sale strategies cannot be explained by the activities of equity and options market makers (exempt from short-sale rules). Short-sales by exempt traders represent only 6.5 percent of reported share volume, leaving the remaining 18.6 percent to traders subject to short-sale rules.

The question then becomes, how do Nasdaq short-sellers trade? Do they "pile on" after poor returns as the critics would have it, or do they act contrarian (i.e., sell when they observe a short-term over-reaction)? Based on our sample, there is no evidence of short-sellers systematically "piling on". In fact, short-sellers actually decrease their shorting activity following negative abnormal returns. Instead, we find strong evidence that short-sellers are contrarian; they increase their short-selling activity following positive abnormal returns.

We are also interested in finding out whether short-sellers time their trades well relative to future returns (i.e., does short-selling intensify on days preceding negative abnormal returns)? The results show that short-sellers time their trades well relative to short-term price trends. Stock prices decline significantly the day following increased short-selling activity. In fact, increased short-selling is followed by negative returns up to five days out, and the relationship is significant up to day three. Hence, there is at least potential for these short-term, short-selling strategies to be profitable. However, absent the data on the ultimate covering of short-sales, we cannot verify when the short-sellers closed out their positions.

The lack of information about short-covering transactions in the data means that we cannot calculate trading profits. However, we are able to examine whether it would be possible to create a profitable long-short trading strategy based on the daily short-selling activity. That is, if the daily short-selling activity was publicly available, could we trade profitably based on this information? We first sort the stocks into quintiles based on short-selling activity on day t and then form a portfolio that is long in stocks with low short-sales and short in stocks with high short-sales. The portfolio is held for one day and is then re-balanced. This strategy generates a significantly positive average abnormal return of 3.8 percent per month during our sample period! Note, however, that the daily rebalancing means that trading costs are likely to be significant.

Our data includes information about trade-size, and we follow the previous literature by using trade-size to proxy for trader type. We divide our sample into small, medium, and large short-sells and explore if short-sellers using different sized trades employ systematically different trading strategies with respect to past momentum. There is strong evidence for contrarian short-selling activity in both the large and medium trade sizes. We attribute these short-sales to institutional traders. For small trades, there is very strong evidence that short-selling activity decreases significantly following price declines (contrarian trading), but we find no significant change in shorting activity following price increases. The most likely explanation for this pattern is that there is a mix of momentum and contrarian traders in the small trade size. It is unclear why institutional traders would use systematically different strategies when executing short-sales of different size. Thus we conjecture that a significant fraction of retail traders are (negative) momentum traders.

The block-trading literature finds that prices move in the direction of large trades, and these traders are typically associated with institutional trading (e.g., Kraus and Stoll (1972) and Holthausen, Leftwich, and Mayers (1990)). By contrast, the stealth trading hypothesis (Barclay and Warner (1993)) and the order-splitting hypothesis (Bernhard and Hughson (1997)) suggests that small or medium-sized trades should be more informative. When it comes to Nasdaq short-sales, we find that it is primarily small trades that are informative, i.e., they predict future negative returns. Recall that we expect that both retail and institutional short-sellers are active in the small short-sale category. By contrast, there is no evidence of a similar ability to predict short-term returns among traders using medium and large short-sales, what we conjecture to be institutional traders. In fact, in some specifications high levels of large short-sales predict significantly higher returns the following day, and the returns remain positive for up to five days out! The most likely explanation for this seemingly poor timing of large short-sales is that those traders who execute block-shorts have a longer investment horizon. They are also more likely to time their trades based on available liquidity.

We consistently find that the link between small-sized trades and future returns is the strongest. For example, a long-short trading strategy based on daily small-sized shorting activity quintiles generates a significant positive average abnormal return of 3.9 percent per month. By contrast, a trading strategy based on daily large-size short-selling activity generates positive but insignificant abnormal returns of 60 basis points.

Our sample covers a very large cross-section of stocks, and we know from previous research that short-selling activity and short-sale costs vary systematically in the cross-section. For example, short-sale costs tend to be lower for large stocks and stocks with high institutional ownership (see D'Avolio (2002) and Cohen et al (2005a)). To examine whether our results are driven by short-sales in a particular category of stocks, we sub-sample by market capitalization, book-to-market, institutional ownership, and whether or not the stock has actively traded put options (a potential substitute for short-selling). We find that short-sellers are strongly contrarian in all the sub-samples. They decrease their short-selling activity following negative abnormal returns and increase their short-selling activity following positive abnormal returns.

To investigate if cross-sectional characteristics matter for predictability, we form long-short portfolios based on double sorts by short-selling activity quintiles and characteristics terciles. We find that portfolios based on overall short-selling activity generate significant positive abnormal returns for small-cap stocks, stocks with low institutional ownership, and stocks with no put options. Indeed, these are stocks where we might expect prices to be relatively less efficient. Short-selling based portfolios generate significant positive abnormal returns both for value and for growth stocks, but the magnitude of the gains is much higher for value stocks. Interestingly, portfolios based on small-sized short-sales generate significant positive abnormal returns for all sub-samples except for large-cap stocks.

Recently, the Securities and Exchange Commission (SEC) adopted Regulation SHO (Reg SHO) to evaluate the need for short-sale rules, and to clamp down on significant failures to deliver stock sold short.[3] The new rule (Rule 203) implies that broker-dealers must locate securities available for borrowing in order to be able to deliver *prior to effecting short-sales*. Rule 203(b)(3) develops additional requirements targeted at stocks that have a substantial amount of failures to deliver, so called ‘threshold’ securities. The rule implies that clearing agencies have to close out all fail-to-deliver positions that exist ten days after the normal settlement date (i.e., 13 consecutive settlement days) by purchasing securities of like kind and quantity. Boni (2004) finds that approximately 4% of U.S. equity issues had fails that would have classified them as ‘threshold’ securities with mandatory close-out requirements under Reg SHO.[4]

The locate and deliver and close-out requirements imply that the costs faced by brokers and clearing agencies enabling investors to short-sell stocks on a threshold list are likely to be significantly higher. We conjecture that these higher costs are passed through to traders in terms of higher costs for borrowing threshold securities. In other words, there is a tightening of the short-sale constraint. We hypothesize that this tightening of the short-sale constraint results in a reduction in future short-selling activity. Indeed, we find strong evidence that short-selling activity declines significantly after a stock has appeared on the threshold list.

How does the tightening of the constraint affect stocks prices? On the one hand, future stock prices may be artificially propped up as pessimistic investors are shut out of the market (Miller (1977)).[5] On the other hand, the fact that securities are on the threshold list is public information (updated daily) so it is likely that the market incorporates this signal that the stock might already be overvalued.[6] Thus we could see positive subsequent returns or negative subsequent returns

[3]Boni (2004) finds that 42% of listed stocks had persistent fails of 5 days or more in the fall of 2004.

[4]See also Evans, Geczy, Musto, and Reed (2003) for evidence on strategic failures to deliver by option market makers, which incidentally are exempt from Reg SHOs deliver and locate requirement.

[5]High levels of failure to deliver may also generate a short squeeze, pushing prices up at least temporarily.

[6]The signaling effect is actually consistent with a long-run version of the Miller hypothesis. If threshold stocks were overpriced before winding up on the threshold list because of short-sale constraints, negative returns when on

depending on which effect dominates. We find no significant relation between threshold stocks and future returns for stocks priced at $5.00 and above. However, stocks on the threshold list with prices below $5.00 do have significantly lower future returns supporting the signaling hypothesis.

In a related paper, Christophe, Ferri, and Angel (2004) study short-selling around earnings announcements based on a sample of 913 Nasdaq stocks in the fourth quarter of 2000.[7] They find that abnormal short-selling is linked to stock returns following earnings announcements. They interpret their findings as suggesting that short-sellers have superior firm-specific information that enables them to predict 'good' or 'bad' earnings announcements. The focus of our study is very different. We study whether short-sellers are contrarian or momentum traders and if their trades preceede abnormal negative returns. Neither strategy necessitates that short-sellers have any superior knowledge of the firm's true value. They could simply be technical traders, reacting to past prices. Interestingly, when we replicate the Christophe et al (2004) methodology for our sample period, we find no significant relationship between post-announcement returns and short-selling activity in the week leading up to the earnings announcement.

Our study proceeds as follows. We summarize our hypotheses in Section I, and describe the data in Section II. We test whether short-sellers are primarily contrarian or momentum investors in section III. We address whether short-selling activity predicts future returns, and if contrarian short-sellers are more successful than short-sellers following momentum strategies in Section IV. A number of robustness checks are conducted in Section V. We investigate how the cost of short-selling affects subsequent short-selling activity and subsequent returns in Section VI. Section VII concludes.

I. Hypotheses

Our hypotheses can be summarized as follows:

- If short-sellers are momentum traders, they should increase their short-selling activity following negative abnormal returns. If, on the other hand, short-sellers are contrarian traders, they should

the threshold list mat just be an indication that the overpricing is now being corrected as bad news is released to the market.

[7] See also Angel, Christophe, and Ferri (2003) for a descriptive introduction to the data.

increase their short-selling activity following positive abnormal returns.

- If short-sellers can predict future returns, an increase in short-selling activity should predict negative abnormal returns and it should be possible to create a profitable long-short portfolio based on measures of short-selling activity.

- If short-sale constraints become more binding when a stock is added to the list of threshold securities, future short-selling should decline significantly after a stock becomes a threshold security.

- A more binding short-sale constraint may result in future prices being overly optimistic as pessimists are shut out of the market (Miller (1977)). Hence, stocks on the threshold list would experience positive abnormal returns in the future. On the other hand, a more binding short-sale constraint is a negative signal that many traders are trying to sell the stock short.[8] If the signaling effect dominates, stocks on the threshold list should experience negative abnormal returns in the future.

- If short-sellers have inside information, we should see more short-selling activity in advance of negative corporate announcements. Alternatively, if short-sellers trade based on deviations of price from their perceived fundamental value, we should see no link between short-sales and negative corporate announcements.

We test these hypotheses in the rest of the paper.

II. Characteristics of short-selling on Nasdaq

A short-sale is generally a sale of a security by an investor that does not own the security. To deliver the security to the buyer, the short-seller borrows the security and is charged interest for loan of security (the loan fee). The rate charged can vary dramatically across stocks depending on loan supply and demand. For example, easy to borrow stocks may have loan fees as low as 0.05% per annum, but some hard to borrow stocks have loan fees greater than 10% per annum (Cohen,

[8] The signaling effect is actually consistent with a long-run version of the Miller hypothesis. If threshold stocks were overpriced before winding up on the threshold list because of short-sale constraints, negative returns when on the threshold list may just be an indication that the overpricing is now being corrected as bad news is released to the market.

Diether, and Malloy (2005a)). If the security price falls (rises), the short-seller will make a profit (loss) when covering the short position by buying the security in the market.

The SEC requires an investor to follow specific rules when executing a short-sale. The rules are aimed at reducing the chances that short-selling will put downward pressure on stock prices. Until May 2, 2005, these rules were different for Exchange-Listed Securities (the tick-test, Rule 10a-1 and 10a-2) and Nasdaq Stock Market Securities (the best-bid test, NASD Rule 3350). Moreover, Nasdaq listed stocks that were traded on other venues (ECNs) had no short-sale restriction. On June 23, 2004, the SEC adopted Regulation SHO which mandates that a pilot be conducted between May 2, 2005 and April 28, 2006 to examine the role of short-sale rules. At the same time, the SEC mandates that all Self Regulatory Organizations (SROs) make tick-data on short-sales publicly available starting January 2, 2005. The SHO-mandated data includes the ticker, price, volume, time, listing market, and trader type (exempt or not exempt from short-sale rules) for all short-sales. However, it does not include information about subsequent covering of short-sales (i.e., purchases).

Our study focuses on Nasdaq-listed stocks.[9] We define the universe of Nasdaq-listed stocks based on all stocks that appear in CRSP with exchange code 3 or 33 (Nasdaq-listed) and share code 10 or 11 (common stocks) at the end of 2004. We download daily data on prices and trading volume for these securities from Yahoo! (finance.yahoo.com).[10] Based on the daily price data, we compute daily returns for each security. We also download intraday data from all SROs that report short-sales for Nasdaq-listed securities and calculate daily short-selling measures. Specifically, we compute the number of trades and shares, classified by whether or not the trader is exempt from short-sale rules and by dollar trade size. We merge the daily short-sale data with return and volume data from Yahoo!. We then filter the sample by only including common stocks with end of year 2004 price greater than or equal to $1. We also exclude stock-days where there is zero volume reported by Yahoo!.[11]

In addition, we obtain monthly short interest data from Nasdaq, and year-end 2004 data on market capitalization, book-to-market, and average daily trading volume (share turnover) for 2004

[9] At this point, only data for Nasdaq and AMEX-listed securities are available.

[10] CRSP data is not yet available for this sample period.

[11] We also set short-sales equal to volume in the few instances where short-sales exceed reported volume. Our results are robust to excluding these stock-days from our analysis.

from CRSP and COMPUSTAT. We obtain institutional ownership data as of the fourth quarter of 2004 from Thompson Financial (13-F filings), and option trading volume data from The Options Clearing Corporation (www.optionsclearing.com). Our final sample covers trading in 2,815 Nasdaq-listed stocks during the first quarter of 2005. To conform with the previous literature, we perform most of our analysis on the 2,278 stocks with a price of at least $5.00, but conduct robustness test using the sample of 543 low-priced stocks.

Table I illustrates the distribution of shorted shares in Panel A, and the number of shorted shares in Panel B by market venue: American Stock Exchange (AMEX), Archipelago (ARCAEX), Boston Stock Exchange (BSE), Chicago Stock Exchange (CHX), National Association of Securities Dealers (NASD),[12] NASDAQ, National Stock Exchange (NSX),[13] and Philadelphia Stock Exchange (PHLX). NASDAQ accounts for just over half the shares sold short, while ARCAEX and NSX each account for roughly one-quarter. The distribution of shorted shares mirrors the distribution of overall trading volume in Nasdaq-listed stocks across market venues.[14] Panel A also shows that short-sale trades are much more evenly distributed across the three venues, indicating that short-sales printed on Nasdaq are significantly larger than short-sales printed on other venues.

Panels B and C of Table I provides descriptive statistics for our daily short-selling data covering 2,815 Nasdaq-listed stocks. The average (median) number of shares sold short per day and stock is 191,690 (16,080) and there are on average (median) 463 (63) short-sales per stock and day. Note that the dispersion across stock-days is significant. To normalize across stocks, we define the relative amount of short-selling (*relss*) as the daily number of shares sold short for a stock-day divided by the total number of shares traded in the stock during the same day. Overall, short-selling represents an astonishing 25.14 percent of Nasdaq share volume! Hence, one in four shares traded on Nasdaq involves a short-seller. This is eight times more short-selling than what was found by Christophe, Ferri, and Angel (2004) based on a three month period in 2000.[15] By comparison, monthly short-interest, defined as the number of shorted shares divided by average daily share volume, is 4.66 during our sample period (see Table II).

[12]NASD operates the Alternative Display Facility (ADF), where trades may be printed.

[13]Formerly known as the Cincinnati Stock Exchange.

[14]In may 2005, Nasdaq traded 55.8% of share volume, Archipelago traded 18.2%, and NSX traded 24.8% (source: www.nasdaq.com).

[15]In a recent paper, Boehmer, Jones and Zhang (2005) find short-selling based on system orders for NYSE stocks to be 14.3 percent of reported volume.

In other words, for the average stock, it would take a little less than five days to cover the short position if short-selling was 100 percent of volume. Or, conversely, starting from zero short shares outstanding, the average short position can be created in about one month (19 trading days) at the rate of short-selling in our sample, provided that no covering takes place during the period (19*0.25=4.75). As a practical matter, short-positions are obviously not created over a one month period. Instead, many short-sales that are likely based on short-term patterns in stock prices would not necessarily be captured by changes in monthly short interest data. Recall that while we do not observe the covering activity, we know that it has to be of the same order of magnitude as the short-selling since the month to month changes in average short interest in our sample is relatively minor (3.3-3.7% of shares outstanding).

Clearly, short-sellers have flourished during the stock market decline of the first half of this decade. We conjecture that this increase in short-selling activity can be explained by a number of factors: increased pessimism among investors following the bubble bursting in March 2000, increased use of algorithmic trading, and the tremendous growth of the hedge fund industry which employs long-short strategies.

In Panel C of Table I, we also divide short-selling activity among traders that are exempt from short-sale rules (equity and options market makers) from those that are not (regular traders). We find that short-selling by traders subject to the short-sale rules represent 18.61 percent of daily share volume on average, while the exempt traders represent 6.53 percent.

We would like to use trade-size to proxy for institutional trading. The challenge we face is the extensive amount of order-splitting in todays' trading environment. The average trade size on Nasdaq has shrunk precipitously after decimalization, and it is now roughly 400 shares. What used to be considered an institutional trade (10,000 shares and above) represents less than a quarter of one percent of all trades and about 16 percent of share volume.[16]. Clearly, institutions do not only trade in traditional blocks anymore.

We use the actual short-sale size distribution within our sample to define the size cutoffs. The distribution has roughly 50 percent of trades less than or equal to $4,400 (200 shares); roughly 45 percent between $4,400 (200 shares) and $37,000 (1,500 shares), and roughly 5 percent above $37,000 (1,500 shares). Hence, we define small short sales as those trades that are less than or

[16]www.nasdaqtrader.com

equal to $4,400, medium short-sales as those trades that are larger than $4,400 but less than or equal to $37,000, and big short-sales as those trades that are larger than $37,000. We hope to capture primarily institutional trades in the large size category, but due to order-splitting we are bound to have both retail and institutional traders in the small-size, and perhaps even the medium-size category.[17]

Table I shows that 10.70 percent of average daily volume are small short-sales, 10.35 percent are medium short-sales, and 4.10 are large short-sales. When broken out by whether or not the trader is subject to short-sale rules, we find that exempt traders are more likely to sell short in large trades than non-exempt ones. This is not surprising since these traders are equity or options market makers. Short-sales for market makers will to a large extent be dictated by their role as intermediaries, and as such they will tend to be contrarian. In the analysis that follows, we will focus on short-sales by traders that are subject to the short-sale rules, and have no easily identifiable exogenous reason for being contrarian traders.

The last panel of Table I reports how average short-selling activity varies by firm characteristics. We define size (ME) and book-to-market (B/M) terciles based on NYSE breakpoints, and find that large-cap stocks and low book-to-market stocks (growth stocks) have greater short-selling on average than small-cap stocks and value stocks. Stocks with high institutional ownership at the end of 2004 and stocks with high trading volume (share turnover) during 2004 (CRSP) have greater short-selling activity than stocks with low institutional ownership and low trading volume. We also find that stocks with a price at or above $5.00 have more short-selling than those with prices below $5.00. Buying put options is an alternative way to make a negative bet on a stock, but stocks with actively traded puts (www.optionsclearing.com) have higher short-selling activity. This is not very surprising since stocks with actively traded puts are likely also to be large, more liquid stocks, with higher valuations (low B/M).

For completeness, we also calculate statistics for two sub-samples by price (not reported): stocks with a year-end 2004 price less than $5.00 (543 stocks), and stocks with a year-end price at $5.00 and above (2,278). short-sales represent a larger fraction of average daily share volume (27.77 percent) for higher priced stocks than for lower priced stocks (13.90 percent).

In Table II, we summarize cross-sectional information on short-sales as well as stock character-

[17] We have varied the breakpoints and find very similar results.

istics. Panel A is constructed from the average daily short-sales for each stock. The cross-sectional average *relss* is very close to the stock-day average in Table I, and average short-selling activity varies from 0 percent to 52 percent of daily share volume in the sample. The average (median) stock has a market capitalization of $1,091.0 ($200.7) million as of year-end 2004, and market-cap ranges from $2.8 million to $290.3 billion. The average (median) stock has a book-to-market (B/M) of 0.54 (0.45), and the average (median) institutional ownership is 40 (35) percent of shares outstanding. We also have information on short positions, and for comparison with *relss* we relate this figure to average daily volume. Short positions would take 4.66 (2.89) days to cover if all trades were short-sales on average (median). Note that there are some extreme short positions within the sample - the maximum value is 152.3 days to cover, or roughly 30 weeks (7.5 months). The average (median) price of sample stocks is $18.32 ($14.00) and the average (median) turnover is 0.88 (0.48) percent. Finally, one third of our sample stocks have actively traded put options.

Panel B of Table II reports the cross-sectional correlations between our short-sale measures and stock-characteristics. All three measures of short-selling activity are significantly positively correlated with size, institutional ownership, short-positions, price, turnover, and a dummy for actively traded put options. By contrast, short-selling activity is significantly negatively correlated to book-to-market. Hence, growth stocks have more short-selling activity than value stocks. The correlation-matrix also shows that large firms tend to have high institutional ownership, a high short-position, higher price, higher turnover, actively traded put options, but lower book-to-market.

III. How do short-sellers react to past returns?

What signals do traders use to decide when to short a stock? While providing a complete answer to this question beyond the scope of our paper, it is reasonable to assume that short-sellers rely heavily on past price-patterns. The major reason for this conjecture is that virtually every book on short-selling uses price-pattern-based technical trading rules as entry and exit signals. Consequently, we analyze how short-sellers react to past abnormal returns. Our study focuses on short-term, short-selling strategies. Therefore, we chose a five-day window preceding the day of the short-sale as our period to measure abnormal returns. As described in the hypothesis section, we will first test if short-sellers are momentum or contrarian traders. Recall that momentum traders are expected to increase their short-sales following negative returns, while contrarian traders are expected to increase short-sales following positive returns.

The results from panel regressions with day and stock fixed effects, and standard errors corrected for clustering by calendar date are in Table III.[18] It is clear from the first column that short-selling activity increases significantly in past market adjusted returns, $ret_{-5,-1}$. The coefficient implies that an abnormal return over the past five days of 10 percent results in an increase in short-selling of 1.72% of average daily share volume. Hence, short-sellers are contrarian on average. Including the previous day's short-sales weakens the magnitude of the effect (column two), but it is still highly significant.

We explore asymmetric responses to past returns in column three by separating past returns into positive market adjusted returns, $r^{+}_{-5,-1}$, and the absolute value of negative market adjusted returns, $r^{-}_{-5,-1}$. Short-selling is significantly higher following positive returns, and significantly lower after negative returns. The magnitude of the coefficient on negative returns is four times as large and highly significant. This can be explained by the 'asymmetry' of returns; positive returns are unbounded while negative returns are limited between 0 and 100 percent.[19] An abnormal negative return of 10 percent during the past five days is associated with a reduction in short-selling corresponding to 2.93 percent of average daily trading volume. Hence, there is strong evidence that traders short less following declining stock prices. These results are robust to controlling for the previous day's short-selling activity. This reinforces our result that short-sellers are contrarian, and not momentum traders, on average.

The rest of the columns of Table III report the results for regressions involving each short-sale size-grouping: small, medium, and large. Small short-selling activity decreases following positive abnormal returns, but the effect is small in magnitude and not statistically significant. Note also that the traders using small-sized shorts are not momentum traders in the traditional sense since they actually reduce their short-selling activity significantly following negative abnormal returns. In other words, they act contrarian after price declines. Medium and large short-sales are contrarian on average, and also when past returns are broken up into positive and negative returns. All the results are robust to including the previous day's short-selling activity.

[18] The results are qualitatively the same if we use firm characteristics instead of stock fixed effects.

[19] For example, compare the return on a (very volatile) stock that moves from $2.00 to $6.00 one week and from $6.00 to $2.00 another week. The returns would be 400 percent and -75 percent respectively. In our sample, the largest positive five-day returns are almost 300 percent while the largest negative five-day returns are roughly 60 percent.

Note also that the magnitude of the coefficients actually tend to decline with trade size (the exception being small-size shorts after positive returns). For example, a 10 percent decrease in abnormal returns is associated with a decrease in small short-sales of 1.53 percent, in medium short-sale of 1.13 percent, and of large short sales of 0.27 percent. This is to be expected since the timing of medium and large size short-sales is likely to be relatively more dependent on the available liquidity.

Recall that institutions are likely to be responsible for virtually all trades in the large category, and most trades in the medium category. Hence, the evidence shows that institutional short-sellers are contrarian. Since it is unclear why institutions would pursue a significantly different trading strategy when trading in the small-size category, we conjecture that it is momentum trading by retail traders that weakens the coefficient on past positive abnormal returns for the small-size category.

IV. Can short-sellers predict future returns?

Having established that short-sellers are contrarian on average during our sample period, we now test whether they are able to predict future abnormal returns. For the shorting strategy to be successful, the stock price has to decline in the future so that the short-seller can cover his position and still make profits large enough to cover trading costs and short-selling costs.

The problem is that we cannot observe the actual covering transactions. We do not know whether short-sellers keep their positions open for one day, a week, a month, or even several months. We are also restricted in that our sample period is short, only three months. To be very conservative, we start by examining if a significant increase in today's short-selling activity is associated with a significant negative abnormal return tomorrow. The short window for measuring short-selling activity (one day) and the short horizon (one day) will make it very difficult to find any pattern of predictive power of short-sale activity.

Table IV reports the results of panel regressions with day fixed effects and standard errors corrected for clustering by calendar date. We regress returns on day $t+1$ on *relss* for day t.[20] Since previous research (Fama and French (1992)) has pointed out that size and book-to-market

[20] We have also run these regressions using the Fama-MacBeth (1973) regression methodology, and the results are very similar.

help explain the cross-section of average returns (and may proxy for risk factors) we control for size ($\log(ME)$) and book-to-market, ($\log(B/M)$) on the right hand side. Note that in our short sample period, only book-to-market is significantly related to future returns.[21] In addition, we add day t market-adjusted returns (r_t) as an independent variable to control for reversals that are present in the daily return data during our sample.

In the first column of Table IV, we report the results of regressing future returns on (non-exempt) short-sales as a fraction of average daily volume, *relss*. Clearly, higher short-selling today predicts a future decline in abnormal returns. The economic magnitude of the effect is also significant - a one standard deviation increase in *relss* predicts a 2.98 basis point decline in next day abnormal returns which corresponds to an annualized compounded return of 7.73 percent.[22]

One concern may be that there is significant positive autocorrelation in short-sale activity, which may itself cause prices to decline on day $t+1$. It turns out that while short-sales are positively correlated in our sample,[23] the effect does not eliminate the predictive ability of today's short-sales. Acknowledging that column two is not a predictive regression, we experiment by including the next day's short-sales on the right hand side. The results show that if short-sales are high tomorrow, returns are actually significantly higher! Once we control for this pattern, higher short-sales today are associated with a larger (54.6 percent per year!) and much more significant negative return. The reason for this results is that short-sellers are contrarian on average. Hence, they sell following positive abnormal returns. Putting future short-sales in the regression thus helps separate days when short-sellers are still building a position (positive future returns) from the days when short-sellers reduce their activity (negative future returns).

We control for past abnormal returns in column three, but the effect is not significant after we control for short-sales and the daily return reversals. We refine the tests in columns four to six by splitting up the past abnormal returns by sign and interacting the signed past returns with short-selling. This weakens the direct effect of short-sales on future abnormal returns, and the results show that there is no significant difference between momentum and contrarian short-sellers on average in predicting future abnormal returns.

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[21] Value stocks did better than growth stocks during our sample period. For example, the average monthly return on the Value-Growth factor, HML (Fama and French (1993)), was 1.05% (source: mba.tuck.dartmouth.edu/pages/faculty/ken.french/.

[22] Calculated as $(1.000298)^{250} - 1$.

[23] In stock-by-stock regressions, the average autoregressive coefficient is 0.202 and the average t-statistic is 1.70.

As mentioned above, we do not know the short-sellers' horizon. It is most likely longer than one day. Therefore, we also test whether today's short-sales predict the returns one, two, three, four, and five days out. Figure 1 plots the coefficient estimates on *relss* as well as the corrected t-statistics. The underlying regression specification is the same as in the first column of Table IV. Short-sales predict negative returns up to five days out, and while the significance declines, the effect is significant for one and three days out.

Previously, we saw that there were significant differences in short-selling strategies between the traders that use small and the traders that use medium and large short-sales. Do these groups of investors also have different abilities in predicting future stock returns? Column seven of Table IV clearly shows that it is the small short-sales that predict future abnormal negative returns. The effect is also economically significant, with a one standard deviation increase in small-sized short-sales resulting in a increase in the next day abnormal return of 5.31 basis points, or an annualized return of 14.21 percent. Surprisingly, large short-sales are a significant predictor of positive abnormal future returns! Note that this does not in and of itself mean that they are unprofitable strategies since they may simply stay short for a longer period of time on average. Moreover, as mentioned in the previous section, medium and large short-sales are relatively more likely to be timed to days when liquidity is high.

Are the small short-sales simply "free-riding" on reversals of momentum? To address this question, we control for past abnormal returns in the last two columns of Table IV. The second to the last column shows that contrarian trading (high short-selling when past abnormal returns are positive) by small-size short-sales significantly predicts future negative returns. What about the momentum traders? The final column shows that they are fighting against an overall pattern of return-reversals in the data. This pattern can be exploited by contrarian traders, but works against the strategy of momentum traders. Once we control for the return-reversals, the last column shows that small momentum short-sells predict negative future abnormal returns. In other words, in the instances when short-sellers trade on momentum, they are able to time their trades to the days when there are continuations in returns.

The second panel of Figure 1 shows the ability of small short-sales in predicting returns one, two, three, four, and five days out. The effect of today's short-sales is consistently negative, and it is statistically significant one, three, and four days out. Hence, the ability of retail-sized short-sales to predict negative abnormal future returns lasts for as long as a week. In addition, the coefficients are uniformly bigger than when we use all short-selling trades (see the first panel).

If returns are predictable, it is at least potentially possible to develop a profitable trading strategy based on the information in the Reg SHO short-sale data. To investigate this, we first compute *relss* and $relss_{small}$ quintiles respectively using all stocks in our sample on date t. We form portfolios on day t using all stocks in our sample with a closing price on day $t-1$ greater than or equal to $5.00. We then calculate the market-adjusted (abnormal) returns on the quintile portfolios on day $t+1$. The portfolios are rebalanced daily.

Table V summarizes the results. First note that abnormal returns tend to decline is short-selling as a fraction of trading volume (Panel A). The last column provides the difference in returns between the low and high *relss* portfolios in percent.[24] A strategy of going long the low *relss* portfolio and short the high *relss* portfolio (Low-High) generates a statistically significant daily average return of 0.185% (3.8% per month). If we extend the holding period to five days using the overlapping holding period methodology of Jegadeesh and Titman (1993), the results are even stronger with a statistically significant average daily return of 0.224% (4.6% per month).

For small short-sales (Panel B), abnormal returns are monotonically declining in *relss*. Trading based on small short-sales would generate a slightly higher average return of 0.189% per day (3.9% per month). Also in this case, the results are strengthened for the five-day holding period with a statistically significant abnormal return to the long-short strategy of 0.226% (4.6% per month).

We examine long-short portfolios based on large short-sales in Panel C. These trades are relatively rare, so when forming quintiles, we end up with zeroes spilling over into the second quintile. Hence, for this exercise, we compare the highest quintile with those stocks where there was no large short-sales during the formation period. This long-short strategy generates positive, but insignificant returns for the one-day holding period. The results are somewhat stronger for the five-day holding period, but the abnormal returns are still insignificant.

The return on this strategy may seem 'too large,' but execution costs and commissions are likely to be significant because of daily rebalancing. Moreover, we need to take the cost of shorting into account. To gauge the importance of trading costs, let us assume that one quarter of the stocks in

[24]Two-thirds to three-quarters of the stocks in the low *relss* portfolio have zero short-sales for the day of portfolio formation.

the portfolio are turned over daily. Based on SEC mandated 11Ac1-5 reports for all market centers reporting execution quality for Nasdaq-listed stocks,[25] we estimate the average effective spread of our portfolio by finding the average effective share-weighted spread for stocks in March of 2005 with similar market-cap as the average of the low-high portfolio. Our estimate of the effective spread is 62 basis points. Thus execution costs for the low-high portfolio would be roughly 6.2 percent per month (not including commissions). By comparison, explicit costs of shorting are relatively small. Cohen, Diether, and Malloy (2005a), estimate these costs to be 3.98 percent per year (32.6 basis points per month) for stocks with market capitalization below the NYSE median. Thus unless a trader managed her costs very effectively (maybe through the use of limit orders) she could easily wipe out the positive return from a low-high portfolio strategy.

In a contemporaneous and independent research , Boehmer, Jones, and Zhang (2005) examine whether short-sellers submitting orders to NYSE's SuperDOT are informed about future abnormal returns. They have a longer sample-period (2000-2004) and are therefore able to look at longer horizon predictability. Despite the difference in sample stocks and time-periods, their results are very similar to ours. NYSE stocks with relatively heavy shorting underperform lightly shorted stocks by an average of 1.25 percent for a 20-day holding period. In our study, we find that small short-sales are more informative of future price moves, while Boehmer et al (2005) find that institutions are better informed. Since we know that institutional traders do use both large and small trades, and Boehmer et al (2005) have access to an indicator for institutional trading (and do not use size as a proxy), the results from the two papers are not inconsistent.

V. Robustness tests: Cross-sectional differences in short-selling

It is quite likely that the relationship between short-selling and past returns, as well as the ability of short-sellers to time their trades before negative returns varies significantly in the cross-section. For example, since we know from the previous literature that it is easier to sell short in larger firms, in more liquid firms, and in firms with higher institutional ownership, it is likely that short-selling is more sensitive to past returns for these stocks.

We sort the stocks into terciles based on CRSP market capitalization as of year-end 2004.

[25] We downloaded the regulatory data from the web-sites of: Archipelago, Island, Instinet, Madoff, NSX, Nasdaq, Knight, and Trimark.

The breakpoints are determined by NYSE stocks. We contrast the effect of past returns on short-selling for small-cap and large-cap stocks in Panel A of Table VI. The overall contrarian pattern of short-sales is present and significant both for small-cap and large-cap stocks. As expected, the magnitude of the coefficient on *relss* is more than twice as large for large-cap stocks compared to small-cap stocks. Clearly, it is easier (and cheaper) for short-sellers to establish a short position in large-cap stocks all else equal. Traders using medium-size and big-size trades are contrarian for all sub-samples (tabulated but not reported). Traders using small short-sales are contrarian following negative abnormal returns, but they do not change their short-selling activity significantly following positive abnormal returns.

The previous literature has tested and confirmed the Miller (1977) hypothesis that short-selling demand seems higher for low growth stocks than it is for value stocks (Jones and Lamont (2002)). We divide our sample into growth stocks (lowest B/M tercile) and value stocks (highest B/M tercile) based on NYSE breakpoints. Table VI Panel B reports the results. There is a strong contrarian pattern both in growth and value stocks, and as expected the magnitude and significance of the coefficient on *relss* is higher for growth than for value stocks. Small-size short-sellers are contrarian following negative abnormal returns, but they do not respond significantly to positive abnormal returns for value stocks and actually reduce their short-sales significantly following positive abnormal returns. Medium and institutional-size traders are consistently contrarian (not reported).

The previous literature has shown that stocks with high institutional ownership are less costly to short, all else equal (D'Avolio (2002)). The suggested reason for this in the literature is that institutions are more likely to be willing to lend stock. Hence, we divide the sample based on institutional ownership to examine our results are driven by stocks with high institutional ownership. The results are in Panel C of Table VI. We find that short-sellers are contrarian both in stocks with high and low institutional ownership, but as expected, the magnitude of the effect of past abnormal returns on future short-sales is almost three times as high for stocks with high institutional ownership. Traders using small-size trades are contrarian following negative returns but do not respond significantly to positive abnormal returns, while those using medium and institutional-size trades are consistently contrarian.

Several authors (Brent, Morse, and Stice (1990), Chen and Singal (2003), and Senchak and Starks (1993)) have explored the interaction between the options market and the stock market to investigate the extent to which short-sale constraints are binding. A trader that wants to express a negative view about a security can either sell the security if he happens to own it, sell the security short, or buy at the money put options. So, for stocks with actively traded put options, there are more alternatives to bet on the decline in stock prices.[26] Therefore, we conjecture that short-selling should be less sensitive to past returns for stocks with actively traded put options. To test this hypothesis, we download daily put option trading volume from the Options Clearing Corporation (www.optionsclearing.com), and divide the sample into stocks with and without traded put options.[27] Panel D of Table VI reports the results. Whether or not a stock has put options, traders are strongly contrarian on average. Both subsamples display contrarian trading after negative abnormal returns and no significant effect of positive abnormal returns by short-sellers using small trades, while medium and institutional-size short-sales are consistently contrarian.

We also repeat the panel regressions of future returns on current short-sales and other control variables that we conducted for the overall sample (Table IV) for the sub-samples by size, book-to-market, institutional ownership, and put option activity. However, in the interest of brevity, we only report the estimated coefficients and the associated t-statistics for *relss* and $relss_{small}$ on future abnormal returns in graphical form in Figures 2 to 5.[28] These estimates come from the predictive regressions for one through five days ahead (see Figure 1).

In Figure 2 we show that higher short-selling predicts consistently negative future abnormal returns for both small-cap and large-cap stocks, but the pattern is only significant for small-cap stocks. The lower graphs show that high $relss_{small}$ predicts significantly lower future abnormal returns up to four days ahead for small-cap stocks, and the effect is also significant at one lag for large-cap stocks. Note also that the magnitude of the coefficients is much larger for $relss_{small}$ than for overall *relss*. We also repeat this exercise, contrasting low and high-liquidity stocks (not reported), and find that the patterns are very similar to the ones just described for small-cap versus large-cap stocks.

Figure 3 shows that for growth stocks, we have consistently negative coefficients but they are not significant. The pattern for value stocks is more puzzling, with an oscillating coefficient.[29]

[26]In addition, they could use single stock futures. However, these are relatively illiquid.

[27]Note that there could be significant OTC trading in put options for securities where there is no activity on the options exchanges, which will reduce our chances of finding a significant result.

[28]The complete results are available from the authors on request.

[29]Recall that we already control for the previous day's abnormal return. However, this may not be sufficient to

Note, however, that the negative coefficient is significant one, three, and even five days out, and the days in between do not eliminate the cumulative effect of *relss* on future returns. As before, $relss_{small}$ is a better predictor of future abnormal returns, and the magnitude of the coefficients is much larger. $relss_{small}$ is a significant predictor of future abnormal returns one and two days ahead for growth stocks, and one, three and five days ahead for value stocks.

Figure 4 shows that short-selling among stocks with low institutional ownership is negatively related to future returns throughout the five day window, but the coefficients are not significant on days two through five. For stocks with high institutional ownership, the relationship is negative but only significant on day three. The estimated coefficient on $relss_{small}$ is larger in magnitude for both sub-samples, and it is also significant for stocks with low institutional ownership (one and three days out).

Figure 5 shows that short-selling among stocks without puts is significantly related to future returns, but the relationship is insignificant for stocks with puts. For $relss_{small}$, we also only find significant predictability for stocks without actively traded put options (one, three and four days out).

The panel regressions behind Figures 2 through 5 assume a specific functional form for the relationship between current short-sales and future abnormal returns. A more general way to test for whether short-sellers have information is to form portfolios based on the level of short-selling activity. We thus repeat the exercise from Table V for our subsamples. That is, we first sort stocks into terciles by characteristics (size, book-to-market, institutional ownership) and into those with and without actively traded puts. For each characteristic-portfolio, we conduct a daily sort of stocks into quintiles by *relss* and $relss_{small}$ respectively. We form a long-short portfolio by buying stocks with low short-sale activity, and shorting stocks with high short-sale activity. If there is information in the amount of short-selling, these portfolios should generate positive and significant abnormal returns.

The results of the double-sorts by characteristics and short-sale activity are in Table VII. For brevity, we only report the low and the high portfolios, and the returns to the long-short (low-high) portfolio. The trading strategy based on *relss* generates significantly positive profits for small-cap stocks, for stocks with low institutional ownership, and for stocks with no put options. The trading

eliminate bid-ask bounce. We plan to explore using mid-quote returns in future work.

strategy generates significantly positive profits both for growth stocks and for value stocks, but the return to the low-high portfolio is much larger for value stocks. These results reinforce the pattern that we found based on the panel regressions. Interestingly, the strategy based on $relss_{small}$ generates significantly positive profits for all sub-samples except large-cap stocks, but the returns to the low-high portfolio shows that profits are higher in small-cap, value stocks, stocks with low institutional ownership, and stocks with no put options. Hence, the portfolio results also verify that it is the small-sized short-sales that are particularly successful at predicting future abnormal returns.

We also investigate the relationship between short-sales and returns for the 543 stocks in our sample that have prices below \$5.00 (low price stocks). We find that short-sellers are contrarian overall and for each separate trade-size grouping. In this sub-sample, daily-selling does not significantly predict future abnormal returns, but monthly short interest is a significant predictor of negative future abnormal returns. Hence, it seems that returns for these stocks react to short-selling activity with a much longer delay than the other stocks in our sample.

Finally, we repeat the analysis with trade-size groupings defined in shares instead of dollars. The results are qualitatively the same as those discussed above.

In summary, we have conducted robustness test along a number of dimensions: market capitalization, liquidity, book-to-market, institutional ownership, whether or not the stock has exchange traded put options, and stock price. No matter how we cut the data, we find strong evidence that short-sellers on average are contrarian traders. The predictive ability of contrarian short-sellers in the aggregate is stronger for small-cap stocks, for less liquid stocks, for value stocks, stocks with low institutional ownership, for stocks without actively traded puts, and for higher priced stocks. It is the traders that use small short-sales that are particularly successful at predicting future abnormal returns.

An important caveat should be kept in mind in interpreting these results. Due to the short sample, we are focusing on the success of very short-term predictability of abnormal returns. It is possible that traders using medium and large short-sales have a longer horizon, and that their short-sales are predicting future negative returns beyond five days out.

VI. Do short-sale constraints affect subsequent short-sales and returns?

Reg SHO also provides unique information on the extent of delivery failures for US stocks. A failure to deliver occurs when a seller of a stock has not provided the shares by the third day after the transaction. Inadvertent failures can occur because of mistakes or delays in the delivery of physical shares. However, in two recent papers, Evans, Geczy, Musto and Reed (2003) and Boni (2005) provide evidence that market makers strategically fail to deliver when stocks are hard to borrow. Boni (2005) also points out that many brokerage firms allow counterparts to fail without requesting a buy-in (a forced purchase of securities in the open market) when costs borrowing costs are high. Hence, significant failures to deliver are likely to be highly correlated with the cost of borrowing stock.

Starting on January 3, 2005, Reg SHO requires clearing firms to monitor failures to deliver, and to report this information to the respective SROs. SROs in turn, are required to make a list of stocks with significant failures to deliver, so called threshold securities, publicly available on a daily basis.

A threshold security is defined as any equity security of an issuer that is registered under Section 12, or that is required to file reports pursuant to Section 15(d) of the Exchange Act where, for five consecutive settlement days there is the following: aggregate fails to deliver at a registered clearing agency are at least 10,000 shares for the security, the level of fails is equal to at least 1/2% of the issuer's total shares outstanding, and the security is included on a list published by an SRO. In order to be removed from the list of threshold securities, a security must not exceed the specified level of fails for a period of five consecutive settlement days.

In our sample, 188 stocks or 6.7 percent appear on Nasdaq's threshold list sometime during the three month period. However, among stocks with a price of at least $5.00 at year-end 2004, only 4.6 percent of stocks appear on the threshold list. This is similar to what was predicted by Boni (2004) based on data that predates Reg SHO. We also find that small-cap stocks, low book-to-market, low institutional ownership, and high volume stocks are more likely to appear on the threshold list. Stocks with prices below $5.00 at year-end 2004 are significantly more likely to be on the threshold list (10.6 percent) compared to higher-priced stocks (2.5 percent). Our time-period is too short to carefully study duration on the threshold list, but we find the mean (median) duration to be 20.2 (15) days.

What happens when a security appears on the threshold list? For short-sales of any security on the threshold list, the selling broker-dealer must deliver the security no later than ten days after the settlement date. This is the so called close-out requirement. If for any reason the security was not delivered within ten days after the settlement date, the rule restricts the broker-dealer, including market makers, from executing additional short-sales for the next 90 days in the security for the person for whose account the failure to deliver occurred, unless the broker-dealer or the person for whose account the short-sale is executed, borrowed the security or entered into a bona-fide arrangement to borrow the security, prior to executing the short-sale. Thus it is likely to be more costly to short securities that appear on the threshold list, and we expect lower short-selling activity for stocks on the threshold list. We test this prediction in Panel A of Table VIII. The regressions include firm and calendar day fixed effects. There is clearly a highly significant negative effect on subsequent short-selling if a security is on the threshold list. The effect is particularly strong among stocks with a lagged price at least equal to $5. We interpret this as evidence that short-sale constraints are indeed more binding (costs are higher) after a stock appears on the threshold list.[30]

Perhaps the more interesting question is how the appearance on the threshold list affects subsequent abnormal returns? As outlined in the hypothesis section, we have two competing hypotheses. Miller (1977) suggests that a more binding short-sale constraint will lead to stock prices that reflect the opinion of optimistic investors. If Miller is correct, stocks on the threshold list should experience positive abnormal returns as short-run overpricing is exacerbated (at least in the short-run). On the other hand, a more binding short-sale constraint is a negative signal that many traders are trying to sell the stock short because they believe the stock is overpriced. If the signaling effect dominates, stocks on the threshold list should experience negative abnormal future returns.

We test these predictions in panel B of Table VIII. The regressions control for past returns, $relss$, $\log(ME)$, and $\log(B/M)$. In addition we include calendar day fixed effects, and standard errors corrected for clustering by calendar day. In column one and column five we univariately regress abnormal returns in day $t+1$ on a threshold dummy from day t. Column 1 uses only stocks with lagged price less than $5, and column 5 uses only stocks with lagged price greater than or equal to $5. There is a dramatic difference between the two types of stocks. There is a significant negative relation between subsequent abnormal returns and the threshold dummy variable for low

[30]Note that this reluctance to sell threshold securities short can also be a result of traders' fear of a short squeeze.

priced stocks. Threshold stocks experience a very large average abnormal return of -.353% per day (t-stat = -2.11). However, for stocks with a lagged price $\geq$ \$5 the threshold coefficient is actually positive and never significant. Even after controlling for *relss*, past returns, $\log(ME)$, and $\log(B/M)$, the coefficient is still significant (t-stat=2.67) for low priced stocks and insignificant for the higher priced stocks. Thus, overall the evidence is decidedly mixed. It appears that the threshold flag is a much stronger signal among low priced stocks.[31]

VII. Can short-sellers predict information events?

Our results show that short-sellers, particularly those using retail-sized trades, are able to predict future (negative) returns at the daily frequency. Does this predictability imply that short-sellers have private or inside information and consequently anticipate whether corporate announcements will be ‘good’ or ‘bad’ news? If this is the case, then short-selling should increase significantly before negative earnings surprises. On the other hand, short-sellers may simply value stocks better than other market participants. If the latter is the case then we expect short-sellers will use the same trading strategy around a corporate announcements as they do at other times, and will not manifest prescience before corporate announcements.

To test whether the pattern of short-sales is consistent with the private information story or the valuation story, we replicate the empirical strategy implemented by Christophe et al (2004). They examine short-selling in 913 Nasdaq-listed stocks around earnings announcements during the fourth quarter of 2000. They show that short-selling activity is significantly higher in advance of negative earnings surprises. They interpret their findings as consistent with the hypothesis that short-sellers have superior (private) firm-specific information that enables them to anticipate the earnings announcement.

We replicate the analysis from Christophe et al (2004) in Table IX (see Table III in their paper for a comparison). We use similar sample-restrictions (see table legend), and arrive at a sample of 1,284 eligible Nasdaq-listed stocks with earnings announcements during the first quarter of 2005. $abss_{-5,-1}$ is defined as the average daily abnormal short-selling during the five days before the earnings announcement (pre-announcement period). It is calculated as the average daily short-

[31]Diether, Lee, and Werner (2005) provide an in-depth analysis of the effects of the mandatory close-out requirements for threshold securities on short sales and returns.

selling during the pre-announcement period divided by the average daily short-selling during the non-event period (all days except for -5 to +1 days relative to earnings announcement day), all minus 1. $relss_{-5,-1}$ is the ratio of the number of shorted shares to the number of traded shares in the pre-announcement period. $r_{-5,-1}$ ($r_{0,1}$) is the return from the closing price on day -6 (-1) to the closing price on day -1 (+1). $abvol_{-5,-1}$ is the stock's abnormal volume in the pre-announcement period, measured as the average daily volume during the pre-announcement period divided by the average daily volume during the non-event period, all minus 1. *normrelss* is the ratio of the number of shorted shares to the number of traded shares during the non-event period.

Table IX reports the results of the following regressions:

$$abss_{-5,-1} = \beta_0 + \beta_1 r_{0,1} + \beta_2 r_{-5,-1} + \beta_3 abvol_{-5,-1} + \varepsilon \quad (1)$$

$$relss_{-5,-1} = \beta_0 + \beta_1 r_{0,1} + \beta_2 r_{-5,-1} + \beta_3 normrelss_{-5,-1} + \varepsilon \quad (2)$$

If the inside information story is correct, β_1 should be negative so that negative returns following an earnings announcement are associated with significantly higher abnormal short-selling preceding the announcement. If short-sellers are momentum traders, β_2 should be negative and if they are contrarian traders, β_2 should be positive. Table XII clearly shows that abnormal amounts of short-selling are not significantly associated with negative future returns. The coefficient (β_1) is even positive, but insignificant. By contrast, since β_2 is significant and positive, short-sellers are strongly contrarian around earnings announcements. Thus, the evidence lends support to the valuation hypothesis as opposed to the inside information story.

One concern is that our results may differ because our sample period is very different from the one used in Christophe et al (2004). To see if general market developments or the methodology used are likely to influence our conclusions, we augment the analysis by adjusting for the market return, by correcting the standard errors for clustering of earnings announcements, and by examining whether short-sellers predict earnings surprises as opposed to returns.[32] Our previous conclusions do not change. Moreover, we find no ability of short-sellers to systematically predict earnings surprises.

Hence, unlike Christophe et al (2004), we are unable to detect any ability among short-sellers

[32] Results are available from the authors on request.

to successfully trade based on firm specific private information during our sample period.[33] There are a few candidate explanations for the different conclusions. The most obvious one is that the Nasdaq Composite Index declined by close to 41.3% during the last quarter of 2000. Hence, as long as the abnormal short-selling measures are defined to be positive and raw returns are used, the estimates of β_1 and β_2 will tend to be negative. A second explanation is that there is a significantly higher frequency of short-selling in our sample compared to the Christophe et al (2004) sample. Hence, it is likely that a different breed of short-sellers, possibly with very different objectives and trading strategies, are active in the markets today.

VIII. Conclusions

Short-sellers definitely have a bad reputation in the media as well as among issuers, and they are often accused of exacerbating stock price declines by trading on negative momentum. However, to date very little evidence has been offered to shed light on whether or not short-sellers "pile on" after poor returns. In fact, we do not know anything about how short-sale transactions are timed relative to past price momentum, nor do we know if short-sellers time their trades well relative to future (negative) abnormal returns. Our paper attempts to fill that void.

We use new SEC-mandated short-sale data that ultimately will cover all stocks listed on U.S. equity markets. Our study focuses on short-selling activity in Nasdaq-listed stocks because of data availability. The data is tick-by-tick, but we choose to aggregate the intradaily data into daily statistics on short-sales for the purposes of this study. We do this to establish some general facts about short-selling before attacking the challenging topic of intraday short-sale strategies.

Overall, we find a tremendous amount of short-selling in our data. On average, short-sales represent 25.1 percent of daily share volume! This is considerably higher than what would be suggested by short interest data, as well as previous evidence on short-selling activity (Christophe et al (2004)). We conjecture that this high frequency of short-sales can be explained by an increased pessimism, the increased use of algorithmic trading, and the growth in the importance of hedge funds in U.S. financial markets.

Our main focus is to investigate how short-sellers respond to past returns, and if their trades pre-

[33] Interestingly, Danske, Richardson, and Tuna (2005) reach the same conclusion based on daily short-selling activity at the NYSE during the period April, 2004 through February, 2005.

dict future negative abnormal returns. We find strong evidence that short-sellers in Nasdaq-listed stocks are contrarian traders. They increase their short-selling activities after positive abnormal returns, and reduce their short-selling following negative abnormal returns. Only for short-sellers using small trades do we find any evidence of momentum trading, and it takes the form of lower short-selling activity following positive abnormal returns. We also find that increased short-selling activity predicts negative abnormal future returns, in some cases as much as five days out. It is primarily small short-sales that predict future negative returns, and short-sellers using small trades are successful at predicting both continuations and reversals in returns.

We also find that a trading strategy that goes long in stocks with low short-selling activity and sells short stocks with high short-selling activity generates significant positive average returns, but these positive returns could easily be wiped out by trading costs and the cost of shorting.

A number of robustness checks by stock characteristics such as size, book-to-market, institutional ownership, and put-option trading, reveal that while there is universal evidence of contrarian trading for all sub-samples. The results also show that the predictability of short-selling on future abnormal returns is higher for small-cap stocks, for less liquid securities, for value stocks, for stocks with low institutional ownership, and for stocks with no traded put options. Additionally, we find in all sub-samples that it is primarily small short-sales that predict future negative returns

Further, we study the effect of increased costs of short-selling by exploiting the so called threshold list. These stocks have significant fails-to-deliver, and are subject to more stringent close-out requirements. We show that short-selling decreases significantly after a stock appears on the threshold list, supporting our hypothesis that the short-sale constraints become more binding. However, we find only mixed evidence of a related effect on subsequent returns. Only for low-priced stocks do we find significant negative relationship between the threshold list and subsequent abnormal returns.

Finally, unlike Christophe et al (2004), we do not find any evidence that short-sellers in 2005 have private information about future earnings surprises. Instead, they seem to be value-based traders that trade on short-term over-valuations relative to fundamentals.

Taken together, our results show that short-sellers are not the villains they are made out to be by media and issuers. They definitely do not "pile on" after poor returns. Instead, traders executing short-sales actually *reduce* the amount of short-selling significantly following negative abnormal returns. Contrary to public perception, short-sellers increase their activity following positive abnormal returns, and they do so immediately preceding reversals (negative abnormal returns). Hence, the evidence is consistent with short-sellers helping correct short-term over-reactions of stock prices. The fact that they are relatively more successful at predicting returns for stocks that are more likely to have pricing errors (small-cap stocks, less liquid stocks, stocks with low institutional ownership, and stocks without put options) is further suggestive evidence that short-sellers may actually help make prices more efficient.

While we provide a rich picture of short-selling activity in this paper, our sample is limited in time and scope. In future work, we plan to extend the sample to include March, April, and June, 2005 data. As CRSP data becomes available, we will also replace the Yahoo! return data used in this version of the paper. In addition, as soon as it becomes available, we will include short-selling data for NYSE and AMEX. Finally, in related work we are trying to establish whether short-sellers primarily are liquidity demanders or if they play an important role as liquidity providers.

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Table I
Summary Statistics

Panel A shows short-sale trading activity of Nasdaq stocks across exchanges. It reports total number of shorted shares in a given exchange for our sample period divided by the total number of shorted shares in all exchanges for our sample period. It also reports the total number of short-sale trades in a given exchange for our sample period divided by the total number of short-sale trades in all exchanges for our sample period. Panels B and C show the descriptive statistics of short-sale related variables for the pooled sample. *Small* short-sale trades are transactions $\leq \$4,400$, *Medium* short-sale trades are transactions $> \$4,400$ and $\leq \$37,000$, and *Big* is for transactions $> \$37,400$. *relss* is the number of shorted shares divided by the number of traded shares on day t. Panel D shows mean *relss* for non-exempt trades across different stock characteristics for the pooled sample. Low (high) ME and B/M refers to market-cap and B/M at the end of 2004 $\leq$ 33rd ($>$ 67th) NYSE percentile. Low (high) *instown* refers to institutional ownership at the end of 2004 $\leq 33\%$ ($> 67\%$). Low (high) *vol* refers to year 2004 share turnover $\leq$ 33rd ($>$ 67th) percentile. Low (high) price refers to stocks with lagged price $< \$5$ (≥ 5). No put refers to stocks without put options, and no threshold refers to stocks that are not on the threshold list in day t. The sample only includes Nasdaq stocks with CRSP share code 10 or 11 and with a price greater than or equal to \$1 at the end of year 2004. Stocks are dropped from the sample if the number of traded shares is less than or equal to zero or such information is missing from Yahoo. The time period is January 3, 2005 to March 31, 2005. The sample size is 2815 stocks.

	Panel A: Short-sale Trading Activity of NASDAQ Stocks Across Exchanges							
	AMEX	ARCHAX	BSE	CHX	NASD	NASDAQ	NSX	PHLX
	Shares Sold Short (In Percent)							
Mean	0.02	23.90	0.00	0.08	0.43	49.96	26.41	0.00
	Short-Sale Trades (In Percent)							
Mean	0.01	29.37	0.00	0.07	0.18	34.70	35.67	0.00
	Panel B: Descriptive Statistics							
	Small	Medium	Big	Total	Small	Medium	Big	Total
	Number of Shares Sold Short (In 000's)				Number of Short-Sale Trades			
Mean	44.11	90.64	56.94	191.69	250.97	197.77	14.02	462.75
Median	5.80	5.45	0.00	16.08	39	6	0	63
Min	0.00	0.00	0.00	0.00	0	0	0	0
Max	15,897.94	33,736.36	26,717.18	63,796	62,999	63,176	18,321	108,518
St. Dev	202.00	602.69	400.16	1,109.15	781.89	1,165.62	165.39	1,821.49
	Panel C: *relss* (In Percent)							
	$relss_{small}$	$relss_{med}$	$relss_{big}$	$relss$	$relss_{small}$	$relss_{med}$	$relss_{big}$	$relss$
	Non-Exempt Short-Sales				Exempt Short-Sales			
Mean	8.67	7.14	2.81	18.61	2.03	3.21	1.30	6.53
Median	6.58	4.62	0.00	16.79	0.58	0.93	0.00	3.11
St. Dev	9.49	8.94	6.70	15.77	4.35	6.21	4.05	9.78
	All Short-Sales							
Mean	10.70	10.35	4.10	25.14				
Median	8.81	8.18	0.00	25.00				
St. Dev	10.72	11.11	8.22	18.76				
	Panel D: Mean of Non-Exempt *relss* (In Percent) Across Stock Characteristics							
	ME	B/M	instown	vol	price		put	threshold
Low	15.30	19.84	12.00	15.10	12.35	No	14.82	18.82
High	26.28	14.60	24.59	22.04	23.88	Yes	25.95	9.73

Table II
Summary Statistics: relss and Stock Characteristics

relss is the number of shorted shares divided by traded shares per day averaged over the sample period. *ME* is the market-cap from December 31, 2004. B/M is lagged book to market equity as defined in Fama and French (1993). *instown* is institutional ownership as a fraction of shares outstanding from the end of 2004. *sratio* is short interest from the previous calendar month divided by average daily volume during the same month. *price* is the stock price from the end of 2004. *vol* is average daily share turnover during 2004. *put* is a dummy variable that equals one if there are actively trade puts for the stocks. The sample only includes Nasdaq stocks with CRSP share code 10 or 11 and with a price greater than or equal to $1 at the end of year 2004. The time period is January 3, 2005 to March 31, 2005.

Panel A: Cross-Sectional Summary Statistics

	relss (non-exempt)	*relss* (exempt)	*relss* (all)	*ME*	B/M	*instown*	*sratio*	*price*	*vol*	*put*
Stocks	2,815	2,815	2,815	2,815	2,462	2,815	2,769	2,815	2,744	2,815
Mean	0.18	0.06	0.25	1,091.00	0.54	0.40	4.66	18.32	8.81	0.33
Median	0.20	0.07	0.27	201.74	0.45	0.35	2.89	14.00	4.80	0.00
St. Dev	0.10	0.04	0.12	7,793.94	0.42	0.29	6.84	25.71	18.84	0.47
Min	0.00	0.00	0.00	2.83	0.00	0.00	0.00	1.00	0.05	0.00
Max	0.43	0.24	0.52	290,313	4.05	1.00	152.29	1,099.99	421.83	1.00

Panel B: Cross-Sectional Correlation

	relss (non-exempt)	*relss* (exempt)	*relss* (all)	$\log(ME)$	$\log(B/M)$	*instown*	$\log(1+sratio)$	$\log(price)$	$\log(vol)$	*put*
relss (non-exempt)	1.00	0.52	0.96	0.71	-0.19	0.55	0.55	0.52	0.32	0.54
relss (exempt)		1.00	0.73	0.45	-0.10	0.39	0.20	0.24	0.19	0.32
relss (all)			1.00	0.71	-0.19	0.56	0.50	0.49	0.31	0.53
$\log(ME)$				1.00	-0.32	0.58	0.42	0.60	0.38	0.61
$\log(B/M)$					1.00	-0.14	-0.22	-0.01	-0.36	-0.33
instown						1.00	0.30	0.30	0.44	0.52
$\log(1+sratio)$							1.00	0.27	0.20	0.33
$\log(price)$								1.00	-0.06	0.26
$\log(vol)$									1.00	0.57
put										1.00

Table III
Panel Regressions: Daily Relative Short-Selling (relss)

The dependent variables are $relss$, $relss_{small}$, $relss_{med}$, and $relss_{big}$. $relss$ is the number of non-exempt shorted shares divided by traded shares on day t. $relss_{small}$ is the number of non-exempt shorted shares for transactions $\leq$ \$4,400 divided by traded shares on day t. $relss_{med}$ is similarly defined using only transactions $>$ \$4,400 and $\leq$ \$37,000, and $relss_{big}$ is also similarly defined using only transactions $>$ \$37,000. $r_{-5,-1}$ is the market adjusted return from the closing price on day $t-6$ to the closing price on day $t-1$. $r^{+}_{-5,-1}$ equals $r_{-5,-1}$ if $r_{-5,-1} > 0$ and zero otherwise. $r^{-}_{-5,-1}$ equals the absolute value of $r_{-5,-1}$ if $r_{-5,-1} < 0$ and zero otherwise. The sample only includes Nasdaq stocks with CRSP share code 10 or 11 and lagged price $\geq$ 5. The regressions include calendar day dummies and stock dummies, and the standard errors take into account clustering by calendar date. The time period is January 3, 2005 to March 31, 2005. T-statistics are in parenthesis. The intercept is estimated but not reported.

	Dependent Variable									
	$relss_t$	$relss_t$	$relss_t$	$relss_t$	$relss_{small,t}$	$relss_{small,t}$	$relss_{med,t}$	$relss_{med,t}$	$relss_{big,t}$	$relss_{big,t}$
$r_{-5,-1}$	0.172	0.123								
	(25.16)	(18.87)								
$r^{+}_{-5,-1}$			0.092	0.061	-0.008	-0.009	0.087	0.067	0.013	0.011
			(10.25)	(6.88)	(1.29)	(1.65)	(14.78)	(11.31)	(3.60)	(3.11)
$r^{-}_{-5,-1}$			-0.293	-0.215	-0.153	-0.107	-0.113	-0.088	-0.027	-0.025
			(23.27)	(16.40)	(17.82)	(13.48)	(15.23)	(11.46)	(4.38)	(4.04)
$relss_{t-1}$		0.189		0.188						
		(29.34)		(29.19)						
$relss_{small,t-1}$						0.208				
						(22.55)				
$relss_{med,t-1}$								0.158		
								(20.71)		
$relss_{big,t-1}$										0.066
										(10.68
R^2	0.33	0.36	0.33	0.36	0.32	0.36	0.34	0.37	0.17	0.17
Stock Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Day Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table IV
Panel Regressions: Daily Abnormal Returns in Percent

The dependent variable is a stock's return on day $t+1$. $relss_t$ is the number of non-exempt shorted shares divided by traded shares on day t. $relss_{small,t}$ is the number of non-exempt shorted shares for transactions $\leq$ \$4,400 divided by traded shares on day t. $relss_{med,t}$ is similarly defined using only transactions $>$ \$4,400 and $\leq$ \$37,000, and $relss_{big,t}$ is also similarly defined using only transactions $>$ \$37,000. $r_{-5,-1}$ is the market adjusted return from $t-5$ to $t-1$. $r^+_{-5,-1}$ equals $r_{-5,-1}$ if $r_{-5,-1} > 0$ and zero otherwise. $r^-_{-5,-1}$ equals the absolute value of $r_{-5,-1}$ if $r_{-5,-1} < 0$ and zero otherwise. r_t is the market adjusted return from day t. ME is the market-cap from December 31, 2004. B/M is lagged book to market equity as defined in Fama and French (1993). The sample only includes Nasdaq stocks with CRSP share code 10 or 11 and lagged price $\geq$ 5. The regressions include calendar day dummies, and the standard errors take into account clustering by calendar date. The time period is January 3, 2005 to March 31, 2005. T-statistics are in parenthesis. The intercept is estimated.

	Dependent Variable: $r_{i,t+1}$								
$relss_t$	-0.189	-1.106	-0.175	-0.176		-0.156			
	(2.12)	(13.55)	(1.96)	(1.95)		(1.36)			
$relss_{t+1}$		2.371							
		(25.95)							
$r_{-5,-1}$			-0.006				-0.006		
			(1.47)				(1.58)		
$r^+_{-5,-1}$				-0.007		-0.012			-0.006
				(1.33)		(1.46)			(0.90)
$r^-_{-5,-1}$				0.004		0.013			0.015
				(0.51)		(1.22)			(1.59)
$r^+_{-5,-1} * relss$					-0.024	0.027			
					(1.41)	(1.08)			
$r^-_{-5,-1} * relss$					-0.012	-0.045			
					(0.45)	(1.37)			
$relss_{small}$							-0.560		-0.360
							(3.13)		(1.75)
$relss_{med}$							0.087		
							(0.89)		
$relss_{big}$							0.195		
							(2.38)		
$r^+_{-5,-1} * relss_{small}$								-0.097	-0.016
								(2.84)	(0.39)
$r^-_{-5,-1} * relss_{small}$								-0.079	-0.126
								(1.50)	(2.25)
r_t	-0.048	-0.051	-0.048	-0.048	-0.049	-0.048	-0.049	-0.048	-0.048
	(5.92)	(6.29)	(5.92)	(5.91)	(6.04)	(5.90)	(5.97)	(6.00)	(5.90)
$\log(ME)$	-0.007	-0.060	-0.009	-0.010	-0.014	-0.010	-0.021	-0.017	-0.016
	(0.39)	(3.44)	(0.50)	(0.51)	(0.67)	(0.51)	(0.99)	(0.79)	(0.76)
$\log(B/M)$	0.064	0.073	0.065	0.064	0.062	0.064	0.065	0.059	0.063
	(2.71)	(3.10)	(2.79)	(2.86)	(2.76)	(2.87)	(2.79)	(2.62)	(2.81)
Day Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table V
Daily relss Portfolios: Abnormal Returns (in Percent)

In day t we compute $relss$ and $relss_{small}$ quintiles using all stocks in our sample. We then form portfolios using all stocks in our sample with a closing price on day $t-1$ greater than or equal to \$5.00. We compute the return on the portfolio in day $t+1$. The portfolios are rebalanced daily. The five day holding period portfolios use the overlapping holding period methodology of Jegadeesh and Titman (1993). $relss$ is the number of non-exempt shorted shares divided by traded shares on day t. $relss_{small}$ is the number of non-exempt shorted shares for transactions $\leq$ \$4,400 divided by traded shares on day t. We proxy for expected returns using the return on the market portfolio The sample only includes Nasdaq stocks with CRSP share code 10 or 11. The time period is January 3, 2005 to March 31, 2005. The t-statistics are adjusted for autocorrelation using the Newey-West (1987) procedure with lag=5.

	Panel A: $relss$ Quintiles					
	Low	2	3	4	High	Low-High
	One Day Holding Period					
Mean	0.104	-0.026	-0.028	-0.126	-0.080	0.185
St. Dev	0.542	0.430	0.445	0.506	0.437	0.683
T-stat	2.302	-0.549	-0.528	-2.077	-1.618	3.027
	Five Day Holding Period					
Mean	0.122	-0.047	-0.045	-0.156	-0.102	0.224
St. Dev	0.174	0.203	0.233	0.281	0.236	0.309
T-stat	3.465	-0.942	-0.793	-2.246	-1.785	3.250
	Panel B: $relss_{small}$ Quintiles					
	Low	2	3	4	High	Low-High
	One Day Holding Period					
Mean	0.048	0.038	-0.031	-0.098	-0.141	0.189
St. Dev	0.401	0.460	0.442	0.482	0.496	0.577
T-stat	1.177	0.687	-0.523	-1.796	-2.585	3.303
	Five Day Holding Period					
Mean	0.064	0.014	-0.057	-0.123	-0.162	0.226
St. Dev	0.150	0.248	0.268	0.248	0.249	0.285
T-stat	1.936	0.235	-0.854	-2.073	-2.685	3.412
	Panel C: $relss_{big}$ Quintiles					
	$relss_{big} = 0$			4	High	Low-High
	One Day Holding Period					
Mean	-0.031			-0.068	-0.062	0.030
St. Dev	0.371			0.557	0.472	0.374
T-stat	-0.790			-1.047	-1.159	0.952
	Five Day Holding Period					
Mean	-0.034			-0.107	-0.086	0.052
St. Dev	0.151			0.332	0.260	0.185
T-stat	-0.971			-1.336	-1.401	1.361

Table VI
Panel Regressions: relss and Stock Characteristics

The dependent variables are $relss$ and $relss_{small}$. $relss$ is the number of non-exempt shorted shares divided by traded shares on day t. $relss_{small}$ is the number of non-exempt shorted shares for transactions $\leq$ \$4,400 divided by traded shares on day t. $r_{-5,-1}$ is the market adjusted return from the closing price on day $t-6$ to the closing price on day $t-1$. $r^{+}_{-5,-1}$ equals $r_{-5,-1}$ if $r_{-5,-1} > 0$ and zero otherwise. $r^{-}_{-5,-1}$ equals the absolute value of $r_{-5,-1}$ if $r_{-5,-1} < 0$ and zero otherwise. ME is the market-cap from December 31, 2004. B/M is lagged book to market equity as defined in Fama and French (1993). $instown$ is institutional ownership at the end of 2004. We classify stocks as small or large (growth or value) using NYSE breakpoints for ME (B/M). The sample only includes Nasdaq stocks with CRSP share code 10 or 11 and lagged price $\geq$ 5. The regressions include calendar day dummies and stock dummies, and the standard errors take into account clustering by calendar date. The time period is January 3, 2005 to March 31, 2005. T-statistics are in parenthesis. The intercept is estimated but not reported.

Panel A	Small-Cap Stocks: Ptile(ME) $\leq$ 0.33			Large-Cap Stocks: Ptile(ME) > 0.67		
	$relss_t$	$relss_t$	$relss_{small,t}$	$relss_t$	$relss_t$	$relss_{small,t}$
$r_{-5,-1}$	0.139			0.287		
	(17.51)			(16.86)		
$r^{+}_{-5,-1}$		0.083	-0.001		0.125	-0.015
		(8.35)	(0.18)		(4.29)	(1.52)
$r^{-}_{-5,-1}$		-0.233	-0.155		-0.453	-0.054
		(15.48)	(14.44)		(12.23)	(4.44)
Panel B	**Growth Stocks: Ptile(B/M) $\leq$ 0.33**			**Value Stocks: Ptile(B/M) > 0.67**		
	$relss_t$	$relss_t$	$relss_{small,t}$	$relss_t$	$relss_t$	$relss_{small,t}$
$r_{-5,-1}$	0.194			0.096		
	(25.97)			(7.41)		
$r^{+}_{-5,-1}$		0.102	-0.015		0.074	-0.012
		(8.53)	(2.19)		(4.39)	(0.95)
$r^{-}_{-5,-1}$		-0.313	-0.167		-0.140	-0.094
		(20.85)	(17.18)		(4.31)	(4.62)
Panel C	**Low Inst. Ownership: $instown \leq 33\%$**			**High Inst. Ownership: $instown > 67\%$**		
	$relss_t$	$relss_t$	$relss_{small,t}$	$relss_t$	$relss_t$	$relss_{small,t}$
$r_{-5,-1}$	0.090			0.271		
	(11.06)			(18.51)		
$r^{+}_{-5,-1}$		0.042	-0.005		0.175	-0.003
		(4.13)	(0.64)		(7.15)	(0.25)
$r^{-}_{-5,-1}$		-0.184	-0.095		-0.373	-0.172
		(9.24)	(7.20)		(16.12)	(12.87)
Panel D	**Stocks With No Put Options**			**Stocks With Put Options**		
	$relss_t$	$relss_t$	$relss_{small,t}$	$relss_t$	$relss_t$	$relss_{small,t}$
$r_{-5,-1}$	0.128			0.250		
	(14.63)			(26.64)		
$r^{+}_{-5,-1}$		0.074	-0.001		0.153	-0.015
		(6.80)	(0.14)		(8.70)	(1.86)
$r^{-}_{-5,-1}$		-0.229	-0.138		-0.354	-0.170
		(12.53)	(10.86)		(21.15)	(16.19)
Stock Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Day Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

Table VII
Daily relss Portfolios Disaggregated by Stock Characteristics: Abnormal Returns (in %)

In day t we compute $relss$ and $relss_{small}$ quintiles using all stocks in our sample. We also form market-cap (ME) terciles using NYSE market-cap breakpoints for year-end 2004 and book to market (B/M) terciles using NYSE B/M breakpoints. We also classify stocks as low (high) institutional ownership stocks if year-end 2004 institutional ownership is $\leq 33\%$ (> 67). We then form double sort portfolios based on the intersection of $relss$ ($relss_{small}$) quintiles and ME terciles, B/M terciles, institutional ownership classification, and put option availability. The portfolios include all stocks in our sample with a closing price on day $t-1$ greater than or equal to \$5.00. We compute the return on the portfolio in day $t+1$. The portfolios are rebalanced daily. $relss$ is the number of non-exempt shorted shares divided by traded shares on day t. $relss_{small}$ is the number of non-exempt shorted shares for transactions $\leq$ \$4,400 divided by traded shares on day t. We proxy for expected returns using the return on the market portfolio. The sample only includes Nasdaq stocks with CRSP share code 10 or 11. The time period is January 3, 2005 to March 31, 2005. The t-statistics are adjusted for autocorrelation using the Newey-West (1987) procedure with lag=5.

Panel A: $relss$ Double Sort Portfolios

	Mean Abnormal Returns							
$relss$	Market-Cap		Book to Market		Inst. Ownership		Put Options	
Quntiles	Small	Large	Low	High	Low	High	No	Yes
Low	0.107	-0.119	0.061	0.178	0.110	-0.059	0.108	-0.341
High	-0.093	-0.031	-0.077	-0.033	-0.115	-0.059	-0.056	-0.099
Low-High	0.200	-0.087	0.138	0.211	0.225	0.000	0.164	-0.242
T-stat	(3.47)	(0.41)	(2.06)	(2.57)	(4.11)	(0.00)	(3.52)	(1.49)

Panel B: $relss_{small}$ Double Sort Portfolios

	Mean Abnormal Returns							
$relss_{small}$	Market-Cap		Book to Market		Inst. Ownership		Put Options	
Quntiles	Small	Large	Low	High	Low	High	No	Yes
Low	0.086	-0.027	-0.007	0.147	0.067	0.039	0.076	-0.043
High	-0.156	-0.107	-0.164	-0.086	-0.156	-0.116	-0.102	-0.184
Low-High	0.242	0.080	0.157	0.232	0.223	0.111	0.178	0.141
T-stat	(3.42)	(0.86)	3.042	(2.56)	(3.39)	(2.10)	(3.54)	(2.50)

Table VIII
Panel Regressions: Threshold Stocks

The dependent variables are *relss*, $relss_{small}$, and a stock's return on day $t+1$. *relss* is the number of non-exempt shorted shares divided by traded shares on day t. $relss_{small}$ is the number of non-exempt shorted shares for transactions $\leq$ \$4,400 divided by traded shares on day t. *threshold* is a dummy variable that equals one if the stocks is on the threshold list and zero otherwise. $r_{-5,-1}$ is the market adjusted return from $t-5$ to $t-1$. $r^{+}_{-5,-1}$ equals $r_{-5,-1}$ if $r_{-5,-1} > 0$ and zero otherwise. $r^{-}_{-5,-1}$ equals the absolute value of $r_{-5,-1}$ if $r_{-5,-1} < 0$ and zero otherwise. r_t is the market adjusted return from day t. ME is the market-cap from December 31, 2004. B/M is lagged book to market equity as defined in Fama and French (1993). The sample only includes Nasdaq stocks with CRSP share code 10 or 11 and lagged price $\geq$ 5. The regressions in Panel A include calendar day dummies, stock day dummies, and the standard errors take into account clustering by calendar date. The regressions in Panel B include calendar day dummies, and the standard errors take into account clustering by calendar date. The time period is January 3, 2005 to March 31, 2005. T-statistics are in parenthesis. The intercept is estimated but not reported.

Panel A		Lagged Price < 5		Lagged Price $\geq$ 5		
	$relss_t$	$relss_t$	$relss_{small,t}$	$relss_t$	$relss_t$	$relss_{small,t}$
$threshold_{t-1}$	-0.011	-0.011	-0.009	-0.023	-0.024	-0.018
	(3.45)	(3.58)	(4.69)	(4.84)	(5.04)	(7.56)
$r_{-5,-1}$	0.063			0.174		
	(11.31)			(25.09)		
$r^{+}_{-5,-1}$		0.032	0.015		0.092	-0.009
		(4.85)	(3.02)		(9.87)	(1.47)
$r^{-}_{-5,-1}$		-0.107	-0.078		-0.293	-0.155
		(9.98)	(10.21)		(23.15)	(18.05)
Stock Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Day Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

Panel B		Lagged Price < 5		Lagged Price $\geq$ 5		
			Dependent Variable: $r_{i,t+1}$			
$threshold_t$	-0.353	-0.374	-0.445	0.054	0.023	0.061
	(2.11)	(2.23)	(2.67)	(0.31)	(0.13)	(0.36)
relss		-0.615	0.101		-0.335	-0.173
		(2.13)	(0.39)		(2.38)	(1.92)
$r_{-5,-1}$			-0.019			-0.006
			(4.13)			(1.47)
r_t			-0.093			-0.048
			(7.22)			(5.92)
$\log(ME)$			-0.120			-0.009
			(3.38)			(0.48)
$\log(B/M)$			0.071			0.066
			(2.18)			(2.90)
Day Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

Table IX
Abnormal Short-Selling and Earnings Announcements

This table shows the results of regression of Table III of Christophe et al (2004). Only Nasdaq-listed common stocks (CRSP share code of 10 or 11, exchange code of 3 or 33) whose ticker is four-digits are included. Dates when the number of shorted shares is greater than the number of traded shares are dropped. Stocks with an earnings announcement record, that were traded every day during the entire sample period, that did not have any missing return or volume dates in Yahoo! and with a price above $10 for the entire 5-day period prior to the announcement are included in this sample. The number of non-exempt shorted shares is aggregated across all exchanges for Nasdaq-listed stocks. As in Christophe et al (2004), $abss_{-5,-1}$ is defined as the average daily abnormal short-selling during the five days before the earnings announcement (pre-announcement period) and is calculated as the average daily short-selling during the pre-announcement period divided by the average daily short-selling during the non-event period (all days except for -5 to +1 days relative to earnings announcement day), all minus 1. $relss_{-5,-1}$ is the ratio of the number of shorted shares to the number of traded shares in the pre-announcement period. $r_{-5,-1}$ ($r_{0,1}$) is the return from the closing price on day -6 (-1) to the closing price on day -1 (+1). $abvol_{-5,-1}$ is the stocks' abnormal volume in the pre-announcement period, measured as the average daily volume during the pre-announcement period divided by the average daily volume during the non-event period, all minus 1. *normrelss* is the ratio of the number of shorted shares to the number of traded shares during the non-event period. T-values are in parenthesis.

Panel A: $abss_{-5,-1} = \beta_0 + \beta_1 r_{0,1} + \beta_2 r_{-5,-1} + \beta_3 abvol_{-5,-1} + \varepsilon$					
	β_0	β_1	β_2	β_3	Adjusted R^2
Full Sample	-0.0013	0.0377	1.7203	0.8181	0.5462
(n = 1284)	(-0.11)	(0.24)	(7.55)	(36.51)	
Stock with put options	-0.0135	0.0512	0.5970	0.7778	0.5860
(n = 727)	(-1.10)	(0.36)	(2.73)	(31.03)	
Stocks with no put options	0.0172	0.1373	3.2913	0.8358	0.5464
(n = 557)	(0.72)	(0.40)	(7.51)	(22.59)	
Panel B: $relss_{-5,-1} = \beta_0 + \beta_1 r_{0,1} + \beta_2 r_{-5,-1} + \beta_3 normrelss_{-5,-1} + \varepsilon$					
	β_0	β_1	β_2	β_3	Adjusted R^2
Full Sample	0.0399	0.0228	0.2551	0.8357	0.4169
(n = 1284)	(5.81)	(0.86)	(6.80)	(29.32)	
Stock with put options	0.0553	0.0206	0.1966	0.7857	0.3031
(n = 727)	(4.60)	(0.70)	(4.32)	(17.22)	
Stocks with no put options	0.0368	0.0290	0.3336	0.8354	0.4046
(n = 557)	(3.95)	(0.57)	(5.28)	(18.62)	

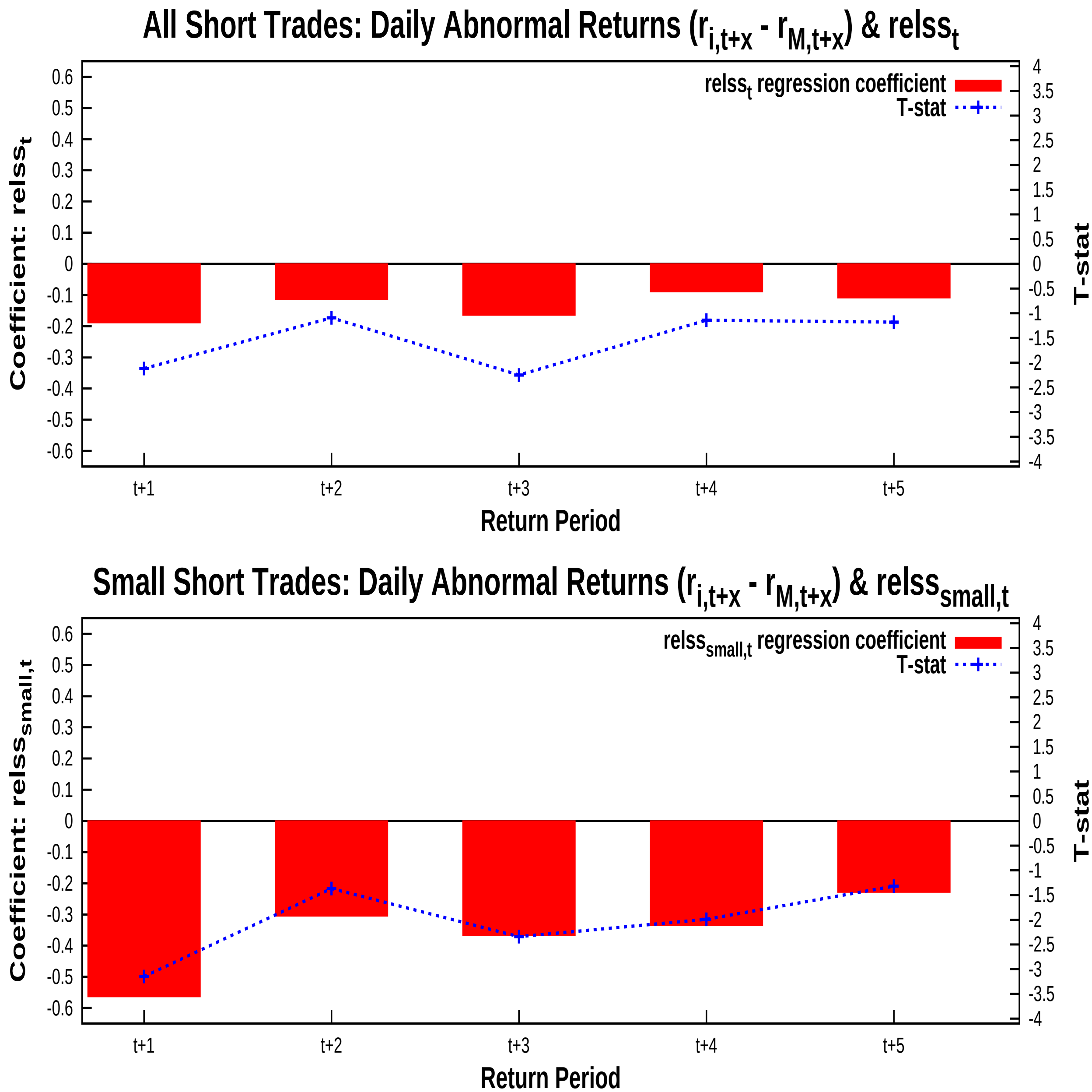

Figure 1: Daily Subsequent Returns and relss Using Cross Sectional Regressions

We regress daily returns on day $t+x$ ($r_{i,t+x}$) in percent on $relss_t$ in the top plot and daily returns on $relss_{small,t}$ in the bottom plot. We use the following control variables: r_t, $\log(ME)$, and $\log(B/M)$. r_t is the market adjusted return from day t. ME is the market-cap from the end of 2004. B/M is lagged book to market equity as defined in Fama and French (1993). The sample only includes Nasdaq stocks with CRSP share code 10 or 11 and lagged price ≥ 5. The regressions include calendar day dummies, and the standard errors take into account clustering by calendar date. The time period is January 3, 2005 to March 31, 2005. The intercept is estimated but not reported.

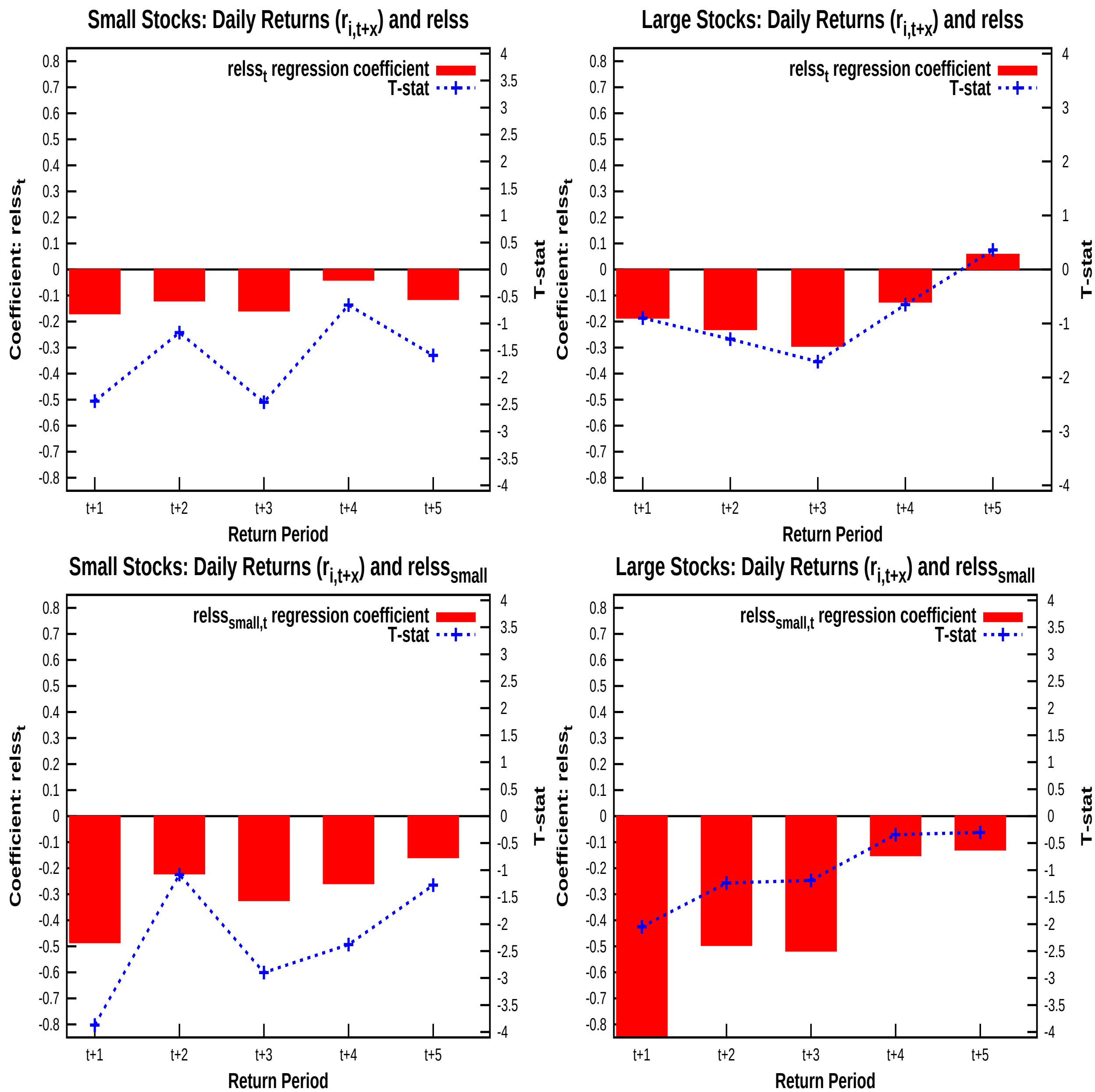

Figure 2: Daily Subsequent Returns and relss by Trade Size and Market-Cap

We regress daily returns on day $t+x$ ($r_{i,t+x}$) in percent on $relss_t$ in the top plots and daily abnormal returns on $relss_{small,t}$ in the bottom plots for small and large stocks. We use the following control variables: r_t, $\log(ME)$, and $\log(B/M)$. r_t is the market adjusted return from day t. ME is the market-cap from the end of 2004. B/M is lagged book to market equity as defined in Fama and French (1993). We classify a stock as small (large) if it is in the bottom (top) NYSE market-cap tercile. The sample only includes Nasdaq stocks with CRSP share code 10 or 11 and lagged price ≥ 5. The regressions include calendar day dummies, and the standard errors take into account clustering by calendar date. The time period is January 3, 2005 to March 31, 2005. The intercept is estimated but not reported.

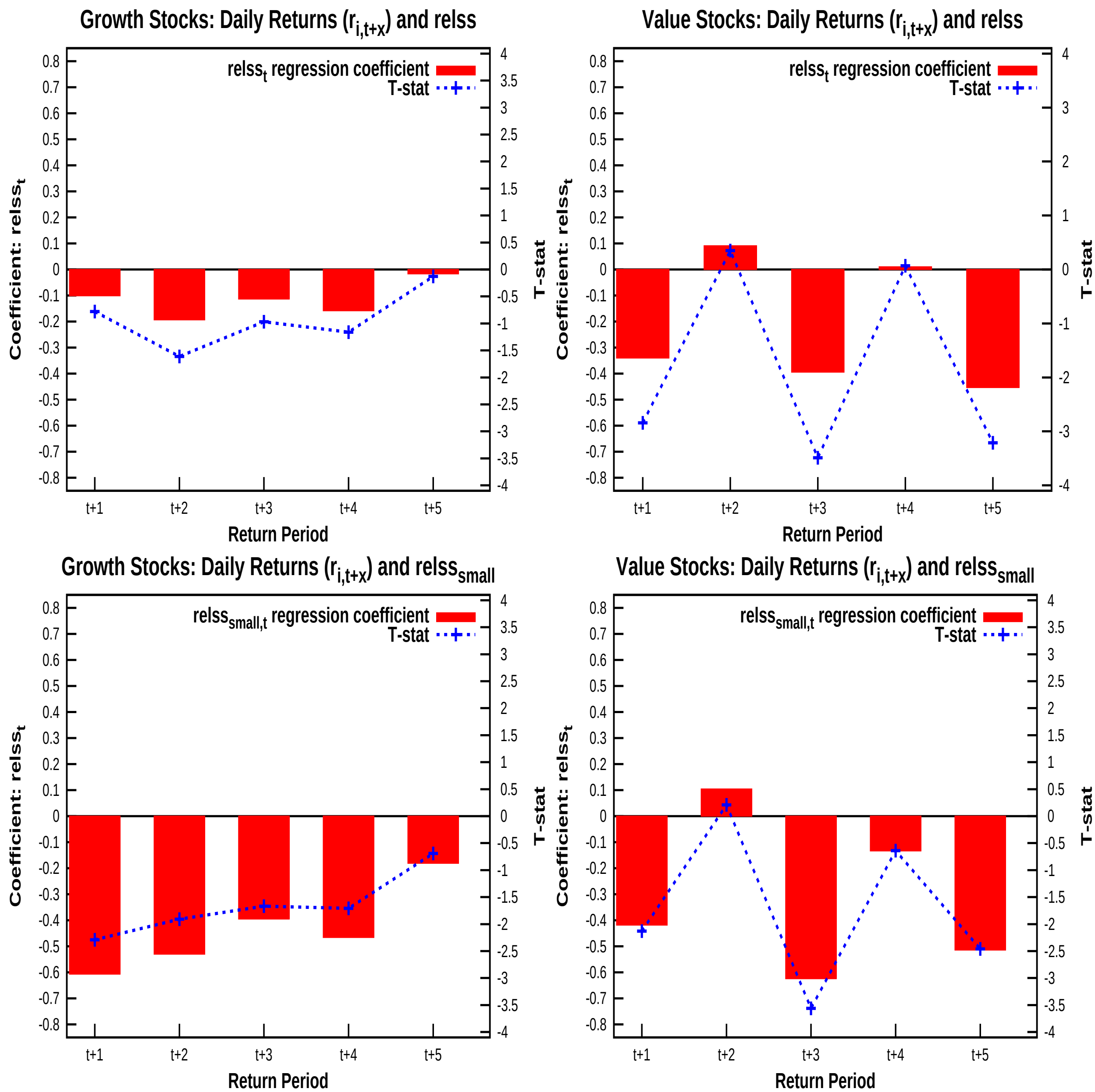

Figure 3: Daily Subsequent Returns and relss by Trade Size and Book to Market

We regress daily returns on day $t+x$ ($r_{i,t+x}$) in percent on $relss_t$ in the top plots and daily abnormal returns on $relss_{small,t}$ in the bottom plots for growth and value stocks. We use the following control variables: r_t, $\log(ME)$, and $\log(B/M)$. r_t is the market adjusted return from day t. ME is the market-cap from the end of 2004. B/M is lagged book to market equity as defined in Fama and French (1993). We classify a stock as growth (value) if it is in the bottom (top) NYSE market-cap tercile. The sample only includes Nasdaq stocks with CRSP share code 10 or 11 and lagged price ≥ 5. The regressions include calendar day dummies, and the standard errors take into account clustering by calendar date. The time period is January 3, 2005 to March 31, 2005. The intercept is estimated but not reported.

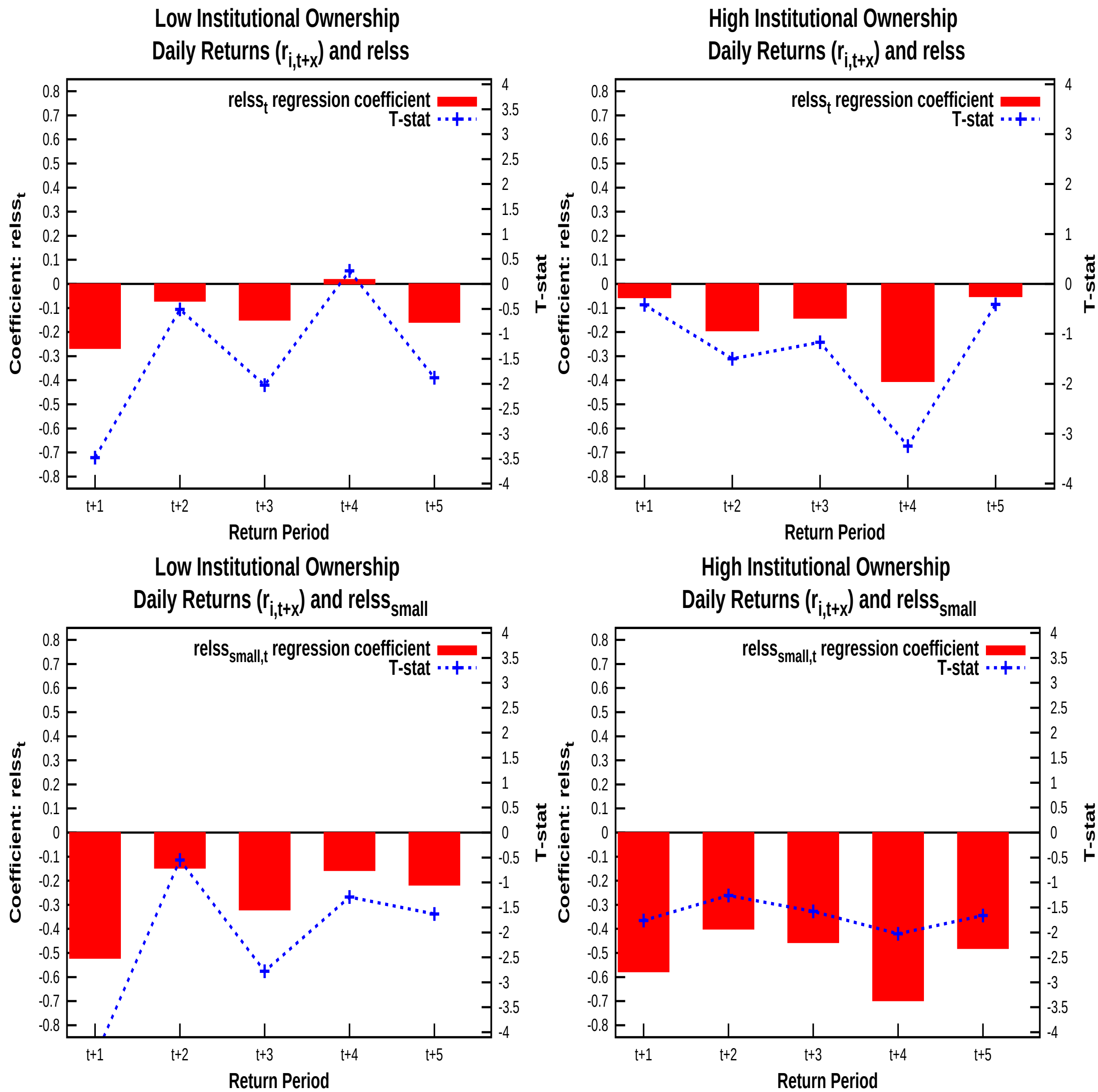

Figure 4: Daily Subsequent Returns and relss by Trade Size and Institutional Ownership

We regress daily returns on day $t+x$ ($r_{i,t+x}$) in percent on $relss_t$ in the top plots and daily abnormal returns on $relss_{small,t}$ in the bottom plots for low and high institutional ownership. We use the following control variables: r_t, $\log(ME)$, and $\log(B/M)$. r_t is the market adjusted return from day t. ME is the market-cap from the end of 2004. B/M is lagged book to market equity as defined in Fama and French (1993). We define low (high) institutional ownership as $\leq 33\%$ ($> 67\%$). The sample only includes Nasdaq stocks with CRSP share code 10 or 11 and lagged price ≥ 5. The regressions include calendar day dummies, and the standard errors take into account clustering by calendar date. The time period is January 3, 2005 to March 31, 2005. The intercept is estimated but not reported.

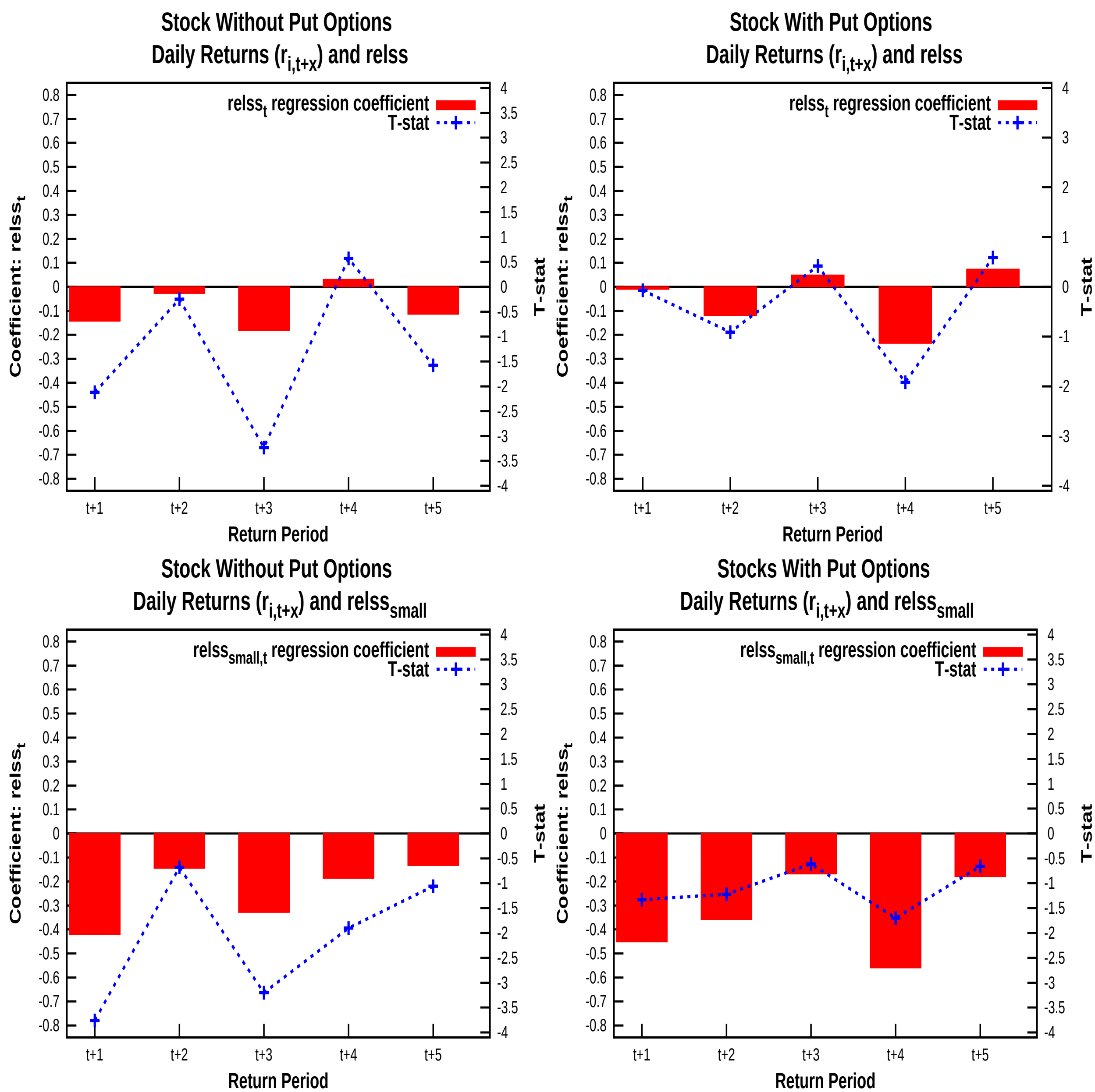

Figure 5: Daily Subsequent Returns and relss by Trade Size and Put Availability

We regress daily returns on day $t+x$ ($r_{i,t+x}$) in percent on $relss_t$ in the top plots and daily abnormal returns on $relss_{small,t}$ in the bottom plots for stock with and without put options. We use the following control variables: r_t, $\log(ME)$, and $\log(B/M)$. r_t is the market adjusted return from day t. ME is the market-cap from the end of 2004. B/M is lagged book to market equity as defined in Fama and French (1993). The sample only includes Nasdaq stocks with CRSP share code 10 or 11 and lagged price ≥ 5. The regressions include calendar day dummies, and the standard errors take into account clustering by calendar date. The time period is January 3, 2005 to March 31, 2005. The intercept is estimated but not reported.