Short-Sale Strategies and Return Predictability

Karl B. Diether,*
Kuan-Hui Lee,†
and Ingrid M. Werner‡

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*Fisher College of Business, The Ohio State University, 2100 Neil Avenue, Columbus, OH 43210, phone: 614-272-6182, e-mail: diether_1@cob.osu.edu.

†Rutgers Business School, Rutgers University, 175 University Avenue, Newark, NJ 07102, phone: 973-353-5938, email: kuanlee@rbsmail.rutgers.edu.

‡Fisher College of Business, The Ohio State University, 2100 Neil Avenue, Columbus, OH 43210, phone: 614-272-6182, phone: 614-292-6460, e-mail: werner_47@cob.osu.edu.

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Abstract

We examine short-selling in U.S. stocks based on new SEC-mandated data for 2005. There is a tremendous amount of short-selling in our sample: short-sales represent 24 percent of NYSE and 31 percent of Nasdaq share volume. Short-sellers increase their trading following positive returns and they correctly predict future negative abnormal returns. These patterns are robust to controlling for voluntary liquidity provision and for opportunistic risk-bearing by short-sellers. The results are consistent with short sellers trading on short-term overreaction of stock prices. A trading strategy based on daily short-selling activity generates significant positive returns during the sample period.

There is currently tremendous interest in short-selling not only from academics, but also from issuers, media representatives, the Securities and Exchange Commission (SEC), and Congress. Academics generally share the view that short-sellers help markets correct short-term deviations of stock prices from fundamental value. This view is by no means universally held, and many issuers and media representatives instead characterize short-sellers as immoral, unethical and downright un-American.[1] In an attempt to evaluate the efficacy of short-sale rules, the SEC introduced new regulation governing short-sales in U.S. markets on January 2, 2005. Washington is also interested in short-selling, and the Congressional Committee of Financial Services (May 22, 2003) and the Senate Judiciary Committee (June 28, 2006) have recently heard testimonies about short-sellers and hedge funds.

Despite this interest, there is relatively little evidence in the academic literature on what short-sellers actually do. In this paper, we study trading strategies used by short-sellers of NYSE and Nasdaq listed stocks. Specifically, we examine the short-horizon relationship between short-selling and previous and subsequent returns. We find that short-selling activity is strongly positively related to past returns. A five-day return of 10 percent results in an increase in short-selling as a fraction of daily share volume of 3.71 (2.15) percentage points for NYSE (Nasdaq) stocks. We also find that short-selling intensifies on days preceding negative returns. An increase in short-selling activity by 10 percent of share volume is associated with a future decline in returns by 0.94 (0.72) percent per month on the NYSE (Nasdaq). A trading strategy that buys stocks with low short-selling activity and sells short stocks with high short-selling activity generates an abnormal return of roughly 1.39 (1.41) percent per month for NYSE (Nasdaq) stocks. In sum, the results show that short-sellers time their trades extremely well relative to short-term price trends.

How should we interpret the fact that short-sellers as a group seem to be able to predict short-horizon abnormal returns? Does it mean that they have inside information about future fundamental values or are they capable of detecting when the current price deviates from the current fundamental value? The first alternative suggests that short-sellers are either corporate insiders or are privy to advance release of material non-public information from the corporation. We find this hard to believe given how many restrictions are levied on trading by corporate insiders. Moreover, Regulation Fair Disclosure (Reg FD) is in effect during our sample period which should limit the ability of outsiders to get advance access to material non-public information.

The second alternative suggests that market frictions (Miller (1977), Diamond and Verrecchia (1987), Harrison and Kreps (1978), and Scheinkman and Xiong (2003)) or behavioral biases (DeBondt and Thaler (1985), Daniel et al (1998), Barberis et al (1998), and Hong and Stein (1999)) may cause price to deviate from fundamental value in the short-run, and that short-sellers are exploiting these situations to their benefit. However, this interpretation requires that short-sellers are more sophisticated than the average investor. Given the cost of short-selling, short-sellers are likely to be predominantly institutional traders. For example, Boehmer et al (2007) find that about 75 percent of all short-sales are executed by institutions while individuals represent less than 2 percent (the rest are specialists and other). Since many institutions are prevented from shorting (e.g., many mutual funds), the ones that may use short-selling as part of their strategy tend to be more sophisticated. Thus, we conjecture that short-sellers as a group are likely to be sophisticated traders.

A third alternative is that short-sellers act as voluntary liquidity providers. According to this story, short-sellers step in and trade when there is a significant and temporary (buy) order-imbalance in the market. As the buying pressure subsides, prices should revert to fundamental value and the short-sellers can cover their positions at a profit. Under this interpretation, the trading patterns and predictability we observe are the direct result of short-sellers receiving compensation for providing immediacy (e.g., Stoll (1978), Grossman and Miller (1988), and Campbell et al (1993)). This interpretation suggests that elevated levels of short-selling should coincide with contemporaneous buy order-imbalances and be followed by reduced order-imbalances in the future.

A fourth explanation is that short-sellers step in to provide additional risk-bearing capacity in periods of elevated uncertainty. If the uncertainty is caused by short-lived asymmetric information (e.g., Copeland and Galai (1983), and Glosten and Milgrom (1985)) or if market makers require compensation for inventory risk (e.g, Ho and Stoll (1981), Biais (1993)), then the elevated short-selling should coincide with high intraday volatility and *wide* spreads. As the information becomes public, volatility and spreads should fall. By contrast, if the uncertainty is associated with differences of opinion (e.g., Varian (1985), and Harris and Raviv (1993)), the elevated short-selling should coincide with high intraday volatility and *low* spreads. In a market with wide dispersion in reservations values, limit orders posted by (non-strategic) competing liquidity providers result in narrower spreads. As opinions converge, volatility should fall and spreads should widen.

While we find evidence that suggests short-sellers use all the strategies mentioned above, past returns remain significant predictors of short-selling activity after controlling for order-imbalances, volatility, and spreads. Perhaps more importantly, higher short-selling activity predicts negative future abnormal returns after controlling for these same variables. In other words, we find evidence of informed trading by U.S. short-sellers.

It is worth pointing out that short-sellers are not all alike. In our stock-level aggregate data on short-sales, we clearly have some traders that speculate on prices reverting to fundamentals. However, we also have traders that use short-sales to hedge a long position in the same stock, to conduct convertible or index arbitrage, traders who seek to hedge their option positions, etc. Many of the trading strategies involving short-sales are based on relative valuations of securities (e.g., merger arbitrage) which reduces the likelihood that predictability will be found in a regression framework. These traders may or may not be selling short because they think the shorted stock is overvalued relative to current fundamentals. Their presence in the data will work against us finding that stock-level aggregate short-sales predict abnormal negative returns. Yet, we do find predictability both in the regression analysis and in the portfolio analysis.

We are not the first to investigate whether short-sellers are informed traders. There is a rather extensive literature studying the relationship between short-selling activity measured as a stock variable (short-interest) and stock returns. While the earlier literature provided mixed evidence, there is growing consensus that short-sellers are informed.[2] For example, researchers find that high short-interest predicts negative abnormal returns for NYSE/AMEX stocks (Asquith and Meulbroek (1995)) and for Nasdaq stocks (Desai et al (2002)), that predictability is strongest in stocks with low institutional ownership (Asquith et al (2005)), that short-sellers target companies that are overpriced based on fundamental ratios (Dechow et al (2001)), that short-sellers targets firms with earnings restatements and high accruals (Efendi et al (2005), and Desai et al (2006)), anticipate downward analyst forecast revisions and negative earnings surprises (Francis et al (2006)), and that short-sellers exploit both post-earnings announcement drift and the accrual anomaly (Cao et al (2006)).

These studies use monthly stock-specific short interest data. This data is disclosed by exchanges around the middle of each month, and consists of the number of shares sold short (a stock variable) at a particular point in time. There are two main problems with using monthly short interest data. The first problem is that monthly short interest data does not permit a researcher to discern whether or not a high level of short interest means that short-selling is more expensive, which is the pre-requisite for the over-reaction story as proposed by Miller (1977). To remedy this shortcoming of the literature, several authors have relied on proxies for short-sale constraints or demand (Chen et al (2002) - breadth of ownership, Diether et al (2002) - analyst disagreement, Nagel (2005) - institutional ownership, and Lamont (2004) - firm's actions to impede short-selling), and even the actual cost of borrowing stock (D'Avolio (2002), Cohen et al (2007b), Jones and Lamont (2002), Geczy et al (2002), Ofek and Richardson (2003), Reed (2003), Ofek et al (2003), and Mitchell et al (2002)) to investigate if short-sale constraints contribute to short-term overreaction 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.

The second problem is that the monthly reporting frequency does not permit researchers to study short-term trading strategies. Recent evidence suggests that many short-sellers cover their positions very rapidly. For example, Cohen et al (2007a) find that almost half the securities lending contracts they study are closed out in two weeks (the median contract length is 11 trading days). Also note that if a trader sells a stock short in the morning, he can cover the position with a purchase before the end of the day without ever having to actually borrow the stock. This suggests that even securities lending data truncates the holding period of short-sellers.[3] The notion that short-sellers focus on short-term trading strategies is consistent with our finding that short-sales represent on average 23.9 percent of NYSE and 31.3 percent of Nasdaq (National Market) reported share volume. By comparison, average monthly short interest for the same period is about 5.4 days to cover for NYSE stocks and 4.4 days to cover for Nasdaq stocks. Hence, it is important to study short-selling activity at a higher frequency. This is our main contribution to the literature.

Previous studies of short-selling have sought to test whether short-sellers time their trades well relative to future returns. However, as far as we know, no one has previously examined how short-sales relate to past returns. This is puzzling since the main argument for stricter short-sale regulation is that short-sellers exacerbate downward momentum. Without evidence on how short-sellers trade relative to past returns, it is impossible to determine whether short-sellers actually have any impact on momentum. Our second contribution to the literature is to examine how short-sellers react to past returns.

We use the regulatory tick-by-tick short-sale data for a cross-section of more than 3,800 individual stocks. While our data permits an intraday analysis of short-selling, we aggregate short-sales for each stock to the daily level for the purpose of this study. Our paper is the first study of daily short-selling to cover both Nasdaq and NYSE stocks. This is our third contribution to the literature.

Our final contribution is that we rely on a very comprehensive dataset. It includes all short-sales executed in the U.S., regardless of where the trade is printed (the AMEX, the Boston Stock Exchange, the Chicago Stock Exchange, the NASD, Nasdaq, the National Stock Exchange, the Philadelphia Stock Exchange, or NYSE) for all NYSE, and Nasdaq-listed stocks. The complete coverage is clearly important as we find that over 50 (23) percent of Nasdaq (NYSE) short-sales are reported away from the primary listing venue during our sample period. By contrast, other authors that study daily short-sales rely on samples that do not cover all short-sales for a particular stock. Christophe et al (2004) focus their analysis on customer short-sales that are subject to Nasdaq's short-sale rules and are reported to Nasdaq's Automated Confirmation Transaction Service

(ACT). Boehmer et al (2007) and Daske et al (2005) focus their analysis on orders entered through NYSE's SuperDOT system that are subject to NYSE's Uptick Rule. According to Boehmer et al (2007), NYSE SuperDOT captures about 70.5 percent of all NYSE reported volume. However, they acknowledge that it is uncertain whether this trading system captures an equally large proportion of short-sale volume. Moreover, as mentioned, we find that 23 percent of total short-sale volume for NYSE-listed stocks is printed away from the NYSE, which suggests that the coverage in these two studies is incomplete.

Our results are generally consistent with the return predictability found in NYSE SuperDOT short-sales for the 2000-2004 period by Boehmer et al (2007). They find that stocks with relatively heavy shorting underperform lightly shorted stocks by a risk-adjusted average of 1.16 percent in the following 20 days of trading and conclude that short-sellers as a group are extremely well-informed. The same conclusion is drawn by Christophe et al (2004) based on short-selling activity in Nasdaq stocks. They find that short-selling activity is concentrated in periods preceding disappointing earnings announcements suggesting that short-sellers have access to non-public material information. However, not all studies find that short-sellers are prescient with regard to earnings announcements. Daske et al (2005) find that short-sales are not concentrated prior to bad news disseminated by scheduled earnings announcements and other informational events.[4] It is possible that the differing sample periods explains the difference because the data used by Daske et al (2005) is post RegFD. Thus during their sample there is much stricter regulation of the release of material non-public information.

Our findings are consistent with a recent paper by Avramov et al (2006) who study the impact of trades on daily volatility. They find that increased activity by contrarian traders (identified as sales following price increases) is associated with lower future volatility, while increased activity by herding investors (identified as buyers after price increases) is associated with higher future volatility. Avramov et al (2006) argue that contrarian traders are rational traders that trade to benefit from the deviation of prices from fundamentals. As these trades make prices more informative, they tend to reduce future volatility. We provide more direct evidence of the information content of contrarian short-sellers in that they predict future returns.

Our results are also reminiscent of a recent study of net individual trade imbalances on the NYSE during the 2000-2003 period by Kaniel et al (2006). They find that individuals are contrarians, and that their trades predict returns up to 20 days out. However, the authors discard the fundamental information hypothesis and instead interpret their evidence as consistent with the liquidity provision hypothesis. The reason is largely that they find it hard to believe that individual traders are more sophisticated than institutions. As discussed above, we have good reason to believe that short-sellers are more sophisticated than the average investor.

Our study proceeds as follows. We summarize our hypotheses in Section 1, and describe the data in Section 2. We examine how short-selling relates to past returns, spreads, order-imbalances, and volatility in Section 3. Cross-sectional differences in the relationship between short-selling and past returns are examined in Section 4. We address whether short-selling activity predicts future returns in Section 5. Cross-sectional differences in predictability are examined in Section 6. We contrast our hypotheses in section 7. A further robustness check is provided in Section 8. Section 9 concludes.

1. Hypotheses

Our hypotheses can be summarized as follows:

- Short-sellers are trading on short-term overreaction if they short-sell following positive returns and their trades are followed by negative returns.

- Short-sellers are acting as voluntary liquidity providers if they short-sell on days with significant buying pressure, and their trades are followed by declining buying pressure and negative returns.

- Short-sellers are acting as opportunistic risk-bearers during periods of elevated asymmetric information if they short-sell on days with high intraday volatility and *wide* spreads, and their trades are followed by days with lower volatility, narrower spreads, and negative returns.

- Short-sellers are acting as opportunistic risk-bearers during periods of differences of opinion if they short-sell on days with high intraday volatility and *narrow* spreads, and their trades are followed by days with lower volatility, wider spreads, and negative returns.

We test these hypotheses in the rest of the paper.

2. Characteristics of short-selling

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 the loan of the 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 percent per annum, but some hard-to-borrow stocks have loan fees greater than 10 percent per annum (Cohen et al (2007b)). 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 Uptick Rule, Rule 10a-1 and 10a-2, NYSE Rule 440B) and Nasdaq National Market (NM) Securities (the best-bid test, NASD Rule 3350). Moreover, Nasdaq NM stocks that were traded on Electronic Communication Networks (ECNs) had no bid-test restriction.

On June 23, 2004, the SEC adopted Regulation SHO to establish uniform locate and delivery requirements, create uniform marking requirements for sales of all equity securities, and to establish a procedure to temporarily suspend the price-tests for a set of pilot securities during the period May 2, 2005 to April 28, 2006 in order to examine the effectiveness and necessity of short-sale price-tests.[5] At the same time, the SEC mandated 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 non-exempt from short-sale rules) for all short-sales. In this study, we do not examine the effects of Regulation

SHO per se, but our study is made possible by the SEC mandated short-sale data. In related work, we study the effects of suspending the price-tests on market quality (Diether et al (2007)).

The data have a few drawbacks. The main drawback is that the sample period is short: January 2 to December 30, 2005. The reason is that the regulatory data only became available starting January 2, 2005 (which limits us on the front end) and that we need CRSP and Compustat data for the analysis (which limits us on the back end). However, the 2005 sample is important since we have several reasons to believe that short-selling strategies have changed dramatically in recent years: e.g., increased investor pessimism following the 2000 bubble, increased use of algorithmic trading, and a tremendous growth of the hedge-fund industry which systematically employs long-short strategies. Nevertheless, our results should be interpreted with caution given the short sample period.

We also do not know anything about the short-sellers in our sample other than the time, price, and size of their trades. In an earlier draft of this paper we conducted the analysis by trade size. However, given that institutions order-split heavily, it is doubtful whether it is possible to use trade size to separate retail from institutional trades.[6] The data also includes a flag for whether or not a short-sale is exempt from the exchanges' short-sale rules. This seems to be a convenient way to separate out market maker short-sales (which are largely exempt) from customer short-sales as done by Christophe et al (2004) and Boehmer et al (2007). However, due to a no-action letter from the SEC, market participants have been relieved from systematically using the "short-exempt" marking rendering the flag useless during the Reg SHO sample period.

Another potential drawback with the regulatory short-sale data is that while we see each individual short-sale, the data does not flag the associated covering transactions. Hence, we cannot determine whether short-sellers' trades are profitable. Such data is not contained in the audit trail from which the regulatory data is drawn and could only be obtained at the clearing level. Instead, we have to rely on indirect measures such as whether or not it is possible to create a profitable trading strategy based on daily short-selling activity.

This study focuses on NYSE and Nasdaq-listed stocks. We define our universe as all NYSE and Nasdaq National Market (NM) stocks that appear in CRSP with share code 10 or 11 (common stock) at the end of 2004. We draw daily data on returns, prices, shares outstanding, and trading volume for these securities for the January 2, 2005 to December 30, 2005 time period from CRSP. We also download intraday data from all SROs that report short-sales and calculate daily short-selling measures. Specifically, we compute the number of short sales and shares sold short. Finally, we compute daily buy order-imbalances using the Lee and Ready (1991) algorithm, and daily effective spreads from TAQ. We merge the daily short-sale data with return and volume data from CRSP. We then filter the sample by only including common stocks with an end-of-year 2004 price greater than or equal to $1. We also exclude stock-days where there is zero volume reported by CRSP.[7]

In addition, we obtain monthly short interest data directly from Nasdaq and the NYSE, and data on market capitalization, book-to-market, and average daily trading volume (share turnover) 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 1,481 stocks for the NYSE and 2,373 for Nasdaq. For most of the analysis we also exclude stocks designated by Reg SHO as Pilot stocks as the short-sale rules changed during the sample period for these securities. The subsample of non Reg SHO Pilot stocks includes 1,079 NYSE and 2,001 Nasdaq stocks. Finally, to conform with the previous literature, we perform most of our portfolio analysis on the stocks with a lagged price of at least $5.

Table 1 illustrates the distribution of shorted shares in the top of Panel A, and the number of short-sale trades in bottom half of Panel A by market venue: American Stock Exchange (AMEX), Archipelago (ARCA), Boston Stock Exchange (BSE), Chicago Stock Exchange (CHX), National Association of Securities Dealers (NASD),[8] NASDAQ, National Stock Exchange (NSX),[9], Philadelphia Stock Exchange (PHLX) and New York stock Exchange (NYSE). The NYSE accounts for almost 77 percent of shares sold short in NYSE-listed stocks, while NASDAQ accounts for 16 percent and ARCAEX accounts for 4 percent. NASDAQ accounts for just over half the shares sold short in Nasdaq-listed stocks, while ARCA and NSX each account for roughly one-quarter. The table clearly highlights that it is important to consider trading outside the market of primary listing. The distribution of shorted shares roughly mirrors the distribution of overall trading volume in NYSE and Nasdaq-listed stocks across market venues.[10] By comparing the two parts of Panel A, we infer that short-sale trades are generally larger in the market of primary listing.

Panels B and C of Table 1 provide descriptive statistics for our daily short-selling data. Note that the dispersion across stock-days is significant, particularly for the Nasdaq sample. 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. On average short-selling represents 23.89 percent (median = 23.96%) of share volume on the NYSE and an astonishing 31.33 percent (median = 31.72%) of Nasdaq share volume. Hence, almost one in four shares traded in NYSE stocks and almost one in three shares traded on Nasdaq involves a short-seller. Note that *relss* is much less skewed than the other measures of short-selling activity. It will be the measure of short-selling that we use throughout this paper.

The last panel of Table 1 reports how average short-selling activity varies with firm characteristics. The previous literature has found that short-interest tends to be higher for large-cap stocks, for low book-to-market stocks, and for stocks with high institutional ownership (D'Avolio (2002) and Jones and Lamont (2002)). 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 have greater short-selling activity than stocks with low institutional ownership. Our results on short-selling activity in the cross-section are thus consistent with the previous literature. Note, however, that the differences between the terciles are much smaller for NYSE than for Nasdaq stocks.

Since the collateral costs for low-price stocks is high (Cohen et al (2007b)), we expect to see less short-selling in these stocks. Indeed, we find that stocks with a price at or above $5 have more short-selling than those with prices below \$5. Buying put options is an alternative way to make a negative bet on a stock, so it would seem that stocks with actively traded put options should have less short-selling activity. We find the opposite - stocks with actively traded puts (www.optionsclearing.com) have higher short-selling activity. The most likely explanation is that stocks with actively traded puts are larger more liquid stocks for which we know short-selling activity.

In Table 2, we summarize the characteristics of the sample. We have information on short interest from each market, and for comparison with *relss* we relate this figure to average daily volume. Recall that 24 percent of share volume in NYSE stocks and 31 percent of daily share volume in Nasdaq stocks are short-sales. By comparison, average monthly short-interest, defined as the stock of shorts at the middle of month t divided by average daily volume during in month $t-1$, is 5.38 for the NYSE and 4.35 for Nasdaq during our sample period. In other words, for the average stock in our sample, it would take between 4 and 5 days to cover the entire short position if buying to cover short-sales was 100 percent of volume. Panel B of Table 2 reports the summary when we exclude the stocks that are covered by the SEC Reg SHO pilot program.

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. To see why, consider the typical Nasdaq stock and assume it has a (constant) average daily volume of 100,000 shares. Further, suppose that its short interest is 4,000 shares in mid-January, that this doubles to 8,000 shares by by mid-February, and that there were 22 trading days between the two readings. Our numbers suggest that short-sales during the month would reach a total of 22*31,000=682,000 shares. To hit the mid-February 8,000 shares of short interest, total purchases to cover short-sales during the month would have to be 678,000 shares, or on average 30,818 shares per day. Note that this does not mean that virtually every short-sale on day t is covered on day t. Denote short interest at month m by S_m, and short-sales on date t in month m by dS_m, t. Further, assume for simplicity that the holding period (in days) for the current and previous month, denoted as hp_m and hp_{m-1} respectively, are the same for all short sales in that particular month. This leads to the following relationship:

$$S_{m+1} = S_m + \sum_{t=1}^{22} dS_{m,t} - \sum_{t=1}^{22-hp_m} dS_{m,t} - \sum_{t=-hp_{m-1}}^{0} dS_{m-1,t}. \tag{1}$$

The first sum is short-sales during the current month, the second sum is covering transactions of short-sales during the current month that take place during the current month, and the third sum is covering transactions in the current month of short-sales that took place in the previous month. It follows that changes in short-interest is positively related to both to increases in holding periods and to increases in daily short-selling activity.

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

Our first hypothesis is that short-sellers trade on short-term overreaction. The main implication of this hypothesis is that short-sellers should increase their short-selling activity after periods of high returns. Consequently, we start by analyzing how short-sellers react to past returns. As our sample is short, our study focuses on short-term, short-selling strategies. We measure past returns using a five-day window preceding the day of the short-sale.

In Table 3 we regress individual stock short-sales during day t ($relss_t$) on past returns, $r_{-5,-1}$. The panel regressions include day and stock fixed effects. We are concerned about both serial correlation and cross-correlation, and consequently we estimate standard errors that cluster by both stock and calendar date (Thompson (2006)).[11] Additionally, the regressions only include stocks with lagged price greater than or equal to \$5. It is clear from the first and fourth columns that short-selling activity increases significantly in past returns both for NYSE and Nasdaq stocks. The coefficient implies that a return over the past five days of 10 percent results in an increase in short-selling of 3.71 percent (2.15 percent) of average daily share volume for NYSE (Nasdaq) stocks. Our results are thus consistent with the hypothesis that short-sellers are trading on short-term overreaction.

One concern is that past and contemporaneous price increases can be caused by factors that themselves would possibly trigger short-selling activity. For example, high past returns could be caused by a period of temporary buying pressure that is purely liquidity-motivated. Short-sellers may in such situations be stepping in as voluntary liquidity providers expecting to benefit from the price decline they anticipate will occur in the near future as the buying pressure subsides. This is our first alternative hypothesis. We use the (buy) order-imbalances to proxy for buying pressure. Thus, we examine the relationship between short-selling and contemporaneous buy order-imbalances. Since our hypothesis is strictly about buy order-imbalances, we define this variable as $oimb_t^+ = oimb_t$ if $oimb_t > 0$ and zero otherwise. Past buy order-imbalances ($oimb^+_{-5,-1}$) are defined analogously.

It is of course also possible that short-sellers step in as opportunistic risk-bearers during periods of increased uncertainty as described in the last two hypotheses. If this is the case, we should see short-selling increase in periods of uncertainty. Depending on whether this increased uncertainty is caused by increases in asymmetric information or a wider divergence of opinion, this increase in uncertainty would coincide with wider or narrower spreads respectively. These two hypotheses suggest that we should examine the relationship between short-selling and contemporaneous measures of volatility. Our proxy for short-term volatility is the intraday $(high - low)/high$ for day t which we denote by (σ_t). We proxy for recent volatility by taking the average intraday volatility over the previous five days ($\sigma_{-5,-1}$). To discriminate between the asymmetric information and the differences of opinion stories, we also include the contemporaneous effective spread ($spread_t$).

Short-selling and trading volume are both positively autocorrelated. To account for this we include lagged short-sales ($relss_{-5,-1}$) and lagged turnover ($\log(tv_{-5,-1})$) on the right hand side. If returns are positively autocorrelated, we risk falsely associating past returns with today's short-selling activity. Therefore, we also include the contemporaneous return (r_t) as an explanatory variable.

Realizing that short-sellers are a heterogeneous group and that there is certainly room for more than one trading strategy, we test these alternative explanations jointly in columns two and five for the NYSE and Nasdaq respectively. To test whether these alternative trading strategies are more important than trading based on short term overreaction, we also keep the past returns in the regression. If we erroneously attributed the association of short-selling to past returns in the first and fourth column to trading on overreaction, we would not find that past returns are significant once we introduce the proxies for buying pressure and uncertainty.

Our first result is that past returns remain a significant predictor of future short-selling even after controlling for the contemporaneous returns, buy order-imbalances, volatility, and spreads, and after controlling for the autocorrelation in short-selling activity and volume. The coefficient is smaller, but still highly significant.

Further, the results show that today's short-selling is highly positively correlated with contemporaneous buy order-imbalances as predicted by the voluntary liquidity provision hypothesis. Both the magnitude and the significance of the coefficient is much higher on the NYSE than on Nasdaq. This is natural as the Uptick rule forces NYSE short-sellers to be passive liquidity-suppliers. In other words, one of the reasons for positive buy order-imbalances to occur is the rules that dictate how short-sales can take place (Diether et al (2007)). There is no evidence that a period of buying pressure in the recent past is associated with increased short-selling, as the coefficient on this variable is negative and even significant in the case of the NYSE.

The results also show that short-selling is positively correlated with contemporaneous volatility in both markets. By contrast, past volatility is only significant in the case of Nasdaq stocks. Since contemporaneous spreads are positively associated with short-selling activity, we infer that there is evidence of short-sellers providing opportunistic risk-bearing in situations of increased asymmetric information.

We conduct two sets of additional robustness tests of our overreaction story. First, in columns three and six of Table 3 we explore asymmetric and possible non-linear responses to past returns. To accomplish this, we sort stocks for each market into quintiles based on their past returns. We define a dummy that takes on a value of one for stocks in the highest (lowest) quintile as *winner* (*loser*). Short-selling is significantly higher for past *winners*, and significantly lower for past *losers*. Note also that the coefficients on the *winner* and the *loser* portfolios are quite similar. In other words, short-sellers do not only short more after price increases, they also short significantly less following price declines. This reinforces our result that short-sellers trade on overreaction. The difference between short-selling of past *winners* and past *losers* is 4.8 percent (3.9 percent) of average daily volume for NYSE (Nasdaq) stocks. These differences are highly significant based on an F-test (not reported).

In sum, by examining the relationship between short-selling and past and contemporaneous variables, we find evidence supporting three of our four hypotheses: short-selling based on short-term overreaction, short-sellers acting as voluntary liquidity providers, and short-sellers acting as opportunistic risk-bearers in situations of increased asymmetric information.

4. Cross-sectional differences in short-selling activity

It is quite likely that the relationship between short-selling and past 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.

To economize on space, we combine Nasdaq and NYSE stocks together.[12] On day t, we form market-capitalization terciles using NYSE market-cap (ME) breakpoints from the end of the last month, book-to-market (B/M) terciles (lagged as in Fama and French (1993)) using NYSE B/M breakpoints. We also classify stocks as low (high) institutional ownership if the previous quarter-end institutional ownership is $\leq 33\%$ ($> 67\%$), and we classify according to put option availability.

We contrast the effect of past returns on short-selling for small-cap and large-cap stocks in the first column of Table 4. we regress individual stock short-sales during day t ($relss_t$) on past returns, $r_{-5,-1}$, for each category. The panel regressions include day and stock fixed effects and standard errors that cluster by both stock and calendar date (Thompson (2006)). 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, and the difference is statistically significant.[13] Clearly, it is easier (and almost certainly cheaper) for short-sellers to establish a short position in large-cap stocks all else equal.

The previous literature has tested and confirmed that short-selling demand seems higher for 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. The second column of Table 4 reports the results. There is a strong contrarian pattern both in growth and value stocks, and magnitudes of the coefficients are very similar for both value and growth stocks. Additionally, the difference between the coefficients is not statistically significant. Thus, if short-selling demand is higher for growth stocks in our sample it doesn't translate into a stronger relation between short-selling activity and short term past returns.

The previous literature has also 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 if our results are driven by stocks with high institutional ownership. The results are in the third column of Table 4. We find that short-sellers are contrarian both in stocks with high and low institutional ownership, and the magnitude of the effect of past returns on future short-sales is virtually identical for both types of stocks.

Several authors (Brent et al (1990), Danielsen and Sorescu (2001), 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 a decline in stock prices.[14] 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 divide the sample into stocks with and without traded put options.[15] The last column of Table 4 reports the results. Whether or not a stock has put options, short-sellers in our sample trade on short-term overreaction, and the magnitude of the effect of past returns on future short-sales is virtually identical for both types of stocks.

In sum, the results do not suggest that our findings that short-selling respond to past returns are driven by a particular group of stocks.

5. Can short-sellers predict future returns?

For the shorting strategy to be successful, the stock price has to decline in the future so that the short-seller can cover her position and still make profits large enough to cover trading costs and costs related to short-selling. In other words, increased short-selling activity should predict future abnormal negative returns.

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. Work by Cohen et al (2007a) suggest that the median holding period for a short-position is 11 trading days, but this is an upper bound as short-sales that are covered before the end of the day are not included in their study. At best we can show whether or not short-sellers could potentially make money if they were to close out their position within a certain time period of the short-sale. Another challenge that we face is that our sample period is short, only one year. Thus, we will evaluate predictability over a relatively short period, two to five days.

If short-sellers are able to predict returns, it is at least potentially possible to develop a profitable trading strategy based on the information in the Regulation SHO short-sale data. To investigate this, we first use a portfolio approach. This analysis has the added benefit that it does not restrict the relationship between short-selling activity and future returns to be linear. We first compute *relss* quintiles for each market on date t and form portfolios on day t using stocks with a closing price on day $t-1$ greater than or equal to \$5. We then compute size and book-to-market adjusted returns based on the standard 25 Value-weighted portfolios (Fama and French (1993)) for each portfolio.[16] The *relss* portfolios are value-weighted and rebalanced daily. We skip one day, $t+1$, to eliminate concerns about patterns induced by bid-ask bounce in CRSP data (Kaul and Nimalendran (1990)).

The results are in Table 5, with NYSE stocks in Panel A and Nasdaq stocks in Panel B. First note that $t+2$ abnormal returns for both NYSE and Nasdaq stocks are monotonically decreasing in short-selling activity. The last column provides the difference in returns between the Low and the High *relss* portfolio in percent per day. 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 0.063 percent per day (1.39 percent per month) for NYSE stocks and 0.064 percent per day (1.41 percent per month) for Nasdaq stocks. This difference is statistically significant based on a t-test adjusted for autocorrelation using the Newey-West (1987) procedure with five lags. If we extend the holding period to four days ($t+2$ to $t+5$) using the overlapping holding period methodology of Jegadeesh and Titman (1993), the portfolios generate a statistically significant average abnormal daily return of 0.042 percent per day (0.92 percent per month) for NYSE and 0.055 percent per day for Nasdaq (1.21 percent per month).

Figure 1 illustrates the daily holding-period returns for Low-High *relss* portfolio based on NYSE stocks in the top panel and Nasdaq stocks in the bottom panel. The solid line is the average abnormal return for a holding period ranging from one day to four days, always skipping day $t+1$. The dashed lines represent the two standard deviation bounds. While the holding period returns decline over time, they are positive and statistically significant throughout.

We prefer using the characteristic benchmarking instead of factor model benchmarking because it is possible that the portfolios do not have stable factor loadings due to the changing composition of the portfolio through time. However, to make sure that our results are not driven by the way we compute abnormal returns in Table 5 and to explicitly control for the momentum effect (Jegadeesh and Titman (1993)), we repeat the exercise based on Fama-French (1993) three factor alphas and four factor alphas with the Carhart (1997) momentum factor included. The factor model regressions are

$$r_{pt} - r_{ft} = a_p + b_p(r_{Mt} - r_{ft}) + s_p(SMB_t) + h_p(HML_t) + e_{pt} \tag{2}$$

$$r_{pt} - r_{ft} = a_p + b_p(r_{Mt} - r_{ft}) + s_p(SMB_t) + h_p(HML_t) + u_p(UMD_t) + e_{pt}, \tag{3}$$

where r_{pt} is the return on the short-selling portfolio on day t, r_{ft} is the daily rate that, over the number of trading days in the month, compounds to the 1-month T-bill rate on day t, $r_{Mt} - r_{ft}$ is the excess return on value-weight index of all stocks on day t, SMB_t is the return on size factor on day t, HML_t is the return on the value factor on day t, and UMD_t is the return on the momentum factor on day t.[17]

The results are in Table 6. In every case, the holding period returns for the Low-High *relss* portfolio are both economically and statistically significant. Compared to Table 5, the abnormal returns for the Low-High *relss* portfolios are slightly lower for Nasdaq stocks, but they are still statistically significant. They are remarkably similar across the tables for NYSE stocks. Generally, the abnormal returns are slightly higher for the four factor alphas compared to the three factor alphas.

The average return on Low-High strategies 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. With effective half spreads of around 30 basis points, execution costs for the Low-High portfolio with the five-day holding period would be roughly 2.7 percent per month (not including commissions).[18] By comparison, explicit costs of shorting are relatively small. Cohen et al (2007b), estimate these costs to be 3.98 percent per year (0.326 percent per month) for stocks with market capitalization below the NYSE median.[19] 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.

6. Cross-sectional differences in predictability

To complete the picture, we also consider whether our return predictability is concentrated in firms with certain characteristics by conducting double-sorts on *relss* and market capitalization, book-to-market, institutional ownership, and options trading respectively. We form value-weighted double-sort portfolios based on the intersection of these measures on day t and compute the return for the portfolios on day $t+2$ (we once again skip a day to avoid concerns about bid-ask bounce). We rebalance the double-sort portfolios daily. Furthermore, 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 are in Table 7. As before, we pool Nasdaq and NYSE stocks for this analysis.[20] Abnormal returns are computed by characteristically adjusting returns using 25 value-weight size-BE/ME portfolios. The evidence shows that significant abnormal returns are generated by long-short *relss* portfolios for all sub-samples except for the large-cap and low institutional ownership categories. Thus, the strategy of buying stocks with low *relss* and shorting stocks with high *relss* generates positive abnormal returns for most characteristic terciles.

The magnitude of the abnormal returns that can be generated by forming portfolios on past *relss* are higher for small cap stocks than for large capitalization stocks and higher for growth stocks than for value stocks. Small caps and value stocks are types of stocks where it is more likely that we will observe short-term overreaction. Hence, these results provide further corroborating evidence that short-sellers primarily target firms with short-term overreaction.

However, the abnormal returns are also statistically significant for stocks with high institutional ownership and for stocks with actively traded put options. These results may be counterintuitive because we believe that over-reaction is least likely among stocks with high institutional ownership and put options. However, bear in mind that traders desire to short-sell only shows up in our data to the extent that they are able to execute a short-sale In other words, they have to be able to borrow stock for delivery to the buyer. Hence, an important factor determining how responsive short-selling is to past prices is the ease borrowing stock at a low loan fee.

The magnitude of the abnormal returns ranges from 1.17 percent per month in the case of small capitalization stocks to 1.50 percent per month for growth stocks. Taken together, these results do not suggest that our findings are driven by a particular group of stocks as the pattern of predictability is quite pervasive.

7. Are short-sellers informed traders, voluntary liquidity providers, or opportunistic risk-bearers?

We have established that short-sellers are capable of predicting future short-term abnormal (negative) returns. However, there are several competing stories that could be consistent with this association between short-selling and future returns. Our first hypothesis, which is consistent with the evidence presented so far, is that short-sellers are informed traders in the sense that they are able to detect when the current market price exceeds the fundamental value of a particular stock.

The relationship between short-selling and future returns could alternatively be associated with the aftermath of either a liquidity demand shock, or a period of heightened uncertainty. According to the first alternative hypothesis, short-sellers increased their activity to provide liquidity to buyers willing to pay a price for immediacy. When the buying-pressure subsides, the stock price will return to its long term level. According to the second alternative hypothesis, short-sellers increased their activity to opportunistically provide liquidity in periods of heightened uncertainty due either to increased informed trading or due to differences of opinion. When the root-cause of the increased uncertainty subsides, the stock price will return to its long term level.

We explore these hypotheses in a panel regression setting. In addition, we use these panel regressions to control for well known patterns in daily returns. Table 8 reports the results of panel regressions with day and stock fixed effects and standard errors corrected for clustering by both stock and calendar date (Thompson (2006)) for NYSE and Nasdaq stocks respectively. To address potential concerns about predictability due to short-term reversals (Jegadeesh (1990) and Lehmann (1990)), we skip a day. Hence, we regress returns on day $t+2$ on *relss* for day t.[21] The regressions only include stocks with lagged price greater than or equal to \$5.

In the first and fifth columns of Table 8, we report the results of regressing future returns on 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 ten percentage point increase in short-selling activity would predict a 0.0427 (0.0325) decline in returns two days hence for NYSE (Nasdaq) stocks. This corresponds to a monthly abnormal return of -0.94 percent for NYSE stocks and -0.72 percent for Nasdaq stocks.

We already control for short-run reversals at the daily horizon by skipping a day. However, we further allow for weekly return-reversals by including recent momentum $r_{-5,-1}$ in the second and sixth specifications of Table 8. There is clear evidence of weekly reversals for both markets, and it is particularly strong for Nasdaq stocks. Nevertheless, *relss* remains a significant predictor of future negative abnormal returns even after controlling for weekly patterns in returns.

There is no obvious reason for why the relationship between short-selling and future returns should be linear. Nor is it clear that past returns should be linearly related to future returns. Hence, we allow for non-linear effects in specifications three and seven. We first sort all stocks on day t into *relss* quintiles, and define a dummy variable *high* (*low*) to be one for all stock in the highest (lowest) quintile of short-selling relative to volume. Similarly, we sort all stocks on day t into recent return ($r_{-1,-5}$) quintiles, and define a dummy variable *winner* (*loser*) to be one for all stocks in the highest (lowest) quintile of past returns. To conserve on space, specifications three and seven control for the non-linearity in *relss* and $r_{-5,-1}$ simultaneously.

The results in specifications three and seven of Table 8 show that *losers* outperform *winners*, and the magnitude is 0.136 percent per day (2.99 percent per month) for NYSE stocks and 0.303 percent per day (6.67 percent per month) for Nasdaq stocks. Yet, high short-selling activity remains a significant predictor of negative future returns. Specifically, stocks in the highest quintile of short-selling activity experience significant negative future returns by about 0.07 percent per day for the NYSE stocks and 0.04 percent per day for Nasdaq stocks. By contrast, the lowest quintile of short-selling activity predicts positive future returns for both NYSE and Nasdaq stocks. The difference in predicted future returns for the *high* minus the *low* quintiles is highly significant, and is 0.154 percent per day (3.39 percent per month) for NYSE and 0.151 percent per day (3.32 percent per month) for Nasdaq stocks.

Finally, we add controls for the voluntary liquidity-provision and the opportunistic risk-bearing hypotheses in specifications four and eight of Table 8. These regressions also include the control for weekly return reversals and add a control for possible relationships between trading volume and future returns (e.g., Conrad et al (1994), Gervais et al (2001), and Llorente et al (2002) suggest that high trading volume is a signal of a demand shock that translates into future positive returns). We measure trading volume as shares traded over the past five days divided by shares outstanding to normalize across stocks, $tv_{-1,-5}$. In our sample, high turnover in the previous week actually predicts negative future returns for both markets, but the effect is only significant for Nasdaq stocks.

As before, we measure the buying pressure as positive buy order-imbalances. Clearly, buying pressure is significantly associated with future negative returns for both NYSE and Nasdaq stocks. Hence, the data supports the voluntary liquidity provision hypothesis. Interestingly, both the magnitude and the significance of the coefficient is larger for Nasdaq stocks. Note that the relationship between contemporaneous buy order-imbalances and short-selling is less mechanic for these stocks as Nasdaq uses a bid-price rule instead of the Uptick rule (Diether et al (2007)). Consequently, it is easier to distinguish between the voluntary liquidity provision hypothesis and the trading on short-term overreaction hypothesis for Nasdaq stocks.

By contrast, the evidence in Table 8 generally does not support the opportunistic risk-bearing hypothesis, at least not over the horizons that we are interested in. Our measure of intraday volatility is not a significant predictor for future abnormal returns for NYSE stocks. For Nasdaq stocks, but not for NYSE stocks, wider spreads predict a return reversal. Hence, there is some support for the notion that short-sellers may be acting as opportunistic risk-bearers during periods of increased information asymmetry on Nasdaq. Even after controlling for the variables suggested by the alternative hypotheses, *relss* remains a significant predictor of future abnormal negative returns.

We go one step further towards separating short-selling activity into voluntary liquidity provision and trading on short-term overreaction in Table 9. Specifically, we first run the following regression:

$$relss_{it} = \alpha_i + \beta_i \cdot oimb^{+}_{it} + \varepsilon_{it}, \quad t = 1, \ldots, -22 \tag{4}$$

for each stock i and date t. This regression assumes that any short-selling that is correlated with contemporaneous buy order imbalances is due to voluntary liquidity provision. This is obviously exaggerating the importance of voluntary liquidity provision, especially for NYSE stocks. The reason is that the Uptick rule mechanically creates a positive relationship between buy order-imbalances and short-selling. It is also possible that short-sellers on Nasdaq that trade on over-reaction are using a passive strategy, again creating a correlation between buy order-imbalances and short-selling. Therefore, we consider this as an upper bound to the importance of voluntary liquidity provision.

We then use the estimated coefficients to calculate the residual *relss*, ($e_{relss_{it}}$), i.e., the amount of short-selling that cannot be explained by voluntary liquidity provision, for stock *i* and date *t* as:

$$e_{relss_{it}} = relss_{it} - \hat{\alpha}_i - \hat{\beta}_i \cdot oimb^+_{it}. \tag{5}$$

In Table 9, we use this variable in lieu of *relss* on the right hand side, but otherwise repeat the analysis from Table 8. Residual *relss* is a significant predictor of future negative abnormal returns for all specifications with a continuous version of the variable. When we allow for a non-linear relationship between residual *relss* and future returns in specifications three and seven, the *high* residual *relss* portfolio is not significant, but the difference between the *low* and the *high* residual *relss* coefficients is in both cases significant based on an F-test (not reported).

In sum, the evidence presented so far suggest that short-sellers engage in two strategies: trading on short-term over-reaction and voluntary liquidity provision. By contrast, the evidence for the opportunistic risk-bearing hypothesis is weak.

8. Voluntary liquidity provision revisited

The voluntary liquidity provision has further implications that we test in this section. If short-sellers are stepping in to serve as voluntary liquidity providers responding to a short-term increase in buying pressure, then increased short-selling activity should predict not only negative abnormal returns, but also declining future buy order-imbalances (subsiding buying pressure).

We test this in panel A of Table 10 for NYSE Stocks and panel B of Table X for Nasdaq stocks respectively. The specification in column one is a regression of buy order-imbalances on day $t+2$ on short-selling activity on day t. The panel regressions include day and stock fixed effects and standard errors that cluster by both stock and calendar date (Thompson (2006)). The coefficient is positive and highly significant. In other words, high short-selling today *does not* predicts declining future buying pressure. The specification in column two adds the contemporaneous buy order-imbalance as a predictive variable, but this does not change the conclusion. For completeness, we also separate out the positive from the negative future buy order-imbalances in columns three to six. Again, there is no evidence that high short-selling today predicts a decline in future buying pressure.

This more direct test of the voluntary liquidity provision hypothesis is revealing. It suggests that while our previous results find support both for trading on short-term overreaction and voluntary liquidity provision hypotheses, the data do not support the notion that the negative abnormal returns following days of high short-selling are caused by declining buying pressure.

Note that this does not mean that voluntary liquidity provision is irrelevant, but it does seem to rule out more mechanical trading as voluntary liquidity providers by short-sellers. Instead, the results suggest that short-sellers carefully select when to trade (after stock market run-ups). When they do trade, the short-sale rules imply that they will tend to be liquidity providers. In other words, while they act as voluntary liquidity providers, the timing of their trades is in fact dictated by their ability to detect that the market price exceeds the stock's fundamental value.

9. Conclusions

We examine new comprehensive data on daily short-selling activity for all NYSE and Nasdaq listed U.S. stocks during 2005. We find that short-sellers in U.S. stocks are surprisingly active market participants. Their trades correspond to 31 and 24 percent of share volume on Nasdaq and the NYSE respectively. This suggests that the costs of borrowing stocks for short-sales are not constraining U.S. short-sellers significantly.

The cross-sectional patterns of short-selling activity in our data confirm findings in the previous literature. Specifically, we find that short-selling activity is higher for large capitalization stocks, growth stocks, stocks with high institutional ownership, high price stocks, and stocks with actively traded put options.

We find strong evidence that short-sellers in both NYSE and Nasdaq stocks increase their short-selling activity after periods of positive returns, on days with significant buying pressure, and on days with high levels of asymmetric information. These patterns are consistent with three types of trading strategies: trading on short-term overreaction, acting as a voluntary liquidity provider, and opportunistically providing risk-bearing services.

These short-sale strategies seem to pay off in our sample. We find that increased short-selling activity predicts negative abnormal future returns in a portfolio setting, as much as five days out. While short-sale data is not available at a high enough frequency to actually trade on the data we analyze in this paper, we find that a hypothetical trading strategy that goes long in stocks with low short-selling activity and sells short stocks with high short-selling activity would generate significant positive abnormal returns of roughly 1.4 percent per month.

To discriminate between the different short-selling strategies, we examine if short-sellers are able to correctly predict negative future abnormal returns in a regression framework. We find that both high short-selling activity and high buying pressure today predicts significant negative future abnormal returns. There is no relationship between our measure of uncertainty and future abnormal returns. This suggests that short-sellers both trade on short-term deviations of price from fundamentals and trade as voluntary liquidity providers. By contrast, the evidence for opportunistic risk-bearing is weak. We attempt to separate the two remaining strategies by orthogonalizing short-selling activity against buying pressure, creating a variable we call residual *relss*. However, both residual *relss* and buying pressure remain significant predictors of future returns.

Finally, we test whether higher short-selling activity today is associated with subsequent decline in buying pressure as would be expected if the dominant strategy was voluntary liquidity provision. The data does not support this prediction. Therefore, we interpret our evidence as showing that U.S. short-sellers are able to detect, and act on, short-term deviations of price from fundamental value.

Taken together, our results show that short-sellers are not the villains they are made out to be by the media and issuers. Instead, traders do seem to target stocks where prices are out of line with fundamental value. Hence, the evidence is consistent with short-sellers helping correct short-term overreaction of stock prices to information.

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Notes

[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]For the earlier literature, see, e.g., Figlewski (1981), Brent et al (1990), and Senchack and Starks (1993).

[3]Jones (2004) finds that such "in-and-out shorting" represented about 5 percent of daily volume is the early 1930s.

[4]An earlier draft of this paper finds that Nasdaq short-sellers are unable to predict negative earnings announcements during our sample period.

[5]On April 20, 2006, the SEC announced that the short-sale Pilot has been extended to August 6, 2007.

[6]For an analysis of short-sales by account type, see Boehmer et al (2007).

[7]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. We do not exclude stocks with very high prices (> $1,000) from our sample. However, we have redone the analysis dropping them from the sample and the results are virtually identical.

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

[9]Formerly known as the Cincinnati Stock Exchange.

[10]NYSE's 2005 market share was 78.6 percent (www.nyse.com). In May 2005, Nasdaq traded 55.8 percent of share volume, Archipelago traded 18.2 percent, and NSX traded 24.8 percent (source: www.nasdaq.com).

[11]The results are very similar if we use firm characteristics instead of stock fixed effects.

[12]We also ran these sub-sample regressions separately for NYSE and Nasdaq stocks and the results are similar: for every sub-sample there is a strong relation between past returns and *relss*.

[13]We test whether the difference in the estimated coefficients is statistically significant by combining the small-cap and large-cap stocks into the following regression:

$$relss_{it} = a_i + a_t \cdot small + a_t \cdot large + \beta_1 r_{-5,-1} \cdot small + \beta_2 r_{-5,-1} \cdot large + e_{it}$$

In the regression, a_i refers to firm fixed effects, a_t refers to calendar day fixed effects, *small* is a dummy that equals one if the stock is small-cap and zero otherwise, and *large* is a dummy that equals one if the stock is large-cap and zero otherwise. We then test if β_1 equals β_2.

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

[15]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.

[16]Specifically, on the last day of June of year 2004 and 2005 we sort NYSE stocks by their market equity (ME). We also sort NYSE stocks independently by their book to market ratio. We use the ME and B/M breakpoints to allocate all stocks into the appropriate ME deciles and ME and B/M quintiles. We then form 25 size-B/M portfolios using all common stock on CRSP with lagged price greater than or equal to $5. The B/M ratio in June of year t is comprised of the book equity (B) for the fiscal year ending in calendar year $t-1$, and market equity (M) from end of December of $t-1$. The portfolios are rebalanced annually.

[17]We obtain daily returns on the factors ($r_M - r_f$, *SMB*, *HML*, and *UMD*) from Ken French's data web-site: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/.

[18]Assuming that the twenty percent of the Low and 20 percent of the High portfolio turns over

each day and that there are 22 trading days in a month, the turnover rate during the month is roughly 9 (0.20*2*22=8.8).

[19]This estimate is almost certainly too high for our sample since it is for stocks below the NYSE median. Our portfolios include the cross-section of all NYSE and Nasdaq stocks and our portfolios are value-weighted.

[20]We also form these portfolios separately for NYSE and Nasdaq stocks and the results are similar: most categories show a large and significant low - high average abnormal return.

[21]We use two other alternate regression frameworks as robustness tests. First, we perform all the regression specifications in Table 7, but we only use day fixed effects (the standard errors are still clustered by both day and stock) and we add the following cross-section control variables: log lagged market-cap (previous month end), log lagged book to market (lagged as in Fama and French (1993), and cumulative returns from day $t-250$ to $t-6$ (momentum effect). The estimated *relss* coefficients and their significance is very similar to the results in Table 8. Second, we run these regressions with cross-sectional controls using the Fama-MacBeth (1973) methodology with Newey-West (1987) correct standard errors, and the estimated coefficients and their significance is once again very similar.

Table 1
Summary Statistics: Shorting Activity

Panel A: Short-sale Trading Activity Across Exchanges

	AMEX	ARCHAX	BSE	CHX	NASD	NASDAQ	NSX	PHLX	NYSE
					Mean Shares Sold Short (In Percent)				
NYSE Stocks	0.00	4.36	0.97	0.37	0.00	16.31	0.82	0.55	76.62
Nasdaq Stocks	0.03	22.72	0.00	0.04	0.65	49.55	27.01	0.00	0.00
					Mean Short-Sale Trades (In Percent)				
NYSE Stocks	0.00	7.99	1.02	0.19	0.00	11.67	0.49	0.11	78.54
Nasdaq Stocks	0.01	29.47	0.00	0.03	0.22	34.51	35.75	0.00	0.00

Panel B: Short-Selling Summary Statistics

	NYSE Stocks			Nasdaq Stocks		
	Mean	Median	Std. Dev	Mean	Median	Std. Dev
Short Sales	253.40	109.45	471.10	229.63	41.98	1075.48
Short Trades	445.01	296.24	492.79	616.89	149.10	1905.97
relss (%)	23.89	23.96	5.64	31.33	31.72	7.92

Panel C: Mean of *relss* (in %) Across Stock Characteristics

	ME		B/M	instown	price		Put
NYSE Stocks			NYSE Stocks			NYSE Stocks	
Small	21.02	Low	24.25	24.01	16.63	No	22.94
Large	23.39	High	22.77	24.21	24.12	Yes	24.33
Nasdaq Stocks			Nasdaq Stocks			Nasdaq Stocks	
Small	28.12	Low	33.85	27.94	24.05	No	28.12
Large	37.82	High	38.05	36.32	32.45	Yes	36.38

Panel A shows short-sale trading activity of NYSE and 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. Panel B shows summary statistics for different short-selling measures. Short Sales (Short Trades) is the number of shorted shares (trades) for a stock average over the sample period. *relss* is the number of shorted shares for a stock divided by traded shares per day averaged over the sample period. Panel C shows average *relss* across different stock characteristics. Low (high) ME and B/M refers to market-cap and book to market (defined as in Fama and French (1993) 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) put refers to whether put options can be traded. The sample only includes NYSE and 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 CRSP. The time period is January 3, 2005 to December 30, 2005. The sample size is 1,481 stocks for NYSE and 2,372 for Nasdaq.

Table 2
Summary Statistics: Stock Characteristics

Panel A: Pilot Stocks Included						
	NYSE Stocks			Nasdaq Stocks		
	Stocks	Mean	Median	Stocks	Mean	Median
relss (%)	1481	23.89	23.96	2373	31.33	31.72
spread	1481	0.11	0.06	2373	0.44	0.25
oimb	1481	8.03	7.95	2373	-0.35	-0.31
σ	1481	0.02	0.02	2373	0.04	0.03
$tv_{-5,-1}$	1481	0.01	0.01	2373	0.01	0.01
price	1481	94.51	30.13	2373	19.06	15.35
ME	1481	7490.75	1733.62	2373	1308.69	279.86
B/M	1364	0.65	0.55	2105	0.52	0.44
instown	1481	0.64	0.72	2373	0.45	0.44
sratio	1481	5.38	4.12	2373	4.35	2.80
put	1481	0.68	1.00	2373	0.39	0.00

Panel B: Pilot Stocks Excluded						
	NYSE Stocks			Nasdaq Stocks		
	Stocks	Mean	Median	Stocks	Mean	Median
relss	1079	23.17	23.25	2001	30.11	30.05
spread	1079	0.13	0.06	2001	0.50	0.30
oimb	1079	9.23	9.39	2001	-0.31	-0.36
σ	1079	0.02	0.02	2001	0.04	0.03
$tv_{-5,-1}$	1079	0.01	0.01	2001	0.01	0.00
price	1079	116.59	28.94	2001	17.99	14.17
ME	1079	7238.68	1522.25	2001	1144.85	214.41
B/M	972	0.67	0.56	1748	0.55	0.46
instown	1079	0.63	0.70	2001	0.43	0.40
sratio	1079	5.32	4.03	2001	4.06	2.44
put	1079	0.65	1.00	2001	0.34	0.00

This table presents cross-sectional summary statistics. *relss* is the number of shorted shares divided by traded shares per day (in percent) averaged over the sample period. *spread* is the effective spread (in %) averaged over the sample period for each stock. *oimb* is buy order imbalance of a stock averaged over the sample period (in %) and is computed as daily buys minus sells scaled by daily volume. Buys and sells are defined as in Lee and Ready (1991). σ is the difference in the high and low price divided by the high price ($(high - low)/high$) averaged over the sample period. $tv_{-5,-1}$ is average daily share turnover of a stock for day $t-5$ to day $t-1$ averaged over the sample period. *price* is the share price of a stock averaged over the sample period. ME is the market-cap (in millions) from December 31, 2004. B/M is lagged book to market equity as defined in Fama and French (1993). *instown* is quarterly institutional ownership as a fraction of shares outstanding from the end of 2004. *sratio* is short interest from December 2004 divided by average daily volume in the same month. *put* is a dummy variable that equals one if there are actively trade puts for the stock. Pilot stocks are stocks that are included in the SEC Reg SHO pilot program. The sample only includes NYSE and 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 December 30, 2005.

Table 3
Panel Regressions: Daily Relative Short-Selling (relss)

	NYSE Stocks			Nasdaq Stocks		
	[1]	[2]	[3]	[4]	[5]	[6]
$r_{-5,-1}$	0.371	0.159		0.215	0.130	
	(24.10)	(15.71)		(26.07)	(19.84)	
r_t		0.828			0.578	
		(26.74)			(30.47)	
$spread_t$		0.017			0.012	
		(1.67)			(7.96)	
$oimb_t^+$		0.002			0.001	
		(36.33)			(15.16)	
$oimb_{-5,-1}^+$		-0.000			-0.000	
		(-5.73)			(-0.93)	
$relss_{-5,-1}$		0.513			0.428	
		(92.58)			(70.12)	
σ_t		0.472			0.221	
		(13.34)			(10.59)	
$\sigma_{-5,-1}$		0.007			0.095	
		(0.12)			(2.76)	
$tv_{-5,-1}$		-0.185			-0.112	
		(-2.83)			(-2.82)	
loser			-0.021			-0.017
			(-21.32)			(-15.20)
winner			0.027			0.022
			(28.55)			(21.18)
$R^2_{demeaned}$	0.017	0.247	0.018	0.004	0.084	0.004
R^2	0.202	0.390	0.203	0.163	0.245	0.163
Stock Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Day Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

We regress daily stock level shorting activity ($relss_t$) on stock level past returns, other stock level control variables, stock fixed effects, and day fixed effects. $relss_t$ is the number of shorted shares divided by traded shares on day t for a given stock. r_t is the return of a stock on day t. $r_{-5,-1}$ is the return for a stock from the closing price on day $t-6$ to the closing price on day $t-1$. $spread_t$ is the day t stock level effective spread (in %). $oimb_t$ is daily buy order imbalance (in %) of a stock and is computed as daily buys minus sells scaled by daily volume. Buys and sells are defined as in Lee and Ready (1991). $oimb_t^+$ equals $oimb_t$ if $oimb_t \geq 0$ and zero otherwise. $oimb_{-5,-1}^+$ is defined analogously using the five day past average of $oimb$ ($oimb_{-5,-1}$) . σ_t is the difference in the high and low price on day t divided by the high price: $(high-low)/high$. $\sigma_{-5,-1}$ is average daily σ from day $t-5$ to day $t-1$. $tv_{-5,-1}$ is average daily share turnover of a stock for day $t-5$ to day -1. *loser* (*winner*) is a dummy that equals one if a stock is in the lowest (highest) $r_{-5,-1}$ quintile for NYSE (Nasdaq) stocks. The sample only includes NYSE (Nasdaq National Market) non RegSHO pilot stocks with CRSP share code 10 or 11 and lagged price ≥ 5. The regressions include calendar day dummies and stock dummies, and the standard errors take into account clustering by calendar date and clustering by stock (Thompson (2006)). $R^2_{demeaned}$ is the reported r-square from a regression that demeans the data to implement the fixed effects and R^2 is the reported r-square from a regression the explicitly includes the dummy variables to implement the fixed effects. The time period is January 10, 2005 to December 30, 2005. T-statistics are in parenthesis.

Table 4
Panel Regressions: relss and Past returns by Sub-Samples

		By Sub-Sample: $relss_{it} = a_i + a_t + \beta r_{-5,-1} + e_{it}$				
	ME		B/M	$instown$		Put
Small (β)	0.223	Low (β)	0.244	0.265	No (β)	0.261
	(27.11)		(24.34)	(16.48)		(22.72)
large (β)	0.466	High (β)	0.238	0.269	Yes (β)	0.257
	(22.68)		(15.89)	(23.91)		(26.62)
Small-Large (β)	-0.242	Low-High (β)	0.006	-0.004	No-Yes (β)	0.004
	(-11.06)		(0.31)	(-0.22)		(0.29)

We regress daily stock level shorting activity ($relss_t$) on stock level past returns, stock fixed effects, and day fixed effects by size, book to market, institutional ownership, and put option sub-samples. The table reports the coefficient estimate on past returns from the regression. $relss_t$ is the number of shorted shares divided by traded shares for a particular stock on day t. $r_{-5,-1}$ is the return from the closing price on day $t-6$ to the closing price on day $t-1$. ME is the previous month end market-cap. B/M is lagged book to market equity as defined in Fama and French (1993). $instown$ is institutional ownership expressed as a fraction of shares outstanding from the end of the last quarter. We classify stocks as small (smallest tercile) or large (largest tercile) using NYSE breakpoints for ME. We classify stocks as low B/M (lowest tercile) or high B/M (highest tercile) using NYSE breakpoints for B/M. Low (high) $instown$ is stocks with $instown \leq 0.33$ (> 0.67). *Put* (*No Put*) refers to stocks with (without) tradeable and active put options. The sample only includes NYSE (Nasdaq) non-Reg SHO pilot stocks with CRSP share code 10 or 11 and lagged price ≥ 5. The regressions include calendar day dummies and stock dummies, and the standard errors take into account clustering by calendar date and clustering by stock (Thompson (2006)). The time period is January 10, 2005 to December 30, 2005. T-statistics are in parenthesis.

Table 5
Daily Value-Weight relss Portfolios: Returns (in Percent)

	Low	2	3	4	High	Low-High
	Panel A: NYSE Stocks (Abnormal Returns in %)					
	Abnormal Returns: Holding Period = $t+2$					
mean	0.026	0.009	0.007	0.002	-0.037	0.063
T-stat	2.031	0.860	0.621	0.179	-2.230	2.932
	Abnormal Returns: Holding Period = $t+2-t+5$					
Mean	0.028	-0.003	0.008	0.001	-0.014	0.042
T-stat	2.425	-0.396	0.934	0.064	-1.255	2.264

	Low	2	3	4	High	Low-High
	Panel B: Nasdaq Stocks (Abnormal Returns in %)					
	Abnormal Returns: Holding Period = $t+2$					
Mean	0.022	0.013	0.013	-0.026	-0.042	0.064
T-stat	0.980	0.610	0.481	-1.173	-2.826	2.521
	Abnormal Returns: Holding Period = $t+2-t+5$					
Mean	0.032	0.012	-0.007	-0.017	-0.023	0.055
T-stat	1.746	0.794	-0.373	-0.891	-1.829	2.480

The table reports average abnormal returns for short-selling activity portfolios. In day t we compute *relss* quintiles using all NYSE (Nasdaq National Market) non-Reg SHO pilot stocks in our sample and then form portfolios using NYSE (Nasdaq National Market) non-Reg SHO pilot stocks with a closing price on day $t-1 \geq \$5.00$. We compute the return on the portfolio in day $t+2$ (we skip a day to avoid concerns about bid-ask bounce). The $t+2$ to $t+5$ day holding period portfolios use the overlapping holding period methodology of Jegadeesh and Titman (1993). *relss* is the number of shorted shares divided by traded shares on day t. Abnormal returns are computed by characteristically adjusting returns using 25 value weight size-BE/ME portfolios computed as in Fama and French (1993). The sample only includes NYSE (Nasdaq National Market) non-Reg SHO pilot stocks with CRSP share code 10 or 11. The time period is January 3, 2005 to December 28, 2005. The t-statistics are adjusted for autocorrelation using the Newey-West (1987) procedure with lag=5.

Table 6
Daily Value-Weight relss Portfolios and the Three and Four Factor Model

Panel A: NYSE Stocks (Abnormal Returns in %)						
	Low	2	3	4	High	Low-High
Abnormal Returns: Holding Period = $t+2$						
a_{3fac}	0.025	0.000	0.003	-0.006	-0.040	0.065
T-stat	1.757	0.031	0.199	-0.448	-2.218	2.975
a_{4fac}	0.027	0.000	0.001	-0.007	-0.041	0.069
T-stat	1.879	0.029	0.092	-0.620	-2.220	3.043
Abnormal Returns: Holding Period = $t+2-t+5$						
a_{3fac}	0.022	-0.013	-0.002	-0.007	-0.020	0.042
T-stat	1.733	-1.149	-0.147	-0.728	-1.659	2.206
a_{4fac}	0.024	-0.012	-0.003	-0.009	-0.021	0.045
T-stat	1.957	-1.118	-0.322	-0.989	-1.678	2.366

Panel B: Nasdaq Stocks (Abnormal Returns in %)						
	Low	2	3	4	High	Low-High
Abnormal Returns: Holding Period = $t+2$						
a_{3fac}	0.037	0.026	0.019	-0.009	-0.023	0.060
T-stat	1.863	1.099	0.678	-0.429	-1.478	2.592
a_{4fac}	0.038	0.027	0.022	-0.009	-0.022	0.061
T-stat	1.956	1.155	0.802	-0.437	-1.448	2.601
Abnormal Returns: Holding Period = $t+2-t+5$						
a_{3fac}	0.044	0.033	0.004	-0.005	-0.004	0.049
T-stat	2.859	1.879	0.215	-0.237	-0.315	2.682
a_{4fac}	0.046	0.034	0.006	-0.005	-0.004	0.050
T-stat	3.064	1.915	0.303	-0.230	-0.254	2.721

The table reports three and for factor model regressions for short-selling activity portfolios. In day t we compute *relss* quintiles using all NYSE (Nasdaq National Market) non-Reg SHO pilot stocks in our sample and then form portfolios using NYSE (Nasdaq National Market) non-Reg SHO pilot stocks with a closing price on day $t-1 \geq \$5.00$. We compute the return on the portfolio in day $t+2$ (we skip a day to avoid concerns about bid-ask bounce). The five day holding period portfolios use the overlapping holding period methodology of Jegadeesh and Titman (1993). *relss* is the number of shorted shares divided by traded shares on day t. The factor model regressions are

$$r_{pt} - r_{ft} = a_p + b_p(r_{Mt} - r_{ft}) + s_p(SMB_t) + h_p(HML_t) + e_{pt}$$
$$r_{pt} - r_{ft} = a_p + b_p(r_{Mt} - r_{ft}) + s_p(SMB_t) + h_p(HML_t) + u_p(UMD_t) + e_{pt},$$

where r_{pt} is the return on the short-selling portfolio, r_{ft} is the daily rate that, over the number of trading days in the month, compounds to the 1-month t-bill rate, $r_{Mt} - r_{ft}$ is the excess return on a value-weight index of all CRSP stocks, SMB_t is the return on size factor, HML_t is the return on the value factor, and UMD_t is the return on the momentum factor. The sample only includes NYSE (Nasdaq National Market) non-Reg SHO pilot stocks with CRSP share code 10 or 11. The time period is January 3, 2005 to December 28, 2005. The t-statistics are adjusted for autocorrelation using the Newey-West (1987) procedure with lag=5.

Table 7
Daily relss Portfolios Disaggregated by Stock Characteristics: Abnormal Returns (in %)

	Mean Abnormal Returns							
relss	Market-Cap		Book to Market		Inst. Ownership		Put Options	
Quintiles	Small	Large	Low	High	Low	High	No	Yes
Low	0.030	0.023	0.027	0.020	0.009	0.043	0.016	0.024
High	-0.024	-0.039	-0.040	-0.039	-0.029	-0.023	-0.041	-0.040
Low-High	0.053	0.062	0.068	0.058	0.038	0.066	0.056	0.064
T-stat	2.800	1.763	2.068	2.186	0.966	2.326	1.964	2.453

The table reports average abnormal returns for short-selling activity portfolios disaggregated by various stock characteristics. In day t we compute *relss* quintiles using all stocks in our sample. We also form market-cap (ME) terciles using NYSE market-cap breakpoints for previous month-end market-cap, and lagged book to market (B/M) terciles using NYSE B/M breakpoints. We also classify stocks as low (high) institutional ownership stocks if the previous quarter-end institutional ownership is $\leq 33\%$ (> 67), and we classify according to put option availability. We then form portfolios from the intersection of the *relss* quintiles and each of the categories. 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 $t+2$ (we skip a day to avoid concerns about bid-ask bounce). The portfolios are rebalanced daily. *relss* is the number of shorted shares divided by traded shares on day t. Abnormal returns are computed by characteristically adjusting returns using 25 value-weight size-B/M portfolios formed as in Fama and French (1993). The benchmark portfolios also contain the restriction that lagged price must be greater than or equal to 5 dollars. The sample only includes NYSE and Nasdaq National Market non-Reg SHO stocks with CRSP share code 10 or 11. The time period is January 3, 2005 to December 28, 2005. The t-statistics are adjusted for autocorrelation using the Newey-West (1987) procedure with lag=5.

Table 8
Panel Regressions: Daily Returns in Percent

	NYSE Stocks				Nasdaq Stocks			
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
$relss_t$	-0.427	-0.378		-0.342	-0.325	-0.284		-0.229
	(-6.75)	(-5.89)		(-5.26)	(-8.28)	(-7.24)		(-5.87)
$r_{-5,-1}$		-0.011		-0.011		-0.021		-0.020
		(-2.50)		(-2.51)		(-7.01)		(-6.75)
low			0.083				0.108	
			(4.90)				(5.08)	
high			-0.071				-0.043	
			(-4.26)				(-2.55)	
loser			0.101				0.172	
			(3.30)				(5.84)	
winner			-0.035				-0.131	
			(-1.26)				(-5.16)	
$spread_t$				0.095				-0.093
				(1.30)				(-7.62)
$oimb_t^+$				-0.001				-0.005
				(-2.37)				(-14.40)
σ_t				0.914				0.034
				(0.79)				(0.06)
$tv_{-5,-1}$				-1.219				-4.807
				(-0.45)				(-3.60)
Day Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Stock Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

We regress day $t+2$ stock returns (r_{t+2}) on past shorting activity ($relss_t$), other stock level control variables, stock fixed effects, and day fixed effects. $relss_t$ is the number of shorted shares divided by traded shares on day t for a given stock. $r_{-5,-1}$ is the return from $t-5$ to $t-1$. *low* (*high*) is a dummy that equals one if a stock is in the lowest (highest) $relss_t$ quintile for NYSE (Nasdaq National Market) stocks on a given day. *loser* (*winner*) is a dummy that equals one if a stock is in the lowest (highest) $r_{-5,-1}$ quintile for NYSE (Nasdaq National Market) stocks on a given day. $spread_t$ is the day t stock level effective spread (in %). $oimb_t$ is daily buy order imbalance (in %) of a stock and is computed as daily buys minus sells scaled by daily volume. Buys and sells are defined as in Lee and Ready (1991). $oimb_t^+$ equals $oimb_t$ if $oimb_t \geq 0$ and zero otherwise. σ_t is the difference in the high and low price on day t divided by the high price: $(high - low)/high$. $tv_{-5,-1}$ is average daily share turnover of a stock for day $t-5$ to day -1. The sample only includes NYSE (Nasdaq National Market stocks) non-Reg SHO pilot stocks with CRSP share code 10 or 11 and lagged price ≥ 5. The regressions include calendar day dummies and stock dummies, and the standard errors take into account clustering by calendar date and clustering by stock (Thompson (2006)). The time period is January 3, 2005 to December 28, 2005. T-statistics are in parenthesis.

Table 9
Panel Regressions: Daily Returns in Percent & Residual Relss

	NYSE Stocks				Nasdaq Stocks			
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
$e_{relss,t}$	-0.226	-0.158		-0.147	-0.225	-0.179		-0.158
	(-3.13)	(-2.13)		(-2.01)	(-5.14)	(-4.07)		(-3.65)
$r_{-5,-1}$		-0.014		-0.014		-0.023		-0.022
		(-3.15)		(-3.09)		(-7.94)		(-7.65)
low			0.021				0.050	
			(1.19)				(2.53)	
$high$			-0.042				-0.015	
			(-2.64)				(-0.89)	
$loser$			0.120				0.184	
			(3.69)				(6.06)	
$winner$			-0.057				-0.150	
			(-1.94)				(-5.72)	
$spread_t$				0.077				-0.097
				(0.98)				(-6.81)
$oimb_t^+$				-0.002				-0.006
				(-4.01)				(-14.13)
σ_t				1.006				0.070
				(0.81)				(0.11)
$tv_{-5,-1}$				-1.036				-4.303
				(-0.37)				(-3.17)
Day Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Stock Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

We regress day $t+2$ stock returns ($r_{i,t+2}$) on past residual shorting activity (e_{relss}), other stock level control variables, stock fixed effects and day fixed effects. $relss_t$ is the number of shorted shares divided by traded shares on day t for a given stock. We compute residual relss (e_{relss}) by first running the following regression every day for every stock:

$$relss_{it} = \alpha_i + \beta_i \cdot oimb_{it}^+ + \varepsilon_{it}, \quad t = 1, \ldots, -22.$$

We then use the estimated coefficients and compute,

$$e_{relss_{it}} = relss_{it} - \hat{\alpha}_i - \hat{\beta}_i \cdot oimb_{it}^+.$$

$r_{-5,-1}$ is the return from $t-5$ to $t-1$. low ($high$) is a dummy that equals one if a stock is in the lowest (highest) $relss_t$ quintile for NYSE (Nasdaq National Market) stocks on a given day. $loser$ ($winner$) is a dummy that equals one if a stock is in the lowest (highest) $r_{-5,-1}$ quintile for NYSE (Nasdaq National Market) stocks on a given day. $spread_t$ is the day t stock level effective spread (in %). $oimb_t$ is daily buy order imbalance (in %) of a stock and is computed as daily buys minus sells scaled by daily volume. Buys and sells are defined as in Lee and Ready (1991). $oimb_t^+$ equals $oimb_t$ if $oimb_t \geq 0$ and zero otherwise. σ_t is the difference in the high and low price on day t divided by the high price: $(high - low)/high$. $tv_{-5,-1}$ is average daily share turnover of a stock for day $t-5$ to day -1. The sample only includes NYSE (Nasdaq National Market stocks) non-Reg SHO pilot stocks with CRSP share code 10 or 11 and lagged price ≥ 5. The regressions include day and stock dummies, and the standard errors take into account clustering by calendar date and clustering by stock (Thompson (2006)). The time period is January 3, 2005 to December 28, 2005. T-statistics are in parenthesis.

Table 10
Panel Regressions: Predicting Future Order Imbalance

	Panel A: NYSE Stocks					
	dependent variable		dependent variable		dependent variable	
	$oimb_{t+2}$	$oimb_{t+2}$	$oimb^{+}_{t+2}$	$oimb^{+}_{t+2}$	$oimb^{-}_{t+2}$	$oimb^{-}_{t+2}$
$relss_t$	12.700	9.881	8.674	6.488	-4.026	-3.208
	(19.54)	(13.85)	(17.48)	(12.85)	(-14.53)	(-11.41)
$oimb_t$		0.045				
		(9.34)				
$oimb^{+}_t$				0.053		
				(10.83)		
$oimb^{-}_t$						-0.039
						(-7.41)
Stock Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Day Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

	Panel B: Nasdaq Stocks					
	dependent variable		dependent variable		dependent variable	
	$oimb_{t+2}$	$oimb_{t+2}$	$oimb^{+}_{t+2}$	$oimb^{+}_{t+2}$	$oimb^{-}_{t+2}$	$oimb^{-}_{t+2}$
$relss_t$	3.917	2.495	0.947	0.467	-2.969	-2.018
	(6.66)	(4.34)	(2.66)	(1.33)	(-9.58)	(-6.78)
$oimb_t$		0.055				
		(16.07)				
$oimb^{+}_t$				0.050		
				(14.70)		
$oimb^{-}_t$						-0.059
						(-17.65)
Stock Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Day Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

We regress daily future stock level buy order imbalance (day $t+2$) on contemporaneous relative short-selling ($relss_t$), contemporaneous buy order imbalance, stock fixed effects, and day fixed effects. $relss_t$ is the number of shorted shares divided by traded shares on day t for a given stock. $oimb_t$ is daily buy order imbalance (in %) of a stock and is computed as daily buys minus sells scaled by daily volume. Buys and sells are defined as in Lee and Ready (1991). $oimb^{+}_t$ equals $oimb_t$ if $oimb_t \geq 0$ and zero otherwise. $oimb^{-}_t$ equals $|oimb_t|$ if $oimb_t < 0$ and zero otherwise. The sample only includes NYSE (Nasdaq National Market) non RegSHO pilot stocks with CRSP share code 10 or 11 and lagged price ≥ 5. The regressions include calendar day dummies and stock dummies, and the standard errors take into account clustering by both calendar date and stock (Thompson (2006)). The time period is January 3, 2005 to December 28, 2005. T-statistics are in parenthesis

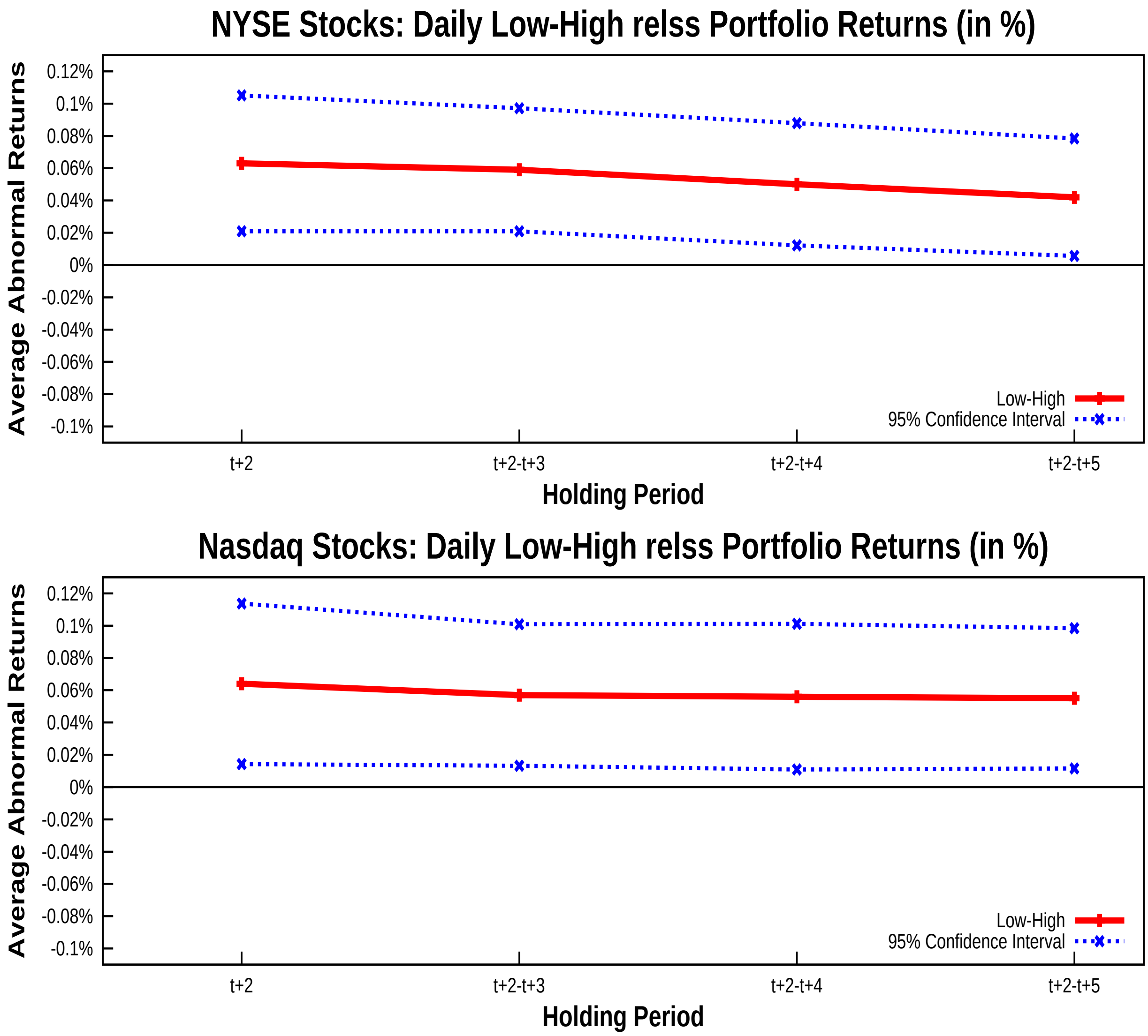

Figure 1
Daily relss Portfolios: Average Abnormal Returns (in Percent)

The figure shows average abnormal returns for short-selling activity portfolios. In day t we compute *relss* quintiles using all NYSE (Nasdaq National Market) non-Reg SHO pilot stocks in our sample. We then form portfolios using NYSE (Nasdaq National Market) non-Reg SHO pilot stocks with a closing price on day $t-1$ greater than or equal to \$5.00. We compute the return on the portfolio in day $t+2$ (we skip a day to avoid concerns about bid-ask bounce). We vary the holding period from one day to 4 trading days. For holding periods greater than one trading day we use the overlapping holding period methodology of Jegadeesh and Titman (1993). *relss* is the number of shorted shares divided by traded shares on day t for a given stock. Abnormal returns are computed by characteristically adjusting returns using 25 value-weight size-BE/ME portfolios. The benchmark portfolios also contain the restriction that lagged price must be greater than or equal to 5 dollars. The sample only includes NYSE (Nasdaq National Market) Non-Reg SHO pilot stocks with CRSP share code 10 or 11. The time period is January 3, 2005 to December 28, 2005. Standard errors are adjusted for autocorrelation using the Newey-West (1987) procedure with lag=5.