Which Shorts are Informed?

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ABSTRACT

We construct a long daily panel of short sales using proprietary NYSE order data. During 2000-2004, shorting accounts for more than 12.9% of NYSE volume, suggesting that short-sale constraints are not widespread. As a group, these short sellers are quite well-informed. Heavily shorted stocks underperform lightly shorted stocks by a risk-adjusted average of 1.16% over the following 20 trading days (15.6% annualized). Institutional non-program short sales are the most informative; stocks heavily shorted by institutions underperform by 1.43% the next month (19.6% annualized). The results indicate that, on average, short sellers are important contributors to efficient stock prices.

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Throughout the financial economics literature, short sellers occupy an exalted place in the pantheon of investors as rational, informed market participants who act to keep prices in line. Theoreticians often generate a divergence between prices and fundamentals by building models that prohibit or constrain short sellers (e.g, Miller (1977), Harrison and Kreps (1978), Duffie, Garleanu, and Pedersen (2002), and Hong, Scheinkman, and Xiong (2006)). Empirical evidence uniformly indicates that when shorting constraints are relaxed, overvaluations become less severe, suggesting that short sellers are moving prices toward fundamentals (examples include Lamont and Thaler (2003), Danielsen and Sorescu (2001), Jones and Lamont (2002), Cohen, Diether, and Malloy (2005)). But there is surprisingly little direct evidence that short sellers know what they are doing.

There is indirect evidence in the existing literature. For example, Aitken et al. (1998) show that in Australia, where some short sales were immediately disclosed to the public, the reporting of a short sale causes prices to decline immediately. Some authors (but not all) find that short interest predicts future returns.[1] Dechow et al. (2001) find that short sellers generate positive abnormal returns by targeting companies that are overpriced based on fundamental ratios such as P/E and market-to-book.

In this paper, we provide direct evidence on the informativeness of short sales using a long panel of all executed short sale orders submitted electronically to the New York Stock Exchange (NYSE). First, we show that there is a surprisingly large amount of shorting activity across both large and small NYSE stocks, which suggests that shorting constraints are not widespread. More importantly, we use these data to explore directly whether short sellers are able to identify overvalued stocks and profit by anticipating price declines in these stocks. We also have data identifying the type of trader initiating the short. This allows us to determine which types of traders, if any, possess private information about equity values.

There are theoretical reasons to expect short sellers to be well informed. For example, Diamond and Verrechia (1987) point out that since short sellers do not have use of the sale proceeds, market participants never short for liquidity reasons, which would imply relatively few uninformed short sellers, all else equal.[2] But there can be a strong hedging motive that is unique to short sales. Naturally, some short sellers take their positions based on fundamental information about a company's valuation, either on an absolute basis or relative to other firms. In contrast, convertible arbitrage hedge funds and options

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[1] For example, Brent, Morse, and Stice (1990) find that monthly short interest does not predict either the cross-section or time-series behavior of returns, Asquith, Pathak, and Ritter (2004) find predictive power only in the smallest stocks, while authors such as Asquith and Meulbroek (1996) and Desai et al. (2002) find more evidence of predictive power in the cross-section. Lamont and Stein (2004) find that aggregate short interest is extrapolative, reacting to past price moves, but has no predictive power for future market moves.

[2] Brokerage firms and regulators require that the proceeds of a short sale plus an additional margin amount (currently equal to 50% of the value of the position in the U.S.) must be kept on deposit in order to minimize the broker's potential losses in the event of a default by the short seller.

market-makers might short a stock as part of their hedging strategy, with little thought to whether the stock itself is over- or undervalued. Index arbitrageurs might long futures or some other basket instrument and short the underlying stocks. Market-makers might short shares as a part of their regular buffering activity. Some of these shorts are based on information or opinions about the firm's share price level; some are not. Thus, it seems important to distinguish between these different types of shorts.

Our data identify the type of customer initiating the short. These account type indicators are not overly detailed, but they do distinguish between individuals, institutions, and member firm proprietary trades, and we can tell if a short sale was executed as part of a program trade. This allows us to explore which of these groups, if any, possess private information about equity values.

In the world of shorting, it is not obvious that institutions are better informed than individuals. It is popular to regard individual stock trading as less informed and even irrational, and there is plenty of supporting evidence. But few individual traders sell short, and those who do are likely to be the most sophisticated, knowledgeable investors. It is also easy to imagine that at least some negative private information is endowed (which is perhaps more likely for individuals) rather than acquired through costly research (the likely avenue for institutions). As part of their regular job duties, certain individuals, such as corporate insiders, suppliers, and the like, might simply know when things are not going well at a given firm. Corporate insiders are forbidden from shorting their own stocks, but others are less restricted. And even corporate insiders might take short positions in companies that are close substitutes. An airline executive with negative information about the whole industry could easily profit from his information by shorting his competitors' stocks. With our data, we can for the first time compare the information possessed by different types of short sellers.

Most of the empirical data on short selling are about the price or quantity of shorting. The clearest pecuniary cost is associated with the rebate rate, which has been studied by D'Avolio (2002), Geczy, Musto, and Reed (2002), Jones and Lamont (2002), Ofek and Whitelaw (2003), Ofek, Richardson, and Whitelaw (2004), and Cohen, Diether, and Malloy (2005). Quantity data are the other major type of empirical data, and these quantities are almost always stock rather than flow data. The most common sources for quantities in the U.S. are the monthly short interest reports of the major exchanges. As mentioned earlier, the evidence is mixed on whether these individual stock short interest reports can be used by an investor to earn excess returns.

Our data are also quantity measures, but of the flow of shorting rather than the stock of shorting. This has a number of advantages. First of all, our data are much finer than traditional monthly short interest data. We have the ability to examine daily or even intraday data on short sales. If many shorts maintain their positions for only a short period of time, daily flow data may be an improvement over coarse monthly short interest data. Jones (2004) provides evidence, albeit from the early 1930's, that short-lived shorts could be prevalent. During that period, shorting and covering on the same day – known at the time as "in-and-out shorting" – averaged about 5% of total daily volume, and a much bigger (but unknown) fraction of overall shorting activity.

A second advantage of order level data is that we can identify many of the characteristics of executed orders, such as the account type and order size. There are four different types of accounts: individual, institution, member-firm proprietary, and other. The account type partitions are:

Account Type Designation	*Description*
Individual	Agency orders that originate from individuals
Institution	Agency orders that do not originate from individuals.
Proprietary	Orders where NYSE members are trading as principal. Excludes all trades by the specialist for his own account.
Other	Includes orders by market-makers from options and other markets.

We further partition institutional and proprietary short sales depending on whether the order is part of a program trade. A program trade is defined as simultaneous orders to trade 15 or more securities having an aggregate total value of at least $1 million. There is some incentive for institutions to batch their trades to qualify as a program trade, because program trades are often eligible for commission discounts from brokers.

Account types are coded by the submitting broker-dealer based on a set of regulations issued by the NYSE. While they are generally unaudited, these classifications are important to the NYSE and to broker-dealers because they are required for a number of compliance issues. For example, NYSE Rule 80A suspends certain types of index arbitrage program trading on volatile trading days, and account type classifications are important for enforcing this ban. The specialist and traders on the floor do not, however, observe this account type indicator for an incoming system order. In general, these market participants observe only the type, size, and limit price (if applicable) of an order. It is possible for the specialist to research a particular order in real-time and obtain information about the submitting broker. However, this takes a number of keystrokes and requires a certain amount of time, and given the pace of trading on the exchange and our conversations with specialists, we conclude that this additional information is seldom if ever observed before execution.

In contrast, during our sample period the specialist is always aware that a particular system sell order is a short sale. For compliance with the uptick rule, short sales must be marked, and during our sample period software at the trading post flags every short sale order to help the specialist comply with the uptick rule.[3] Should the uptick rule become binding on an order to short sell, the display book software enforces a limit price to comply with the uptick rule. This means that the specialist might be one of the few market participants with an ability to incorporate this information into trading strategies, though a specialist's market-making obligations would constrain his ability to exploit this information fully.

To our knowledge, we are the first academic researchers to partition short sales by account type. NYSE account types have been used in a handful of other related papers. For example, Kaniel, Saar, and Titman (2004) use NYSE account types to investigate investor sentiment, and Boehmer and Kelley (2005) use account types to investigate the relationship between the informational efficiency of prices and the amount of institutional trade. Other authors who study shorting flow data include Christophe, Ferri, and Angel (2004), Daske, Richardson, and Tuna (2005), and Diether, Lee, and Werner (2005), but all these panels are much shorter than ours and do not distinguish among different trader types.

We also observe other aspects of the short-sale order, notably the order size. In looking at all trades, both Barclay and Warner (1993) and Chakravarty (2001) find that medium-size orders are the most informed, which they label the stealth-trading hypothesis. When we look at large vs. small short sale orders, we find somewhat different results. Like these earlier researchers, we find that small short sale orders are on average uninformed, and medium-sized short sale orders of 500 to 5,000 shares are more informed. In contrast to the stealth trading findings, however, we find that the largest short sale orders (those of at least 5,000 shares) are the most informative about future price moves. Thus, it appears that informed short sellers use larger orders than other informed traders.

It is worth pointing out that there are two aspects of shorting flow we do not observe in our data. First, we do not observe short covering in our dataset.[4] We can see additions to short interest, but not the subtractions, so we are unable to use our data to impute the level of short interest between the monthly publication dates. Also, we do not observe all of the short sales that take place. We observe all short sale orders that are submitted electronically or otherwise routed through the NYSE SuperDOT system. We do not observe short sales that are manually executed on the NYSE trading floor by a floor broker. Also, we do not observe short sales that take place away from the NYSE. Short sales executed on regional exchanges, in the upstairs market, or offshore are not included in this sample, nor are shorts created

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[3] During our sample period, the uptick rule applied to all stocks listed on the NYSE and AMEX. The rule applies to most short sales and requires them to execute at a price that is either (a) higher than the last sale price (an uptick), or (b) the same as the last sale price, if the most recent price change was positive (a zero-plus tick). Since May 2005 the uptick rule has been suspended for approximately one-third of NYSE stocks as part of Regulation SHO. Short sale orders in these NYSE pilot stocks must still be marked by the submitting broker, but these are masked by the NYSE's display book software, which means the specialist and floor are unable to observe which sell orders are shorts.

[4] While it would be valuable to know when short positions are reversed, this information is not available to any US market venue, because brokers are not required to disclose whether a buy order is intended to cover a short. In fact, market venues only observe short sales in order to ensure compliance with short-sale price restrictions.

synthetically using total return swaps or other derivatives. Nevertheless, we believe that our sample captures a substantial fraction of shorting activity, and our aim in this paper is to explore the informativeness of this order flow.

As stated above, we observe all short sale orders that are submitted to the NYSE trading floor via electronic means. While we do not know exactly what fraction of total shorting is executed this way, based on overall volume figures we do know that system order data capture a substantial fraction of overall trading activity. According to the NYSE online fact book at nysedata.com, during 2002 shares executed via the NYSE SuperDOT system are 70.5% of NYSE volume. If short sale orders are routed and executed similarly, our sample would account for 70.5% of all short sales in 2002. Of course, we cannot be sure that this is so. Given the uptick rule, short sellers may prefer the hands-on order management of a floor broker. Short sales may also be executed in London or elsewhere outside the United States to avoid domestic restrictions.

The paper is structured as follows. Section I discusses the sample in more detail, both in terms of overall shorting flow and the account type subdivisions. Section II examines the information in aggregate shorting flow for the cross-section of future stock returns. Section III partitions shorting flow by account type and by order size to see which kinds of short sales are most informative about the cross-section of future returns. Section IV conducts a number of additional robustness tests. One must be careful in interpreting the empirical results, and this is the focus of Section V. Section VI concludes briefly.

I. Sample and summary statistics

The sample consists of all NYSE system order data records related to short sales from January 2000 through April 2004. We cross-match to CRSP and retain only common stocks, which means we exclude securities such as warrants, preferred shares, American Depositary Receipts, closed-end funds, and REITs.[5] This leaves us a daily average of 1,239 NYSE-listed common stocks. For each trading day, we aggregate all short sales in each stock that are subject to the uptick rule. A few short sales are exempt from the uptick rule. These include relative-value trades between stocks and convertible securities, arbitrage trades in the same security trading in New York vs. offshore markets, and short sales initiated by broker-dealers at other market centers as a result of bona fide market-making activity. These exempt short sales are marked separately in the system order data, and their share volume amounts to only 1.5%

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[5] Some care is required in matching stocks. NYSE data, including both SOD and TAQ, use the ticker symbol as the primary identifier. However, ticker symbols are often reused, and ticker symbols in CRSP do not always match the ticker symbols in NYSE data, especially for firms with multiple share classes. We use tickers and CUSIPs to ensure accurate matching.

of total shorting volume in our sample. We exclude these orders because they are less likely to reflect negative fundamental information about the stock.

We measure shorting flow three different ways. First, we simply count the number of executed short sale orders in a given stock on a given day, regardless of size. Jones, Kaul, and Lipson (1994) find that the number of trades, rather than total volume, is most closely associated with the magnitude of price changes, and our use of the number of executed short sale orders is in the same spirit. Our second measure is the total number of shares sold short in a given stock on a given day. Our final measure is the fraction of volume executed on the NYSE in a given stock on a given day that involves a system short seller.

Table I Panels A and B provide summary statistics about overall shorting flow measures, undifferentiated by account type. NYSE common stocks experience an average of 146 executed short-sale orders in a given day, with a mean of 99,747 shares sold short via system orders per stock per day. Note that a small number of stocks account for most of the shorting, as the median stock has 27,425 shares sold short daily and the 75th percentile of 95,417 shares per day is still below the mean.

One striking result is that during our sample period shorting via system orders averages 12.86% of overall NYSE trading volume (equal-weighted across stocks). In fact, shorting via system orders becomes more prevalent as our sample period progresses, accounting for more than 17.5% of NYSE trading volume during the first four months of 2004. Recall that these are lower bounds on the incidence of shorting at the NYSE, since our sample does not include specialist short sales or short sales that are handled by a floor broker. Nevertheless, this number is somewhat surprising, since aggregate short interest in NYSE stocks during 2004 is only 2.0% of shares outstanding. The short interest numbers suggest that shorting is relatively uncommon, while the shorting flow numbers indicate that shorting is quite pervasive. The dichotomy between these two numbers also means that short positions are on average shorter-lived than long positions. To see this, note first that if shareholders are homogeneous (so there is no Jensen's inequality effect), then:

$$D_i = 1 / T_i, \tag{1}$$

where D_i is the length of time between opening and unwinding a position in stock i, and T_i is the turnover (shares traded / shares outstanding) in stock i. For example, if 1% of the shares trade each day, then it takes 100 days for the entire stock of outstanding shares to turn over, and the average holding period is 100 days. Assuming a constant short interest and homogeneity, the same relationship holds for the subset of positions held by shorts:

$$\text{Duration of short positions} = \text{short interest in shares / shorting volume in shares} \tag{2}$$

and similarly for longs:

$$\begin{aligned} \textit{Duration of long positions} &= \textit{total long positions / non-shorting volume} \\ &= \textit{(shares outstanding + short interest) / non-short volume in shares} \end{aligned} \tag{3}$$

In 2004, for example, based on aggregate data from the NYSE online fact book, aggregate short interest averages 7.6 billion shares, while aggregate shorting volume totals 51.2 billion shares for the year, which means that the average short position lasts 7.6 / 51.2 = 0.15 years, or about 37 trading days. In contrast, the average duration for a long position is 1.20 years. The dichotomy is similar when we use our sample of short sales instead of all short sales. These dramatic differences in duration suggest that short selling is dominated by short-term trading strategies.

Panel B shows contemporaneous correlations, first-order autocorrelations and cross-autocorrelations of our various daily shorting measures along with stock returns. Contemporaneous correlations are calculated cross-sectionally each day, and time-series average correlations are reported. All three shorting flow measures are positively correlated, with correlations ranging from 0.20 to 0.80. The number of executed short sale orders and the number of shares sold short are the most strongly positively correlated (ρ = 0.80). These measures are not standardized in any way, and so it is not surprising that they are less strongly correlated with shorting's share of total volume, which is standardized. All the shorting measures are persistent, with average first-order daily autocorrelations between 0.41 and 0.54.[6] Finally, these simple correlations suggest that price increases attract informed short sellers. While the magnitudes are small, the cross-sectional correlation is positive between shorting activity in a stock and that stock's return on the same or previous day, while the correlation with the next day's return is negative (and these correlations are statistically different from zero).

Panel C sorts stocks into 25 size and book-to-market portfolios and measures average shorting activity within each portfolio. Most notable is shorting's share of overall trading volume, at the bottom of the panel. There are no strong patterns either across or down the panel, as the mean shorting share varies only modestly from 10.5% to 15.2% of overall NYSE trading volume. Consistent with short interest data, there is a bit less shorting of small firms, but even there shorting is quite prevalent. While there may still be costs or impediments to short selling, these numbers suggest that many market participants are overcoming these hurdles, even in the smallest NYSE stocks. It could be that these are inframarginal short sales, and the constraints continue to bind for some market participants. But the pervasiveness of shorting suggests that shorting constraints are not very severe, at least for stocks in the NYSE universe.

II. The cross-section of shorting and future returns

A. Simple sorts

If short sellers are informed, the stocks they short heavily should underperform the stocks they avoid shorting. A portfolio approach is a natural way to measure these cross-sectional differences (see also Pan and Poteshman, 2006) and has several advantages. First, it is easy to interpret, because it

[6] Autocorrelations and cross-autocorrelations are calculated stock by stock, and the table reports cross-sectional average autocorrelations and cross-autocorrelations.

replicates the gross and/or risk-adjusted returns to a potential trading strategy, assuming (counterfactually) that one could observe all these shorting flow data in real time. Second, compared to a regression approach the aggregation into portfolios can reduce the impact of outliers. Finally, portfolios are able to capture certain non-linearities that might characterize the relationship between shorting activity and future returns.

Thus, in the time-honored asset pricing tradition, we begin by sorting stocks into portfolios based on our shorting flow measures. Each day, we sort into quintiles based on shorting activity during the previous five trading days. The four middle columns of Table II Panel A show how these sorts are correlated with other stock characteristics that have been studied previously. Shorting activity is positively correlated with trading volume, no matter how the shorting is measured. Shorting does not seem to be strongly correlated with daily stock return volatility, however. The unstandardized shorting measures (number of trades and shares sold short) are strongly positively correlated to size. This is unsurprising, because large cap stocks simply have more shares outstanding, and one would expect more trading and thus more shorting of these stocks. The standardized shorting measure (shorting's share of volume) has a more modest but opposite correlation to market cap. On average, large stocks tend to experience light shorting by these measures. There is not much of a relationship between the shorting flow measures and book-to-market ratios. As might be expected, a bit more shorting activity is found in stocks that have high market values relative to book. For example, the quintile with the smallest number of shares shorted has an average book-to-market ratio of 0.77, while the heavily shorted quintile has a book-to-market ratio of 0.60. Average book-to-market differences are even smaller for shorting's share of overall trading volume. Thus, there is at best only weak evidence that short sellers target stocks with high market-to-book as potentially overpriced. As one might expect, uncovering a mispriced stock involves more than just studying book vs. market values.

Throughout the paper, we follow the same general approach regardless of how stocks are partitioned. After firms are sorted into quintiles each day, we skip one day (to eliminate any possibility that prices for firms in a particular quintile are disproportionately at either the bid or the ask) and then hold a value-weighted portfolio for 20 trading days. This process is repeated each trading day, so there are overlapping 20-day holding period returns. To deal with this overlap, we use a calendar-time approach to calculate average daily returns and conduct inference (see, among many examples, Jegadeesh and Titman (1993) who apply this method to returns on momentum portfolios). Each trading day's portfolio return is the simple average of 20 different daily portfolio returns, and 1/20 of the portfolio is rebalanced each day. To be precise, the daily return R_{pt} on portfolio p is given by:

$$R_{pt} = \tfrac{1}{20}\sum_{k=1}^{20} Q_{t-k-5,t-k-1}^{ip} w_{t-1}^{ip} R_{it} \;, \tag{4}$$

where $Q^{ip}_{t-k-5,t-k-1}$ is an indicator variable set to one if and only if the i^{th} security is assigned to portfolio p based on short-selling activity during the time interval [t–k–5, t–k–1], w^{ip}_{t-1} are market-value weights at time t–1 (actually from the previous calendar month-end in this case) normalized such that

$$\sum_i Q^{ip}_{t-k-5,t-k-1} w^{ip}_{t-1} = 1 \tag{5}$$

for each portfolio p, date t, and portfolio formation lag k, and R_{it} is the return on security i on date t.

Average daily calendar-time returns are reported in percent multiplied by 20 (to correspond to the holding period and also so that the returns cover approximately one calendar month), with t-statistics based on an i.i.d. daily time series. The Fama-French alpha on portfolio p is the intercept (scaled up by 20) in the following daily time-series regression:

$$R_{pt} - R_{ft} = \alpha_p + \beta_{p1} RMRF_t + \beta_{p2} SMB_t + \beta_{p3} HML_t + \varepsilon_{pt}. \tag{6}$$

The four right-most columns of Table II show these raw returns and alphas for each of the shorting quintile portfolios. The basic result is that short sellers are well-informed over this horizon.[7] Most notable is the next month's value-weighted return on heavily shorted stocks (quintile 5) vs. the return on lightly shorted stocks (quintile 1). The raw returns on heavily shorted stocks are actually negative, averaging -0.24% per month for those stocks with the most executed short sale orders. In contrast, the corresponding portfolio of lightly shorted stocks experiences an average return of 2.55% over the next 20 trading days. These numbers suggest that short sellers are good at relative valuation, and are particularly good at avoiding shorting undervalued stocks. However, short sellers are not necessarily identifying stocks that are overvalued, since the alphas on the heavily shorted stocks are just about zero. This suggests that perhaps it is better to think of short sellers as keeping prices in line rather than bringing prices back into line.

Looking at the return differences, heavily shorted stocks underperform lightly shorted stocks, no matter what shorting measure is used. We focus on shorting's share of overall trading volume, because this measure is the most orthogonal to size, book-to-market, and trading activity, each of which has been shown to be related to average returns. Even though we are sorting on a measure that is mostly orthogonal to size and book-to-market characteristics, these portfolios could still have different exposures to priced risks. On a risk-adjusted basis, the heavily shorted stocks underperform lightly shorted stocks by an average of 1.16% per (20-day) month, or 15.64% annualized. Even though the sample is only 4 1/3 years long, the average return difference is highly statistically significant, with a t-statistic of 3.67.

[7] Shorting flow also contains information about future returns at other horizons, both shorter and longer than 20 trading days. In fact, it appears to take up to 60 trading days for all of the information contained in shorting flow to be fully incorporated into prices. This is discussed further in Section 2.C.

B. Double sorts

Researchers have identified several characteristics that are associated with cross-sectional differences in average returns. To confirm that shorting activity is not simply isomorphic to these previously documented regularities, we conduct double sorts based on some of these other characteristics known to be associated with returns. Note that some of these other characteristics are not available at high frequencies, so we first sort stocks into quintiles based on size, market-to-book, stock return volatility, or turnover for the previous month. Within a characteristic quintile, we then sort a second time into quintiles each day based on shorting flow over the past five trading days. The result is a set of stocks that differ in shorting activity but have similar size, market-to-book, volatility, or turnover.

Again we skip a day, and value-weighted portfolio returns are calculated using a 20-day holding period. We then roll forward one day and repeat the portfolio formation and return calculation process. As before, we use a calendar-time approach to calculate returns and conduct inference, and Table III reports the daily value-weighted risk-adjusted return difference (multiplied by 20) between the heavily shorted and lightly shorted quintiles. Return differences are reported for each of the shorting activity measures.

Table III Panel A controls for the firm's market capitalization. The shorting effect is present across all five size quintiles. The results are strongest for the smallest quintile, where heavily shorted stocks underperform lightly shorted stocks by 2.20% to 3.33% per month. The shorts' information advantage in small stocks makes sense given the relative paucity of research coverage and other readily available sources of information about these firms. Based on the evidence in Table I Panel C, even small stocks experience significant shorting activity, so it is certainly possible for some investors to short these stocks. However, small stocks may be expensive to short (see, for example, the evidence in Geczy, Musto, and Reed (2002)), and it is important to remember that the return differences throughout this paper do not account for any potential costs of shorting. In contrast to Diether, Lee, and Werner (2005), who use a much shorter sample period, the shorting effect is also fairly strong for the large-cap quintile, with excess returns between 0.74% and 1.16% per month, depending on the shorting measure. This is striking because many so-called anomalies in finance do not appear in large-cap stocks, but the evidence here indicates that short sellers as a group are earning substantial excess returns even on bellwether stocks. We also perform a closely related double sort, first on institutional ownership (based on SEC 13f filings) and then on shorting flow. We do not report these results in detail, but, in contrast to the short-interest evidence in Asquith, Pathak, and Ritter (2005), heavily shorted stocks underperform lightly shorted stocks across all institutional ownership quintiles. This provides additional evidence that shorts are informed across a wide spectrum of NYSE firms.

In Table III Panel B, we sort first by book-to-market and then by shorting activity. Our prior here was that low book-to-market might be a necessary but not sufficient condition for a stock to be overvalued. If true, then short sellers might further evaluate these stocks, identify those low book-to-market stocks that are indeed overvalued, and short them heavily. If the short sellers are correct, these heavily shorted stocks will eventually experience negative returns.

This is partially borne out in the data. For stocks in the lowest book-to-market quintile, shorting activity does have strong predictive power for the cross-section of returns in the following month. Stocks with the most short sale transactions underperform those with the fewest orders by 1.52% per month. Sorting by the number of shares shorted gives a return difference of 1.30% per month, and sorting by shorting's share of volume gives a return difference of 1.23%. All of these are economically large and statistically different from zero.

In contrast to our priors, shorting activity seems to predict next month's returns across all book-to-market quintiles, and in fact may be slightly stronger in the highest book-to-market quintile, where the return difference is as high as 3.08% per month. For our preferred measure – shorting's share of overall volume – the excess return differences are quite similar across all five book-to-market quintiles, ranging from 1.04% to 1.33% per month. We conclude from this that low book-to-market is neither a necessary nor sufficient condition for a stock to be overvalued. It appears that short sellers are able to identify and short overvalued stocks across the book-to-market spectrum, with stocks underperforming in the month after heavy shorting.

In Table III Panel C we control for individual stock return volatility. Ang, Hodrick, Xing, and Zhang (2004) find that firms with volatile stock returns severely underperform on a risk-adjusted basis. One might guess that the volatility effect might be related to our short-selling effect, if the volatility reflects severe differences of opinion and thus heavy (and ex post informed) short selling. However, the data indicate that the volatility effect does not chase out the return differences based on shorting activity.[8] For both low volatility and high volatility firms, heavy shorting is an indicator of negative returns to come in the following month. Still, the biggest effects are in the most volatile stocks, with return differences between 1.87% and 4.55% per month. In these most volatile stocks, short sellers seem to be particularly well-informed.

In Table III Panel D we examine the predictive power of shorting activity controlling for trading volume. Brennan, Chordia, and Subrahmanyam (1998) and Lee and Swaminathan (2000) find that high-volume firms underperform low-volume firms, which makes it important to rule out the possibility that our shorting activity measures are simply reflecting overall trading activity. Indeed, shorting flow

[8] In results not reported, we also confirm that our shorting flow measures do not chase out the underperformance of very volatile stocks. In addition, even the most volatile stocks are being shorted on a regular basis, which suggests that short sale constraints cannot easily account for Ang et al.'s return findings.

strongly explains the cross-section of future returns regardless of the amount of overall turnover. Using shorting's share of trading volume as the second sort variable, return differences average 0.86% to 1.43% per month across trading volume quintiles. This establishes that the shorting effect in this paper is independent of the earlier volume regularity. Again, it is interesting to note that these excess returns are also being earned in the most active stocks. In the most active quintile, the heavy shorting quintile underperforms the light shorting quintile by as much as 1.81% per month. As discussed in the double sorts with size, these results are striking, because anomalies in finance tend to be found in less active, illiquid stocks. But it is important to remember that these return differences are not tradable and are simply returns to private information, and there is no requirement that there be less private information about active stocks.

C. Short sales vs. other sales

Do short sellers trade on better or different information than regular sellers?[9] As noted earlier, Diamond and Verrechia (1987) observe that since short-sale proceeds cannot be used for consumption, short sales are never undertaken for liquidity reasons, which means short sales should be more informed than other sales, all else equal. Short sellers may also receive different types of signals about fundamentals, in which case their trades would differ considerably from those of other informed sellers.

To investigate the differences between the two types of sellers, we compare our shorting activity measures to signed order imbalances measured over the same time interval. We use order imbalances (OIB) because they are also flow measures, and a recent line of research such as Chordia and Subrahmanyam (2004) argues that order imbalances may be good proxies for the direction and intensity of informed trading.

OIBs are calculated by identifying the side that initiates each trade using the Lee and Ready (1991) algorithm. Trades that take place above the prevailing quote midpoint (or at the midpoint but at a higher price than the previous trade) are assumed initiated by buyers, and the OIB is calculated as buyer-initiated volume less seller-initiated volume.[10] Using TAQ data, we calculate order imbalances for each stock over the same 5-day horizon used to calculate the shorting activity measure, and normalize by the total trading volume in the stock over the same period. We sort stocks first into quintiles based on OIB, and then within each quintile we sort stocks into quintiles based on short selling activity.

The results are in Table III Panel E. Order imbalances have little effect on the predictive power of shorting flow. When short sale flow is measured by the number of orders or number of shares, return

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[9] We thank the referee for suggesting this investigation.

[10] Note that short sales and OIB are not inherently correlated. Like all transactions, short sales are included in the calculation of OIB. But due to the uptick rule, short sales are less likely to take place below the prevailing quote midpoint than other sales, and are therefore less likely to be classified as seller-initiated for OIB purposes.

differences range from 1.33% to 1.98% per month across the various OIB quintiles. When short sale flow is measured relative to overall volume, there is some evidence that short sales are not very informed when OIB is most positive. However, even when OIB is most negative, short sale activity still seems to be quite informed, with heavily shorted stocks underperforming lightly shorted stocks by an average of 1.89% over the following month. Thus, it appears that the information possessed by short sellers is largely orthogonal to the information that lies behind seller-initiated trades.

D. Regression results

The disadvantage of double sorts is that it is only possible to control for one other characteristic at a time. To control simultaneously for multiple characteristics, we adopt a regression approach based on Fama and MacBeth (1973). Each day, we run cross-sectional predictive regressions including the shorting activity measure as well as firm and/or stock characteristics. There is one cross-sectional regression per day, and the shorting activity variable is again calculated by averaging shorting over the previous five days. The dependent variable is the raw or risk-adjusted return over the next 20 trading days, again skipping one day after measuring shorting activity. Risk-adjusted returns are calculated using the Fama and French (1993) three-factor model using the previous calendar quarter of daily data to estimate factor loadings for each stock. We use a Fama-MacBeth approach to conduct inference, with Newey-West standard errors (using 20 lags) to account for the resulting overlap. Rather than continue to report similar results for the three different shorting activity measures, from now on we use shorting's share of trading volume, which as discussed earlier is the most orthogonal of our shorting measures to size, book-to-market, and trading activity variables that have been previously studied. In addition, each day we standardize the cross-sectional distribution of our explanatory variables to have zero mean and unit standard deviation. Shorting becomes somewhat more prevalent as our sample period progresses, so this normalization is designed to mitigate the effects of any trend that might otherwise affect inference in the Fama-MacBeth framework.

The results are in Table IV. The effect of the shorting flow measure is virtually the same using raw or risk-adjusted returns, so only the Fama-French alphas are discussed. We begin with a benchmark simple regression of future returns on shorting activity. In the cross-section, a one standard deviation increase in shorting activity results in risk-adjusted returns over the next 20 days that are 0.53% lower, on average. The confidence interval on this estimate is quite small, with a t-statistic greater than 10. The shorting results are virtually unchanged when we include standardized characteristic controls, including size, book-to-market, and turnover, as well as volatility and returns over the previous month.

The third specification in the table also includes order imbalances as explanatory variables. As discussed in the previous section, the idea is to investigate whether short selling is any different from other selling in terms of ability to predict the future cross-section of returns. Here we allow buy imbalances and sell imbalances to have different effects based on results in the order imbalance literature. Specifically, we calculate as the fraction of volume initiated by buyers less the fraction of volume initiated by sellers and standardize the variable to have unit cross-sectional standard deviation each day. The positive imbalance variable is defined as max(0, OIB), while the negative imbalance variable is defined as min(0,OIB).

What is the right null for this regression? If markets are efficient with respect to all publicly available information, the coefficients on OIB and shorting flow should in fact be different. Because order imbalances are identified using publicly available trade and quote data, OIB can be observed essentially in real time. As a result, prices should be efficient with respect to OIBs, and OIBs should not predict future returns. In contrast, short sales are not publicly observed, so short sale flow can be related to future returns as long as it is not collinear with OIB.

The regression results in Table IV indicate that negative order imbalances are informative about the future cross-section of returns, but in the opposite direction to our short sale flow data. The negative sign on negative OIB indicates a reversal over the next 20 days, consistent with the inventory-effect interpretation in Chordia, Roll, and Subrahmanyam (2004). That is, following heavy seller-initiated trading, prices tend to rebound. Specifically, when negative order imbalances get larger (more negative) by one standard deviation, returns are a statistically significant 0.53% higher in the next month. In contrast, in the 20 days following heavy short selling, prices fall, and the coefficient on shorting flow is virtually unchanged by the inclusion of the order imbalance variables. This indicates that the information in short sales is quite distinct from the information that gives rise to sell order imbalances.

III. Trading by different account types

We now turn to the question asked in the title of the paper. System short sales on the NYSE can be partitioned into six different account types: individual, institutional (program and non-program), member-firm proprietary (program and non-program), and other. What might we expect going into the exercise? As noted in the introduction, it is not obvious that individual shorts would be less informed than institutional or member-firm proprietary shorts. It is also hard to know what to expect for program vs. non-program trades. As mentioned earlier, program trades are defined as simultaneous trades in 15 or more stocks worth at least $1 million. One well-known type of program trade is index arbitrage, which involves trading baskets of stocks when they become slightly cheap or dear relative to index derivatives such as futures. Index arbitrage short positions seem unlikely to contain any information about the cross-section. However, hedge funds and other institutions often use program trades to quickly and cheaply trade a large number of names, since the commission rate is often lower for computerized program trades. Such program trades often mix buys and sells together. Clearly, in such cases the hedge funds believe they have private information about the cross-section that is not yet incorporated into price. Our priors about proprietary trades are also fairly diffuse. If these proprietary trading desks are mostly acting as market-makers, they are likely to be uninformed over the longer term about fundamentals.[11] However, proprietary trading desks often trade like hedge funds, and one might expect those shorts to be more informed.

Table V Panel A helps to provide some sense of the distribution of shorting across account types. Shorting by individuals on the NYSE is fairly rare, as they tend to account for 1% to 2% of overall shorting volume. This is not peculiar to shorting; overall NYSE order flow exhibits similar patterns (see, for example, Jones and Lipson, 2004). Part of the explanation is that individuals account for only a small amount of overall trading volume. But part of this paucity of individual orders is due to the brokerage routing decision. Many, if not most, brokerage firms either internalize retail orders in active stocks or route these orders to regional exchanges or third-market dealers in return for payment. As a result, very few orders from individuals make their way to the NYSE. Institutions submit most short sale orders, and account for about 74% of the total shares shorted via system orders. Member-firm proprietary shorts represent about 20% of total shorting. Somewhat surprisingly, if we slice firms by market cap, volatility, or prior return, there is not much variation in these fractions of overall shorting volume.

A. Simple sorts

To investigate the information in short sales by different account types, we begin again with a sorting approach. Each day, stocks are sorted into quintiles based on shorting's share of trading volume by the specified account type over the previous five days. Returns are calculated for each of these five value-weighted portfolios, and the focus continues to be on the daily return difference between the heavy shorting quintile and the light shorting quintile. Calendar-time differences in Fama-French alphas are calculated for holding periods from 10 to 60 trading days. Reported alphas are daily values in percent and are multiplied by 20 to approximate a monthly excess return.

The results are detailed in Table V, beginning in Panel B. For comparison to earlier results, we focus first on 20-day holding periods. Recall for comparison that using aggregate shorting by all account types, the heavy shorting quintile underperforms the light shorting quintile by a cumulative 1.16% over 20 trading days, and this underperformance is strongly statistically distinct from zero, with a t-statistic of 3.67.

Next we look at short sales initiated by various account types, with the results also reported in Table V Panel B. Institutions and member-firm proprietary short sales that are not part of a program trade are the most informed. Over a 20-day holding period, stocks with heavy shorting by institutions

[11]Member-firm proprietary desks can supply liquidity without competing directly with the specialist. For example, a block desk may purchase a large block of stock from a customer early in the day (in the upstairs market) and then proceed to gradually trade out of the position on the exchange floor.

underperform the light shorting quintile by a significant 1.43%, which is 19.6% annualized. The corresponding figure for member-firm proprietary non-program shorts is 1.34% or 18.3% annualized, and both return differences are statistically quite different from zero. The non-program institutional and proprietary alphas are not statistically distinguishable from each other, but they are reliably more informed than all other account types. In fact, we cannot reject the hypothesis that short sales by other account types (individual, institutional and proprietary program trades, and other accounts) are completely uninformed, as none of the alphas are statistically different from zero. For example, the quintile of stocks most heavily shorted by individuals underperforms the light shorting quintile by only 0.14% over the next month.

One might worry that these negative relative returns are only temporary, with reversals at longer horizons. Among other things, such reversals could indicate manipulation by short sellers or overreaction by other market participants to the presence of short sales. To investigate, we look at holding periods of 10, 20, 40, and 60 trading days. We continue to skip one day between measuring short sales and calculating holding period returns. Daily alphas are computed using a calendar-time approach but are reported scaled up by 20 (to reflect a monthly return) regardless of the actual holding period. We focus on institutional and proprietary non-program shorts, which are the only short sellers that are reliably informed. Table V Panel B shows that heavily shorted stocks experience the biggest underperformance in the first 10 days. Using institutional non-program shorts as an example, the 10-day relative alpha is -1.13%, and on average repeating the strategy over the next ten days yields a 20-day relative alpha of -2.27% (the number in the table). This is bigger in magnitude than the 20-day holding period alpha of -1.43%. While the alphas are closer to zero with longer holding periods, it is still the case that heavily shorted stocks continue to underperform for at least 60 days. Figure 1 shows the daily evolution of these excess returns up to 60 days. Here the alphas are not monthly but instead correspond to the holding period. Cumulative excess returns tend to flatten slightly at the longer horizons, suggesting that more of the information possessed by short sellers is impounded into price in the first few trading days, but some information possessed by short sellers is impounded into price over longer horizons, with short sale flow remaining informative even three months later. Thus, while much of the information in short sales seems to be shorter-lived than one month, some of the information takes up to 60 trading days to find its way into prices, and there is no evidence of reversals.

Much of the 2000-2004 sample period is characterized by a substantial and extended market decline. One might wonder if the predictive power of shorting flow is most valuable in a declining market. Figure 2 addresses this question, and more generally shows the profits and losses over time from this hypothetical "trading strategy." Specifically, it shows the raw return differences between the heavy shorting and light shorting quintiles for each month of the 20-day holding period calendar-time strategy, based on shorting relative to trading volume. Considering all shorting activity, heavily shorted stocks underperform lightly shorted stocks in about two-thirds of the months, and the results are fairly consistent throughout the sample. For institutional short-sellers, the worst month is March 2002, when heavily shorted stocks actually outperform lightly shorted stocks by 2.20%. Their best month is January 2001, when heavily shorted stocks underperform lightly shorted stocks by 9.30%. Overall, the low standard deviation of 2.27% per month for relative returns means a great deal of statistical power against the null, even though the sample is only a bit more than four years long. The results are similar when quintiles are assigned using all shorting or non-program proprietary shorting activity. These graphs are similar to those for many tradable regularities, with favorable return differentials in many but by no means all months. We also checked formally whether the results were different across calendar years and found no evidence of nonstationarity.

Our sample period was also characterized by a number of high-profile frauds and collapses, including Enron, Worldcom, and Adelphia, among others. Worldcom and Adelphia are not in our sample because they were listed on Nasdaq. But one might worry that the results are being driven by a small number of extreme observations where short sellers made the bulk of their profits. This is not the case; the results are not driven by a small number of outliers. When we exclude firms in the far left tail of the holding period return distribution (the worst 1% or 5%), the magnitudes of underperformance are naturally slightly reduced, but the qualitative results are unchanged. The remaining 95% or 99% of stocks continue to reliably underperform if they have been heavily shorted.

We also confirm that the results are not driven by the bursting of the so-called "tech bubble", with sharp declines in technology firm stock prices. Note that the sample is already limited to NYSE firms and excludes the vast majority of technology stocks which are listed on Nasdaq. We partition the sample into tech vs. non-tech firms using the SIC codes in Loughran and Ritter (2004) and recalculate return differences based on shorting activity. There is no evidence that the results are driven by technology stocks. For some shorting measures, the return differences are bigger for tech firms, and for other shorting measures, the return differences are smaller. More importantly, for non-tech firms the difference in Fama-French alphas between heavily shorted and lightly shorted stocks is always significant and bigger than 1% per month.

An important question is how the information possessed by these short sellers gets into price. One possibility is that the market is looking carefully for evidence of shorting in order to copy their trading behavior. This is consistent with the data in Aitken et al. (1998), where the disclosure of a short sale on the tape in Australia led to an immediate decline in price. The corresponding disclosure in the US is monthly short interest, so one might guess that once short interest is published, prices react to the surprise changes in short interest. To determine whether this accounts for our return differences, we identified the short interest release date each month during our sample and excluded it from the portfolio holding period. The results are in Table V Panel C, and excluding the short interest release date makes virtually no difference in the measured underperformance of heavily shorted stocks. Whatever the nature of the information possessed by short sellers, the release of short interest does not appear to be an important mechanism for incorporating that information into prices.

B. Regression results

We next look at shorting by account type in a regression framework. As in Section 2, this allows us to control for various stock or firm characteristics all at once. It also allows us to simultaneously compare short selling across account types. Based on the simple sorts, non-program shorting by institutions contains the most information about the cross-section of future stock returns. But shorting by various account types is positively contemporaneously correlated, so an important question is whether short sellers of various account types are acting on similar information. Perhaps there is a common factor describing this shorting behavior, in which case it is enough to look at institutional shorting alone. Alternatively, perhaps other account types are shorting based on orthogonal sources of information about share price. For example, institutions may be trading based on fundamental information, while member firm proprietary trading desks may be trading based on their knowledge of order flow in a stock. These two signals may or may not be related.

To investigate this, we run cross-sectional predictive regressions to determine which account types' shorting contributes incremental explanatory power for future returns. There is one cross-sectional regression per day, and like all other tests in the paper it uses five days' worth of shorting information. The dependent variable is the return over the next 20 trading days. We use a Fama-MacBeth approach to conduct inference, with Newey-West standard errors with 20 lags to account for the overlap in holding period returns. As before, each explanatory variable is standardized to have cross-sectional mean zero and a standard deviation of one each trading day.

The results are in Table VI, and here we find some evidence that program trades are also informed. When we include one account type at a time, controlling for other firm characteristics and order imbalances, more short selling by each account type except individuals implies reliably lower returns over the next 20 days. Heavy shorting by individuals is the exception and does not seem to be informative about future returns.

When all six account types are put into the regression at the same time, both types of member-firm proprietary shorts become insignificant. Institutional shorting, both program and non-program, are the only short sales with incremental explanatory power for the cross-section of returns next month. This is somewhat surprising, since proprietary and other account types showed strong univariate predictive power. It suggests that shorting by these account types is correlated with institutional shorting, but the institutional shorting dominates in terms of information content. The magnitude of the coefficient estimates confirms the superior informativeness of non-program institutional shorting, as all else equal a one standard deviation cross-sectional increase in non-program institutional shorting implies an average return over the next month that is 0.39% lower.

Coefficients on the control variables generally have the same sign as in Table IV, except that positive OIB now significantly lowers future returns in most models. Negative OIB remains significantly negative; and order imbalances in both directions are associated with subsequent return reversals. But as before, controlling for order imbalances leaves the predictive ability of shorting intact. In fact, adding the two OIB variables to the model leaves the estimated coefficients on shorting and their standard errors essentially unchanged. This suggests that whatever influence order imbalances have on subsequent returns, their effect is small and largely orthogonal to that of shorting. Finally, we have also run these regressions with various subsets of control variables and the results are the same.

C. Order size

Because we can observe individual short sale orders in every NYSE stock, it becomes possible to look at the informativeness of large short sales vs. small short sales. Our prior was that small short sales would be uninformed. In fact, the stealth trading results of Barclay and Warner (1993) and Chakravarty (2001) suggest that medium-sized shorts might be the most informative.

Short sale orders are partitioned into five order size categories: less than 500 shares, 500 to 1,999 shares, 2,000 to 4,999 shares, 5,000 to 9,999 shares, and orders of at least 10,000 shares. By coincidence it turns out that the median short sale order size is exactly 500 shares. Larger orders are less common: 31% of short sale orders are between 500 and 1,999 shares, 10% are between 2,000 and 4,999 shares, 5% are between 5,000 and 9,999 shares, and only 4% are for 10,000 shares or more.

Table VII Panel A reports some summary statistics on the mix of order sizes across account types. The average institutional short sale order is 550 shares if part of a program trade and 743 shares otherwise. There is an even bigger differential for proprietary trades: the average size is 398 shares for shorts that are part of a program trade, and 729 shares for non-program shorts. Interestingly, both individual and other account type shorts tend to be larger on average. The average individual short is 820 shares, while the average short from the “other” account type is 1,015 shares.

Some researchers partition by trade size and argue that large trades are institutional, while small trades are retail. Table VII Panel A shows that, at least for short sales, this is an unwarranted generalization. Individuals account for only 1% of the short sale orders less than 500 shares and account for at most 2% of the short sale orders in other order size categories. The vast majority of all shorting is non-retail, and this is true for all order sizes. Program trades account for 45% of short sales less than 500 shares, but only 10% of short sales orders for 10,000 shares or more. Finally, it is worth noting that the “other” account type submits a disproportionate number of large short sale orders. While this account type is responsible for only 7% to 9% of the orders under 5,000 shares, it accounts for 31% of the 10,000+ share orders.

We use a double sort method to investigate large and small short sales separately. Each day, we first sort stocks into quintiles based on shorting activity over the past five days, with shorting activity measured as shorting's fraction of overall trading volume in that stock. Within a quintile, we then sort a second time into quintiles based on the fraction of that stock's short sale orders that are of a given size. The result is a set of stocks with similar overall shorting activity but different shorting activity at a given order size. We repeat this exercise for four order size categories. There are so few short sale orders of 10,000 shares or more that the sorts do not work well, so we combine the two biggest order size categories into a single category covering short sales of at least 5,000 shares.

For each order size category, value-weighted returns and Fama-French alphas are calculated for a 20-day holding period using the calendar-time approach and are reported in Panels B and C of Table VII. Return differences are calculated as the return on the quintile with the most shorts in a given size bucket minus the return on the quintile with the least prevalent shorts in a given size bucket. This number is negative if stocks with heavy shorting of a given order size underperform.

An example may help to sort out the two sorts. Suppose we want to investigate the informativeness of small short sales. First sort stocks based on shorting's share of trading volume over the past five days, and consider for example the lowest quintile, which consist of lightly shorted stocks. For each stock in this quintile, calculate the fraction of its short sale orders that are for less than 500 shares. Sort a second time into quintiles based on this small order fraction. Now calculate value-weighted returns over the next 20 days for the sub-quintile with the most small short sale orders vs. the sub-quintile with the fewest small short sale orders and compute the difference. In our example, Table VII Panel C gives the Fama-French alpha on this return difference as 0.69%. That is, among stocks with the least overall shorting activity, stocks with many small short sale orders actually *outperform* stocks with few small short sale orders by 0.69% over the next month, though this number is not statistically distinguishable from zero.

Nevertheless, this result is quite striking, because small short sales are worse than uninformed. In fact, they seem to appear at exactly the wrong times, and one shouldn't follow these small shorts at all. If one could identify and instead *buy* the stocks where shorting is dominated by small orders, these would outperform stocks where small short sales are less prevalent. In fact, this result holds across this entire row of the table regardless of overall shorting activity, with 20-day average returns between 0.50% and 0.96%.

In contrast, when large short sale orders dominate the mix, stocks tend to underperform. The results are fairly weak for short sales between 2,000 and 5,000 shares. Stocks with heavy shorting in this size bucket underperform by 0.52% to 0.93% over the next 20 days, and the numbers are only sometimes significantly different from zero. The numbers are strongest for the biggest short sale orders. When orders to short at least 5,000 shares are most prevalent, the stock underperforms by a risk-adjusted average of 1.13% to 2.03% in the following month. While not all of these are distinguishable from zero, there is a consistent monotonic relationship between short sale order size and informativeness, indicating that short sellers who choose to submit large orders on average are better informed about future stock price moves.

Perhaps this is not surprising. The better a trader's information, the more she should want to trade. But this is not the usual result in the literature on the informativeness of different order sizes. Earlier stealth trading results, which are calculated using all buys and sells rather than just short sales, come to different conclusions. The results on small short sales are similar: they appear to be completely uninformed. The stealth trading results would suggest that medium-sized shorts contain the most information. But we find that the information in short sales is monotonic in order size. The larger the short sale, the more informative it is about future price moves. In contrast to the stealth trading results, the biggest short sales of over 5,000 shares appear to have the biggest ability to predict future price moves.

While we are not sure why this is so, one possibility is that these short sellers possess short-term information and cannot afford to be patient in executing their orders. Another possible explanation is that the uptick rule might inhibit the kind of slicing and dicing that we see on many other institutional orders. If the uptick rule reduces the probability of getting an order executed, perhaps short sellers cannot afford the execution uncertainty associated with splitting orders and submit large orders instead. If this second explanation is true, we might see this result change for those stocks that become exempt from the uptick rule during the Regulation SHO pilot program currently being conducted by the SEC.

IV. Shorting flow vs. short interest

Most of the existing literature on the informativeness of short sales uses monthly short interest data, and there is some evidence that monthly short interest can predict the future cross-section of returns. One might worry that our shorting measures are highly collinear with monthly changes in short interest, with little additional information provided by the higher frequency intermediate flows. Certainly our shorting flow measures are correlated with monthly changes in short interest, because they are a component of that monthly change. The monthly change in short interest is the sum of shares shorted in our sample over the relevant days plus manual NYSE short sales plus off-NYSE short sales less all covering transactions. The null hypothesis is that the monthly changes in short interest are sufficient to capture the information possessed by short sellers.

To investigate this, we use a double sort method. The first sort is based on monthly short interest changes for the previous month, in shares. The second sort is based on one of the three shorting flow measures for the past five days. As before, the portfolio holding period is 20 days, and we calculate a new set of portfolios and holding period returns for each trading day. The results are in Table VIII Panel A, and they show the difference in value-weighted cumulative 20-day Fama-French alphas following heavy vs. light shorting. Short interest does not drive out the shorting flow measures. For instance, using shorting normalized by trading volume, heavily shorted stocks underperform lightly shorted stocks by 0.96% to 1.60% per month across the short interest quintiles, with all five values statistically different from zero.

In Table VIII Panel B, we reverse the sorting order to see if our shorting flow measure drives out the predictive value of short interest. First we sort on our shorting flow measure, and then we sort on changes in short interest and examine future returns on stocks with the biggest increases in short interest vs. the biggest decreases. In 13 of 15 cases, the shorting flow measures drive out short interest. That is, once we control for shorting flow, changes in short interest are no longer significant predictors of the future cross-section of returns. This indicates that our measures dominate short interest as a proxy for the information in short sales.

V. Implementability and frictions

Before the reader begins to raise money for a hedge fund trading on these return differentials, it is important to emphasize again that these shorting flow measures are not publicly observable, which means that these excess returns are not achievable. Instead, these return differences should be viewed as *indications* of the returns to private information possessed by shorts in aggregate. They are indications because we do not observe the entire trading history of short-sellers. We would be able to calculate exact excess returns to a class of short sellers only if we knew all of the shorts and all of the covering trades. As it stands, the returns reported here are the gross returns available to a hypothetical bystander who observes system shorting flow in all stocks and trades in a particular way thereafter.

As discussed earlier, some market participants may be able to see pieces of this flow. The NYSE specialist can observe the short-selling system order flow, though only in the small number of stocks that he trades. The specialist may have some ability to shade his trading accordingly, but the market-making requirements for specialists probably limit the ability to profit from this information. Brokerage firms obviously observe the part of the shorting flow that they handle, and they could use that information to copy their customers' shorts if they believe that their customers are informed. But the complete flow data for this sample period are observable only to the econometrician, and only after the fact.

We also want to reiterate that all of the returns reported here are gross returns, because frictions are completely ignored. Even if a market participant could observe the short sale flow information, she might not be able to locate shares to borrow for shorting, and even if she could locate shares, borrowing those shares might be expensive for some stocks. Both of these frictions would reduce her returns. We do not have data on the cost of borrowing individual stocks, because major share lenders, such as brokerage firms and custodians, consider these data highly proprietary. However, aggregated across a broad portfolio of stocks, other researchers with access to these data find that institutions do not generally face a large pecuniary cost for borrowing shares. Only a small number of individual stocks carry negative rebate rates, and a broad portfolio of stocks might cost 1% per year to short, which is far lower than the magnitude of the excess returns to private information reported here. Of course, lending fees would be increasing in the amount borrowed, so there could be scale limits for an institutional trader making use of these shorting flow data. Individuals generally find it more expensive to borrow shares. Most brokers pay no interest to individuals on their short sale proceeds, which means that individuals face an opportunity cost on their short sales equal to the short-term riskless rate.

There are other costs associated with short sales that are harder to measure. For example, the share lender can terminate the loan at any time, demanding the return of the shares. If this happens, the share borrower must either find another share lender or close out the short position by purchasing the required shares in the open market. This is known as recall risk. It is a particular concern of those who short inactively traded, closely held, or otherwise difficult to borrow stocks, because a recall may force the short seller to close the position at an unfavorable price. Such recalls seem to be fairly rare for NYSE stocks, but we are unaware of any data quantifying the effect, if any, on short sellers. Additional costs are associated with the collateral required to initiate and maintain a short position. In the United States, Federal Reserve margin requirements require a short seller to deposit with its broker the proceeds of the short sale plus collateral equal to 50% of the value of the shares sold short. The short seller continues to earn interest or dividends on the posted collateral, so the main cost is that this collateral cannot be pledged to any other use while the short position is open.

So far, we have also ignored run-of-the-mill trading costs. The implicit trading strategies considered here have a holding period of 20 trading days, so it is possible for the whole portfolio to turn over every month. It turns out that there is considerable persistence in shorting activity, and the persistence is virtually identical whether we consider all shorting activity as a fraction of trading volume or just non-program institutional shorting. In either case, when the portfolio is rebalanced at the end of 20 days, on average 35% of the stocks remain in the same extreme portfolio, and the other 65% must be liquidated. Using NYSE TAQ data, we calculate the average effective spread for each stock each day and assume that a trader must pay the effective half-spread in order to accumulate or liquidate a position. The returns net of transaction costs are naturally a bit lower, but are still far from zero. For non-program institutional shorting, heavily shorted stocks underperform lightly shorted stocks by 1.13% per month net of trading costs, compared to 1.43% per month on a gross basis. That is, trading costs subtract a total of about 30 basis points per month. These trading costs may seem quite small, but trading costs have fallen substantially in recent years with the advent of decimals and increased competition between liquidity providers. In reality, these trading costs may actually be slightly overstated on the short side. The uptick rule implicitly forces short sellers to be less aggressive in demanding liquidity, which reduces realized trading costs. However, the uptick rule may increase opportunity costs for short positions that end up not being taken or are initiated with a delay. Overall, share borrowing costs and trading costs appear to be far too small to account for the excess returns we measure.

VI. Conclusion

In this paper, we use proprietary system order data from the New York Stock Exchange to examine the incidence and information content of all short sales and various subsets. There are two striking results. First, short selling is quite common. Shorting accounts for 12.9% of trading volume on average during our 2000-2004 sample period, and we conclude from this surprising prevalence that unless the marginal investor is very different from the average investor, shorting constraints are easily surmounted for even the smallest cap NYSE stocks.

The second and main result is that these short sellers are extremely well-informed. We quantify this information content in a number of different ways. Perhaps the simplest is a portfolio sorted into quintiles based on one week's shorting activity. Over the next 20 trading days, a value-weighted portfolio of heavily shorted stocks underperforms lightly shorted stocks by a cumulative 1.16% on average on a risk-adjusted basis (15.6% annualized). Of the six account types present in the data – individual, institutional (program and non-program), member-firm proprietary (program and non-program), and other – non-program institutional shorts are the most informed. Compared to stocks that are lightly shorted by institutions, the quintile of stocks most heavily shorted by institutions in a given week underperforms by 1.43% over the next 20 trading days (more than 19.6% on an annualized basis). These alphas do not account for the cost of shorting, and they cannot be achieved by outsiders, because the internal NYSE data that we use are not generally available to market participants. But these gross excess returns to shorting indicate that institutional short sellers have identified and acted on important value-relevant information that has not yet been impounded into price. The price effects are permanent, which suggests that short sellers are not manipulating or otherwise temporarily depressing the share price. The results are strongly consistent with the emerging consensus in financial economics that short sellers possess important information, and that their trades are important contributors to more efficient stock prices.

In future work, we are interested in understanding more about the source of the underperformance in heavily shorted stocks. There is some evidence that short sellers possess information about fundamentals. For example, Christophe, Ferri, and Angel (2004) find that negative earnings surprises are preceded by abnormal short selling. Francis, Venkatachalam, and Zhang (2005) show that short sellers are able to predict downward analyst forecast revisions, while Desai, Krishnamurthy, and Venkataraman (2006) find that short sellers are able to anticipate earnings restatements. However, Daske, Richardson, and Tuna (2005) do not find that short sellers anticipate negative earnings shocks. We think this is a promising area of research, and our high frequency data are ideal for investigating short selling immediately surrounding these kinds of corporate events.

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Table I. Summary statistics

The sample consists of all common stocks listed on the NYSE and extends from January 2000 through April 2004. Shorting's share of volume (*sfrac*) is shares sold short on a given day as a percentage of NYSE trading volume in that stock on that day. All shorting is aggregated per stock per day. Reported figures are time-series averages of cross-sectional statistics, except for the right half of Panel B, which reports cross-sectional averages of stock-by-stock autocorrelations and cross-autocorrelations. In Panel B, correlations different from zero at p=0.05 are given in bold.

Panel A: Daily system shorting per stock

	Number of executed short sale orders (*orders*)	Shares sold short (*shares*)	Shorting share of volume (*sfrac*)
Mean	146	99,747	12.86%
Cross-sectional Std Dev	194	232,541	10.59%
25%	23	6,331	4.90%
50%	77	27,425	10.27%
75%	192	95,417	18.10%
Avg. number of stocks	1,239	1,239	1,239

Panel B: Correlations and autocorrelations between returns and system shorting measures

Contemporaneous Correlations			
	$orders_t$	$shares_t$	$sfrac_t$
ret_t	**0.07**	**0.06**	**0.11**
$orders_t$		**0.80**	**0.30**
$shares_t$			**0.20**

Daily autocorrelations and cross-autocorrelations				
	ret_{t-1}	$orders_{t-1}$	$shares_{t-1}$	$sfrac_{t-1}$
ret_t	**0.00**	**-0.02**	**-0.02**	**-0.02**
$orders_t$	**0.09**	**0.54**	**0.40**	**0.34**
$shares_t$	**0.07**	**0.38**	**0.41**	**0.29**
$sfrac_t$	**0.08**	**0.31**	**0.28**	**0.42**

Panel C: Short-selling measures for 25 size and book-to-market portfolios

B/M	size: small	2	3	4	big
Daily shares sold short					
low	16,722	33,722	55,648	115,378	341,726
2	16,201	28,523	49,568	114,064	341,813
3	12,065	23,143	55,611	111,969	293,845
4	10,413	23,455	56,070	121,150	265,750
high	14,779	39,875	94,559	171,220	336,642
Shorting's share of trading volume					
low	11.6%	14.0%	15.1%	15.2%	12.7%
2	11.8%	14.3%	15.2%	15.0%	13.0%
3	11.4%	13.6%	15.1%	15.1%	13.6%
4	10.7%	13.4%	14.9%	15.1%	14.5%
high	10.5%	14.0%	15.1%	14.5%	13.3%

Table II. Portfolios based on recent system shorting

The sample consists of all common stocks listed on the NYSE and extends from January 2000 through April 2004. Firms are sorted into quintiles based on the specified short-selling activity measure over five trading days. After skipping one day, value-weighted portfolios are held for 20 trading days. This process is repeated each trading day, so that each trading day's portfolio return is an average of 20 different portfolios, with 1/20 of the portfolio rebalanced each day. Daily calendar-time returns and Fama-French three factor alphas are reported in percent multiplied by 20 to reflect an approximately monthly return, with t-statistics based on the daily time series.

	daily short orders	daily shares shorted	shorting share of volume	daily turnover	daily ret. σ (ann'd.)	market cap. ($millions)	book/mkt	value-weighted return	pf5-pf1 (t-stat)	Fama French alpha	pf5-pf1 (t-stat)
Portfolios sorted by number of executed short sale orders											
1 (least)	4	10,069	9%	0.40%	34.7%	1149	0.82	2.55		1.88	
2	12	27,100	13%	0.50%	33.4%	1968	0.75	1.53		0.95	
3	22	56,583	15%	0.58%	32.7%	3629	0.71	1.16		0.68	
4	40	120,129	16%	0.62%	31.9%	7976	0.65	0.64	-2.79	0.30	-1.91
5 (most)	93	391,415	16%	0.64%	32.2%	33180	0.52	-0.24	-6.80	-0.03	-7.24
Portfolios sorted by number of shares shorted											
1 (least)	5	7,337	9%	0.37%	31.7%	1163	0.77	2.36		1.70	
2	13	22,697	13%	0.50%	32.6%	2006	0.73	1.41		0.85	
3	24	49,997	15%	0.58%	32.6%	3720	0.68	1.04		0.58	
4	41	109,811	16%	0.64%	32.8%	7764	0.66	0.72	-2.60	0.40	-1.74
5 (most)	89	415,449	16%	0.65%	35.3%	33245	0.60	-0.24	-6.26	-0.04	-6.51
Portfolios sorted by shorting's share of volume											
1 (least)	16	59,208	5%	0.50%	35.3%	10162	0.75	0.97		1.16	
2	29	110,100	9%	0.53%	33.3%	13091	0.67	0.15		0.28	
3	37	137,824	13%	0.55%	32.6%	11848	0.66	-0.32		-0.29	
4	43	147,462	17%	0.58%	32.2%	8417	0.67	-0.10	-0.54	-0.25	-1.16
5 (most)	46	152,020	25%	0.59%	32.2%	4539	0.69	0.42	-1.56	0.00	-3.67

Table III. Return differences on short-sale portfolios after controlling for characteristics

The sample consists of all common stocks listed on the NYSE and extends from January 2000 through April 2004. Firms are first sorted into quintiles based on the given characteristic. Within each quintile, firms are then sorted into quintiles based on the short-selling measure for the past five days. Daily value-weighted returns are calculated using a calendar-time approach with a holding period of 20 trading days. Daily Fama-French three factor alphas are given in percent, multiplied by 20, for the return on the quintile with heavy short selling less the return on the quintile with light short selling. In Panel E, the order imbalance is calculated using Lee and Ready (1991) and is the share of volume initiated by buyers less the share volume initiated by sellers, normalized by total volume. This variable is calculated over the same 5-day interval as the shorting measure.

	Panel A: First sort is market capitalization					Panel B: First sort is book/market				
	low	2	3	4	high	low	2	3	4	high
Second sort: number of executed short sale orders										
pf5 – pf1	-3.24	-1.60	-0.81	-1.09	-0.76	-1.52	-1.13	-1.67	-1.56	-3.08
t-stat	-7.47	-3.92	-1.70	-2.69	-2.27	-3.57	-2.60	-3.49	-3.52	-5.87
Second sort: shares sold short										
pf5 – pf1	-2.20	-1.64	-0.64	-1.20	-0.74	-1.30	-1.09	-1.58	-1.48	-2.44
t-stat	-4.36	-3.61	-1.17	-2.45	-1.97	-3.13	-2.56	-3.26	-3.35	-4.20
Second sort: shorting's share of trading volume										
pf5 – pf1	-3.33	-1.80	-1.60	-1.19	-1.16	-1.23	-1.33	-1.14	-1.04	-1.07
t-stat	-9.91	-5.67	-4.95	-4.46	-2.93	-2.43	-2.65	-2.55	-2.23	-1.74

	Panel C: First sort is return volatility					Panel D: First sort is share turnover				
	low	2	3	4	high	low	2	3	4	high
Second sort: number of executed short sale orders										
pf5 – pf1	-1.10	-1.77	-1.62	-2.27	-4.55	-2.62	-2.19	-1.48	-2.30	-1.81
t-stat	-2.58	-4.13	-3.50	-4.53	-5.82	-5.76	-5.93	-3.49	-4.44	-2.85
Second sort: shares sold short										
pf5 – pf1	-1.29	-1.71	-1.62	-2.07	-4.13	-2.38	-1.85	-1.37	-2.04	-1.72
t-stat	-2.99	-4.03	-3.52	-4.04	-5.02	-5.35	-4.98	-3.23	-3.75	-2.54
Second sort: shorting's share of trading volume										
pf5 – pf1	-0.77	-0.90	-1.09	-1.64	-1.87	-0.99	-1.43	-0.86	-1.10	-1.38
t-stat	-2.04	-2.03	-2.11	-2.60	-2.48	-2.13	-3.55	-1.81	-1.73	-2.10

	Panel E: First sort is past 5-day order imbalance				
	low	2	3	4	high
Second sort: number of executed short sale orders					
pf5 – pf1	-1.84	-1.59	-1.55	-1.62	-1.98
t-stat	-5.09	-4.84	-5.50	-5.12	-5.51
Second sort: shares sold short					
pf5 – pf1	-1.39	-1.33	-1.44	-1.64	-1.98
t-stat	-3.84	-4.01	-5.00	-5.25	-5.47
Second sort: shorting's share of trading volume					
pf5 – pf1	-1.89	-1.04	-0.82	-0.54	-0.26
t-stat	-4.94	-2.87	-2.56	-1.63	-0.72

Table IV. Cross-sectional return regressions with controls

Fama-MacBeth regressions of daily observations for all common stocks listed on the NYSE, Jan 2000 through Apr 2004. The dependent variable is the cumulative return or Fama-French three-factor alpha over the following 20 trading days. Shorting share is defined as shares sold short as a percentage of NYSE volume in that stock over the previous five trading days. Size, book-to-market, return volatility, and turnover are calculated using data from the previous calendar month. Order imbalance is calculated using Lee and Ready (1991) and is the share of volume initiated by buyers less the share volume initiated by sellers, normalized by total volume. This variable is calculated over the same 5-day interval as the shorting measure. Positive OIB is defined as max(OIB,0); negative OIB is min(OIB,0). All explanatory variables are normalized to have cross-sectional mean zero and unit standard deviation each day, except for OIB, which is not demeaned but is standardized to have unit standard deviation before partitioning into positive and negative values. The t-statistics are reported below the parameter estimates and are based on the time-series of coefficient estimates from the cross-sectional regressions using Newey-West with 20 lags.

LHS Variable	Intercept	Shorting share	Log mktcap	Book to market	Return volatility	Previous month return	Turnover	Positive OIB	Negative OIB	adj R^2
Raw returns	1.38	-0.54								0.3%
	1.98	-8.65								
	1.95	-0.53	-1.13	0.42	0.41	-0.03	-0.43			7.5%
	2.81	-10.00	-6.89	2.88	1.51	-2.26	-3.17			
	1.80	-0.52	-1.10	0.42	0.39	-0.03	-0.41	0.08	-0.51	7.6%
	2.58	-8.69	-6.74	2.91	1.47	-2.26	-3.07	1.18	-4.06	
Fama-French	0.56	-0.53								0.3%
alphas	5.09	-10.18								
	0.91	-0.50	-0.62	0.17	0.39	-0.02	-0.35			3.7%
	6.10	-11.00	-6.66	1.69	1.79	-1.80	-3.04			
	0.76	-0.49	-0.59	0.17	0.38	-0.02	-0.33	0.09	-0.53	3.8%
	4.33	-9.64	-6.31	1.72	1.74	-1.79	-2.94	1.61	-3.72	

Table V. Different types of short-sellers and different holding periods

The sample consists of all common stocks listed on the NYSE January 2000 – April 2004. Firms are sorted into quintiles based on shorting's share of trading volume for the past five days. Average Fama-French alphas for the value-weighted return on the heaviest shorting quintile less that of the lightest shorting quintile are reported for holding periods of 10, 20, 40, and 60 trading days. In Panel B, calendar-time daily alphas are multiplied by 20 and are expressed in percent. T-tests are based on the time-series of daily alphas. In Panel C, we obtain NYSE monthly short interest release dates, and we omit those days from the portfolio formation process and from the holding period returns.

Panel A: Fractions of system shorting by account type

		Daily average shares shorted per stock	Fraction of total shorting volume					
			Individual	Institution		Proprietary		Other
				Non-prog.	Program	Non-prog.	Program	
Market Value of Equity	Small	17,158	1.9%	60.3%	14.0%	8.9%	9.8%	5.1%
	Medium	56,306	1.2%	57.3%	16.9%	9.5%	10.6%	4.6%
	Big	230,125	1.4%	58.5%	14.2%	12.8%	7.1%	5.9%
Stock Return Volatility	Low	87,228	1.2%	56.5%	17.7%	11.5%	7.3%	5.7%
	Medium	97,248	1.4%	57.1%	16.0%	12.1%	7.9%	5.5%
	High	105,834	1.8%	59.4%	12.2%	12.7%	7.7%	6.2%
Past Week Return	Low	95,421	1.6%	60.6%	13.0%	12.2%	6.9%	5.7%
	Medium	89,497	1.2%	57.7%	16.2%	11.6%	7.8%	5.5%
	High	119,308	1.3%	57.3%	14.9%	12.1%	8.9%	5.5%

Panel B: Fama-French alphas by account type and holding period

Holding	All short sales		Individual		Institution Non-program		Institution Program		Proprietary Non-program		Proprietary Program		Other	
Period	alpha	t(alpha)	alpha	t(alpha)	alpha	t(alpha)	alpha	t(alpha)	alpha	t(alpha)	alpha	t(alpha)	alpha	t(alpha)
10	-1.66	-4.37	-0.54	-1.24	-2.27	-5.70	-0.78	-1.96	-1.71	-4.82	0.07	0.21	-0.66	-1.81
20	-1.16	-3.67	-0.14	-0.37	-1.43	-4.28	-0.52	-1.51	-1.34	-4.54	0.17	0.55	-0.51	-1.63
40	-1.00	-3.53	-0.02	-0.04	-1.14	-3.77	-0.27	-0.84	-1.33	-5.07	0.06	0.24	-0.65	-2.33
60	-0.75	-2.77	0.03	0.07	-0.83	-2.89	-0.20	-0.62	-1.09	-4.44	0.14	0.54	-0.40	-1.58

Panel C: skip all short interest release dates

Holding	All short sales		Individual		Institution Non Program		Institution Program		Proprietary Non Program		Proprietary Program		Other	
Period	alpha	t(alpha)	alpha	t(alpha)	alpha	t(alpha)	alpha	t(alpha)	alpha	t(alpha)	alpha	t(alpha)	alpha	t(alpha)
10	-1.65	-4.30	-0.57	-1.29	-2.31	-5.63	-0.96	-2.38	-1.47	-4.15	-0.02	-0.06	-0.59	-1.57
20	-1.18	-3.69	-0.15	-0.38	-1.53	-4.44	-0.60	-1.72	-1.16	-3.91	0.07	0.24	-0.45	-1.42
40	-1.01	-3.51	-0.02	-0.07	-1.17	-3.74	-0.32	-0.96	-1.19	-4.42	-0.02	-0.05	-0.57	-1.98
60	-0.71	-2.61	-0.05	-0.13	-0.84	-2.87	-0.15	-0.47	-0.97	-3.89	0.10	0.40	-0.35	-1.36

Table VI. Multiple regression analysis of shorting by different account types

Fama-MacBeth regressions of daily observations for all common stocks listed on the NYSE, Jan 2000 through Apr 2004. The dependent variable is the Fama-French three-factor alpha over the following 20 trading days. Shorting is measured as a percentage of NYSE volume in that stock over the previous five trading days. Size, book-to-market, return volatility, and turnover are calculated using data from the previous calendar month. Order imbalance is calculated using Lee and Ready (1991) and is the share of volume initiated by buyers less the share volume initiated by sellers, normalized by total volume. This variable is calculated over the same 5-day interval as the shorting measure. Positive OIB is defined as max(OIB,0); negative OIB is min(OIB,0). All explanatory variables are normalized to have cross-sectional mean zero and unit standard deviation each day, except for OIB, which is not demeaned but is standardized to have unit standard deviation before partitioning into positive and negative values. T-statistics are below the parameter estimates and are based on the time-series of coefficient estimates from the cross-sectional regressions using Newey-West standard errors with 20 lags.

	Short selling during the previous week by													
Intercept	Individual	Institution Non-Prog	Proprietary Non-Prog	Institution Program	Prop Program	Other	Log mktcap	Book to market	Return volatility	Previous month return	Turnover	Positive OIB	Negative OIB	adj R^2
1.00	-0.03						-0.54	0.18	0.44	-0.02	-0.36	-0.21	-0.63	3.7%
6.07	-0.64						-5.80	1.79	2.03	-2.07	-3.19	-4.14	-4.49	
0.79		-0.44					-0.55	0.18	0.41	-0.02	-0.32	0.04	-0.57	3.8%
4.56		-9.15					-5.75	1.78	1.88	-1.89	-2.84	0.68	-4.05	
0.97			-0.12				-0.53	0.18	0.43	-0.02	-0.35	-0.17	-0.62	3.8%
5.88			-2.48				-5.68	1.79	2.00	-2.03	-3.08	-3.31	-4.45	
0.97				-0.23			-0.58	0.18	0.39	-0.02	-0.37	-0.15	-0.59	3.8%
5.75				-4.37			-6.24	1.77	1.82	-2.01	-3.26	-2.75	-4.22	
0.98					-0.18		-0.59	0.18	0.42	-0.02	-0.36	-0.16	-0.60	3.8%
5.80					-3.49		-6.00	1.80	1.97	-1.95	-3.16	-3.09	-4.28	
0.98						-0.11	-0.54	0.18	0.44	-0.02	-0.36	-0.19	-0.62	3.7%
5.85						-2.55	-5.80	1.81	2.04	-2.01	-3.16	-3.65	-4.41	
0.76	0.00	-0.39	-0.06	-0.15	-0.10	-0.05	-0.59	0.16	0.36	-0.02	-0.33	0.10	-0.52	4.2%
4.40	0.01	-7.88	-1.25	-2.76	-1.85	-1.04	-6.05	1.63	1.68	-1.70	-2.90	1.83	-3.71	

Table VII. The information in short sale orders of various sizes

The sample consists of all common stocks listed on the NYSE and extends from January 2000 through April 2004. Panel A provides a breakdown by account type for short sale orders in a given size range; each row sums to 100%. For Panels B and C, firms are first sorted into quintiles based on shorting as a fraction of total volume over the past five days. Within each quintile, firms are then sorted into quintiles based on the prevalence of a given order size among short orders in that stock for the past five days. Daily value-weighted returns (Panel B) and Fama-French alphas (Panel C) are calculated using a calendar-time approach with a holding period of 20 trading days. Daily mean returns and alphas are given in percent, multiplied by 20, for the return on the quintile with the most short sale orders of the given size less the return on the quintile with the fewest short sale orders of the given size.

Panel A: Shorting at various order sizes by account type

Order size (in shares)	Fraction of all short sale orders in the given order size category					
	Individual	Institution		Proprietary		Other
		Non-prog.	Program	Non-prog.	Program	
1 – 499	1%	32%	26%	15%	19%	8%
500 – 1,999	1%	51%	19%	10%	11%	7%
2,000 – 4,999	2%	53%	20%	10%	7%	9%
5,000 – 9,999	2%	52%	14%	11%	4%	17%
10,000 –	1%	45%	8%	13%	2%	31%
	Average short sale order size (in shares)					
	820	743	550	729	398	1,015

	Panel B: Raw returns First sort is shorting's share of volume					Panel C: Fama-French alphas First sort is shorting's share of volume				
	low	2	3	4	high	low	2	3	4	high
Second sort: fraction of short sale orders < 500 shares										
pf5 – pf1	1.62	1.51	1.56	1.37	0.61	0.69	0.83	0.96	0.94	0.50
t-stat	2.44	2.62	3.21	3.01	1.41	1.22	1.60	2.22	2.27	1.20
Second sort: fraction of short sale orders [500, 2000) shares										
pf5 – pf1	-0.74	0.17	-0.27	-0.34	-0.07	-0.40	0.14	-0.26	-0.52	-0.08
t-stat	-1.75	0.37	-0.61	-0.80	-0.17	-0.97	0.32	-0.62	-1.26	-0.19
Second sort: fraction of short sale orders [2000, 5000) shares										
pf5 – pf1	-1.83	-1.21	-1.25	-1.12	-0.65	-0.93	-0.52	-0.81	-0.80	-0.62
t-stat	-2.95	-2.65	-3.04	-2.96	-1.90	-1.79	-1.33	-2.16	-2.26	-1.86
Second sort: fraction of short sale orders $\geq$ 5,000 shares										
pf5 – pf1	-2.75	-2.14	-1.85	-1.50	-1.29	-1.34	-2.03	-1.59	-1.13	-1.38
t-stat	-2.63	-3.88	-3.88	-3.38	-3.10	-1.53	-3.00	-2.61	-1.97	-2.23

Table VIII. Shorting flow vs. changes in short interest.

The sample consists of all common stocks listed on the NYSE and extends from January 2000 through April 2004. The shorting activity measure is for the past five days; the change in short interest is from the previous calendar month. Daily value-weighted returns and alphas are calculated using a calendar-time approach with a holding period of 20 trading days. Daily mean returns and alphas are given in percent, multiplied by 21, for the return on the quintile with the highest value of the second sort characteristic minus the return on the low quintile.

	Panel A: First sort is change in short interest					Panel B: Second sort is changes in short interest				
	low	2	3	4	high	low	2	3	4	high
Second sort: number of executed short sale orders						First sort: number of shorting trades				
pf5 – pf1	-1.71	-1.57	-2.71	-1.29	-1.54	-0.42	-0.20	-0.63	-0.03	0.12
t-stat	-3.71	-3.63	-6.40	-3.00	-3.53	-1.43	-0.75	-2.26	-0.10	0.27
Second sort: shares sold short						First sort: shares sold short				
pf5 – pf1	-1.58	-1.48	-2.41	-0.91	-1.04	-0.70	-0.48	-0.11	-0.04	0.02
t-stat	-3.73	-3.43	-5.86	-2.11	-2.59	-2.59	-1.84	-0.40	-0.12	0.04
Second sort: shorting's share of trading volume						First sort: shorting's share of trading volume				
pf5 – pf1	-1.23	-1.54	-1.60	-1.04	-0.96	0.07	-0.37	-0.29	0.03	-0.12
t-stat	-2.53	-3.60	-3.64	-2.44	-2.08	0.15	-0.96	-0.85	0.09	-0.38

Figure 1. Risk-adjusted return differences on short-sale portfolios of different account types

The sample consists of all common stocks listed on the NYSE and extends from January 2000 through April 2004. Firms are sorted into quintiles based on short selling (shares sold short by the specified account type as a percentage of NYSE trading volume) over the past five days. We show average Fama-French alphas for holding periods up to 60 trading days. Alphas are for the heaviest shorting quintile less the lightest shorting quintile and are expressed in percent.

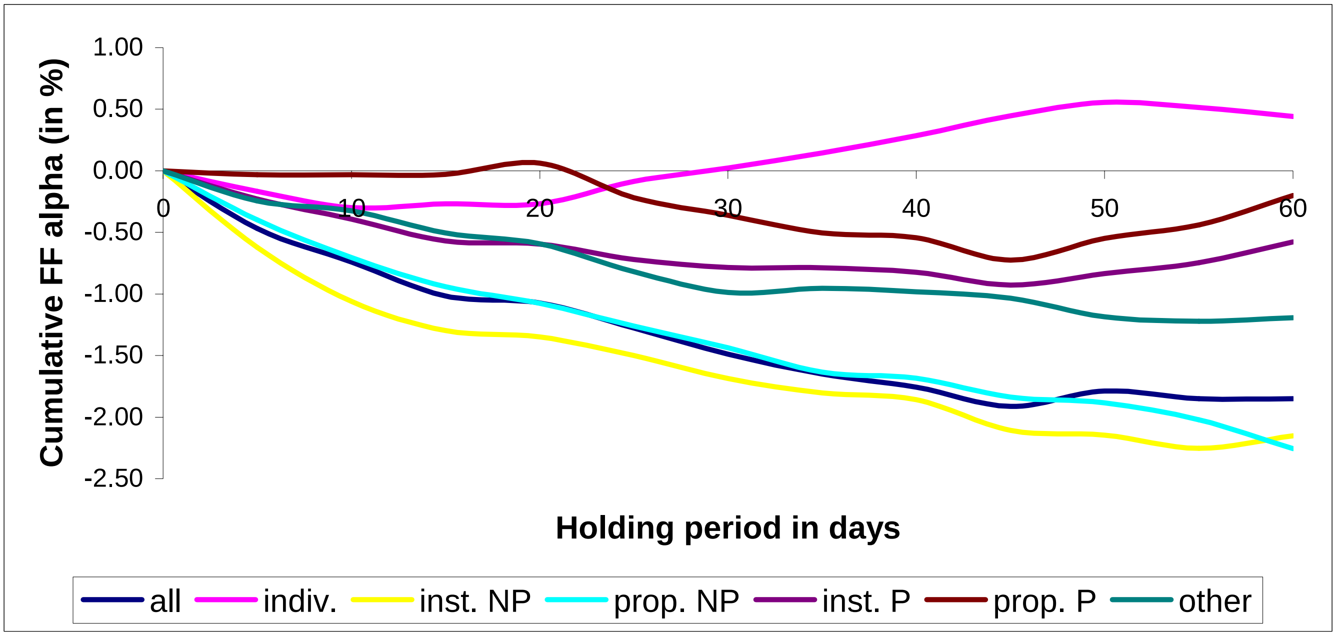

Figure 2. Return differences on short-sale portfolios

The sample consists of all common stocks listed on the NYSE and extends from January 2000 through April 2004. Firms are first sorted into quintiles based on shorting activity over the past five trading days (shares sold short as a percentage of NYSE trading volume). The figure reports average value-weighted return differences (quintile 5 – quintile 1), calculated as the calendar-time daily return difference cumulated over each calendar month and expressed in percent. Institutional and proprietary shorting measures exclude executions that are part of a program trade.