The Narrowness of Shorting Profitability

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Abstract

I examine the persistence in stock level short-selling profitability by using contract level shorting data. I do find that short-sellers are profitable on average using an approach that takes into account the exact timing of the opening and closing of short positions. But I also find that this profitability is driven by the set of stocks for which short-sellers previously had strongly profitable outcomes. I find that if short-selling contracts for a given stock are profitable in the last six months that on average short sellers continue to make profitable trades in that stock in the future. For stocks with the 30% highest short-selling profitability in the last 6 months, raw short-selling profitability for those same stocks in the following month is a statistically significant 2.49% (3.51% on a risk adjusted basis). Furthermore, when short sellers initiate new short positions among the set stocks that short sellers experienced strongly successful trades from 18 months to 12 month ago, these short sellers experience a significant one 1% higher average return than for stocks that weren't in that group.

Over the past ten to fifteen years many studies find a link between short-selling activity and future returns. For example, monthly short interest predicts future average returns.[1] Other measures of shorting activity predict future returns over shorter horizons.[2] Additionally, many papers find a link between short-selling costs (e.g, the required interest payment on the loan of shares) and future returns.[3] Furthermore, some studies examine whether short sellers are able to anticipate events or are simply better at processing publicly available information. Engelberg, Reed, and Riggenberg (2012), for example, find that short-sellers' information advantage comes from processing publicly available information better. These stylized facts have led (along with theoretical models) to the largely consensus view among academics that short sellers generally act as arbitragers and help eliminate or at least mitigate mispricing in the cross-section.

In this paper, I examine persistence in stock level short-selling profitability. In other words, I examine whether short-sellers are persistently profitable in the same set of stocks. Examining persistence in stock level short-selling profitability can yield insights into effectiveness of short-sellers as arbitragers. It also can yield insight into the nature of the information advantage held by short-sellers. Persistence in profitability yields insight into the limits of the informational advantage.

Short sellers are typically viewed (in the academic literature) as classic arbitragers. In this traditional and largely consensus academic view, they scan the cross-section of stocks looking for mispricing and then help drive prices back to fundamental value. Effective arbitragers will be able to identify and help mitigate mispricing throughout the cross-section of stocks. In this paper I test whether short sellers are indeed able to act in this way. I examine this general hypothesis

[1] See, for example, Asquith, Pathak, and Ritter (2005) and Desai, Ramesh, Thiagarajan, and Balachandran (2002)

[2] See, for example, Boehmer, Jones, and Zhang (2005) and Lamont (2005), and Diether, Lee, and Werner (2007).

[3] See, for example, Jones and Lamont (2002) and Cohen, Diether, and Malloy (2006).

by looking at persistence in short selling profitability. One potential reason for the existence of persistence in profitability at the stock level is that the profitable trading is largely driven by exploiting momentum patterns. If momentum is the cause of persistence, then short-sellers are generally playing a limited role as arbitragers. Furthermore, if persistence in profitability is driven by momentum patterns then it suggests many short-sellers close their positions too early and are showing limited skill with respect to the closing of their positions. On the other hand, persistence in profitability could be unrelated to cross-sectional price momentum patterns. In this case, persistence in profitability is revealing because it informs us about the narrowness of the short-sellers information environment. Short sellers may only have an information advantage in certain types of stocks. In this case, short sellers are effective arbitragers but the effectiveness is limited to a relatively narrow set of stocks. In the extreme, short-sellers may not hold an advantage for certain types of stocks, but really just for a certain set of stocks. In other words, short sellers may have an informational advantage in a largely fixed (or slow moving) set of stocks. In this case, short-sellers act as arbitragers in a quasi-fixed (or at least slow moving) set of stocks.

I do find that short-sellers are profitable on average using an approach that takes into account the exact timing of the opening and closing of short positions. On the other hand, I also find that this profitability is driven by the set of stocks for which short-sellers previously had strongly profitable outcomes. This persistence in stock level profitability is very strong. For example, when short sellers initiate new short positions among the set stocks that short sellers experienced strongly successful trades from 18 months to 12 month ago, these short sellers experience a significant one percent higher average return than for stocks that weren't in that group. These results suggest that short-sellers have an informational advantage in a largely fixed (or slow moving) set of stocks. They don't seem to operate as effective arbitragers in a wide cross-section of stocks.

I can examine the persistence in stock level short-selling profitability by using contract level shorting data. I use a panel of daily contract level data that spans six years (September 1999 to August 2005). These data allow me to directly measure the profitability of short-selling contracts both before and after short-selling costs. These data also allow me to construct the returns to short-selling strategies that explicitly takes into account the timing of the initiation of the contract and the closing of the short-selling position. I find that short-sellers are profitable on average. If I use a size (market-cap) matched benchmark portfolio or a size-book to market matched benchmark portfolio as the long side of the trade, then short-sellers show strong profitability on average both before and after shorting costs. For example, the size matched average return is, a significant, 1.23% per month before shorting costs and 1.08% after taking into account short-selling costs.

I do not know the identity of the short-sellers and cannot track individual short-sellers over time. Thus I cannot test hypotheses related to the persistence in profitability of individual short-sellers. However, I do examine persistence at the stock level. This allows me to test whether short-sellers operate effectively as arbitragers in a broad cross-section of stocks, and whether they enjoy an information advantage for many stocks or is it rather narrow set of stocks that changes slowly over time. I find that if short-selling contracts for a given stock are profitable in the last six months that on average short sellers continue to make profitable trades in that stock in the future. Specifically for stocks with the 30% highest short-selling profitability in the last 6 months raw short-selling profitability for those same stocks in the following month is a statistically significant 2.49% (3.51% on a risk adjusted basis). Some of this profitability is related to price momentum, but even after controlling for momentum in various ways the results remain significant and large in magnitude. Additionally, the persistence in profitability still exists even when using lagged versions of past profitability beyond one year. Finally, when these persistent stocks are removed from the sample, the average return on the short-selling portfolio is no longer significant or large in magnitude. Thus future short-selling profitability is driven by the set of stocks where short-sellers had previously very successful profitable outcomes.

Short-sellers are the most persistently successful in small-cap stocks, low institutional ownership stocks, high share turnover stocks, and highly volatility stocks. The most important characteristic seems to be volatility.

There are additional limitations to the data. First, I do not observe the long positions of the short-sellers. I do not know if they engaged in a pairs trade where there is a short position in a stock and a long position in a different stock or index. Thus I compute profits relative to a series of hypothetical long sides of the pairs trade. Specifically, I use a number of simple benchmark portfolios. Second, I do not know the motivation of the short-sellers. Thus it is possible that some of the short-sale contracts represent hedging and not information trades or trades based on a perception of mispricing. In general, I do not think this is the case for most of the contracts because the median shorting cost is close to 3% per annum in the sample. Thus the typical contract would represent an expensive hedging instrument.

The remainder of the paper is organized as follows. Section I reviews the related literature. Section II describes the mechanics of short-selling and how to compute the returns of a short-selling strategy. Section III describes the data. Section IV describes the basic methodology and presents empirical results regarding short-selling profitability. Section V examines persistence in profitability. Section VII concludes.

I. Related Literature

Many papers explore the theoretical link between short-selling activity and asset prices.[4] Miller (1977) suggests that short-sale constraints may prevent negative information or opinions from

[4] See Miller (1977), Harrison and Kreps (1978), Jarrow (1980), Diamond and Verrecchia (1987), Allen, Morris, and Postlewaite (1993), Morris (1996), Duffie, Garleanu, and Pedersen (2002), Hong and Stein (2003), Scheinkman and Xiong (2003), and Rubinstein (2004).

being expressed in stock prices. He argues that a stock's price will reflect the valuations of optimistic investors because pessimists simply sit out of the market when short-selling is not allowed. Miller's (1977) hypothesized effect is most dramatic when short-selling is prohibited, but his hypothesis predicts overpricing as long as there are short-sale constraints. Differences of opinion can arise from overconfidence (Scheinkman and Xiong (2003)) or from differences in prior beliefs which are updated rationally as information arrives (Morris (1996)). Regardless of how the differences of opinion arise, all of the models predict if there are short-sale constraints, prices may become too high today and consequently will experience low subsequent returns.

In contrast to Miller's (1977) hypothesis, Diamond and Verrecchia (1987) argue that rational uninformed agents take the presence of short sale constraints into account when forming their valuations. Thus in their model there is no overpricing conditional on public information because all participants recognize that negative opinions have not made their way into the order flow. Diamond and Verrecchia's (1987) model *does* predict that short sale constraints impede the flow of private information, and that the release of negative private information (e.g., via an unexpected increase in shorting activity) leads to negative returns.

Empirically, much of the literature focuses on the link between monthly short interest (shares sold short divided by shares outstanding) and future returns. In general, these studies find that when short interest is high subsequent average returns are low. For example, Asquith and Meulbroek (1995) and Desai, Ramesh, Thiagarajan, and Balachandran (2002) find significant average abnormal returns for stocks with high short interest on, respectively, the NYSE and Nasdaq exchanges for 1976 to 1993 and 1988 to 1994. Figlewski and Webb (1993), Figlewski (1981), and Dechow, Hutton, Meulbroek, and Sloan (2001) also find that stocks with high short interest experience low subsequent returns. Not all past studies find a significant relation between monthly short interest and future returns. Desai, Ramesh, Thiagarajan, and Balachandran (2002) argue that the weak results in early studies could be due to the use of small and/or biased samples. Recently, some papers have examined the link between daily measures of shorting activity and future returns. Boehmer, Jones, and Zhang (2005) and Diether, Lee, and Werner (2007) both find that high daily shorting activity predicts low subsequent average returns.

Other studies use proxies for short-sale constraints and/or demand to investigate the link between short-selling and future returns. Chen, Hong, and Stein (2002) use breadth of mutual fund ownership, Diether, Malloy, and Scherbina (2002) use dispersion in analysts' earnings per share forecasts, Nagel (2005) uses residual institutional ownership, and Lamont (2004) uses actions by firms that impede short-selling. All of these studies find that when their proxies indicate that short-selling demand is high, future returns are low on average.

Recent studies examine the role of shorting costs in the lending market and the equity market (see D'Avolio (2002), Cohen, Diether, and Malloy (2006), Jones and Lamont (2002), Geczy, Musto, and Reed (2002), Ofek and Richardson (2003), Reed (2002), Ofek, Richardson, and Whitelaw (2004), and Mitchell, Pulvino, and Stafford (2002)). Jones and Lamont (2002) and Cohen, Diether, and Malloy (2006) focus on and find evidence of a significant relation between shorting costs and future returns. Jones and Lamont (2002) using a small database of loan fees from 1926 to 1933, find that stocks with high loan fees experience low subsequent returns. However, the effect is modest; the authors only find large negative size-adjusted returns (−2.52% in the following month) among stocks that are both expensive to short and new to the loan crowd (another proxy for high shorting demand). Cohen, Diether, and Malloy (2006) find that high costs predict low future returns. On average stocks with loan fees greater than 5% per annum experience a significant subsequent average abnormal return lower than -2% the following month. Furthermore, stocks that experience an increase in their lending fee, quantity shorted, or both also experience significantly negative subsequent average abnormal returns.

Overall, the previous literature finds a link between shorting activity and future returns and shorting costs and future returns. Certainly the preceding evidence is suggestive that short-sellers actually are profitable, but it is indirect and may under or overstate how successful short-sellers are in terms of picking mispriced stocks or timing their trades. Furthermore, very little is known about the dynamics of their trades and whether short-sellers can be persistently profitable. In this paper I attempt to fill this void in the literature.

II. Returns to Short-Selling

If a short-seller borrows a stock (via her broker) and sells the stock short, then the short-seller does not get access to the proceeds of the sale. Instead, the proceeds are held in a collateral account[5] until the short-seller closes out her position by returning the borrowed shares. The collateral account is, of course, accruing interest. The account usually has a rate of return close to LIBOR or the Fed funds rate. The short-seller does not receive all of the interest from the collateral account. A portion of the interest (the loan fee) is payed to the lender. The portion received by the short-seller is called the rebate rate. The loan fee is the direct cost of shorting, and it is the price that equilibrates supply and demand in the equity lending market. Loan fees can be larger than the collateral account interest rate. In this situation the lender is receiving all of the interest from the collateral account plus the short-seller is paying an additional interest charge out of pocket. This situation mechanically corresponds with a negative rebate rate. Finally, the short-seller is also required to pay any dividends to the lender if the firm sold short pays a dividend.

If a short-seller takes a short position in General Motors, then the return on her position before short-selling costs is,

$$r_{\text{before costs}} = r_f - r_{gm}, \tag{1}$$

[5] The collateral requirement is usually slightly higher than the full proceeds. The most common requirement is 102%. For simplicity, I focus on the case where the collateral requirement is 100% of the proceeds.

and the return on her position after accounting for short-selling costs is,

$$
\begin{aligned}
r_{\text{after costs}} &= r_f - r_{gm} - fee \\
&= \text{rebate rate} - r_{gm},
\end{aligned}
\tag{2}
$$

where r_f is the rate of return on the collateral account, r_{gm} is the return on General Motors (GM), and fee is the loan fee that the short-seller must pay to short GM. The short-seller is taking a long position in the riskfree rate (or a rate very close to the riskfree rate) implicitly as part of the short-selling process because the proceeds are held in a collateral account. The direct cost of shorting is the loan fee and one can see how it lowers the return of the short-selling position in equation (2). Note, that $r_f - fee$ is equal to the rebate rate: the portion of the collateral account interest rate that the short-seller receives.

Suppose, that a short-seller forms a zero cost portfolio by buying Toyota and shorting GM. The short-seller does not have access to the short-sale proceeds so she must borrow inorder to form a zero cost portfolio. Assuming she can do this at the same rate as the collateral account interest rate (r_f), then the return on her portfolio before shorting costs is,

$$
r_{\text{before costs}} = r_{toy} - r_{gm} \tag{3}
$$

and the return on her portfolio after accounting for short-selling costs is,

$$
\begin{aligned}
r_{\text{after costs}} &= r_{toy} - r_{gm} - fee \\
&= r_{toy} - r_{gm} + (\text{rebate rate} - r_f),
\end{aligned}
\tag{4}
$$

where r_{toy} is the return on Toyota. Regardless of whether the short-seller engages in a pairs trade or simply shorts a stock and consequently implicitly takes a long position in the riskfree rate, the direct cost of shorting is the loan fee.

III. Data

A. Data Description

I use a proprietary database of stock lending contracts from a large institutional investor during the period of September 1999 to August 2005. I do not name the institution because of a confidentiality agreement. However, the institution is an active lender. The institution is particularly active in the small-cap lending market. The database contains daily contract level short-selling data. For each contract-day I have the following variables: loan fees, rebate rates, shares on loan, collateral amounts, rate of return on the collateral account, estimated income from each loan, and broker firm names.

In this paper I examine the profitability of short-selling contracts. To do this I have to be able to uniquely identify the short-selling contracts over time. The basic unit of observation is the contract-day. The database does not have an explicit contract identifier, but I can track the contracts over time with a very high degree of accuracy. I can uniquely identify virtually all the contracts over time because the data specify the size of the contract, the date the contract began, and the broker used for the contract.

I identify 286,896 contracts during the period of September 1, 1999 to August 31, 2005. I only include a contract in the sample if it lasts at least one day. I exclude contracts that start and end on the same trading day because I confine our study to the daily and not the intra-daily horizon. I also exclude contracts that cannot be matched with daily return data from CRSP.

B. Summary Statistics

Table I presents summary statistics for a pooled sample of all 286,896 contracts. The loan fee variable is the loan fee on the first day of the contract expressed per annum. The median (average) loan fee is 2.46% (3.16%). There is substantial variation in loan fees across contracts. The 25th percentile is 0.16% and the 75th percentile is 5.21%. Furthermore, about 46% of the sample had a negative rebate rate on the first day of the contract (loan fee greater than the collateral account interest rate). The substantial overall costs for the sample suggests that most or at least a large portion of the contracts are not driven by hedging concerns. The median contract size is over $57,000. The average is much larger than the median which reflects the fact that there are some very large contracts in the data. The median contract lasts 16 trading days, and the average is 55.33 days. Thus, the contract data are *not* primarily comprised of very short term contracts lasting only a few days. Even the 25th percentile is 6 days. Of course, I exclude intra-day contracts from the data which inflates the numbers relative to the universe of all contracts in the lending database. If the contracts that start and end during the same trading day are included, the median contract length is about 7 trading days.

I also merge the contract data with information from a variety of other sources. I draw data on daily returns, prices, shares outstanding, and other items from CRSP, and book equity COMPUSTAT. Table I also presents summary statistics for the characteristics of the stocks sold short. The typical short contract for this sample involves a small low priced growth stock. This is a clear manifestation of the small-cap lending tilt of the data provider. On the other hand, some contracts involve very large stocks. For example, there are contracts involving both Microsoft and Intel in the sample.

Despite a tendency to short growth stocks, the short-sellers show little tendency to short past winners. Both short-term (t-5 to t-1) and longer term past returns (t-125,t-6) are close to the 50th percentile relative to CRSP on average (where percentiles are computed using on common stocks on CRSP as the contract day start. This seems to be at odds with the findings of Diether, Lee, and Werner (2007); they find that short-selling activity is significantly higher in days where the return over the past 5 days was high. This difference may be caused by the different nature of the samples. I exclude contracts that start and end in the same trading day, and the contracts represent loans from one particular lender rather than all short-selling transactions in a given day.

The data are drawn from one lender so it's important to assess whether the lending fees are representative. To asses that I compare the loan fees in my contract level sample to the Markit lending data[6] The Markit sample and my contract level sample overlap from January of 2002 to August 2009. I construct a matching Markit sample by replacing the contract loan fee with the corresponding value-weight average loan fee reported by Markit. Table II reports these results. Both the median and average loan fee are higher for the contract level data. The average loan fee for the contract sample is 2.78% during this period and only 1.81% using Markit data. In general, this indicates that the lender is relatively expensive. This may indicate some pricing power or simply that the lender rarely recalls shares and can demand a price premium. These data also indicate that these contracts are tilted toward stocks that are expensive to short on average given the average Markit loan fee.

IV. The Short-Selling Portfolio

Many past studies find that shorting quantity and shorting fees predict future returns. Certainly, these studies suggest that short-sellers are likely profitable. However, these approaches do miss whether or not short-seller close their trades in a way that leads to profitability. Given, that I use a measure of profitability that takes this timing into account. First, I form an aggregate short-selling portfolio. In day $t-1$, I compute the number of shares on loan by our lender for every stock in the sample. The weight on a stock in the portfolio is the dollar value of shares sold short (closing price times shares sold short) divided by the dollar value of all shares on loan by our lender in day $t-1$. Thus the weight on stock i (w_{it}) in the short-selling portfolio

[6] Markit Securities Finance (MSF) provides institutional fund flow, short interest, and borrow cost data and analysis on over 30,000 global equities and 120,000 global bonds. The data are sourced from 120 custodian banks, 36 prime brokers, and over 300 hedge funds. The dataset is available at the daily frequency, and contains virtually all of the securities lending transactions on a daily basis in the United States.

(P) is

$$w_{it} = \frac{\sum_{j=1}^{C_{it}} s_{ijt-1} P_{it-1}}{\sum_{i=1}^{N_t} \sum_{j=1}^{C_{it}} s_{ijt-1} P_{it-1}}, \tag{5}$$

where s_{ijt-1} is the number of shares of stock i on loan for contract j on day $t-1$, P_{it-1} is the price of stock i on day $t-1$, C_{it} is the number of contracts that involve shorting stock i on day t, and N_t is the number of stocks in the portfolio (and the number on loan by the lender) on day t. Thus, the before cost return on the short-selling portfolio $(-r_{pt})$ in day t is

$$\begin{aligned} -r_{pt} &= \sum_{i=1}^{N_t} w_{it}(-r_{it}) \\ &= \sum_{i=1}^{N_t} \left(\frac{\sum_{j=1}^{C_{it}} s_{ijt-1} P_{it-1}}{\sum_{i=1}^{N} \sum_{j=1}^{C_{it}} s_{ijt-1} P_{it-1}} \right) (-r_{it}), \end{aligned} \tag{6}$$

where r_{it} is the return on stock i in day t.

I also compute the after short-selling cost return on the portfolio. The direct daily cost of short-selling is equal to the daily loan fee. For each contract I compute the daily loan fee as the daily rate that, over the number of trading days in a year (250 days), compounds to the reported (annual) loan fee. Many times there are multiple short-selling contracts for a particularly stock on a given day. Most of the time these contracts have the same or very similar loan fees, but there is variation. Thus the return in day t for every contract is potentially different even when the contracts represent short positions in the same stock. Thus, the weight of contract j that shorts stock i on day t (w_{ijt}) in the short-selling portfolio (P) is

$$w_{ijt} = \frac{s_{ijt-1} P_{it-1}}{\sum_{i=1}^{N_t} \sum_{j=1}^{C_i} s_{ijt-1} P_{it-1}}, \tag{7}$$

and the after short-selling cost return on the portfolio is

$$-r_{pt} = \sum_{i=1}^{N} \sum_{j=1}^{C_i} w_{ijt} \left(-r_{it} - f_{ijt} \right), \tag{8}$$

where f_{ijt} is the daily loan fee for contract j shorting stock i on day t.

I form the short-selling portfolio every trading day and compute the return both before and after shorting costs. I also benchmark the returns using a series of benchmark portfolios. First, I simply benchmark relative to the riskfree rate $(r_f - r_p)$. The daily riskfree rate is computed as the daily rate that, over the number of trading days in the month, compounds to the 1-month t-bill rate. If the short-seller takes no explicit long position (i.e., a pairs trade) then the short-seller is implicitly taking a long position in the riskfree security because the short-sale proceeds are put into the collateral account where they earn a rate of return close to the t-bill rate (minus the loan fee). Second, I benchmark relative to the CRSP daily value-weight stock index $(r_M - r_p)$. Third, I characteristically adjust the returns (as in Grinblatt and Moskowitz (1999) and Daniel, Grinblatt, Titman, and Wermers (1997)) using size benchmark portfolios $(r_{ME} - r_p)$: 10 value-weight size portfolios. Lastly, I characteristically adjust the returns (as in Grinblatt and Moskowitz (1999) and Daniel, Grinblatt, Titman, and Wermers (1997)) using size-book to market benchmark portfolios $(r_p - r_{ME,B/M})$: 25 value-weight size-book to market portfolios.[7] In each of these last three cases, the benchmark portfolio represents the long side of the zero-cost portfolio as described in section III. The long position is funded by borrowing because the short-seller does not have access to the short-sale proceeds.

Table III presents average returns for the short-selling portfolio. I multiply all the daily

[7] I form the size and the size-book to market (B/M) portfolios as in Fama and French (1993). On the last day of June of year t I sort NYSE stocks by their market equity (ME). I also sort NYSE stocks independently by their book to market ratio. I use the ME and B/M breakpoints to allocate all stocks into the appropriate ME deciles and ME and B/M quintiles. I then form 10 value-weight size and size-B/M portfolios using all common stock on CRSP. I compute daily returns on the portfolio from July of year t to June of year $t+1$. The B/M ratio in June of year t is comprised of the book equity (B) for the fiscal year ending in calendar year $t-1$, and market equity (M) from end of December of $t-1$. The portfolios are rebalanced annually.

returns by 21 inorder to make the numbers more comparable to the typical monthly return found in the literature. I account for autocorrelation in daily returns by using Newey-West (1987) standard errors with a lag length of one. Panel A contains the before short-selling cost returns and Panel B contains the after cost returns. Short-sellers do make positive returns on average both before and after costs from just the short-selling position ($r_f - r_p$). The average return on $r_f - r_p$ is 0.38% before costs and 0.23% after costs. However, these magnitudes are not significant. If the long position is the CRSP value-weight index of stocks, then the average return is slightly larger (0.45% before costs and 0.30% after costs) but still insignificant. The short-selling portfolio displays significantly positive average returns when a size-matched or size-B/M matched portfolio is used as the long position. For example, when the size-matched portfolio is used the average return is 1.23% before costs and 1.08% after costs. The t-statistics are quite large both before and after costs (3.12 and 2.75 respectively). Thus the relative performance of the shorted stocks is very poor; the shorted stocks perform significantly worse over the horizon they are shorted than stocks with similar market-cap or similar market-cap and book to market ratio.

I prefer using the characteristic benchmarking instead of factor model benchmarking because it has a natural correspondence with long/short zero cost portfolios. In addition, it is possible that the short-selling portfolio does not have stable factor loadings because of the changing composition through time. However, I also compute abnormal returns using the Fama-French (1993) three factor model and a four factor model that adds a momentum factor (Carhart (1997)). Panel C of Table III presents the results of the three and four factor model regressions. The Fama-French (1993) three factor model results are virtually identical to the size-B/M benchmarked average returns. The before shorting cost alpha is 1.32% (t-statistic = 2.91) and the after cost alpha is 1.18% (t-statistic = 2.59). The four factor model alphas are only slightly smaller both before and after costs. They are also both highly significant. These results seem to suggest that short-sellers often have better information or are able to spot mispricing better than the previous literature has been able to identify.

In Table IV I split the shorting portfolio based on stock and contract characteristics. Table IV shows that in certain sub-groups, short-sellers are very profitable. For example, even after taking into account shorting costs contracts involving micro-cap stocks (smallest market-cap quartile) and beginning of contract fees over 1% earning an average monthly return of 2.6%.

V. Persistence in Profitability

In this section I examine persistence in short-selling profitability on the stock level. Specifically, I examine whether short-sellers tend to be profitable in the same stocks over time. One reason that short-sellers may be tend to consistently profitable in the same set of stocks is that that they have a narrow informational advantage and are trading on that advantage. Another possibility is that short sellers on average may pull out of stock too quickly and other short-sellers (or the same short-sellers) realize this and short the stock again.

A. Predicting Future Profitability with Past Profitability

I measure past stock level short-selling profitability ($shortret_{-6,-1}$) as the share-weighted average of the cumulative return of all contracts that end in the last six months. I recompute the measure every month. I also form a measure based on the number of contracts ended in the last 6 months that experience positive returns. $count_{-6,-1}$ is the number of contracts with positive cumulative returns minus the number with negative cumulative minus the median count for the same NYSE market-cap quintile. I group largest three market-cap quintiles are together because relatively few larger-cap stocks are covered at the beginning of the sample. Table V presents summary statistics for $shortret_{-6,-1}$ and $count_{-6,-1}$. Table V indicates that on average the past contracts that ended in during the past six months experience positive returns.

The average $shortret_{-6,-1}$ is 2.87.

I form three (bottom 30%, middle 40%, and top 30%) daily short-selling portfolios based on this measure. The weight on a stock in the portfolio is the dollar value of shares sold short divided by the dollar value of all shares on loan by our lender in the respective past profitability category. I then compute the returns on the portfolios both before and after shorting costs as I described in previous section. Table VI reports the results for the past shortret portfolios. The table indicates a strong pattern of persistence in profitability. The high portfolio (comprised of stocks with the highest past short-selling profitability) experienced a before short-selling cost return ($r_f - r_p$) of 2.49%. The average return is significant and large. The after costs returns are also large (2.28% per month), but not quite significant at the 5% level. If the returns are size-B/-adjusted then the average abnormal before shorting cost return shoots up to a remarkable 3.53% per month. This indicates a strong pattern of persistence at the stock level.

Table VI also indicates that most of the abnormal performance of short-sellers comes from stocks these stocks. In other words, short-selling performance appears to be driven by short-activity where short seller were successful previously. This may indicate that short-sellers have an information advantage in a pretty narrow set of stocks and the composition of those stocks is consistent over time.

Another possibility is that this persistence is largely a manifestation of price momentum. Past short-selling profitability implies that these stocks performed poorly over the last 6 months. Another possibility is that short sellers on average may pull out of stock too quickly and other short-sellers (or the same short-sellers) realize this and short the stock again. To examine this I form portfolios that simply short the stocks for the entire month instead of tracking and mimicking the actual positions of the short-sellers in each of these stocks. The results for these portfolios are found in panel C of Table VIII. The high past $shortret$ portfolio in this case does not exhibit significant average returns on a excess or risk adjusted basis. The excess return

$(r_f - r_p)$ is very close to zero: 0.14% per month. Thus a large portion of the profitability is driven by the short-sellers timing and selectivity. There ability to selectively choose the worst performing stocks leads to a substantial improvement in profitability, but they appear to only have this kind of timing and selectivity among persistent set of stocks.

One downside to the portfolio framework is that it includes all contracts on a given day. Therefore, I could be picking up a different kind of continuation. Specifically $shortret_{-6,-1}$ is picking up short-sellers that closed early, but they are still some short-sellers that keep their contracts open and then close their position with good timing. This can be viewed as a more sophisticated type of momentum. To test this idea I turn to a regression framework. Specifically, I regresses stock level average short-selling profitability in month t on past stock level short-selling profitability. I measure current profitability ($shortret_t$) as the share-weighted average of the cumulative returns of all shorting contracts that begin in month t. In some regression specifications I regress current profitability ($shortret_t$) on a high past short-selling dummy ($high_{shortret(t-6,t-1)}$) where the dummy equals one if the stock is in the top 30 percent $shortret(t-6, t-1)$ percentile. The regressions also include calendar month dummies and the standard errors take into account clustering by both calendar date and clustering by stock (Thompson (2006)). Table IX presents the results. The regression results are similar to the portfolio results. Past profitability is a strong predictor of future profitability. Future contracts in stocks with high $shortret_{-6,-1}$ average future profitability of 3.12% (t-stat = 8.52).

I also run specifications with the following control variables (in addition to calendar date dummies): $\log(ME)$, $\log(B/M)$, r_{t-1}, $r_{t-6,t-1}$, $instown$, tv, and σ. ME is market-cap from the end of month t-1. B/M is the book to market ratio computed as in Fama and French (1993). r_{-1} is last month's return. $r_{t-6,t-2}$ is the return from month $t-6$ to $t-2$. $instown$ is institutional ownership measured as a percentage of shares outstanding lagged one quarter. tv is the average daily exchange-adjusted share turnover during the previous 12 months. σ is the standard deviation of daily returns (multiplied by 21) during the past twelve months.

Adding the control variables does reduce the magnitude of the past short-selling profitability coefficient but it is still large and significant; The high dummy variable is a significant 1.23%. Thus persistence in profitable is robust to past price momentum and other standard control variables. This approach does indicate that some of this effect is related to momentum as the coefficient is less than half the size (but still significant) when only past-return control variables are used.

Next, I use the same regression framework and extend the results using lagged versions of $shortret_{-y,-x}$. If short-sellers have an informational advantage in a large fixed (or slow moving) set of stocks, then $shortret_{-y,-x}$ should predict future shorting profitability for many lags. I consider lags of past $shortret$ out one year: $shortret_{-17,-12}$. Table IX presents the results. The relation between past profitability and future profitability is significant even when using $shortret_{-17,-12}$. The coefficient is about 1/3 size: 0.98% per month. However, much of the decrease appears to be the momentum effect. In panel B I add control variables and the coefficient on stock with high $shortret_{-17,-12}$ is 0.78% per month. These results support the hypothesis that short-sellers are mostly successful in the same set of stocks month to month.

B. Characteristics of Persistence in Profitability

Next, I examine the characteristics of the stocks that manifest short-selling persistence in profitability. I define a stock as persistent if $shortret_{t-6,t-1}$ is in the top 30% and $shortret_t$ is in the top 30%. I define a stock as non-persistent if the stock is in top 30% of $shortret_{t-6,t-1}$ but the bottom 70% of $shortret_t$. I regress persistence in profitability on past stock characteristics. Once again, the regressions include calendar month dummies and the standard errors take into account clustering by both calendar date and clustering by stock (Thompson (2006)). In the regression specifications I use the same stock variables as in Table IX except that I add analyst coverage ($analyst$). Analyst coverage is measured as the number of analyst that covered the stock in month $t-1$. I also iteratively replace the control variables with a series of dummy variables. I split stocks into small/large ($instown_{low}/instown_{high}$) dummies based on 30% and 70% market-cap ($instown$) percentiles for all NYSE stocks on CRSP every month. Additionally, I split stocks into tv_{low} and tv_{high} ($\sigma_{low}/\sigma_{high}$ or $analyst_{low}/analyst_{high}$) dummies based on 30% and 70% tv (σ and $analyst$) percentiles for all stocks on CRSP every month.

Table XI reports the results of the persistence regressions. The coefficient on past returns (month $t-6$ to $t-2$) is significant in every regression. Thus, the persistent stocks experience worse raw returns in the past than non-persistent stocks even though both groups were in the top 30% of past short-selling profitability ($shortret_{t-6,t-1}$). This does suggest that price momentum plays a role in short-selling persistence but the previous results also suggest that the short-sellers are able to selectively identify the stocks where the continuation in prices is strongest.

Both past market-cap and institutional ownership are significantly negatively related to persistence. A small-cap stock is about 8 percentage points more likely to be a persistent stock. The same is true for low and high institutional ownership stocks. Stocks in the low institutional ownership category are about 7 percentage points more likely to be persistent even after controlling for market-cap. One possibility is that both of these variables proxy for the efficiency of the stocks. Mispricing for small-cap low institutional ownership stocks may be more likely to be big and may last longer.

Finally, both past share turnover and volatility are positively related to persistence. Stocks in the high turnover category are about 4 percentage points more likely to be persistent and stocks in the high past volatility category are about 17 percentage points more likely to be persistent. Thus volatility appears to be the most important single variable. Short-sellers are much more likely to exhibit persistence in highly volatile stocks. Mechanically it makes sense that highly volatile stocks are more likely to be persistent since they are more likely to have big price drops both in the past and the current period. It also may be the case that highly volatile stocks are more likely to have large departures from fundamental value and that these departures could be more frequent. More frequent departures would allow short-sellers to find consistent profit opportunities.

VI. Conclusion

Over the past ten to fifteen years many studies find a link between short-selling activity or short-selling costs and future returns. These stylized facts have led (along with theoretical models) to the largely consensus view among academics that short sellers generally act as arbitragers and help eliminate or at least mitigate mispricing in the cross-section. In this paper I also examine the informational advantage of short sellers, and more generally the effectiveness of short sellers as arbitragers. Effective arbitragers will be able to identify and help mitigate mispricing throughout the cross-section of stocks. In this paper I test whether short sellers are indeed able to act in this way. I examine this general hypothesis by looking at persistence in short selling profitability.

I examine the persistence in stock level short-selling profitability by using contract level shorting data. I use a panel of daily contract level data that spans six years (September 1999 to August 2005). These data allow me to directly measure the profitability of short-selling contracts both before and after short-selling costs. These data also allow me to construct the returns to short-selling strategies that explicitly takes into account the timing of the initiation of the contract and the closing of the short-selling position.

I do find that short-sellers are profitable on average using an approach that takes into account the exact timing of the opening and closing of short positions. But I also find that this profitability is driven by the set of stocks for which short-sellers previously had strongly profitable outcomes. This persistence in stock level profitability is very strong. I find that if short-selling contracts for a given stock are profitable in the last six months that on average short sellers continue to make profitable trades in that stock in the future. Specifically for stocks with the 30% highest short-selling profitability in the last 6 months raw short-selling profitability for those same stocks in the following month is a statistically significant 2.49% (3.51% on a risk adjusted basis). Some of this profitability is related to price momentum, but even after controlling for momentum in various ways the results remain significant and large in magnitude. Additionally, the persistence in profitability still exists even when using lagged versions of past profitability beyond one year. Finally, when these persistent stocks are removed from the sample, the average return on the short-selling portfolio is no longer significant or large in magnitude. Thus future short-selling profitability is driven by the set of stocks where short-sellers had previously very successful profitable outcomes.

These results suggest that short-sellers have an informational advantage in a largely fixed (or slow moving) set of stocks. Thus, short sellers don't seem to have an informational advantage across the whole cross-section. Nor do they seem to have an informational advantage among the whole cross-section of stocks most likely to experience mispricing (e.g., small/volatile stocks). Thus short-sellers. don't seem to operate as effective arbitragers in a wide cross-section of stocks.

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Table I: Summary Statistics for Short-Sale Contracts

This table presents pooled summary statistics for short-sale contracts. Loan Fee is the interest rate per annum a short-sellers pays to the lender. The rebate rate is the interest rate from the collateral account that is rebated back to the short-seller. The loan fee plus the rebate rate equals that interest rate earned off of the collateral where borrow shares are held. Rebate Rate $< 0\%$ refers to when lender receives all the interest from the collateral account plus additional interest payments from the short-seller. Contract size refer to the number of shares borrowed by the short-seller. Contract length refers to the number of trading day the shares were on loan. Price is the price of the stock sold short on the first day of the short-sale. ME is the market-cap of the stock sold short on the first day of the contract. B/M is lagged book to market ratio computed as in Fama and French (1993). $tv_{-125,-1}$ is the average daily exchange-adjusted share turnover during the previous six months before the start of the contract. $\sigma_{-125,-1}$ is the standard deviation of daily returns (multiplied by 21) during the past six months before the start of the contract. $r_{-5,-1}$ ($r_{-125,-6}$) is the return on the stock sold-short from day $t-5$ ($t-125$) to day $t-1$ ($t-6$) where day t is the first day of the contract. Ptile refers to the percentile where percentiles are computed based on the cross-section of all stocks on a trading day. The percentiles for price, market-cap, and book to market are computed using only NYSE stocks. The time period is September 1, 1999 to August 31, 2005.

	Panel A: Contract Summary Stats (N=286,896)			
	Mean	Median	25 Ptile	75 Ptile
Loan Fee	3.16	2.46	0.16	5.21
Rebate Rate < 0%	0.46	0.00	0.00	1.00
Contract Size ($)	571331.46	57028.49	10125.00	347855.22
Contract Length (days)	55.33	16.00	6.00	52.00
Ptile$_{nyse}$ Price	27.03	14.00	3.00	45.00
Ptile$_{nyse}$ ME	29.26	17.00	5.00	47.00
Ptile$_{nyse}$ B/M	41.63	35.00	9.00	73.00
Ptile $tv_{-125,-1}$	73.99	80.00	61.00	92.00
Ptile $\sigma_{-125,-1}$	64.18	70.00	46.00	86.00
Ptile $r_{-5,-1}$	45.80	42.00	13.00	79.00
Ptile $r_{-125,-6}$	49.90	50.00	18.00	82.00

	Panel B: Estimated Correlations		
	Loan Fee	Contract Size ($)	Contract Length
Loan Fee	1.000	-0.232	0.076
Contract Size ($)	-0.232	1.000	-0.082
Contract Length (days)	0.076	-0.082	1.000

Table II: Contract Level Lending Sample vs Markit Lending Sample

This table presents pooled summary statistics for short-sale contracts. Loan Fee is the interest rate per annum a short-sellers pays to the lender. The rebate rate is the interest rate from the collateral account that is rebated back to the short-seller. The loan fee plus the rebate rate equals that interest rate earned off of the collateral where borrow shares are held. Rebate Rate $< 0\%$ refers to when lender receives all the interest from the collateral account plus additional interest payments from the short-seller. Contract size refer to the number of shares borrowed by the short-seller. Contract length refers to the number of trading day the shares were on loan. Price is the price of the stock sold short on the first day of the short-sale. ME is the market-cap of the stock sold short on the first day of the contract. B/M is lagged book to market ratio computed as in Fama and French (1993). $tv_{-125,-1}$ is the average daily exchange-adjusted share turnover during the previous six months before the start of the contract. $\sigma_{-125,-1}$ is the standard deviation of daily returns (multiplied by 21) during the past six months before the start of the contract. $r_{-5,-1}$ ($r_{-125,-6}$) is the return on the stock sold-short from day $t-5$ ($t-125$) to day $t-1$ ($t-6$) where day t is the first day of the contract. Ptile refers to the percentile where percentiles are computed based on the cross-section of all stocks on a trading day. The percentiles for price, market-cap, and book to market are computed using only NYSE stocks. The time period is September 1, 1999 to August 31, 2005.

	Contract Level Data: Jan 2002 – Aug 2005			
	Loan Fee			
	Mean	Median	25 Ptile	75 Ptile
All stocks	2.78	1.73	0.13	3.76
Micro-cap stocks	4.89	3.45	2.46	6.45
Small-call stocks	1.12	0.18	0.11	1.25
Large-cap stocks	0.23	0.12	0.10	0.15

	Matched Markit Sample: Jan 2002 – Aug 2005			
	Loan Fee			
	Mean	Median	25 Ptile	75 Ptile
All stocks	1.81	0.70	0.15	2.37
Micro-cap stocks	2.92	1.92	0.88	3.78
Small-call stocks	1.03	0.25	0.14	1.00
Large-cap stocks	0.46	0.15	0.10	0.27

Table III: Daily Short-Selling Portfolio Returns (in monthly %)

The table presents excess and abnormal returns for a portfolio of all short-selling contracts. In day $t-1$, I compute the number of shares on loan by our lender for every stock. The weight on a stock in the portfolio is the dollar value of shares sold short (price times shares sold short) divided by the dollar value of all shares on loan by our lender. I then compute the return in day t. Panel A reports portfolio average returns before short-selling costs and panel B reports average returns after short-selling costs (loan fee). I report portfolio returns using a series of benchmark portfolios (the benchmark portfolio represents the long position). First, I benchmark relative to the riskfree rate ($r_f - r_p$). The daily riskfree rate is the daily rate that, over the number of trading days in the month, compounds to the 1-month t-bill rate. Second, I benchmark relative the the CRSP value-weight stock index ($r_M - r_f$). Third, I use size benchmark portfolios (r_{ME}): 10 value-weight size portfolios. Lastly, I use size-book to market benchmark portfolios ($r_{ME,B/M}$): 25 value-weight size-B/M portfolios. In Panel C I regress $r_f - r_p$ on the three and four factor models:

$$r_f - r_p = a_p + b_p(r_M - r_f) + s_p(SMB) + h_p(HML) + e_p$$
$$r_f - r_p = a_p + b_p(r_M - r_f) + s_p(SMB) + h_p(HML) + u_p(UMD) + e_p,$$

SMB is the return on size factor, HML is the return on the value factor, and UMD is the return on the momentum factor. All returns are in percent and multiplied by 21 to make them comparable to monthly returns. T-statistics are computed with a Newey-West lag of 1 and are in parentheses. The time period is September 7, 1999 to August 31, 2005.

Panel A: *Before* Short-Sale Costs Portfolio Returns					
	$\frac{Stocks}{Day}$	$r_f - r_p$	$r_M - r_p$	$r_{ME} - r_p$	$r_{ME,B/M} - r_p$
Mean	456	0.38	0.45	1.23	1.32
		(0.42)	(0.83)	(3.12)	(3.21)

Panel B: *After* Short-Sale Costs Portfolio Returns					
	$\frac{Stocks}{Day}$	$r_f - r_p$	$r_M - r_p$	$r_{ME} - r_p$	$r_{ME,B/M} - r_p$
Mean	456	0.23	0.30	1.08	1.17
		(0.26)	(0.56)	(2.75)	(2.86)

Panel C: Three and Four Factor Model Regressions							
dep var	Cost	a	b	s	h	u	R^2
$r_f - r_p$	Before	1.32	-1.13	-0.81	-0.31		0.75
		(2.91)	(-48.96)	(-22.68)	(-6.28)		
$r_f - r_p$	After	1.18	-1.13	-0.81	-0.31		0.75
		(2.59)	(-49.01)	(-22.70)	(-6.28)		
$r_f - r_p$	Before	1.26	-1.12	-0.86	-0.34	0.12	0.75
		(2.79)	(-45.01)	(-21.69)	(-7.11)	(3.31)	
$r_f - r_p$	After	1.11	-1.12	-0.86	-0.34	0.12	0.75
		(2.47)	(-45.05)	(-21.70)	(-7.12)	(3.30)	

Table IV: Daily Short-Selling Portfolios (% per month) by Contract and Stock Characteristics

The table present excess and abnormal returns for daily short-selling portfolios for large contracts, micro-cap stocks, and beginning of contract loan fee greater than 1%. In day $t-1$, I compute the number of shares on loan by our lender for every stock in CRSP. The weight on a stock in the portfolio is the dollar value of shares sold short (price time shares sold short) divided by the dollar value of all shares on loan by our lender in the respective contract size (dollar value of shares sold short) quartile. I form a portfolio for large contract only where large contracts are contracts in the top 30%. I also form a portfolio using only contracts where the loan fee at the start of the contract are greater than 1%. Finally, I form a portfolio using only micro-cap stocks where micro-cap is defined as stocks in the small quartile (NYSE breakpoints) based date. The benchmark portfolios are the riskfree rate and size-B/M portfolios (25 value-weight size-B/M portfolios). All returns are in percent and multiplied by 21 to make them comparable to monthly returns. T-statistics are computed with a Newey-West lag of 1, and are in parentheses. The time period is September 7, 1999 to August 31, 2005.

	Before Cost		After Costs	
	$r_f - r_p$	$r_{ME/BM} - r_p$	$r_f - r_p$	$r_{ME/BM} - r_p$
All	1.89	1.89	1.89	1.17
	(3.20)	(3.20)	(3.20)	(2.86)
Large Contracts	0.40	1.20	0.26	1.18
	(0.44	(2.79)	(0.29)	(2.80)
$Fee > 1\%$	0.79	1.96	0.42	1.59
	(0.90)	(3.82)	(0.47)	(3.09)
Micro-Cap	0.82	2.18	0.56	1.92
	(0.81)	(3.75)	(0.56)	(3.30)
Micro-Cap and Large Contracts	0.99	2.23	0.60	1.84
	(0.98)	(3.15)	(0.60)	(2.60)
Micro-Cap and $Fee > 1\%$	1.73	3.31	1.02	2.60
	(1.27)	(2.84)	(0.75)	(2.23)

Table V: Stock Level Summary Statistics for Shorting Performance Measures

This table presents pooled summary statistics for stock level variables measure short-selling performance in a stock. $shortret_{-6,-1}$ (past six-month shorting performance) is the share-weighted average of the cumulative return of all contracts that ended between month $t-6$ to $t-1$ and $count_{-6,-1}$ is the number of contracts with positive cumulative returns minus the number with negative cumulative minus the median count for the same NYSE market-cap quintile. The largest three market-cap quintiles are grouped together because relatively few larger-cap stocks are covered at the beginning of the sample. Number of contracts is refers to the number of active contracts at the end of the month in a given stock. The time period is September 1, 1999 to August 31, 2005.

	Mean	Median	25 Ptile	75 Ptile
$shortret_{-6,-1}$	2.87	0.25	-3.17	5.57
$count_{-6,-1}$	0.83	0.00	-5.00	5.00
Number of Contracts	7.60	4.00	2.00	9.00

Table VI: Daily Short-Selling Portfolios (in %) by Past Shorting Profitability

The table presents excess and abnormal returns for short-selling portfolios disaggregated by past stock level short-selling profitability. I measure past stock level short-selling profitability ($shortret_{t-6,t-1}$) as the share-weighted average of the cumulative return of all contracts that end in the last six months. In day $t-1$, we compute the number of shares on loan by our lender for every stock. The weight on a stock in the portfolio is the dollar value of shares sold short (price times shares sold short) divided by the dollar value of all shares on loan by our lender. I then compute the return in day t. The benchmark portfolios are the riskfree rate and size-B/M portfolios (25 value-weight size-B/M portfolios). The time period is September 7, 1999 to August 31, 2005.

	Panel A: Returns to shorting contracts			
	Before Cost		After Costs	
	$r_f - r_p$	$r_{ME/BM} - r_p$	$r_f - r_p$	$r_{ME/BM} - r_p$
Low	-0.14	0.97	-0.30	0.81
	(-0.13)	(1.70)	(-0.28)	(1.42)
Middle	-0.30	0.51	-0.43	0.37
	(-0.29)	(0.83)	(-0.42)	(0.61)
High	2.49	3.53	2.28	3.32
	(2.06)	(3.97)	(1.89)	(3.74)
High - Low	2.62	2.56	2.42	2.35
	(2.50)	(2.51)	(2.30)	(2.31)

Table VII: Simple 1-Month Holding Portfolios formed on based Past Shorting Profitability

The table presents excess and abnormal returns for short-selling portfolios disaggregated by past stock level short-selling profitability. I measure past stock level short-selling profitability ($shortret_{t-6,t-1}$) as the share-weighted average of the cumulative return of all contracts that end in the last six months. I form portfolios that simply short the stocks for the entire month in an equal-weight portfolio instead. The benchmark portfolios are the riskfree rate and size-B/M portfolios (25 value-weight size-B/M portfolios). The time period is September 7, 1999 to August 31, 2005.

	$r_f - r_p$	$r_{ME,B/M} - r_p$
Low	-0.68	0.35
	(-0.67)	(0.57)
Middle	0.30	1.21
	(0.27)	(1.67)
High	0.14	1.29
	(0.11)	(1.43)
High - Low	0.82	0.94
	(0.79)	(0.93)

Table VIII: Monthly Regressions of Future Returns to Short Selling and Past shorting Performance

The table regresses stock level returns to short-selling contracts in month t on past stock level short-selling profitability and stock level control variables. $shortret_t$ is the share-weighted average of the cumulative returns of all shorting contracts that begin in month t for a given stock and $count_t$ is the number of contracts with positive cumulative returns minus the number with negative cumulative minus the median count for the same NYSE market-cap quintile (the largest three market-cap quintiles are grouped together). $shortret_{t-6,-t1}$ (past six months profitability) the share-weighted average of the cumulative return of all contracts that ended between month $t-6$ to $t-1$ and $count_{t-6,t-1}$ is the number of contracts with positive cumulative returns minus the number with negative cumulative minus the median count for the same NYSE market-cap quintile. $high_{shortret(t-6,t-1)}$ ($high_{count(t-6,t-1)}$ is a dummy variable that equals 1 if a stock is greater than the 70th $shortret_{t-6,t-1}$ ($count_{t-6,t-1}$) percentile in a given month. ME is market-cap from the end of month t-1. B/M is the book to market ratio computed as in Fama and French (1993). r_{-1} is last month's return. $r_{t-12,-t2}$ is the return from month $t-12$ to $t-2$. $instown$ is institutional ownership measured as a percentage of shares outstanding lagged one quarter. tv is the average daily exchange-adjusted share turnover during the previous 12 months. σ is the standard deviation of daily returns (multiplied by 21) during the past twelve months. The sample includes all stocks on CRSP with share code equal to 10 or 11 and with lending activity sometime in the past 6 months. The time period is October, 1999 to August, 2005. T-statistics are in parenthesis, and 1% and 5% statistical significance are indicated with ** and and *, respectively.

	Dep Var: $shortret_t$					Dep Var: $count_t$	
$shortret_{t-6,t-1}$	0.080**	0.041**					
	(6.60)	(3.06)					
$high_{shortret(t-6,t-1)}$			3.123**	1.028**	1.226**		
			(8.52)	(2.66)	(3.15)		
$count_{t-6,t-1}$						0.015**	
						(2.97)	
$high_{count(t-6,t-1)}$							0.140
							(1.08)
r_{-1}		-0.023**		-0.023**	-0.025**	-0.004	-0.005*
		(-2.73)		(-2.68)	(-2.95)	(-1.71)	(-2.05)
$r_{-6,-2}$		-0.026**		-0.029**	-0.029**	-0.005**	-0.007**
		(-5.40)		(-6.29)	(-6.25)	(-3.12)	(-4.28)
$\log(ME)$		0.398**			0.413**	0.055	0.050
		(4.71)			(4.84)	(1.87)	(1.73)
$\log(B/M)$		-0.514**			-0.481*	-0.035	-0.029
		(-2.71)			(-2.54)	(-0.53)	(-0.45)
$instown$		-0.044**		-0.034**	-0.044**	-0.015**	-0.015**
		(-6.97)		(-5.33)	(-6.91)	(-6.06)	(-6.32)
tv		0.416**		0.446**	0.388**	0.052	0.042
		(3.86)		(4.15)	(3.63)	(1.50)	(1.21)
σ		0.143**		0.114**	0.147**	0.033**	0.034**
		(6.24)		(5.50)	(6.37)	(5.28)	(5.53)
Monthly Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
SE Clustered by Month	Yes	Yes	Yes	Yes	Yes	Yes	Yes
SE Clustered by Stock	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table IX: Monthly Regressions of Future Shorting Performance on Past shorting Performance

The table regresses stock level returns to short-selling contracts in month t on past stock level short-selling profitability and stock level control variables. $shortret_t$ is the share-weighted average of the cumulative returns of all shorting contracts that begin in month t for a given stock $shortret_{-6,-1}$ the share-weighted average of the cumulative return of all contracts that ended between month $t-6$ to $t-1$. $high_{shortret(t-6,t-1)}$ is a dummy variable that equals 1 if a stock is greater than the 70th $shortret_{t-6,t-1}$ percentile in a given month. Controls are ME, B/M, r_{-1}, $r_{t-12,-t2}$, $instown$, tv and σ (see Table VIII).The sample includes all stocks on CRSP with share code equal to 10 or 11 and with lending activity sometime in the past 6 months. The regressions include calendar month dummies and the standard errors take into account clustering by both calendar date and clustering by stock (Thompson (2006)). The time period is October, 1999 to August, 2005. T-statistics are in parenthesis, and 1% and 5% statistical significance are indicated with ** and and *, respectively.

	Panel A: No Controls, dep Var $= shortret_t$						
$high_{shortret(-6,-1)}$	3.123**						
	(8.52)						
$high_{shortret(-7,-2)}$		2.721**					
		(7.51)					
$high_{shortret(-8,-3)}$			2.320**				
			(6.52)				
$high_{shortret(-9,-4)}$				2.399**			
				(6.64)			
$high_{shortret(-10,-5)}$					2.072**		
					(5.76)		
$high_{shortret(-15,-10)}$						0.872**	
						(2.63)	
$high_{shortret(-17,-12)}$							0.980**
							(2.97)

	Panel B: With Control Variables, dep Var $= shortret_t$						
$high_{shortret(-6,-1)}$	1.226**						
	(3.15)						
$high_{shortret(-7,-2)}$		0.987**					
		(2.60)					
$high_{shortret(-8,-3)}$			0.772*				
			(2.13)				
$high_{shortret(-9,-4)}$				1.089**			
				(2.98)			
$high_{shortret(-10,-5)}$					0.992**		
					(2.76)		
$high_{shortret(-15,-10)}$						0.590	
						(1.81)	
$high_{shortret(-17,-12)}$							0.780*
							(2.40)

Table X
Linear Probability Model: Persistence and Stock Characteristics

I regress persistence in short-selling profitability ($persistent$) on past stock characteristics. I define a stock as persistent if $shortret_{t-6,t-1}$ is in the top 30% and $shortret_t$ is in the top 30% by month non-persistent if the stock is in top 30% of $shortret_{t-6,t-1}$ but the bottom 70% of $shortret_t$. $shortret_t$ is the share-weighted average of the cumulative returns of all shorting contracts that start in month t and $shortret_{t-6,-t1}$ is the share-weighted average of the cumulative returns of all contracts that end between month $t-6$ to $t-1$. ME is market-cap from the end of month $t-1$. B/M is the book to market ratio computed as in Fama and French (1993). r_{-1} is last month's return. $r_{t-6,-t-2}$ is the return from month $t-6$ to $t-2$. $instown$ is institutional ownership lagged one quarter. tv is the average daily exchange-adjusted share turnover during the previous 6 months. σ is the standard deviation of daily returns (multiplied by 21) during the past 6 months. $analyst$ is the number of analyst that covered a stock in month $t-1$. I split stocks in small/large ($instown_{low}/instown_{high}$) based on 30% and 70% market-cap ($instown$) percentiles for all NYSE stocks on CRSP every month. I split stocks in tv_{low} and tv_{high} ($\sigma_{low}/\sigma_{high}$ or $analyst_{low}/analyst_{high}$) based on 30% and 70% tv (σ and $analyst$) percentiles for all stocks on CRSP every month. The regressions include calendar month dummies and the standard errors take into account clustering by both calendar date and clustering by stock (Thompson (2006)). The time period is October, 1999 to August, 2005. T-statistics are in parenthesis.

	dep var: $persistent$					
r_{t-1}	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000
	(-0.98)	(-1.29)	(-0.88)	(-1.00)	(-0.82)	(-0.32)
$r_{t-6,t-2}$	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001
	(-4.18)	(-4.74)	(-4.01)	(-4.14)	(-4.17)	(-4.32)
log(ME)	-0.015		-0.016	-0.014	-0.007	-0.026
	(-2.11)		(-2.26)	(-2.02)	(-0.94)	(-3.84)
$log(B/M)$	-0.013	-0.010	-0.014	-0.013	-0.009	-0.013
	(-2.05)	(-1.69)	(-2.28)	(-2.04)	(-1.43)	(-1.97)
$instown$	-0.001	-0.001		-0.001	-0.001	-0.001
	(-3.28)	(-3.28)		(-3.50)	(-3.06)	(-3.94)
tv	0.009	0.008	0.009		0.007	0.014
	(2.35)	(2.11)	(2.49)		(2.21)	(4.10)
σ	0.003	0.003	0.003	0.003		
	(3.80)	(4.11)	(3.72)	(4.50)		
$analyst$	-0.017	-0.019	-0.019	-0.018	-0.019	
	(-1.33)	(-1.73)	(-1.52)	(-1.49)	(-1.56)	
$small$		0.037				
		(1.63)				
$large$		-0.040				
		(-1.58)				
$instown_{low}$			0.021			
			(1.07)			
$instown_{high}$			-0.050			
			(-2.62)			
tv_{low}				-0.000		
				(-0.01)		
tv_{high}				0.041		
				(2.55)		
σ_{low}					-0.080	
					(-4.57)	
σ_{high}					0.086	
					(5.91)	
$analyst_{low}$						0.017
						(0.86)
$analyst_{high}$						-0.012
						(-0.59)
Observations	8,523	8,523	8,523	8,523	8,523	8,523
Monthly Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
SE Clustered by Month	Yes	Yes	Yes	Yes	Yes	Yes
SE Clustered by Stock	Yes	Yes	Yes	Yes	Yes	Yes