The Role of Fundamental Analysis in Information Arbitrage: Evidence from Short Seller Recommendations

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Abstract

We examine whether information arbitrageurs attempt to exploit the return predictability in valuation and fundamental signals. Using a unique database of short sell recommendations, we document that firm fundamentals, such as magnitude of accruals, sales growth, gross margin, and SG&A expenses, and valuation indicators, such as book-to-market ratio and return momentum, contain valuable information correlated with the trading behavior of short sellers. We show that our empirical model explaining short seller recommendations is successful in predicting both short interest and future returns for a broader sample in an *out-of-sample* period. We present an important application of the model in distinguishing between valuation and arbitrage motivated short selling. Overall, these findings present additional insights into the decision process of short sellers and validate the importance of fundamental analysis in the information arbitrage process.

Keywords: Information arbitrage; short selling, fundamental analysis, stock returns.

A significant body of research has shown that various valuation and financial statement indicators predict subsequent returns. For example, Lakonishok, Shleifer and Vishny (1994) find that valuation multiples, such as P/E ratio and B/M ratio, predict future returns. Sloan (1996) documents a strong association between accruals and future returns. Abarbanell and Bushee (1997, 1998) document that information contained in fundamental variables is related to both future earnings and returns.[1] These studies argue that investors can earn "abnormal" returns by trading on various signals of financial performance, as the market fails to fully incorporate the information in historical financial data into prices in a timely manner. Although the evidence on return predictability is strong, there is little *direct* evidence on whether information arbitrageurs attempt to exploit such predictability. In this study, we examine a unique database of short seller recommendations to better understand the trading strategies of information arbitrageurs.

A *direct* examination of the trading behavior of information arbitrageurs is important because there is significant debate in the literature on the interpretation of return predictability.[2] One set of studies suggests that return predictability tends to be exaggerated due to data errors and biased methodologies (Kothari (2001), Kraft et al. (2006)). Another set of papers has attempted to reconcile the predictable return behavior within a risk based framework (Fama and French (1995), Francis et al. (2005)). A third set of papers argues that return predictability is difficult to exploit as it is confined to stocks where arbitrage is costly and risky (Ali et al. (2003), Mashruwala et al. (2006)). To the extent that return predictability can be fully explained by methodological biases, risk, or market frictions, we expect to see no systematic relation between the trading behavior of information arbitrageurs and the information contained in fundamental

[1] Among related work, Lev and Thiagarajan (1993) show that financial statement ratios are related to contemporaneous returns. Piotroski (2000), Mohanram (2005) and Beneish et al. (2001) document that fundamental analysis can help separate winners and losers among value stocks, growth stocks, and among the subset of extreme performers, respectively.

[2] Lee (2001) defines information arbitrage as trading aimed at exploiting market imperfections.

signals. On the other hand, a finding that information arbitrageurs attempt to exploit the return predictability in fundamental signals would provide new insights about the information arbitrage process and about how price efficiency is maintained in financial markets.

We focus on short sellers as representing an important group of information arbitrageurs for two reasons. First, earlier studies examining trading strategies based on valuation or fundamental signals have found that a large fraction of total abnormal returns is earned on the short positions in the hedge portfolio. For example, results in Beneish and Vargus (2002) suggest that the returns to the accruals anomaly are due to overpricing of income-increasing accruals. Second, and more importantly, extant theoretical and empirical literature supports the notion that short sellers play an important role in the information arbitrage process. Theoretical models predict that short sellers tend to be informed traders, as short selling costs disproportionately discourage liquidity traders from selling short (Diamond and Verrecchia (1987)). In support of theoretical predictions, prior empirical research documents that heavily shorted firms subsequently exhibit poor performance.[3] Yet, despite their characterization as informed arbitrageurs, we know relatively little about their trading behavior, mainly due to lack of publicly available data on short sellers' recommendations or holdings.

A few studies in the literature have examined the characteristics of firms with high reported short interest; the motivation being that reported short interest proxies for short selling demand from informed traders targeting overvalued securities. These studies find that short interest is related to valuation multiples, such as book-to-market ratio (Dechow et al. (2001)), accruals (Desai et al. (2006), Hirshleifer et al. (2005)), post-earnings announcement drift (Cao et

[3] Asquith and Meulbroek (1995), Desai, Ramesh, Thiagarajan and Balachandran (2002), Christophe, Ferri and Angel (2004), Boehmer, Jones and Zhang (2007), and Diether, Lee and Werner (2005), among others, document a negative association between short interest and future returns. Dechow, Hutton, Meulbroek, and Sloan (2001) discuss the various legal and institutional constraints related to short selling.

al. (2007)) and firm liquidity (D'Avolio (2002)). However, the reported short interest in the U.S. aggregates the demand for short selling that is motivated by a pessimistic opinion on firm valuation (valuation shorts) and various arbitrage or hedging strategies (arbitrage shorts).[4] In a recent study, Asquith et al. (2005) argue that the reported short interest is an imprecise proxy for the short selling demand from information arbitrageurs, especially in recent years, due to the increasing use of various "market neutral" trading strategies by institutional investors.[5]

Our study is distinguished from prior work on short seller behavior partly because we examine the information content of a much broader set of fundamental signals for short sellers, but mainly because we provide *direct* evidence on the trading behavior of information arbitrageurs by examining a unique database of short sell recommendations. Furthermore, while prior research has shown that valuation and fundamental variables predict returns, our study furthers these analyses by documenting that information arbitrageurs attempt to exploit this predictability. Such a finding not only enhances our understanding of the information arbitrage process but also highlights the role of fundamental analysis in price formation.

The *short database* includes *every* recommendation issued by an independent research firm for its institutional clients since its inception in 1998 until June 2005. Importantly, these recommendations are only motivated by a perceived overvaluation of the firm's stock and are unrelated to arbitrage strategies, thus providing a more precise signal of valuation-motivated shorting than aggregate short interest. Consistent with this reasoning, we find that firms in the

[4] Examples of hedging or arbitrage related short selling include short positions undertaken by convertible arbitrageurs who typically long the convertible bond and short the underlying stock, or by merger arbitrageurs who long the target and short the acquirer in stock-for-stock mergers, or by index arbitrageurs who assume long-short positions based on pricing discrepancies between the index futures (or ETFs) and the component stocks. Mitchell, Pulvino, and Stafford (2004) conclude that, for firms with pending mergers or convertible bonds outstanding, the short sales due to arbitrage activities is likely to be much larger than valuation motivated shorts. Boehmer, Jones, and Zhang (2007) examine a proprietary system order dataset for NYSE stocks and report that over 25% of the total short sale daily volume in a stock can be attributed to program trading.

[5] During the time period covered by our study (1990-2004), the total number of hedge funds has increased from 610 to 7,436 and the assets under management from $39 billion to $972 billion (Agarwal and Naik (2005)).

short database experience mean raw return (market-adjusted return) of -4.03% (-4.89%) in the month when the short report was issued and –9.71% (-15.02%) in the subsequent 12 months. We document that the sample firms report a disproportionately large number of negative news events during the subsequent 12 months – the most common being reporting lower than expected earnings, lowering guidance on future earnings / sales, and analyst downgrades. These findings suggest that the short recommendations are on average informative about future performance.

Based on the short database, we build a parsimonious model that predicts short recommendations using context-specific financial performance measures. The short sellers' primary motive lies in identifying firms that are expected to perform poorly. Prior research on short seller behavior has focused primarily on signals generated by valuation ratios and accruals. We expand the set of explanatory variables by integrating evidence from both the accounting and finance literatures and examine the incremental explanatory power of each variable on short seller behavior. Given prior evidence that short sellers are sensitive to earnings quality, we include financial statement variables that are identified by Beneish (1999) as being related to earnings manipulation. We also examine the importance of valuation multiples (Dechow et al. (2001)) and firm liquidity in identifying promising candidates for short selling.

The logistic regression analysis, estimated over the sample period 1997-2004, indicates that accounting information, especially indicators of earnings quality, plays a critical role in predicting short recommendations. Short sellers are more likely to target firms with high accruals that have also experienced large increases in sales, SG&A expenses, and gross profit margin. These findings are intuitive, as a significant growth in sales and gross margin, coupled with high accruals, may signal that earnings growth is not sustainable. Our results also suggest that short recommendations target firms with low book-to-market ratio and high one-year return

momentum, suggesting that short sellers tend to be contrarians, betting that the strong past performance of targeted firms will revert quickly. Finally, consistent with short sellers' preference for liquid securities to minimize short squeeze risk, we find that short recommendations tend to be in relatively liquid stocks. Overall, these findings suggest that the return predictability associated with fundamental signals represents an economically meaningful opportunity that informed arbitrageurs attempt to exploit. Thus, our examination of short seller recommendations documents a direct link between the literature on the predictive ability of fundamental signals and the literature on the trading strategies of information arbitrageurs.

We validate the short recommendation model by examining both short interest and future returns in an *out-of-sample* period (1990-1996). Specifically, we sort firms into decile portfolios constructed each year based on the predicted probability from the estimated model. We observe a monotonic trend in short interest across decile portfolios, increasing from about 0.5% for firms in the lowest decile to over 3.2% for firms in the highest decile. This finding is particularly noteworthy, as the model does not include short interest as an explanatory variable. Yet, the model is able to predict short interest in an *out-of-sample* period. A monotonic pattern is also observed for average monthly abnormal returns. The intercept from a regression of monthly portfolio returns on the Fama-French factors decreases from 1.3% for firms in the lowest decile to about –0.80% for firms in the highest decile. These abnormal returns are both economically large and statistically significant. Thus, although the short recommendation model is developed from a small set of potential short targets identified by a single research firm, the model is successful in forecasting both short interest and future returns for a broader sample in an *out-of-sample* period.[6] Importantly, these findings validate the importance of accounting-based signals

[6] As far as we are aware, no publicly available data set exists with broad coverage on short recommendations or holdings of short sellers. Because the research firm examined here faces time and resource constraints, we expect

for a broad group of information arbitrageurs and suggests that the selection criteria is correlated across short sellers and, to some extent, constant across time.

The short interest model can help design better empirical tests in many different settings. As an application, we present an approach to distinguish between valuation shorts, which are bearish bets undertaken by information arbitrageurs, and arbitrage shorts, which are motivated by various hedging strategies. Specifically, we retain firms in the highest decile portfolio based on aggregate short interest and sort them into three groups (30%, 40%, and 30%) based on the predicted probability from the model. Intuitively, this categorization identifies firms with high short interest and high predicted probability as valuation shorts and firms with high short interest but low predicted probability as arbitrage shorts. Consistent with this categorization, the average monthly abnormal return for firms identified as valuation shorts is negative and highly significant. In contrast, firms identified as arbitrage shorts exhibit no abnormal returns. Moreover, firms identified as arbitrage shorts have *high* book-to-market ratios (value firms), high percentage with convertible bonds outstanding, and high percentage with membership in the S&P 500 index, suggesting that short selling in these firms is motivated by arbitrage reasons. On the other hand, firms identified by the model as valuation shorts exhibit low book-to-market ratios (glamour firms), lower percentage with convertible bonds outstanding, and have fewer firms included in the S&P 500 index. The latter finding is quite striking, as neither convertible bonds nor index membership are included as explanatory variables in the model. Consistent with theoretical predictions, the incremental forecasting power of short interest with respect to future returns is significantly higher when valuation shorts are distinguished from arbitrage shorts. Thus, we illustrate the usefulness of conducting fundamental analysis in context.

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that many firms that are suitable targets for short selling are not identified as such in our database, thus reducing the predictive power of the short interest model. Despite this limitation, we find that the model can predict both short interest and future returns for a broad sample in an out-of-sample period.

The rest of the paper proceeds as follows. Section I briefly discusses related literature and the hypotheses. Details about the data, summary statistics, and methodology are provided in Section II. Section III presents the logistic model and describes the out-of-sample findings and robustness tests. The application pertaining to distinguishing information shorts from arbitrage shorts is described in Section IV. The conclusions are presented in Section V.

I. Prior Literature and Hypotheses

In this section, we briefly summarize the related literature on short selling and develop the hypotheses that underlie the empirical tests that follow.

A. The Literature on Short Selling

Prior empirical work broadly supports Miller's (1977) prediction that stock prices could be biased upward when short constraints exist and investor's beliefs about security value are widely dispersed (see, for example, Boehme, Danielson and Sorescu (2006), Chen, Hong and Stein (2002), Jones and Lamont (2002), Nagel (2005), among others). Extant empirical evidence also supports Diamond and Verrecchia's (1987) prediction that short sellers are informed traders (see, for example, Senchack and Starks (1993) and Arnold, Butler, Crack, and Zhang (2005)). Several papers (see footnote 2) document that heavily shorted firms subsequently experience poor returns. Along similar lines, Francis, Venkatachalam, and Zhang (2005) find that downward revisions in analysts' forecasts are more severe for firms with high unexpected short interest.

Researchers have also examined the characteristics of firms with high reported short interest. Dechow, Hutton, Meulbroek and Sloan (2001) document that firms with high short interest trade at high multiples of price-to-fundamentals ratios. Desai, Krishnamurthy and Venkataraman (2006) find that short sellers increase positions in firms that subsequently restate

earnings and, in particular, target restating firms with high accruals, suggesting that short sellers are sensitive to earnings quality. Hishleifer, Teoh and Yu (2005) and Cao, Dhaliwal and Kolasinski (2007) provide evidence suggesting that short sellers assume positions based on accounting anomalies, including the post earnings announcement drift. Another strand of research has examined the lending rates for stock loans, based on proprietary databases. These studies conclude that short sellers have difficulty in borrowing smaller, less liquid securities, with low institutional ownership (D'Avolio (2002) and Geczy et al. (2002)).

In an attempt to discriminate between valuation and arbitrage shorts, Asquith et al. (2005) classify high short interest in firms with convertible bonds outstanding as being arbitrage motivated and the high short interest in the remaining firms as being valuation motivated. During the time period covered by our study (1990-2004), firms with convertible bonds outstanding comprised only about 20% of firm-years (excluding financials and firms in regulated industries) on Compustat. Clearly, short interest in many firms with no convertible bonds would be arbitrage motivated, and vice-versa, as acknowledged by Asquith et al. (2005), who encourage researchers to develop better approaches to addressing the problem. In a recent study, Boehmer, Jones and Zhang (2007) examine a proprietary system order dataset for NYSE stocks that distinguishes between institutional and proprietary short sales that were part of a program trade. They document that short selling that were not part of a program trade are informative about future returns, but short selling associated with program trade are not, emphasizing once again the importance of disentangling the components of short interest.

B. Hypotheses Development

Our objective is to better understand the trading strategies of short sellers, and in particular, examine whether short sellers attempt to exploit the return predictability of valuation

and financial variables. Thus, we hypothesize that short sellers use fundamental (accounting based) information to identify target firms. If the short recommendation model based on short recommendations from a single research firm sufficiently describes the selection criteria of the broader group of valuation shorts, the model should forecast both short interest and future returns in an *out-of-sample* period. Finally, we examine if the model can distinguish between valuation and arbitrage shorts. Firms identified as valuation shorts should experience poor subsequent returns. In contrast, firms identified as arbitrage shorts should not experience poor returns but instead should exhibit characteristics associated with arbitrage strategies, such as index membership and convertible bonds. These arguments can be summarized as follows:

H1: Short sellers use fundamental (accounting based) variables to identify target firms.

H2: The short recommendation model should forecast both short interest and abnormal returns in an out-of-sample period.

H3: Controlling for short interest, which aggregates both valuation and arbitrage shorts, we expect that (a) firms identified as valuation shorts should experience negative abnormal returns, and (b) firms identified as arbitrage shorts should exhibit characteristics that are associated with arbitrage strategies.

II. Data and Methodology

A. Sample Selection

We obtain the data for the study from an independent research firm. At periodic intervals, the firm alerts its subscribing clients about potential short targets via a detailed research report. The first report was issued in September 1998 and the last report available to us was issued in June 2005. The firm issues about 8-10 reports a year. While the firm assimilates information from many sources, we were informed that they primarily rely on their own analysis and avoid conventional Wall Street sources such as brokerage analyst reports, conference calls, discussions with corporate executives, etc. The primary objective of the report is to identify a promising

short target and to present arguments detailing why the prior performance of the identified firm is not sustainable and is likely to reverse significantly. The recommendations reflect the research firm's proprietary technology to synthesize information contained in publicly observable variables regarding future performance. These recommendations are clearly motivated by fundamental reasons and are unrelated to arbitrage or hedging strategies. Each report begins with a brief history and description of the firm and its business, followed by an analysis of the firm's financials, the firm's and the industry's growth potential, and the competitive environment in which the firm operates. Often the report will question the use of aggressive accounting practices. The report also tracks insider sales and at times questions the firm's governance.

The initial sample in the short database consists of 67 firms identified in the reports during 1998-2005 as promising short candidates. The targeted firms experienced significant price increases during the year prior to the issuance of the short report. The mean buy and hold return is 77.9%, and the mean market-adjusted return is 72.4% (Table I, Panel A). Interestingly, the sample firms experienced sharp reversals in their stock market performance after the issuance of the report. In the month in which the report is issued (month 0), the average market-adjusted return is -4.89% (t-statistic of -2.50). The performance continues to decline in the 12 month period after the issuance of the report and the sample firms underperformed the market, on average, by 15.0% (t-statistic of -2.18). Even the mean and median raw returns of the sample firms are negative over the subsequent 12 months (-9.71% and -18.32%, respectively).[7]

To better understand the reasons for poor stock market performance, we searched for

[7] It is important to note that the reported annualized returns are only indicative, as they reflect a naïve strategy of assuming short positions in each stock for one year. In reality, holding period for each stock would depend both on the stock's performance and on investor idiosyncrasies. For example, short sellers may quickly cover positions when a stock experiences a significant drop in price shortly after report issuance. Or, a sharp increase in stock price might force some short sellers without deep pockets to cover at a loss before their expectations are realized. Finally, some positions may remain open for a period greater than one year. Our conversations with valuation motivated short sellers suggests that holding periods greater than one year are not unusual.

significant negative news events for sample firms in *Factiva* during the 12 months period after the issuance of the report. Panel B of Table I summarizes the findings. Of the 67 sample firms, we could identify some form of 'bad news' events for 42 firms. The most frequent negative news related to 'reported lower than expected earnings' (24 events), 'analyst downgrades' (23 events), and 'lowered guidance on future earnings / sales' (20 events). Eight sample firms came under some form of regulatory scrutiny and news reports for seven firms identified accounting concerns. Not surprisingly, some firms had multiple types of bad news events. For example, Rite Aid Corp, identified in a short report on November 13 1998, reported (1) on March 12, 1999, that earnings will miss analysts' estimates, (2) on March 13, 1999 that its accounting practices are under review by federal regulators, and (3) on June 1, 1999, that it is restating the last three years of earnings. During the one-year period after the issuance of the report, Rite Aid Corp's stock price dropped by 83%.

At the same time, we could identify no significant negative news for 25 of the 67 firms in the short database. Indeed, some firms in the short database performed spectacularly well during the subsequent 12 months. For example, Extended Stay America, identified in a short report on December 18, 2003, was acquired by the Blackstone Group at a significant (24%) premium, in March 2004, resulting in price run-up of 54% subsequent to report issuance. Thus, it is clear that the research firm is not successful in identifying poor performers at all times. However, on average, the firms in the short database experienced a significant reversal in their fortunes subsequent to report issuance and exhibited a disproportionate share of negative news events, mainly related to fundamental variables. These findings suggest that the short database

represents an appropriate sample for modeling the behavior of informed short sellers.[8]

In the empirical analysis, we exclude (a) two firms that appeared more than once in the database, retaining only the first occurrence, (b) seven firms in the Financials (SIC 6000-6999), Utilities (SIC 4900-4999) or Communications (SIC 4800-4899) industries, and (c) four firms with insufficient data on CRSP and Compustat in the year prior to being listed in the short database. After these screens, the short database contains 54 firms.[9] In selecting control firms, we retain all firms with Compustat data since 1990 and exclude firms (a) with sales or total assets less than or equal to $1 million, (b) with a positive ADR ratio (Compustat annual data item #234), and (c) in the financial, communications, and utilities industry, thus yielding 87,716 firm-year observations. We retain firms if CRSP data is available, thus eliminating Compustat observations that relate to non-public firms and subsidiaries. The CRSP screen reduces the sample to 66,022 firm-year observations.

Since the short database covers the period 1998-2005, we classify the eight-year period 1997-2004 as the estimation period (35,143 observations) and the seven-year period 1990-1996 as the *out-of-sample* prediction period (30,879). In the estimation period, we retain one firm-year for each sample firm, corresponding to the fiscal year preceding the date when the firm was identified in the short database, eliminating 295 observations for sample firms in other years. The remaining firm-year observations are classified as control firms. Thus, the estimation period data consists of 54 firm-years for sample firms and 34,794 firm-years for control firms. For the out of sample prediction period, a similar selection procedure leaves us with 30,879 firm-year observations. Since not all firm-years will have the necessary data for all variables used in the

[8]An alternate approach to would be to use analysts' sell recommendations to model poorly performing firms. However, our objective is not just to model poorly performing firms but also to shed light on the decision process of short sellers which motivates our decision to focus on the database of short recommendations.

[9] Some variables, such as operating and total accruals, cannot be computed meaningfully for financial firms. Firms in two-digit SIC codes 48 and 49 were excluded as these represent regulated industries.

regression analysis, the actual number of observations varies depending upon data availability.

B. Model

The short recommendation model is estimated using 54 firm-years as sample observations and 34,794 firm-years as control observations. Our approach takes annual snapshots of the financial information for the cohort of sample and control firms every September during the estimation period. The following example illustrates the procedure for matching firm-years with the financial data. Consider all firms with Compustat fiscal year of 1998. Given Compustat's reporting convention, the fiscal year-end for all these firms would fall between June 1998 and May 1999. Assuming a four month reporting lag, the data for fiscal year 1998 would be available for all cohort firms (year = 1998) by September 1999. Thus, we use the 1998 fiscal year-end financial data for the annual snapshot of firms in September 1999.[10] Further, for sample firms identified as short targets during the period from October 1999 to September 2000, the pre-event financial data is from the 1998 fiscal year.[11]

During the prediction period, we follow a similar approach and calculate the predicted probabilities every September based on the coefficients from the short recommendation model and the available annual financial information each September for all cohort firms. Firms are assigned annually to decile portfolios based on predicted probabilities every September and remain in the assigned decile portfolio from October through September of the next year. The short interest ratio for the portfolio is computed in October and the abnormal returns are estimated over a twelve-month holding period, from October to September of the next year. In other words, for the fiscal year 1995, all the relevant annual data are available for all firms by

[10] This approach ensures that the annual accounting information for all the sample and control firms (universe of eligible Compustat) firms is available when the model is estimated.

[11] The fiscal year 1998 is designated as year -1. Since our firms were targeted in calendar years 1998-2005, the Compustat years corresponding to year –1 spans 1997-2004, which we call the estimation period.

September 1996. The short interest for these firms is computed in October 1996 and the abnormal returns are estimated from October 1996 to September 1997. The short recommendation model can be expressed as:

$$S_i = L\ (\alpha + \beta_i * \mathbf{X}_i + \epsilon_i) \qquad (1)$$

where S_i is a indicator variable that equals '1' for sample firms and equals '0' for control firms, X_i is the vector of valuation and fundamental variables that predict poor performance, ϵ_i is the residual error term, and L indicates that the model is based on a logistic regression.

The selection of explanatory variables is motivated by prior evidence on short seller behavior and the literature on contextual fundamental analysis (see Beneish et al. (2001)). The short seller is interested in identifying firms whose performance is likely to reverse. Hence we focus on valuation and fundamental variables that are related to return reversals. Prior work has documented that firms with low BM ratios and high accruals underperform (Lakonishok et al. (1994) and Sloan (1996)). These variables have also been shown to be related to aggregate short interest (Dechow et al. (2001), Hirshleifer et al. (2005), Cao et al. (2007)). Thus, we include the BM ratio and two measures of accruals, total accruals (TOTACC) and operating accruals (OPACC), as explanatory variables. Prior evidence also shows that short sellers appear sensitive to earnings quality (Desai et al. (2006)).[12] Thus, we include seven financial statement variables that are identified by Beneish (1999) as being related to earnings manipulation.[13] The first variable is days' sales in receivables index (DSRI). Since a large increase in receivables could indicate revenue inflation or relaxation of credit policy to generate higher sales, we expect that

[12] There is no universally accepted definition of earnings quality (see Schipper and Vincent (2003)). However, given that short sellers' interest lies in identifying firms whose performance is not sustainable, we consider earnings to be of poor quality if they are not likely to be sustained and hence use variables that have been shown to be associated with lack of earnings persistence (see Sloan (1996) and Richardson, Sloan, Soliman and Tuna (2005)).

[13] Note that the financial statement variables used in the study have been formally defined by prior research, thus alleviating concerns regarding data mining.

DSRI will be positively related to short selling. We include the gross margin index since improved margins accompanied by high accruals might suggest that the increased margins are not sustainable. The asset quality index *AQI* measures the extent of capitalization of assets with uncertain benefits, such as goodwill. It may also be indicative of a firm's propensity to engage in cost deferral by capitalizing expenses. Thus, we expect a positive association between *AQI* and short selling. Short sellers may target firms with high sales growth (SGI), consistent with the notion that firms may inflate their reported revenues in an attempt to mislead investors about future growth prospects. *DEPI* measures the depreciation rate and indicates whether the firm has made income-increasing accounting choices and/or increased its estimate of the useful lives of depreciable assets. Such tactics delay reporting an earnings decline, which may be a useful signal for short sellers. An increase in leverage (*LVGI*) suggests that debt covenants are more likely to be binding, generating more incentives for financial statement manipulation. Lev and Thiagarajan (1993) suggest that analysts perceive an increase in sales, general and administrative expenses (*SGAI*) as a negative signal about the future prospects of the firm. Therefore, we expect that firms with higher levels of *LVGI* and *SGAI* are more likely to be targeted in the short report. In addition, we include prior return momentum, measured as one-year buy-and-hold return over the period October_{t-1} to September_{t}. Our objective is to determine whether fundamental analysis helps short sellers identify firms whose strong past performance is not sustainable.

Since financial statement ratios are likely to vary across industries, we estimate the models using both raw and industry-adjusted values. Specifically, for each explanatory variable, we subtract the industry median (calculated annually, industries based on 2 digit SIC code) from the raw values for each firm to compute the industry-adjusted values. Finally, following D'Avolio (2002), we include two proxies for firm liquidity. Book value of total assets (SIZE)

and average share turnover (*TURNOVER*) capture the short sellers' reluctance to take positions in small, illiquid stocks.[14] TURNOVER is calculated as the arithmetic average of the daily share turnover (ratio of shares traded to total shares outstanding) over the period October $_{t-1}$ to September $_{t}$. Appendix A presents the detailed definitions of all the variables.

C. Summary Statistics

The sample firms are not clustered in time. When we divide the eight-year estimation period into two four-year periods (1998-2001 and 2002-2005), we find that each sub-period contains roughly equal number of observations. Furthermore, the maximum number of observations in a given year is ten (in 2002). We find modest evidence of industry concentration. 'Business Services' (SIC two-digit code 73) accounts for 14 observations (26%). In addition, chemicals and allied products (SIC 28) and industrial & commercial machinery and computer equipment (SIC 35) each account for four observations (7% each). All other industries (based on two-digit SIC) have fewer than four firms. Thus, the sample represents a fairly broad cross-section of firms, representing 23 different industries.

Table II presents the summary statistics for sample firms in the fiscal year prior to the date of the short report (year -1). Since mean accounting ratios could be affected by outliers, we focus on the medians, although mean values are also reported for completeness. In the year prior to being identified as a short target, the sample firms have low BM ratios (glamour stocks), consistent with Dechow et al. (2001), and experience a large run-up in stock price (positive momentum firms). The mean (median) value of total assets is $857 million ($405 million) and

[14] While institutional ownership may be a better proxy for loanable supply, we do not have access to institutional ownership data at this time. Hence, we use firm size as an alternative proxy, motivated by prior evidence of a strong correlation between size and institutional ownership (see Sias and Starks (1997)). We have replicated the entire analysis using market value of equity instead of book value of total assets and find similar results. Since market value of equity is more closely correlated (relative to book value of assets) with other explanatory variables, such as prior return and the book to market ratio, we report results using the latter measure of firm size.

market value of equity is $1,090 million ($691 million), suggesting that the research firm does not target large firms. This is not surprising as short sellers are unlike to have a substantial informational advantage in large firms. The industry adjusted trading volume and turnover statistics suggest that the sample firms are relatively more liquid than their industry cohorts. We also note that the sample firms exhibit superior accounting performance, as measured by ROA, sales growth, and improvements in margins, but higher total accruals and operating accruals compared to median industry firm. The other financial ratios are not significantly different when compared to the median firm in the industry.

III. Results

In this section, we present the main results of the study. We first describe the results of the short recommendation model, estimated over Compustat years 1997-2004 using a logistic regression (Hypothesis H1). To test for out-of-sample predictability, we examine differences in aggregate short interest and abnormal stock performance across decile portfolios formed on predicted probability over the prediction period (1990-1996) (Hypothesis H2). The prediction period is based on prior period data because a reasonable time series of short interest and return data are not available after the end of the estimation period. In the application, we test whether our model can distinguish between valuation and arbitrage shorts (Hypothesis H3).

A. Estimation Period Results

In Table III, we report the coefficients of logistic regressions that relate short recommendations to various fundamental and valuation signals. The dependent variable is an indicator variable that equals '1' if the observation is for a sample firm in year –1 and equals '0' otherwise. In models 1 and 2, the explanatory variables are unadjusted, while in models 3 and 4,

the explanatory variables are industry-median adjusted.[15] In models 2 and 4, we replace operating accruals with total accruals. The main findings are similar across all the models, suggesting that the findings are robust to alternative accruals measures and to industry effects. In the interests of brevity, the discussions below focus on model 3, although the coefficients from all four models are reported in Table III.

Focusing first on financial statement variables, the results suggest that the short recommendations are sensitive to the information conveyed by financial ratios. Specifically, the coefficients on operating accruals (*OPACC*), sales growth index (*SGI*), and the selling, general and administrative expenses index (*SGAI*) are positive and significant at the five-percent level or better. Evidence in Sloan (1996) indicates that the earnings of firms with high accruals are strongly mean reverting, suggesting that high accruals are indicative of poor earnings quality. Thus, it is likely that strong sales and price growth, coupled with the large accrual component in the reported earnings, may have attracted the attention of the research firm. The positive coefficient on *SGAI* suggests that the research firm views an increase in SG&A as a bearish indicator, consistent with Lev and Thiagarajan (1993). The negative coefficient on gross margin index suggests that the research firm targets firms with increase in gross margin, ceteris paribus.

With regards to valuation indicators, the coefficient on prior momentum is positive and that on BM ratio is negative (both significant at the five percent level), suggesting that the research firm believes in a contrarian investment strategy, targeting glamour firms that have experienced a large price run-up. Lakonishok, Shleifer and Vishny (1994) attribute poor performance of glamour stocks to naïve extrapolation of past performance. Thus, it appears that the research firm identifies stocks whose price has been bid up due to such extrapolation and might be expected to reverse. Finally, the coefficient on average turnover is positive and

[15] To minimize the effect of outliers, all variables are winsorized at the 0.5% and 99.5% level.

significant at the five-percent level, consistent with the short sellers' preference for liquid stocks (D'Avolio (2002)). The other variables are not statistically significant.

B. Out of Sample Results

One potential concern with the above analysis is the extent to which our findings could be generalized, as our model is developed from a small set of short recommendations from a single research firm. Specifically, the concern relates to whether the model can predict the trading behavior of a broader group of valuation-motivated short sellers beyond the specific time period of study. Ideally, analyses of short seller behavior would be conducted using the short recommendations of all short sellers. In practice, however, such an analysis is not possible because publicly available datasets with broad coverage on short recommendations or holdings do not exist. However, to the extent that short sellers assume positions on similar cues and the *out-of-sample* tests (described below) validate our model, such concerns are mitigated.

To validate the model, we examine whether the firms identified by the model as valuation shorts exhibit both short interest and abnormal return patterns consistent with this classification during the out-of-sample period. Specifically, if the model sufficiently describes the trading behavior of a broader group of short sellers, firms identified by the model as promising short targets should exhibit high short interest. Further, to the extent that the high short interest reflects valuation shorts and not arbitrage shorts, the future returns of firms identified as valuation short targets should be reliably negative (hypothesis H2).

Table IV and Table V present the results of the out-of-sample performance of each of the four short recommendation models reported in Table III. We use annual firm level data from the prediction period 1990-1996 and the coefficients of the logistic regression models obtained from the estimation period (1997-2004, presented in Table III) to calculate the predicted probability of

being a short recommendation. We sort the entire population of firms *each year* into deciles based on the predicted probability and report the results of tests using these decile portfolios.

In Table IV, we report the average short interest ratio for each decile portfolio over the out-of-sample period. The results suggest that the model does a good job of identifying firms with high short interest ratios, out-of-sample. Specifically, for model 3, the firms in decile portfolio 10, comprising firms with the highest predicted probability, have average short interest of 3.24%. In sharp contrast, the firms in decile portfolio 1, comprising firms with the lowest predicted probability, have an average short interest of 0.47%. Remarkably, the pattern of short interest shows a monotonic increase from decile 1 to decile 10. The difference in mean short interest between deciles 1 and 10 is highly statistically significant (t-statistic of 24.5). The results for models 1, 2 and 4 are similar; in every case, the monotonic pattern in short interest persists and the average short interest ratio in decile 10 is significantly higher than that in decile 1. These findings are particularly noteworthy, as the logistical model does not include short interest as an explanatory variable.

To further confirm that the model is indeed identifying valuation shorts, we report on the subsequent stock market performance for the decile portfolios in Table V, estimated as follows. We calculate the monthly returns of an equally weighted portfolio of all firms in each decile during 1990-1996 and generate a monthly time series of portfolio returns for each decile. We match these calendar month portfolio returns with the return factors RmRf, SMB, and HML that are designed to mimic the impact of the market, firm size, and book-to-market factors on firm returns. We report the regression intercept from calendar time regressions as an estimate of the abnormal performance of each decile portfolio.

The results in Table V, based on the three-factor model, suggest that the firms identified

as valuation shorts significantly under perform.[16] The abnormal performance of the decile 10 portfolio (model 3), comprising firms with the highest predicted probability, is –0.76% per month (significant at the 5% level). The large magnitude of abnormal return suggests that these findings are also economically significant. In contrast, firms in the decile 1 portfolio (low predicted probability) exhibit significantly positive abnormal returns of 1.25% per month. Consistent with the results documented in Table IV for short interest, there is a near monotonic pattern in the intercepts (abnormal returns) across the ten decile portfolios. The spread in returns between the extreme decile portfolios (decile 1 and decile 10) is 2.01% per month. The performance is very similar for models (1), (2), and (4). The firms in the decile 10 portfolio exhibit significant underperformance for each model, ranging from –0.59% to –0.74% per month. The corresponding returns for decile 1 portfolio range from 1.04% to 1.18% per month.

C. Implications of Empirical Findings

Several important implications emerge from the finding that the short recommendation model can predict both short interest and future returns in an out-sample period (hypothesis H2). First, the findings suggest that the short recommendation model captures the trading behavior of a broader group of valuation-motivated short sellers. Although each short seller would likely assume positions using a proprietary technology based on multiple signals, short sellers in aggregate appear to be sensitive to information contained in a parsimonious set of fundamental and valuation signals, as captured by the model, which to some extent is constant across time.

Second, and more importantly, these findings suggest that the return predictability associated with fundamental and valuation signals represents an economically meaningful opportunity that informed arbitrageurs attempt to exploit. These findings provide new insights into the decision process of short sellers. Specifically, they appear to behave as contrarians,

[16] The factor returns are obtained from Ken French's website. We thank him for making the data publicly available.

targeting glamour firms that have experienced a large run-up in price. Importantly, they appear to be particularly sensitive to information contained in accounting ratios, and in particular, target firms with poor earnings quality. Since, on average, firms with high momentum continue to earn positive abnormal returns (Jegadeesh and Titman, 1993), one plausible interpretation of our findings is that the information in financial ratios helps short sellers in identifying the subset of high momentum stocks whose performance is not sustainable, illustrating the importance of context-based fundamental analysis. Thus, these findings provide a direct empirical link between the literature on predictive ability of fundamental signals and literature on the trading strategies of information arbitrageurs.

D. Robustness Tests

In this section, we discuss several robustness tests that were conducted to verify that the results continue to hold under reasonable alterations to the empirical methodology.[17] We find that our inferences remain unchanged.

First, since our methodology involves pooled time series estimation and we use all Compustat firms (excluding financials and regulated firms) as control firms, it is possible that the observations are not independent and that the significance levels are overstated. To address this issue, we replicated the analysis reported in Tables III-V using an alternative approach to selecting control firms. Specifically, each year, we sort the universe of eligible Compustat firms on the basis of total assets and select every 10^{th} firm as a control firm. The results of the logistic estimation are very similar to those reported in Table III. The coefficients on accruals, BM, prior momentum, and turnover are statistically significant in each of the four models. The coefficients on SGA and SGAI are significant in two out of four models. The level of short interest for the

[17] While the detailed results of the various robustness tests are not reported in tables, they are available from the authors upon request. In the interests of brevity, we only tabulate abnormal return results from estimating model 3, which uses operating accruals and industry-adjusted accounting data.

decile of firms with the highest predicted probability is 3.41% compared to 0.47% for firms in the lowest decile (model 3). Finally, the out-of-sample return analysis (from model 3, reported in column 1 of Table VI) indicates that the firms in the highest decile experience abnormal returns of -0.56% per month and firms in the lowest decile experience abnormal returns of 1.22% per month, both significant at the 10 percent level or better. These results suggest that our results are not sensitive to the use of the universe of Compustat firms as control firms.

Second, we replicate the analysis after excluding low priced stocks (stock price below $10) from control firms since short sellers prefer to target large, liquid firms and avoid small, low priced firms. The out-of-sample abnormal returns for firms in the highest (lowest) decile of predicted probability, reported in column 2 of Table VI, are a statistically significant -0.58% per month (-0.11% per month, not significant). Thus, while the firms in the highest decile of predicted probability continue to perform poorly, the superior performance of firms in the lowest decile of predicted probability (documented earlier in Table V) is confined to small and low priced firms that are expected to have large transaction costs.

Third, we elected to conduct the out-of-sample analysis over a period preceding the estimation period instead of over a period following the estimation period. As discussed earlier, this approach is necessitated by data availability issues, since our estimation period ends in 2004 and we have a short time series of data subsequent to this period. However, one concern is whether the research firm has used prior period data (prior to 1998) to predict poor performers and then used this model to identify potential targets in subsequent periods. If so, the out-of-sample tests may not be independent of the estimation period analysis. To mitigate concerns regarding potential learning effects, we conduct the following additional analysis. We take annual snapshots in 1998-2000, thus estimating the model over three years (Compustat years

1997-1999). The out of sample analysis is conducted over the years 2001-2003 as the short interest data available to us ends in December 2003. Thus, both the estimation and out-of-sample analysis are conducted using a significantly shorter time series of data. Despite this limitation, we find that the main results are broadly similar to those documented earlier. Specifically, in the logistic estimation, the coefficients on accruals, BM, and sales growth are significant across each of the four models. The coefficients on prior momentum, SGAI and GMI are significant in many of the models. The short interest of firms in the highest decile of predicted probability is 5.21% compared to 1.03% for firms in the lowest decile (model 3, using industry-adjusted data and operating accruals). The abnormal return of firms in the highest decile is -0.60% per month (p-value = 0.13) and for those in the lowest decile is 2.94%, significant at the one percent level (Table VI, column 3). Importantly, we note that the returns decline monotonically as we move from decile 1 to decile 10. Thus, despite the significant drop in sample size, the monotonic pattern in short interest and abnormal returns continue to hold, suggesting that the key results are not merely the outcome of learning effects. Rather, the results suggest that the model does a good job of identifying valuation motivated short selling.[18]

IV. Application: Distinguishing Valuation Shorts from Arbitrage Shorts

As described earlier, the short interest data in the United States aggregates both valuation and arbitrage shorts. Asquith et al. (2005) suggest that the increased incidence of arbitrage shorts in recent years has caused the relation between short interest and future returns to weaken.

[18] We also conducted an additional test to examine whether the short recommendations contain information over and above an alternative model that fits on firms that have performed poorly. We set the dependent variable in the estimation period regression to equal '1' for the one percent of firms that have the lowest returns each year, and '0' otherwise, and examine the predictive power of the same set of explanatory variables. In out of sample tests, we find a U-shaped pattern in short interest (declining from 1.25% in decile 1 to 0.87% in decile 5, and then increasing to 2.78% in decile 10). We do not find a monotonic pattern in abnormal returns. This suggests that our methodology of identifying valuation shorts using short recommendations yields results that are more robust in an out of sample period than the alternative methodology. Results are available from the authors on request.

Given the continuing growth in institutions that engage in arbitrage strategies, this problem is expected to become even more acute over time, suggesting that distinguishing between valuation shorts and arbitrage shorts presents an important avenue for future research. In this section, we present an application of the short interest model to distinguish between valuation and arbitrage shorts (hypothesis H3), using a two-way sort of the data. Specifically, each year, we group all firms into decile portfolios based on the short interest in October. We retain firms in the two extreme decile portfolios to maximize the spread in short interest ratio. Following the approach in Tables IV and V, we independently classify the firms into three groups each year based on the predicted probability from the short interest model. The low group (medium, high) has firms in the lowest 3 deciles (middle 4 deciles, highest 3 deciles). Thus, this two-way independent sort generates six groups (2 extreme short interest groups * 3 predicted probability groups).

Our approach relies on the notion that the short recommendation model successfully describes the trading behavior of valuation-motivated short sellers. Thus, if both aggregate short interest and the predicted probability from the model are high, we classify the short selling in those firms as being valuation motivated. On the other hand, we classify high short interest in firms with low predicted probability as arbitrage motivated. To test our classification, we examine both future returns and firm characteristics of the six groups. Firms classified as valuation shorts should experience significant negative future returns. In contrast, firms classified as arbitrage shorts should not experience negative future returns but should exhibit firm characteristics associated with arbitrage trading, such as index membership or convertibles bonds (Hypothesis 3). We also examine characteristics of firms with low short interest but high predicted probability. We hypothesize that these firms are subject to short sale constraints that discourage short sellers from assuming short positions in these firms.

Following the approach in Table V, we estimate the intercept from calendar time regressions for an equally weighted portfolio of firms in each of the six groups. Although, we have performed the analysis for each of the four models reported in Table III, in the interests of brevity, we only report abnormal returns for model 3 in Table III (using industry-adjusted data and operating accruals). The results are qualitatively similar across all models.

From Panel A of Table VII, we note that abnormal returns are not significantly different from zero (0.08%) for firms with high short interest but low predicted probability. We conjecture (and provide confirmatory evidence in panel B) that the high short interest for these firms is motivated by arbitrage strategies. On the other hand, the abnormal return is -0.71% per month (significant at one percent level) for firms with high short interest and high predicted probability, consistent with short interest in these firms being valuation shorts. The differences between the two groups are not the outcome of a finer sort on the level of short interest, as the average short interest in both groups is similar (7.43% and 8.74%, respectively). Interestingly, firms with high predicted probability but low short interest exhibit an abnormal return of –1.08% per month. We conjecture that the short interest is low for these firms due to short-sale constraints. Finally, for firms with low short interest and low predicted probability, the abnormal return is 1.19% per month (significant at five percent level).

We examine several firm characteristics in panel B of Table VII. We first examine firms with low predicted probability that have either high short interest (arbitrage shorts, column 2), or low short interest (column 1). Firms with low predicted probability and high short interest are significantly larger and have higher turnover than firms with low predicted probability and low short interest. Importantly, 56% of the firms with low predicted probability and high short interest have convertibles securities outstanding and 20% are members of the S&P 500 Index. In

comparison, the corresponding proportions for firms with low predicted probability and low short interest are only 12% and 1% respectively; suggesting that high short interest for firms in column 2 is motivated by arbitrage strategies.

We next examine firms with high predicted probability that have either low short interest (short sale constrained, column 3) or high short interest (valuation shorts, column 4). Consistent with the short-constraint hypothesis, firms with high predicted probability but low short interest are significantly smaller and have lower share turnover relative to firms with high predicted probability and high short interest. The fraction of firms that are S&P500 constituents or have convertible bonds outstanding is not economically different across two groups. Further, there is little economic difference in the BM ratio. Thus, although the model identifies a set of firms that subsequently experience significantly negative returns, the existence of short sale constraints discourages short selling in these firms. These findings support the arguments presented by Chen et al. (2002) and Boehme et al. (2006), among others, that aggregate short interest is an imprecise proxy of the extent to which firms are short sale constrained.

As discussed earlier, Asquith et al. (2005) categorize firms as valuation or arbitrage shorts based on whether the firm has issued convertible bonds. This raises the question – does the model have explanatory power over and above the Asquith et al. classification scheme? As a final additional test, we replicated the analysis in Panel A of Table VII after excluding firms with convertibles bonds outstanding; a sub-sample where the convertibles indicator cannot distinguish valuation shorts from arbitrage shorts. The results of this analysis strongly validate our model.[19] Specifically, we document that the firms with high short interest but low predicted probability from our model experience abnormal returns of 0.39% per month (not significant). In contrast, the firms with high short interest and high predicted probability experience abnormal returns of

[19] Detailed results are available from the authors upon request.

-0.68% per month (significant at the 5% level). Thus, our model does a good job of distinguishing information and arbitrage shorts, even within a selected sample of firms that excludes a large amount of arbitrage related short selling.

The short recommendation model can also be used in several applications that benefit from identifying poorly performing firms ex ante. To apply our model, researchers should identify decile portfolio break points each year based on the predicted probability distribution using model coefficients reported in Table III. As a quick guide, we note that a predicted probability greater than 50 basis points corresponds to firms in the highest predicted probability decile for most years during the sample period. The intercept from the Fama-French monthly calendar time regression for portfolio of firms with predicted probability greater than 50 basis points is -1.09% (t-stat=-2.85). Thus, as a quick alternative approach, researchers and investment professionals may use a predicted probability cutoff of 50 basis points for identifying poor performers.

V. Conclusions

This paper provides new insights into the decision process of information arbitrageurs. We examine a unique database of short sell recommendations that are motivated by a pessimistic opinion on firm valuation. We find that the firms in the short database experience significantly poor returns during the first year after the issuance of short recommendation. Based on the short database, we build a parsimonious model that describes the trading behavior of short sellers. We find that the information contained in financial statement variables, such as accruals, gross margin, sales growth, and SG&A, and in valuation indicators, such as BM ratio and prior momentum, is related to the information set of short sellers. We designate firms with high

predicted probability from this model as potential targets of valuation motivated short sellers. The *out-of-sample* tests strongly validate our model. We document that firms identified as valuation shorts have high short interest and experience poor subsequent stock performance and that firms identified as arbitrage shorts are more likely to be members of S&P500 Index and have convertible bonds outstanding.

The key contributions of the study are threefold. First, and most importantly, the study provides new insights into the information arbitrage process. We document that information arbitrageurs attempt to exploit the return predictability in valuation and fundamental signals, suggesting a direct link between the literature on the predictive ability of fundamental signals and the literature on the trading behavior of information arbitrageurs. Second, the study validates the importance of accounting-based information for short sellers by examining a database of short recommendations. Our approach furthers the analyses from prior research on short seller behavior using reported short interest. We argue that short recommendations provide a more precise signal of valuation motivated shorting than reported short interest, which aggregates both valuation and arbitrage shorts. Third, we document that the short recommendation model can distinguish between valuation shorts and arbitrage shorts. This distinction is important because the information content of these two sources of short interest is different and the increasing use of arbitrage related short selling in recent years has contributed to a weakened relation between short interest and future returns.

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Table I
Performance of firms in the short database

The table presents the performance statistics for the sample of firms identified by an independent research firm as potential targets for short selling. The sample comprises all 67 firms that were targeted for short selling by the firm from September 1998, until June 2005. Panel A lists the mean (median) raw buy and hold return and the market-adjusted buy and hold return for year -1, the event month, and year +1. Panel B reports the types of 'bad news' events that were reported in year +1.

Panel A: Returns

	Months (-12, -1)	Month 0	Months (+1, +12)
Raw returns (%)	77.90 ***	-4.03 **	-9.71
	(24.55) ***	(-4.03) *	(-18.32) **
Market-adjusted returns (%)	72.36 ***	-4.89 **	-15.02 **
	(31.85) ***	(-3.57) **	(-17.12) ***

Panel B: Summary of 'bad news' events in year +1

Events	# Observations
Firms with 'bad news' reported	42
Reported lower than expected earnings	24
Lowered guidance on future earnings / sales	20
Analyst downgrade	23
Earnings restatement, earnings or audit delay, accounting concerns	7
Regulatory action, Lawsuit, SEC investigation	8
Top management turnover	2
Ratings cut, ratings watch, covenant violation	3
Firms with no 'bad news' reported	25

*, ** and *** denote significance at the 10-, 5- and 1-percent level respectively.

Table II
Summary statistics

The table presents summary statistics for the sample of firms identified by an independent research firm as potential targets for short selling. The sample comprises of every report issued by the firm from September 1998, until June 2005. The table presents both unadjusted and industry-adjusted values for sample firms, where industry groups are based on two-digit SIC codes obtained from Compustat. All of the statistics are presented as of year prior to the issuance of the report. The variable definitions are reported in Appendix 1.

Sample characteristics in year -1					
	Mean	Median	Industry-adjusted Mean	Industry-adjusted Median	# Obs
Performance variables					
Equity BM ratio	0.3166 ***	0.2381 ***	-0.2138 ***	-0.2070 ***	53
Prior 1-yr. return	38.84 ***	9.40 **	40.18 ***	15.88 ***	54
ROA	0.0005	0.0350 **	-0.0047	0.0096 *	54
Financial variables					
DSRI	1.1772 ***	0.9524 ***	0.1997	-0.0174	54
GMI	-1.2541	0.9806 ***	-2.2570	-0.0381 ***	54
SGAI	1.1642 ***	0.9890 ***	0.1617	-0.0115	51
AQI	0.9772 ***	0.9956 ***	-0.0212	-0.0016	54
SGI	2.2056 ***	1.3358 ***	1.0863 ***	0.2725 ***	54
DEPI	1.4436 ***	0.9417 ***	0.4872	-0.0080	54
LVGI	0.9887 ***	0.9728 ***	-0.0114	-0.0183	54
TOTACC	0.2650 ***	0.1159 ***	0.2468 ***	0.1099 ***	54
OPACC	-0.0238	-0.0378 **	0.0383 **	0.0150 *	54
Firm characteristics					
Total assets	857.53 ***	405.16 ***	659.89 ***	158.24 ***	54
MVE	1089.77 ***	691.06 ***	919.84 ***	571.57 ***	54
Trading volume	7.29 ***	3.95 ***	6.70 ***	3.35 ***	54
Turnover (%)	0.69 ***	0.60 ***	0.41 ***	0.30 ***	54

*, ** and *** denote significance at the 10-, 5- and 1-percent level respectively.

Table III
Logistic regressions modeling the short seller's decision to target a firm

The table presents the coefficients from logistic regressions modeling the short seller's decision to target a firm. The regressions use all firms with available data, excluding financial firms (SIC 6000-6999), utilities (4900-4999), and communications firms (4800-4899). The dependent variable is an indicator variable that takes the value of one if the firm was targeted by the short seller, and takes the value of zero otherwise. The explanatory variables include financial statement ratios identified by Beneish (1999), operating accruals, total accruals, book-to-market ratio, firm size, prior one-year return, and average daily turnover in the prior one year. All data are winsorized at the 0.5% and 99.5% levels. The specific variable definitions are in Appendix 1. Models (1) and (2) are estimated using raw data and models (3) and (4) are estimated using industry-adjusted data.

Dependent variable: '1' for target, '0' otherwise

	Unadjusted, winsorized		Industry-median adjusted, winsorized	
Model	(1)	(2)	(3)	(4)
Intercept	-5.7745 ***	-5.9375 ***	-6.9265 ***	-6.9941 ***
Performance variables				
BM	-2.3495 ***	-2.0908 ***	-2.1931 ***	-2.1489 ***
Prior 1-year return	0.2308 *	0.2289 *	0.2768 **	0.2662 **
Financial variables				
DSRI	-0.0200	-0.0210	0.0128	0.0162
GMI	-0.2040	-0.2286 *	-0.2205 *	-0.2397 *
SGAI	0.7913 **	0.6395 *	0.8383 **	0.6644 *
AQI	-0.2267	-0.0318	-0.2929	-0.0809
SGI	0.2648 ***	0.1494 *	0.5047 ***	0.2910 **
DEPI	-0.2518	-0.4099	-0.2141	-0.4101
LVGI	-0.1991	-0.1406	-0.2058	-0.1595
TOTACC		2.0702 ***		2.3394 ***
OPACC	2.8047 ***		3.0838 ***	
Firm characteristics				
Size	0.0000	0.0000	0.0000	0.0000
Turnover	47.6647 *	39.1111	57.0076 **	49.3988 *
Pseudo R^2 (%)	9.2	10.2	10.1	11.3

*, ** and *** denote significance at the 10-, 5- and 1-percent level respectively.

Table IV
The level of short interest
categorized by the predicted probability from the short recommendation model

The table presents the mean level of short interest for decile portfolios formed on predicted likelihood of being targeted by informed short sellers. The estimation period for the model is 1997 to 2004, based on the sample of firms identified by an independent research firm as potential targets for short selling. The coefficients of the estimation model are presented in Table III. The decile portfolios are assigned based on the predicted values during the period 1990 to 1996. Specifically, for a firm with available data during 1990 to 1996, the predicted likelihood of being targeted is obtained by multiplying the coefficients reported in Table III with the firm's characteristics for the given year. Decile portfolios based on this predicted probability are constructed each year. Reported are the mean levels of short interest (as a proportion of shares outstanding) for each of the ten portfolios.

Short interest (%)				
	Unadjusted		Industry-median adjusted	
From Table II	Model (1)	Model (2)	Model (3)	Model (4)
Decile 1 (Low)	0.510	0.518	0.465	0.480
2	0.666	0.605	0.634	0.618
3	0.792	0.807	0.810	0.793
4	0.872	0.898	0.850	0.911
5	0.966	0.932	1.044	0.956
6	1.077	0.989	1.055	1.049
7	1.134	1.240	1.193	1.243
8	1.545	1.376	1.590	1.441
9	1.947	1.948	1.960	2.030
Decile 10 (High)	3.312	3.466	3.239	3.274
t for High-Low	24.48	25.40	24.75	24.88

Table V
Post-event abnormal returns
categorized by the predicted probability from the short recommendation model

The table presents the abnormal returns for decile portfolios formed on predicted likelihood of being targeted by informed short sellers. The estimation period for the model is 1997 to 2004, based on the sample of firms identified by an independent research firm as potential targets for short selling. The coefficients of the estimation model are presented in Table III. The decile portfolios are assigned based on the predicted values during the period 1990 to 1996. Specifically, for a firm with available data during 1990 to 1996, the predicted likelihood of being targeted is obtained by multiplying the coefficients reported in Table III with the firm's characteristics for the given year. Decile portfolios based on this predicted probability are constructed each year. Reported are the average monthly abnormal returns for the ten portfolios, measured as the intercept from a regression of monthly portfolio returns on the three Fama-French (FF) factors RmRf, SMB, and HML.

Abnormal returns

	Unadjusted		Industry-median adjusted	
From Table II	Model (1)	Model (2)	Model (3)	Model (4)
Decile 1 (Low)	0.0111 ***	0.0104 ***	0.0125 ***	0.0118 ***
2	0.0074 ***	0.0073 ***	0.0073 **	0.0073 **
3	0.0015	0.0031	0.0050 **	0.0069 ***
4	0.0049 **	0.0043 **	0.0033	0.0020
5	0.0007	0.0012	0.0014	0.0024
6	-0.0007	0.0012	0.0002	-0.0015
7	0.0004	-0.0002	-0.0004	-0.0003
8	-0.0002	-0.0024	-0.0013	-0.0013
9	-0.0042 *	-0.0044 **	-0.0055 ***	-0.0059 ***
Decile 10 (High)	-0.0074 **	-0.0059 *	-0.0076 **	-0.0064 **

*, ** and *** denote significance at the 10-, 5- and 1-percent level respectively.

Table VI
Sensitivity analysis of post-event abnormal returns
categorized by the predicted probability from the short recommendation model

The table presents the abnormal returns for decile portfolios based on the predicted likelihood of being targeted by informed short sellers. We estimate three alternative specifications of the logistic regression model, similar to those in Table III – including only every tenth firm (ranked yearly by total assets) as control firms, excluding firms if the share price is below $10, and using 1997-1999 as the estimation period and 2000-2003 as the out of sample period. The decile portfolios are assigned based on the predicted values during the out of sample period. Specifically, for a firm with available data in the out of sample period, the predicted likelihood of being targeted is obtained by multiplying the coefficients (from the estimation period logistic regressions) with the firm's characteristics for the given year. Decile portfolios based on this predicted probability are constructed each year. Reported are the average monthly abnormal returns for the ten portfolios, measured as the intercept from a regression of month portfolio returns on the three Fama-French (FF) factors RmRf, SMB, and HML.

Abnormal returns

	Include every 10th firm as control	Exclude if share price < $10	Estimation period 1997-1999
	1	2	3
Decile 1 (Low)	0.0122 ***	-0.0011	0.0294 ***
2	0.0076 ***	0.0010	0.0161 **
3	0.0044 *	-0.0002	0.0161 *
4	0.0036	0.0007	0.0117 **
5	0.0015	0.0009	0.0075 *
6	0.0008	-0.0019	0.0023
7	-0.0006	0.0009	0.0026
8	-0.0026	-0.0023	0.0017
9	-0.0045**	-0.0039 **	0.0008
Decile 10 (High)	-0.0056 *	-0.0058 ***	-0.0060

*, ** and *** denote significance at the 10-, 5- and 1-percent level respectively.

Table VII

Abnormal return and firm characteristics categorized by the predicted probability and the level of short interest

The table presents the abnormal returns (panel A) and firm characteristics (panel B) for subsets of data categorized using a two-way sort based on the predicted likelihood of being targeted by informed short sellers and the actual level of short interest. For the period from 1990 to 1996, the firms are sorted into deciles every year based on the level of short interest (normalized by the number of shares outstanding). We retain the two extreme deciles to maximize the spread in short interest. We also independently sort the firms into three groups based on the predicted likelihood of being targeted by informed short sellers (deciles 1-3, 4-7, and 8-10). The predicted likelihood is obtained by multiplying the coefficients (from the estimation period logistic regressions) with the firm's characteristics for the given year. Decile portfolios based on this predicted probability are constructed each year. In panel A, we report the average monthly abnormal returns (average short interest, %) [number of observations] for the six portfolios, measured as the intercept from a regression of month portfolio returns on the three Fama-French (FF) factors RmRf, SMB, and HML. In panel B, we report the average firm characteristics for these groups. The significance levels in panel B test for differences between the low (decile 1) and high (decile 10) actual short groups, holding the predicted probability constant.

Panel A: Abnormal return

Predicted probability	Low (deciles 1 - 3)	Medium (deciles 4 - 7)	High (deciles 8 - 10)
Low short interest (decile 1)	1.19 ***	0.14	-1.08 **
	(0.03)	(0.04)	(0.04)
	[1320]	[900]	[435]
High short interest (decile 10)	0.08	-0.72 ***	-0.71 ***
	(7.43)	(7.26)	(8.74)
	[264]	[623]	[1237]

Panel B: Firm characteristics

Predicted probability	Low (deciles 1-3)		High (deciles 8-10)	
Short interest	Low (decile 1)	High (decile 10)	Low (decile 1)	High (decile 10)
MVE ($ mill)	48.6	726.9 ###	229.0	926.8 ###
BM	1.55	1.22 ###	0.32	0.27 ###
Average turnover (%)	0.13	0.42 ###	0.25	0.76 ###
% with cvt. sec.	12.3	56.4 ###	19.5	24.0 #
% in S&P 500 Index	0.53	19.7 ###	0.23	5.01 ###

*, ** and *** denote significance at the 10-, 5- and 1-percent level respectively.
#, ## and ### denote significance at the 10-, 5- and 1-percent level respectively of the difference between high and low short interest groups.

Appendix A
Variable definitions

The table presents the definitions of the variables used in the analysis. All #s pertain to the data item numbers from the Compustat annual files.

Performance variables	
Equity BM ratio	$\#60_t / [\#25_t * \#199_t]$
Prior 1-yr. return	Raw return from October of year 't-1' through September of year 't'
Return on assets	$\#18_t / \#6_t$
Financial variables	
DSRI (Days in sales rec. index)	$[\#2_t / \#12_t] / [\#2_{t-1} / \#12_{t-1}]$
GMI (Gross margin index)	$[(\#12_{t-1} - \#41_{t-1}) / \#12_{t-1}] / [(\#12_t - \#41_t) / \#12_t]$
SGAI (Selling, general, and admn. expenses index)	$[\#189_t / \#12_t] / [\#189_{t-1} / \#12_{t-1}]$
AQI (Asset quality index)	$[(1-(\#4_t + \#8_t)) / \#6_t] / [(1-(\#4_{t-1} + \#8_{t-1})) / \#6_{t-1}]$
SGI (Sales growth index)	$\#12_t / \#12_{t-1}$
DEPI (Depreciation index)	$[(\#14_{t-1} - \#65_{t-1}) / (\#14_{t-1} - \#65_{t-1} + \#8_{t-1})] / [(\#14_t - \#65_t) / (\#14_t - \#65_t + \#8_t)]$
LVGI (Leverage index)	$[(\#5_t + \#9_t) / \#6_t] / [(\#5_{t-1} + \#9_{t-1}) / \#6_{t-1}]$
TOTACC (Total accruals)	$[\#18_t - \#308_t - \#311_t] / [(\#6_t + \#6_{t-1}) / 2]$
OPACC (Operating accruals)	$[\#18_t - \#308_t] / [(\#6_t + \#6_{t-1}) / 2]$
Firm characteristics	
Total Assets	$\#6_t$
Equity market value	Share Price * Number of shares outstanding at September month end, from CRSP.
Trading volume	The average of the daily trading volume (price * number of shares traded) from October of year 't-1' to September of year 't'.
Turnover	The average of the daily turnover (number of shares traded / Number of shares outstanding) from October of year 't-1' to September of year 't'.