SHORT-SELLING PRIOR TO ANALYST RECOMMENDATIONS

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Abstract

This paper investigates short-selling five days prior to analyst recommendations by using a complete data set from Reg SHO database during January, 2005 to July, 2007. Empirical tests uncover the evidence that short-sellers significantly increase their short positions prior to negative analyst recommendations, which is consistent with the informed trading hypothesis. This finding is robust to model specification. Further, this paper also examines which of the two competing hypotheses-prediction and tipping-could better explain short-sellers' informative front-running. The tests indicate that short-sellers use book-to-market ratio as a filter to narrow down their pool of candidates, while market capitalization doesn't play a role in short-sellers' decision process. However, earnings management seems to influence short-sellers' attitude towards analyst recommendations. For these "aggressive" firms, short-selling transactions seem to deviate from analyst recommendations, which imply that short-sellers may scrutinize the firms by themselves rather than mechanically listen to analysts' tips. This piece of evidence tends to favor prediction hypothesis.

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1. Introduction

The popularity of short-selling as a research topic has been soaring in recent years. Among all aspects of short-sellers' transactions, the most controversial yet widely discussed is whether short-sellers are informed traders. As analyst recommendations are generally considered as informative and influential, short-sellers-if sophisticated as presumed-may change their short positions prior to the anticipated analyst recommendations. Specifically, we expect short-sellers to increase their short-selling positions before the release of negative analyst recommendations, and shrink the amount of shares shorted preceding positive analyst recommendations. This paper employs a unique and complete data set to investigate short-sellers' trading patterns prior to the release of analyst recommendations during January, 2005 through July, 2007.

This study primarily attempts to explore two issues. The first one is to examine whether short-sellers do have the predictability of forthcoming analyst recommendations. Since analyst recommendations are regarded as proxy for "additional information to market", if short-sellers are informed traders with private information, they will trade in the direction of the imminent recommendations in advance of its release. The testable implication is that short-sellers' abnormal short-selling prior to the analyst recommendations should be negatively related to the optimism of analyst recommendations.

In order to justify this hypothesis, we implement several tests on the pre-recommendation short-selling around the announcement of analyst recommendation date. Firstly, we capture the relationship between pre-recommendation abnormal short-selling and the direction of analyst recommendation by constructing a multivariate regression. With a couple of control variables in place, the estimated regression coefficients reveal that short-sellers do adjust their short positions accordingly with respect to the expected forthcoming analyst recommendation. For those stocks with upcoming negative recommendations, short-sellers are observed to significantly expand their short sizes. For the robustness consideration, we also implement a non-parametric test on the linkage between the level of short-selling and three-day event period abnormal returns around the analyst recommendations. The results confirm that abnormally adjustment of short-sales is significantly affected by the stock price reactions to recommendations. In other words, abnormally large increase in short-sales indicates subsequent negative analyst recommendations. This finding is consistent with Christophe, Ferri and Hsieh (2010) and Blau and Wade (2009), which documents abnormally high short-selling in the days leading up to downgrade announcement.

One may notice that there are two competing explanations for informed short-selling prior to analyst recommendations. The first one is prediction hypothesis that short-sellers are generally more sophisticated in processing public information and better at stock selection. Therefore, their choices of short-sale are likely to coincide with analysts' opinions. An alternative supposition, labeled tipping hypothesis, argues that analysts may tip their preferred clients before the public release of recommendations. If short-sellers utilize the tips obtained from brokerage firms, it is natural to observe short-sellers' front-running.

To shed some light on these two explanations, this paper firstly examines whether short-sellers' trading decisions benefit from fundamental analysis based on public available information. Specifically, we investigate if the distinction between growth and value stocks, and that between large-cap and small-cap stocks have affected short-sellers' decision on short positions prior to analyst recommendations. While the literature provided evidence that short-sellers prefer growth stocks and large-cap stocks, the results of our tests suggest the odd. Growth stocks are not consistently short-sellers' favorite; the book-to-market ratios are more likely a filter with which short-sellers narrow down their pool of candidates, and then pin down the final short targets according to their anticipation for future analyst recommendations. By contrast, market capitalization does not seem to play a role in short-sellers' decision procedure before analyst recommendations.

As previous literature implies short-sellers are capable in recognizing accounting irregularities, this paper also investigates if the magnitude of earning management influence short-sellers' judgment. It is expected if short-sellers informed trading is resulted from early access to analyst recommendations, their trading pattern should display consistency across firms regardless of aggressiveness in accounting accruals. However, it appears that short-sellers only follow analyst recommendations on conservative firms; for the aggressive firms, analyst recommendations have less explanatory power in short-sellers' trading positions. This finding tends to favor the prediction hypothesis that short-sellers' informed trading is resulted from their independent analysis other than analyst tips in advance.

Our final contribution is our use of a relatively comprehensive data set. While previous studies more or less suffer from the skepticism upon data, our study is built on a justified data set with superior data availability. Our data set comes from *Reg SHO* Data which contains all trades tick-by-tick with a short sale component reported to the NYSE. The high frequency of data allows for detecting any atypical rise or decline in short-selling sizes, which is clearly important as our focus is concentrated on abnormal changes in short-sales within several days surrounding analyst recommendations.

Our study proceeds as follows. The next section summarizes all related literature both on short-selling and analyst recommendations. Data selection and description are presented in Section 3. In Section 4, we carry out multivariate regressions on the relationship between pre-recommendation abnormal short selling and the information content of corresponding analyst recommendations. It is followed by a double check of non-parametric tests. Then we move on to investigate based on what information kernels do short-sellers cast their positions prior to analyst recommendations. Section 5 concludes.

2. Related Research and Literature

2.1 Short-Selling: Informative or Uninformative?

It is usually assumed that short-sellers are more sophisticated than the average investor. Not only is shorting relatively costly[1], it is also under more stringent regulation supervision. Almazan et al. (2004) find that only 30% of mutual funds are allowed to sell short by charter. Boehmer, Jones and Zhang (2008) document that 75% of all short sales are implemented by institutional investors, while individuals take up a portion less than 2%. As a consequence, short sellers are likely to be sophisticated traders and will only trade on really profitable opportunities.

[1] For a more complete discussion about the costs associated with this special type of trading, refer to, e.g. Jones and Lamont (2002).

If short-sellers are perceived to be superior to other investors, they are more likely to trade on information other than noise. The discussion around “whether short-selling is informative” is not new. There are several common approaches to testify this argument. The oldest but most extensively used is to examine the price movement after the announcement or execution of short-selling transactions. It is assumed that short-sellers are better equipped to discern the mispriced stocks and time trades relative to future returns. Thereby, we expect to observe negative stock returns subsequent to large short-selling. Plenty studies have sought to examine whether this is the case. Another stream of testable implication is that short-sellers, by exploiting the situations where stock prices deviate from fundamentals, help to accelerate the market efficiency and facilitate price discovery. In the following sections, we will summarize the two branches of previous studies, respectively.

2.1.1 Can Short-Selling Predict Negative Returns?

Numerous empirical studies are devoted to analyze stock prices around short-selling transactions. Senchack and Starks (1993) discover that stocks with unexpected increases in short interest will generate statistically significant negative abnormal returns around the announcement of a short-sale. Asquith and Meulbroek (1995) find significantly negative abnormal returns for stocks with high short interest on the New York (NYSE) and American (AMEX) Stock Exchanges for 1976-1993. This finding has been further confirmed by Choie and Hwang (1994) with regard to performance relative to S&P 500 Index. Desai et al. (2002) extend this finding to stocks on Nasdaq, and also unravel the linkage between high short interest and lower company survival rates.

One limitation of these studies is their use of monthly stock-specific short interest data. This data only provides the number of shares sold short at a particular point in time, usually around the middle of each month. The low frequency of data does not allow the researchers to gain a complete big picture of short-sellers' action and unable them to study short-horizon trading strategies, especially when evidence accumulates that short sellers open and cover their positions very rapidly[2]. To remedy this shortcoming and complement the previous studies, researchers look for alternative data sets. Aitken et al. (1998) examine daily short sales on the Australian Stock Exchange for three years 1994 to 1996, and support the view that daily short sales could forecast future negative abnormal returns. Angel et al. (2003), on the other hand, confirm the negative association between high daily short selling and subsequent abnormal returns using proprietary Nasdaq data over three months.

2.1.2 Can Short-Selling Facilitate Price Discovery?

Diamond and Verrechia (1987) develop a theoretical model which implies that only informative traders will participate in short selling due to relatively high execution cost and regulation requirement. Therefore, they believe that short-sellers are broadly rational and informed investors whose trading behaviors precipitate the prices of mispriced stocks to converge to their fundamentals. However, some other theoretical studies assert the opposite. Brunnermeier and Pedersen (2005) argue that short-selling of large institutions could induce followers to sell the same stock within a short period; this ripple effect may lead to serious overshooting of prices and destabilization of the financial market. This trading pattern is described as "predatory trading". Goldstein and Guembel (2008) agree with this claim. They propose that

[2] For the literature of this area, see, e.g., Jones (2004); Diether (2008); and Diether, Lee and Werner (2009).

short sellers' manipulative and predatory trading strategies account for less informative prices.

Does short-selling assists in impounding information into prices, or exacerbate price volatility? Plenty of empirical studies provide their own answers. Boehmer, Jones and Zhang (2008) utilize a unique flow data for stocks shorted on NYSE during 2000 to 2004, and posit that short sellers' trading contribute to more efficient prices. Diether, Lee and Werner (2007) provide evidence short sellers are contrarian traders whose trading reduces future volatility. Bris, Goetzmann, and Zhu (2006) carry out a cross-border study analyzing 47 equity markets, and document that markets with short-selling mechanism are more efficient than others without.

The existence of short-sale constraint also provides another perspective to address this price discovery proposition. If short-sales constraint is severely binding, larger amount of negative information is withheld from being reflected into prices, and more seriously the stock price may deviate from the efficient level. The studies that attempt to shed some light on this insight normally vary from each other by their selection of proxy for short-sale constraint. Chen, Hong, and Stein (2002) use the breadth of ownership as a reliable proxy for how restrictively short-sales constraint bind, where breadth of ownership is constructed as the number of investors with long positions in a stock. They find that stocks with declines in breadth of ownership, which implies more binding short-sale constraint, are generally overpriced than the counterparts with high breadth. Nagel (2004) amends Cheng, Hong, and Stein's (2002) proxy into the percentage of shares owned by institutions, yet draws similar conclusion. Chang, Cheng and Yu (2007) find that individual stock returns at the Hong Kong stock market become less skewed with the lift of short-sales restrictions, suggesting that short-selling facilitates incorporating information into prices. Reed

(2007) also documents that the deviation of stock price from efficient value is more severe among stocks with severe short-sale constraint. Therefore, regardless of the difference in proxy selection, a general agreement is reached among these studies that the presence of short-sale constraint impedes in price discovery; short-selling activities enhance market efficiency by moving mispriced stocks back to their values.

2.2 Short-Selling and Characteristics of Stocks

It is definitely of interest to understand the information source short-sellers use to identify overpriced stocks. The investigation of this issue could be translated into the dissection of stocks shorted: what kind of stocks are short-sellers' favorite? Dechow et al. (2001) finds that short-sellers position themselves in the stocks with low ratios of fundamentals, which is consistent with that short-sellers use public available information. Christophe et al. (2004) detect that short-sellers employ a book-to-market strategy for determining pre-announcement short-selling. That short-sellers prefer growth stocks to value stocks is also confirmed by Dechow et al. (2001), Geczy et al. (2001), and Jones and Lamont (2002). Besides, market capitalization is another piece of public information that seems to influence short-sellers' establishing short positions. Jones and Lamont (2002) support the contention that large cap stocks are more popular among short-sellers, which is due to the fact that large cap stocks are both inexpensive and easy to borrow. Diether et al. (2009) analyze the cross-sectional patterns of short-selling activity and confirm that short-selling is higher for large-cap stocks.

Meanwhile, short sellers are generally considered as advanced users of accounting information. The magnitude of earnings management is one important feature short-sellers pay special attention to. Staley (1997) depicts how short sellers explore firm-specific financial reports and glean all related signs for unhealthy financial situation. According to Staley, short sellers keep an eye on those firms with exaggerated earnings. Efendi, Kinney and Swanson (2005) study short-sellers' expertise in identifying accounting irregularities by spotting abnormal short-selling in advance of a restatement announcement. They document short sellers' position increases as the announcement date approaches, which they believe supports their argument that short-sellers do have specialty in recognizing accounting misstatement. Similarly, Dechow et al. (1996) provide evidence that short-sellers could also foresee SEC allegations of the fraud. Desai, Krishnamurthy, and Venkataramaran (2006) claim short-sellers target firms with high accruals.

2.3 Analyst Recommendation and Information Value

Although the objectivity and integrity of analyst recommendations has always been the easy target of academic bombardment, there is mounting evidence and growing consensus that analyst recommendations contain profitable information. A series of research justify this argument by implementing a return-based analysis. Bjerring, Lakonishok, and Vermaelen (1983) find that an investor could have achieved significantly abnormal returns following the investment advice of a leading Canadian brokerage house, taking transaction costs into account. Stickel (1995) analyzes the stock price movement around the announcement of analyst recommendations, and observe significant mean abnormal returns for the event days -10 to +10. The research interest of Womack (1996) is focused on newly-issued "Buy" and "Sell" recommendations. The author documents 3.0 percent increase in size-adjusted prices after new "Buy" recommendations and 4.7 percent drop subsequent to new "Sell" recommendations. Unlike the previous studies, Barber et al. (2001) takes and investor-oriented, calendar-time perspective to purchase (selling short) stocks with the most (least) favorable consensus recommendations. This trading strategy yields annual abnormal returns greater than four percent. All these studies imply that analyst recommendations are informative and have investment value.

3. Data and Sample Selection

In this section, we describe the data used in this study. Following Diether, Lee and Werner (2009), we use the tick-by-tick transactions level short-sale data, aggregated to the daily level. The original data set is named *Reg SHO* Data which contains all trades with a short sale component reported to the NYSE. This data set stems from the SEC's enforcement of Regulation SHO which aims at limiting the downward pricing pressure from short selling of large scale. All members of self-regulatory organizations (SRO) were mandated to make their short-sale transactions publicly available. In our study, we use the whole data set available ranging from January 2005 to July 2007[3]. The time span is even longer than that of Diether, Lee and Werner (2009). Among all the short transactions, some sales are marked "short exempt" if the seller is perceived as an exception to the tick test of Rule 10a-1, or the price test of an exchange or national securities association. The exemption may result from that the seller involves in market making activities. Since the focus of our study is the short sales with the purpose of making profit from anticipated price deterioration, we exclude all these "short exempt" trades.

In spite of its uniqueness and completeness, one may also notice that there are three major drawbacks. Above all, there is no way to discriminate the motivation

[3] On 23 June 2004, the SEC establish Regulation SHO to carry out short-sale price tests on a set of pilot securities during period 2 May 2005 to 28 April 2006. Later on, the short-sale Pilot plan was extended to August 2007

behind the short sales. If the short sellers short a stock in order to hedge a position in a pending delivery due in a couple of days, it would be improper to assert that the seller anticipates price falling, or consider the short-selling uninformative as the subsequent price does not decline. Secondly, the data set only provides the size of each short trade, but doesn't identify when the shorts are reversed. Without the knowledge of the trading horizon, it would be impossible to calculate short-sellers' trading returns and gauge the profitability associated with these short transaction. Moreover, this data set does not provide the short-sellers' specifics. This fact restricts the exploration regarding the connection between short-seller and analysts, making the confirmation or rebuttal of the tipping hypothesis more challenging.

The starting sample contains 4,753 listed common stocks during January 3, 2005 to 06 July, 2007. In our sample, the average daily shorting size ranges from 188 million to 1.30 billion. The average daily shorting volume is measured as summing up all short-sales executed within a single day. We merged this data set with CRSP to obtain corresponding trading details. According to CRSP data base, during the same sample period, the trading volume of the shorted stocks ranges from 779 million to 5.09 billion, with a mean of 2.59 billion. One may notice that the dispersion of short-sales and trading volume is considerably large. D'Avolio (2002) finds that stocks with too low prices may be difficult to short. In case of that, we follow Christophe, Ferri and Angel (2004) to eliminate stocks whose prices below $10. The statistics of average daily short-selling and trading volume are summarized in the Panel A of Table 1. The short size of a stock to its daily trading volume is averagely more than 20%.

Annual fundamental information of the stocks shorted comes from COMPUSTAT. The market capitalization is calculated as the product of the amount of shares outstanding and the stock price. Similarly, book value of a stock is measured as multiplying the book value per share by the number of common shares outstanding. All stocks with negative book-to-market ratio and market capitalization are eliminated. If we partition the stocks under consideration into quintiles, the mean, minimum, maximum and standard deviation for each quintile are presented in Panel B of Table 1. One may notice that the sample covers a wide range of stocks.

[Insert Table 1 Here]

The analyst recommendations come from *First Call* database. It is a real-time database providing the subscribers with the first-hand daily commentary from professional practitioners including portfolio managers, economists and analysts. As to serve the interest of this research, we only analyze a small portion of the daily comments: the recommendations made by 10 most reputable U.S. brokerage research teams. We collect the "All-America the leaders" name list from the October issues of *Institutional Investors*[4] from 2005 to 2007, collate the names of these brokerage firms with those available in First Call, and ten U.S. brokerage firms are left[5]. This conduct of only considering comments from leading brokerage firms, following Womack (1996), is intuitive in the sense that these opinions generally lead to stronger market reactions.

[4] Institutional Investor organizes annual polls among buy-side institutions to rank research departments and individual security analysts of U.S. brokerage firms. Although some regard this competition equivalent to a "beauty contest", the winning analysts are generally perceived to be more skilful and normally compensated generously.

[5] The composition of the leading firms with renewable research teams does not change much all through the three years.

Each comment recorded in *First Call* normally contains following several elements: (1) the report time and date when the piece of information is made available on *First Call*, (2) the name, ticker and other identifier of the related stock, (3) the name of the brokerage firm that releases the comment, (4) a headline describing the topic, and (5) the content of the comments including earning forecast or recommendation. *First Call* adopts a five-point scale to reflect analysts' optimism to the related stock (1=strong buy, 2=buy, 3=hold, 4=sell, 5=strong sell). In order to facilitate more intuitive interpretation of this quantitative coding, we reverse the ranking so that more favourable recommendations correspond to larger numbers (i.e. 1=strong sell, 2=sell, 3=hold, 4=buy, 5=strong buy). We keep only recommendations that occurred between 08 March 2005 and 31 July 2007 so as to coordinate with short-selling data. The 08 March 2005 cut-off is chosen for the consideration of 40 pre-recommendation days. We also eliminate those recommendations with possible contamination from other events. The distribution of analyst recommendation dated from 2005 to 2007 is demonstrated in table 2. One may notice that recommendations available is growing through the three years, and mean for recommendations is consistently above 3, which implies that analysts are inclined to issue overly optimistic recommendations to the covered stocks.

[Insert Table 2 Here]

While a substantial portion of earlier literature raises various questions about the objectivity and credibility of analyst recommendations[6], consensus is reached that

[6] For studies focused in this area, see, e.g. Lin and McNichols (1998); Michaely and Womack (1999); and Hong and Kubik (2003).

analyst recommendations do provide incremental information to the market[7]. To roughly testify this idea, we provide a simple data summary of cumulative abnormal returns prior to, at the time of, and subsequent to the recommendation date. The daily abnormal return is calculated as the difference between individual stock return and CRSP market value-weighted return. Cumulative abnormal return is produced by summing up daily abnormal returns over n days. To put in a mathematical way,

$$AR_{it} = R_{it} - R_{mt} \tag{1}$$

where R_{it} is the raw return for stock *i* on day *t*, and R_{mt} denotes the CRSP market value-weighted return for the same day *t*.

$$CAR_{i\tau} = \sum_{t=a}^{b} AR_{it} \tag{2}$$

where $CAR_{i\tau}$ is the cumulative abnormal returns for stock *i* during period τ (from date *a* to date *b*). Table 3 presents the average cumulative abnormal returns for stocks five days prior to, around, and subsequent to "Sell" and "Buy" recommendations. "Sell" recommendations are defined as recommendations rated 3 or below, and "Buy" are recommendations with a rating equal to 4 or above[8].

[Insert Table 3 Here]

Table 3 indicates that analyst recommendations lead to strong market reaction: on average price declines immediately after "Sell" recommendations, and rises after

[7] Numerous studies have explored this topic. Such examples are Bjerring et al. (1983); Stickel (1995); Womack (1996); and Barber (2001).

[8] The classification for "Buy" and "Sell" recommendations is consistently used throughout this whole paper, unless stipulated otherwise.

"Buy" recommendations. Buy recommendations are accompanied with considerably positive abnormal returns during three-day event period, while sell recommendations are followed by negative abnormal returns. These findings resonate with previous studies that analyst recommendations are informative and generally consist of a "surprise" to some extent.

4. Estimation and Analysis

4.1 Short-Selling Activities Prior to Analyst Recommendations

According to our hypothesis, if short sellers conduct informed trading prior to analyst recommendations, we expect to observe that short-selling activities significantly increase before sell recommendations and decrease before buy recommendations. In order to gauge the magnitude of abnormal increase or decrease in short sales, we capture the changes in intensity of short-sales by using the difference between: (1) short-selling five days prior to analyst recommendations and (2) short-selling during non-recommendations period. Since the dispersion across stocks is severe and possibly biases our result, we adopt the relative definition of short-selling. Throughout the whole study, we define the relative amount of short-selling as the number of a firm's stocks sold short divided by the number of its shares traded on the same day. To put it formally,

$$RELSS_{it} = \frac{SS_{it}}{Vol_{it}}, \tag{3}$$

where $RELSS_{it}$ denotes the relative amount of short-selling of stock *i* on day *t*. SS_{it} is the amount of shares of stock *i* sold short on day *t*. Similarly, Vol_{it} is the trading volume measure of stock *i* on the same day *t*.

In this section, we define abnormal short selling as the percentage change of relative short selling during five days preceding analyst recommendations. That is,

$$ABSS_{it}(-6,-2) = \frac{RELSS_{it}(-6,-2)}{AVESS_{it}} - 1, \quad (4)$$

where $RELSS_{it}(-6,-2)$ represents the average daily relative amount of stock i shorted during the prior-recommendation period, and $AVESS_{it}$ is the average daily relative short selling of stock i during non-recommendation period. Non-recommendation period is defined as the days within (-40, +40) period and outside of days -6 to +1. By employing this abnormal short selling measure, we implicitly assume that daily short-selling within the non-recommendation window is a fair proxy for "normal" size of daily short selling transactions.

As mentioned before, the focus of this study is to examine if short-sellers' behaviors reveal information contained in the analyst recommendations that later become public. To serve this purpose, we use the following model to capture the linkage between short-selling and the content of analyst recommendations:

$$ABSS(-6,-2) = \beta_0 + \beta_1 Sell + \beta_2 AR(-1,+1) + \beta_3 AR(-6,-2) + \varepsilon, \quad (5)$$

where $Sell$ is a dummy variable to capture the direction of analyst recommendations. Once the numeric representation of recommendation is equal to or below 3, the variable $Sell$ takes the value 1; otherwise, it takes 0. $AR(-1,+1)$ is the abnormal return on the stock during the 3-day event window around the analyst recommendation. And $AR(-6,-2)$ is the contemporary abnormal return in the stock during the target period (-6, -2).

$Sell$ and $AR(-1,+1)$ are two alternative proxies for the surprise contained in analyst recommendations. As shown in the data statistic section and proved again and again by early literature, the direction of analyst recommendations are positively related with the abnormal returns around recommendations.

$AR(-6,-2)$ serves as a control variable. It represents the stock price movement contemporaneous with the short-selling activities five days leading up to the analyst recommendations. This control variable is justified because the higher the stock price, the more likely short-sellers would perceive the stock over-priced, and thereby short sell it. Moreover, prior studies find that stocks with higher price are easier to short, hence become more ready targets for short-sellers. With this control variable in place, we prevent mistakenly attributing the price effect to short-sellers' sophistication and predictability

[Insert Table 4 Here]

We apply OLS to estimate the model (4). Results are presented in the panel A of Table 4. Apparently, the results are consistent with our hypothesis that abnormal short-selling before the analyst recommendation, $ABSS(-6,-2)$, is significantly affected by the direction of analyst recommendation, $Sell$. If a "Sell" opinion is about to release, the short-sellers start to short the related stocks five days leading up to the recommendation announcement date. It suggests that short-selling before the analyst recommendations is probably motivated by the informative content of the forthcoming analyst recommendations.

We also could notice that the coefficient for $AR(-6,-2)$ is significantly positive, which implies that the contemporaneous abnormal return is another driving factor for short-selling activities.

4.2 Another Model Specification

For robustness consideration, we further utilize another model specification to support the early conclusion. While the dependent variable for model (5) is the ratio of short-selling before analyst recommendation to average short selling, which captures the level of abnormal short-selling, one may be curious to see what will happen if average short-selling is moved to the right side of the model. Here comes the model (6) that directly explains the short-selling five days prior to analyst recommendations. Formally put, the model is as below:

$$\begin{aligned} RELSS(-6,-2) = \gamma_0 + \gamma_1 Sell + \gamma_2 AR(-1,+1) + \gamma_3 AR(-6,-2) \\ +\gamma_4 AVESS + \varepsilon, \end{aligned} \tag{6}$$

where $RELSS(-6,-2)$ is the relative short-selling during the five days before the release of analyst recommendations; $AVESS$ is the relative short-selling during non-announcement period; $Sell$ is the dummy variable for recommendations equal to or below 3; $AR(-1,+1)$ is the abnormal returns for the 3-day event period; $AR(-6,-2)$ is the abnormal returns for the period (-6, -2).

As explained in the last section, $Sell$ and $AR(-1,+1)$ are two variables serving as proxies for information embedded in analyst recommendations. The variable $AR(-6,-2)$ eliminates the possibility that unusual rise or fall of stock prices prior to analyst recommendation could also affect short-selling intensity. Finally, as literature points out, the average trading volume, $AVESS$, could be one key constraint and explanatory factor for the level of short-selling.

The results of this model specification, model (6), are summarized in the Panel B of Table 4. Apparently, our findings are corroborated by this modified model specification. The coefficient for the variable $Sell$ is still statistically significant at the level of 5%. γ_1=0.00415 implies that the relative short-selling prior to "sell" recommendation is 0.415% larger than that before "buy" recommendations. Similar to the results obtained in model (5), one could not reject that the coefficient γ_2 is zero, which says, 3-day event-period abnormal returns do not impact the short-selling prior to the recommendations to a statistically significant extent. The coefficient γ_3 is significantly different from zero, meaning that abnormal returns during (-6, -2) period does influence the contemporaneous short-selling transactions. As asserted above, $AVESS$ is an important explanatory variable for short-selling. The shares traded frequently are more likely to be shorted as well.

Generally, the finding of the model (6) resonates with our hypothesis and completes the conclusion of model (5). It is substantiated that the results presented in Panel A of table 4 is not due to manipulative model selection. It is considered persuasive to argue that short-sellers are involved in informed trading preceding analyst recommendations, and better seize the profits once the recommendations are made public.

4.3 Nonparametric Test of the reliance of Short-Selling on Recommendations

Following Dechow et al. (2001) and Christophe et al. (2004), we further implement a nonparametric test of the abnormal short-selling and the event-period abnormal returns. This nonparametric χ^2-test is to investigate if unusually high or low short-selling in the pre-recommendation period is dependent on the stock's event-period abnormal returns. We adopt the event-period abnormal return as the representation for the information content conveyed in the analyst recommendation for two reasons: firstly, it is more convenient to partition our sample into several subsamples based on the magnitude of abnormal returns; besides, it is the conventional conduct implemented by previous studies [9]. As the abnormal short-selling is our research interest, again the variable $ABSS(-6,-2)$ is under consideration. In addition, we also construct another metric $ABRELSS(-6,-2)$, measured as the difference between $RELSS(-6,-2)$ and $AVESS$. In other words, $ABSS(-6,-2)$ calibrates the percentage change of short-selling occurring prior to, and outside of the analyst recommendation, while $ABRELSS(-6,-2)$ captures how the level of short-selling during pre-announcement period differs from that during non-recommendation period. To demonstrate in mathematical forms, the two metrics are calculated as:

$$ABSS_{it}(-6,-2) = \frac{RELSS_{it}(-6,-2)}{AVESS_{it}} - 1, \tag{4}$$

$$ABRELSS_{it}(-6,-2) = RELSS_{it}(-6,-2) - AVESS_{it} \tag{7}$$

For either of the two metrics, we partition the whole sample into three subsamples based on the magnitude of abnormal short-selling: the top 30%, the middle 40%, and the bottom 30%. Then we observe how stocks categorized into each of the three subsamples behave during the 3-day around analyst recommendations. Similarly, we also sort the stocks in our sample based on three-day event-period abnormal returns into three categories: the highest 30% group which contains the top 30% performers, the middle 40% group which contains the mediocre performers, and the lowest 30% group whose members relatively underperform the rest 70% stocks. According to our previous expectation, the stock shorted most heavily would be more likely to underperform other than outperform, and fall into the bottom 30% abnormal return group. On the contrary, if short-selling is totally independent from analyst

[9] See, e.g., Dechow (2001) and Christophe (2004).

recommendation and the abnormal returns resulted in, it is expected to discover that the three subsamples based on short-selling intensity would distribute randomly across three categories of abnormal return groups. That is to say, we expect to find within each of the abnormal return groups, 30% stocks have experienced heavy short-selling, 40% stocks are moderately shorted, and 30% stocks have seldom been shorted. The converse is true: within each of the short-selling category, the best-, the mediocre-, and the worst-performers take the proportions roughly 30%, 40% and 30% respectively.

[Insert Table 5 Here]

Panel A of Table 5 shows that the group most heavily shorted, the top 30% $ABSS(-6,-2)$ group, tends to underperform during the analyst recommendation 3-day event period. 32.75% of the stocks in this group fall into the category for the worst 30% performers, while only 28.39% stocks in this group yield relatively higher returns. Comparatively, only 25.41% of stocks in the least shorted group are considered under-performers. The χ^2 statistic also confirms that the null hypothesis that abnormal short-selling preceding analyst recommendations and afterward abnormal returns are independent could be rejected at the level of 0.16%.

Panel B by employing another metric for abnormal short selling double checks the robustness of the implication above. Obviously, the results tell a similar story: the stocks that have been largely shorted would generally see a decline in abnormal returns during the analyst recommendation period, while those thinly shorted, on the other hand, generally perform better. For the χ^2 test based on the metric $ABRELSS_{it}(-6,-2)$, the null hypothesis of independence could be rejected at the level of 0.22%. That is to say, there is strong association between short-selling in the period leading up to the analyst recommendations and the event-period abnormal returns.

4.4 What Leads to Short-Sellers' Decision before Analyst Recommendations?

The earlier discussion tends to argue that short-sellers have better understanding of the shares shorted, and sensitive to the timing of analyst recommendations. The stocks intensively shorted would possibly receive unfavorable analyst recommendations later, and watch decline in price. However, there is an undeveloped area that hasn't been explored so far: how do short-sellers make their short-selling decisions before analyst recommendations? As indicated above, we hypothesize that short-sellers are more sophisticated market participants than the rest of investors, and thereby able to trade in advance to the analyst recommendations. Yet the sophistication could come from either better interpretation of public-available information or better information source such as early access to analyst reports. These two explanations are normally labeled as prediction hypothesis and tipping hypothesis, respectively. This section is designed to shed some light on this topic. Firstly, we'll test if short-sellers have some constant trading manner. Specifically, we examine if short-sellers treat growth stocks and value stocks differently, and if short-sellers' attitude towards large-cap stocks differ from that towards small-cap stocks. Then, we consider if short-sellers and analysts have similar predictability in firm earnings management. The basic hypothesis is: if analysts tip their favorite clients of the upcoming recommendations, short-sellers should share analysts' opinions of the firms, including their engagement in earnings management.

4.4.1 Growth Stocks versus Value Stocks

A large body of literature documents the abnormality that value stocks compared with growth stocks are generally more preferred and compensated with a premium. Fama and French (1992), among others, is such an example. When it comes to short-selling, Jones and Lamont (2002) find that there is larger short selling demand for growth stocks than for value stocks[10]. As an extension, Christophe et al. (2004) examines if short-sellers have a thing for growth stocks especially when a negative earnings surprise is anticipated. However, they believe short-sellers moves do not significantly vary across stocks with high and low book-to-market ratios prior to earnings announcement, though they generally target growth stocks.

These findings naturally trigger one request: is it the short-sellers' special preference of growth stocks push for short-selling of larger scale before analyst recommendations? To investigate this possibility, we collect the whole sample of stocks with positive book-to-market ratios and partition the stocks into quintiles. Lowest Quintile contains the stocks with lowest book-to-market ratios whereas Highest Quintile contains the stocks with highest book-to-market ratios. For the consideration of parsimony, only the extreme cases-Lowest Quintile and Highest Quintile-are considered in this section.

[Insert Table 6 Here]

Panel A of Table 6 shows, within either quintile, abnormal short-selling five-day preceding the release of analyst recommendations, grouped by the direction of the recommendations, and stocks' 3-day abnormal returns. As usual, two metrics, $ABSS_{it}(-6,-2)$ and $ABRELSS_{it}(-6,-2)$, of abnormal short-selling are both

[10] This finding is also consistent with Dechow et al. (2001) and Geczy et al. (2001).

applied. A noteworthy phenomenon occurs in the Highest Quintile that short-selling appears to be less intensive before "Sell" recommendation than "Buy" recommendation. Negative $ABSS_{it}(-6,-2)$ and $ABRELSS_{it}(-6,-2)$ prior to "Sell" recommendation for value stocks show that the intensity of abnormal short-selling even drops below its normal level and therefore does not support our previous hypothesis.

Panel B of Table 6 attacks the same problem from another perspective. It shows the between-quintile difference in short-selling before same sort of recommendations, be it a "Sell" or a "Buy". The results show that relative short selling in the non-recommendation period ($AVESS$) is roughly the same for growth and value stocks. In advance of a favorable analyst recommendation (a "Buy"), short-sellers shrink their short-selling transactions of growth stocks more severely than they do to value stocks; but short-sellers short more growth stocks other than value stock with the anticipation of a negative recommendation (a "Sell"). However, the statistics of Panel B confirm that such distinction between growth and value stocks does not significantly impact short-sellers behavioral patterns.

One possible critique for the results presented in Table 6 may be omission of controls for other possible confounding factors. As a resolution, we develop the following models to further dissect the problem.

$$ABSS(-6,-2) = \beta_0 + \beta_1 Sell + \beta_2 AR(-1,+1) + \beta_3 AR(-6,-2) + \beta_4 HighBM + \beta_5 Interaction + \varepsilon, \quad (8)$$

$$RELSS(-6,-2) = \gamma_0 + \gamma_1 Sell + \gamma_2 AR(-1,+1) + \gamma_3 AR(-6,-2) + \gamma_4 AVESS + \gamma_5 HighBM + \gamma_6 Interaction + \varepsilon, \quad (9)$$

where the variable $HighBM$ is a dummy variable that takes on the value 1 if the stock considered is grouped in the Highest Quintile based on its book-to-market ratio, and 0 otherwise. The variable $Interaction$ is the product of $Sell$ and $HighBM$ that takes on the value 1 if the stock is categorized into the Highest Quintile and an unfavorable analyst recommendation is forthcoming.

The variable $HighBM$ is utilized to indicate whether book-to-market ratios enter short-sellers' trading decision process and influence the short-sale position established preceding to analyst recommendations. The variable $Interaction$ examines the collective role played by book-to-market ratios and short-sellers' anticipation of forthcoming analyst recommendations. Short-sellers may spot some deeply overpriced or underpriced stocks which are likely to receive desirable or undesirable analyst recommendations in the near future, and then refer to the book-to-market ratios to double check if the stock under consideration is a ready target for short-selling. The results for model (8) and (9) are presented in Panel A and B of Table 7, respectively.

[Insert Table 7 Here]

The results summarized in Table 7 do not support that short-sellers establish their shorting positions based on book-to-market ratios. That β_4 and γ_5 are positive but statistically insignificant demonstrates that the abnormal short-selling preceding to the analyst recommendations is not directly associated with the book-to-market ratio of the target stock. The short-sellers do no specifically discriminate between value stocks and growth stocks, or have some preference for either group of stocks before the analyst recommendations. However, significantly negative β_5 and γ_6 provide evidence that book-to-market ratios are still a “filter” kicking in the short-sellers decision-making procedure. That is to say, once short-sellers have spotted some prospect targets, they won’t short as much if the target is a value stock.

4.4.2 Large-Cap Stocks versus Small-Cap Stocks

Market capitalization is another influential factor to short-selling frequently discussed in previous literature. Jones and Lamont (2002) report that large cap stocks are relatively easy and inexpensive to borrow and short compared to their small cap counterparts. Diether et al. (2009) also document similar findings. The short-constraint on small cap stocks may impede in short-sellers’ actions even if they anticipate a forthcoming price deterioration due to unfavorable analyst recommendations. In order to examine whether short-selling prior to analyst recommendations is primarily biased by the existence of short-constraint, we present the following table to demonstrate the association between pre-recommendation abnormal short-selling, the desirability of the analyst recommendations, and market capitalization. We keep all stocks with positive market cap and partition them into quintiles based on the market cap. Only results for the lowest and highest quintiles are presented in the table. The lowest quintile includes stocks from the smallest 20% firms while the highest quintile includes stocks issued by the largest 20% companies.

[Insert Table 8 Here]

Similar to the last section, Panel A of Table 8 checks whether the within-quintile abnormal short-selling before “Buy” recommendations differs from that before “Sell” recommendations. Generally we expect to observe expanding abnormal short-selling prior to unfavorable recommendations and associated price decline, and shrinking abnormal short-selling prior to favorable recommendations and related price rise. However, one may notice that it is the opposite for small cap stocks. It seems that short-sellers are less capable to forecast analysts' recommendation for small cap stocks.

As to further explore how the distinction between big-cap and small-cap stocks interferes short-sellers' move prior to analyst recommendations, we provide Panel B. Panel B estimates the short-selling prior to a same recommendation across market capitalization quintiles. One interesting discovery is that relative short-selling during non-recommendation period, $AVESS$, for large-cap is even smaller than that for small-cap. It seemingly contradicts with the view of previous literature that stocks with low market capitalization face more binding short-sale constraints and therefore less popular among short-sellers. However, it doesn't need to be the case once we recall that the variable $AVESS$ is measured as the amount of shares shorted during non-recommendation divided by the size of trading volume. In other words, the number of stocks short-sold may differ from large-cap stocks from small-cap stocks, but the short-selling normalized by the trading volume do not vary among large- and small-cap stocks. The results concerning pre-recommendation short-sales are mixed. While short-sellers might be more active in the large-cap stocks prior to "Sell" recommendations, they short less large-cap stocks preceding "Buy" recommendation.

We also estimate the following two models to address the possible criticism of insufficient control variables. The two models investigate how market capitalization information is channeled into short-sellers' positions:

$$\begin{aligned} ABSS(-6,-2) = {} & \beta_0 + \beta_1 Sell + \beta_2 AR(-1,+1) + \beta_3 AR(-6,-2) \\ & + \beta_4 HighME + \beta_5 CrossTerm + \varepsilon, \end{aligned} \tag{10}$$

$$RELSS(-6,-2) = \gamma_0 + \gamma_1 Sell + \gamma_2 AR(-1,+1) + \gamma_3 AR(-6,-2)$$
$$+\gamma_4 AVESS + \gamma_5 HighME + \gamma_6 CrossTerm + \varepsilon, \quad (11)$$

where $HighME$ is a binary variable that takes 1 if the stock is grouped into the Highest Quintile with respect to its market capitalization. The dummy variable $CrossTerm$ is the product of $Sell$ and $HighME$ which takes the value 1 only if the stock is both large-cap and commented better to be sold by professional analysts.

The variable $HighME$ is included in the models to test if short-sellers establish their short-selling positions on the basis of market capitalization. As implied in the previous studies, short-sellers may prefer large-cap stocks better and this inclination towards stocks of big firms may partly explain short-sellers' transactions prior to analyst recommendations. The variable $CrossTerm$ examines whether market capitalization is equivalent to a "filter" for short-sellers to narrow down the short-selling candidates so that short-sellers could pin down the stocks with forthcoming "Buy" or "Sell" recommendations more precisely. Panel A and B of Table 9 display the estimation results for model (10) and (11), respectively.

[Insert Table 9 Here]

The results for model (10) and (11) do not substantiate the conjecture that market capitalization could be one explanatory factor for abnormal short-sales prior to analyst recommendations. The statistically insignificant β_4 and γ_5 imply that controlling for the anticipation for forthcoming analyst recommendations short-sellers do not exhibit constant preference for large-cap stocks in the sense of abnormal short selling. And market capitalization is neither a filter for short-sellers to screen possible short-selling targets, which could be seen from β_5 and γ_6 that are not significantly different from zero. Therefore, unlike book-to-market ratios, there is no reliable evidence that hints at a trading strategy based on market capitalization. The abnormal trading behaviors prior to analyst recommendation are considered to be irrelevant with the stocks' market cap.

4.4.3 "Aggressive" Firms versus "Conservative" Firms

Accrual accounting, while reflecting real economic transactions, also provides managerial discretion to obscure facts and mislead investors. Prior research has proven that management could undertake earnings management to window-dress their financial reports so as to meet or beat market consensus in earnings targets (Healy (1985)). However, as there are various incentives for the firm to manage earnings, even analysts are proven to find it difficult to anticipate earnings management fully. This also explains why earnings forecast could deviate from the true numbers greatly under some circumstances. A growing body of literature resonates with this claim[11].

On the other hand, short-sellers appear to be able to discriminate "aggressive" firms from "conservative" firms. Efendi, Kinney and Swanson (2005) carry out an investigation of short sellers' trading with respect to firms that announce an accounting restatement. They discover short-sellers' positions significantly increase preceding the firm restatement announcement, and peaks in the announcement month, which leads to the belief that short-sellers have sufficient expertise to identify accounting abnormality. Dechow et al. (1996) provide a similar study that documents increasing short-selling prior to an SEC allegation of the fraud. Besides, there is also more direct evidence supporting the view that short-sellers dissect firms' accounting

[11] One may refer to Hanna (1999), Degeorge, Patel, and Zechhauser (1999), Barber and Kang (2001), Abarbanell and Lehavy (2003) for a glimpse of this idea.

information to glean proper stocks to short. Staley (1997) portrays short-sellers' use of accounting information, and especially points out that short sellers recognize firms with materially exaggerated earnings.

Therefore, it may be of considerable interest to compare short-sellers and analysts with regard to their predictability in company accounting accrual. And the findings may also help us to weigh two propositions - prediction hypothesis and tipping hypothesis – from a new perspective. If short-sellers benefit from analysts' tips in advance, their trading patterns should display consistence across companies regardless of the accounting treatments. Contrarily, if short-sellers do scrutinize the firms' financial statement in order to cast short positions, it is likely that their judgment deviates from that of analysts from time to time.

Following prior research, we estimate earnings manipulation by using accrual-based measures. Current accruals are calculated as:

$$Current\ Accruals = \\ \Delta[accounts\ receivables + inventory + other\ current\ assets] - \\ \Delta[accounts\ payable + taxes\ payable + other\ current\ liabilities] \qquad (12)$$

Since accruals may vary greatly across industries and are severely influenced by the firms' economic conditions, one should take into account these industry features as to extract real accruals. Thereby, we follow Teoh, Wong and Rao's (1998) lead to adopt the cross-sectional modified Jones (1991) model to separate the normal and abnormal components of accruals. The model proposes that the change in revenues, serving as the proxy for the firm's exogenous economic conditions, may influence the normal amount of accruals to a great extent. As management could also play around with credit sales, subtracting increases in trade receivables from the change in revenues may better capture the "normal" level of accounting accruals. Therefore, we firstly regress current accruals on the change in sales revenues excluding the change in trade receivables for the sample of all firms with the same 2-digit SIC code. Then the expected or "normal" current accrual is estimated using the fitted coefficients. The real accrual minus the expected portion yields the abnormal accruals.

The cross-sectional regression could ensure that industry-wide impact is eliminated from the accounting accruals, and the residual is due to management discretion. And it is also a common practice in literature[12]. Thereby, we could obtain the accrual numbers for the stocks shorted. The earnings management profile of these firms is reported in Table 10.

[Insert Table 10 Here]

Then we examine whether the magnitude of the firm earnings management enters into short-sellers' consideration. We sort the whole sample of stocks shorted by their abnormal accrual and partition them into three groups: "conservative" group for the bottom 30% firms, "moderate" group for the middle 40%, and "aggressive" group for the top 30%. And we testify whether short-sellers demonstrate consistent trust in analyst recommendations across three groups. The results are summarized in the following table.

[Insert Table 11 Here]

[12] See DeAngelo (1990), DeFond and Jiambalvo (1994) for example.

Table 11 reports results of abnormal short-selling in advance to analyst recommendations on three different groups of firms. Panel A and Panel B adopt the two different specification mentioned earlier respectively, in order to testify the robustness. We find that analyst recommendations only count in the conservative firms group while short-sellers don’t exhibit special interest in those aggressive firms even they were recommended “sell” by analysts. This finding could serve as a piece of evidence that short-sellers don’t always listen to analyst recommendations literally, and their informed trading may possibly be resulted from their own analysis other than early access to analyst reports.

5. Conclusions

This paper investigates short-selling five days prior to analyst recommendations by using a complete data set from Reg SHO database during January, 2005 to July, 2007. We hypothesize that short-sellers will engage in large short-selling as they anticipate a negative analyst recommendation and a subsequent drop in stock price.

Two empirical specifications are constructed to unravel the association between pre-recommendation abnormal short-selling and the direction of the imminent analyst recommendations, with several control variables in place. The results uncover that abnormal increase in short-selling is normally followed by a “Sell” recommendation, and the negative relationship is statistically significant. A non-parametric test further confirms the results are not an artifact of special model design.

This study also investigates the two alternative explanations of short-sellers’ pre-recommendation trading. One is labeled prediction hypothesis that attributes short-sellers’ front-running behaviors to better prediction ability. And the competing proposition is called tipping hypothesis, asserting that short sellers benefit from a tip from the analysts. To compare these two claims, we examine if short-sellers pay attention to the stock-specific features, say fundamental ratios and accounting treatment for instance. Firstly, we explore the role played by book-to-market ratio and market capitalization in short-sellers' decision process. The empirical results suggest that short-sellers do not exhibit consistent interest in either growth or value stocks, but they do use book-to-market ratio to screen the candidate stocks for possible targets. Yet, there is little evidence that market capitalization is a relevant factor.

Then we turn to earnings management of the shorted firms. Accrual accounting leaves management leeway to manipulate financial reports and mislead investors, and even analysts may not be fully aware of it. Yet as sophisticated investors, short-sellers appear to be able to identify firms with poor earnings quality. Our results show that short-sellers' trading behaviors differ from analyst recommendations with regard to aggressive firms. To put it in another way, short-sellers' opinions systematically deviate from that of analysts on these high abnormal accrual firms. We assume that this finding proves that short-sellers do scrutinize firm financial reports so as to pick their targets other than mechanically follow analysts' tips. This finding supports the prediction hypothesis.

References

Abarbanell, J., and Lehavy, R., (2003), “Can Stock Recommendations Predict Earnings Management and Analysts’ Earnings Forecast Errors?” *Journal of Accounting Research* 41, 1-31.

Asquith, P., Mikhail M., and Au A, (2005), “Information Content of Equity Analyst Reports,” *Journal of Financial Economics* 75, 245-282.

Aitken, M. J., Frino, A., McCorry M.S., and Swan P.L., (1998), “Short Sales Are Almost Instantaneously Bad News: Evidence from the Australian Stock Exchange,” *Journal of Finance* 53, 2205-2223.

Asquith, P., and Meulbroek, L., (1996), “An Empirical Investigation of Short Interest,” Working per, Harvard Business School.

Ball, R., and Brown, P., (1968), “An Empirical Evaluation of Accounting Numbers,” *Journal of Accounting Research* 6, 159-178.

Barber, B., Lehavy, R., McNichols, M., and Trueman, B., (2001), “Can Investors Profit from the Prophets? Security Analyst Recommendations and Stock Returns,” *Journal of Finance* 56, 531-563.

Bernard, V. L., and Thomas, J. K., (1989), “Post-Earnings-Announcement Drift: Delayed Price Response or Risk Premium,” *Journal of Accounting Research* 27 (supplement), 1-36.

Bernard, V. L., and Thomas, J. K., (1990), “Evidence that Stock Prices Do Not Fully Reflect the Implications of Current Earnings for Future Earnings,” *Journal of Accounting and Economics* 13, 305-340.

Bjerring, J. H., Lakonishok, J., and Vermaelen, J., (1983), “Stock Prices and Financial Analysts’ Recommendations,” *Journal of Finance* 38, 187-204.

Blau, B. M. and Pinegar, J.M., (2009), “Earnings Announcement, Price Convexity, and Short Selling Profits,” working paper, Utah State University.

Blau, B. M. and Wade, C., (2009), “Informed or Speculative: Short Selling Analyst Recommendations,” working paper, Utah State University and University of Mississippi.

Boehmer, E. C. and Wu, J., (2008), “Short Selling and the Informational Efficiency of Prices,” working paper, University of Georgia.

Boehmer, E. C. and Zhang, X., (2008), “Which Shorts are Informed,” *Journal of Finance*, forthcoming.

Brent, A., Morse, D., and Stice, E.K., (1990), “Short Interest: Explanations and Tests,” *Journal of Financial and Quantitative Analysis* 25, 273-289.

Brown, L. D., (1997), “Earnings Surprise Research: Synthesis and Perspectives,” *Financial Analyst Journal* 53, 13-19.

Cao, B., Dhaliwal, D. S., and Kolasinski, A., (2006), "Bears and Numbers: Investigating How Short Sellers Exploit and Affect Earnings-Based Pricing Anomalies," Working paper, Sloan School of Management, Massachusetts Institute of Technology.

Chen, J., Hong, H., and Stein, J., (2002), "Breadth of Ownership and Stock Returns," *Journal of Financial Economics* 66, 171-205.

Chen, H., and Singal, V., (2003), "Role of Speculative Short Sales in Price Formation: The Case of the Weekend Effect," *Journal of Finance* 58, 685-706.

Choie, K., Hwang, S. J., (1994), "Predictability of Short-Selling and Exploitability of Short Information," *Journal of Portfolio Management* 20, 33-38.

Christophe, S., Ferri, M., and Angel, J., (2004), "Short-Selling Prior to Earnings Announcements," *Journal of Finance* 59, 1845-75.

Cohen, L., Diether, K., and Malloy, C., (2007), "Supply and Demand Shifts in the Shorting Market," *Journal of Finance* 62, 2061-96.

Cowles, A., (1933), "Can Stock Market Forecasters Forecast?" *Econometrica* 1, 309-324.

Danielsen, B., and Sorescu, S., (2001), "Why Do Option Introductions Depress Stock Prices? A Study of Diminishing Short Sale Constraints," *Journal of Financial and Quantitative Analysis* 36, 451-484.

Daske, H., Richardson, S., and Tuna, I., (2005), "Do Short Sale Transactions Precede Bad News Events?" working paper, University of Pennsylvania.

D'Avolio, G., (2002), "The Market for Borrowing Stocks," *Journal of Financial Economics* 66, 271-306.

Dechow, P. M., Hutton, A. P., Meulbroek, L., and Sloan, R. G., (2001), "Short Sellers, Fundamental Analysis and Stock Returns," *Journal of Financial Economics* 61, 77-106.

Desai, H., Krishnamurthy, S., and Venkataraman, K., (2006), "Do Short Sellers Target Firms with Poor Earnings Quality? Evidence from Earnings Restatements," *Review of Accounting Studies* 11, 71-90.

Desai, H., Ramesh, K., Thiagarajan, S. R., and Balachandran, B. V., (2002), "An Investigation of the Information Role of Short Interest in the Nasdaq Market," *Journal of Finance* 57, 2263-2287.

Diamond, D. W., and Verrecchia, R. E., (1987), "Constraints on Short-Selling and Asset Price Adjustment to Private Information," *Journal of Financial Economics* 18, 277-311.

Diether, K., (2008), "Short-Selling, Timing and Profitability," Working paper, Ohio State Univerisity.

Efendi, J., Kinney, M., and Swanson E., (2005), "Can Short Sellers Predict Accounting Restatement?" Working paper, Texas A&M University.

Figlewski, S., (1981), "The Informational Effects of Restrictions on Short Sales: Some Empirical Evidence," *Journal of financial and Quantitative Analysis* 16, 463-476.

Francis, J., Venkatachalam, M., and Zhang, Y., (2006), "Do Short Sellers Convey Information about Changes in Fundamentals or Risk?" Working paper, Fuqua School of Business, Duke University.

Geczy, C. C., Musto, D. K., and Reed A., V., (2002), "Stocks are Special too: An Analysis of the Equity Lending Market," *Journal of Financial Economics* 66, 241-269.

Gordon, A.J., Peterson, M.A., (2002), "Implications of a Reduction in Tick Size on Short-Sell Order Execution," *Journal of Financial Intermediation* 11, 37-60.

Holden, C. W., and Subrahmanyam, A., (1992), "Long-Lived Private Information and Imperfect Competition," *Journal of Finance* 47, 247-270.

Hong, H., and Kubik, J. D., (2003), "Analyzing the Analysts: Career Concerns and Biased Earnings Forecasts," *Journal of Finance* 58, 313-151.

Jegadeesh, N., Kim, J., Krische, S. D., and Lee, C. M. C., (2004), "Analyzing the Analysts: When Do Recommendations Add Value?" *Journal of Finance* 59, 1083-1124.

Jones, C., (2004), "Shorting Restrictions, Liquidity, and Returns," Working paper, Columbia University.

Jones, C., and Lamont, O., (2002), "Short Sales Constraints and Stock Returns," *Journal of Financial Economics* 66, 207-239.

Krische, S. D., and Lee, C.M.C., (2000), "The Information Content of Analyst Stock Recommendations," Working paper, Cornell University.

Malmendier, U., and Shanthikumar, D., (2007), "Are Small Investors Naïve about Incentives?" *Journal of Financial Economics* 85, 457-489.

Maurice, J. O., Litzenberger, R. H., and McEnally, R. W., (1977), "The Adjustment of Stock Prices to Announcements of Unanticipated Changes in Quarterly Earnings," *Journal of Accounting Research* 15, 207-225.

Womack, K. L., (1996), "Do Brokerage Analysts' Recommendations Have Investment Value?" *Journal of Finance* 51, 137-167.

Nagel, S., (2005), "Short Sales, Institutional Investors, and the Cross-Section of Stock Returns," *Journal of Financial Economics* 78: 277-309.

Ofek, E., Richardson, M., and Whitelaw, R., (2004), "Limited Arbitrage and Short Sales Restrictions: Evidence from the Options Markets," *Journal of Financial Economics* 74: 305-342.

Reed, A. V., (2001), "Costly Short-Selling and Stock Price Adjustment to Earnings Announcements," Working paper, The University of North Carolina at Chapel Hill.

Senchack, A. J., and Starks, L. T., (1993), "Short-Sale Restrictions and Market Reaction to Short-Interest Announcements," *Journal of financial and Quantitative Analysis* 28, 177-194.

Staley, K.F., (1997), "The Art of Short Selling," New York, NY: Wiley Publishing Company.

Stickel, S. E., (1992), “Reputation and Performance among Security Analysts,” *Journal of Finance* 47, 1811-1836.

Stickel, S. E., (1995), “The Anatomy of the Performance of Buy and Sell Recommendations,” *Financial Analyst Journal* 5, 25-39.

Teoh, S., Wong, T.J., and Rao, G.R.(1998), “Are Accruals during Initial Public Offerings Opportunistic?” *Review of Accounting Studies* 3, 175-208.

Turner, L., Dietrich, J.R., Anderson, K., and Bailey, A.J., (2001), “Accounting Restatements,” Working paper, SEC.

Wu, M., (2002), “Earnings Restatements: A Capital Markets Perspective,” Working paper, New York University.

Table 1

Key Characteristics of Short-Selling: Jan, 2005 to July, 2007

The daily shorted shares are the average number of shares sold short during a day. Similarly, daily trading volume is the average number of shares traded on a day. Shorted shares to trading volume are (shorted shares of stock j/the trading volume of stock j). We partition the whole sample of stocks shorted into quintiles on the basis of Book-to-Market ratio (B/M ratio) and Market Capitalization, respectively. Quintile 1 contains the 20% stocks with the lowest B/M ratio or smallest market cap, while Quintile 5 contains the 20% stocks with the highest B/M ratio or largest market cap.

Panel A: Shorted Shares

	Daily Shorted Shares □million)	Daily Trading Volume (million)	Shorted S□ares to Trading Volume (%)
Mean	595	2□95	25.76
Minimum	188	779	4.51
Maximum	1298	5092	57.61
Std	119	550	10.65

Panel B: Firm Characteristics of Shares Shorted

	Quintile 1	Quintile 2	Quintile 3	Quintile 4	Quintile 5
B/M ratio					
Mean	0.151	0.282	0.397	0.540	0.837
Minimum	0.004	0.227	0.337	0.465	0.624
Maximum	0.227	0.337	0.465	0.624	9.880
Std	0.056	0.032	0.037	0.046	0.545
Market Cap(million)					
Mean	1,249	2,995	6,410	14,427	67,682
Minimum	20	2,056	4,092	9,478	21,981
Maximum	2,055	4,091	9,471	21,965	406,072
Std	458	575	1,601	3,358	58,434

Table 2

The Monthly Distribution of Analyst Recommendations: Jan, 2005 to July, 2007

This table presents the distribution of analyst recommendations during the whole sample period. Only recommendations from leading brokerage firms and also available on *First Call* database is included in our sample. While *First Call* adopts a scale of five to indicate the analysts' opinion towards a specific stock, we reverse the scale so that larger number represents more favorable recommendations (1=Strong Sell, 2=Sell, 3=Hold, 4=Buy, 5=Strong Buy).

year (1)	month (2)	N (3)	% (4)	Mean (5)	Std Dev (6)
2005	3	206	0.62%	3.2427	0.7898
	4	546	1.65%	3.3443	0.9019
	5	635	1.91%	3.3575	0.9380
	6	707	2.13%	3.4611	0.7856
	7	955	2.88%	3.2440	0.8319
	8	865	2.61%	3.4798	0.8923
	9	1051	3.17%	3.3406	0.7783
	10	1409	4.25%	3.4060	0.9045
	11	854	2.58%	3.3326	0.8200
	12	938	2.83%	3.3785	0.9617
2006	1	1447	4.36%	3.1942	0.8896
	2	1029	3.10%	3.2313	0.8882
	3	1780	5.37%	3.2191	0.9117
	4	1326	4.00%	3.2888	0.8584
	5	1257	3.79%	3.2015	0.8935
	6	1373	4.14%	3.3948	0.8938
	7	1455	4.39%	3.2564	0.8021
	8	1213	3.66%	3.3248	0.8703
	9	913	2.75%	3.1950	0.9064
	10	1142	3.44%	3.1403	0.6625
	11	896	2.70%	3.3125	0.8067
	12	1254	3.78%	3.2057	0.8067
2007	1	1453	4.38%	3.2849	0.8688
	2	1224	3.69%	3.3399	0.8863
	3	1306	3.94%	3.5038	0.9200
	4	1471	4.44%	3.3236	0.8829
	5	1643	4.95%	3.4175	0.8597
	6	1435	4.33%	3.3791	0.8515
	7	1381	4.16%	3.3555	0.8497
Total		33164		3.3033	0.8627

Table 3
Abnormal Returns Around Analyst Recommendations: Jan, 2005 to July, 2007

$$AR_{it} = R_{it} - R_{mt} \quad (1)$$

$$CAR_{i\tau} = \sum_{t=a}^{b} AR_{it} \quad (2)$$

Abnormal return is calculated by subtracting the cumulative value-weighted market return from holding period return. The recommendations with a score equal to or below 3 are considered as "Sell" recommendations, and those with a score above 3 are considered "Buy" recommendations. Only recommendations from leading brokerage firms and also available on *First Call* database are included in our sample. In this case, only 10 brokerage firms are under consideration.

Panel A: Abnormal Returns (%) around Sell Recommendations			
	(-6,-2)	(-1,+1)	(+2,+6)
Mean	0.14**	-0.43***	0.06
Median	0.04	-0.42	-0.01
Minimum	-26.34	-49.38	-15.74
Maximum	35.95	47.98	14.17
Std	3.61	4.92	3.31
Panel B: Abnormal Returns (%) around Buy Recommendations			
	(-6,-2)	(-1,+1)	(+2,+6)
Mean	0.45***	1.54***	0.19**
Median	0.18	1.13	0.09
Minimum	-16.89	25.65	-16.08
Maximum	19.95	26.19	13.66
Std	3.44	3.81	3.34

*, ** and *** indicate statistically significance at the 10%, 5% and 1% levels, respectively.

Table 4
Results of OLS Regressions: Abnormal Short-Selling and Short-Selling Five Days Prior to Analyst Recommendations: Jan, 2005 to July, 2007

$$ABSS(-6,-2) = \beta_0 + \beta_1 Sell + \beta_2 AR(-1,+1) + \beta_3 AR(-6,-2) + \varepsilon, \quad (5)$$

$$RELSS(-6,-2) = \gamma_0 + \gamma_1 Sell + \gamma_2 AR(-1,+1) + \gamma_3 AR(-6,-2)$$
$$+\gamma_4 AVESS + \varepsilon, \quad (6)$$

The results of OLS regression of these two models are shown in the below table. The variable $ABSS(-6,-2)$ is the average daily abnormal relative short selling for a stock in the pre-recommendation five-day period, calculated as the daily average relative short selling in the five days prior to recommendations divided by the daily average relative short selling during non-recommendation period, all minus 1. The variables $RELSS(-6,-2)$ and $AVESS$ represent the daily relative short selling during (-6, -2) period and non-recommendation period respectively. The variable $AR(-1,+1)$ is the stock 3-day event-period cumulative abnormal return, measured as 3-day holding period return minus contemporary market value-weighted return. The variable $AR(-6,-2)$ is the control variable, represents the abnormal returns during the pre-recommendation period (-6, -2). Standard errors are in parentheses below coefficient.

Panel A: Equation (5)

β_0	β_1	β_2	β_3	Adjusted R^2
-0.00126	0.01559**	0.12452	1.79806***	0.0753
(0.00627)	(0.00771)	(0.07829)	(0.10076)	

Panel B: Equation (6)

γ_0	γ_1	γ_2	γ_3	γ_4	Adjusted R^2
0.02032***	0.00415**	0.02224	0.43964***	0.91615	0.4339
(0.00472)	(0.00196)	(0.01983)	(0.02557)	(0.01741)	

*, ** and *** indicate statistically significance at the 10%, 5% and 1% levels, respectively.

Table 5

Chi-Square Tests of the Relationship between Abnormal Short-Selling and the Event-Period Abnormal Returns: Jan, 2005 to July, 2007

$$ABSS_{it}(-6,-2) = \frac{RELSS_{it}(-6,-2)}{AVESS_{it}} - 1, \tag{4}$$

$$ABRELSS_{it}(-6,-2) = RELSS_{it}(-6,-2) - AVESS_{it} \tag{7}$$

These nonparametric tests examine if the intensity of short-selling during pre-recommendation (-6, -2) period is associated with 3-day event period abnormal returns around analyst recommendation. The variable ABSS(-6,-2) is the average daily abnormal relative short selling for a stock in the pre-recommendation five-day period, calculated as the daily average relative short selling in the five days prior to recommendations divided by the daily average relative short selling during non-recommendation period, all minus 1. The variable ABRELSS(-6,-2) is another alternative metric for average daily abnormal relative short selling, measured as the difference between daily average relative short selling in the five days prior to recommendation and the daily average relative short selling during non-recommendation period. The whole sample is partitioned based on the magnitude of abnormal returns during (-1, +1) into three categories: Low 30%, Moderate 40% and High 30%. Similarly, we also split the whole sample based on the abnormal short selling into three groups: Bottom 30%, Middle 40% and Top 30%. The probability is the level of significance at which the independent hypothesis can be rejected.

Panel A: Abnormal Short-Selling ABSS(-6,-2)

AR(-1,+1)		Low 30%	Moderate 40%	High 30%	Total
ABSS(-6,-2)					
Bottom 30%	N	264	452	315	1030
	%	7.68	13.15	9.16	
	Row %	25.61	43.84	30.55	
	Column %	25.41	32.92	30.7	29.99
Middle 40%	N	437	520	418	1375
	%	12.71	15.13	12.16	
	Row %	31.78	37.82	30.40	
	Column %	42.06	37.87	40.74	39.99
Top 30%	N	338	401	293	1032
	%	9.83	11.66	8.52	
	Row %	32.75	38.86	28.39	
	Column %	32.53	29.21	28.56	30.02
Total	N	1039	1373	1026	3438
	Row %	30.22	39.94	29.84	100.00
				χ^2 Statistic	17.39
				probability	0.0016

Panel B: Abnormal Short-Selling ABRELSS(-6,-2)					
AR(-1,+1)		Low 30%	Moderate 40%	High 30%	Total
ABRELSS(-6,-2)					
Bottom 30%	N	264	446	321	1031
	%	7.68	12.97	9.34	
	Row %	25.61	43.26	31.13	
	Column %	25.41	32.48	31.29	29.99
Middle 40%	N	433	527	418	1375
	%	12.59	15.33	12.07	
	Row %	31.49	38.33	30.18	
	Column %	41.67	38.38	40.45	39.99
Top 30%	N	342	400	290	1032
	%	9.95	11.63	8.44	
	Row %	33.14	38.76	28.10	
	Column %	32.92	29.13	28.27	30.02
Total	N	1039	1373	1026	3438
	Row %	30.22	39.94	29.84	100.00
				χ^2 Statistic	16.69
				probability	0.0022

Table 6

Abnormal Short Selling Prior to Analyst Recommendations, for Stocks Grouped by Book-to-Market Ratios: Jan, 2005 to July, 2007

The variable ABSS(-6,-2) is the average daily abnormal relative short selling for a stock in the pre-recommendation five-day period, calculated as the daily average relative short selling in the five days prior to recommendations divided by the daily average relative short selling during non-recommendation period, all minus 1. The variable ABRELSS(-6,-2) is another alternative metric for average daily abnormal relative short selling, measured as the difference between daily average relative short selling in the five days prior to recommendation and the daily average relative short selling during non-recommendation period. The Lowest Quintile contains the 20% of stocks with the lowest book-to-market ratios, while the Highest Quintile contains 20% of stocks with the highest book-to-market ratios. The means of abnormal returns and abnormal short-selling are presented in the following table. The two-tailed t-tests evaluate the differences in means and Wilcoxon z-test examines the differences in median.

Panel A: Control for Book-to-Market

	Lowest Quintile				Highest Quintile			
	Buy	Sell	Difference		Buy	Sell	Difference	
			t-value	Wilcoxon z			t-value	Wilcoxon z
N	286	481			230	525		
AR(-1,+1)	0.018	-0.009	7.35***	9.17***	0.015	-0.002	5.12***	6.83***
ABSS(-6,-2)	-0.005	0.010	-0.87	-1.35	0.020	-0.008	1.44	1.26
ABRELSS(-6,-2)	-0.003	0.001	-0.86	-1.14	0.004	-0.004	1.53	1.28
AVESS	0.253	0.262	-2.16**	-2.12**	0.256	0.267	-2.64***	-2.467**

Panel B: Control for Recommendations

	Buy				Sell			
	Lowest Quintile	Highest Quintile	Difference		Lowest Quintile	Highest Quintile	Difference	
			t-value	Wilcoxon z			t-value	Wilcoxon z
N	286	230			481	525		
AR(-1,+1)	0.018	0.015	1.04	-1.33	-0.009	-0.002	-2.25**	-1.67*
ABSS(-6,-2)	-0.005	0.020	-1.15	1.39	0.010	-0.008	1.23	1.19
ABRELSS(-6,-2)	-0.003	0.004	-1.22	1.44	0.001	-0.004	1.28	1.01
AVESS	0.253	0.256	-0.53	0.414	0.262	0.267	-1.70*	-1.62

*, ** and *** indicate statistically significance at the 10%, 5% and 1% levels, respectively.

Table 7
Results of OLS Regressions: Impact of High Book/Market Ratio on Abnormal Short-Selling and Short-Selling Five Days Prior to Analyst Recommendations: Jan, 2005 to July, 2007

$$ABSS(-6,-2) = \beta_0 + \beta_1 Sell + \beta_2 AR(-1,+1) + \beta_3 AR(-6,-2) + \beta_4 HighBM + \beta_5 Interaction + \varepsilon, \quad (8)$$

$$RELSS(-6,-2) = \gamma_0 + \gamma_1 Sell + \gamma_2 AR(-1,+1) + \gamma_3 AR(-6,-2) + \gamma_4 AVESS + \gamma_5 HighBM + \gamma_6 Interaction + \varepsilon, \quad (9)$$

The results of OLS regression of these two models are shown in the below table. The variable $ABSS(-6,-2)$ is the average daily abnormal relative short selling for a stock in the pre-recommendation five-day period, calculated as the daily average relative short selling in the five days prior to recommendations divided by the daily average relative short selling during non-recommendation period, all minus 1. The variables $RELSS(-6,-2)$ and $AVESS$ represent the daily relative short selling during (-6, -2) period and non-recommendation period respectively. The variable $AR(-1,+1)$ is the stock 3-day event-period cumulative abnormal return, measured as 3-day holding period return minus contemporary market value-weighted return. The variable $AR(-6,-2)$ is the control variable, represents the abnormal returns during the pre-recommendation period (-6, -2). The whole sample of stocks with positive book-to-market ratios are sorted into quintiles based on the level of book-to-market ratios. The dummy variable $HighBM$ takes on the value 1 if the stock's book-to-market ratio is categorized into the highest quintile; and 0 otherwise. The binary variable $Interaction$ is the product of the variable $Sell$ and the variable $HighBM$, that takes on the value 1 if the stock is both recommended to be sold by professional analyst and of high book-to-market ratio. Standard errors are in parentheses below coefficient.

Panel A: Equation (8)

β_0	β_1	β_2	β_3	β_4	β_5	Adjusted R^2
-0.006	0.028***	0.162**	1.845***	0.019	-0.050**	0.079
(0.007)	(0.009)	(0.081)	(0.104)	(0.016)	(0.020)	

Panel B: Equation (9)

γ_0	γ_1	γ_2	γ_3	γ_4	γ_5	γ_6	Adjusted R^2
0.022***	0.007***	0.032	0.450***	0.906***	0.004	-0.013**	0.429
(0.005)	(0.002)	(0.021)	(0.023)	(0.018)	(0.004)	(0.005)	

*, ** and *** indicate statistically significance at the 10%, 5% and 1% levels, respectively.

Table 8

Abnormal Short Selling Prior to Analyst Recommendations, for Stocks Grouped by Market Capitalization: Jan, 2005 to July, 2007

The variable ABSS(-6,-2) is the average daily abnormal relative short selling for a stock in the pre-recommendation five-day period, calculated as the daily average relative short selling in the five days prior to recommendations divided by the daily average relative short selling during non-recommendation period, all minus 1. The variable ABRELSS(-6,-2) is another alternative metric for average daily abnormal relative short selling, measured as the difference between daily average relative short selling in the five days prior to recommendation and the daily average relative short selling during non-recommendation period. The Lowest Quintile contains the 20% of stocks with the lowest market capitalization, while the Highest Quintile contains 20% of stocks with the highest market capitalization. The means of abnormal returns and abnormal short-selling are presented in the following table. The two-tailed t-tests evaluate the differences in means and Wilcoxon z-test examines the differences in median.

Panel A: Control for Market Capitalization

	Lowest Quintile				Highest Quintile			
	Buy	Sell	Difference		Buy	Sell	Difference	
			t-value	Wilcoxon z			t-value	Wilcoxon z
N	201	528			345	407		
AR(-1,+1)	0.026	-0.004	5.84***	7.82***	0.008	-0.007	6.57***	7.43***
ABSS(-6,-2)	0.036	0.005	1.38	1.26	0.008	0.016	-0.61	-0.67
ABRELSS(-6,-2)	0.008	-0.001	1.50	1.37	0.002	0.003	-0.42	-0.55
AVESS	0.265	0.268	-0.73	-0.45	0.243	0.255	-3.45***	-3.52***

Panel B: Control for Recommendations

	Buy				Sell			
	Lowest Quintile	Highest Quintile	Difference		Lowest Quintile	Highest Quintile	Difference	
			t-value	Wilcoxon z			t-value	Wilcoxon z
N	201	345			528	407		
AR(-1,+1)	0.026	0.008	5.79***	5.38***	-0.004	-0.007	0.64	-1.88*
ABSS(-6,-2)	0.036	0.008	1.39	0.98	0.005	0.016	-0.72	1.07
ABRELSS(-6,-2)	0.008	0.002	1.21	1.03	-0.001	0.003	-1.01	1.01
AVESS	0.265	0.243	4.96***	5.20***	0.268	0.255	3.72***	-4.19***

*, ** and *** indicate statistically significance at the 10%, 5% and 1% levels, respectively.

Table 9

Results of OLS Regressions: Impact of Market Capitalization on Abnormal Short-Selling and Short-Selling Five Days Prior to Analyst Recommendations: Jan, 2005 to July, 2007

$$ABSS(-6,-2) = \beta_0 + \beta_1 Sell + \beta_2 AR(-1,+1) + \beta_3 AR(-6,-2)$$

$$+\beta_4 HighME + \beta_5 CrossTerm + \varepsilon, \qquad (10)$$

$$RELSS(-6,-2) = \gamma_0 + \gamma_1 Sell + \gamma_2 AR(-1,+1) + \gamma_3 AR(-6,-2)$$

$$+\gamma_4 AVESS + \gamma_5 HighME + \gamma_6 CrossTerm + \varepsilon, \qquad (11)$$

The results of OLS regression of these two models are shown in the below table. The variable $ABSS(-6,-2)$ is the average daily abnormal relative short selling for a stock in the pre-recommendation five-day period, calculated as the daily average relative short selling in the five days prior to recommendations divided by the daily average relative short selling during non-recommendation period, all minus 1. The variables $RELSS(-6,-2)$ and $AVESS$ represent the daily relative short selling during (-6, -2) period and non-recommendation period respectively. The variable $AR(-1,+1)$ is the stock 3-day event-period cumulative abnormal return, measured as 3-day holding period return minus contemporary market value-weighted return. The variable $AR(-6,-2)$ is the control variable, represents the abnormal returns during the pre-recommendation period (-6, -2). The whole sample of stocks with positive market capitalization is sorted into quintiles based on the level of market cap. The dummy variable $HighME$ takes on the value 1 if the stock's market capitalization is categorized into the highest quintile; and 0 otherwise. The binary variable $CrossTerm$ is the product of the variable $Sell$ and the variable $HighME$, that takes on the value 1 if the stock is both recommended to be sold by professional analyst and of high market capitalization. Standard errors are in parentheses below coefficient.

Panel A: Equation (10)

β_0	β_1	β_2	β_3	β_4	β_5	Adjusted R^2
-0.005	0.020**	0.157*	1.845***	0.01	-0.008	0.077
(0.007)	(0.009)	(0.082)	(0.104)	(0.014)	(0.019)	

Panel B: Equation (11)

γ_0	γ_1	γ_2	γ_3	γ_4	γ_5	γ_6	Adjusted R^2
0.022***	0.005***	0.03	0.449***	0.906***	0.002	-0.002	0.428
(0.005)	(0.002)	(0.021)	(0.027)	(0.018)	(0.004)	(0.005)	

*, ** and *** indicate statistically significance at the 10%, 5% and 1% levels, respectively.

Table 10

Statistics of Asset-Scaled Abnormal Accruals and Expected Accruals, in Percent, for Stocks Shorted

The expected accruals are estimated by regressing current accruals on the difference between the change in sales revenue and the change in trade receivables across all firms with the same 2-digit SIC code. Using the coefficients from the fitted equations, we could obtain the expected accruals for the shorted stocks. Abnormal accruals are total current accruals excluding the expected component. The two-tailed t-test evaluates the means while sign tests are for medians.

	Abnormal Accrual	Expected Accrual
Mean	-2.20%***	1.47%***
Median	0.13%***	-0.35%***
%positive	52.42%	31.13%
Observations	3363	3363

*, ** and *** indicate statistically significance at the 10%, 5% and 1% levels, respectively.

Table 11

Results of OLS Regressions: Impact of Earnings Management on Abnormal Short-Selling and Short-Selling Five Days Prior to Analyst Recommendations: Jan, 2005 to July, 2007

$$ABSS(-6,-2) = \beta_0 + \beta_1 Sell + \beta_2 AR(-1,+1) + \beta_3 AR(-6,-2) + \varepsilon, \quad (5)$$

$$RELSS(-6,-2) = \gamma_0 + \gamma_1 Sell + \gamma_2 AR(-1,+1) + \gamma_3 AR(-6,-2) + \gamma_4 AVESS + \varepsilon, \quad (6)$$

The whole sample of shorted stocks is sorted into three groups according to the magnitude of firm earnings management. The following table presents the results of the regression (5) and (6) for the three different groups of firms respectively. Standard errors are in parentheses below coefficient.

Panel A: Equation (5)

	β_0	β_1	β_2	β_3		Adjusted R^2
Bottom 30%	-0.007	0.025*	0.305**	1.939***		0.098
	(0.012)	(0.015)	(0.146)	(0.187)		
Middle 40%	0.000	0.013	0.129	1.813***		0.059
	(0.010)	(0.013)	(0.135)	(0.195)		
Top 30%	0.001	0.012	-0.030	1.619***		0.072
	(0.012)	(0.015)	(0.156)	(0.180)		

Panel B: Equation (6)

	γ_0	γ_1	γ_2	γ_3	γ_4	Adjusted R^2
Bottom 30%	0.017*	0.006*	0.062*	0.465***	0.926***	0.461
	(0.009)	(0.003)	(0.037)	(0.048)	(0.037)	
Middle 40%	0.032***	0.003	0.021	0.452***	0.875***	0.386
	(0.009)	(0.003)	(0.034)	(0.050)	(0.032)	
Top 30%	0.010	0.004	-0.009	0.405***	0.957***	0.474
	(0.009)	(0.004)	(0.040)	(0.046)	(0.033)	

*, ** and *** indicate statistically significance at the 10%, 5% and 1% levels, respectively.