Spring 2016

Two Essays on Short Selling

Zhaobo Zhu
Old Dominion University

TWO ESSAYS ON SHORT SELLING

by

Zhaobo Zhu
B.A. July 2007, China University of Petroleum (East China), China
M.B.A May 2011, Louisiana State University at Baton Rouge
M.A. May 2012, Kent State University

A Dissertation Submitted to the Faculty of
Old Dominion University in Partial Fulfillment of the
Requirements for the Degree of

DOCTOR OF PHILOSOPHY

FINANCE

OLD DOMINON UNIVERSITY
May 2016

Approved by:

____
Licheng Sun (Director)

____
Mohammad Najand (Member)

____
David Selover (Member)

ABSTRACT

TWO ESSAYS ON SHORT SELLING

Zhaobo Zhu
Old Dominion University, 2016
Director: Dr. Licheng Sun

This dissertation provides some new evidence that the information contained in short selling is informative about future returns, confirming the role of short sellers in the price discovery process.

The first essay examines the cross-sectional relation between the change in short interest and expected stock returns. NYSE/AMEX stocks with large decreases (increases) in short interest over past medium-term horizon experience significant and positive (negative) abnormal returns. Moreover, the positive abnormal returns are larger in absolute value and are more persistent than negative abnormal returns. The return spread between bottom and top deciles is economically and statistically significant and persistent. The return predictability of the change in short interest is not subsumed by the level of short interest and other well-known determinants of stock returns, and is robust in different calendar months and investor sentiment. These results imply that public information contained in the change in short interest is so slowly incorporated into prices. Moreover, the asymmetry in the speed of price adjustment casts doubts on the implication of short-sale constraints and the limits to arbitrage.

The second essay provides new evidence that momentum and long-term reversals would be separate phenomena. We can identify *ex ante* momentum stocks that exhibit persistent momentum and those that exhibit weak momentum but persistent reversals, using information in

short selling. Underreaction and overreaction theories apply to different sets of momentum stocks. The consistent momentum strategy based on short interest succeeds during periods in which the standard momentum strategy fails. The success of the consistent momentum strategy is mainly due to the robust return predictability of short interest in these periods. These evidence confirms that short sellers contribute to price discovery. The information in short selling provides a great hedge or complement to anomaly-based strategies.

ACKNOWLEDGMENTS

I would like to thank my major advisor, Dr. Licheng Sun, for his consistent support and encouragement. I also thank Dr. Mohammad Najand (committee member), Dr. David Selover (committee member), Dr. John Doukas, Dr. Kenneth Yung, Jiancheng Shen, Jian Yi at Old Dominion University and Dr. Min Chen at San Francisco State University for their help in my Ph.D. study. All remaining errors are my own responsibility.

TABLE OF CONTENTS

LIST OF TABLES

Table Page

LIST OF FIGURES

INTRODUCTION

Short sellers trade actively in equity markets and significantly contribute to the price discovery (e.g., Boehmer, Jones, and Zhang 2008; Boehmer and Wu, 2012). Many empirical studies show that short sellers are sophisticated and informed investors whose activities are informative about future stock returns and firm fundamentals. Specifically, high (low) short interest predicts significant negative (positive) abnormal returns (Asquith et al., 2005; Boehmer et al., 2010). Short sellers target overpriced stocks with low fundamental-to-price ratios and anticipate future firm fundamentals (Dechow et al., 2001; Curtis and Fargher, 2014; Deshmukh, Gamble, and Howe, 2015). Moreover, some studies show that short sellers become more sophisticated over time and efficiently avoid shorting underpriced stocks (Wu and Zhang, 2015).

In this dissertation, I provide some new empirical evidence on the role of short sellers in the price discovery process. This dissertation contributes to the literature on short selling in two main ways. First, I examine the return predictability of dynamic changes in short selling activities and find evidence on the incremental return predictability of the change in short interest. This finding provides a big picture of the predictive information contained in short interest. The results also shed new light on the implication of short-sale constraints, the limits to arbitrage, and market efficiency. Second, I examine the role of short selling in explaining momentum. The empirical study on the role of short selling in the context of momentum is limited, though there are a large amount of studies that examines the sources of momentum profits. There is still a debate on the relation between past returns and short selling. In this dissertation, I am interested in how the interaction of past returns and short selling predicts future returns. I find that short selling efficiently explains the momentum-reversal pattern. Overall, empirical results in my dissertation suggest that the information contained in short selling is informative about future stock returns. These evidence confirms that short sellers are sophisticated and informed investors who contribute to the price discovery.

The first essay examines the cross-sectional relation between the change in short interest and expected stock returns. I show that the dynamic change in short selling activities own the incremental return predictive information beyond the level of short interest. NYSE/AMEX stocks with large decreases (increases) in short interest over past medium-term horizon experience significant and positive (negative) abnormal returns. Moreover, the positive abnormal returns are larger in absolute value and are more persistent than negative abnormal returns. The return spread between bottom and top deciles is economically and statistically significant and persistent. The return predictability of the change in short interest is not subsumed by the level of short interest and other well-known determinants of stock returns, and is robust in different calendar months and investor sentiment. These results imply that public information contained in the change in short interest is so slowly incorporated into prices. Moreover, the positive information is incorporated into prices more slowly than the negative information. The asymmetry in the speed of price adjustment casts doubts on the implication of short-sale constraints and the limits to arbitrage.

The second essay examines the role of short selling in explaining the sources of momentum profits. The empirical results show that momentum and long-term reversals would be separate phenomena. We can identify ex ante momentum stocks that exhibit persistent momentum and those that exhibit weak momentum but persistent reversals, using information in short selling. Underreaction and overreaction theories apply to different sets of momentum stocks. The consistent momentum strategy based on short interest succeeds during periods in which the standard momentum strategy fails. The success of the consistent momentum strategy is mainly due to the robust return predictability of short interest in these periods. These evidence confirms that short sellers contribute to price discovery. The information in short selling provides a great hedge or complement to anomaly-based strategies.

THE CHANGE IN SHORT INTEREST AND THE CROSS SECTION OF STOCK RETURNS

INTRODUCTION

The existing literature on short selling argues that short sellers are informed and sophisticated investors whose shorting activities are informative about future stock returns. To be specific, the static recent level of short interest is informative about future returns. Asquith, Pathak, and Ritter (2005) show that heavily shorted stocks experience significant negative abnormal returns, and Boehmer, Huszar, and Jordan (2010) show that lightly shorted stocks experience significant positive abnormal returns. In addition, a dynamic large increase in short interest over previous one month predicts a negative abnormal return[1]. Diamond and Verrecchia (1987) develop a theoretical model in which short-sale constraints reduce the speed of incorporation of private negative information into stock prices, and argue that an unexpected large increase in short interest signals bad news. Senchack and Starks (1993) provide weak empirical evidence on the implication of the unexpected increase in short interest in Diamond and Verrecchia (1987)[2].

This paper contributes to the literature by examining the cross-sectional relation between the change in short interest and stock returns. I show that the dynamic changes in short selling

---

[1] Several recent studies such as Diether et al. (2008) use high frequent short selling trading transaction data to examine return predictability of short selling activities. The sample period of these data is, however, very short. This study uses the change in monthly short interest data to measure the change in short selling. Moreover, because the underlying rationale of this study is different from that of these studies, this paper uses monthly short interest data.
[2] Motivated by Diamond and Verrecchia (1987), Senchack and Stark (1993) select a small sample of stocks with large unexpected increases in short interest over previous month and find that these stocks experience short-run significant but small magnitude of negative abnormal returns around the short interest announcement date. Compared with other studies about short selling, their work is closer to my work, though this paper differs from it in many ways.

activities own the incremental return predictive information beyond the recent level of short interest in the cross section. Though the recent level of short interest reflects a stock's current short selling activity and the market's view on the firm's current fundamental and prospect in current economic environment, a firm's fundamental and corresponding competitive position in the changing environment are dynamic over time. The change in short selling activity reflects the change in market's view on firm's current fundamental and prospect due to the change in firm's fundamental and prospect and corresponding competitive position in its competitive environment over time. If stock prices efficiently reflect firms' fundamentals over time, the change in short interest should be informative about future returns.

The following simple example illustrates that the recent level of short interest provides an incomplete picture of future stock returns and the change in short interest provides incremental predicative information[3]. Consider two stocks with the same current level of short interest but with different paths of short selling activities over previous one year. Stock A experiences increasing short selling activities due to more severe competition in its industry or worse industry environment. In contrast, stock B experiences decreasing short selling activities due to its increasing competitive advantage in its industry or improving industry environment. Since short selling takes the firm's prospect into account, the trend in firm's fundamental and its relative competitive position in the dynamic competitive environment will last for a while. We expect that stock B outperforms stock A in future stock returns. If we consider only the recent level of short interest, we ignore how current level of short interest is generated. I conjecture that the path of generation of current level of short interest over time provides predictive information.

---

[3] Akbas, Jiang, and Koch (2014) examine the cross-sectional relation between the trend in firm profitability and stock returns based on the similar logic.

Empirical results support my conjecture that stocks with large decreases in short interest outperform stocks with large increases in short interest given the same current level of short interest.

Empirically, I find that NYSE/AMEX stocks with large increases (decreases) in short interest over past medium-term horizon experience significant and positive (negative) abnormal returns. The significant positive abnormal returns generated by stocks with large increases in short interest are persistent in subsequent three years, while the negative abnormal returns generated by stocks with large decreases in short interest are significant only in subsequent seven months. Specifically, stocks in the bottom (top) decile of short interest increases over previous one year generate significant average monthly return of 0.52% (-0.32%) after controlling for market return, size, book-to-market ratio, and momentum effect. The long-short strategy generates average monthly risk-adjusted return of 0.84% (t=5.11). Moreover, the relation between the magnitude of the change in short interest and the magnitude of cross-sectional stock returns is almost monotonic. The positive abnormal return of the bottom decile in absolute value is often larger than the negative abnormal return of the top decile.

There are three main potential explanations for the short-interest-change return predictability in the cross section. First, the fundamental-based rationale may explain it. Dechow et al. (2001) show that short sellers target firms with low fundamental-to-price ratios that predict low future returns and unwind their positions when these ratios reverse. Deshmukh, Gamble, and Howe (2015) show a significant relation between increases in short interest over previous one quarter and subsequent declines in firm operation performance. These studies suggest that short sellers adjust their short positions based on past, current and anticipated fundamentals. If prices efficiently reflect fundamentals in a given time horizon, the adjustment of short selling activities will significantly be related to the corresponding price adjustment. The second potential rationale is based on the rational expectation model proposed by Diamond and Verrecchia (1987). But this model is limited to two consecutive short interest announcement dates and does not explain the outcome of the decrease in short interest. The third potential rationale is that the market underreacts to information contained in the change in short interest due to investors' limited attention or relatively slow speed and limited breadth of dissemination of these public information. Moreover, investors' divergent opinions on these information may magnify this underreaction.

The return predictability of the change in short interest is not subsumed by the recent level of short interest and other well-known return determinants such as size, book-to-market ratio and momentum effect. The return spread of the long-short hedge portfolio is particularly large among small stocks, both value and growth stocks, and both past winners and past losers. It is robust to different formation and holding periods, price screens, microstructural concern, and different measures of the change in short interest. Moreover, the hedge portfolio generates statistically and economically significant positive abnormal returns in nine among twelve calendar months.

In addition, some previous studies show that investor sentiment efficiently explains many market anomalies due to short-sale constraints (Stambaugh, Yu, and Yuan, 2012; Antoniou, Doukas, and Subrahmanyam, 2013). Stambaugh et al. (2012) show that both anomaly-based long-short strategies and short legs are more profitable following high sentiment. In contrast, I find that the long-short, the short leg and the long leg of short-interest-change strategy are more profitable following low sentiment after controlling for contemporaneous risk factors based on predictive regressions. Moreover, Cooper, Gutierrez, and Hameed (2004) show that the momentum profit is negative following negative market returns over previous 12 to 36 months.

In contrast, I find that the short-selling strategy is economically profitable following negative market returns. The long-short portfolio experiences similar magnitude of returns following positive and negative market returns. Overall, the strategy based on the change in short interest seems to provide a great hedge or complement to anomaly-based strategies.

This paper differs from previous studies like Senchack and Starks (1993) in five main ways. First, the empirical hypotheses of this paper are mainly based on fundamental-based rationale, while prior empirical studies are motivated by the implication of short-sale constraints. Second, due to different motivations, this paper examines both predictive information contained in the *increase* and *decrease* in short interest, while prior empirical studies like Senchack and Starks (1993) focus on examining the implication of unexpected large increase in short interest in two consecutive announcement dates proposed by Diamond and Verrecchia (1987). This paper is particularly interested in the predictability of the *decrease* in short interest. Third, due to different motivations, I am interested in return predictability of the change in short interest over past relative long horizon, not just two consecutive announcement dates. Fourth, I use a more reasonable measure of the change in short interest than prior empirical studies, though all these measures generate similar empirical results. Fifth, this paper examines the cross-sectional relation between the change in short interest and stocks returns, while prior empirical studies mainly use sample matching method to select a small sample of stocks with large increases in short interest.

Empirical results of this paper have some significant implications. First, the change in short interest owns the incremental predictive information beyond the recent level of short interest, complementing the return predictability of information contained in short selling. This confirms the role of short sellers in price discovery in a different angle. Second, the return predictability of the change in short interest casts a doubt on market efficiency. We are interested in why prices adjust to reflect public information contained in the change in short interest so slowly. Third, the asymmetric speeds of price adjustments to good news and bad news conflicts with the implication of short-sale constraints. The positive information is incorporated into stock prices more slowly than the negative information. Moreover, the persistent positive abnormal return of the long portfolio is against the limits to arbitrage proposed by Shleifer and Vishny (1997). However, the large and persistent positive abnormal returns of the long portfolio only apply to NYSE/AMEX stocks. The evidence from NASDAQ stocks is consistent with the implication of short-sale constraints and limits to arbitrage because the short leg realizes higher negative abnormal returns and the long leg generates insignificant positive abnormal returns. This conflict proposes a puzzle, though it's not a focus of this paper[4]. Fourth, the return predictability of the long leg become significant and stronger in recent decade, indicating that short sellers become more sophisticated over time and have the ability to avoid underpriced stocks. This finding is generally consistent with Wu and Zhang (2015). The short leg, however, loses significant return predictability in recent decade mostly due to increasing trading and arbitrage activities. Last, the robustness of return predictability of this short-selling strategy in calendar months, following different investor sentiments and market states suggests that information contained in short selling activity is useful in hedging the potential losses of anomaly-based strategies and improving the profitability of these strategies. Overall, these evidence suggests that short sellers are informed and sophisticated investors whose activities predict future returns.

[4] Though there is inconsistence for two samples based on portfolio analyses, Fama-MacBeth (1973) regression analyses show that the coefficients of the change in short interest are consistent for two samples.

LITERATURE REVIEW

The theoretical literature on short selling focuses on the effect of short-sale constraints on the dissemination of information and stock returns. In Miller's (1977) framework, investors have heterogeneous beliefs on the valuation of the stock, so negative information is incorporated into the stock price more slowly than does positive information due to binding short-sale constraints. Miller (1977) argues that on average stocks are overpriced due to short-sale constraints. Empirically, inspired by the implication of short-sale constraints, using high short interest as proxy for binding short-sale constraints, Desai et al. (2002) and Asquith et al. (2005) show that stocks with high short interest experience subsequent significant negative abnormal returns. However, inconsistent with the implication of short-sale constraints, Boehmer et al. (2010) find that stocks with low short interest experience subsequent significant positive abnormal returns. The related strand of empirical studies examines the ability of short sellers to identify overpriced stocks. For example, Dechow et al. (2001) show that short sellers target overpriced firms based on fundamental-to-price ratios that predict low future returns. Curtis and Fargher (2014) show that short sellers target only overpriced firms among past losers based on several measures of overpricing.

In contrast, Diamond and Verrecchia (1987) develop a rational expectation model in which rational investors already take into account the effect of short-sale constraints on stock prices when they trade, so on average stock prices are correct in equilibrium. Diamond and Verrecchia (1987) also argue that an unexpected large increase in short interest signals bad news. Empirically, Senchack and Starks (1993) find that stocks with large increases in short interest in two consecutive announcement dates experience significant but small negative abnormal returns, supporting DV's argument.

Another strand of empirical studies examines the ability of short sellers to analyze firm fundamentals and anticipate future firm announcements and performance. Deshmukh et al. (2015) find that the increases in short interest over past one quarter predict subsequent long-term negative operating performance. Karpoff and Lou (2010) find that short sellers can identify firms with financial statement manipulation because abnormal short interest increases steadily in one year and a half before the public announcement of these misconducts.

Some recent studies make use of high frequent short selling transaction data to examine the role of short sellers in price discovery. For example, Diether et al. (2008) find that short sellers target recent winners and profit from their subsequent decreases in prices. Engelberg, Reed, and Ringgenberg (2012) argue that short sellers' superior information analysis ability contributes most to their profits. This paper differs from them because this paper use low frequent monthly short interest data to examine the predictive information contained in the change in short selling.

In addition, previous studies do not explicitly examine the cross-sectional relation between the change in short interest and stock returns. Previous studies focus on the relation between the level of short interest and future returns and the relation between the short-horizon abnormal increases in short interest and subsequent negative abnormal stock returns or firm announcements. This study differs from them in several ways. First, this paper examines the return predictability of both the increase and the decrease in short interest, while previous studies focus on the increase in short interest. This paper stresses the striking findings about the decrease in short interest over past medium-to-long-term horizon. Second, I examine the cross section of stock returns, while previous studies use event studies or sample matching method to select a small sample of stocks with large increases in short interest. Third, the measure of the change in short interest in this paper differs from those in previous studies. The measure of the change in short interest in this study is normalized and sounds more reasonable. Last, inspired by the fundamental-based rationale, the measure of the change in short interest in this study capture information in the fundamental changes in dynamic competitive environment over past relative long horizon rather than past two consecutive short interest announcement dates.

DATA AND METHODOLOGY

The monthly short interest data for stocks listed in NYSE/AMEX/NASDAQ are from Compustat. The sample period for NYSE/AMEX stocks is from January 1988 to December 2014. The sample period for NASDAQ stocks is from July 2003 to December 2014 because Compustat does not cover short interest data for NASDAQ stocks before July 2003. In the main analysis of this paper, I use NYSE/AMEX short interest data because of longer sample period. NADSAQ short interest data are used in robustness tests. The short interest for a specific stock in month t is the number of uncovered shares sold short around the 15th of each month. The short interest ratio (SIR_t) in month t, normalized short interest, refers to the ratio of short interest to total shares outstanding in month t. The normalized short interest (SIR) is to minimize the potential bias caused by the firm size.

The sample consists of only common stocks (share code is 10 or 11 in CRSP) listed in NYSE, AMEX, and NASDAQ. I exclude stocks without monthly short interest data. Data about stock prices, the number of shares outstanding, trading volume are from CRSP. Financial variables to calculate book-to-market ratios are from Compustat. I also exclude stocks with prices less than $1 ($5) at the end of formation period in the main analysis (robustness test).

The Measure of the Change in Short Interest

I use cumulative percentage changes in short interest ratios to measure the change in short interest (SIRG) in a given time period:

$$\mathrm{SIRG}_{t\text{-}j:\,t} = \sum_{t,t-j}^{j} \frac{\mathrm{SIR}_t - \mathrm{SIR}_{t-1}}{\mathrm{SIR}_{t-1}} \tag{1}$$

where SIRG refers to the change in short interest, that is, the cumulative growth rates in short interest ratio over past J-month; J is the length of formation period.

The relation between SIRG and SIR is similar to the relation between stock cumulative return and stock price. Previous studies use the simple difference between SIR_t and SIR_{t-1} (ΔSIR) to measure the change in short interest. Compared to the simple difference in SIR, the measure in this study sounds more reasonable, capturing more information. For example, if stock A's SIR increases from 2% to 4% and stock B's SIR increases from 1% to 3%, the increases in short interest for both stocks are 2% based on the simple difference in SIR. But stock A experiences 100% increase in SIR and stock B experience 200% increase in SIR based on %ΔSIR. Intuitively, stock B experience more severe short sales than stock A based on %ΔSIR. Previous studies also use the simple percent increase in short interest ($\%\Delta SI = (SI_t - SI_{t-1})/SI_{t-1}$) to measure the change in short interest, but these studies focus on the increase in short interest in two consecutive short interest announcement dates. Because this study investigates the predictive information contained in the change in short interest over past relatively long horizon, I use cumulative %ΔSIR[5].

[5] I also use the simple %ΔSIR, that is, $\frac{\mathrm{SIR}_t - \mathrm{SIR}_{t-j}}{\mathrm{SIR}_{t-j}}$. In the robustness tests, I report the results for ΔSIR.

In the main analysis, I set an upper bound for the SIRG from t-1 to t. Theoretically, like stock return, the $SIRG_{t-1:t}$ could be infinitely large for the upper bound and -100% for the lower bound. Because cumulative $SIRG_{t-1:t}$ is used to capture the information contained in the change in short selling activities, some outliers with extreme large $SIRG_{t-1:t}$ would contaminate the cumulative changes in short interest ($SIRG_{t-j:t}$). Thus, I limit $SIRG_{t-1:t}$ to 100%. In the robustness tests, I relax this limitation.

EMPIRICAL RESULTS

Portfolio Analysis

Following the portfolio method in Jegadeesh and Titman (1993), I sort NYSE/AMEX stocks into ten groups each month based on their magnitudes of cumulative changes in short interest over past J-month ($SIRG_{t-j:t}$). Stocks in the top (bottom) decile experience the largest (smallest) magnitudes of cumulative increases in short interest over past J-month[6]. I do not skip 1-month between the formation period and the holding period because the latest short interest data is available to many investors (especially institutions) around the middle of each month and portfolios are formed at the end of each month. I skip 1-month in the robustness test. In the main analysis, the long-leg and short-leg portfolios are held for 1-month.

Table 1 reports the average equally-weighted monthly raw returns and Fama-French-Carhart alphas for these portfolios. There are four interesting empirical findings. First, the bottom decile

[6] Unlike other related studies that use a specified cutoff like 5% to select a sample of highly shorted stocks or stocks with large increases in short interest, I rank stocks based on their relative rankings on the change in short interest. In a specific month, stocks in bottom (top) decile may not experience large absolute decreases (increases) in short interest sometimes.

of stocks with the largest decreases in short interest generates a significant positive average abnormal return of 0.52% (t=3.15) in the subsequent 1-month. Second, the top decile of stocks with the largest increases in short interest generates a significant negative average abnormal return of -0.32% (t=-2.86) in the subsequent 1-month. Third, the long-short strategy that buys the bottom decile and sells the top decile generates an average monthly risk-adjusted return of 0.86% (t=5.11). Fourth, the relation between the magnitude of the change in short interest and the magnitude of cross-sectional stock returns is almost monotonic.

[Insert Table 1 here]

These empirical results cast a doubt on market efficiency. The market seems to underreact to information contained in public short interest data. Moreover, positive information seems to be incorporated into stock prices more slowly than negative information. This asymmetric speed of price adjustment is against the implication of short-sale constraints. In addition, the significant and persistent positive abnormal return from the long leg is also against the implication of the limits to arbitrage. The limits to arbitrage cannot explain the persistent and positive abnormal return. Interestingly, the persistent and positive abnormal return generated by stocks with large decrease in short interest is consistent with 'good news in low short interest' in Boehmer et al. (2010).

Controlling for Other Important Variables

In this subsection, I examine the return predictability of the change in short interest controlling for other well-known determinants of stock returns, using two-way sorts. These variables include firm size, book-to-market ratio, momentum effect, and the level of short interest (Fama and French, 1992; 1996; Asquith et al., 2005). For example, when I examine size effect, I first sort stocks into quintiles each month based on their market capitalizations at the end of prior month. Then, I sort stocks into quintiles based on their changes in short interest within each size quintile for two-way dependent sorts. For independent sorts, I independently sort stocks into quintiles based on SIRG and size respectively and then intersect SIRG quintiles and size quintiles to form 25 (5x5) portfolios.

Panel A of Table 2 reports average monthly raw returns for 25 portfolios and raw and risk-adjusted returns for long-short portfolios based on SIRG, controlling for the stock's market capitalization (size effect). The empirical results show that the long-short portfolio based on SIRG generates economically and statistically significant profits in at least three size groups. For example, using two-way dependent sorts, the hedge portfolio generates an average raw return of 0.95% per month (t=3.91) among smallest stocks and average raw return of 0.33% per month (t=2.54) among largest stocks. The 3-factor alphas for these hedge portfolios are significant 1.21% and 0.47% respectively among smallest and largest stocks. So the return predictability of SIRG is not limited to small stocks.

Panel B of Table 2 reports returns for these hedge portfolios based on SIRG, controlling for the book-to-market ratio. The empirical results show that the long-short hedge portfolio earns economically and statistically significant alphas in at least four BM groups. Moreover, the return predictability of SIRG is strongest among value and growth stocks. Panel C of Table 2 reports results after controlling for the momentum effect. Similar to the results in Panel B, the hedge portfolio generates significant returns in at least four momentum groups. Moreover, the return predictability is strongest in past winner and loser quintiles. These results suggest that return predictability of SIRG is not subsumed by traditional well-known determinants of stock returns such as firm size, BM ratio, and momentum.

Last, I examine whether the return predictability of SIRG is subsumed by the recent level of short interest. Panel D and E of Table 2 report the results. Panel D shows that the hedge portfolio based on SIRG generates positive and significant raw returns at 5% significance level in three SIR quintiles and 10% significance level among lightly shorted stocks, based on two-way dependent sorts. The results are robust after controlling for market, size, book-to-market ratio, and momentum. Though raw return of the hedge portfolio among heavily shorted stocks is not significant based on independent sorts, the magnitude of return is even larger than other two significant return spreads. A potential reason is that the number of stocks is small due to two-way independent sorts in extreme SIR groups. In contrast, Panel E shows that the raw return of the long-short hedge portfolio based on SIR is significant in only one of five SIRG quintiles, though alpha spreads are significant in all quintiles. Overall, these results indicate that the change in short interest owns incremental return predicative information beyond the level of short interest.

[Insert Table 2 here]

Regression Analysis

The portfolio analysis indicates that the change in short interest owns incremental return predicative information beyond the level of short interest. However, the portfolio analysis cannot control for several significant variables simultaneously due to the insufficient number of stocks after N-way independent or dependent sorts. Fama-MacBeth (1973) regressions allow us to examine the significance of the change in short interest after controlling for several important variables simultaneously. In this section, I run the following monthly firm-level cross-sectional Fama-MacBeth (1973) regressions:

$$R_{i,t+1:t+k} = a + b1*MOM_{i,t-1} + b2*\log(Size_{i,t-1}) + b3*\log(BM_{i,t-1}) + b4*SIR_{i,t-1}$$

$$+ b5*SIRG_{i,t-1} + b6*TO_{i,t-1} + b7*IO_{i,t-1} + b8*REV_{i,t} + u_t \quad (2)$$

Table 3 reports the mean coefficients of these variables from Fama-MacBeth regressions during the period of 1988 to 2014. I run two sets of regressions. In the first set, the dependent variable $R_{i,t+1:t+6}$ is the average monthly raw return during month t+1 to month t+6. MOM is the past cumulative return during month t-6 to t-1. Log($Size_{i,t-1}$) is the natural logarithm of market capitalization at the end of month t-1. Log($BM_{i,t-1}$) is the natural logarithm of book-to-market ratio at the end of previous year. $SIR_{i,t-1}$ is the relative short interest ratio at month t-1. $TO_{i,t-1}$ is the turnover at month t-1. $IO_{i,t-1}$ is the institutional ownership in previous quarter. Nagel (2005) find that institutional ownership as a proxy for short-sale constraints helps explain some well-known anomalies. $SIRG_{i,t-1}$ is the cumulative growth rate in short interest ratio over past 12-month. There is 1-month gap between dependent variable and independent variables.

Panel A of Table 3 reports the results for the first set of regressions. Results show that past medium-term return and book-to-market ratio are significant return predictors in all models. Model 7 and 9 show that smaller firms experience significantly higher future returns after excluding stocks with prices less than $5. Institutional ownership is also a significant predictor. These results are consistent with previous studies. Most importantly, the negative coefficients of SIR and SIRG in all models indicate that both the level of short interest (SIR) and the change in short interest (SIRG) significantly and negatively predict future returns. Overall, consistent with the portfolio analysis, the regression results indicate that the change in short interest owns incremental predictive information, controlling for other significant return predictors.

In the second set of regressions, the dependent variable $R_{i,t}$ is the return at month t. I also include the past 1-month return ($REV_{i,t-1}$) as a control variable in the model specification. There is no 1-month gap between dependent variable and independent variables, consistent with the main portfolio analysis in the section 4.1. Panel B of Table 3 reports the results. It is expected that the coefficient of past 1-month return (REV) is highly significant and the coefficient of past medium-term return (MOM) is insignificant. Most importantly, the coefficients of SIR and SIRG are significant and negative in all models. These results are consistent with the main portfolio analysis, further confirming that both the level of short interest and the change in short interest provide incremental predictive information respectively.

[Insert Table 3 here]

Long-Term Performance

In this section, I examine the return predictability of the change in short interest in event time. I track the average raw and risk-adjusted returns for the long portfolio, the short portfolio, and the long-short portfolio in each of the 36-month holding period. The path of event-time returns provides a clear picture of riskiness and persistence of the strategy based on the change in short interest.

Table 4 reports the results. Empirical results show that stocks with largest decreases in short interest experience significant and persistent positive abnormal returns in the holding period of three-year, but stocks with largest increases in short interest experience significant negative abnormal returns only in the first seven months after formation period and reverse after the fifteenth month, though the magnitude of reversal is very small. Specifically, the long-short strategy generates significant and persistent profits in the holding period of 36-month due to good performance of the long leg and weak reversal of the short leg.

[Insert Table 4 here]

Figure 1 shows the graphical represnetations of cumulative risk-adjusted returns of the long portfolio, the short portfolio, and the long-short portfolio in the 36-month holding period. The cumulative abnormal return of long-leg represents a beautiful upward straight line, indicating that investors consistently underreact to the information contained in the large decreases in short interest. The short-leg experiences weak reversal after one year and a half, indicating that overreaction also exists in the data. However, long-term underreaction dominates overreaction.

[Insert Figure 1 here]

Figure 2 reports the cumulative raw returns of the long portfolio, the short portfolio, and the long-short portfolio in the sample period of 1988 to 2014. For long-only position, initial investment of one dollar at the beginning of 1989 reaches up to fifty dollars at the end of 2014. The return of long-short strategy reaches up to 6000%.

[Insert Figure 2 here]

Seasonality

Many market anomalies show some striking seasonal patterns. For example, momentum profit is negative in January, short-term reversal and long-term reversal are strongest in January, and positive abnormal returns generated by low short interest are extraordinarily high in January (Jegadeesh ant Titman, 1993; Jegadeesh, 1990; DeBondt and Thaler, 1985). I examine whether the return predictability of the change in short interest is robust in difference calendar months in this section.

Table 5 reports the results. Panel A reports the raw returns and Panel B reports risk-adjusted returns. Panel A shows that the long-short hedge portfolio experiences (significant) positive returns in (six) ten of twelve months. The raw return of hedge portfolio is significantly higher in January (1.8%) than in non-January (0.56%). Panel B shows that alphas of the hedge portfolios are economically and statistically significant in nine of twelve months. The alpha of hedge portfolio is significantly higher in January (1.83%) than in non-January (0.69%). However, in other eight non-January calendar months, the hedge portfolio also generates comparable alphas. More specifically, for January, the alpha of the portfolio of stocks with largest decreases in short interest is significant and positive, and the alpha of the portfolio of stocks with largest increases in short interest is negative but insignificant. Overall, these results indicate that the return predictability of the change in short interest is quite robust in different calendar months, confirming the usefulness of predictive information contained in the change in short interest.

[Insert Table 5 here]

Return Predictability Conditional on Investor Sentiment

Investor sentiment is significantly related with the cross-section of stock returns (Baker and Wurgler, 2006). More specifically, Stambugh et al. (2012) argue that investor sentiment significantly explains many market anomalies. They find that both anomaly-based long-short strategies and short legs are more profitable following high sentiment, but returns of long legs have no significant relation with sentiment. Antoniou et al. (2013) find that momentum is profitable only following high investor sentiment periods. In this section I examine whether investor sentiment significantly explains the return predictability of the change in short interest.

I conduct both portfolio analysis and predictive regression analysis to examine the effect of investor sentiment on the return predictability of the change in short interest. I mainly use two sentiment proxies: (1) monthly sentiment index constructed in Baker and Wurgler (2006); and (2) the past 12-month market return (Cooper, Gutierrez, and Hameed, 2004). In portfolio analysis, a high-sentiment (low-sentiment) month refers to the month in which the BW sentiment index is above (below) the median value of index in the sample period or past 12-month market return is positive (negative). Then I calculate average monthly returns for following high-sentiment and low-sentiment periods respectively.

Table 6 reports results from portfolio analysis. Panel A reports results based on the BW (2006) sentiment index. Results show that the profit of the long portfolio is higher following low sentiment and the profit of the short portfolio is higher following high sentiment. Moreover, the return spreads following both high and low sentiment are economically significant (1.15% and 1.07% for the long portfolio and the short portfolio respectively). The return spread is also significant at 10% significance level for the long portfolio. However, the return spread is not significant for the long-short portfolio, though the profit of the long-short portfolio is higher following low sentiment. Furthermore, the FF 4-factor risk-adjusted return spreads are insignificant for the long leg, the short leg and the long-short strategy. Panel B reports the results based on the past 12-month market return. Results show that the return spreads following positive and negative markets are insignificant for the long leg, the short leg, and the long-short strategy. Overall, the results indicate that investor sentiment has no significant effect on the return predictability of the change in short interest based on alpha spreads.

[Insert Table 6 here]

The high or low sentiment classification in the portfolio analysis is a simple binary classification, so I conduct an alternative predictive regression analysis. Following Cooper et al. (2004) and Stambugh et al. (2012), I examine the effect of investor sentiment by regressing monthly excess returns on the lagged sentiment index. I run the predictive regressions with and without controlling for other well-known risk factors.

The predictive regression model is as follow:

$$R_t = a + b*SENT_{t-1} + c*MKT_t + d*SMB_t + e*HML_t + f*MOM_t + u_t \qquad (3)$$

where R_t is the excess return in month t of long-leg, short-leg, or long-short portfolio; $SENT_{t-1}$ is the investor sentiment index in Baker and Wurgler (2006) in month t-1; MKT_t, SMB_t, HML_t, and MOM_t are Fama-French-Carhart risk-factor exposures.

Table 7 reports the results of predictive regression analysis. In the regression specification without controlling for FF risk factors, the coefficients of the long-leg, short-leg and long-short strategy are negative, indicating that long-leg and long-short strategy are more profitable following low sentiment but short-leg is more profitable following high sentiment. In the regression with controlling for four risk factors, the coefficient of the short-leg becomes positive and significant, but the coefficients of the long-leg and the long-short strategy are still negative, indicating that all long-leg, short-leg and long-short strategy are more profitable following low sentiment after controlling for contemporaneous risk factors. Basically, these results are consistent with portfolio analysis, though the return differences are insignificant in portfolio analysis. Overall, these results suggest that the long-short strategy is more profitable following low sentiment, hedging and improving other anomaly-based strategies because these strategies are more profitable following high sentiment.

[Insert Table 7 here]

Robustness Tests

In this section, I conduct a number of robustness tests to verify the results presented in previous sections. Specifically, I verify previous results by conducting portfolio and regression analyses with following specifications: (1) different formation periods and holding periods, (2) price screens, (3) NASDAQ stocks, (4) one-month skipping between the formation period and the holding period, (5) different measures of the change in short interest, (6) subsample.

Table 8 reports the results for these robustness tests. Panel A of Table 8 shows that the return predictability of the change in short interest is robust for different formation and holding periods, though the magnitude of abnormal return of long-short strategy decreases with the increase in the length of holding period. However, the positive (negative) abnormal return from long-leg (short-leg) is significant in most formation and holding periods. The formation period of 6- to 12-month seems contains more predicative information, while short-leg in the shorter formation period generates insignificant abnormal return.

Many market anomalies are strongest among small stocks, so I drop stocks with prices less than $5 in the robustness tests. I also skip 1-month between the formation and holding periods to mitigate the microstructural bias. I also examine NASDAQ stocks in the robustness tests because NYSE/AMEX stocks are used in the main analysis due to longer sample period. The last main concern is the measure of the change in short interest. I relax the limitation on the upper bound of $SIRG_{t-1:t}$.

Panel B reports results for NYSE/AMEX stocks. Empirical results support the robustness of return predictability of the change in short interest under different specifications. The long-leg (short-leg) generates positive (negative) and significant abnormal returns. The long-short strategy generates economically and statistically significant abnormal returns in all specifications.

Panel C reports results for NASDAQ stocks. The long-short strategy also generates economically and statistically significant abnormal returns in all specifications. However, an important difference is that most profit is from the short-leg and the long-leg generates insignificant positive return. These results suggest that investors seem to underreact to bad news contained in the increases in short interest for NASDAQ stocks more slowly than that for NYSE/AMEX stocks. On the other hand, positive information is incorporated into NASDAQ stock prices faster than NYSE/AMEX stock prices. Panel D reports the results of Fama-MacBeth (1973) regressions for NASDAQ stocks. Consistent with results for NYSE/AMEX stocks, the coefficients of SIRG in all models are negative and significant.

Panel E reports the results for two subperiods. Empirical results show that the long-short portfolio generate significant positive abnormal returns in both subperiods. The main profit of the hedge portfolio, however, is from different legs. The short leg generates significant negative abnormal return, and the long leg generates insignificant positive abnormal return during 1988-2001. In contrast, the long leg generates significant positive abnormal return and the short leg generates insignificant negative abnormal return during 2002-2014. The large positive abnormal return in the second subperiod seems consistent with the argument in Wu and Zhang (2015) that short sellers are becoming more sophisticated over time because they strengthen their ability to use non-anomaly information to avoid shorting underpriced stocks. The short-interest-change strategy is obviously superior to other anomaly-based strategies in recent decade. Chordia, Subrahmanyam, and Tong (2014) show that many anomalies become less profitable in recent decade due to increasing trading and arbitrage activities.

In the previous section, I compare two measures of the change in short selling activities. In this section, I report the results for the simple first difference between SIR_{t-j} and SIR_t (ΔSIR) as proxy for the change in short selling activities. Panel F reports the results for the alternative measure. Empirical results show that ΔSIR also contains similar predictive information in cross section. Similar to results based on %ΔSIR, the long portfolio for NYSE/AMEX stocks generates significant positive abnormal return and the short portfolio for NASDAQ stocks generates significant negative abnormal return. In contrast, the short portfolio for NYSE/AMEX stocks generates insignificant negative abnormal return and the long portfolio for NASDAQ stocks generates insignificant positive abnormal return. Overall, both measures of the change in short interest predict future return in cross section, indicating that changes in short selling activities contain predictive information. The return predictability is also robust for different formation and holding periods. Moreover, the longer the formation period, the stronger the return predictability, consistent with fundamental-based rationale. An unreported result show that the simple %ΔSIR generates similar return predictability.

[Insert Table 8 here]

CONCLUSION

This paper examines the cross-sectional relation between the change in short interest and stock returns. I find that NYSE/AMEX stocks with large increases (decreases) in short interest experience significant and positive (negative) abnormal returns. Specifically, stocks in the bottom (top) decile of short interest increases over previous one year generate significant average monthly return of 0.52% (-0.32%) after controlling for market, size, book-to-market ratio, and momentum effect. The long-short strategy generates average monthly risk-adjusted return of 0.84% (t=5.11). But the return predictability is asymmetric. The positive return of the bottom decile in absolute value is often larger and more persistent than the negative return of the top decile.

The return predictability of the change in short interest is not subsumed by the level of short interest and other well-known return determinants such as size, book-to-market ratio and momentum effect. The return spread of hedge portfolio is particularly large among small stocks, both value and growth stocks, and both past winners and past losers. It is robust to different formation and holding periods, price screen, one-month skip between formation and holding periods, and different measures of the change in short interest. Moreover, the hedge portfolio generates statistically and economically significant and positive abnormal returns in nine among twelve calendar months. In addition, the return predictability is not affected by investor sentiment.

These empirical results cast a doubt on market efficiency. Stock prices adjust so slowly to reflect public information contained in the change in short interest. The asymmetric speed of incorporation of good news versus bad news into stock prices is against the implication of short-sale constraints and limits to arbitrage. Last, an important practical implication of the results is that the information contained in the change in short interest may offer a great hedge or complement to anomaly-based trading strategies.

SHORT SELLING AND PRICE MOMENTUM

INTRODUCTION

Jegadeesh and Titman (1993) document that momentum strategies, which buy past winners and sell past losers, realize significant profits in the subsequent 1-year. This anomaly is quite robust and exists around the world. Moreover, some studies show that positive momentum returns are followed by reversals after the first 1-year holding period (Lee and Swaminathan, 2000; Jegadeesh and Titman, 2001). Though the momentum anomaly has been well known for two decades, the debate on the sources of momentum profits still lasts. Understanding the momentum-reversal pattern helps better understand the sources of momentum profits. Among many theories and models that try to explain momentum, behavioral models seem to reconcile medium-term momentum and long-term reversal well (Daniel, Hirshleifer, and Subrahmanyam, 1998; Barberis, Shleifer, and Vishny, 1998; Hong and Stein, 1999). Many studies provide empirical evidence to support these behavioral models (Lee and Swaminathan, 2000; Cooper, Gutierrez, and Hameed, 2004).

However, some studies argue that short-term momentum and long-term reversals are two separate phenomena (George and Hwang, 2004; Conrad and Yavuz, 2016). These studies further decompose standard momentum portfolio into *consistent* momentum portfolio and *contrarian* portfolio based on some stock characteristics and find that *consistent* momentum portfolio exhibits persistent momentum and no reversal. For example, Conrad and Yavuz (2016) decompose standard momentum portfolio into *consistent* momentum portfolio and *contrarian* portfolio based on firm size and book-to-market ratio or stocks' returns in the first 6-month holding period. They show that *consistent* momentum portfolio experiences persistent momentum but no reversal and *contrarian* portfolio experiences no momentum but significant reversal.

This paper examines the role of short selling in explaining momentum-reversal pattern. Specially, this paper examines whether we can distinguish *ex ante* stocks that experience persistent momentum from those that experience weak momentum but persistent reversals in the first 1-year and subsequent 2-5-year holding period respectively, using information contained in short selling (short interest) at the formation period. I decompose standard momentum stocks into several distinct portfolios based on the interaction of past returns and short interest ratio. More specifically, I decompose past winners (losers) into lightly shorted winners (losers), normally shorted winners (losers), and heavily shorted winners (losers) based on stocks' short interest ratios at the end of formation period. Then I construct an *early-stage* momentum portfolio that buys lightly shorted winners and sells heavily shorted losers. In contrast, the *late-stage* momentum portfolio is to buy heavily shorted winners and sell lightly shorted losers.

Like size and boo-to-market ratio in Conrad and Yavuz (2016), short interest ratio is also a unique stock characteristic that can predict future returns at least in the short run. Moreover, short interest is an index that contains information from comprehensive stock characteristics including size and BM ratio (Dechow et al., 2001; D'Avolio, 2002; Kot, 2007). Both theoretical and empirical studies have demonstrated that short sellers are sophisticated and informed investors and their shorting activities can predict future returns (Diamond and Verrecchia, 1987). Heavily shorted stocks experience significant negative abnormal returns (Desai et al., 2002; Asquith, Pathak, and Ritter, 2005), and lightly shorted stocks experience significant positive abnormal returns (Boehmer, Huszar, and Jordan, 2010). However, there is still a debate on the relation between short selling and past returns. So in this paper I consider them together in predicting future returns. We expect that the interaction of past returns and short interest ratio better predicts future returns. In this paper, I focus on the incremental ability of short selling in identifying *consistent* or *contrarian* momentum stocks.

I find that short interest helps identify stocks that exhibit strong and persistent momentum and those that exhibit weak and insignificant momentum in the first 1-year holding period. For example, lightly (heavily) shorted winners experience an average Fama-French 3-factor alpha of 0.43% (0.05%) and the return spread of 0.39% is highly significant. Lightly (heavily) shorted losers experience an average alpha of -0.3% (-1.01%) and the return spread of 0.71% is highly significant. I find similar results after controlling for size, BM ratio, trading volume and institutional ownership, especially for past losers. For past losers, the alpha spread is still significant even in the third year. For past winners, the alpha spread is marginally significant in the second year.

Empirical evidence on the *early-stage* and *late-stage* momentum portfolios suggests that there is no absolutely pervasive link between short-term momentum and long-term reversal if we condition on some additional stock information like short interest. The *early-stage* momentum strategy experiences strong and persistent momentum but no reversal. Specifically, the alpha of the *early-stage* strategy is 1.02% (t-value is 4.07), compared to the alpha of 0.57% generated by the standard momentum strategy in the first 1-year holding period. Moreover, the *early-stage* strategy experiences no reversal in the subsequent 2-5 years. In contrast, the *late-stage* momentum strategy experiences an insignificant alpha of 0.11% in the first year and significant reversals in the second (-0.48%) and third (-0.28%) years and negative alphas in the fourth (-0.15%) and fifth (-0.25%) years. I find similar results after controlling for size or BM ratio.

I also examine the performance of these two distinct momentum portfolios in January (Jegadeesh and Titman, 1993) and following different investor sentiments (Antoniou, Doukas, and Subrahmanyan, 2013) and market states (Cooper et al., 2004). I find that the *early-stage* portfolio experiences an average alpha of 1.95% in January, but the *late-stage* portfolio experiences an alpha of -1.85% in January. The *early-stage* portfolio experiences significant alphas following both high and low sentiments, consistent with some prior evidence that investor sentiment cannot explicitly explain momentum profits (Stambaugh, Yu, and Yuan, 2012; Conrad and Yavuz, 2016). In contrast, the *late-stage* portfolio experiences positive (negative) and insignificant return following high (low) sentiment. In addition, the early-stage portfolio performs much better than the late-stage and standard momentum portfolios following both positive and negative market returns. In the long run, the early-stage portfolio experience positive returns (weak reversals) following high (low) sentiment, but the late-stage portfolio experience stronger reversals following both sentiments. Similar results appear following up and down market states. Overall, short interest consistently identifies *consistent* momentum stocks and *contrarian* stocks.

The second part of this paper further examines why information contained in short selling (short interest) can help identify *ex ante consistent* momentum stocks that exhibit persistent momentum and *contrarian* stocks that exhibit weak momentum but significant reversals, especially in January and following different sentiments and market states. The existing literature on short selling ignores the return predictability of short interest in January and different sentiments and market states. One main contribution of this paper is to conduct seasonality and time series analysis of return predictability of the level of short interest.

Empirical results show that low short interest predicts significant larger positive abnormal returns in January than in non-January. This finding sheds new light on the *good news* in low short interest in Boehmer et al. (2010). The positive abnormal return by low short interest is smaller in absolute value than the negative abnormal return by high short interest in non-January. So the puzzling finding in Boehmer et al. (2010) is mainly driven by the January effect. Moreover, high short interest owns the ability to predict negative abnormal returns in January, helping identify *true* losers and *false* winners in January. These evidence also explains good performance of the early-stage momentum portfolio in January.

Moreover, low short interest predicts significant positive abnormal returns following both high and low investor sentiments. High short interest predicts significant (insignificant) negative abnormal returns following high (low) sentiment. The hedge portfolio that buys lightly shorted stocks and sells heavily shorted stocks generates significant profits following both high and low sentiments. The return spreads following high and low sentiments for low, high, and low-high short interest are insignificant. The robust return predictability of the low and high short interest explains why the early-stage (late-stage) portfolio performs well (poorly) following both high and low sentiments. In addition, lightly shorted stocks perform better following down market and heavily shorted stocks experience worse returns following up market. The return spreads of UP-DOWN market are insignificant for low, high, and low-high short interest when the holding period is 6-month. Unlike other anomalies that perform better following high sentiment or up market, the short-interest strategy generates robust profits, providing a great hedge or complement to other anomaly-based strategies.

This paper contributes significantly to the literature on momentum and short selling. First, this paper shows that we can identify *ex ante* stocks that exhibit persistent momentum and those that exhibit weak momentum but persistent reversals, using information in short selling. These results provide evidence that short-term momentum and long-term reversals could not be pervasively related. Underreaction and overreaction theories apply to different sets of standard momentum stocks. This paper uses a unique characteristic, short interest, to identify this pattern. Second, a practical implication is that the *consistent* (*early-stage*) momentum strategy based on short selling generates significant profits even in recent two decades and during periods in which the standard momentum strategy fails. The standard momentum strategy generates small returns due to increasing arbitrage activities (Hanson and Sunderam, 2013). The interaction of past returns and short interest better predicts future returns. The information contained in short selling provides a great hedge or complement to anomaly-based strategies. Third, the seasonality analysis shows that the January effect largely explains the puzzling large magnitude of positive abnormal returns generated by low short interest in Boehmer et al. (2010). Short-selling strategy generates robust profits following different investor sentiments and market states. These results confirm that short sellers are sophisticated and informed investors, consistent with the role of short sellers in the price discovery documented in previous studies.

LITERATURE REVIEW

Momentum

Jegadeesh and Titman (1993) document that strategies that buy stocks with highest recent returns and sell stocks with lowest recent returns generate significant positive returns in the subsequent one year. The strategy works in other asset classes and industries and around the world (Moskowitz and Grinblatt, 1999; Chui, Titman, and Wei, 2010; Asness, Moskowitz, and

Pedersen, 2013). Lee and Swaminathan (2000) and Jegadeesh and Titman (2001) find that momentum profits reverse in the long horizon.

A number of studies have been trying to explain the sources of momentum profits since the discovery of this anomaly. Conrad and Kaul (1998) argue that the cross-sectional variation in the mean returns drives momentum profits. Johnson (2002) argues that time-varying expected dividend growth rates can produce momentum profits in a single-firm model. Sagi and Seasholes (2007) show that some firm-specific variables (such as revenues, costs, and growth options) can explain momentum. Liu and Zhang (2008) find that industrial production growth rate can explain much of momentum profits. On the other hand, two behavioral-based hypotheses seem to explain medium-term momentum and long-term reversal well. Underreaction theory argues that momentum profit is mainly due to investor delayed reaction to firm-specific information (Jegadeesh and Titman, 1993; Barberis et al., 1998; Hong and Stein, 1999). Overreaction theory argues that investor overconfidence and biased self-attribution cause short-term price overreaction and long-term reversal (Daniel, Hirshleifer, and Subrahmanyam, 1998).

Short Selling

A number of studies document that short sellers are sophisticated and informed investors and their shorting activities can predict future returns. Desai et al. (2002) and Asquith et al. (2005) find heavily shorted stocks experience significant negative abnormal returns for NYSE/AMEX/NASDAQ stocks. The underlying rationale is that stocks are more likely to be overpriced when short-sale constraints exist (Miller, 1977), and subsequent correction of overpricing leads to lower returns. Boehmer et al. (2010) find that lightly shorted stocks experience significant positive abnormal returns. Short sellers target overpriced firms based on price to fundamental ratios (Dechow et al., 2001). Among firms with declining stock prices, short sellers seem to target only overpriced firms based on several measures of overpricing (Curtis and Fargher, 2014). Short seller trade on short-term price overreaction (Diether et al., 2008). Wu and Zhang (2014) show that short sellers become smarter in time series based on the evidence that they avoid underpriced stocks and increasingly use non-anomaly signals in recent decade. Short arbitrage can efficiently explain some anomalies like accrual (Hirshleifer, Teoh, and Yu, 2011).

Short Selling and Momentum

Ali and Trombley (2006) construct an index to measure short-sale constraints, using some stock variables such as size, turnover, institutional ownership and cash flow in D'Avolio (2002). They find that this short-sale constraints index can efficiently explain the profit from short-leg. This paper differs from them in several ways. First, I use short interest data directly that better reflects short selling activities. Second, I stress the role of information contained in short selling in explaining momentum in both long and short legs. Third, this paper stresses the efficiency of time-varying return predictability of short interest in identify true winners and losers. Hanson and Sunderam (2013) use short interest data to examine the evolution of momentum profits. They mainly focus on the time series of the relation between short arbitrage and momentum profits. This paper examines the relation between short selling and momentum in both cross section and time series. Kot (2007) shows that the level of short interest is negatively related to past medium-term returns. This paper examines how short interest interact with past returns in predicting future momentum returns.

DATA AND METHODOLOGY

The main sample of this paper consists of all common stocks (share code is 10 or 11) with available monthly short interest data listed on NYSE and AMEX over the period of January 1988 to December 2014. Monthly short interest data are from Compustat. Because Compustat does not have short interest data for NASDAQ stocks before July 2003, the sample period for NASDAQ stocks is from July 2003 to December 2014. The complete sample consisting NASDAQ stocks will be used in the robustness test. Closed-end funds, REITs, trusts, and ADRs are excluded from the sample. Stock information such as price, trading volume and the number of outstanding shares are from Center for Research in Security Prices (CRSP). Institutional ownership data is from Thomson Reuters. The short interest ratio (SIR_t) = the total number of uncovered shares shorted (SI) / the total number of shares outstanding in month t.

Following the method in Lee and Swaminathan (2000), I form 30 (10x3) portfolios based on independent sorts of past J-month cumulative returns and the level of short interest at time t. I assign all sample stocks into ten groups based on their past J-month returns. Within each decile, stocks are further divided into three groups based on their level of short interest at time t. In the robustness test, I also use the two-way dependent sort. To avoid short-term reversal (Jegadeesh, 1990), I skip one-month between formation and holding periods. Stocks with prices less than $5 at the end of formation period are excluded. Portfolios are rebalanced monthly and hold for K-month. The monthly return of a specific portfolio held for K-month at time t is the equal-weighted average of returns from time t+1 to t+K-1.

THE INTERACTION OF SHORT SELLING AND PRICE MOMENTUM

Univariate Sorts on Past Returns and Short Interest

I start the empirical analysis by examining the performance of simple momentum strategies and short-selling strategies separately. Table 9 reports the results. Following Jegadeesh and Titman (1993), I assign stocks into ten portfolios based on their J-month cumulative returns and hold them for K-month. I skip one-month between formation and holding periods. Portfolios are rebalanced monthly. Panel A in Table 9 reports the average monthly returns for simple momentum strategies. For example, the simple momentum strategy for (J=6, K=6) generates average monthly raw return of 0.69 percent (t-statistic is 2.31) and Fama-French three-factor adjusted return of 0.91 percent (t-statistic is 3.53). It is expected that the momentum profit in my sample period of 1988 to 2014 is smaller than that documented in Jegadeesh and Titman (1993, 2001) due to the increase in arbitrage capital and trading activities in recent decade (Hanson and Sunderam, 2013; Chordia, Subrahmanyam, and Tong, 2014).

Panel B and C in Table 9 reports average monthly returns for short-selling strategies with different portfolio rankings. In Panel B, following prior studies, I divide all sample stocks into ten groups based on the level of short interest ratio (SIR) at time t. The formation period J is 1-month for the short selling strategy. I skip one-month between formation and holding period. The portfolio of stocks with smallest level of short interest ratio is S1, and the portfolio of stocks with highest level of short interest ratio is S10. Panel B shows that heavily shorted stocks (S10) experience average return of -0.66 percent (t=-4.88) in subsequent month, consistent with prior studies. Because the portfolio is rebalanced monthly, the negative abnormal return is still significant over 12-month holding period. Consistent with Boehmer, Huszar and Jordan (2010), lightly shorted stocks (S1) experience significant positive abnormal return of 0.49 percent in subsequent month (t=4.21). Moreover, the positive abnormal return is persistent in 12-month.

Because I use two-way independent sorts of past return and short interest to form 30 (10x3) portfolios, I also test the return predictability of short interest when sample stocks are divided into only three portfolios based on the SIR. Panel C in Table 9 reports the results. Heavily (lightly) shorted stocks still generate significant negative (positive) monthly abnormal returns of -0.24 percent (0.19 percent) even in the 12-month holding period, even though the magnitude of abnormal return in absolute value is smaller than that in Panel B. This evidence further suggests that short interest has strong return predictability.

[Insert Table 9 here]

The Interaction of Past Returns and Short Interest

In this subsection, I examine the returns of portfolios sorted independently on past returns and short interest ratio. To form 30 two-way independent sorted portfolios, firstly I form 10 equally-weighted portfolios based on stocks' past J-month returns. Then I form 3 equally-weighted portfolios based on stocks' short interest ratio at time t. Finally, I intersect these portfolios. Portfolio M1 is the past loser portfolio and M10 is the past winner portfolio. S1 is the lightly shorted stock portfolio and S3 is the heavily shorted portfolio. The stocks in M10S1 is lightly shorted winners, and the stocks in M1S3 are heavily shorted losers.

Similar to Lee and Swaminathan (2000), I also define two modified momentum strategies. The early-stage momentum strategy is to buy lightly shorted winners (M10S1) and sell heavily shorted losers (M1S3). The late-stage momentum strategy is to buy heavily shorted winners

(M10S3) and sell lightly shorted losers (M1S3). Examining the performance of these two stage strategies would better explain the sources of momentum profits.

Table 10 reports the average monthly raw returns of these portfolios. Table 11 reports the corresponding Fama-French 3-factor adjusted returns. There are several important empirical findings. First, controlling for past extreme returns, lightly shorted stocks significantly outperform heavily shorted stocks. The spread based on risk-adjusted returns is stronger and more persistent. For example, for (J=6, K=6), Table 11 shows that lightly shorted losers outperform heavily shorted losers by 0.71 percent per month (t=3.82), while lightly shorted winners outperform heavily shorted winners by 0.39 percent per month (t=2.71). This outperformance is robust in different (J, K). Moreover, the outperformance is asymmetric between past winner portfolio and past loser portfolio. The spread in past loser portfolio is larger than that in past winner portfolio. These results are consistent with return predictability of short interest documented in prior studies. The asymmetry in spread between past loser and winner portfolios is consistent with Ali and Trombley (2006) that losers contribute more to momentum profits due to short-sale constraints.

[Insert Table 10 here]

[Insert Table 11 here]

These results also extend prior studies on short selling. There is still a debate on whether short sellers amplify and accelerate price declines, though the consensus is almost reached on the ability to correct mispricing of overpriced stocks when their prices are increasing. My results show that only heavily shorted losers experience significant negative abnormal returns, but heavily shorted winners still experience insignificant positive abnormal returns in short run. The persistent underperformance of heavily shorted losers in long horizon documented in subsequent subsection implies that these firms have severe problems in fundamentals. Lack of reversal of heavily shorted losers implies that short sellers seem well informed and just target firms with real problems in fundamentals. The underperformance of heavily shorted winners in the long horizon further supports that short sellers target bad firms.

Second, controlling for the level of short interest, the momentum profit is highest among heavily shorted stocks. In an unreported robustness test, following Hong, Lim, and Stein (2000), I form ten portfolios based on SIR and three portfolios based on past returns. The unreported table shows that momentum profits concentrate in lightly shorted and heavily shorted stock portfolios. For example, for (J=6, K=6), Table 11 shows that the momentum return is 1.06 percent per month (t=3.5) among heavily shorted stocks and 0.73 percent and 0.72 percent among lightly and normally shorted stocks respectively. The difference is mainly due to short leg. The spread among past losers (M1S1-M1S3) is 0.71 percent, while the spread among past winners (M10S1-M10S3) is only 0.39 percent.

These two findings mentioned above suggest that short selling activities contain useful information to identify true winners and true losers among broad past winners and losers. High SIR signals more negative information that has not been reflected in current price and low SIR signals more positive information that has not been incorporated into current price. Combing past returns, lightly shorted winners and heavily shorted losers are more likely to experience stronger and more persistent price continuation than heavily shorted winners and lightly shorted losers. These results are consistent with underreaction explanation of momentum (Jegadeesh and Titman, 1993; Barberis, Shleifer and Vishny, 1998; Hong and Stein, 1999). Investor react with delay to both positive and negative private information contained in short selling due to many reasons such as information asymmetry, short-sale constraints, and limited ability to learn and interpret private and public information.

Third, the early-stage strategy generates economically and statistically significant positive abnormal return, but the late-stage strategy generates economically and statistically insignificant return. Table 11 shows that for (J=6, K=6), early-stage strategy earns average monthly abnormal return of 1.45 percent (t=5.08), compared with the return of 0.35 percent (t=1.33) by late-stage strategy. The difference between two strategies is larger when K=1. In contrast, the simple momentum strategy generates average monthly abnormal return of 0.91 percent (t=3.53). The early-stage strategy outperforms simple strategy by 72% and 59% for K=1 and 6 respectively.

Controlling for Other Cross-Sectional Determinants of Momentum Profits

In this subsection, I examine whether the interaction pattern above is robust after controlling for several significant firm-level characteristics that significant affect momentum profits. These firm-level characteristics are size, book-to-market ratio, trading volume, and institutional ownership as a proxy for short-sale constraints. First, I equally divide all sample stocks into three portfolios based on their ranks on the specific control variable. Then within each group, I use two-way independent sorts to form 30 (10x3) portfolios based on their past returns and short interest ratio. In the unreported report, I also use the three-way independent sorts. The results are basically similar for two methods. The merit of the way I report here is that each portfolio we are interested has enough stocks.

Controlling for Size

Many studies show that momentum profits are negative related to stock size (Jegadeesh and Titman, 1993; Hong, Lim, and Stein, 2000). Asquith et al. (2005) find that heavily shorted stocks are mainly small- and medium-sized stocks. To examine whether the size effect subsumes the effect of short selling, I examine the returns of interested portfolios independently sorted on past returns and SIR in three size subsamples. First, I equally divide all sample stocks into three size groups (small, middle, and big) based on their market capitalizations at the end of prior month. Then within each size group, I form 30 portfolios independently sorted based on past returns and SIR. Panel A in Table 12 reports the results. To have a better comparison, Panel A also reports returns for simple momentum strategy in three size groups.

The results show that the effect of short selling on momentum is robust in different size groups, though the effect is more pronounced in smaller size group. First, the spread between heavily shorted losers and lightly shorted losers reach 0.7 percent (t=4.19) among big stocks. However, the spread among past winners is insignificant (t=0.92) but positive (0.18 percent) among big stocks. Second, lightly shorted winners experience significant positive abnormal returns of 0.57 percent in small size group and marginal significant positive returns of 0.24 percent in big size group. Heavily shorted losers experience significant negative abnormal returns in all three size groups. Third, momentum profits are highest among heavily shorted stocks in all three size groups. Fourth, the early-stage momentum strategies have economically and statistically significant returns in all three size groups.

[Insert Table 12 here]

Controlling for Book-to-Market Ratio

Daniel and Titman (1999) and Sagi and Seasholes (2007) show that momentum profits are higher among firms with low Book-to-Market (BM) ratios. In this subsection, I test the robustness of the interaction pattern in three BM ratio groups. Stocks' BM ratios in year t are calculated based on book value and market value in previous year's annual report (year t-1).

Panel B in Table 12 reports the results. The profitability of simple momentum strategy is highest among stocks with low BM ratios. Overall, the identification effect of short interest on momentum is robust in all three BM ratio groups. The spread between lightly and heavily shorted losers is significant in all three BM ratio groups. Heavily shorted losers experience significant negative abnormal returns in all three subgroups. However, the spread between lightly shorted winners and heavily shorted winners is significant only in value stock (high BM ratio) group, though the sign of spread is expected in low and middle BM ratio groups. But lightly shorted winners generate significant positive abnormal returns in all three subgroups. The early-stage strategy generates significant momentum returns in all three subgroups, significantly outperforming the late-stage strategy and simple strategy.

Controlling for Trading Volume

Lee and Swaminathan (2000) document a positive relation between past trading volume and momentum profits. They show that momentum profits concentrate in high volume stocks. In this subsection, I test the robustness of the interaction pattern in three trading volume subgroups.

Panel C in Table 12 reports the results. Consistent with Lee and Swaminathan (2000), the simple momentum profit is highest among high volume stocks. Overall, the identification effect of short interest on momentum is robust in all three volume groups. The spread between lightly and heavily shorted losers is significant in all three volume groups. But the spread between lightly shorted winners and heavily shorted winners is significant only in low volume group, though the sign of spread is expected in middle and high volume groups. The early-stage strategy generates significant momentum returns in all three volume groups, significantly outperforming the late-stage strategy and simple strategy.

Short-Sale Constraints

Numerous studies show that short-sale constraints limit the arbitrage of profitability in the short leg of anomalies. Ali and Trombley (2006) use some firm characteristics to construct an index to measure short-sale constraints and find that momentum profit is positive related to short-sale constraints and short-leg drives this result. D'Avolio (2002) and Nagel (2005) argue that institutional ownership (IO) is a proxy for short-sale constraints. Asquith et al. (2005) find that the negative relation between short interest and abnormal returns is stronger for stocks with low institutional ownership. Antoniou et al. (2013) find that momentum profits are higher among stocks with low IO than among stocks with high IO in both high and low sentiment periods. Since prior studies show that institutional ownership is related to both short selling and momentum profit, I examine the robustness of interaction pattern in three IO groups.

Panel D in Table 12 reports the results. Consistent with prior studies, simple strategy performs best in low IO group. The spread between heavily shorted losers and lightly heavily losers is significant in all three IO groups, but the spread for past winners is significant only in low IO group. The identification effect of short interest is strong in all three IO groups for past losers and only works in low IO group for past winners. The early-stage strategy generates economically and statistically significant positive abnormal returns in all three IO groups, outperforming significantly both late-stage and simple strategies. However, inconsistent with prior argument that heavily shorted stocks experience lower returns in low IO group, there is no significant difference in abnormal returns among heavily shorted losers in all three IO groups. One potential reason is that the effect of IO disappears after controlling for past extreme returns.

In contrast, lightly shorted winners experience significantly higher positive abnormal returns in low IO group (0.97%) than in high IO group (0.15%). Based on these evidence, the identification effect of short selling on momentum is not driven by the short-sale constraints.

Regression Analysis

The portfolio analysis indicates that the information contained in short selling has incremental explanation on the sources of momentum profits. However, the portfolio analysis cannot control for several significant variables simultaneously due to the insufficient number of stocks after N-way independent sorts. Fama-MacBeth (1973) regressions allow us to examine the incremental effect of short selling on momentum after controlling for several important variables simultaneously. In this subsection, I run the following monthly firm-level cross-sectional Fama-MacBeth (1973) regressions:

$$\begin{aligned} R_{i,t+1:t+6} = {} & a + b1PastReturn_{i,t} + b_2 log(Size_{i,t}) + b_3 log(BM_{i,t}) + b_4 SIR_{i,t} + b_5 TO_{i,t} + b_6 IO_{i,t} \\ & + b_7 PastReturn_{i,t} * SIR_{i,t} + b_8 PastReturn_{i,t} * log(Size_{i,t}) + b_9 PastReturn_{i,t} * log(BM_{i,t}) \\ & + b_{10} PastReturn_{i,t} * TO_{i,t} + b_{11} PastReturn_{i,t} * IO_{i,t} + e_{i,t} \qquad (3) \end{aligned}$$

The dependent variable $R_{i,t+1:t+6}$ is the average monthly return during month t+1 to t+6. $PastReturn_{i,t}$ is the past cumulative return during month t-6 to t-1. Here I skip 1-month between dependent variable and independent variables. $Log(Size_{i,t})$ is the market capitalization at the end of month t-1. $Log(BM_{i,t})$ is the book-to-market ratio at the end of previous year. $SIR_{i,t}$ is the relative short interest ratio at month t-1. $TO_{i,t}$ is turnover at month t-1. $IO_{i,t}$ is the institutional ownership in previous quarter.

Panel A in Table 13 reports the results for all sample stocks. Model 1 indicates that past returns positively predict future returns, suggesting the existence of momentum profit. Model 2 indicates that SIR is significantly and negatively related to future return, consistent with prior studies. Model 3 indicates that high turnover significantly predicts low future return, consistent with Lee and Swaminathan (2000). Model 4 indicates that significant return predictability of turnover disappears after controlling for SIR. Model 5 indicates that SIR has a significant and positive effect on momentum, consistent with portfolio analysis. Model 7, 9 and 10 indicate that the incremental effect of SIR on momentum is robust after controlling for other significant variables simultaneously. The coefficient of *PastReturn*SIR* is largest in Model 10 than in other models, suggesting that the increment effect of SIR increases after controlling for institutional ownership. Panel B reports the results for subsample that includes only past winners and past losers. Consistent with results in Panel A, short interest (SIR) predicts future returns with a significant and negative coefficient and has a significant and positive effect on price continuation. Overall, the negative coefficients of short interest (SIR) in the subsample confirm the usefulness of short interest in identifying *true* winners and losers.

[Insert Table 13 here]

Long-Term Performance

In this subsection, I explicitly examine the momentum-reversal pattern based on the information in short selling measured by short interest. Table 14 reports average monthly returns of momentum portfolios in the first five years after portfolio formation. Panel A reports the raw returns and Panel B reports the risk-adjusted returns. Consistent with Jegadeesh and Titman (2001), simple momentum strategy generates positive monthly returns in the first year and negative monthly returns in the second to fifth years. The simple momentum strategy reverses after the first year. After adjusting risk factors, simple momentum strategy still experiences reversal in the second and fifth year. However, the magnitude of reversal is relative small and insignificant in both raw and risk-adjusted returns. This result is also consistent with Jegadeesh and Titman (2001) that show reversal is relative small in their second sample period of 1982 to 1998. The sample period of this paper is from 1988 to 2014, so it is expected that momentum experience both small magnitude of price continuation in the first year and price reversal after the first year. Panel C shows that the results are almost robust in the long run after controlling for the size or book-to-market ratio.

There are several important findings about the short-selling-based momentum in Table 14. First, momentum profits are positive and significant in both short interest portfolios (S1 and S3) in the first year, but become negative after the first year. Second, the return predictability is persistent in both past loser and past winner portfolios in the long horizon. Heavily shorted losers (M1S3) significant underperform lightly shorted losers (M1S1) in the first three years and insignificantly underperform in the fourth and fifth years. Lightly shorted winners (M10S1) significantly outperform heavily shorted winners (M10S3) in the first two years and insignificantly outperform in the next three years. Third, both early-stage and late-stage strategies experience reversals after the first year based on raw returns in Panel A, but Panel B shows that early-stage strategy still experience positive risk-adjusted returns in the second, third and fourth year and very weak reversal in the fifth year.

[Insert Table 14 here]

An unreported table reports the risk-adjusted event-time returns of various short selling and momentum portfolios over the next five years. Figure 3 gives the graphical representations of buy-and-hold risk-adjusted returns to various strategies and portfolios. Panel A in Figure 3 shows that early-stage momentum strategy consistently experiences price continuation in the 5-year holding period, consistent with long-term underreaction hypothesis. In contrast, the late-stage momentum strategy experiences weak price continuation in the first year and strong reversal after the first year. These results suggest that long-term underreaction and overreaction coexist in the data. Panel B and C in Figure 3 give further evidence of coexistence of underreaction and overreaction to the information in the data. Lightly shorted winners (M10S1) experience relative strong price continuation in the first ten months, then reverse in the next year, and experience relative strong price continuation in the fifth year again. In contrast, heavily shorted winners (M10S3) experience no obvious price continuation in the first half year and then experience significant negative abnormal returns in the next two years. The performance is relatively stable form month 29 to 60. Past losers have similar phenomenon. Lightly shorted losers (M1S1) experience relative strong price continuation in the first year and experience strong reversal over the next four years. In contrast, heavily shorted losers (M1S3) experience strong price continuation in the next four years and weak reversal in the fifth year.

[Insert Figure 3 here]

Figure 4 shows the comparison of cumulative returns of simple, early-stage and late-stage momentum strategies over 1988 to 2014. Panel A and B show the comparison for past winners and past losers respectively. The figure shows that the early-stage strategy outperforms both simple and late-stage strategy, though early-stage strategy also suffered from loss in recent momentum crashes in 2009. But the speed of recovery of early-stage strategy is faster than other two strategies. Panel B shows that lightly shorted winners always outperform heavily shorted winners in time series. Panel C shows strong reversal of lightly shorted losers. This figure shows the superiority of the early-stage strategy.

[Insert Figure 4 here]

In sum, lightly shorted past winners and losers can be explained by short-term market underreaction to information and long-term overreaction effect. Heavily shorted past winners and losers can be fully explained by underreaction to information in both short and long horizons. Aggregately, the early-stage strategy is consistent with market underreaction to information in long horizon, and overreaction effect dominates in explaining the late-stage strategy. These evidence suggests that information contained in short selling is useful in explaining traditional momentum profits. The decomposition based on short interest efficiently identifies the specific momentum portfolios that contribute to the sources of momentum profits.

Seasonality

Jegadeesh and Titman (1993, 2001) document that simple momentum strategies fail in January. We are interested in whether the information from short selling improves momentum profits in January. No prior study has examined the return predictability of short interest in seasonality, so it is an empirical issue. If short interest can efficiently and consistently identify true past winners and losers among broad past winners and losers, short interest is a powerful variable to explain the sources of momentum profits.

Table 15 reports the results. Empirical results show that the simple momentum strategy generates risk-adjusted returns of -0.11 percent and -0.56 percent for 1-month and 6-month holding periods respectively in sample period of 1988 to 2014, consistent with Jegadeesh and Titman (1993, 2001). The loss of simple momentum strategy in January is mainly due to positive abnormal return of past losers. Fortunately, the return predictability of short interest is robust in January and among past extreme returns. For example, when K=1, heavily shorted losers (M1S3) experience abnormal return of -0.27 percent (t=-0.31), while lightly shorted losers (M1S1) experience abnormal return of 1.4 percent (t=1.47). This spread of 1.68 percent (t=3.47) suggests that short interest efficiently identifies true losers in January. In addition, lightly shorted winners (M10S1) experience significant positive abnormal return of 1.67 percent in January, while heavily shorted winners (M10S3) incur loss of -0.45 percent in January. The early-stage strategy experiences substantial abnormal return of 1.95 percent (t=1.49) in January, while late-stage strategy loses -1.85 percent. The small t-value may be due to small number of observations.

[Insert Table 15 here]

The Interaction Pattern Conditional on Investor Sentiment

Based on the behavioral model of Hong and Stein (1999), Antoniou, Doukas, and Subrahmanyam (2013) show that momentum profits arise following high investor sentiment and are small and insignificant following low investor sentiment. Stambaugh, Yu, and Yuan (2012) find the similar results, using a different measurement of investor sentiment. Short-sale constraints play an important role in their arguments because the difference in short-leg returns explains most of the difference in momentum profits following high verse low sentiment. Short-sale constraints efficiently prohibit arbitraging the overpricing of past losers during high sentiment period. Subsequent slow correction of mispricing following high sentiment leads to high short-leg profits.

In this subsection, I examine whether information contained in short selling can identify true winners and losers following both high and low sentiments. I use the monthly sentiment index created by Baker and Wurgler (2006, 2007) to define high and low sentiment periods. Following Antoniou et al. (2013), I use a weighted moving average of sentiment index from month t-3 to t-

1 to get a modified sentiment value in month t. If the modified value in month t falls within the top (bottom) 40% of the modified sentiment index time series, then the month t is high (low) sentiment month. I also use the 30% cutoff point and get the similar results. Because the momentum strategy rebalance portfolios monthly, the strategy with 6-month holding period covers stocks from six different formation periods that cover high and low sentiment months. So I also reports the results for 1-month holding period.

Table 16 reports the results. All returns are FF 3-factor adjusted returns. Panel A reports the results for 1-month holding period. First, the spread between lightly shorted stocks and heavily shorted stocks is significant among both past losers and past winners following both high and low sentiment periods. Heavily shorted losers (M1S3) significantly underperform lightly shorted losers (M1S1) by 0.7 (1.31) percent per month following high (low) sentiment period. Heavily shorted losers (M1S3) still experience negative abnormal return of -0.87 percent per month (t=-1.88) following low sentiment period, while lightly shorted losers experience positive return. Second, the early-stage strategy experience significant positive abnormal return following low sentiment, and late-stage strategy experience negative abnormal return following high sentiment. Compared to return of 0.43 percent per month (t=0.75) by simple momentum strategy following low sentiment, the identification effect of short interest on momentum becomes more pronounced following low sentiment. These evidence further suggests the usefulness of short selling in explaining the sources of momentum profits. The interaction pattern of short selling and momentum is robust following both high and low sentiment periods.

[Insert Table 16 here]

The Interaction Pattern Conditional on Market State

Based on the overreaction hypothesis of Daniel et al. (1998), Cooper, Gutierrez, and Hameed (2004) show that positive and significant momentum profit arises following positive market return, but the momentum profit is negative following negative market return over the sample period of 1929 to 1995. In this subsection, I examine whether the interaction pattern of short selling and momentum is robust following both up and down markets.

Table 17 reports the results. All returns are FF 3-factor adjusted returns. Panel A reports the results for 1-month holding period and Panel B reports the results for 6-month holding period. First, I examine the simple momentum profits following positive and negative markets in my sample period of 1988 to 2014. The empirical result shows that the momentum return is 1.25 percent per month (t=4.98) following positive prior 3-year market return and is -0.99 percent per month (t=-0.94) following negative prior 3-year market return for (J=6, K=6). This result is consistent with Cooper et al. (2004). Because the simple momentum strategy experiences substantial losses in several months in my sample period, the magnitude of negative return following negative market return is larger than that in Cooper et al. (2004). Second, the spread between lightly shorted stocks and heavily shorted stocks is significant following both positive and negative market returns when K=1. Panel A shows that when K=1, past losers (M1) experience monthly risk-adjusted return of 0.94 percent (t=1.32) following negative market return, but lightly shorted losers (M1S1) experience monthly return of 1.81 percent (t=3.05) and heavily shorted losers (M1S3) experience monthly return of 0.3 percent (t=0.48). Past winners (M10) experience monthly return of -0.24 percent following negative market return, but lightly shorted winners (M10S1) experience monthly return of 0.6 percent following down market. These evidence suggest that information in short interest efficiently identifies past winners and losers with stronger and more persistent price continuation even following negative market return. Third, compared to bad performance of simple momentum strategy and late-stage strategy following down market, the early-stage strategy still earns positive return when K=1.

[Insert Table 17 here]

Table 18 reports the risk-adjusted monthly returns for the early-stage and late-stage portfolios conditional on different investor sentiments and market states in the long run. The results show that the early-stage strategy experience persistent momentum but insignificant reversals in the long run following both high and low sentiments. But the late-stage strategy experience weak momentum and persistent reversals in the long run following both sentiments. These results confirm the role of short interest in distinguishing the momentum-reversal pattern in stock returns.

[Insert Table 18 here]

Robustness Tests

NASDAQ Stocks

Previous empirical results are based on NYSE/AMEX stocks due to relatively longer sample period. In this subsection, I include NASDAQ stocks to test the robustness. Compustat does not cover monthly short interest data for NASDAQ stocks before July 2003, so the sample period for all three exchanges is from July 2003 to December 2014. Panel A in Table 19 reports the results. It is excepted that the simple momentum profit is small and insignificant in recent decade due to momentum crashes in 2009 and the increase in arbitrage capital and trading activities (Daniel and Moskowitz, 2013; Hanson and Sunderam, 2013; Chordia et al., 2014). However, the early-stage strategy still earns economically and statistically significant profits, compared to the poor performance of the simple strategy and the late-stage strategy. The success of the early-stage strategy is due to significant negative return generated by heavily shorted losers (M1S3) and positive return by lightly shorted winners (M10S1). For example, when K=1, heavily shorted losers generate monthly return of -0.73 percent (t=-2.49), while lighted shorted losers generate return of 0.00 percent. Lightly shorted winners generate monthly return of 0.43 percent (t=1.67), while heavily shorted winners generate return of -0.21 percent (t=-0.87). Overall, including NASDAQ stocks generates similar results.

Subperiod

A number of studies show that momentum profit has become smaller and insignificant since 2000 and experiences momentum crashes in 2009 (Daniel and Moskowitz, 2013; Chordia et al., 2014). In this subsection, I divide the whole sample period into two periods: 1988-2000 and 2001-2014. Panel B in Table 19 reports the results. Panel B show that simple momentum strategy performs worse in second subperiod than in the first subperiod. Lightly shorted winners (losers) significantly outperform heavily shorted winners (losers) in both subperiods. The information contained in short selling efficiently identifies true winners and losers in both periods. The early-stage strategy generates economically and statistically significant returns in both periods. However, the profit from short-leg (M10S3) is significantly larger during 1988-2000 than during 2001-2014. No obvious difference is in long-leg (M10S1). This evidence also implies that more arbitrage capitals decrease the arbitrage profit in short-leg. Overall, the interaction pattern is robust in both subperiods.

Two-Way Dependent Sorts

Previous results are based on two-way independent sorts on past returns and the level of short interest. The merit of two-way independent sorts is that stocks in each specific portfolio independently meet corresponding sorting criteria at the same time. The concern is that the number of stocks in portfolios may be unequal and the result may be due to some extreme stocks. In contrast, the merit of two-way dependent sorts is ensure equal number of stocks in each portfolio. Panel C in Table 19 reports the results. I form 10 portfolios based on their past J-month returns. Then within each of 10 portfolios, stocks are further assigned into three portfolios based on their short interest ratio at month t. The empirical results show that the interaction pattern is robust based on two-way dependent sorts. The identification effect of short interest seems better for past losers using dependent sorts than using independent sorts.

[Insert Table 19 here]

RETURN PREDICTABILITY OF SHORT INTEREST IN TIME SERIES

Why does the early-stage momentum strategy consistently generate significant profits in time series? The empirical evidence above shows that the early-stage strategy experiences economically and statistically significant returns in January, following low sentiment period and down market, in recent decade, and post-holding period, compared to poor performance of simple momentum strategy in these periods. Prior studies prove the return predictability of short interest in cross section. In this section, I examine the return predictability of short interest in time series. The empirical results help us better understand the identification effect of short interest in the interaction pattern above and return predictability of short interest in cross section.

Return Predictability of Short Interest and Seasonality

It is well known that simple momentum strategy is negatively affected by the January effect (Jegadeesh and Titman, 1993, 2001). Past losers will reverse and past winners experience weak price continuation in January. Many anomalies such as long-term and short-term reversals are also affect by January effect (DeBondt and Thaler, 1985; Jegadeesh, 1990). If short interest has strong return predictability in January, information in short interest help improve momentum profit in January. In this section, I test whether return predictability of short interest is significantly affected by January effect.

Table 20 reports the results. Panel A reports results for sample that eliminates stock prices less than $5 at the beginning of formation period. Empirical results show that lightly shorted stocks experience significant positive FF 3-factor adjusted return of 1.39 percent (t=3.28) in January, compared to average return of 0.39 percent (t=3.73) in non-January. The average 4-factor adjusted returns is 1.43 percent (t=3.31) in January and 0.38 percent (t=3.5) in non-January. This evidence shows that low short interest predicts significant positive abnormal returns in both January and non-January, but positive return generated by low short interest is significant higher in January.

In contrast, heavily shorted stocks generate similar magnitude of four-factor adjusted returns in January and non-January. Heavily shorted stocks experience average 3-factor adjusted return of -0.4 percent (t=-1.0), compared to average return of -0.72 percent (t=-5.39) in non-January. The 4-factor adjusted return is -0.58 percent (t=-1.85), compared to return of -0.5 percent (t=-3.89) in non-January. The difference in the return predictability of high short interest in January vs. non-January is ignorable. These results imply that the predictability of high short interest can help improve the profitability of simple momentum strategy in January because high short interest help identify *true* losers in January.

[Insert Table 20 here]

The significant higher positive abnormal returns generated by low short interest in January shed new light on ‘the good news in low short interest’ proposed by Boehmer et al. (2010). Boehmer et al. (2010) show that low short interest predicts significant positive 4-factor adjusted return in subsequent month. To examine the January effect on return predictability of low short interest in Boehmer et al. (2010), I reexamine the sample with stocks with prices larger than $0. Panel B reports the results. Empirical results show that lightly shorted stocks generate significant average 4-factor adjusted return of 4.55 percent in January and 1.5 percent in February, compared to average return of 0.45 percent in non-January. This evidence suggests that positive abnormal return generated by low short interest in Boehmer et al. (2010) is mainly driven by the January effect and size effect. Moreover, the magnitude of positive abnormal return by low short interest (0.45 percent) is smaller than the magnitude of negative abnormal return by high short interest (-0.57 percent) in absolute value in non-January, weakening the argument of Boehmer et al. (2010).

Return Predictability of Short Interest and Investor Sentiment

A number of studies argue that time-varying investor sentiment could explain market anomalies. Stambaugh et al. (2012) empirically show that the profitability of anomalies is higher following high sentiment, and the higher profits are mainly from short-legs due to short-sale constraints (Miller, 1977). However, no study has examined the return predictability of short interest following high and low sentiments. We are interested in whether time-varying sentiment could explain the return predictability of short interest in cross section. In this section, I conduct both portfolio and predictive regression analysis to test the return predictability of short interest following different sentiment periods.

Existing literature on short selling documents that short sellers are sophisticated and informed investors who make use of fundamental information and signals from anomalies (Dechow et al., 2001; Hirshleifer et al., 2011; Hwang and Liu, 2014). I conduct an alternative test to examine whether short sellers are sophisticated and informative, based on the return predictability of short interest following different sentiment index. If low (high) short interest generates significant positive (negative) abnormal future returns following both high and low sentiment periods and the difference of abnormal returns between high and low sentiment periods is insignificant, we can conclude that short sellers are sophisticated and informed investors due to robust return predictability of short interest regardless of sentiment.

During high sentiment, investors are more likely to be optimistic, so stock prices are more likely to be overpriced. Optimistic investors are reluctant to short sell, but pessimistic investors or informed rational investors are likely to short sell during high sentiment period. Due to the limits of arbitrage (Shleifer and Vishny, 1997) and short-sale constraints, these informed rational investors or pessimistic investors are also reluctant to short sell during high sentiment period, but they are more likely to short sell at the end of high sentiment period if they are good at timing. Assuming that informed short sellers have good timing ability, we expect that heavily shorted stocks experience negative returns following high sentiment period. During low sentiment period, stock prices are less likely to be overpriced, so pessimistic and informed rational investors are expected to engage in fewer short selling activities. We expected that the corresponding level of short interest is lower during low sentiment period than during high sentiment period. Because short-sale constraints still exist during low sentiment period, stocks are also likely to be overpriced during low sentiment period, though the degree of overpricing is lower than that during high sentiment period. So we expect that heavily shorted stocks will experience smaller magnitude of negative returns following low sentiment period.

During high sentiment period, stocks are lightly shorted due to two reasons. The first is that the stocks are still underpriced or at least not overpriced. The second is the limits of arbitrage that defer short selling. Boehmer et al. (2010) argue that positive information will be incorporated into stock price slowly. In addition, existing capitals during high sentiment period are more likely to flow into these lightly shorted stocks following high sentiment period, compared to heavily shorted stocks. Based on the argument above, the lightly shorted stocks are more likely to experience positive return following high sentiment period, compared to heavily shorted stocks. During low sentiment period, lightly shorted stocks are more likely to be underpriced or at least not overpriced. More capitals will flow into these underpriced lightly shorted stocks following low sentiment period. The lightly shorted stocks are expected to experience larger magnitude of positive returns following low sentiment period than following high sentient period, ceteris paribus.

Table 21 reports the results of portfolio analysis. First, when the holding period K=1, heavily shorted stocks experience average monthly FF 3-factor adjusted return of -0.88 percent (t=-3.3) following high sentiment and -0.4 percent (t=-1.5) following low sentiment. Lightly shorted stocks experience average monthly 3-factor adjusted return of 0.55 percent (t=1.94) following high sentiment and 1.01 percent (t=3.58) following low sentiment. These results show that low (high) short interest predicts significant and positive (negative) abnormal returns following both high and low sentiment, though high short interest predicts insignificant negative abnormal returns following low sentiment. Second, the return differences are insignificant following high versus low sentiment for both low and high short interest, but the signs of difference are expected. The return spread is -0.47 percent (t=-1.18) for low short interest. The return spread is -0.48 percent (t=-1.27) for high short interest. The insignificance supports the robust return predictability of short interest in time series. Third, the short-selling strategy that buys lightly shorted stocks and sells heavily shorted stocks generates significant average monthly 3-factor adjusted return of 1.43 (1.42) percent following high (low) sentiment period. The profitability is mainly from short (long) leg following high (low) sentiment. The results are robust when K=6. Overall, the empirical results are consistent with my hypotheses. These results suggest that the robust return predictability of short interest can improve profitability of market anomalies following both high and low sentiment periods. The results in Table 8 show that short interest help identify true winners and losers following low sentiment period.

[Insert Table 21 here]

The empirical results in Table 21 are based on binary classification of high or low sentiment period based on ranks of sentiment index in time series. I also conduct a predictive regression analysis to test the robust return predictability of short interest on lagged sentiment index. Table 22 reports the results. I regress the excess returns of long-leg (lightly shorted stocks), short-leg (heavily shorted stocks), or long-short strategy on lagged weighted 3-month moving average sentiment index defined in the previous section. Empirical results show that the coefficients of lagged sentiment index for both long-leg and short-leg are insignificant and the signs of coefficients are expected, consistent with portfolio analysis in Table 21. The insignificance of the coefficients of long-leg and short-leg suggests that the level of short interest owns robust predictive information regardless of lagged investor sentiment.

[Insert Table 22 here]

Return Predictability of Short Interest and Market State

The argument in the sentiment applies to predictability of short interest following up and down markets. Investors are more likely to be optimistic in up market, so the stock prices are more likely to be overpriced. Heavily shorted stocks are more likely to experience negative returns and lightly shorted stocks continue to earn positive returns following up market. In contrast, heavily shorted stocks are less overpriced and lightly shorted stocks are more likely to be underpriced in down market. So heavily shorted stocks may experience smaller magnitude of negative return following down market, and lightly shorted stocks will experience larger magnitude of positive returns due to slow incorporation of positive private information and more capital inflows following down market.

Table 23 reports the results. Panel A reports the results when past 12-month return prior holding period is used to define market state. When K=1, heavily shorted stocks generate average monthly 3-factor adjusted return of -1.00 percent (t=-6.32) following up market and 0.05 percent (t=0.12) following down market. Lightly shorted stocks generate average monthly 3-factor adjusted return of 0.5 percent (t=3.14) following up market and 1.44 percent (t=2.76) following down market. The return spread between up and down markets is significant for both lightly and heavily shorted stocks when K=1. The short selling strategy generates average monthly 3-factor adjusted return of 1.51 (1.39) percent following up (down) market. The profitability of the strategy is mainly from short (long) leg following up (down) market. The results are almost robust when K=6. The t-value for the spread is insignificant, but the spread is economically significant. These results suggest that the robust return predictability of short interest can improve profitability of market anomalies following both up and down markets.

[Insert Table 23 here]

CONCLUSION

This paper provides evidence that short-term momentum and long-term reversals could not be pervasively related. We can identify ex ante stocks that exhibit persistent momentum and those that exhibit weak momentum but persistent reversals, using information contained in short selling. The early-stage momentum strategy that buys lightly shorted winners and sells heavily shorted losers experiences persistent momentum and no reversal in the long run. In contrast, the late-stage strategy that buys heavily shorted winners and sells lightly shorted losers experiences weak momentum but persistent reversals in the long run. These results are robust after controlling for some well-known variables such as size and book-to-market ratio. Underreaction and overreaction theories seem to apply to different sets of momentum stocks. These results are consistent with some arguments that some single behavioral model or theory cannot explicitly explain complicated patterns in stock returns.

Moreover, the early-stage strategy succeeds during periods in which standard momentum strategy fails. The early-stage strategy generates significant profits in January and following both high and low investor sentiments. The interaction of past returns and short interest better predicts future returns. The information contained in short selling provides a great hedge or complement to anomaly-based strategies.

The seasonality analysis shows that the January effect largely explains the puzzling large positive abnormal returns generated by low short interest. The strategy based on short interest generates robust profits following different investor sentiments. These results confirm that short sellers are sophisticated and informed investors and contribute to the price discovery.

CONCLUSIONS

In this dissertation, I provide more empirical evidence on the role of short sellers in the price discovery process. This dissertation contributes to the literature on short selling in two main ways. First, I examine the return predictability of dynamic changes in short selling activities and find evidence on the incremental return predictability of the change in short interest. This finding provides a big picture of the predictive information contained in short interest. The results also shed new light on the implication of short-sale constraints, the limits to arbitrage, and market efficiency. Second, I examine the role of short selling in explaining momentum. The empirical study on the role of short selling in the context of momentum is limited. I am particularly interested in how the interaction of past returns and short selling predicts future returns. I find that short selling efficiently explains the momentum-reversal pattern. Overall, empirical results in my dissertation suggest that the information contained in short selling is informative about future stock returns. These evidence confirms that short sellers are sophisticated and informed investors who contribute to the price discovery.

The first essay examines the cross-sectional relation between the change in short interest and expected stock returns. I show that the dynamic change in short selling activities own the incremental return predictive information beyond the level of short interest. NYSE/AMEX stocks with large decreases (increases) in short interest over past medium-term horizon experience significant and positive (negative) abnormal returns. Moreover, the positive abnormal returns are larger in absolute value and are more persistent than negative abnormal returns. The return spread between bottom and top deciles is economically and statistically significant and persistent. The return predictability of the change in short interest is not subsumed by the level of short interest and other well-known determinants of stock returns, and is robust in different calendar months and investor sentiment. These results imply that public information contained in the change in short interest is so slowly incorporated into prices. Moreover, the positive information is incorporated into prices more slowly than the negative information. The asymmetry in the speed of price adjustment casts doubts on the implication of short-sale constraints and the limits to arbitrage.

The second essay examines the role of short selling in explaining the sources of momentum profits. The empirical results show that momentum and long-term reversals would be separate phenomena. We can identify ex ante momentum stocks that exhibit persistent momentum and those that exhibit weak momentum but persistent reversals, using information in short selling. Underreaction and overreaction theories apply to different sets of momentum stocks. The consistent momentum strategy based on short interest succeeds during periods in which the standard momentum strategy fails. The success of the consistent momentum strategy is mainly due to the robust return predictability of short interest in these periods. These evidence confirms that short sellers contribute to price discovery. The information in short selling provides a great hedge or complement to anomaly-based strategies.

BIBLIOGRAPHY

Ali, A., and M. A. Trombley. 2006. Short Sales Constraints and Momentum in Stock Returns. Journal of Business Finance & Accounting 33:587-615.

Antoniou, C., J. Doukas, and A. Subrahmanyam. 2013. Cognitive Dissonance, Sentiment, and Momentum. Journal of Financial and Quantitative Analysis 48:245-275.

Asness, C.S., T. J. Moskowitz, and L. H. Pedersen. 2013. Value and momentum everywhere. Journal of Finance 68:929-985.

Asquith, P., P. Pathak, and J. Ritter. 2005. Short Interest, Institutional Ownership, and Stock Returns. Journal of Financial Economics 78:243–76.

Baker, M., and J. Wurgler. 2006. Investor Sentiment and the Cross-Section of Stock Returns. Journal of Finance 61:1645-1680.

Barberis, N., A. Shleifer, and R. Vishny. 1998. A model of investor sentiment. Journal of Financial Economics 49:307–343.

Boehmer, E., Z. R. Huszar, and B. D. Jordan. 2010. The good news in short interest. Journal of Financial Economics 96:80-97.

Carhart, M. 1997. On persistence in mutual fund performance. Journal of Finance 52: 57–82.

Chui, A., S. Titman, and K.C.J Wei. 2010. Individualism and momentum around the world. Journal of Finance 65: 361–392.

Christophe, S., M. Ferri, and J. Angel. 2004. Short-Selling Prior to Earnings Announcements. Journal of Finance 59:1845–75.

Conrad, J., and G. Kaul. 1998. An anatomy of trading strategies. Review of Financial Studies 11: 489–519.

Conrad, J., and M. D. Yavuz. 2016. Momentum and Reversal: Does What Goes Up Always Come Down? forthcoming at Review of Finance

Cooper, M. J., R. C. Gutierrez, and A. Hameed. 2004. Market States and Momentum. Journal of Finance 59:1345-1365.

Curtis, A., and N. L. Fargher. 2014. Does Short Selling Amplify Price Declines or Align Stocks with Their Fundamental Values? Management Science 60:2324-2340.

Daniel, Kent, D. Hirshleifer, and A. Subrahmanyam. 1998. Investor psychology and investor security market under-and overreactions. Journal of Finance 53:1839–1886.

Daniel, K., and T. J. Moskowitz, 2013. Momentum crashes. Working paper. Columbia Business School and University of Chicago.

DeBondt, W. F. M., and R. Thaler. 1985. Does the stock market overreact? Journal of Finance 40:793–808.

Dechow, P., A. Hutton, L. Meulbroek, and R. Sloan. 2001. Short-sellers, Fundamental Analysis and Stock Returns. Journal of Financial Economics 61:77–106.

Desai, H., K. Ramesh, S. Thiagarajan, and B. Balachandran. 2002. An Investigation of the Information Role of Short Interest in the Nasdaq Market. Journal of Finance 52:2263–87.

Deshmukh, S., K. J. Gamble, K. M. Howe. 2015. Short Selling and Firm Operating Performance. Financial Management 44:217-236.

Diamond, D., and R. Verrecchia. 1987. Constraints on Short-Selling and Asset Price Adjustment to Private Information. Journal of Financial Economics 18:277–311.

Diether, K. B., K. H. Lee, and I. M. Werner. 2008. Short-sale strategies and return predictability. Review of Financial Studies 22:575–607.

Fama, E. F., and K. R. French. 1993 Common risk factors in the returns on stocks and bonds. Journal of Financial Economics 33:3-56.

Fama, E.F. and J. MacBeth. 1973. Risk, Return and Equilibrium: Empirical Tests. Journal of Political Economy 81:607-636.

George, T., and C. Hwang. 2004. The 52-week high and momentum investing. Journal of Finance 59: 2145-2176.

Hanson, S. G., and A. Sunderam, 2013. The growth and limits of arbitrage: Evidence from short interest. Review of Financial Studies 27:1238-1286.

Hirshleifer, D., S. H. Teoh, and J. J.Yu. 2011. Short arbitrage, return asymmetry, and the accrual anomaly. Review of Financial Studies 24:2429–61.

Hong, H., T. Lim, and J. C. Stein. 2000. Bad News Travels Slowly: Size, Analyst Coverage, and the Profitability of Momentum Strategies. Journal of Finance 55:265-295.

Hong, H., and J. Stein. 1999. A Unified Theory of Underreaction, Momentum Trading and Overreaction in Asset Markets. Journal of Finance 54:2143–84.

Jegadeesh, N. 1990. Evidence of Predictable Behavior of Security Returns. Journal of Finance 45:881-898.

Jegadeesh, N., and S. Titman. 1993. Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency. Journal of Finance 48:65–91.

Jegadeesh, N., and S. Titman. 2001. Profitability of Momentum Strategies: An Evaluation of Alternative Explanations. Journal of Finance 56: 699-720.

Johnson, T. C. 2002. Rational Momentum Effects. Journal of Finance 57:585-608.

Karpoff, J.M. and X. Lou. 2010. Short Sellers and Financial Misconduct. Journal of Finance 65: 1879-1913.

Kot, H.W. 2007. What Determines the Level of Short Selling Activity? Financial Management 36: 123-141.

Lee, C. M. C., and B. Swaminathan. 2000. Price momentum and trading volume. Journal of Finance 55:2017–2069.

Liu, L. X., and L. Zhang. 2006. Momentum Profits, Factor Pricing, and Macroeconomic Risk. Review of Financial Studies 21:2417-2448.

Miller, E. 1977. Risk, Uncertainty, and Divergence of Opinion. Journal of Finance 32:1151–68.

Moskowitz, T. J., and M. Grinblatt. 1999. Do industries explain momentum? Journal of Finance 54: 1249–1290.

Nagel, S. 2005. Short Sales, Institutional Investors, and the Cross-section of Stock Returns. Journal of Financial Economics 78:277–309.

Sagi, J. S., and M. S. Seasholes. 2007. Firm-specific attributes and the cross-section of momentum. Journal of Financial Economics 84:389-434.

Senchack, A.J. and L. Starks. 1993. Short-Sale Restrictions and Market Reaction to Short Interest Announcement. Journal of Financial and Quantitative Analysis 28: 177-194.

Shleifer, A., and R. Vishny. 1997. The limits of arbitrage. Journal of Finance 52:35–55.

Stambaugh, R. F., J. Yu, and Y. Yuan. 2012. The short of it: Investor sentiment and anomalies. Journal of Financial Economics 104:288-302.

Wu, J., and A. Zhang. 2015. Have Short Sellers Become More Sophisticated? Evidence from Market Anomalies. Working Paper. University of Georgia and University of Nevada Las Vegas.

Table 1. Returns of Portfolios Sorted on the Change in Short Interest

This table presents average monthly raw and risk-adjusted returns for portfolios of stocks sorted on their past 12-month cumulative changes in short interest. Each month, common stocks listed in NYSE/AMEX are first sorted in ascending order based on their past 12-month cumulative changes in short interest (SIRG). I then assign these sorted stocks into deciles. The top (bottom) decile includes stocks with the largest (smallest) magnitudes of cumulative growth rates in short interest ratio. The bottom decile is the *buy* portfolio (Portfolio 1). The bottom decile is the *sell* portfolio (Portfolio 10). Each portfolio is held for 1-month and portfolio returns are equally weighted. I exclude stocks with prices less than $1 at the end of formation period. Fama-French 4-factors are market premium, firm size, book-to-market ratio, and momentum. Average returns are presented in percentages. The Newey-West (1987) t-statistics are in parentheses. The sample period is from January 1988 to December 2014.

	Raw	CAPM	FF3	FF4
1	1.40	0.56	0.38	0.52
	(4.38)	(2.84)	(2.45)	(3.15)
2	1.33	0.41	0.19	0.35
3	1.15	0.22	0.02	0.16
4	1.22	0.29	0.1	0.24
5	1.18	0.25	0.07	0.17
6	1.16	0.24	0.07	0.17
7	1.06	0.13	-0.05	0.09
8	1.01	0.05	-0.14	-0.01
9	0.85	-0.1	-0.3	-0.17
10	0.74	-0.26	-0.49	-0.32
	(2.07)	(-1.37)	(-4.01)	(-2.86)
1-10	0.66	0.82	0.87	0.84
	(4.32)	(5.37)	(5.68)	(5.11)

Table 2. Returns of Portfolios Double-Sorted on SIRG and Other Variables

This table presents average monthly raw and risk-adjusted returns for portfolios of stocks double-sorted on their past 12-month cumulative changes in short interest (SIRG) and other four well-known variables (size, book-to-market ratio, momentum, and the level of short interest) that predict future returns. Both two-way dependent sorting and independent sorting are used. For the dependent sorting, each month, stocks are first sorted into quintiles based on one of four variables; then within each variable quintile, stocks are further sorted into quintiles based on their past 12-month cumulative changes in short interest. The 25 double-sorted portfolios are held for 1-month. All portfolio returns are equally weighted. Fama-French 3-factor and 4-factor alphas are also presented for the long-short portfolios. For the independent sorting, variable quintiles interact with SIRG quintiles to form 25 independently double-sorted portfolios. I exclude stocks with prices less than $1 at the end of formation period. Average returns are presented in percentages. The Newey-West (1987) t-statistics are in parentheses. The sample period is from January 1988 to December 2014. Panel A controls for size (market capitalization); Panel B controls for book-to-market ratio (BM); Panel C controls for past 6-month cumulative returns (momentum); Panel D controls for current level of short interest.

Panel A: Controlling for Firm Size

	Dependent Sort								Independent Sort		
	SIRG					Raw	FF3	FF4	Raw	FF3	FF4
Size	1	2	3	4	5	1-5	1-5	1-5	1-5	1-5	1-5
1	1.40	1.26	1.07	1.01	0.45	0.95	1.21	1.07	1.12	1.20	1.23
						(3.91)	(5.30)	(4.67)	(4.56)	(5.23)	(4.66)
2	1.21	1.29	1.36	1.20	0.96	0.25	0.38	0.19	0.29	0.42	0.22
						(1.34)	(2.27)	(1.05)	(1.54)	(2.46)	(1.17)
3	1.48	1.23	1.16	1.16	1.05	0.43	0.57	0.43	0.40	0.56	0.38
						(2.96)	(4.32)	(2.92)	(2.38)	(3.92)	(2.27)
4	1.22	1.19	1.01	0.95	0.27	0.27	0.38	0.23	0.32	0.43	0.31
						(1.89)	(2.96)	(1.56)	(2.15)	(3.01)	(1.93)
5	1.07	1.14	1.01	1.03	0.74	0.33	0.47	0.32	0.23	0.33	0.20
						(2.54)	(3.61)	(2.36)	(1.45)	(2.04)	(1.21)

Table 2 (continued)

Panel B: Controlling for Book-to-Market Ratio (BM)

	Dependent Sort								Independent Sort		
	SIRG					Raw	FF3	FF4	Raw	FF3	FF4
BM	1	2	3	4	5	1-5	1-5	1-5	1-5	1-5	1-5
1	1.14	1.05	0.92	0.89	0.47	0.67	0.69	0.71	0.79	0.80	0.89
						(3.88)	(4.00)	(3.91)	(3.51)	(3.66)	(3.63)
2	1.13	1.07	1.18	1.10	0.82	0.31	0.43	0.39	0.33	0.46	0.44
						(2.45)	(2.68)	(2.35)	(2.00)	(2.73)	(2.51)
3	1.38	1.21	1.21	1.09	1.13	0.25	0.37	0.33	0.22	0.34	0.32
						(1.67)	(2.49)	(2.34)	(1.52)	(2.32)	(2.23)
4	1.35	1.19	1.40	1.10	1.15	0.20	0.30	0.24	0.16	0.26	0.21
						(1.25)	(1.85)	(1.50)	(1.01)	(1.69)	(1.35)
5	1.74	1.63	1.53	1.33	1.20	0.55	0.83	0.75	0.65	0.86	0.82
						(2.29)	(3.59)	(3.02)	(2.82)	(3.80)	(3.43)

Panel C: Controlling for Past 6-month Returns (Momentum)

	Dependent Sort								Independent Sort		
	SIRG					Raw	FF3	FF4	Raw	FF3	FF4
MOM	1	2	3	4	5	1-5	1-5	1-5	1-5	1-5	1-5
1	1.35	1.18	1.38	0.99	0.52	0.84	1.05	0.92	0.87	1.04	0.92
						(3.71)	(4.35)	(3.59)	(4.24)	(4.62)	(3.87)
2	1.13	1.30	1.25	1.14	0.91	0.22	0.29	0.30	0.32	0.39	0.40
						(1.50)	(2.04)	(1.89)	(1.96)	(2.50)	(2.28)
3	1.22	1.22	1.14	1.09	0.96	0.26	0.30	0.25	0.32	0.36	0.31
						(1.94)	(2.12)	(1.76)	(2.25)	(2.57)	(2.17)
4	1.19	0.96	1.00	0.93	0.91	0.28	0.37	0.37	0.26	0.35	0.36
						(1.94)	(2.48)	(2.39)	(1.83)	(2.36)	(2.34)
5	1.65	1.06	1.18	0.99	0.87	0.78	0.87	0.96	0.80	0.88	0.95
						(4.40)	(4.72)	(5.18)	(4.64)	(4.97)	(5.13)

Table 2 (continued)

Panel D: Controlling for the Level of Short Interest (SIR)

	Dependent Sort								Independent Sort		
	SIRG					Raw	FF3	FF4	Raw	FF3	FF4
SIR	1	2	3	4	5	1-5	1-5	1-5	1-5	1-5	1-5
1	1.41	1.47	1.22	1.34	1.12	0.29	0.28	0.32	0.39	0.37	0.47
						(1.68)	(1.62)	(1.72)	(1.77)	(1.69)	(2.10)
2	1.38	1.16	1.42	1.15	0.92	0.46	0.37	0.46	0.69	0.61	0.69
						(3.10)	(2.71)	(3.00)	(4.18)	(3.88)	(4.01)
3	1.40	1.16	1.24	1.08	1.00	0.41	0.33	0.38	0.41	0.31	0.37
						(3.32)	(2.27)	(2.55)	(2.13)	(1.70)	(1.97)
4	1.21	1.09	1.21	1.01	0.98	0.23	0.14	0.23	0.64	0.45	0.67
						(1.41)	(0.93)	(1.46)	(2.58)	(2.01)	(2.84)
5	0.94	0.78	0.87	0.64	0.53	0.41	0.36	0.43	0.46	0.24	0.31
						(2.16)	(1.81)	(2.02)	(1.10)	(0.60)	(0.68)

Panel E: Controlling for Past 12-Month Cumulative Changes in Short Interest (SIRG)

	Dependent Sort								Independent Sort		
	SIR					Raw	FF3	FF4	Raw	FF3	FF4
SIRG	1	2	3	4	5	1-5	1-5	1-5	1-5	1-5	1-5
1	1.44	1.38	1.35	1.29	1.37	0.07	0.53	0.46	0.38	0.96	0.76
						(0.28)	(2.61)	(2.24)	(0.83)	(2.46)	(1.70)
2	1.24	1.21	1.27	1.29	0.91	0.33	0.73	0.54	0.40	0.90	0.60
						(1.42)	(3.82)	(2.72)	(1.33)	(3.67)	(2.33)
3	1.32	1.30	1.19	1.13	0.89	0.43	0.82	0.65	0.45	0.86	0.70
						(1.97)	(4.65)	(3.64)	(1.82)	(3.94)	(3.23)
4	1.12	1.14	1.13	0.97	0.80	0.32	0.72	0.53	0.22	0.64	0.46
						(1.41)	(3.92)	(2.81)	(0.88)	(2.97)	(2.08)
5	0.89	0.94	0.91	0.74	0.49	0.40	0.80	0.59	0.44	0.83	0.60
						(1.59)	(3.95)	(2.88)	(1.58)	(3.40)	(2.57)

Table 3. Fama-MacBeth Regression Analysis

This table presents the coefficient estimates of Fama-MacBeth (1973) cross-sectional regressions. The regressions are estimated monthly from 1988 to 2014. The sample consists of common stocks listed in NYSE/AMEX. In Panel A, the dependent variable is the average monthly return in the 6-month holding period. The independent variables include the natural logarithm of firm size measured by the market capitalization at the end of month t-1 (ME), the natural logarithm of book-to-market ratio measured at the end of prior year (BM), the past 6-month cumulative return (MOM), the short interest ratio at month t-1 (SIR), the past J-month cumulative changes in short interest (SIRG), the monthly trading volume scaled by outstanding shares at the end of month t-1 (TO), and institutional ownership in the most recent quarter (IO). There is 1-month gap between formation period and holding period. In model 1-6, the formation period J=12, and stocks with prices less than $1 are excluded. In Model 7, J=12 and price screen is $5. In model 8, J=6 and price screen is $1. In model 9, J=6 and price screen is $5. The Newey-West (1987) t-statistics are in parentheses.

In Panel B, the dependent variable is the return in the month t+1. There is no 1-month gap between dependent variable and independent variables. For example, firm size is calculated at the end of month t. The independent variable REV is the return in previous month t. In model 1-3, K=12 and price screen is $1. In model 4, K=6 and price screen is $1. In model 5, K=6 and price screen is $5.

Panel A: Dependent Variable is the Average Monthly Return over Month t+1 to t+6, Skipping 1-Month

	1	2	3	4	5	6	7	8	9
MOM	0.0043	0.004	0.0044	0.004	0.0049	0.0047	0.0034	0.0056	0.0041
	(2.76)	(2.56)	(2.82)	(2.59)	(3.25)	(3.19)	(2.37)	(3.81)	(2.92)
ME	0.0001	0.0000	0.0000	0.0000	0.0000	-0.0002	-0.0003	-0.0001	-0.0003
	(0.30)	(0.04)	(0.25)	(0.05)	(-0.23)	(-1.26)	(-2.11)	(-0.36)	(-1.96)
BM	0.002	0.002	0.002	0.0019	0.0019	0.0014	0.001	0.0019	0.0008
	(5.87)	(5.84)	(5.71)	(5.75)	(5.86)	(4.30)	(3.38)	(5.79)	(2.97)
SIR		-0.046		-0.0426	-0.0423	-0.0421	-0.0233	-0.0507	-0.0334
		(-7.01)		(-6.18)	(-6.80)	(-6.86)	(-4.31)	(-8.31)	(-6.24)
SIRG			-0.0006	-0.0004	-0.0004	-0.0005	-0.0003	-0.0007	-0.0005
			(-6.44)	(-4.31)	(-4.49)	(-4.60)	(-3.03)	(-4.86)	(-3.45)
TO					0.0009	-0.001	0.0002	-0.0006	-0.0008
					(0.25)	(-0.29)	(0.07)	(-0.19)	(-0.25)
IO						0.0022			0.0017
						(2.82)			(2.40)
Adjusted R^2	0.033	0.038	0.034	0.039	0.045	0.045	0.046	0.043	0.046
Obs.	325814	325814	325814	325814	325814	275412	296960	353746	272196

Table 3 (continued)

Panel B: Dependent Variable is the Return in Month t+1

	1	2	3	4	5
MOM	0.0007	0.0041	0.0061	0.0045	0.0036
	(0.23)	(1.33)	(1.95)	(1.50)	(1.23)
ME	-0.0001	-0.0002	-0.0003	-0.0001	-0.0001
	(-0.23)	(-0.41)	(-0.65)	(-0.22)	(-0.37)
BM	0.002	0.0021	0.0019	0.0024	0.0013
	(2.97)	(3.07)	(2.73)	(3.59)	(2.15)
SIR	-0.0522	-0.0565	-0.0618	-0.0616	-0.0478
	(-4.35)	(-4.45)	(-4.67)	(-4.88)	(-4.20)
SIRG	-0.0004	-0.0004	-0.0004	-0.001	-0.0009
	(-2.03)	(-2.16)	(-1.98)	(-4.05)	(-3.31)
TO	0.0093	0.0106	0.011	0.0144	0.0089
	(1.09)	(1.25)	(1.33)	(1.77)	(1.14)
IO			0.0012		
			(0.59)		
REV		-0.0203	-0.0251	-0.0219	-0.0194
		(-3.74)	(-4.62)	(-4.40)	(-3.78)
Adjusted R^2	0.041	0.047	0.050	0.045	0.048
Obs.	325814	325814	275412	356075	322516

Table 4. Return Predictability of the Change in Short Interest in Event Time

This table presents monthly raw returns and Fama-French 4-factor alphas for portfolios formed based on past 12-month cumulative changes in short interest (SIRG) in event time. G1 represents the long portfolio, G10 represents the short portfolio, and G1-G10 represents the long-short portfolio. *, **, and *** represent statistically significance at the 10%, 5%, and 1% levels, respectively. The sample consists of commons stocks with short interest data listed in NYSE/AMEX. The sample period is from January 1988 to December 2014.

	Raw Return			FF4 Alpha		
Month	G1	G10	G1-G10	G1	G10	G1-G10
1	1.40	0.74	0.66	0.52***	-0.32***	0.84***
2	1.30	0.77	0.53	0.42**	-0.28**	0.70***
3	1.31	0.72	0.59	0.42**	-0.34***	0.76***
4	1.23	0.67	0.55	0.35**	-0.36***	0.71***
5	1.24	0.71	0.53	0.36**	-0.33***	0.68***
6	1.24	0.80	0.44	0.34**	-0.24**	0.58***
7	1.32	0.78	0.54	0.42**	-0.25**	0.67***
8	1.24	0.82	0.41	0.33*	-0.17	0.51***
9	1.22	0.89	0.33	0.34**	-0.12	0.45***
10	1.27	0.85	0.42	0.36**	-0.18	0.54***
11	1.31	0.99	0.32	0.41**	-0.03	0.44***
12	1.30	0.95	0.35	0.40**	-0.08	0.48***
13	1.34	0.97	0.37	0.43***	-0.06	0.49***
14	1.31	0.99	0.32	0.40**	-0.05	0.45***
15	1.38	1.08	0.29	0.47***	0.06	0.41***
16	1.32	1.14	0.18	0.38**	0.09	0.30**
17	1.31	1.21	0.11	0.38**	0.20	0.18
18	1.37	1.25	0.12	0.45***	0.20	0.25*
19	1.33	1.29	0.04	0.42**	0.25	0.16
20	1.41	1.22	0.19	0.47***	0.10	0.37**
21	1.44	1.22	0.22	0.47***	0.05	0.43***
22	1.37	1.27	0.09	0.36**	0.08	0.28*
23	1.28	1.25	0.03	0.27	0.08	0.20
24	1.35	1.27	0.08	0.36*	0.09	0.27*
25	1.32	1.15	0.16	0.35**	0.02	0.33**
26	1.28	1.14	0.14	0.34*	0.02	0.32**
27	1.33	1.17	0.16	0.41**	0.08	0.33**
28	1.26	1.16	0.10	0.33*	0.05	0.28*
29	1.33	1.12	0.22	0.39**	0.04	0.35**
30	1.29	1.11	0.18	0.34**	0.01	0.33**
31	1.35	1.11	0.25	0.43**	0.02	0.41***
32	1.35	1.05	0.29	0.43**	-0.02	0.45***
33	1.28	1.13	0.15	0.37**	0.06	0.31**
34	1.29	1.12	0.17	0.39**	0.04	0.34**
35	1.30	1.07	0.22	0.36*	-0.04	0.40**
36	1.22	1.14	0.08	0.31*	0.05	0.26*

Table 5. Seasonal Patterns of the Return Predictability of the Change in Short Interest

This table presents the average monthly raw returns and Fama-French 4-factor alphas of the long portfolio, the short portfolio, and the long-short portfolio based on past 12-month cumulative changes in short interest in each calendar month. G1 is the long portfolio, G10 is the short portfolio, and G1-G10 is the long-short portfolio. These portfolios are held for 1-month. The sample consists of common stocks listed in NYSE/AMEX. Stocks with prices less than $1 are excluded. Average returns are presented in percentages. The Newey-West (1987) t-statistics are in parentheses. The sample period is from January 1988 to December 2014.

Panel A: Raw Return

	All	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Feb-Dec
G1	1.40	2.55	2.08	1.56	1.50	2.91	0.58	1.06	0.10	-0.33	-0.60	1.43	3.14	1.30
	(4.38)	(2.97)	(2.82)	(2.68)	(1.82)	(2.89)	(1.14)	(1.33)	(0.10)	(-0.29)	(-0.49)	(1.47)	(6.35)	(3.88)
G10	0.74	0.75	0.97	1.94	0.30	1.39	-0.93	0.13	-0.39	-1.12	-0.14	1.04	2.87	0.74
	(2.07)	(0.62)	(0.91)	(3.03)	(0.26)	(1.62)	(-1.00)	(0.12)	(-0.33)	(-0.87)	(-0.09)	(0.89)	(3.98)	(2.00)
G1-G10	0.66	1.80	1.11	-0.38	1.20	1.53	1.51	0.93	0.48	0.79	-0.47	0.39	0.26	0.56
	(4.32)	(2.81)	(1.88)	(-0.86)	(2.82)	(2.36)	(2.65)	(2.21)	(0.99)	(1.54)	(-0.68)	(1.07)	(0.52)	(3.61)

Panel B: Fama-French-Carhart Alpha

	All	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Feb-Dec
G1	0.52	1.29	1.40	-0.67	0.45	1.07	0.19	0.39	-0.05	-0.06	-0.83	0.18	1.50	0.38
	(3.15)	(2.62)	(3.59)	(-1.30)	(1.21)	(2.01)	(0.70)	(0.89)	(-0.13)	(-0.11)	(-1.65)	(0.55)	(4.25)	(2.24)
G10	-0.32	-0.54	0.11	-0.22	-0.77	-0.30	-0.42	-0.49	-0.32	-1.16	-0.17	-0.41	-1.03	-0.31
	(-2.86)	(-1.32)	(0.31)	(-0.78)	(-1.78)	(-1.02)	(-1.45)	(-1.92)	(-0.96)	(-3.41)	(-0.41)	(-1.55)	(-1.48)	(-2.66)
G1-G10	0.84	1.83	1.29	-0.45	1.22	1.37	0.61	0.88	0.27	1.10	-0.65	0.59	2.53	0.69
	(5.11)	(6.19)	(2.81)	(-0.95)	(5.43)	(2.66)	(2.13)	(1.92)	(0.79)	(1.68)	(-0.89)	(1.71)	(3.61)	(3.94)

Table 6. Return Predictability of the Change in Short Interest and Investor Sentiment: Portfolio Analysis

This table presents the average raw and risk-adjusted returns following low and high levels of investor sentiment. The specification is as follow:

$$R_{i,t} = a_H*D_{H,t} + a_L*D_{L,t} + b*MKT_t + c*SMB_t + d*HML_t + e*MOM_t + u_t$$

where $R_{i,t}$ is the excess return in month t of the long portfolio, the short portfolio, or the long-short portfolio. D_H and D_L are dummy variables that indicate following high or low investor sentiment. G1 is the long portfolio, G10 is the short portfolio, and G1-G10 is the long-short portfolio. Panel A presents the results based on the investor sentiment index in Baker and Wurgler (2006). Panel B presents the results based on the past 12-month market return as proxy for sentiment. Average returns are presented in percentages. The Newey-West (1987) t-statistics are in parentheses. The sample period for Panel A is from January 1988 to December 2010. The sample period for Panel B is from January 1988 to December 2014.

Panel A: Investor Sentiment Index in Baker and Wurgler (2006)

	Raw Return			FF4 Alpha		
	G1	G10	G1-G10	G1	G10	G1-G10
High	0.55	-0.14	0.69	0.42	-0.30	0.71
	(1.25)	(-0.27)	(2.80)	(2.03)	(-1.76)	(3.11)
Low	1.70	0.93	0.78	0.72	-0.34	1.06
	(3.86)	(1.79)	(3.15)	(3.54)	(-2.03)	(4.65)
High-Low	-1.15	-1.07	-0.09	-0.31	0.04	-0.35
	(-1.85)	(-1.46)	(-0.25)	(-1.08)	(0.19)	(-1.10)

Panel B: Past 12-Month Market Return as Proxy for Investor Sentiment

	Raw Return			FF4 Alpha		
	G1	G10	G1-G10	G1	G10	G1-G10
High	1.17	0.54	0.62	0.50	-0.37	0.87
	(4.32)	(1.70)	(4.69)	(3.87)	(-3.01)	(6.10)
Low	0.97	0.18	0.79	0.63	-0.12	0.75
	(0.80)	(0.14)	(1.42)	(1.23)	(-0.42)	(1.40)
High-Low	0.20	0.37	-0.17	-0.13	-0.25	0.11
	(0.16)	(0.28)	(-0.29)	(-0.27)	(-0.77)	(0.21)

Table 7. Return Predictability of the Change in Short Interest and Investor Sentiment: Predictive Regression Analysis

This table presents estimates of coefficients b in the following predictive regression:

$$R_{i,t} = a + b*SENT_{t-1} + c*MKT_t + d*SMB_t + e*HML_t + f*MOM_t + u_t$$

where $R_{i,t}$ is the excess return in month t of the long portfolio, the short portfolio, or the long-short portfolio. $SENT_{t-1}$ is the 1-month lagged investor sentiment index in Baker and Wurgler (2006). Regression A does not control for contemporaneous Fama-French-Carhart four factors (MKT, SMB, HML, and MOM) in the regression. Regression B controls for these four factors in the regression. The Newey-West (1987) t-statistics are in parentheses. The sample period is from 1988 to 2010.

	Regression A			Regression B		
	G1	G10	G1-G10	G1	G10	G1-G10
$\hat{b}$	-1.10	-0.41	-0.69	-0.36	0.67	-1.03
	(-1.88)	(-0.59)	(-2.13)	(-1.33)	(3.02)	(-3.43)

Table 8. Robustness Tests

This table reports the results of robustness tests. Panel A presents the Fama-French 4-factor alphas of portfolios based on past J-month cumulative changes in short interest and held for K-month. Other specifications are the same in Table 1. The sample consists of common stocks with monthly short interest data listed in NYSE/AMEX from 1988 to 2014. Price screen is $1. There is no 1-month gap between formation and holding periods.

Panel B reports the robustness results for NYSE/AMEX stocks with different formation periods, price screens, measures of the change in short interest, and microstructure. The holding period is 1-month for all tests. In model 1-7, J=12. In model 1, J=12, price screen is $1, and 1-month gap between formation and holding periods. In model 2, price screen is $5, and no 1-month gap. In model 3, price screen is $5, and 1-month gap. In model 4, SIRG has no limit on upper bound, price screen is $0, and no 1-month gap. In model 5, SIRG has no limit on upper bound, price screen is $1, and no 1-month gap. In model 6, SIRG has no limit on upper bound, price screen is $5, and no 1-month gap. In model 7, SIRG's upper bound is 500%, price screen is $1, and no 1-month gap. In model 8, J=6, SIRG has no limit on upper bound, price screen is $1, and no 1-month gap.

Panel C reports the robustness results for NASDAQ stocks. The sample period is from July 2003 to December 2014. In model 1, J=12, K=1, price screen is $1 and no 1-month gap. In model 2, J=12, K=1, price screen is $1 and 1-month gap. In model 3, J=12, K=1, price screen is $5 and no 1-month gap. In model 4, J=6, K=1, price screen is $1 and no 1-month gap. In model 5, J=12, K=1, SIRG has no limit on upper bound, price screen is $1 and no 1-month gap. In model 6, J=12, K=1, SIRG has no limit on upper bound, price screen is $5 and 1-month gap. In model 7, J=12, K=6, price screen is $1 and no 1-month gap. In model 8, J=6, K=6, price screen is $1 and 1-month gap.

Panel D reports the results for two subperiods. The specifications are the same with those in Table 1.

Panel E presents the coefficient estimates of Fama-MacBeth (1973) monthly cross-sectional regressions for NASDAQ stocks. The dependent variable in Model 1 and 2 is the average monthly return of the first month after formation period. The dependent variable in Model 3-6 is the average monthly return in the holding period of 6-month. The independent variables include the natural logarithm of firm size measured by the market capitalization at the end of month t-1 (ME), the natural logarithm of book-to-market ratio measured at the end of prior year (BM), the past 6-month cumulative return (MOM), the past 1-month return (REV), the short interest ratio at month t-1 (SIR), the past J-month cumulative changes in short interest (SIRG), the monthly trading volume scaled by outstanding shares at the end of month t-1 (TO), and institutional ownership in the most recent quarter (IO). There is no 1-month gap between formation period and holding period in Model 1 and 2. There is 1-month gap between formation period and holding period in Model 3-6. J=12 in Model 1-4 and J=6 in Model 5 and 6. The price screen is $1 in Model 1-5 and $5 in Model 6. The Newey-West (1987) t-statistics are in parentheses. The sample period is from July 2003 to December 2014.

Table 8 (continued)

Panel A: NYSE/AMEX Stocks with Different Formation and Holding Periods

K / J		1	3	6	9	12	24
1	G1	0.56	0.53	0.50	0.52	0.37	0.49
		(4.27)	(3.56)	(3.12)	(3.15)	(2.25)	(4.16)
	G10	-0.10	-0.33	-0.35	-0.32	-0.36	0.16
		(-0.84)	(-3.16)	(-3.15)	(-2.86)	(-3.21)	(1.45)
	G1-G10	0.66	0.86	0.85	0.84	0.73	0.33
		(5.53)	(6.84)	(5.76)	(5.11)	(4.05)	(3.27)
6	G1	0.49	0.49	0.45	0.41	0.28	0.45
		(3.59)	(3.21)	(2.72)	(2.43)	(1.76)	(3.72)
	G10	-0.09	-0.25	-0.27	-0.32	-0.21	0.20
		(-0.85)	(-2.35)	(-2.34)	(-2.90)	(-1.82)	(1.72)
	G1-G10	0.58	0.74	0.71	0.73	0.50	0.25
		(7.46)	(6.24)	(5.36)	(4.95)	(3.05)	(5.98)
12	G1	0.45	0.47	0.42	0.40	0.31	0.41
		(3.25)	(2.97)	(2.60)	(2.44)	(1.86)	(3.36)
	G10	-0.03	-0.18	-0.21	-0.23	-0.09	0.22
		(-0.31)	(-1.82)	(-1.86)	(-2.17)	(-0.73)	(1.96)
	G1-G10	0.48	0.65	0.63	0.63	0.40	0.19
		(6.44)	(5.78)	(5.10)	(4.67)	(2.56)	(5.91)

Panel B: NYSE/AMEX Stocks

	1	2	3	4	5	6	7	8
G1	0.42	0.33	0.27	0.68	0.51	0.31	0.53	0.56
	(2.41)	(2.83)	(2.13)	(3.34)	(3.38)	(2.89)	(3.21)	(3.95)
G10	-0.28	-0.24	-0.28	-0.20	-0.23	-0.19	-0.22	-0.20
	(-2.58)	(-2.22)	(-2.61)	(-1.64)	(-2.03)	(-1.81)	(-1.98)	(-1.67)
G1-G10	0.70	0.57	0.55	0.89	0.74	0.50	0.75	0.76
	(4.31)	(4.99)	(4.33)	(5.06)	(5.41)	(4.97)	(4.98)	(5.89)

Panel C: NASDAQ Stocks

	1	2	3	4	5	6	7	8
G1	0.25	0.22	0.02	0.38	0.35	0.07	0.24	0.12
	(0.89)	(0.77)	(0.09)	(1.48)	(1.15)	(0.36)	(0.77)	(0.54)
G10	-0.59	-0.47	-0.40	-0.48	-0.60	-0.52	-0.55	-0.51
	(-3.32)	(-2.63)	(-2.71)	(-2.39)	(-2.85)	(-2.80)	(-3.49)	(-3.45)
G1-G10	0.83	0.69	0.42	0.86	0.95	0.59	0.80	0.63
	(3.25)	(2.76)	(1.90)	(3.54)	(3.34)	(2.33)	(3.06)	(3.13)

Table 8 (continued)

Panel D: Fama-MacBeth (1973) Regression Analysis for NASDAQ Stocks

	1	2	3	4	5	6
MOM	0.0013	-0.0003	-0.0021	-0.0028	-0.0007	-0.0011
	(0.33)	(-0.08)	(-0.98)	(-1.29)	(-0.32)	(-0.63)
ME	0.0005	-0.0005	0.0008	-0.0007	0.0007	0.0004
	(0.77)	(-0.67)	(2.41)	(-2.02)	(2.11)	(1.88)
BM	0.0016	0.0012	0.0007	-0.0002	0.0008	-0.0001
	(1.59)	(1.07)	(1.60)	(-0.36)	(1.99)	(-0.18)
SIR	-0.0308	-0.0346	-0.0305	-0.0461	-0.0322	-0.0239
	(-2.33)	(-2.44)	(-6.68)	(-7.27)	(-7.64)	(-5.65)
SIRG	-0.0009	-0.0011	-0.0004	-0.0005	-0.0011	-0.0008
	(-2.44)	(-2.90)	(-2.20)	(-2.75)	(-3.64)	(-3.08)
TO	-0.003	-0.001	-0.0041	-0.002	-0.004	-0.0047
	(-0.64)	(-0.19)	(-2.15)	(-0.96)	(-2.19)	(-3.02)
IO		0.0026		0.0084		
		(0.90)		(5.22)		
REV	-0.0208	-0.0205				
	(-2.87)	(-2.76)				
Adjusted R^2	0.028	0.029	0.023	0.028	0.023	0.021
Obs.	168365	143573	165772	142613	184119	136042

Panel E: Subperiods

	Raw	CAPM	FF3	FF4
	1988-2001			
G1	1.23	0.29	-0.02	0.18
	(3.06)	(1.01)	(-0.10)	(0.87)
G10	0.65	-0.43	-0.77	-0.48
	(1.47)	(-1.40)	(-4.36)	(-3.03)
G1-G10	0.58	0.72	0.75	0.65
	(3.00)	(3.52)	(3.53)	(2.59)
	2002-2014			
G1	1.57	0.84	0.71	0.78
	(3.16)	(3.23)	(3.18)	(3.37)
G10	0.84	-0.08	-0.24	-0.18
	(1.48)	(-0.36)	(-1.66)	(-1.31)
G1-G10	0.72	0.92	0.95	0.96
	(3.08)	(4.06)	(4.28)	(4.25)

Table 8 (continued)

Panel F: ΔSIR (SIR_{t-j} and SIR_t) for NYSE/AMEX Stocks

K / J		1	3	6	12
1	G1	0.50	0.60	0.68	0.54
		(4.18)	(4.86)	(4.81)	(3.55)
	G10	0.16	0.06	-0.09	-0.16
		(1.43)	(0.51)	(-0.82)	(-1.44)
	G1-G10	0.34	0.54	0.77	0.70
		(3.33)	(4.70)	(6.24)	(5.07)
6	G1	0.45	0.51	0.55	0.44
		(3.71)	(3.82)	(3.85)	(2.76)
	G10	0.19	0.04	-0.10	-0.15
		(1.68)	(0.33)	(-0.89)	(-1.31)
	G1-G10	0.26	0.47	0.65	0.59
		(5.94)	(7.72)	(7.19)	(4.61)

Table 9. Monthly Returns of Portfolios based on Past Returns or Short Interest

Panel A presents equal-weighted average monthly raw returns and Fama-French 3-factor adjusted returns in percentages for simple price momentum strategies for NYSE/AMEX common stocks with monthly short interest data. All sample stocks are assigned into ten portfolios in ascending order based on their past J-month cumulative returns and held for K-month. M1 represents the loser portfolio and M10 represents the winner portfolio. Portfolios are rebalanced monthly. Stocks with prices less than $5 at the end of formation period are excluded. I skip one month between formation and holding periods. The Newey-West (1987) t-statistics are in parentheses. The length of lag depends on K where K=1, 6 or 12 months. The sample period is from January 1988 to December 2014. Panel B presents equal-weighted average monthly raw returns and Fama-French 3-factor adjusted returns in percentages for heavily and lightly shorted stock portfolios. All NYSE/AMEX common stocks with monthly short interest data are sorted based on their short interest ratios at month t and then equally assigned into ten portfolios. S1 represents lightly shorted stock portfolio and S10 represents heavily shorted stock portfolio. S1-S10 represents short selling strategy portfolio. The portfolios are rebalanced monthly and held for K-month where K=1, 6, or 12 months. Stocks with prices less than $5 at the end of formation period are excluded. I skip one month between formation and holding periods. The Newey-West (1987) t-statistics are in parentheses. The length of lag depends on K where K=1, 6 or 12 months. The sample period is from January 1988 to December 2014. In Panel C, stocks are equally divided into three groups based on SIRs, all else being equal in Panel B.

Panel A: Returns to Price Momentum

		Raw Return K			FF3 Alpha K		
J		1	6	12	1	6	12
6	M1	0.70	0.68	0.84	-0.66	-0.70	-0.54
		(1.57)	(1.53)	(1.91)	(-3.07)	(-3.59)	(-2.92)
	M10	1.42	1.37	1.21	0.32	0.20	0.03
		(4.21)	(3.18)	(3.40)	(2.11)	(1.43)	(0.22)
	M10-M1	0.72	0.69	0.37	0.99	0.91	0.57
		(2.22)	(2.31)	(1.52)	(3.44)	(3.53)	(2.80)
11	M1	0.58	0.71	0.93	-0.86	-0.72	-0.50
		(1.22)	(1.51)	(2.01)	(-3.63)	(-3.36)	(-2.51)
	M10	1.47	1.27	1.16	0.34	0.11	-0.02
		(4.18)	(3.45)	(3.16)	(2.08)	(0.74)	(-0.16)
	M10-M1	0.90	0.57	0.22	1.20	0.83	0.48
		(2.51)	(1.67)	(0.80)	(3.82)	(2.95)	(2.16)

Table 9 (continued)

Panel B: Returns to Lightly and Heavily Shorted Stock Portfolios

		Raw Return K			FF3 Alpha K		
J		1	6	12	1	6	12
1	S1	1.30	1.24	1.22	0.49	0.41	0.37
		(5.93)	(5.31)	(4.99)	(4.21)	(3.54)	(3.11)
	S10	0.69	0.74	0.81	-0.66	-0.63	-0.57
		(1.79)	(1.92)	(1.95)	(-4.88)	(-4.71)	(-4.22)
	S1-S10	0.62	0.50	0.41	1.16	1.04	0.94
		(2.76)	(2.47)	(1.95)	(8.11)	(8.11)	(7.10)

Panel C: Returns to Lightly and Heavily Shorted Stock Portfolios

		Raw Return K			FF3 Alpha K		
J		1	6	12	1	6	12
1	S1	1.22	1.19	1.16	0.28	0.24	0.19
		(5.07)	(4.71)	(4.45)	(2.92)	(2.40)	(1.88)
	S3	0.94	0.99	1.03	-0.30	-0.28	-0.24
		(2.84)	(2.95)	(3.03)	(-2.96)	(-2.65)	(-2.30)
	S1-S3	0.27	0.20	0.13	0.58	0.52	0.44
		(2.08)	(1.77)	(1.10)	(6.36)	(6.45)	(5.15)

Table 10. Raw Returns of Portfolios based on Past Returns and Short Interest

This table presents average monthly raw returns of portfolios based on two-way independent sorts on past J-month returns and short interest ratio (SIR) at month t. At the beginning of each month, all NYSE/AMEX common stocks with monthly short interest data are sorted in ascending order based on their past J-month returns and then equally assigned into ten portfolios. M1 represents the loser portfolio and M10 represents the winner portfolio. The stocks are then independently sorted based on their SIRs and assigned into three portfolios. S1 represents the lightly shorted stock portfolio and S3 represents the heavily shorted stock portfolio. Ten portfolios based on past returns and three portfolios based on SIR are intersected to form 30 independently sorted portfolios. Stocks with prices less than $5 at the end of formation period are excluded. I skip one month between formation and holding periods. The Newey-West (1987) t-statistics are in parentheses. The sample period is from January 1988 to December 2014. The 30 intersected portfolios are rebalanced monthly and held for K-month where K=1, 6, or 12 months. The early-stage strategy is to buy lightly shorted winners and sell heavily shorted losers. The late-stage strategy is to buy heavily shorted winners and sell lightly shorted losers. Panel A reports returns when J=6 months. Panel B reports returns when K=11 month.

Panel A: J=6

	K=1				K=6				K=12			
	S1	S2	S3	S1-S3	S1	S2	S3	S1-S3	S1	S2	S3	S1-S3
M1	0.99	0.88	0.42	0.57	0.87	0.85	0.48	0.38	0.89	1.01	0.70	0.19
	(2.40)	(1.98)	(0.85)	(2.52)	(2.18)	(2.02)	(0.99)	(1.99)	(2.31)	(2.37)	(1.46)	(1.09)
M10	1.63	1.42	1.29	0.34	1.48	1.36	1.30	0.18	1.28	1.25	1.13	0.15
	(5.06)	(4.13)	(3.46)	(1.84)	(4.40)	(3.83)	(3.34)	(1.22)	(3.90)	(3.54)	(2.91)	(1.06)
M10-M1	0.64	0.54	0.87		0.61	0.51	0.82		0.39	0.24	0.43	
	(1.92)	(1.54)	(2.45)		(2.27)	(1.78)	(2.30)		(1.95)	(0.96)	(1.52)	
Early	1.21				0.99				0.58			
	(3.15)				(2.85)				(1.89)			
Late	0.31				0.42				0.24			
	(0.91)				(1.44)				(1.09)			

Table 10 (continued)

Panel B: J=11

	K=1				K=6				K=12			
	S1	S2	S3	S1-S3	S1	S2	S3	S1-S3	S1	S2	S3	S1-S3
M1	0.71	0.83	0.39	0.32	0.85	0.96	0.54	0.30	1.04	1.14	0.80	0.24
	(1.65)	(1.66)	(0.77)	(1.44)	(1.98)	(2.10)	(1.08)	(1.59)	(2.41)	(2.48)	(1.60)	(1.38)
M10	1.61	1.59	1.28	0.33	1.46	1.28	1.15	0.31	1.26	1.25	1.03	0.23
	(4.78)	(4.44)	(3.26)	(1.61)	(4.27)	(3.47)	(2.82)	(1.78)	(3.76)	(3.39)	(2.56)	(1.49)
M10-M1	0.91	0.76	0.89		0.61	0.32	0.61		0.22	0.11	0.24	
	(2.60)	(1.91)	(2.33)		(2.09)	(0.93)	(1.62)		(0.89)	(0.38)	(0.79)	
Early	1.22				0.92				0.47			
	(3.08)				(2.43)				(1.39)			
Late	0.58				0.31				0.00			
	(1.67)				(1.00)				(-0.02)			

Table 11. Risk-Adjusted Returns of Portfolios based on Past Returns and Short Interest

This table presents average monthly Fama-French 3-factor alphas of portfolios based on two-way independent sorts on past J-month returns and short interest ratio (SIR) at month t. At the beginning of each month, all NYSE/AMEX common stocks with monthly short interest data are sorted in ascending order based on their past J-month returns and then equally assigned into ten portfolios. M1 represents the loser portfolio and M10 represents the winner portfolio. The stocks are then independently sorted based on their SIRs and assigned into three portfolios. S1 represents the lightly shorted stock portfolio and S3 represents the heavily shorted stock portfolio. Ten portfolios based on past returns and three portfolios based on SIR are intersected to form 30 independently sorted portfolios. Stocks with prices less than $5 at the end of formation period are excluded. I skip one month between formation and holding periods. The Newey-West (1987) t-statistics are in parentheses. The sample period is from January 1988 to December 2014. The 30 intersected portfolios are rebalanced monthly and held for K-month where K=1, 6, or 12 months. The early-stage strategy is to buy lightly shorted winners and sell heavily shorted losers. The late-stage strategy is to buy heavily shorted winners and sell lightly shorted losers. Panel A reports returns when J=6 months. Panel B reports returns when K=11 month.

Panel A: J=6

	K=1				K=6				K=12			
	S1	S2	S3	S1-S3	S1	S2	S3	S1-S3	S1	S2	S3	S1-S3
M1	-0.20	-0.48	-1.03	0.84	-0.30	-0.50	-1.01	0.71	-0.26	-0.34	-0.80	0.53
	(-0.84)	(-1.94)	(-4.17)	(4.02)	(-1.50)	(-2.59)	(-4.31)	(3.82)	(-1.44)	(-1.84)	(-3.56)	(3.12)
M10	0.67	0.34	0.11	0.56	0.43	0.22	0.05	0.39	0.22	0.09	-0.15	0.37
	(3.67)	(1.79)	(0.63)	(3.32)	(2.94)	(1.41)	(0.28)	(2.71)	(1.68)	(0.70)	(-1.09)	(2.83)
M10-M1	0.86	0.82	1.14		0.73	0.72	1.06		0.49	0.43	0.65	
	(3.04)	(2.50)	(3.58)		(3.28)	(2.81)	(3.50)		(2.85)	(2.07)	(2.66)	
Early	1.70				1.45				1.02			
	(5.21)				(5.08)				(4.07)			
Late	0.30				0.35				0.11			
	(1.03)				(1.33)				(0.58)			

Table 11 (continued)

Panel B: J=11

	K=1				K=6				K=12			
	S1	S2	S3	S1-S3	S1	S2	S3	S1-S3	S1	S2	S3	S1-S3
M1	-0.55	-0.65	-1.10	0.54	-0.38	-0.42	-0.97	0.59	-0.19	-0.24	-0.74	0.55
	(-2.39)	(-2.43)	(-4.00)	(2.49)	(-1.84)	(-1.99)	(-3.82)	(2.75)	(-0.95)	(-1.20)	(-3.17)	(2.92)
M10	0.59	0.48	0.07	0.52	0.42	0.13	-0.10	0.52	0.21	0.08	-0.24	0.45
	(3.22)	(2.44)	(0.34)	(2.61)	(2.57)	(0.76)	(-0.58)	(3.12)	(1.39)	(0.54)	(-1.75)	(3.42)
M10-M1	1.15	1.13	1.16		0.80	0.55	0.87		0.40	0.32	0.49	
	(3.67)	(3.25)	(3.29)		(3.28)	(1.93)	(2.65)		(1.97)	(1.35)	(1.97)	
Early	1.69				1.39				0.94			
	(4.69)				(4.40)				(3.51)			
Late	0.62				0.29				-0.05			
	(2.02)				(1.11)				(-0.27)			

Table 12. Returns of the Intersected Portfolios Controlling for Other Firm Variables

This table presents average monthly Fama-French 3-factor alphas of portfolios independently sorted on past 6-month returns and short interest ratios in different size/volume/institutional ownership subsamples. First, all sample stocks are equally divided into three groups based on the magnitude of size, trading volume, or institutional ownership. Second, I form 30 two-way independently sorted portfolios described in Table 2. Stocks with prices less than $5 at the end of formation period are excluded. I skip one month between formation and holding periods. The Newey-West (1987) t-statistics are in parentheses. The sample period is from January 1988 to December 2014. The holding period (K) is 6-month. The abnormal returns of the loser and winner portfolios and simple momentum strategies are also reported. Panel A, B and C reports returns of interested portfolios in three size, volume, and institutional ownership groups respectively.

Panel A: Returns of Portfolios in Three Size Subsamples

	Size=1				Size=2				Size=3			
	S1	S2	S3	S1-S3	S1	S2	S3	S1-S3	S1	S2	S3	S1-S3
M1	-0.54	-0.78	-1.37	0.83	-0.10	-0.34	-0.80	0.70	-0.08	-0.18	-0.78	0.70
	(-1.75)	(-3.70)	(-5.73)	(2.57)	(-0.44)	(-1.56)	(-2.55)	(2.33)	(-0.44)	(-0.93)	(-3.39)	(4.19)
M10	0.57	0.38	0.06	0.51	0.26	0.28	0.06	0.20	0.24	0.28	0.07	0.18
	(2.76)	(2.05)	(0.27)	(1.99)	(1.47)	(1.50)	(0.27)	(1.06)	(1.61)	(1.77)	(0.29)	(0.92)
M10-M1	1.12	1.17	1.43		0.36	0.62	0.86		0.32	0.45	0.85	
	(3.17)	(4.26)	(4.37)		(1.43)	(2.16)	(2.09)		(1.29)	(1.88)	(2.41)	
Early	1.95				1.06				1.02			
	(6.51)				(2.73)				(3.30)			
Late	0.60				0.16				0.14			
	(1.66)				(0.54)				(0.47)			
M1	-1.01				-0.53				-0.43			
	(-4.96)				(-2.24)				(-2.27)			
M10	0.34				0.16				0.17			
	(2.12)				(0.99)				(1.03)			
Simple	1.35				0.69				0.60			
	(5.28)				(2.25)				(2.20)			

Table 12 (continued)

Panel B: Returns of Portfolios in Three BM ratio Subsamples

	BM=1				BM=2				BM=3			
	S1	S2	S3	S1-S3	S1	S2	S3	S1-S3	S1	S2	S3	S1-S3
M1	-0.23	-0.43	-0.89	0.66	0.04	-0.37	-0.51	0.55	-0.16	-0.38	-0.76	0.61
	(-0.86)	(-1.72)	(-3.90)	(3.17)	(0.15)	(-1.71)	(-2.10)	(2.38)	(-0.62)	(-1.71)	(-2.66)	(2.05)
M10	0.44	0.19	0.08	0.36	0.43	0.31	0.22	0.21	0.63	0.24	-0.15	0.78
	(2.04)	(0.88)	(0.35)	(1.36)	(2.09)	(1.58)	(1.16)	(0.99)	(3.07)	(1.22)	(-0.67)	(3.22)
M10-M1	0.67	0.62	0.97		0.39	0.68	0.73		0.79	0.62	0.62	
	(2.16)	(1.84)	(2.90)		(1.24)	(2.79)	(2.65)		(2.52)	(1.94)	(1.68)	
Early	1.33				0.94				1.39			
	(4.52)				(2.77)				(3.77)			
Late	0.31				0.18				0.01			
	(0.83)				(0.61)				(0.03)			
M1	-0.64				-0.30				-0.55			
	(-2.98)				(-1.42)				(-2.53)			
M10	0.18				0.32				0.22			
	(0.99)				(1.99)				(1.29)			
Simple	0.82				0.62				0.77			
	(2.91)				(2.56)				(2.61)			

Table 12 (continued)

Panel C: Returns of Portfolios in Three Volume Subsamples

	Volume=1				Volume=2				Volume=3			
	S1	S2	S3	S1-S3	S1	S2	S3	S1-S3	S1	S2	S3	S1-S3
M1	-0.15	-0.41	-0.73	0.58	-0.34	-0.31	-0.67	0.32	-0.71	-0.74	-1.53	0.81
	(-0.78)	(-2.12)	(-3.94)	(3.42)	(-1.78)	(-1.65)	(-3.10)	(1.86)	(-2.95)	(-2.70)	(-4.90)	(3.18)
M10	0.73	0.24	0.28	0.46	0.35	0.16	0.21	0.14	0.39	0.14	-0.01	0.40
	(4.77)	(1.77)	(1.83)	(2.51)	(2.13)	(1.05)	(1.59)	(0.77)	(1.74)	(0.66)	(-0.03)	(1.55)
M10-M1	0.88	0.65	1.01		0.69	0.47	0.88		1.10	0.88	1.52	
	(4.39)	(2.90)	(4.25)		(3.22)	(1.94)	(3.68)		(3.17)	(2.24)	(3.38)	
Early	1.46				1.01				1.92			
	(6.92)				(3.96)				(4.46)			
Late	0.43				0.55				0.70			
	(1.73)				(2.64)				(1.84)			
M1	-0.43				-0.48				-1.12			
	(-2.63)				(-2.68)				(-4.41)			
M10	0.41				0.25				0.17			
	(3.61)				(2.03)				(0.84)			
Simple	0.84				0.72				1.29			
	(4.52)				(3.58)				(3.51)			

Table 12 (continued)

Panel D: Returns of Portfolios in Three IO Subsamples

	IO=1				IO=2				IO=3			
	S1	S2	S3	S1-S3	S1	S2	S3	S1-S3	S1	S2	S3	S1-S3
M1	-0.23	-0.49	-0.98	0.75	-0.13	-0.36	-0.89	0.76	-0.22	-0.35	-1.06	0.83
	(-0.95)	(-2.07)	(-4.76)	(2.60)	(-0.46)	(-1.49)	(-3.13)	(3.24)	(-0.75)	(-1.28)	(-3.90)	(3.07)
M10	0.97	0.49	0.13	0.96	0.61	0.24	0.29	0.32	0.15	0.43	0.26	-0.11
	(4.39)	(2.07)	(0.07)	(4.10)	(2.78)	(1.35)	(1.51)	(1.49)	(0.81)	(2.38)	(1.42)	(-0.59)
M10-M1	1.21	0.98	1.00		0.74	0.60	1.18		0.38	0.79	1.32	
	(4.33)	(3.47)	(3.27)		(2.04)	(1.99)	(3.12)		(1.25)	(2.27)	(3.79)	
Early	1.96				1.50				1.21			
	(6.61)				(3.83)				(3.48)			
Late	0.25				0.42				0.49			
	(0.87)				(1.15)				(1.44)			
M1	-0.64				-0.58				-0.64			
	(-3.85)				(-2.43)				(-2.65)			
M10	0.39				0.37				0.27			
	(2.34)				(2.31)				(1.69)			
Simple	1.04				0.95				0.91			
	(4.49)				(3.05)				(3.00)			

Table 13. Fama-MacBeth Regressions

This table reports the results of Fama and MacBeth (1973) cross-section regressions. The dependent variable is the average monthly return over the 6-month holding period. The independent variables include the past 6-month cumulative return (PastReturn), the natural logarithm of firm market capitalization (Size) at the end of month t-1, the natural logarithm of book-to-market ratio measured at the end of prior year (BM), the short interest ratio (SIR), the trading volume scaled by outstanding shares (TO), institutional ownership (IO), and interaction variables. The sample period is from January 1988 to December 2014. The Newey-West (1987) t-statistics are in parentheses. T is the number of monthly cross-sectional regressions.

Table 13 (continued)

	1	2	3	4	5	6	7	8	9	10
Intercept	0.0177	0.0195	0.0185	0.0194	0.0199	0.0198	0.0183	0.0154	0.0179	0.0155
	(4.90)	(5.62)	(5.02)	(5.42)	(5.79)	(5.57)	(4.98)	(4.18)	(4.99)	(4.07)
PastReturn	0.0035	0.0032	0.0043	0.0038	0.0022	0.0030	0.0306	0.0037	0.0027	0.0417
	(2.47)	(2.27)	(3.17)	(2.81)	(1.64)	(2.25)	(4.63)	(2.65)	(2.05)	(6.50)
Size	-0.0003	-0.0004	-0.0003	-0.0004	-0.0004	-0.0004	-0.0003	-0.0002	-0.0003	-0.0002
	(-2.14)	(-2.42)	(-2.04)	(-2.27)	(-2.52)	(-2.34)	(-1.85)	(-1.45)	(-2.16)	(-1.25)
BM	0.0012	0.0012	0.0012	0.0012	0.0012	0.0012	0.0011	0.0011	0.0011	0.0011
	(4.30)	(4.21)	(4.28)	(4.34)	(4.15)	(4.29)	(3.87)	(4.29)	(4.12)	(3.95)
SIR		-0.0402		-0.0372	-0.0413	-0.0382	-0.0435		-0.0399	-0.0433
		(-6.96)		(-7.35)	(-6.40)	(-7.15)	(-7.97)		(-6.80)	(-7.30)
TO			-0.0079	-0.0018		-0.0020	0.0022		-0.0019	0.0020
			(-2.38)	(-0.52)		(-0.57)	(0.60)		(-0.58)	(0.59)
IO								0.0013	0.0028	0.0020
								(1.58)	(3.98)	(2.45)
PastReturn*SIR					0.0467	0.0466	0.0673		0.0591	0.0833
					(3.61)	(3.50)	(4.97)		(3.86)	(5.11)
PastReturn*Size							-0.0014			-0.0021
							(-4.04)			(-5.94)
PastReturn*BM							-0.0023			-0.0030
							(-3.16)			(-4.29)
PastReturn*TO							-0.0080			-0.0074
							(-1.76)			(-1.53)
PastReturn*IO										0.0052
										(2.11)
Adjust R^2	0.028	0.034	0.037	0.040	0.036	0.043	0.050	0.031	0.045	0.054
T	317	317	317	317	317	317	317	315	315	315
No. of obs.	347088	347088	347088	347088	347088	347088	347088	293921	293921	293921

Table 14. Long-Term Performance of Intersection Portfolios

This table presents average monthly returns of portfolios independently sorted on past 6-month returns and short interest ratio in the first, second, third, fourth and fifth years. Stocks with prices less than $5 at the end of formation period are excluded. I skip one month between formation and holding periods. The Newey-West (1987) t-statistics are in parentheses. The sample period is from January 1988 to December 2014. Panel A reports average monthly raw returns of these portfolios. Panel B reports average monthly Fama-French 3-factor alphas of these portfolios. Panel C reports results after controlling for size or book-to-market ratio.

Panel A: Raw Returns

	Year 1			Year 2			Year 3			Year 4			Year 5		
	S1	S3	S1-S3	S1	S3	S1-S3	S1	S3	S1-S3	S1	S3	S1-S3	S1	S3	S1-S3
M1	0.89	0.70	0.19	1.32	1.24	0.08	1.36	1.27	0.08	1.35	1.38	-0.03	1.36	1.47	-0.10
	(2.31)	(1.46)	(1.09)	(3.40)	(2.58)	(0.44)	(3.64)	(2.65)	(0.42)	(3.61)	(2.99)	(-0.15)	(3.56)	(3.52)	(-0.62)
M10	1.28	1.13	0.15	1.00	0.99	0.01	1.21	1.24	-0.03	1.19	1.30	-0.10	1.26	1.26	0.00
	(3.90)	(2.91)	(1.06)	(2.78)	(2.41)	(0.10)	(3.17)	(2.93)	(-0.22)	(3.09)	(3.17)	(-0.68)	(3.38)	(2.75)	(0.01)
M10-M1	0.39	0.43		-0.31	-0.25		-0.15	-0.04		-0.16	-0.08		-0.10	-0.21	
	(1.95)	(1.52)		(-1.96)	(-1.26)		(-1.09)	(-0.21)		(-1.10)	(-0.45)		(-0.74)	(-1.05)	
Early	0.58			-0.24			-0.06			-0.18			-0.21		
	(1.89)			(1.00)			(-0.30)			(-0.91)			(-1.22)		
Late	0.24			-0.33			-0.12			-0.05			-0.11		
	(1.09)			(-1.81)			(-0.73)			(-0.30)			(-0.45)		
M1	0.84			1.28			1.28			1.35			1.47		
	(1.91)			(2.91)			(3.00)			(3.20)			(3.75)		
M10	1.21			1.03			1.19			1.28			1.22		
	(3.40)			(2.74)			(3.04)			(3.35)			(3.06)		
Simple	0.37			-0.25			-0.09			-0.08			-0.25		
	(1.52)			(-1.42)			(-0.65)			(-0.55)			(-1.74)		

Table 14 (continued)

Panel B: Fama-French 3-Factor Alphas

	Year 1			Year 2			Year 3			Year 4			Year 5		
	S1	S3	S1-S3	S1	S3	S1-S3	S1	S3	S1-S3	S1	S3	S1-S3	S1	S3	S1-S3
M1	-0.26	-0.80	0.53	0.22	-0.17	0.40	0.20	-0.22	0.42	0.15	-0.07	0.22	0.20	0.17	0.04
	(-1.44)	(-3.56)	(3.12)	(1.39)	(-0.93)	(2.62)	(1.13)	(-1.27)	(2.38)	(0.89)	(-0.45)	(1.42)	(1.09)	(0.92)	(0.22)
M10	0.22	-0.15	0.37	-0.06	-0.26	0.20	0.03	-0.08	0.11	0.02	0.00	0.02	0.13	-0.05	0.18
	(1.68)	(-1.09)	(2.83)	(-0.38)	(-1.55)	(1.64)	(0.16)	(-0.48)	(0.86)	(0.12)	(-0.02)	(0.16)	(0.82)	(-0.27)	(1.02)
M10-M1	0.49	0.65		-0.29	-0.09		-0.17	0.13		-0.13	0.07		-0.07	-0.22	
	(2.85)	(2.66)		(-1.86)	(-0.51)		(-1.13)	(0.78)		(-0.91)	(0.43)		(-0.49)	(-1.02)	
Early	1.02			0.11			0.25			0.09			-0.04		
	(4.07)			(0.55)			(1.16)			(0.49)			(-0.22)		
Late	0.11			-0.48			-0.28			-0.15			-0.25		
	(0.58)			(-2.97)			(-1.76)			(-0.91)			(-1.21)		
M1	-0.54			-0.03			-0.09			-0.02			0.23		
	(-2.92)			(-0.19)			(-0.64)			(-0.12)			(1.38)		
M10	0.03			-0.13			-0.06			0.05			0.00		
	(0.22)			(-0.85)			(-0.37)			(0.30)			(-0.01)		
Simple	0.57			-0.10			0.04			0.06			-0.23		
	(2.80)			(-0.66)			(0.24)			(0.53)			(-1.53)		

Table 14 (continued)

Panel C: FF 3-Factor Alphas after Controlling for Size or Book-to-Market Ratio

	Size=1					Size=2					Size=3				
	Year 1	Year 2	Year 3	Year 4	Year 5	Year 1	Year 2	Year 3	Year 4	Year 5	Year 1	Year 2	Year 3	Year 4	Year 5
Early	1.45	0.37	0.42	0.13	-0.23	0.86	0.12	0.36	0.10	-0.11	0.65	-0.24	0.00	0.22	-0.01
	(4.83)	(1.31)	(1.51)	(0.46)	(-0.96)	(3.09)	(0.57)	(1.34)	(0.48)	(-0.46)	(2.26)	(-1.02)	(0.01)	(1.28)	(-0.03)
Late	0.18	-0.85	-0.24	-0.47	-0.23	-0.05	-0.45	0.06	-0.27	-0.11	0.17	-0.27	-0.37	-0.12	-0.33
	(0.61)	(-2.81)	(-0.89)	(-1.49)	(-0.66)	(-0.21)	(-2.28)	(0.28)	(-1.27)	(-0.46)	(0.68)	(-1.44)	(-1.96)	(-0.56)	(-1.47)

	BM=1					BM=2					BM=3				
	Year 1	Year 2	Year 3	Year 4	Year 5	Year 1	Year 2	Year 3	Year 4	Year 5	Year 1	Year 2	Year 3	Year 4	Year 5
Early	0.83	-0.24	-0.30	0.10	-0.22	0.70	0.38	0.37	0.03	0.21	0.89	0.35	0.63	0.30	0.28
	(3.31)	(-1.18)	(-1.04)	(0.38)	(-1.00)	(2.55)	(1.60)	(1.59)	(0.11)	(0.83)	(2.79)	(1.16)	(2.42)	(0.94)	(0.92)
Late	0.04	-0.36	-0.34	-0.62	-0.08	-0.05	-0.55	-0.04	-0.43	-0.54	-0.10	-0.29	-0.23	0.30	-0.40
	(0.14)	(-1.60)	(-1.54)	(-2.37)	(-0.20)	(-0.20)	(-2.34)	(-0.19)	(2.05)	(-2.14)	(-0.36)	(-1.14)	(-0.99)	(1.24)	(-1.68)

Table 15. Returns of Intersection Portfolios in January vs. Non-January

This table presents average monthly Fama-French 3-factor alphas of portfolios independently sorted on past 6-month returns and short interest ratio at month t in January and non-January. Stocks with prices less than $5 at the end of formation period are excluded. I skip one month between formation and holding periods. Monthly portfolios are rebalanced monthly. The Newey-West (1987) t-statistics are in parentheses. The sample period is from January 1988 to December 2014.

	January				February - December			
	S1	S2	S3	S1-S3	S1	S2	S3	S1-S3
M1	1.40	0.81	-0.27	1.68	-0.40	-0.67	-1.20	0.80
	(1.47)	(1.36)	(-0.31)	(3.47)	(-1.73)	(-2.72)	(-5.02)	(3.58)
M10	1.67	-0.07	-0.45	2.12	0.59	0.43	0.16	0.43
	(2.39)	(-0.14)	(-0.83)	(3.29)	(3.11)	(2.01)	(0.82)	(2.54)
M10-M1	0.27	-0.88	-0.17		0.99	1.10	1.36	
	(0.19)	(-0.89)	(-0.14)		(3.35)	(3.14)	(4.07)	
Early	1.95				1.79			
	(1.49)				(5.28)			
Late	-1.85				0.56			
	(-1.42)				(1.81)			
M1	0.38				-0.84			
	(0.47)				(-4.04)			
M10	0.28				0.35			
	(0.72)				(2.05)			
Simple	-0.11				1.19			
	(-0.10)				(3.94)			

Table 16. Returns of Intersection Portfolios Conditional on Investor Sentiment

This table presents average monthly Fama-French 3-factor alphas of interacted portfolios described in Table 2 following high and low investor sentiment periods. The sample period is from January 1988 to December 2010. To identify whether a specific formation period is in high or low sentiment, I calculate a weighted moving average value for the most recent 3-month. The weight is 1/2 for month t, 1/3 for month t-1, and 1/6 for month t-2. If the weighted value belongs to the top (bottom) 40% of time series of modified values, the formation period is high (low) sentiment period. Panel A reports the returns for K=1. Panel B reports the returns for K=6.

Panel A: K=1

	High Sentiment				Low Sentiment				High - Low			
	S1	S2	S3	S1-S3	S1	S2	S3	S1-S3	S1	S2	S3	S1-S3
M1	-0.46	-0.25	-1.16	0.70	0.45	-0.42	-0.87	1.31	-0.90	0.17	-0.30	-0.61
	(-1.08)	(-0.62)	(-2.55)	(1.92)	(1.04)	(-1.02)	(-1.88)	(3.54)	(-1.50)	(0.29)	(-0.46)	(-1.17)
M10	1.16	0.95	0.39	0.77	0.48	-0.14	-0.22	0.70	0.68	1.09	0.61	0.07
	(3.51)	(2.71)	(1.16)	(2.64)	(1.43)	(-0.40)	(-0.66)	(2.36)	(1.46)	(2.20)	(1.30)	(0.18)
M10-M1	1.62	1.21	1.55		0.03	0.28	0.64		1.58	0.93	0.90	
	(2.76)	(1.96)	(2.46)		(0.06)	(0.45)	(1.01)		(1.91)	(1.06)	(1.02)	
Early	2.32				1.34				0.98			
	(3.69)				(2.12)				(1.10)			
Late	0.84				-0.67				1.51			
	(1.39)				(-1.09)				(1.76)			
M1	-0.73				-0.41				-0.32			
	(-1.88)				(-1.03)				(-0.59)			
M10	0.73				0.02				0.71			
	(2.52)				(0.07)				(1.73)			
Simple	1.46				0.43				1.04			
	(2.59)				(0.75)				(1.29)			

Table 16 (continued)

Panel B: K=6

	High Sentiment				Low Sentiment				High - Low			
	S1	S2	S3	S1-S3	S1	S2	S3	S1-S3	S1	S2	S3	S1-S3
M1	-0.46	-0.41	-1.04	0.58	0.05	-0.56	-0.73	0.78	-0.51	0.15	-0.31	-0.20
	(-1.45)	(-1.16)	(-2.39)	(1.76)	(0.15)	(-1.57)	(-1.66)	(2.35)	(-1.13)	(0.30)	(-0.51)	(-0.43)
M10	0.76	0.56	0.22	0.53	0.38	-0.03	-0.02	0.40	0.38	0.58	0.24	0.13
	(2.88)	(2.02)	(0.83)	(2.37)	(1.43)	(-0.10)	(-0.08)	(1.76)	(1.01)	(1.49)	(0.65)	(0.43)
M10-M1	1.22	0.97	1.26		0.33	0.54	0.71		0.89	0.43	0.56	
	(2.89)	(1.98)	(2.29)		(0.77)	(1.08)	(1.27)		(1.49)	(0.62)	(0.71)	
Early	1.80				1.11				0.69			
	(3.18)				(1.94)				(0.86)			
Late	0.68				-0.07				0.76			
	(1.56)				(-0.16)				(1.22)			
M1	-0.75				-0.48				-0.27			
	(-2.10)				(-1.34)				(-0.52)			
M10	0.46				0.08				0.38			
	(1.91)				(0.33)				(1.11)			
Simple	1.21				0.56				0.65			
	(2.54)				(1.17)				(0.96)			

Table 17. Returns of Intersection Portfolios Conditional on Market State

This table presents average monthly Fama-French 3-factor alphas of intersected portfolios described in Table 2 following positive and negative lagged 36-month market returns. If past 36-month value-weighted market return is positive (negative), then the market state is UP (DOWN) market. In an unreported table, if past 12-month value-weighted market return is positive (negative), then the market state is UP (DOWN) market. The formation period is 6-month. The holding period in Panel is 1-month and the holding period in Panel B is 6-month.

Panel A: K=1

	UP				DOWN				UP -DOWN			
	S1	S2	S3	S1-S3	S1	S2	S3	S1-S3	S1	S2	S3	S1-S3
M1	-0.56	-0.79	-1.27	0.71	1.81	1.24	0.30	1.52	-2.37	-2.03	-1.57	-0.80
	(-2.18)	(-3.22)	(-4.72)	(3.16)	(3.05)	(2.19)	(0.48)	(2.90)	(-3.68)	(-3.30)	(-2.32)	(-1.42)
M10	0.68	0.54	0.24	0.44	0.60	-0.76	-0.60	1.20	0.08	1.30	0.84	-0.76
	(3.33)	(2.55)	(1.14)	(2.41)	(1.27)	(-1.54)	(-1.25)	(2.82)	(0.15)	(2.43)	(1.61)	(-1.65)
M10-M1	1.24	1.33	1.51		-1.21	-2.00	-0.90		2.45	3.34	2.40	
	(3.48)	(3.66)	(4.02)		(-1.46)	(-2.38)	(-1.03)		(2.74)	(3.65)	(2.55)	
Early	1.95				0.31				1.64			
	(5.15)				(0.35)				(1.73)			
Late	0.80				-2.41				3.21			
	(2.18)				(-2.85)				(3.50)			
M1	-0.95				0.94				-1.90			
	(-4.36)				(1.32)				(-2.49)			
M10	0.43				-0.24				0.67			
	(2.53)				(-0.50)				(1.27)			
Simple	1.38				-1.18				2.56			
	(4.57)				(-1.16)				(2.32)			

Table 17 (continued)

Panel B: K=6

	UP				DOWN				UP - DOWN			
	S1	S2	S3	S1-S3	S1	S2	S3	S1-S3	S1	S2	S3	S1-S3
M1	-0.58	-0.71	-1.31	0.73	1.26	0.70	0.64	0.62	-1.85	-1.41	-1.96	0.11
	(-2.99)	(-3.35)	(-5.11)	(3.62)	(2.79)	(1.42)	(1.08)	(1.32)	(-3.77)	(-2.64)	(-3.03)	(0.22)
M10	0.47	0.33	0.14	0.33	0.24	-0.38	-0.45	0.69	0.22	0.71	0.59	-0.37
	(2.86)	(1.93)	(0.77)	(2.25)	(0.65)	(-0.96)	(-1.09)	(2.05)	(0.54)	(1.66)	(1.32)	(-1.00)
M10-M1	1.05	1.04	1.45		-1.02	-1.08	-1.09		2.07	2.12	2.54	
	(4.02)	(3.53)	(4.34)		(-1.68)	(-1.58)	(-1.41)		(3.15)	(2.87)	(3.03)	
Early	1.78				-0.40				2.18			
	(5.27)				(-0.51)				(2.57)			
Late	0.72				-1.71				2.43			
	(2.61)				(-2.67)				(3.50)			
M1	-0.97				0.76				-1.73			
	(-5.05)				(0.98)				(-2.08)			
M10	0.28				-0.23				0.51			
	(1.78)				(-0.56)				(1.10)			
Simple	1.25				-0.99				2.25			
	(4.98)				(-0.94)				(2.00)			

Table 18. Long-Term Performance of Interaction Portfolios Conditional on Sentiment

This table presents average monthly Fama-French 4-factor adjusted returns for the interaction portfolios based on past returns and short interest for five years after the formation period. To identify whether a specific formation period is in high or low sentiment, I calculate a weighted moving average value for the most recent 3-month. The weight is 1/2 for month t, 1/3 for month t-1, and 1/6 for month t-2. If the weighted value belongs to the top (bottom) 40% of time series of modified values, the formation period is high (low) sentiment period. If past 36-month value-weighted market return is positive (negative), then the market state is UP (DOWN) market. The sample period is from 1988 to 2014.

	High Sentiment					Low Sentiment					High - Low				
	Year 1	Year 2	Year 3	Year 4	Year 5	Year 1	Year 2	Year 3	Year 4	Year 5	Year 1	Year 2	Year 3	Year 4	Year 5
Early	1.42	0.15	0.37	0.14	0.19	0.58	-0.05	-0.24	0.02	-0.22	0.85	0.20	0.61	0.12	0.42
	(3.10)	(0.15)	(1.13)	(0.47)	(0.64)	(1.24)	(-0.14)	(-0.74)	(0.05)	(-0.73)	(1.31)	(0.41)	(1.33)	(0.29)	(0.98)
Late	0.39	-0.36	-0.34	0.00	-0.08	-0.18	-0.59	-0.30	-0.19	-0.49	0.58	0.23	-0.04	0.19	0.41
	(1.17)	(-1.15)	(-1.10)	(0.00)	(-0.25)	(-0.54)	(-1.86)	(-0.95)	(-0.63)	(-1.45)	(1.21)	(0.52)	(-0.09)	(0.45)	(0.87)

	UP Market					DOWN Market					UP - DOWN				
	Year 1	Year 2	Year 3	Year 4	Year 5	Year 1	Year 2	Year 3	Year 4	Year 5	Year 1	Year 2	Year 3	Year 4	Year 5
Early	1.30	0.20	0.21	-0.01	0.05	-0.53	-0.38	0.41	0.58	-0.44	1.83	0.58	-0.20	-0.59	0.48
	(4.72)	(0.93)	(1.04)	(-0.06)	(0.26)	(-0.83)	(-0.76)	(0.92)	(1.49)	(-1.14)	(2.64)	(1.08)	(-0.41)	(-1.38)	(1.15)
Late	0.35	-0.47	-0.23	-0.17	-0.19	-1.20	-0.53	-0.54	-0.04	-0.55	1.56	0.05	0.30	-0.14	0.36
	(1.65)	(-2.48)	(-1.21)	(-0.92)	(-0.94)	(-2.43)	(-1.21)	(-1.27)	(-0.09)	(-1.31)	(2.90)	(0.11)	(0.66)	(-0.31)	(0.79)

Table 19. Robustness Tests

Panel A presents average monthly Fama-French 3-factor alphas of intersected portfolios independently sorted on past returns and short interest ratios. The sample stocks are commons stocks listing in NYSE/AMEX/NASDAQ. The sample period is from July 2003 to December 2014. The formation period is 6-month. Panel B presents average monthly FF 3-factor alphas of intersected portfolios described in Table 2 in two subperiods: 1988-2000 and 2001 to 2014. Panel C reports average monthly FF 3-factor alphas of portfolios dependently sorted on past 6-month returns and short interest ratio. First, all sample stocks are equally divided into ten groups based on their past 6-month returns. Then within each of ten portfolios, stocks are further equally divided into three groups based on their levels of short interest ratios at month t.

Panel A: Returns of Portfolios for NYSE/AMEX/NASDAQ Stocks

	K=1				K=3				K=6			
	S1	S2	S3	S1-S3	S1	S2	S3	S1-S3	S1	S2	S3	S1-S3
M1	0.00	-0.11	-0.73	0.73	-0.16	-0.04	-0.72	0.56	-0.25	-0.11	-0.60	0.35
	(0.01)	(-0.52)	(-2.49)	(2.82)	(-0.59)	(-0.21)	(-2.65)	(2.41)	(-0.85)	(-0.48)	(-1.98)	(1.23)
M10	0.43	0.02	-0.21	0.64	0.21	-0.08	-0.30	0.51	0.21	-0.16	-0.32	0.53
	(1.67)	(0.08)	(-0.87)	(2.72)	(0.96)	(-0.30)	(-1.39)	(2.82)	(0.88)	(-0.64)	(-1.50)	(3.16)
M10-M1	0.42	0.13	0.51		0.37	-0.03	0.43		0.45	-0.06	0.27	
	(0.99)	(0.32)	(1.13)		(1.04)	(-0.09)	(1.00)		(1.22)	(-0.13)	(0.59)	
Early	1.16				0.94				0.80			
	(2.47)				(2.21)				(1.72)			
Late	-0.22				-0.13				-0.08			
	(-0.49)				(-0.35)				(-0.18)			
M1	-0.37				-0.41				-0.38			
	(-1.50)				(-1.79)				(-1.56)			
M10	0.04				-0.09				-0.12			
	(0.16)				(-0.41)				(-0.56)			
Simple	0.41				0.32				0.26			
	(0.99)				(0.84)				(0.62)			

Table 19 (continued)

Panel B: Returns of Intersected Portfolios from 1988 to 2000

	K=1				K=3				K=6			
	S1	S2	S3	S1-S3	S1	S2	S3	S1-S3	S1	S2	S3	S1-S3
M1	-0.77	-0.91	-1.61	0.84	-0.78	-1.00	-1.66	0.88	-0.90	-0.99	-1.64	0.74
	(-2.74)	(-2.44)	(-4.46)	(3.11)	(-2.97)	(-3.16)	(-4.62)	(3.33)	(-3.64)	(-3.55)	(-5.05)	(3.17)
M10	0.55	0.46	0.02	0.53	0.37	0.29	0.03	0.34	0.38	0.34	0.09	0.29
	(2.48)	(1.68)	(0.08)	(2.42)	(1.98)	(1.47)	(0.12)	(1.72)	(2.26)	(2.37)	(0.46)	(1.65)
M10-M1	1.32	1.36	1.62		1.15	1.29	1.68		1.28	1.33	1.74	
	(3.41)	(2.63)	(3.83)		(3.49)	(3.36)	(3.93)		(4.39)	(4.18)	(4.49)	
Early	2.16				2.03				2.03			
	(4.70)				(4.72)				(5.37)			
Late	0.79				0.81				0.99			
	(2.23)				(2.33)				(3.14)			
M1	-1.19				-1.23				-1.26			
	(-3.92)				(-4.15)				(-4.59)			
M10	0.27				0.19				0.24			
	(1.43)				(1.11)				(1.62)			
Simple	1.46				1.42				1.50			
	(3.74)				(3.99)				(4.78)			

Table 19 (continued)

2001-2014

	K=1				K=3				K=6			
	S1	S2	S3	S1-S3	S1	S2	S3	S1-S3	S1	S2	S3	S1-S3
M1	0.19	-0.15	-0.71	0.89	0.25	-0.07	-0.70	0.95	0.22	-0.10	-0.63	0.85
	(0.57)	(-0.50)	(-2.43)	(3.18)	(0.96)	(-0.29)	(-2.58)	(3.76)	(0.81)	(-0.46)	(-2.18)	(3.41)
M10	0.64	0.14	0.02	0.62	0.39	0.09	-0.04	0.43	0.34	0.02	-0.11	0.45
	(2.33)	(0.50)	(0.06)	(2.59)	(1.53)	(0.30)	(-0.18)	(1.99)	(1.37)	(0.09)	(-0.40)	(2.11)
M10-M1	0.45	0.29	0.72		0.13	0.16	0.65		0.13	0.13	0.53	
	(1.07)	(0.69)	(1.58)		(0.38)	(0.41)	(1.51)		(0.35)	(0.33)	(1.12)	
Early	1.35				1.08				0.98			
	(2.99)				(2.48)				(2.16)			
Late	-0.17				-0.30				-0.32			
	(-0.37)				(-0.77)				(-0.81)			
M1	-0.33				-0.31				-0.31			
	(-1.23)				(-1.34)				(-1.30)			
M10	0.24				0.11				0.05			
	(1.01)				(0.44)				(0.22)			
Simple	0.57				0.42				0.37			
	(1.37)				(1.08)				(0.91)			

Table 19 (continued)

Panel C: Two-Way Dependent Sorts on Past Returns and Short Interest

	K=1				K=3				K=6			
	S1	S2	S3	S1-S3	S1	S2	S3	S1-S3	S1	S2	S3	S1-S3
M1	-0.25	-0.52	-1.21	0.97	-0.27	-0.55	-1.18	0.91	-0.34	-0.61	-1.15	0.81
	(-1.23)	(-2.05)	(-4.63)	(4.32)	(-1.41)	(-2.45)	(-4.54)	(4.37)	(-1.83)	(-2.90)	(-4.61)	(4.12)
M10	0.58	0.38	0.03	0.55	0.44	0.21	-0.04	0.48	0.42	0.20	0.00	0.42
	(3.26)	(2.11)	(0.14)	(3.14)	(2.70)	(1.21)	(-0.23)	(3.06)	(2.86)	(1.28)	(0.03)	(2.85)
M10-M1	0.83	0.90	1.24		0.70	0.76	1.14		0.76	0.80	1.15	
	(3.06)	(2.58)	(3.55)		(3.15)	(2.63)	(3.42)		(3.49)	(2.86)	(3.53)	
Early	1.79				1.62				1.57			
	(5.12)				(4.85)				(5.08)			
Late	0.27				0.22				0.35			
	(0.90)				(0.86)				(1.34)			

Table 20. Seasonal Pattern of the Return Predictability of Short Interest

This table presents average monthly Fama-French 3-factor and Fama-French-Carhart 4-factor alphas of lightly and heavily shorted stock portfolios and zero-cost portfolios in January and non-January. All NYSE/AMEX common stocks with monthly short interest data are ranked based on their short interest ratios at month t, then are assigned into ten portfolios based on their rankings on SIR. I skip one-month between formation and holding period. Portfolios are rebalanced monthly. The Newey-West (1987) t-statistics are in parentheses. The holding period is 1-month. The sample period is from January 1988 to December 2014. Panel A reports results for sample stocks with prices equal and larger than $5 at the end of formation period. Panel B reports results for stocks with prices larger than $0 at the end of formation period.

Panel A: Stock Price >= $5

	FF 3-Factor Alpha			FFC 4-Factor Alpha		
	ALL	January	Feb. - Dec.	ALL	January	Feb. - Dec.
S1	0.49	1.39	0.39	0.51	1.43	0.38
	(4.75)	(3.28)	(3.73)	(4.78)	(3.31)	(3.50)
S10	-0.67	-0.41	-0.72	-0.49	-0.58	-0.50
	(-5.18)	(-1.00)	(-5.39)	(-4.07)	(-1.85)	(-3.89)
S1-S10	1.16	1.80	1.11	0.99	2.01	0.88
	(7.85)	(3.16)	(7.23)	(6.98)	(4.30)	(5.87)

Panel B: Stock Price >= $0

	FF 3-Factor Alpha			FFC 4-Factor Alpha		
	ALL	January	Feb. - Dec.	ALL	January	Feb. - Dec.
S1	0.71	4.59	0.29	0.89	4.55	0.45
	(4.28)	(7.04)	(1.95)	(5.56)	(6.08)	(3.03)
S10	-0.77	0.10	-0.93	-0.47	-0.17	-0.57
	(-0.56)	(0.19)	(-6.08)	(-3.70)	(-0.49)	(-4.20)
S1-S10	1.48	4.48	1.21	1.35	4.72	1.01
	(8.01)	(5.29)	(6.65)	(7.32)	(6.08)	(5.52)

Table 21. Returns Predictability of Short Interest Conditional on Investor Sentiment

This table presents average monthly FF 3-factor alphas of lightly and heavily shorted stock portfolios and zero-cost portfolios following high and low sentiment periods. In Panel A, all NYSE/AMEX common stocks with monthly short interest data are ranked based on their short interest ratios at month t, then are assigned into ten portfolios based on their rankings on SIR. Stocks with prices less than $5 at the end of formation period are excluded. I skip one-month between formation and holding period. Portfolios are rebalanced monthly. To identify whether a specific formation period is in high or low sentiment, I calculate a weighted moving average value for the most recent 3-month. The weight is 1/2 for month t, 1/3 for month t-1, and 1/6 for month t-2. If the weighted value belongs to the top (bottom) 40% of time series of modified values, the formation period is high (low) sentiment period. The Newey-West (1987) t-statistics are in parentheses. The sample period is from January 1988 to December 2010. In Panel B, stocks are equally divided into three portfolios based on their SIRs, all else being equal.

Panel A

	K=1			K=6		
	High Sentiment	Low Sentiment	High - Low	High Sentiment	Low Sentiment	High - Low
S1	0.55	1.01	-0.47	0.52	1.01	-0.49
	(1.94)	(3.58)	(-1.18)	(1.97)	(3.81)	(-1.33)
S10	-0.88	-0.40	-0.48	-0.88	-0.30	-0.59
	(-3.30)	(-1.50)	(-1.27)	(-3.28)	(-1.10)	(-1.53)
S1-S10	1.43	1.42	0.01	1.40	1.31	0.09
	(4.55)	(4.47)	(0.03)	(4.69)	(4.34)	(0.22)

Panel B

	K=1			K=6		
	High Sentiment	Low Sentiment	High - Low	High Sentiment	Low Sentiment	High - Low
S1	0.33	0.68	-0.36	0.27	0.63	-0.36
	(1.65)	(3.42)	(-1.27)	(1.42)	(3.27)	(-1.33)
S3	-0.40	-0.14	-0.26	-0.34	-0.08	-0.26
	(-2.09)	(-0.72)	(-0.96)	(-1.75)	(-0.40)	(-0.95)
S1-S3	0.72	0.82	-0.10	0.61	0.71	-0.10
	(3.64)	(4.08)	(-0.34)	(3.05)	(3.50)	(-0.34)

Table 22. Regression Analysis of Return Predictability of Short Interest and Investor Sentiment

This table reports estimates of the coefficient b in the regression $R_{i,t} = a + bS_{t-1} + u_t$, where $R_{i,t}$ is the excess return of lightly shorted stocks (S1), heavily shorted stocks (S10), or long-short strategy (S1-S10) in month t, and S_t is the weighted 3-month moving average investor sentiment index defined before.

	S1	S10	S1-S10
$\hat{b}$	0.00	-0.0069	0.0069
t-statistics	(0.00)	(-0.89)	(1.43)

Table 23. Returns Predictability of Short Interest Conditional on Market State

This table presents average monthly FF 3-factor alphas of lightly and heavily shorted stock portfolios and zero-cost portfolios following positive and negative market returns. In Panel A, all NYSE/AMEX common stocks with monthly short interest data are ranked based on their short interest ratios at month t, then are assigned into ten portfolios based on their rankings on SIR. Stocks with prices less than $5 at the end of formation period are excluded. I skip one-month between formation and holding period. Portfolios are rebalanced monthly. If past 12-month value-weighted market return is positive (negative), then the market state is UP (DOWN) market. In Panel B, stocks are equally divided into three portfolios based on their SIRs, all else being equal in Panel A.

Panel A

	K=1			K=6		
	UP	DOWN	UP - DOWN	UP	DOWN	UP - DOWN
S1	0.50	1.44	-0.94	0.51	1.31	-0.80
	(3.14)	(2.76)	(-1.75)	(3.34)	(2.39)	(-1.40)
S10	-1.00	0.05	-1.05	-0.92	0.07	-1.00
	(-6.32)	(0.12)	(-2.18)	(-5.71)	(0.13)	(-1.66)
S1-S10	1.51	1.39	0.12	1.43	1.24	0.19
	(8.27)	(2.58)	(0.20)	(7.82)	(2.85)	(0.41)

Panel B

	K=1			K=6		
	UP	DOWN	UP - DOWN	UP	DOWN	UP - DOWN
S1	0.21	1.05	-0.84	0.21	0.91	-0.70
	(2.08)	(2.69)	(-2.13)	(2.18)	(1.95)	(-1.49)
S3	-0.54	0.28	-0.81	-0.50	0.36	-0.86
	(-4.68)	(0.95)	(-2.49)	(-4.39)	(0.99)	(-2.16)
S1-S3	0.75	0.77	-0.02	0.71	0.55	0.16
	(6.70)	(2.31)	(-0.07)	(6.29)	(1.90)	(0.52)

Figure 1. Long-Term Performance of Portfolios Base on the Change in Short Interest

This figure presents the 36-month cumulative Fama-French-Carhart alphas of the long leg, the short leg, and the long-short hedge portfolio based on the past 12-month change in short interest. See Table 1 for the description of portfolio construction. G1 is the long portfolio and G10 is the short portfolio.

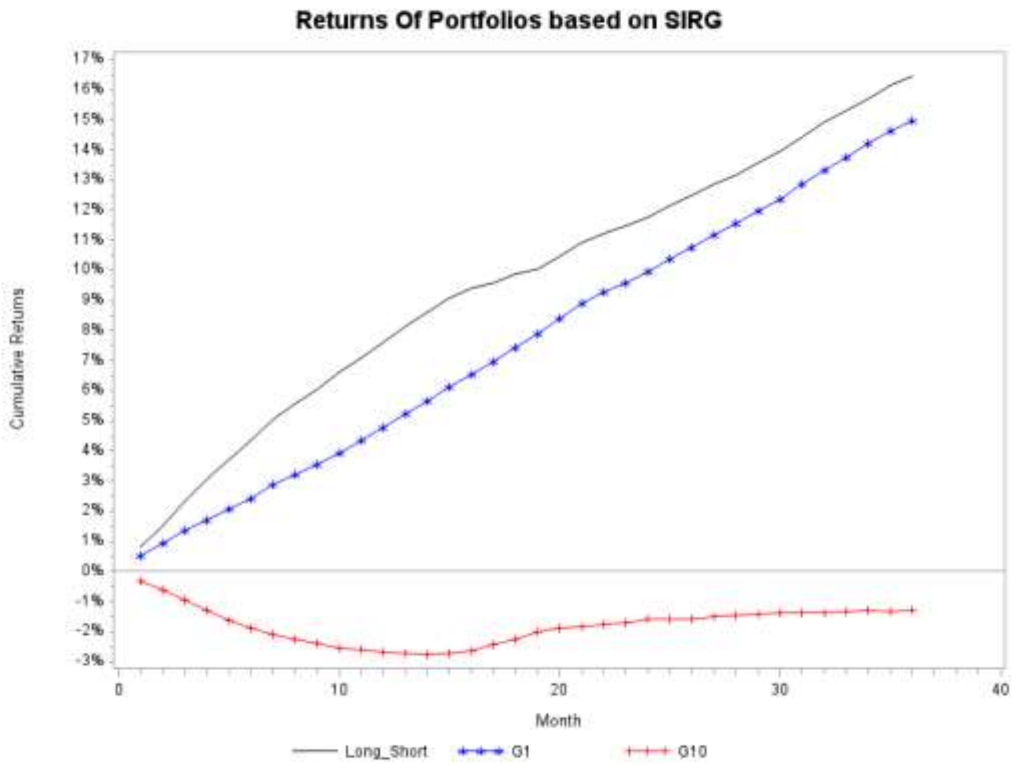


Figure 2. Performance of Long-Short Strategy Based on SIRG: 1988-2014

This figure represents performance of the long leg, the short leg, and the long-short strategy based on the change in short interest. See Table 1 for the description of portfolio construction.

Panel A

Panel B

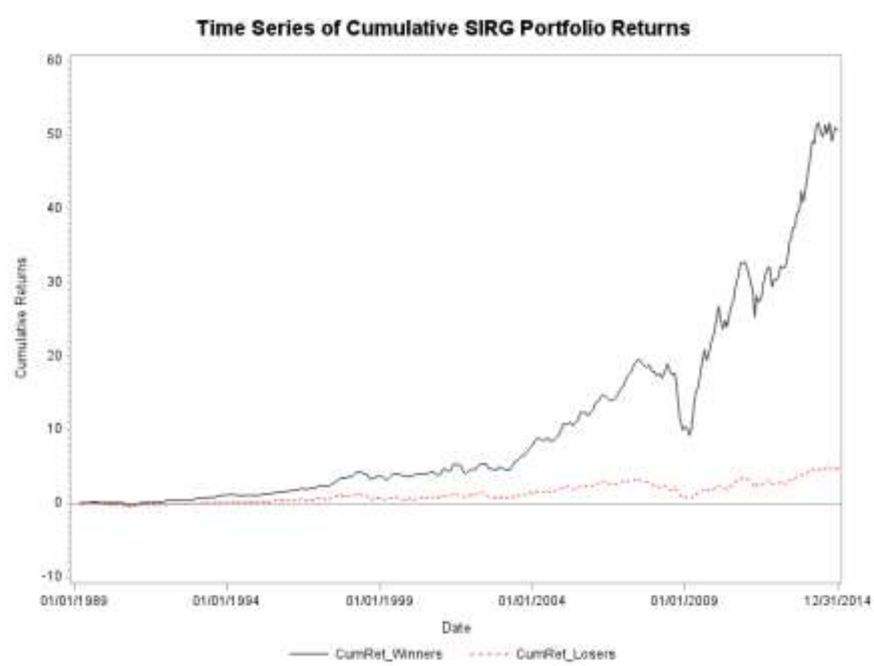
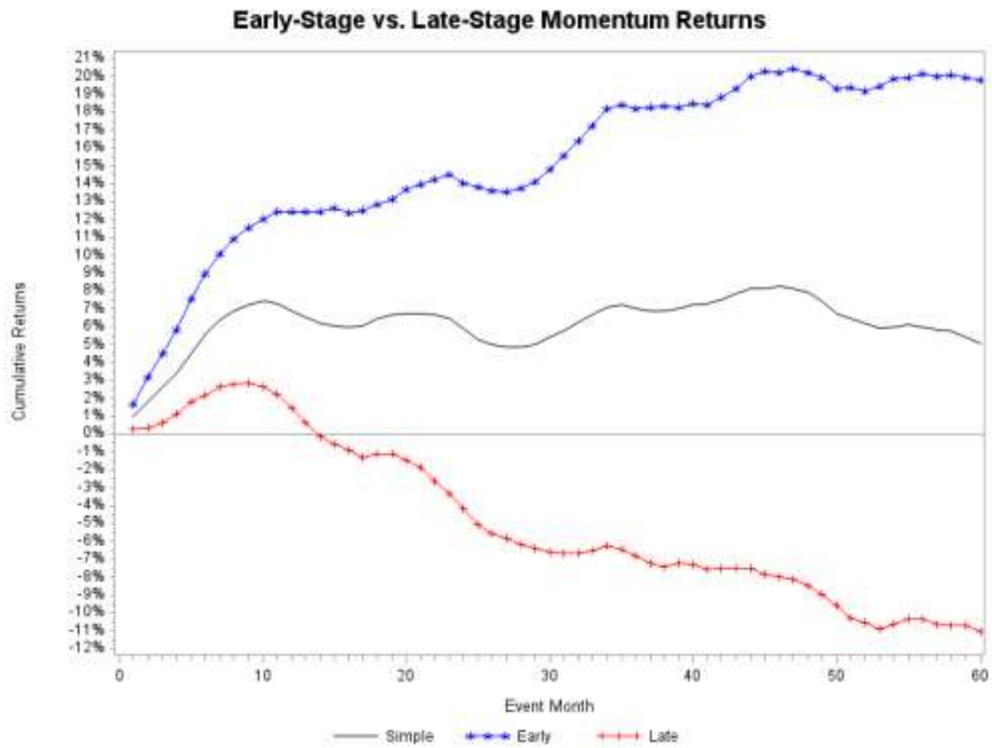


Figure 3. Long-Term Performance of the Interaction Portfolios

Panel A



Panel B

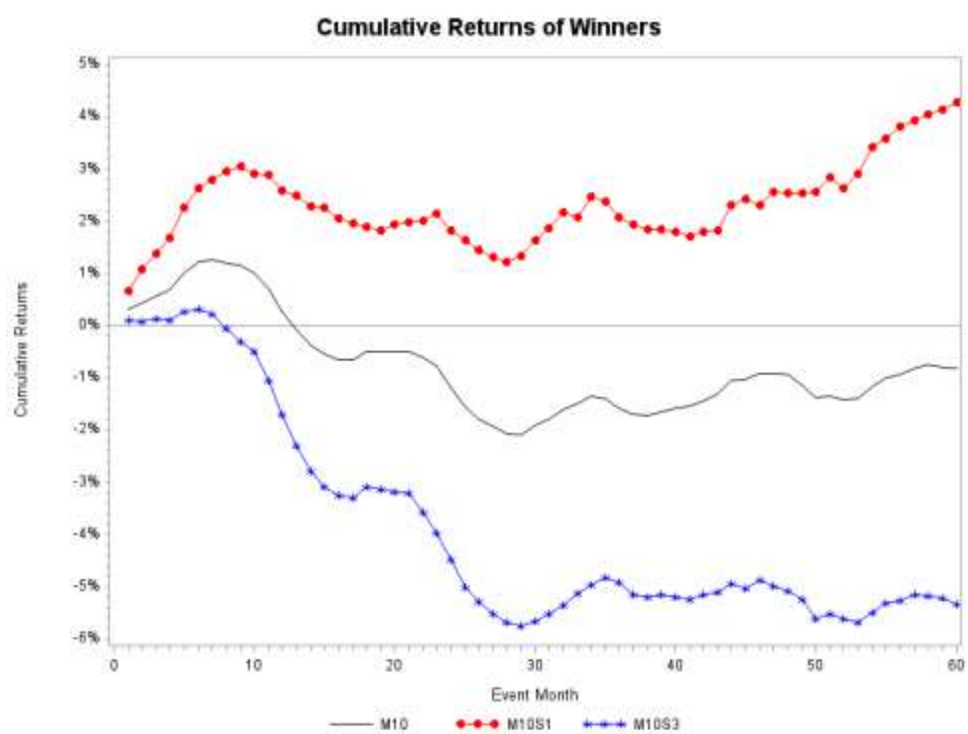


Figure 3 (continued)

Panel C

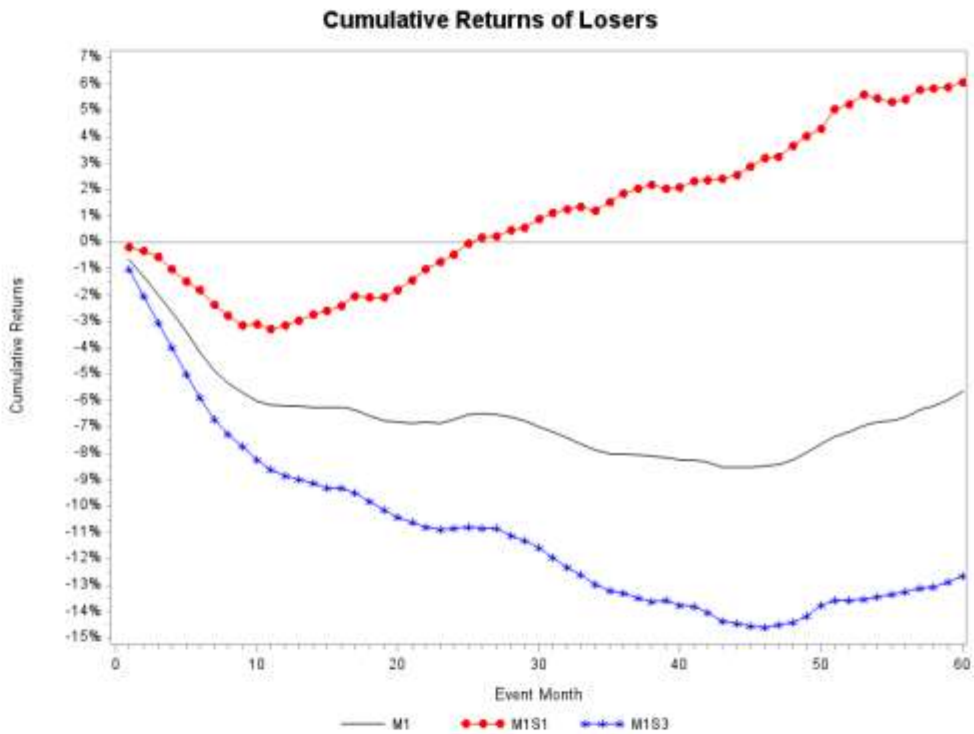
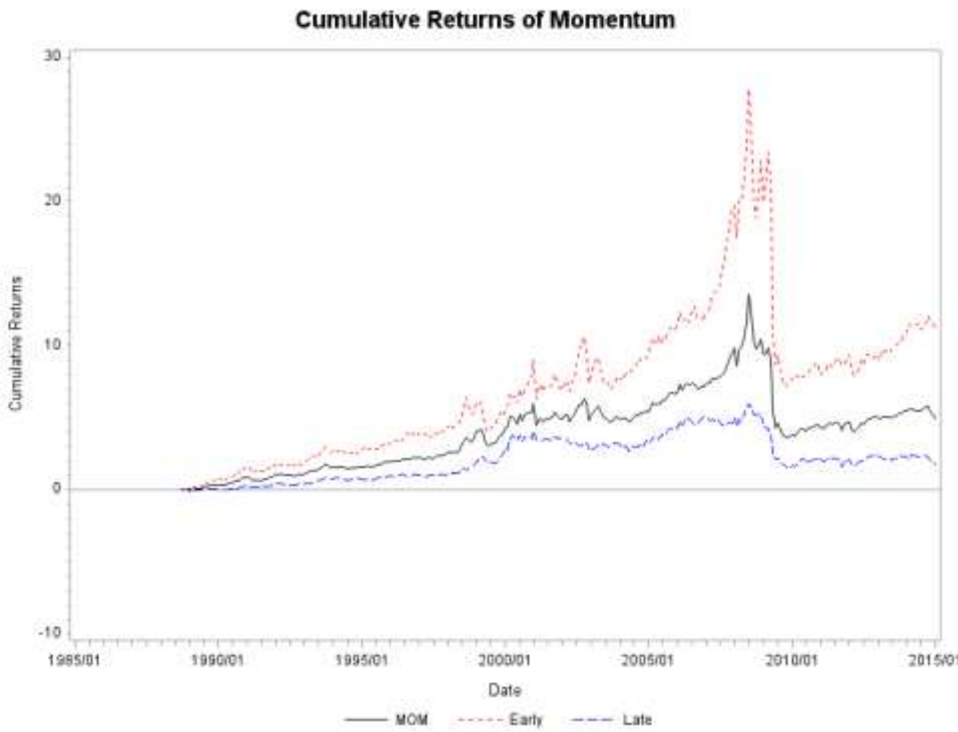


Figure 4. Performance of the Interaction Portfolios: 1988-2014

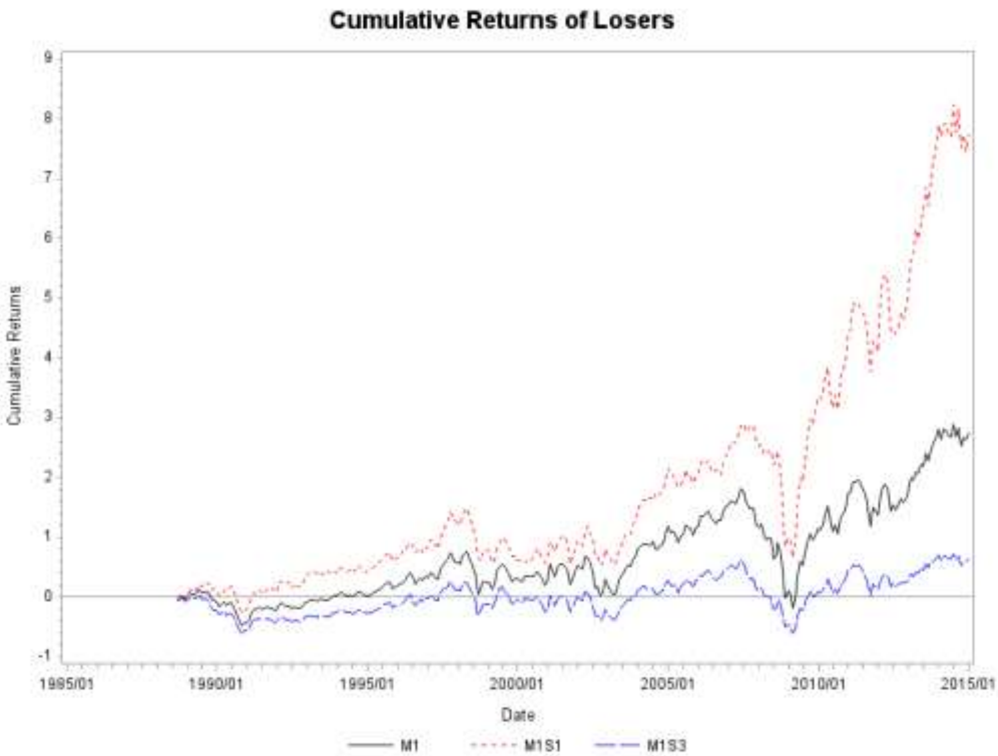
Panel A



Panel B

Figure 4 (continued)

Panel C



VITA

ZHAOBO ZHU

Department of Finance
Strome College of Business
Old Dominion University
Norfolk, VA 23529, USA

846 47th Street, Apt#4
Norfolk, VA 23508
Phone: (716) 867- 6601
Email: zxzhu001@odu.edu

EDUCATION

Ph.D. in Finance, Old Dominion University, USA	2012-2016
M.A. in Economics, Kent State University, USA	2011-2012
M.B.A. in Finance, Louisiana State University at Baton Rouge, USA	2009-2011
B.A. in English, China University of Petroleum (East China)	2003-2007

RESEARCH INTERESTS

Empirical Asset Pricing, Short Selling, Behavioral Finance

PUBLICATIONS

1. The Interaction of Short-Term Reversal and Momentum Strategies (with Kenneth Yung)
   Journal of Portfolio Management*, forthcoming, 2016*

ACADEMIC TEACHING EXPERIENCE

Spring 2016	Principle of Microeconomics (ECON 202S)	ODU
Summer & Fall 2015	Introductory Financial Management (FIN 323)	ODU

ACADEMIC ASSISTANT EXPERIENCE

- Old Dominion University, Department of Finance — 08/2012 – 05/2015
- Kent State University, Department of Economics — 08/2011 – 05/2012
- Louisiana State University at Baton Rouge — 08/2009 – 05/2011

PROFESSIONAL SERVICE

Reviewer: the 2013 & 2015 Academy of International Business (AIB) Annual Conference

SKILLS

Computer: SAS, STATA, Eviews, CRSP, Compustat, Bloomberg, Thomson ONE
Language: Chinese (native), English (fluent)

FELLOWSHIPS, SCHOLARSHIPS AND AWARDS

Research/Teaching Assistantships and Fellowship awarded by ODU	2012 – 2015
Graduate Assistantships awarded by Kent State University	2011 – 2012
Graduate Assistantships and Scholarships awarded by LSU	2009 – 2011
Scholarships awarded by China University of Petroleum (East China)	2004 – 2006