Journal of Financial Markets 46 (2019) 100502

Contents lists available at ScienceDirect

Journal of Financial Markets

journal homepage: www.elsevier.com/locate/finmar

Short selling and market anomalies☆

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A R T I C L E I N F O

Article history:
Received 26 November 2018
Received in revised form 10 July 2019
Accepted 10 July 2019
Available online 15 July 2019

JEL classification:
G12
G14

Keywords:
Financial information
Market anomalies
Short selling

A B S T R A C T

We assess the importance of well-known market anomalies for shorting strategies and how it changes over the 1988–2014 period. We find that anomalies contribute to both relative short interest (RSI) and RSI's negative information content about future earnings surprises and analyst actions. Anomalies explain more than half of the RSI-return relation. These results neither attenuate over time nor vary with market sentiment. RSI on least-shorted firms contains unique return-predictive information, which becomes increasingly important over time while RSI on most-shorted firms does not. Our findings suggest that a significant portion of short sellers' informational advantage comes from exploiting market anomalies.

1. Introduction

Studies on capital market anomalies report that firm-specific variables derived from firms' financial filings or from analyst forecasts can predict future stock returns in the cross-section.[1] It is well known that a large fraction of the anomalous returns comes from the short leg (i.e., extreme firms that experience subsequent lower returns). The likely overpricing of these extreme firms is hard to be arbitraged away because shorting these stocks seems costly and risky.[2] Therefore, while these anomalies can provide tradable information for long-only investors, such as actively managed mutual funds (Ali et al., 2008), a more interesting question is to what extent these anomalies can help short sellers to form equity strategies.[3] Furthermore, how does the importance of these anomalies to short sellers evolve, because anomalies can attenuate over time (Green et al., 2011; McLean and Pontiff, 2016) when more investors follow these strategies and generate a “crowded trade” effect (Stein, 2009).

☆ We greatly appreciate the comments from Tarun Chordia (the editor), an anonymous referee, Philipp Krueger, Adam Reed, Tong Yao, George Jiang, Ankur Pareek, and Xiaoyan Zhang and participants at the Financial Management Association meetings. Andrew Zhang is grateful for financial support from the Lee School of Business Summer Faculty Research Grant Award at the University of Nevada, Las Vegas.

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[1] See for example, Hirshleifer and Teoh (2003), Fama and French (2008), Li et al. (2009), Hirshleifer et al. (2011), Frazzini et al. (2012), Chorida et al. (2013), Hou et al. (2014), and Akbas et al. (2015).

[2] We use such terms as “anomaly,” “overpricing,” and “underpricing,” etc. to refer to the return predictability related to some firm-specific variables. We are agnostic about different perspectives on these anomalies (i.e., rational vs. behavioral perspective).

[3] Some short selling activities are conducted by hedge funds. There is evidence that hedge funds arbitrage some market anomalies, as shown by Fodor et al. (2009) and Green et al. (2011).

https://doi.org/10.1016/j.finmar.2019.07.001
1386-4181/

We address these questions by investigating how short sellers form their strategies using a broad set of well-known equity market anomalies. We also examine how their strategies contribute to their return performance. In particular, we study short sellers' trading activities and return performance in relation to these anomalies to estimate how (much) market anomalies contribute to short sellers' trading activities and performance. We include 18 anomalies that are mostly discussed in the literature, highly-publicized, and more likely to be traded by short sellers over the 1988–2014 period. We conduct individual analysis on each anomaly and also synthesize all anomalies into two composite measures to help draw inferences.

Short sellers' trading is proxied by relative short interest (RSI), defined as total short position scaled by concurrent shares outstanding (Dechow et al., 2001).[4] We first examine whether RSI is related to asset pricing anomalies in a systematic manner to provide evidence on whether short sellers' trade on market anomalies. We compare RSI on the long leg of an anomaly (i.e., predicting higher returns) to RSI on the short leg of an anomaly (i.e., predicting lower returns). If short sellers are skilled at using return-predictive information on the long (short) leg of an anomaly, we would expect to see low (high) RSI on the long (short) leg. We find that RSI is significantly lower in firms on the long leg than in firms on the short leg, despite the fact that firms on the long leg have larger market capitalization and greater institutional ownership. Furthermore, our temporal analysis shows that this cross-sectional pattern remains the same in later years and after academic publication of these anomalies. The sustained higher short interest on the short leg than on the long leg during the later years coincides with the period when the magnitude of the negative alphas on the short leg of nearly all anomalies has materially shrunk. This finding is consistent with the view that sophisticated investors' increasing shorting in these stocks can reduce overpricing of these stocks over time. Interestingly, we find the cross-sectional pattern in RSI remains the same whether market sentiment is high or low market. This indicates that short sellers are equally responsive to anomalies regardless of market sentiment, despite the fact that anomalies are more significant following high market sentiment (Stambaugh et al., 2012). This finding suggests that short sellers do not time market sentiment.

Next, we examine how the use of market anomalies contributes to short sellers' performance. The literature documents a negative RSI-return relation, with negative abnormal returns on high RSI firms and positive abnormal returns on low RSI firms (Asquith et al., 2005; Boehmer et al., 2010). However, the source of this negative RSI-return relation is still unclear. To gauge how anomalies contribute to the RSI-return relation, we conduct three related tests.

First, we follow the convention in the literature and examine extreme portfolios only. In particular, we only examine firms that are most shorted (i.e., high-RSI firms, or the short leg of RSI) and firms that are least shorted (i.e., low-RSI firms, or the long leg of RSI). Among the high-RSI firms, we split them into two subsets: overlapping and non-overlapping firms. Overlapping firms refer to firms simultaneously on the short leg of RSI and anomalies, and non-overlapping firms are those on the short leg of RSI but not on the short leg of anomalies. We posit that RSI of the overlapping firms likely reflects short arbitrage of market anomalies. If short sellers use market anomalies to target overpriced firms, these overlapping firms are likely the greatest source of profits (earned by short sellers via negative abnormal returns). Similarly, among the low-RSI firms, overlapping firms refer to firms simultaneously on the long leg of RSI and anomalies; non-overlapping firms are those on the long leg of RSI but not on the long leg of anomalies. We posit that RSI of the overlapping firms among the low-RSI firms likely reflects short avoidance in underpriced firms.[5] If short sellers use market anomalies to avoid underpriced firms, these overlapping firms are likely the greatest source of positive abnormal returns associated with low RSI firms.

Two findings emerge from this analysis. First, consistent with the literature, high-RSI firms have a significant negative alpha of 62 bps. Furthermore, such abnormal returns are entirely driven by firms that are also on the short leg of anomalies (i.e., overlapping firms). Short arbitrage of market anomalies has generated the entirely abnormal returns to short sellers on these most shorted stocks. When we examine this leg separately for each subperiod and different market conditions, the negative alpha on this leg becomes insignificant in later years and following periods of low market sentiment, during which the negative alpha on the short leg of most anomalies has also decreased and even become insignificant. The results also suggest that the bearish information used by short sellers on most shorted stocks is largely from anomalies.

Second, the low-RSI firms have a significant alpha of 47 bps, which can be interpreted as losses that have been avoided by short sellers. To the extent that short sellers are informed traders, the short position on this leg reveals positive information that market participants can use to earn abnormal returns by simply longing these stocks (Boehmer et al., 2010). When we separate firms on this leg based on market anomalies, the overlapping and non-overlapping firms generate a significant alpha of 105 bps and 48 bps, respectively, with a significant difference of 57 bps. Different from the short leg of RSI, the long leg of RSI contains return predictive information beyond anomalies. While these results remain the same around academic publication of market anomalies and during high and low market sentiment periods, only in later years do the non-overlapping firms have a significant positive alpha of 68 bps. Taken together, these results suggest that the information used by short sellers to avoid shorting the wrong firms largely (but not solely) comes from market anomalies, with non-anomaly information becoming increasingly important over time. Alternatively stated, it appears that with more competition in trading on common equity strategies, short sellers seem to adopt other information to avoid shorting the wrong firms in later years.

[4] We note that not all short selling is driven by overvaluation, and some short position is set up to hedge. However, on average, shorting is conducted for valuation purposes (e.g., Hirshleifer et al., 2011).

[5] We use "avoid/avoidance" to refer to the long leg of RSI where short position is smallest in the cross-section. While most firms on the long leg have a trivial amount of short interest, they do not necessarily have zero RSI.

The second test, where we include all sample firms and sort them into 5 $\times$ 5 sublets independently on RSI and anomaly, offers two additional insights. First, the use of anomalies can affect shorting performance even for stocks with the same level of RSI. RSI on the short leg of anomalies can earn more abnormal returns for short sellers than the RSI on other stocks. Second, stock returns nearly monotonically decrease in RSI for each quintile of anomalies, and the negative RSI-return relation is not limited to extreme firms and is also independent of anomalies. These results suggest that the average RSI in the cross-section of stocks has return predictive information beyond anomalies, suggesting that short sellers are informed (Diamond and Verrecchia, 1987).

In our third test, we use a parsimonious and intuitive model to further quantify how much information contained in anomalies can help explain RSI in the cross-section and the negative RSI-return relation. Specifically, we first regress RSI on anomalies and other determinants of RSI. We then obtain the regression residuals (residual RSI) to form portfolios and examine future returns predictability. The intuition is that, if the return predictability of RSI is mainly driven by anomaly information, residual RSI should have little power in predicting future returns because, by construction, it is independent of anomalies. But if short sellers use other return-predictive information beyond the anomalies, residual RSI should still be able to predict future returns even after controlling for predicted RSI. We find that anomalies explain 14% of the cross-sectional variations of RSI and are a significant determinant of RSI; a one standard decrease in anomaly implies an increase in RSI equal to 24% sample mean. The 18 market anomalies together explain about 60% of the negative RSI-return relation, suggesting that information other than these anomalies used by short sellers accounts for 40% of the return performance. The *residual* RSI still generates significant hedge spread in abnormal returns, further revealing that RSI contains return-predictive information beyond anomalies. This finding aligns well with previous analysis that RSI is informative to other market participants beyond market anomalies.

Our study centers on important issues in capital markets research and contributes to the literature in the following ways. First, while market anomalies have increasingly become common equity strategies for long-side market participants, we provide evidence that these anomalies are also important equity strategies for short sellers and generate the entire abnormal returns earned by average short sellers on the most heavily shorted stocks. In addition, RSI contains valuable information that is important to capital markets (Pownall and Simko, 2005; Kecskés et al., 2013) and short sellers use information in accounting variables, such as the book-to-market ratio, to locate target firms in the cross-section (Dechow et al., 2001). Our findings indicate that short sellers use a broad set of market anomalies to form informed strategies. The use of these common equity strategies helps explain the distribution of short interest and the negative RSI-return relation in the cross-section. Since anomalies are public information, our finding that market anomalies (non-anomalies) explain about 60% (40%) of the negative RSI-return relation echoes with Engelberg et al. (2012) that short sellers' trading advantage primarily comes from their superior ability to analyze publicly available information. These results are also consistent with Boehmer et al. (2019), who find that short sellers use both public news and private information to anticipate earnings events and analyst recommendation changes.

Second, we examine both short arbitrage activities and short avoidance activities. Market anomalies provide useful information for short sellers to locate likely underpriced firms to avoid, with this information explaining the entire potential losses that shorters have avoided in the early period and a significant part of these losses in the recent period. Our study complements Boehmer et al. (2010) by linking the positive abnormal returns from short avoidance to well-known market anomalies. In addition, our temporal analysis results suggest that as anomaly signals become more popular among traders and less predictive on the short leg over time, short sellers rely more on other return-predictive information to avoid shorting the wrong firms. Therefore, over time, RSI contains more non-anomaly return-predictive information, particularly on stocks that are least shorted. We add to the literature by providing complementary evidence that short sellers persistently use public information, but over time they have adapted to using more elusive information when anomaly strategies become more crowded.[6]

2. Sample and variable construction

Our sample contains all domestic common stocks (share code 10 or 11) listed on the NYSE, AMEX, and NASDAQ in the CRSP database from 1988 to 2014. Following the asset pricing literature (e.g., Fama and French, 2008), we exclude financial firms (4-digit SIC codes between 6000 and 6999). We also exclude firms with share prices below $5 at the end of each month to mitigate concerns such as bid-ask bounce, thin trading, and the barrier to shorting low-priced stocks.[7] We obtain firm accounting information from Compustat, institutional ownership from 13F filings, and analyst earnings forecast from I/B/E/S.

[6] Some recent works examine the evolvement of various market anomalies over time (e.g., Green et al., 2011; Chorida et al., 2013; Hwang and Liu, 2013; McLean and Pontiff, 2016) and the importance of unique strategies for mutual funds (Titman and Tiu, 2011; Sun et al., 2012; Amihud and Goyenko, 2013). Hanson and Sunderam (2014) show that arbitrageurs as a group have reacted to heightened competition by favoring smaller stocks.

[7] Stocks with a price below $5 are generally considered hard to short (e.g., Asquith et al., 2005).

2.1. *Measure of short selling activities*

Short selling activities are measured by relative short interest (RSI), computed as monthly short interest standardized by concurrent shares outstanding (Dechow et al., 2001). Monthly short interest data are obtained from the three major stock exchanges before 2003 and from Compustat after 2003.[8] Firms are required to have non-missing short interest to be included in our sample.

2.2. *Market anomalies*

There are a large number of anomalies (i.e., firm specific characteristics that predict stock returns in the cross-section). From these return predictors, we examine 18 well-known anomalies that serve as a reasonable proxy for public information used by sophisticated investors. Appendix A presents the details of these anomaly variables, including book-to-market (*BM*), momentum (*MOM*), idiosyncratic volatility (*IVOL*), operating accruals (*ACC*), total accruals (*TACC*), discretionary accruals (*DACC*), net operating assets (*NOA*), investments-to-assets (*CAPX*), abnormal investments (*AI*), asset growth (*AG*), net equity issues (*NS*), external financing (*XFIN*), distress risk (*CHS*), return on assets (*ROA*), return on equity (*ROE*), analyst forecast revision (*FRV*), analyst earnings forecast dispersion (*DISP*), and earnings surprise (*SUE*). We follow the convention in the literature to construct these variables.

Our selection of these anomalies is motivated by two considerations. First, the anomaly needs to be not only published in the academic literature but also less costly to execute among industry practitioners. This requirement excludes certain documented anomalies due to their high trading costs and liquidity concerns. For example, anomalies such as idiosyncratic skewness (Boyer et al., 2010), maximum daily return (Bali et al., 2010), etc. are excluded.[9] Second, an anomaly is required to be published in academic journals for some years so that it is well known to market participants. This requirement excludes some popular trading strategies that become known only in recent years, such as gross margin (Novy-Marx, 2013). While we strive to include a representative set of anomalies that have attracted attention from both academics and practitioners, our choice is admittedly arbitrary given many anomaly variables reported in the literature.[10] Unfortunately, researchers still lack an adequate understanding of which firm characteristics contains unique and/or complementary information about expected returns, which partially explains why studies have used different sets of anomalies.[11] Since our research questions primarily focus on the role of market anomalies to short sellers, our list of anomalies at least provides a lower-bound estimate in this direction.

2.3. *Composite measures of market anomalies*

For some of our analyses, we employ two composite measures that incorporate all 18 anomalies. The composite measures have at least two merits. First, they can capture the common component of these firm-specific variables in the cross-section due to their correlations. Second, since each return predictive variable can provide additional information that is not fully captured by other variables, the composite measures encompass all comprehensive public information contained in each of these anomalies and thus are a better proxy for public information used by short sellers. Such measures also help infer the relevance of other (i.e., non-anomalies) information for the trading decisions and investment performance of short sellers.

Specifically, the first composite measure ranks all firms into percentiles for every month based on each anomaly signal and then we average the percentile ranks across all anomalies for each firm.[12] We denote the average percentile rank as *PERC*. The second composite measure retrieves the first principal component of these predictors during each month for each firm and is denoted as *PRIN*. While *PERC* treats each anomaly with equal importance and thus contains unique return predictive information from each anomaly variable, *PRIN* puts more emphasis on the commonalities among these anomaly variables and thus reflects common return predictive information from each anomaly variable.

[8] Exchanges start to report short interest twice per month since September 2007. To be consistent with the short interest data from the earlier period we keep the data at the monthly frequency.

[9] The literature also shows that illiquid and smaller stocks earn higher returns than liquid and large stocks, but we do not include size and illiquidity as anomalies because they are also related to trading frictions. Instead, we conduct our analysis conditional on liquidity and market capitalization (Asquith et al., 2005; Drake et al., 2011) or control for them in the regression analysis.

[10] For example, Green et al. (2013) show that 330 "return predictive signals" have been reported.

[11] Another challenge in choosing anomaly variables is the lack of clear guidance on which anomalies can predict returns ex ante.

[12] Based on the literature, we adjust the signs for some predictors, including *IVOL*, *ACC*, *RSST*, *NOA*, *CAPX*, *AI*, *AG*, *NS*, *XFIN*, *CHS*, and *DISP*, so that firms with a greater percentile rank are consistently on the long leg (i.e., have higher predicted returns). When the 18 variables are aggregated into composite measures, if any individual signal is missing, it is not included. We do not require a firm to have non-missing values in all anomaly variables at the same time. This approach avoids losing too many observations and is also reasonable because many anomaly variables have similar return predictive properties and exhibit high pairwise correlations. For robustness checks, we also use a cross-sectional median or mean to replace missing variables and obtain qualitatively similar results.

2.4. Control variables

Asquith et al. (2005) find that firms with high institutional ownership (*IO*) have high RSI because higher IO represents a larger supply of lendable shares. Beneish et al. (2015) find that short supply of lendable shares presents a binding constraint to arbitrageurs. We thus include IO to control for share supply. Hirshleifer et al. (2011) find that greater liquidity reduces the price impact faced by short sellers when they are forced to cover their short positions and thus indicates a lower risk of a short squeeze. We use Amihud's (2002) illiquidity measure (*ILLIQ*) to control for price impact due to illiquidity. We also include a *CONVERTIBLE* dummy that equals one if the firm has convertible bond outstanding to control for shorting as a result of convertible arbitrage (Choi et al., 2010). We follow the convention in the literature to construct these control variables (see Appendix A).

2.5. Summary statistics

Table 1 presents time series average of the cross-sectional mean, median, and standard deviation of RSI and anomaly variables. All continuous variables are winsorized at the 0.5 and 99.5 percentiles in each cross-section to reduce the influence of potential outliers. Average firms have 3.23% of RSI, with a median RSI of 1.89%, indicating the skewed distribution of RSI in our sample.[13] The summary statistics of each anomaly variable are consistent with those in the literature. We also conduct correlation analysis on RSI and anomalies variables. In untabulated results, we find that RSI is significantly correlated with many anomaly variables, revealing that short interest is related to anomalies in the cross-section. In addition, the pairwise correlations are significant between many anomalies. Such collinearity highlights the difficulty in pinpointing the relation between short interest and any single anomaly. It is thus useful to use composite measures to summarize return predictive information of these anomaly variables to study short sellers' trading strategies.

3. Preliminary evidence on RSI and market anomalies

Since we are interested in whether and how short sellers' trading strategies and performance rely on the public information contained in anomalies, we form quintile portfolios to examine RSI in month t based on anomaly variables measured in month t-1, and evaluate the portfolio return performance in month $t+1$. We allow a minimum of a four-month lapse (relative to month t-1) to ensure the availability of accounting information (used to construct market anomaly variables) to short sellers and other market participants.[14] In this procedure, we essentially skip one month when forming portfolios to minimize the concerns of bid-ask bounces and monthly return reversals (Jegadeesh, 1990).

Table 1
Summary statistics.

	Mean	Median	Std. Dev.
RSI	3.23	1.89	4.08
BM	0.65	0.52	0.64
MOM	0.22	0.11	0.58
NS	0.08	0.01	0.28
ACC	−0.03	−0.03	0.09
ROA	0.02	0.05	0.16
ROE	0.03	0.1	0.39
DISP	0.01	0.003	0.01
CHS	−8.22	−7.9	5.41
XFIN	0.06	−0.003	0.24
FRV	−0.01	−0.002	0.03
AG	0.32	0.09	0.97
IVOL	0.02	0.02	0.01
AI	0.09	−0.09	0.93
NOA	0.59	0.63	0.25
CAPX	0.08	0.05	0.11
DACC	0.01	0.01	0.20
TACC	0.08	0.04	0.23
SUE	0.17	0.15	5.05

Notes: This table reports the time series average of cross-sectional mean, median, and standard deviation for RSI and 18 anomaly variables for the sample period 1988–2014. All variables are defined in Appendix A. All continuous variables are winsorized at the 0.5 and 99.5 percentiles.

[13] For this reason, when conducting regression analysis on RSI, we also use log transformed RSI as a dependent variable for robustness check and find similar results (not reported).

[14] For example, in March 1998 (month t), RSI portfolios are based on RSI in March, using anomaly variables constructed in February 1998 (month t-1) with accounting information from the most recent fiscal year from Compustat (i.e., October 1997 or earlier).

Table 2
Portfolio returns by relative short interest and anomaly variables.

	Raw Ret			CAPM alpha		
	Long	Short	Long-Short	Long	Short	Long-Short
RSI	1.27	0.59	0.69***	0.47**	−0.62***	1.09***
BP	1.25	0.73	0.52**	0.37*	−0.44**	0.81***
MOM	1.58	0.60	0.98***	0.53**	−0.62***	1.15***
NS	1.27	0.58	0.7***	0.39**	−0.59***	0.98***
CAPX	1.14	0.70	0.44***	0.15	−0.40**	0.54***
ACC	1.13	0.73	0.4***	0.06	−0.36*	0.42***
DISP	1.14	0.79	0.35	0.15	−0.40**	0.56***
CHS	1.25	0.44	0.81***	0.4***	−0.85***	1.25***
XFIN	1.34	0.44	0.9***	0.46***	−0.73***	1.18***
FRV	1.44	0.68	0.76***	0.34**	−0.48**	0.82***
AI	1.22	0.84	0.38***	0.18	−0.17	0.36***
NOA	1.08	0.71	0.37	−0.08	−0.28	0.20
TACC	1.22	0.62	0.61***	0.18	−0.58***	0.75***
AG	1.27	0.47	0.8***	0.26	−0.73***	0.99***
ROA	1.12	0.69	0.43**	0.12	−0.55**	0.67***
ROE	1.15	0.70	0.45**	0.18	−0.51**	0.69***
DACC	1.37	0.94	0.43***	0.28*	−0.17	0.45***
IVOL	1.12	0.52	0.60*	0.38***	−0.74***	1.11***
SUE	1.52	0.43	1.09***	0.43**	−0.64***	1.08***
PERC	1.56	0.09	1.47***	0.71***	−1.18***	1.90***
PRIN	1.45	0.90	0.55**	0.54***	−0.32	0.85***

Notes: This table reports portfolio returns. We sort sample firms into five quintiles by RSI, each of the 18 anomaly variables, and composite measures of *PERC* and *PRIN*, respectively, in month *t*, and compute returns and CAPM alphas in month $t+1$ to the long leg, the short leg, and the long-short hedge portfolio, where the short and long legs refer to firms in the two extreme portfolios that have low and high average returns, respectively. For the RSI portfolio, the short leg includes firms with highest RSI and the long leg includes firms with lowest RSI. We adjust *t*-statistics by Newey and West (1987) for heteroscedasticity and autocorrelation. *, **, and *** indicate statistical significance at the 0.1, 0.05, and 0.01 levels, respectively.

We use CAPM to obtain risk-adjusted return since we include book-to-market (*BP*) and momentum (*MOM*) anomalies in our analysis. We also use three alternative methods to calculate abnormal returns.[15] Our main results are robust to all three methods, and we only report the CAPM results for brevity.

3.1. RSI-return relation

The short selling literature documents a negative RSI-return relation that heavily shorted firms earn abnormally low returns and underperform lightly shorted firms. In the first row of Table 2, we sort firms into quintiles by RSI and form the long and short RSI legs. Stocks on the short leg have high RSI and are most shorted, and stocks on the long leg have low RSI and are least shorted. We then compute returns to each leg as well as to the long-short hedge portfolio.

Consistent with the existing literature, the RSI-return relation is strongly negative in our sample with the heavily shorted stocks having largest negative returns. This is indicated by the significant and positive spread in return (69 bps) and alpha (109 bps) for the RSI hedge portfolio. The negative 62 bps alpha on the short leg represents the abnormal returns to average short sellers on heavily shorted stocks. Since RSI in least shorted stocks is nearly zero and most stocks on the long leg have zero RSI, the positive 47 bps alpha can be interpreted as losses short sellers have avoided by not shorting these stocks. Diamond and Verrecchia (1987) show that short sellers are informed traders. Our finding suggests that short sellers are informed about not only stocks that are overpriced but also those that are underpriced. That is, short sellers seem to be able to identify not only which stocks to short but also which ones to avoid (Boehmer et al., 2010).

3.2. Market anomalies

Firms on the short leg, namely those with high *IVOL*, *ACC*, *TACC*, *DACC*, *NOA*, *CAPX*, *AI*, *AG*, *NS*, *XFIN*, *CHS*, and *DISP* and low *BM*, *MOM*, *ROE*, *FRV*, *ROA*, and *SUE*, earn abnormally lower returns in subsequent months, compared to firms on the long leg, namely firms with opposite characteristics (see Appendix A for studies that document these anomaly variables). To understand whether and how short sellers use information conveyed by these market anomalies over time, we first examine how

[15] The first *is DGTW*-adjusted returns using the characteristic-matched benchmark of Daniel et al. (1997). The second method we use regresses excess returns on four factors that include the Fama-French three factors (Fama and French, 1993a, 1993b), plus Carhart's momentum factor (Carhart, 1997). Recently, Fama and French (2016) propose a 5-factor model, which includes MKTRF, SMB, HML, CMA, and RMW.

market anomalies have changed during our sample period. We form quintile portfolios based on market anomaly variables with monthly rebalancing to incorporate the most recent information available to short sellers.

Table 2 reports, for each anomaly, the raw returns (in Panel A) and the risk-adjusted returns (in Panel B) represented by the intercept from the CAPM model. Many anomalies have larger alphas (in magnitude) on the short leg than on the long leg; hence a great part of the long-short hedge spread is driven by the short leg. As a result, while using market anomalies can be a tradable strategy for long-side investors such as mutual funds, such strategy could potentially be more important for short sellers who typically exploit the short leg of an anomaly.

The bottom two rows present portfolio returns sorted on composite anomaly measures of *PERC* and *PRIN*. Anomalies are present in our entire sample period. For example, the long-short hedge raw returns and alphas of *PERC* are 147 bps and 190 bps, respectively. The results for *PRIN* are somewhat weaker: the hedge alpha spread is less than half of the hedge alpha spread of *PERC*. The weaker results with the *PRIN* measure compared to the *PERC* measure reflect the fact that *PRIN* uses the common information across individual anomalies while *PERC* gives equal weight to information contained in each anomaly.

3.3. Short sellers' use of anomalies

We first examine whether short sellers exploit information contained in these anomalies. If they do, one would expect to observe more shorting (i.e., higher RSI) on the short leg of each anomaly than on the long leg. Table 3 reports the average RSI for the long leg, short leg, and the hedge spread of each anomaly.[16] Each row is named after the anomaly variable to represent sorting based on that variable. For example, "*ACC*" reports the level of RSI for portfolios sorted on accruals (*ACC*).

Table 3 shows that short selling is generally higher on the short leg than the long leg, suggesting that short sellers exploit these anomalies by trading on the return-predicative information conveyed by these anomalies. For example, the high (low) BM stocks have a mean RSI of 2.51% (4.68%). The more (less) short interest in growth (value) stocks that have lower (higher) returns is consistent with Dechow et al. (2001), who argue that short sellers use book-to-market ratios to short stocks. Accordingly, the negative RSI hedge spread for market anomalies reflects a systematic relation between RSI and these anomalies and provides evidence on the use of market anomalies in a shorting strategy. We note that several anomalies, including *AI*, *NOA*, and *DACC*, do not have more RSI on the short leg than on the long leg. We also examine *PERC* and *PRIN* to gauge the use of anomaly information in the bottom two rows. The hedge spread in RSI for long-short portfolios is negative and significant.

Table 3
Average relative short interest by market anomalies.

	Long	Short	Long - Short
BM	2.51	4.68	−2.17***
MOM	3.54	4.32	−0.78***
NS	2.95	4.39	−1.44***
CAPX	3.18	4.03	−0.85***
ACC	3.52	3.84	−0.32***
DISP	3.32	4.40	−1.07***
CHS	2.8	3.93	−1.13***
XFIN	2.89	4.40	−1.51***
FRV	3.64	4.30	−0.66***
AI	3.64	3.44	0.19
NOA	4.06	3.42	0.64***
TACC	3.59	4.40	−0.81***
AG	3.21	4.69	−1.48***
ROA	3.65	4.26	−0.61***
ROE	3.43	4.16	−0.73***
DACC	3.86	3.48	0.38***
IVOL	2.26	3.80	−1.54***
SUE	3.18	3.62	−0.44***
PERC	2.46	4.31	−1.85***
PRIN	3.38	4.88	−1.49***

Notes: This table reports the time-series average of portfolio RSI for each of the 18 anomaly variables and the two composite measures, *PERC* and *PRIN*. In month *t*-1, we sort sample firms into quintiles by a chosen anomaly variable and compute the average RSI for the long leg, the short leg, and the difference in RSI between the two legs in month *t*. We then compute the time-series average of the portfolio RSI. The short and long legs refer to firms that have low and high average returns, respectively. All *t*-statistics are adjusted by Newey and West (1987) for heteroscedasticity and auto-correlation. *, **, and *** indicate statistical significance at the 0.1, 0.05, and 0.01 levels, respectively.

[16] RSI has a skewed distribution. We also use cross-sectional median RSI and find similar results (untabulated).

Table 4
Average measures of short-sale constraint and relative short interest on composite anomalies.

	PERC			*PRIN*		
	Long	Short	Long - Short	Long	Short	Long - Short
Panel A: Average measure of short sale-constraints: market capitalization ($M), institutional ownership, and illiquidity						
MARKETCAP	5234	890	4345***	5946	1971	3975***
IO	0.53	0.41	0.12***	0.60	0.57	0.03***
ILLIQ	0.38	0.79	−0.41***	0.22	0.30	−0.08***
Panel B: Average RSI sorted on *PERC* and *PRIN* by short sales constraints						
MARKETCAP						
Small	1.30	3.06	−1.76***	2.37	3.83	−1.48***
Large	2.50	4.60	−2.10***	3.13	4.55	−1.42***
Large - Small	1.20	1.55	−0.35***	0.80	0.76	0.04
ILLIQ						
Low	2.89	5.96	−3.07***	3.64	5.51	−1.87***
High	1.07	2.26	−1.19***	1.72	2.79	−1.06***
High - Low	−1.82	−3.69	1.88***	−1.94	−2.79	0.84***
IO						
Low	1.28	2.99	−1.71***	2.36	3.83	−1.45***
High	3.80	6.39	−2.59***	4.37	6.06	−1.69***
High - Low	2.52	3.40	−0.88***	2.02	2.28	−0.25**

Notes: This table reports the average RSI by short sales constraints. Short and long legs refer to firms in the bottom and top quintiles of anomalies that have low and high average returns, respectively. In Panel A, we show the results of sample firms sorted into five quintiles by composite anomalies measures of *PERC* and *PRIN*. In Panel B, we report the results of sample firms sorted into three terciles by a chosen short sales constraint proxy, which includes market capitalization (*MARKETCAP*), institutional ownership (*IO*), and illiquidity (*ILLIQ*). We also provide the results of firms sorted into five quintiles by *PERC* and *PRIN*. We use Fama and MacBeth (1973) to compute the average RSI for the long and short legs of composite anomalies measures and the difference between the two legs for the most and least constrained firms, respectively. All *t*-statistics are adjusted by Newey and West (1987) for heteroscedasticity and auto-correlation. *, **, and *** indicate statistical significance at the 0.1, 0.05, and 0.01 levels, respectively.

Asquith et al. (2005) find that the level of short interest is positively related to firm size and institutional ownership (IO), while Drake et al. (2011) find liquidity is positively related to short interest. In Table 4, we examine these three variables that represent short sale constraints. Panel A reports that firms on the short leg of anomalies have smaller market capitalization, lower IO, and higher illiquidity.

To provide further evidence that short sellers use information contained in anomalies in their trading, we examine RSI distribution across the long and short legs of anomalies in the cross-section of short sales constraints. If short sellers exploit anomaly information through shorting (avoiding) firms on the short (long) leg of anomalies, we expect shorting to be more active among firms with less short sales constraints in the cross-section. To examine these conjectures, we first sort firms into terciles by short sales constraints, and then within each tercile, we sort firms into quintiles by *PERC* and *PRIN*, respectively. Panel B of Table 4 reports the average RSI sorted on *PERC* (*PRIN*) by short sale constraints proxied by market capitalization, illiquidity, and IO, respectively. Consistent with the prediction that short sellers' trading on anomalies varies by short sales constraints, more shorting is observed in the least constrained firms than in the most constrained firms. For example, the long-short RSI differential for a hedge portfolio sorted by *PERC* is −2.10% among large-cap firms, −3.07% with low illiquidity firms, and −2.59% with high IO firms. In contrast, the differentials are −1.76% for small-cap firms, −1.19% for high illiquidity firms, and −1.71% for low IO firms. The differences in hedge RSI between the least constrained and the most constrained firms are all significant at the conventional level. Hirshleifer et al. (2011) find a similar pattern on accrual anomaly and interpret it as a short arbitrage of accrual anomaly. Similarly, the result that the short leg of market anomaly has greater RSI than the long leg with the pattern varying with short sale constraints indicates systematic usage of market anomalies by short sellers.

4. Importance of anomalies to short sellers' return performance

The discussion thus far shows that short sellers have larger short positions on the short leg of anomalies than on the long leg. Since the short leg also underperforms the long leg, we expect the RSI-anomaly relation to explain the RSI-return relation in the cross-section. The use of market anomalies in shorting strategies can boost return performance to short sellers if extra alphas can be generated. We use several approaches to analyze this issue, including two sub-portfolio analyses and one regression analysis.

4.1. Overlapping of RSI and anomalies

We first use a naïve but intuitive method to investigate the relation between returns and short sellers' use of anomalies. Specifically, we follow the convention in the literature and only examine firms in extreme portfolios (i.e., the short and long legs of RSI portfolios). For this purpose, among firms on the short leg of RSI (i.e., high RSI), if they are also on the short leg of anomalies, they are defined as overlapping firms; otherwise, they are defined as non-overlapping firms. Among firms on the

Table 5
Returns of Overlapping vs. Non-overlapping Firms and Double-Sorted Portfolios.

Panel A. Overlapping and non-overlapping portfolio returns						
	Raw Ret			CAPM Alpha		
	(1)	(2) *PERC*	(3) *PRIN*	(4)	(5) *PERC*	(6) *PRIN*
High RSI (Short)	0.59			−0.62***		
Overlapping		−0.45	0.61		−1.83***	−0.68**
Non-overlapping		0.99	1.14		−0.14	0.06
Difference		−1.44***	−0.53**		−1.69***	−0.74***
Low RSI (Long)	1.27			0.47**		
Overlapping		1.78	1.83		1.05***	1.04***
Non-overlapping		1.10	1.32		0.48**	0.50***
Difference		0.68***	0.50**		0.57***	0.54**
Low-High (L-S)	0.69***			1.09***		
Overlapping		2.23***	1.22***		2.88***	1.72***
Non-overlapping		0.11	0.19		0.62***	0.44***
Difference		2.12***	1.03***		2.26***	1.28***

Panel B. Returns and alphas on portfolios formed by 5 × 5 independent double sort on RSI and anomaly						
Anomaly Quintiles	High RSI (Short)	2	3	4	Low RSI (Long)	Low-High (Long-Short)
PERC	B.1. Raw Returns					
Short Leg (S)	−0.45	0.08	0.14	0.60	0.40	0.85***
2	0.67	0.86	0.94	1.1	1.04	0.37
3	1.09	1.05	1.19	1.39	1.31	0.22
4	1.06	1.26	1.26	1.47	1.51	0.46***
Long Leg (L)	1.54	1.33	1.30	1.60	1.78	0.24
L-S	1.97***	1.25***	1.16***	1.01***	1.38***	−0.61***
PRIN						
Short Leg (S)	0.60	0.97	0.83	1.01	0.95	0.35
2	1.07	0.92	1.11	1.18	1.37	0.30
3	0.98	1.07	1.3	1.29	1.40	0.43*
4	1.08	1.38	1.07	1.35	1.69	0.61***
Long Leg (L)	1.33	1.19	1.49	1.56	1.83	0.50
L-S	0.73***	0.22	0.65***	0.55***	0.67***	0.15
PERC	B.2. CAPM Alpha					
Short Leg (S)	−1.83***	−1.24***	−1.09***	−0.59**	−0.55**	1.28***
2	−0.59***	−0.30*	−0.17	0.05	0.20	0.78***
3	−0.07	−0.01	0.19	0.45***	0.52***	0.59***
4	0.02	0.28**	0.32**	0.59***	0.75***	0.73***
Long Leg (L)	0.56***	0.42***	0.43***	0.76***	1.06***	0.51***
L-S	2.36***	1.66***	1.52***	1.35***	1.62***	−0.77***
PRIN						
Short Leg (S)	−0.68***	−0.28	−0.39	−0.10	−0.03	0.67***
2	−0.05	−0.17	0.06	0.15	0.47**	0.52**
3	−0.10	0.08	0.35*	0.36**	0.57***	0.67***
4	0.06	0.45**	0.15	0.46***	0.89***	0.82***
Long Leg (L)	0.29	0.27	0.56***	0.67***	1.04***	0.73**
L-S	0.99***	0.55**	0.95***	0.77***	1.07***	0.06

Notes: This table reports raw returns and CAPM alphas to 5 × 5 portfolios formed by independent double sort on RSI and anomalies (*PERC* and *PRIN*). Panel A groups firms in two extreme RSI quintiles into overlapping and non-overlapping firms based on whether the firm is also in an extreme anomaly quintile and reports returns and alphas to high-RSI firms, low-RSI firms, and the low-high portfolio (columns (1) and (4)), as well as returns and alphas for overlapping and non-overlapping firms based on RSI and *PERC* in columns (2) and (4) columns (*PRIN* columns (3) (6)). Panel B reports average returns (upper panel) and alphas (lower panel) for each intersection and hedge portfolios. Among high-RSI firms (i.e., on the short leg of RSI), those that are also on the short leg of anomalies are overlapping firms; otherwise, they are non-overlapping firms. Among low-RSI firms (i.e., on the long leg of RSI), those that are also on the long leg of anomalies are overlapping firms; otherwise, they are non-overlapping firms. We adjust *t*-statistics by Newey and West (1987) for heteroscedasticity and auto-correlation. The short and long legs refer to firms that have low and high average returns, respectively. *, **, and *** indicate statistical significance at the 0.1, 0.05, and 0.01 levels, respectively.

long leg of RSI (i.e., low RSI), if they are also on the long leg of anomalies, they belong to overlapping firms; otherwise, they are defined as non-overlapping firms. Table 5 reports returns based on *PERC* and *PRIN*, where the 1st and 4th columns repeat the RSI-return results from the first row of Table 2 for ease of comparison.

There are several interesting observations. First, among high-RSI firms, overlapping firms always generate larger negative returns than non-overlapping firms. To put this into perspective, short sellers earn an alpha of 62 bps from the heavily shorted stocks, and overlapping firms generate a negative alpha of 183 bps. In contrast, non-overlapping firms, those that are also heavily shorted but not on the short leg of *PERC*, only generate a marginally significant alpha of 14 bps to short sellers.[17] In other words, the negative abnormal returns to high-RSI stocks predominantly occur in extreme losers of *PERC* stocks. This evidence suggests that abnormal negative returns to high RSI firms documented in the literature are almost fully accounted for by short arbitrage of anomalies. These findings suggest that short sellers of the most heavily shorted stocks are informed of market anomalies. Note that the majority of the most heavily shorted firms are not on the short leg of anomalies (i.e., non-overlapping firms), although these firms have similar high short interests to overlapping firms. To the extent that short positions are built on short sellers' bearish information, the heavy short positions in non-overlapping firms are likely driven by non-anomaly (bearish) information. Such non-anomaly information, which in aggregate appears noisy and not return predictive, generates higher short interest and lower returns on the short leg of the RSI compared to stocks on the long leg of RSI. The importance of this non-anomaly information for the RSI-return relation is explored in the Fama-MacBeth regression analysis in our third test.

Second, among low-RSI firms, overlapping firms generate more positive alphas than non-overlapping firms. Recall that the least shorted firms on average have a positive alpha of 47 bps. Among the least shorted firms, those that are also on the long leg of *PERC* are overlapping firms and have a positive alpha of 105 bps, which is 57 bps higher than the alpha from the firms that are not on the long leg of *PERC*, or non-overlapping firms. To the extent the positive alpha on the long leg of RSI represents the losses short sellers avoid by not having a large short position on these firms, most of the losses that can be avoided are from avoiding firms that are also on the long leg of anomalies. Short sellers' choice on what stocks to avoid is largely driven by their use of market anomalies to identify underpriced stocks. We note that non-overlapping firms still have a significant alpha of 48 bps. This is different from the short leg of RSI; the long-leg RSI has return-predictive information beyond and above anomalies.

Third, the hedge spread in alpha of least-minus-most shorted stocks is 109 bps over the entire sample period, with 288 bps among the overlapping firms and 62 bps among the non-overlapping firms. These returns are all significant at the 1% level. As a result, the negative RSI-return relation documented in the literature is mainly driven by firms that are on the long and short legs of market anomalies.

4.2. Double-sorted portfolios formed on RSI and anomalies

Overall, the first test in Subsection 4.1 solely examines the two extreme RSI portfolios and shows that the return predictability of RSI is mostly driven by firms in the extreme anomaly portfolios. While this test is intuitive and straightforward, a substantial amount of information contained in RSI for average firms that are not in extreme portfolios is not captured. In the second test, we extend the analysis to all RSI portfolios by sorting sample firms by RSI and anomalies into 5×5 subsets. We report results on these 25 portfolios and the hedge portfolios in Panel B or Table 5.

A couple of interesting results emerge. First, the anomaly-return relation is significant across all RSI quintiles and is most evident among high RSI portfolio. For stocks having the same level of RSI, short sellers who use anomalies to short overpriced stocks and avoid underpriced stocks generate good performance. For example, Panel B.2 shows that for stocks in the second highest RSI quintile, those on the short (long) leg of *PERC* earn a significant negative (positive) alpha of 124 bps *PERC*(42 bps). Therefore, anomaly signals can benefit short sellers in building short positions in firms even when these firms are not the most or least shorted. Accordingly, the importance of anomalies for the return predictability of RSI uncovered in the first test is not limited to extreme RSI firms.

Second, stock returns nearly monotonically decrease in RSI for each anomaly quintile so that the RSI-return is always negative even for stocks that are not in extreme portfolios. For example, Panel B.2 shows that for stocks in the second quintile of *PERC*, stocks in the second highest RSI have a negative alpha of 30 bps, and stocks in the second lowest RSI have an alpha of 5 bps. From the overlapping analysis on the most shorted stocks in our first test, it is tempting to conclude that stock-picking skills beyond applying anomaly-based equity strategies is not important for shorting. In fact, there is a substantial variation of returns in the cross-section of stocks along either RSI or anomalies dimension. The RSI-return relation is strongest on the short leg of anomalies. Therefore, even among stocks that are the most overpriced by anomaly signals, the RSI is not equally return predictive. On the short leg of *PERC*, short sellers can earn 124 bps alpha from shorting stocks with second highest RSI and can only earn 59 bps alpha from shorting stocks with second lowest RSI, as shown in Panel B.2. Therefore, to determine the right stocks to short among stocks with same anomaly signals is still an important skill for shorting performance. Moreover, stocks in the same quintile of anomalies have different RSI levels by construction. For example, on the short leg of *PERC*, stocks in the five RSI quintiles have a range of RSI from a high of 10.26% to a low of 0.21% (untabulated). The difference in RSI across stocks conditional on anomalies is likely due to non-anomaly information. It is thus interesting to see how important such non-anomaly information is for the RSI-return relation, an issue explored in the third test (i.e., the FM regression analysis).

[17] The two numbers, 183 and 14, do not average to 62 because the average returns to two portfolios are not equal to the returns to a single portfolio where these two are combined. Also note that sample firms are sorted into five quintiles separately by RSI and anomalies to form overlapping and non-overlapping portfolios.

We also compute the alpha for each RSI quintile averaged across five *PERC* quintiles and then compute the hedge alpha spread for the low-minus-high RSI quintiles. The resulting anomaly-neutral hedge alpha spread is 77 bps (t-stat. = 5.03, untabulated). That is, the negative RSI-return relation is not limited to extreme firms and is also independent of anomalies. This evidence suggests that the cross-sectional RSI has return predictive information above and beyond anomalies, supporting the view that short sellers are informed (Diamond and Verrecchia, 1987).

4.3. Fama-MacBeth regression of RSI on anomalies

Our third test is Fama-MacBeth regressions of RSI on anomalies. We use a two-stage method to draw inferences on the relative importance of anomaly signals for short selling activity and associated return performance. In the first stage, we use a parsimonious model to quantify the short selling activity arising from anomalies in the cross-section. In particular, we regress RSI on the return predictive information contained in anomaly variables, and in the second stage we examine portfolio returns sorted on residual RSI which, by construction, represents shorting driven by information other than anomalies. If the negative (positive) abnormal returns of high (low) RSI firms and the negative RSI-return relation are only driven by trading on the information contained in anomalies, residual RSI should have little return predictability. If short sellers use additional information other than these anomalies, residual RSI should still predict future returns.

Panel A of Table 6 reports the FM regression results. RSI is regressed on anomalies and control variables including Log(*MARKETCAP*), Log(*ILLIQ*), *CONVERTIBLE* dummy, and *IO*.[18] We standardize *PERC* by dividing the decile rank of *PERC* (0–9) by 10 to obtain a standardized measure between 0 and 1. *PRIN*, by construction, is standardized between 0 and 1. We note two important results. First, anomaly information contained in anomalies (represented by *PERC* or *PRIN*) is a significant determinant of RSI. For example, the coefficient estimate of *PERC* is −2.75 and significant at 1% level. For a one standard deviation change in *PERC* (i.e., 0.28), the associated change in RSI is equal to 24% of the sample RSI mean, or nearly 20% of sample standard deviation of RSI. Second, the average adjusted R-squared is 13.59% for *PERC* and 11.79% for *PRIN*, suggesting that anomalies can explain a significant part of the cross-sectional variation of RSI. These results further support our conjecture that short sellers skillfully use common equity strategies.

We next examine the RSI-return relation after controlling for anomalies. Specifically, we form quintile portfolios each month based on the residual RSI and examine the RSI-return relation. Panel B.2 of Table 6 reports the raw returns and alphas to portfolios sorted on residual RSI. The hedge alpha spread is 43 bps by residual RSI from regressing (raw) RSI on *PERC*,

Table 6
Fama-MacBeth regression of relative short interest on anomalies.

Panel A. Fama-MacBeth Regression of RSI on Anomalies

	PERC		*PRIN*	
	Coef	t-stat	Coef	t-stat
Anomalies	−2.75***	(−22.15)	−0.59***	(−11.29)
Log(MARKETCAP)	−0.13***	(−3.94)	−0.26***	(−6.23)
CONVERTIBLE	1.15***	(9.46)	0.92***	(4.90)
Log(ILLIQ)	−0.35***	(−10.24)	−1.20***	(−7.35)
IO	5.12***	(12.08)	5.59***	(11.77)
Intercept	2.40***	(15.43)	1.69***	(8.96)
Avg. Nobs	2623		2623	
Avg. Adj. R^2 (%)	13.59		11.79	

Panel B. Returns to portfolios sorted on residual RSI without/with controlling for predicted RSI

Sorted on:	Raw Ret			CAPM alpha		
	Long (Low)	Short (High)	L-S (L-H)	Long (Low)	Short (High)	L-S (L-H)
			B.1. Sorted on raw RSI			
Raw RSI	1.27	0.59	0.69***	0.47 b	−0.62***	1.09***
			B.2. Sorted on residuals from regressing RSI on *PERP*			
Residual RSI Control for	0.99***	0.68*	0.31***	−0.04	−0.47***	0.43***
predicted RSI	1.09***	0.71*	0.38***	0.16	−0.42**	0.57***
			B.3. Sorted on residuals from regressing RSI on *PRIN*			
Residual RSI Control for	1.25***	0.96***	0.29**	0.22	−0.15	0.37***
predicted RSI	1.35***	0.99***	0.36***	0.40**	−0.10	0.50***

Notes: Panel A reports Fama-MacBeth regression of RSI on composite measures of anomalies and control variables. Anomalies refer to *PERC* and *PRIN* constructed from the 18 anomaly variables and standardized between 0 and 1. Panel B reports raw returns and CAPM alphas to portfolios sorted on raw RSI, residual RSI, and residual RSI controlling for predicted RSI. All t-statistics are adjusted by Newey and West (1987) for heteroscedasticity and auto-correlation. *, **, and *** indicate statistical significance at the 0.1, 0.05, and 0.01 levels, respectively.

[18] We also use log transformed RSI as dependent variables since RSI distribution is highly skewed. We obtain similar results (not reported).

representing a decrease of 60% in the hedge alpha spread sorted by raw RSI (109 bps) reported in Panel B.1. Since these 18 anomalies are likely to be a subset of public information used by short sellers, these estimates provide a lower bound on the role of public information in explaining the RSI-return relation. These estimates suggest that at least 60% of the RSI-return relation can be explained by public financial information in these anomalies; other information beyond these anomalies used by short sellers at most accounts for 40% of the return performance.

Since residual RSI and predicted RSI are mechanically connected, a single sort on residual RSI may not fully exclude anomaly information in the cross-section of RSI. To alleviate this concern, we first sort firms into quintiles by predicted RSI, and then within each quintile, we further sort firms into quintiles by residual RSI. We then average the returns across five predicted RSI quintiles to compute returns to each residual RSI portfolios. This way, each of the five residual RSI portfolios has the same level of predicted RSI. Panel B.3 of Table 6 reports the results. About 47% of RSI-return relation is explained by these anomalies when we use *PERC* to proxy for anomalies. Overall, these findings show that the public information contained in anomalies can explain a significant portion of, but cannot fully explain, the RSI-return relation in the cross-section and short sellers appear to use non-anomaly information to generate additional abnormal returns. The return predictability of residual RSI indicates that RSI can reveal useful information to other market participants beyond these anomalies.[19]

Table 7
Shorting and future earnings surprise, analyst revision, and analyst recommendation change.

	Anomaly = *PERC*			Anomaly = *PRIN*	
	Model 0	Model 1	Model 2	Model 3	Model 4
			Panel A. Analyst Forecast Revision		
RSI	−2.91*** (−12.22)	−1.20*** (−6.02)	−4.55*** (−8.95)	−2.37*** (−8.82)	−4.04*** (−8.07)
Anomalies		1.15*** (24.59)	0.93*** (17.88)	0.63*** (8.98)	0.48*** (7.76)
RSI x Anomalies			7.61*** (9.17)		3.78*** (3.73)
Log(MARKETCAP)	0.11*** (24.45)	0.05*** (12.90)	0.06*** (14.37)	0.07*** (16.51)	0.07*** (17.74)
IO	0.15*** (4.92)	−0.02 (−0.66)	−0.05 (−1.55)	0.01 (0.40)	−0.01 (−0.18)
Intercept	−1.13*** (−26.66)	−1.33*** (−26.06)	−1.24*** (−23.66)	−1.15*** (−18.12)	−1.09*** (−18.51)
Avg. Nobs	1716	1716	1716	1716	1716
Avg. Adj. R^2 (%)	3.59	9.16	9.65	7.51	8.09
			Panel B. Analyst Recommendation Change		
RSI	−20.63*** (−11.32)	−5.69*** (−3.52)	−17.84*** (−5.85)	−10.43*** (−4.00)	−13.31*** (−3.09)
Anomalies		9.42*** (13.05)	8.45*** (11.32)	4.51*** (7.30)	4.18*** (5.75)
RSI x Anomalies			27.41*** (4.76)		6.79 (1.12)
Log (MARKETCAP)	1.23*** (12.32)	0.78*** (9.27)	0.80*** (9.54)	1.02*** (10.51)	1.03*** (10.40)
IO	2.22*** (5.36)	0.79**b (2.01)	0.69* (1.75)	1.32** (2.55)	1.29** (2.50)
Intercept	−12.54*** (−16.46)	−14.55*** (−17.48)	−14.10*** (−16.63)	−13.13*** (−14.87)	−13.01*** (−14.28)
Avg. Nobs	2234	2234	2234	2234	2234
Avg. Adj. R^2 (%)	1.09	2.26	2.28	1.61	1.61
			Panel C. Standardized Unexpected Earnings		
RSI	−5.55*** (−6.30)	−2.87*** (−3.24)	−14.72*** (−6.45)	−4.20*** (−3.39)	−8.64*** (−3.22)
Anomalies		1.82*** (10.17)	1.10*** (5.08)	1.70*** (5.31)	1.22*** (4.12)
RSI x Anomalies			26.61*** (7.53)		9.99** (2.34)
Log (MARKETCAP)	0.06** (2.34)	−0.02 (−0.75)	−0.01 (−0.52)	0.08*** (6.92)	0.09*** (6.88)
IO	−0.77*** (−4.27)	−0.97*** (−5.53)	−1.04*** (−5.80)	−0.15 (−1.03)	−0.17 (−1.18)
Intercept	0.35* (1.82)	−0.19 (−0.83)	0.19 (0.78)	−1.38*** (−7.11)	−1.18*** (−6.66)
Avg. Nobs	2356	2356	2356	2356	2356
Avg. Adj. R^2 (%)	0.2	0.7	0.8	1.72	2.07

Notes: This table reports Fama-MacBeth regression of future earnings surprise (*SUE*), analyst revision (*FRV*), and analyst recommendation change (Recommendation Change) on RSI, anomaly, and the interaction term. RSI is relative short interest in month *t*. Anomalies refer to *PERC* and *PRIN* constructed from the 18 anomaly variables constructed in month *t*-1 and standardized between 0 and 1. Analyst recommendation change is the 6-month change in mean recommendation from IBES scaled by 6-month-ago mean recommendation. *FRV* is the mean analyst EPS forecast for the closest quarter minus the mean analyst forecast 6-month ago, then scaled by stock price. *SUE* is the EPS released during a 3-month period starting from $t+1$ for the closest quarter minus EPS four quarters ago, then scaled by stock price in announcement month. All dependent variables are constructed in month $t+1$. The two control variables, Log(*MARKETCAP*) and *IO*, are constructed in month *t*. The sample period is from 1988 to 2014 for all models except for analyst recommendation change, which starts from 1994 due to data availability. All *t*-statistics (in parentheses) are adjusted by Newey and West (1987) for heteroscedasticity and autocorrelation. *, **, and *** indicate statistical significance at the 0.1, 0.05, and 0.01 levels, respectively.

[19] Note that the portion of the RSI-return relation not explained by our proxies for market anomalies cannot be entirely contributed to shorters' private information. It's possible that shorters may also use other known market anomalies in their shorting strategies that we have not included.

4.4. Shorting and future earnings

Both anecdotal evidence and academic studies suggest that short sellers may be privy to private information and trade before the release of such information.[20] Guo and Wu (2018) suggest that short sellers are often informed about the future profit margins of firms. Boehmer et al. (2019) find heavier shorting before negative earnings surprises, analyst downgrades, and downward revisions in analyst earnings forecasts. In contrast, Engelberg et al. (2012) find that short sellers' trading advantages largely come from their superior ability to process publicly available information. The above-mentioned studies typically examine shorting activities around specific corporate events, and do not systematically consider market anomalies as a possible information source.

We show that public information proxied by equity anomalies is an important information source for short sellers. To reconcile our evidence with previous studies, we hypothesize that short sellers' informativeness about future earnings is largely derived from their active use of market anomalies. This hypothesis is motivated by many studies that find anomalies signal future earnings. Jiang et al. (2009) find that *IVOL* is inversely related to future earning shocks. Engelberg et al. (2019) find that anomalies predict changes in analysts' price targets and recommendations in a direction that the long (short) leg has increases (decreases) in price targets and recommendations. These findings suggest that the return predictive power of many anomalies is likely induced by their information content about future earnings and analyst actions. As a result, the use of anomalies will enhance short sellers' informational advantage and boost their performance.

To test this hypothesis, we run a Fama-MacBeth regression of future earnings surprises and analyst recommendation changes on RSI and anomalies controlling for IO and size. We construct three dependent variables for month $t+1$ including *FRV* (analyst forecast revision), analyst recommendation change, and *SUE* (earnings surprise), and regress each on RSI (measured in month t) and anomalies (measured in t-1).[21] In Table 7, the baseline model is Model 0. For all three dependent variables, the coefficient on RSI is always significant and negative, indicating that short interest contains negative information about future earnings surprises, as well as analyst forecasts and recommendations, consistent with Boehmer et al. (2019) and Guo and Wu (2018). In Models 1 and 3, we include anomalies in the regression. We find that the coefficients on *PERC* and *PRIN* are positive and significant. This is in general consistent with previous findings that anomalies are predictive of future earnings surprises and analyst actions (e.g., Christophe et al., 2004). Moreover, the coefficient on RSI, while significant and negative, is substantially reduced in magnitude. For example, in Panel A, the coefficient on RSI is cut by more than 50% from -2.91 in Model 0 to -1.20 in Model 1. This indicates that a significant portion of short sellers' informativeness of future analyst revisions is from the use of anomalies in their trading strategy. In Models 2 and 4, we include an interaction term of RSI and anomalies. We find that the coefficients on RSI and anomalies remain significant. Interestingly, the coefficient on the interaction term is consistently significant and positive, indicating that for firms with the same level of RSI, a decrease in anomalies, that is, a change from the long leg of anomalies toward the short leg, will worsen the negative predictability of RSI about future earnings surprises, as well as analyst revisions and recommendations. We also conduct FM regression analysis for each RSI quintile. The above findings are more evident among firms with high RSI (untabulated). While interesting, it is beyond the scope of this study to determine what non-anomaly information short sellers use to generate returns. Our message is that public information as proxied by anomalies helps short sellers predict the change in future fundamentals and analyst actions.

5. Sub-period analysis

Given that anomalies appear to attenuate over time (Green et al., 2011; McLean and Pontiff, 2016) due to a likely "crowded trade" effect when sophisticated investors happen to follow common trading strategies (Stein, 2009), and anomalies change with time-varying market sentiment (Baker and Wurgler, 2006; Stambaugh et al., 2012), we examine whether and how short sellers change their use of market anomalies over time and what is the effect of this change, if any, on the RSI-return relation.

5.1. Early and recent periods

We first divide the full sample period into two equal periods: 1988–2000 (the early period) and 2001–2014 (the later period). We find that the majority of anomaly variables decline in magnitude over time (untabulated). The average RSI increases from 1.46% in the early period to 4.85% in the later period. We also find that the negative alpha on the short leg, while statistically and economically significant in the early period, becomes significantly smaller during the recent period. In addition, in the early period, the hedge alpha spread is mostly driven by the short leg; in the later period, more hedge alpha spread is driven by the long leg. This begs the question of whether short arbitrage of the anomaly that usually involves shorting firms on the short leg of anomalies contributes to the diminishing alpha on the short leg of these anomalies during

[20] For example, see Desai et al. (2002), Christophe et al. (2004), Desai et al. (2006), Christophe et al. (2010), and Henry et al. (2015).

[21] For analyst recommendation changes, we change the sign of the mean recommendation measure in *IBES* so that a greater value of the change in recommendation signifies an analyst upgrade. All dependent variables are monthly updated. We also use *ROE* as the dependent variable and obtain similar results (unreported). We also note that the number of observations in this *FM* regression is less than in previous tests due to the data availability of analyst forecasts and recommendations.

Table 8
CAPM Alphas for Overlapping vs. Non-overlapping Firms: Early and Later Period.

	Early Period (1988–2000)			Later Period (2001–2014)			*t*-stat (Later-Early)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
		PERC	*PRIN*		*PERC*	*PRIN*		*PERC*	*PRIN*
High RSI (Short)	−1.00***			−0.27			1.96		
Overlapping		−2.69***	−1.00***		−1.04***	−0.36		3.04	1.22
Non-overlapping		−0.36	−0.08		0.07	0.23		1.31	1.06
Difference		−2.33***	−0.93***		−1.11***	−0.59**		3.34	0.81
Low RSI (Long)	0.06			0.87[a]			2.92		
Overlapping		0.71**	0.66**		1.37***	1.41***		2.55	1.91
Non-overlapping		−0.13	0.27		0.68***	0.76***		2.76	1.59
Difference		0.84***	0.39		0.69***	0.65**		−0.81	0.69
Low-High (L-S)	1.06***			1.14[a]			0.28		
Overlapping		3.40***	1.67***		2.42***	1.77***		−1.88	0.18
Non-overlapping		0.23	0.35*		0.61***	0.53**		1.45	0.56
Difference		3.17***	1.32***		1.80***	1.24***		−2.87	−0.12

Notes: This table reports portfolio CAPM alphas to portfolios formed on RSI (1st and 4th columns), the alphas for overlapping and non-overlapping firms based on RSI and anomalies (*PERC* and *PRIN*) for the early period (2–3 columns) and the later period (5–6 columns), and the *t*-statistics for the difference in alphas between the two periods (7–9 columns). Among high-RSI firms (i.e., on the short leg of RSI), those that are also on the short leg of *PERC* and *PRIN* are overlapping firms; otherwise, they are non-overlapping firms. Among low-RSI firms (i.e., on the long leg of RSI), those that are also on the long leg of *PERC* and *PRIN* are overlapping firms; otherwise, they are non-overlapping firms. We adjust *t*-statistics for portfolios formed in each period by Newey and West (1987) for heteroscedasticity and auto-correlation and use *, **, and *** indicate statistical significance at the 0.1, 0.05, and 0.01 levels, respectively.

the later period. To answer this question, we examine the average RSI on the long and short legs of each anomaly during the early and later periods respectively. We find that the negative hedge RSI spread increases significantly from the early to the later period for these anomalies. Since the short leg of most anomalies also has a diminished alpha over time, such an increase seems consistent with the view that significantly more shorting activity can make market anomalies less evident over time (Green et al., 2011).

To see whether and how the change in anomalous returns over time affects abnormal returns to short sellers (i.e., the returns to high RSI firms) and the negative RSI-return relation, we turn to the overlapping approach again and examine the respective contribution of overlapping and non-overlapping firms to the RSI-return relation during the early and later periods separately. The results are reported in Table 8. First, the RSI-return relation remains unchanged over time, with a hedge alpha spread (L-S) by RSI of 106 bps in the early period and 114 bps in the later period. However, this relation is driven by the short leg of the RSI in the early period (−100 bps in column (1)), but is mostly driven by the long leg of RSI in the later period (87 bps in column (4)). The change in alpha over time is significant on each leg. Also, short sellers do not earn abnormal returns from their short positions on the short leg of the RSI in later years. The return predictive information revealed through the RSI is important only in stocks that are heavily shorted during the early period and only in stocks that are avoided by short sellers during the later period.

Second, among high-RSI firms, during each period, overlapping firms always generate larger negative stock returns than non-overlapping firms. Moreover, the negative alpha on these firms is driven by overlapping firms. Even though high-RSI firms have an insignificant alpha of −0.27 during the later period, short sellers still earn 104 bps from their short positions in firms on this leg that are also on the short leg of *PERC*. Therefore, the use of anomaly strategies by short sellers continues to generate extra returns for short sellers during the later period.

Third, among low-RSI firms, overlapping firms generate significantly more positive alphas than non-overlapping firms in both periods; non-overlapping firms do not generate a significant alpha in the early period but have a significant one in the later period. For example, firms that are least shorted and also on the long leg of *PERC* have no significant alpha during the early period but have a significant alpha of 68 bps (column (5)) during the later period. In the later period, the RSI generates a hedge alpha spread of 114 bps (column (4)), with a spread of 242 bps (column (6)) for overlapping firms and 61 bps (column (6)) for non-overlapping firms. This evidence indicates that while anomalies fully explain the RSI-return relation in the early period, they cannot in the later period and RSI has increasingly more return predictive information beyond market anomalies over time. While market anomalies continue to be an important equity strategy for short sellers to avoid shorting the wrong firms, short sellers start using non-anomaly return-predictive information to locate good firms and build less short positions.[22]

[22] Andrew Lo, an expert on the hedge fund industry, comments that "the whole hedge fund industry is a series of crowded trades." (Strasburg and Pulliam, January 14, 2011, *The Wall Street Journal*). Lewellen (2011), Titman and Tiu (2011), Sun et al. (2012), and Amihud and Goyenko (2013) show that trading strategy uniqueness is important for investment performance.

Table 9
Fama-MacBeth regression of relative short interest on anomalies: Early and later period.

Panel A. Fama-MacBeth Regression of RSI on Anomalies

	PERC				*PRIN*			
	Early Period (1988–2000)		Later Period (2001–2014)		Early Period (1988–2000)		Later Period (2001–2014)	
	Coef	*t*-stat	Coef	*t*-stat	Coef	*t*-stat	Coef	*t*-stat
Anomalies	−1.93***	(−17.38)	−3.50***	(−25.31)	−0.42***	(−9.97)	−0.75***	(−8.66)
Log(MARKETCAP)	0.11***	(5.35)	−0.34***	(−9.84)	0.04	(1.78)	−0.54***	(−10.94)
CONVERTIBLE	0.89***	(6.35)	1.39***	(7.41)	1.57***	(6.81)	0.32**	(1.25)
Log(ILLIQ)	−0.11***	(−11.85)	−0.57***	(−13.06)	−0.18***	(−12.04)	−2.13***	(−9.09)
IO	1.66***	(13.26)	8.27***	(21.47)	1.67***	(10.41)	9.16***	(22.64)
Intercept	1.20***	(17.35)	3.50***	(22.34)	0.57***	(4.23)	2.72***	(10.81)
Avg. Nobs	2898		2376		2898		2376	
Avg. Adj. R^2 (%)	7.52		19.13		6.52		16.60	

Panel B. CAPM alphas to hedge portfolio sorted on residual RSI and on residual RSI controlling for predicted RSI

Sorted on:	Early Period (1988–2000)			Later Period (2001–2014)			*t*-stat (Later- Early)		
	Long (Low)	Short (High)	L-S (L-H)	Long (Low)	Short (High)	L-S (L-H)	Long (Low)	Short (High)	L-S (L-H)
Raw RSI	0.06	−1.00***	1.06***	0.87***	−0.27	1.14***	2.92	1.96	0.28
	Sorted on residuals from regressing RSI on *PERC*								
Residual RSI	−0.48*	−0.79***	0.31*	0.39**	−0.17	0.55***	2.85	1.75	1.12
Control for predicted RSI	−0.23	−0.75***	0.52***	0.54***	−0.11	0.65***	2.64	1.82	0.62
	Sorted on residuals from regressing RSI on *PRIN*								
Residual RSI	−0.30	−0.04	0.26	0.52**	0.04	0.48***	1.86	1.08	0.90
Control for predicted RSI	−0.22	0.24	0.46**	0.61***	0.06	0.55***	1.28	0.89	0.38

Notes: Panel A reports Fama-MacBeth regression of RSI on composite measures of anomalies and control variables during early and later periods. Anomalies refer to *PERC* and *PRIN* constructed from the 18 anomaly variables and standardized between 0 and 1. Panel B reports CAPM alphas to portfolio sorted on residual RSI and alphas to portfolios sorted on residual RSI after controlling for predicted RSI for the early and later periods, respectively, and the *t*-statistics for the difference in alphas between the two periods. We adjust *t*-statistics in each period by Newey and West (1987) for heteroscedasticity and autocorrelation. *, **, and *** indicate statistical significance at the 0.1, 0.05, and 0.01 levels, respectively.

Panel A of Table 9 reports the Fama-MacBeth regression results for the early and later periods. The first striking result is that the adjusted R-squared increases from period to period by more than 10 percentage points, indicating anomalies become a more important determinant of RSI in the cross-section over time. Second, the coefficient estimates of *PERC* and *PRIN* are always significant in both periods. We notice that both the mean and standard deviation of RSI increase over time, making the value of the coefficient not directly comparable between these two periods, but we can still gauge the change in the importance of market anomalies for RSI over time. For example, when using *PERC* to proxy for anomalies, a change of one standard deviation in *PERC* (i.e., 0.28) is associated with changes of 0.54% and 0.98% in RSI, which are around 20% of the sample standard deviation in the early and later periods, respectively. Together, market anomalies continue to be an important equity strategy for short sellers during the later period when these anomalies become better known to the market.

Panel B reports the CAPM alphas for portfolios sorted on residual RSI during both periods. Overall, anomalies can explain less of the hedge alpha spread generated by (raw) RSI in recent period. While anomalies still affect shorting strategies and contribute to the RSI-return relation, shorters start to use non-anomaly return-predictive information in the later period. As a result, the contribution of non-anomaly information to the RSI-return relation becomes increasingly more important over time.

5.2. Before and after academic publication of anomalies

We now use the academic publication date to examine the impact of anomalies on RSI during the before and after publication periods respectively. To have a meaningful analysis, we require at least 60 monthly observations for the pre- and post-publication periods.[23] This requirement excludes SUE from the analysis since this anomaly is first published in 1960s (Ball and Brown, 1968). When examining the temporal changes around the publication, these two composite measures are updated to reflect the availability of a certain anomaly variable. In particular, we use all the anomalies that have (not) been published until month *t* to construct the after-publication (before-publication) composite measures for that month. These

[23] If an anomaly is initially mentioned in early studies but only becomes better recognized in later years, we use the more recent publication date. A typical example is the BM ratio. Stattman (1980) and Rosenberg et al. (1985) show that firms with high BM ratios have higher returns than those with low BM ratios, but BM anomaly only became more prominent after the Fama and French (1993a, 1993b) paper.

Table 10
Fama-MacBeth regression of relative short interest on anomalies: Before and after publications.

Pane A. Fama-MacBeth Regression of RSI on Anomalies

	PERC				*PRIN*			
	Pre-Publication		Post-Publication		Pre-Publication		Post-Publication	
	Coef	*t*-stat	Coef	*t*-stat	Coef	*t*-stat	Coef	*t*-stat
Anomalies	−2.14***	(−24.58)	−2.91***	(−23.85)	−0.57***	(−13.64)	−0.67***	(−13.72)
Log(MARKETCAP)	−0.09*	(−1.84)	−0.19***	(−5.56)	−0.13***	(−3.18)	−0.35***	(−6.81)
CONVERTIBLE	1.01***	(7.37)	1.34***	(9.45)	1.29***	(6.55)	1.01***	(4.97)
Log(ILLIQ)	−0.34***	(−7.36)	−0.41***	(−10.45)	−0.41***	(−8.54)	−1.46***	(−6.77)
IO	4.10***	(8.63)	6.06***	(13.40)	4.19***	(8.60)	6.59***	(12.94)
Intercept	1.95***	(10.10)	2.76***	(17.67)	1.08a***	(6.09)	2.19***	(10.03)
Avg. Nobs	2516		2790		2516		2790	
Avg. Adj. R^2 (%)	11.69		15.12		11.46		13.24	

Panel B. CAPM alphas to hedge portfolio sorted on residual RSI and on residual RSI controlling for predicted RSI

Sorted on	Pre-Publications			Post-Publications			*t*-stat (Post-Pre)		
	Long (Low)	Short (High)	L-S (L-H)	Long (Low)	Short (High)	L-S (L-H)	Long (Low)	Short (High)	L-S (L-H)
Raw RSI	0.51**	−0.71***	1.23***	0.56***	−0.62***	1.19***	0.21	0.29	−0.17
	Sorted on residuals from regressing RSI on *PERP*								
Residual RSI	0.06	−0.59***	0.65***	0.13	−0.55***	0.68***	0.30	0.15	0.16
Control for predicted RSI	0.29	−0.52**	0.81***	0.27	−0.48**	0.76***	−0.09	0.11	−0.29
	Sorted on residuals from regressing RSI on *PRIN*								
Residual RSI	0.28	−0.20	0.48***	0.34*	−0.42**	0.76***	0.22	−0.82	1.47
Control for predicted RSI	0.53**	−0.19	0.73***	0.42**	−0.37*	0.79***	−0.46	−0.65	0.35

Notes: Panel A reports Fama-MacBeth regression results of RSI on composite measures of anomalies and control variables during the pre- and post-publication periods. Anomalies refer to *PERC* and *PRIN* constructed from the 18 anomaly variables and standardized between 0 and 1. Panel B reports portfolio results CAPM alphas sorted on residual RSI, alphas sorted on residual RSI, controlling for predicted RSI, for pre- and post-publication periods, respectively, and the *t*-statistics for the difference in alphas between the two periods. We adjust *t*-statistics in each period by Newey and West (1987) for heteroscedasticity and auto-correlation. *, **, and *** indicate statistical significance at the 0.1, 0.05, and 0.01 levels, respectively.

composite measures can reflect the evolution of capital market anomalies and thus represent the lower boundary of public financial information available to short sellers in a dynamic manner.[24]

We first examine portfolio returns sorted on composite measures of *PERC* and *PRIN*. Untabulated results show that by these two measures, we do not find a significant drop in hedge alpha spread after academic publication. We also examine average RSI for the long leg, short leg, and the hedge RSI spread of *PERC* and *PRIN* around academic publication. The hedge spread in RSI for long-short portfolios formed on these two measures are negative and significant in all periods. More importantly, the hedge spread becomes larger in the post-publication period. Such an increase provides additional evidence that short sellers increasingly use anomaly information in their shorting strategies. This result is also consistent with the view that short sellers learn from published mispricings (McLean and Pontiff, 2016).

We also compute CAPM alphas to overlapping and non-overlapping firms before and after publication periods. For this purpose, we relate *PERC* and *PRIN* for each firm-month observation to RSI and stock return in the cross-section. As a result, the RSI-return relation during pre- and post-publication periods just corresponds to the pre- and post-publication of these two composite measures during each period. We find (untabulated) that both the long and short legs of RSI have significant alphas during each period and the RSI-return relation does not change around publication. Further, among high-RSI firms, overlapping firms always generate significantly larger negative stock returns than non-overlapping firms and completely explain the negative alphas to the short leg of RSI. Among low-RSI firms, overlapping firms always generate significantly more positive alphas than non-overlapping firms during each period; however, non-overlapping firms also have significant positive alpha during each period. Overall, this evidence suggests that the academic publication does not reduce the importance of the anomalies for shorting performance.

We conduct further Fama-MacBeth regressions and use a two-stage method to draw inferences on the relative importance of anomaly signals for short selling activity and associated return performance over time. Panel A in Table 10 reports the regression results. The average R-squared increased 2%–4% from the pre- to post-publication periods when using either *PERC* or *PRIN* to proxy for anomalies. *PERC* explains 38% (35%) of the mean RSI during the pre-publication (post-publication) period. A one standard deviation change in *PERC* is associated with a change of 16% (18%) of standard deviation in RSI during the pre-publication (post-publication) period. Panel B reports portfolio alphas sorted on the residual RSI. While the hedge alpha of the residual RSI generally increases over time, the increase is insignificant. For example, when using *PERC* to proxy for public information, the residual RSI generates a 65 (68) bps hedge alpha before (after) academic publication. Importantly, the

[24] By construction, during some months we will have both before-publication and after-publication measures of these composite variables, with each measure constructed from a different set of anomalies based on each anomaly's publication date.

Table 11
CAPM Alphas for Overlapping vs. Non-overlapping Firms across Market Sentiment.

	Low Sentiment			High Sentiment			*t*-stat (High −Low)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
		PERC	*PRIN*		*PERC*	*PRIN*		*PERC*	*PRIN*
High RSI (Short)	−0.35*			−0.92***			−1.84		
Overlapping		−1.22***	−0.53*		−2.48***	−0.80***		−2.25	−0.49
Non-overlapping		0.01	−0.32		−0.31	−0.93***		−0.95	−1.63
Difference		−1.23***	−0.21		−2.17***	0.14		−2.50	−1.09
Low RSI (Long)	0.33			0.61**			0.97		
Overlapping		0.78***	0.81**		1.31***	1.22***		1.99	1.06
Non-overlapping		0.18	0.31***		0.38	0.59**		0.65	0.94
Difference		0.61***	0.50**		0.93***	0.64**		1.81	0.40
Low-High (L-S)	0.68***			1.53***			−2.93		
Overlapping		2.00***	1.34***		3.79***	2.02***		3.43	1.16
Non-overlapping		0.16	0.63***		0.69***	1.52***		1.97	3.11
Difference		1.84***	0.71*		3.10***	0.50*		2.62	−0.42

Notes: This table reports portfolio CAPM alphas to portfolios formed on RSI (1st and 4th columns), the alphas for overlapping and non-overlapping firms based on RSI and anomalies (*PERC* and *PRIN*) for low market sentiment (2−3 columns) and high sentiment (5−6 columns), and the *t*-statistics for the difference in alphas between the two (7−9 columns). We sort sample firms into five quintiles by anomalies and separately by RSI and divide the full sample period into low and high sentiment periods based on orthogonalized sentiment index (Baker and Wurgler, 2006) in month *t* and compute average portfolio returns in month *t*+1. Among high-RSI firms (*i.e.*, on the short leg of RSI), those that are also on the short leg of *PERC* and *PRIN* are overlapping firms; otherwise, they are non-overlapping firms. Among low-RSI firms (*i.e.*, on the long leg of RSI), those that are also on the long leg of *PERC* and *PRIN* are overlapping firms; otherwise, they are non-overlapping firms. We adjust *t*-statistics in each period by Newey and West (1987) for heteroscedasticity and auto-correlation. *, **, and *** indicate statistical significance at the 0.1, 0.05, and 0.01 levels, respectively.

fraction of the RSI-return relation that is explained by anomalies increases slightly after academic publication. For example, relative to the hedge alpha spread by RSI [123 (119) bps during the pre-publication (post-publication) period], anomalies can explain 42% (47%) of this alpha spread during the pre-publication (post-publication) period. This evidence is consistent with our previous finding in Table 8 that short sellers increasingly rely on more non-anomaly information for their shorting strategy over time.

5.3. Low and high market sentiment

Baker and Wurgler (2006) find market sentiment affects the cross-section of stock returns. Stambaugh et al. (2012) show that anomaly-based mispricing occurs only following a period of high market sentiment. Guo and Wu (2018) find the negative relation between change-in-RSI and abnormal returns among firms with speculative credit ratings is similar following high and low market sentiments. To examine whether our results are robust to time variations in market sentiment, we use the monthly market-based sentiment series constructed by Baker and Wurgler (2006). Specifically, we divide the full sample into low and high sentiment periods based on the sentiment index in portfolio formation month *t* and examine RSI-anomalies and RSI-return relations during each period.

We first examine alphas for anomalies during each market sentiment period (untabulated). Consistent with Stambaugh et al. (2012), the hedge alpha spread by anomalies is significantly greater in the high sentiment period than that in low sentiment period. We then compute the difference in RSI between the long and short legs of anomalies during each market sentiment period. We find that while the RSI-anomalies relation remains significant and negative during each period, the negative spread in RSI is not significantly greater (in magnitude) during the high sentiment period. When using *PERC* to measure anomalies, the difference in this negative spread between periods is 0.28%, or 8% of the sample mean RSI, which is economically trivial. These findings suggest that short sellers are equally responsive to anomalies during periods of high and low sentiment, indicating that they do not time market sentiment.

We also conduct overlapping analysis for these two market sentiment periods and report the results in Table 11. For both the most and least shorted stocks, the abnormal returns are driven by overlapping firms during both low and high sentiment periods. The RSI-return relation is significantly more evident following a period of high sentiment, with most of the hedge alpha spread by RSI derived from overlapping firms. This evidence indicates that while short sellers are equally responsive following periods of high and low market sentiment, they can earn more abnormal returns and avoid more potential losses by using information from anomalies following a high sentiment period. We also conduct a FM regression for each sentiment period (untabulated). Overall, we do not find short sellers actively time market sentiment.

6. Conclusions

Equity short sellers are sophisticated traders who play an increasingly important role in capital markets. In this study, we examine how short sellers use anomaly information in their trading strategies and add several interesting findings to the literature.

First, we find that short sellers use well-known equity anomalies in their shorting strategies, and continue to rely on it when these anomalies become better known after academic publications and during recent years. Anomalies can explain a significant part of RSI and the RSI-return relation in the cross-section of stocks. Analysis of long and short legs reveals that short sellers increasingly use anomaly signals not only in short arbitrage to exploit potential overpricing, but also in short avoidance to stay away from underpriced firms.

The abnormal returns among least and heavily shorted firms are largely explained by firms that are also on the extreme legs of anomalies, and this pattern neither weakens over time nor varies with market sentiment. Regression analysis finds that market anomalies can explain more than half of the investment returns to short sellers. Overall, the evidence shows that short sellers, while viewing anomaly information important, also possess additional valuable information that is predictive of stock returns in cross-section to boost their performance.

Appendix A. Variable definitions

A.1. Anomaly variables

Book-to-Market (*BM*). Stattman (1980), Rosenberg et al. (1985), and Fama and French (1993a, 1993b) show that firms with high BM ratios have higher returns than those with low *BM* ratios. We define *BM* as equity book-to-market ratio, where book equity is shareholder equity (item *SEQ*), plus deferred taxes and investment tax credit (item *TXDITC*) if available, minus preferred stock redemption value (item *PSTKRV, PSTKL*, or *PSTK*, in that order) if available, all items obtained from Compustat tape. Market equity is market capitalization in December (from CRSP).

Momentum (*MOM*). Guided by Jegadeesh and Titman (1993), Jegadeesh and Titman (2001), and Fama and French (2008), we compute the raw returns over the previous 11 months ending in month *t*-1.

Idiosyncratic Volatility (*IVOL*). Longstaff (1989) finds that a cross-sectional regression coefficient on total variance for size-sorted portfolios carries an insignificant negative sign. Ang et al. (2006) present evidence that stock returns are negatively related to idiosyncratic risk. Following Ang et al. (2006), we define *IVOL* as the annualized standard deviation of residual returns from regressing daily excess returns on the Fama and French (1993a, 1993b) three factors with at least 15 observations in month *t*-1.

Operating Accruals (*ACC*). Many studies show that stocks with higher accruals tend to have lower future returns (e.g., Sloan, 1996; Dechow et al., 2008). Following Sloan (1996), we calculate operating accruals using the indirect balance sheet method. It is estimated as the change in non-cash current assets (item *ACT* - item *CHE*) less the change in current liabilities excluding the change in short-term debt (item *LCT* - item *DLC*) and the change in taxes payable (item *TXP*) minus depreciation and amortization expense (item *DP*), deflated by average total assets (item *AT*).

Total Accruals (*TACC*). Richardson et al. (2005) find total accruals are negatively associated with stock returns. Following these authors, we define this variable as the sum of the change in non-cash working capital (*WC*), the change in net non-current operating assets (*NCO*), and the change in net financial assets (*FIN*), scaled by average book assets. WC is current operating assets (*COA*) minus current operating liabilities (*COL*), where *COA* is current assets (item *ACT*) minus cash and short term investments (item *CHE*); *COL* is current liabilities (item *LCT*) minus debt in current liabilities (item *DLC*). *NCO* is non-current operating assets (*NCOA*) minus non-current operating liabilities (*NCOL*), where *NCOA* is total assets (item *AT*) minus current assets (item *ACT*) minus investments and advances (item *IVAO*); *NCOL* is total liabilities (item *LT*) minus current liabilities (item *LCT*) minus long-term debt (item *DLTT*). *FIN* is financial assets (*FINA*) minus financial liabilities (*FINL*), where *FINA* is short-term investments (item *LVST*) plus long-term investments (item *OVAP*); *FINL* is the sum of long-term debt (item *DLTT*), debt in current liabilities (item *DLC*), and preferred stock ((items *PSTK, PSTKRV, PSTKL*, in that order).

Net Operating Assets (*NOA*). Hirshleifer et al. (2004) document that *NOA* is a strong negative predictor of long-run stock returns. Following this study, we define *NOA* as the difference between operating assets (item *AT* minus item *CHE*) and operating liabilities (item *AT* minus the sum of items *DLC, DLTT, MIB, PSTK*, and *CEQ*), scaled by average total assets (item *TA*).

Investment to Assets (*CAPX*). Cochrane (1996) derives a negative relation between investment and expected returns. Li and Zhang (2010) document a negative relation between average stock returns and investment to assets in the cross-section. We define *CAPX* as capital investments (item *CAPX*) divided by lagged book assets (item *AT*).

Abnormal Investments (*AI*). Titman et al. (2004) document a negative relation between abnormal investment and average subsequent returns and interpret their evidence as investors underreacting to empire-building behavior of managers. We define $AI_{j,\,t-1} = 3\mathrm{CE}_{j,\,t-1}/(CE_{j,\,t-2} + CE_{j,\,t-3} + CE_{j,\,t-4}) - 1$, in which $CE_{j,\,t-1}$ is firm *j*'s capital expenditure (item *CAPX*) scaled by lagged sales (item *SALE*).

Asset Growth (*AG*). Cooper et al. (2008), Lam and Wei (2011), and Lipson et al. (2011) show that companies that grow their total assets more earn lower subsequent returns. We compute asset growth as the growth rate in book asset (item *AT*) from last year.

Net Equity Issues (*NS*). Early literature finds that equity issuers tend to exhibit negative long-run returns (Loughran and Ritter, 1995) and stock repurchases generally result in positive returns (Lakonishok and Vermaelen, 1990; Ikenberry et al., 1995). Daniel and Titman (2006), and Pontiff and Woodgate (2008) construct a measure of net equity issues that includes both issuance and repurchase of common stocks and document a negative relation between net equity issues and future returns. We define net equity issues as the change in the natural log of the split-adjusted shares outstanding from 12 months.

External Financing Activity (*XFIN*). In the literature, in addition to equity issuance, other corporate financing activities such as the issuance of corporate debt and the omission of dividends are also inversely related to future stock returns (e.g., Michaely et al., 1995; Spiess and Affleck-Graves, 1999; Billett et al., 2006). Bradshaw et al. (2006) combine a firm's financing activities in various capital markets to construct a more comprehensive measure of external financing activity (*XFIN*) and find a negative relation between *XFIN* and future stock returns. We define *XFIN* as the sum of financing from the equity market (item *SSTK*, minus item *PRSTKC* and item *DV*) and debt market (item *DLTIS*, minus item *DLTR*, plus item *DLCCH*), all scaled by average book asset (item *AT*).

Financial Distress Risk (*CHS*). Early studies use Altman's Z-Score and Ohlson's O-Score to measure financial distress risk and find stock returns are negatively related to this risk in the cross-section (Dichev, 1998; Griffin and Lemmon, 2002). Campbell et al. (2008) estimate a dynamic panel model using a logit specification to construct a measure of distress risk and confirm that stocks with higher distress risk have lower subsequent returns. We apply the coefficients in the third column in Table 4 in Campbell et al. (2008) to construct CHS based on the CRSP tape as of month *t*-1 and Compustat quarterly tapes two months before month *t*-1.

Profitability (*ROA* and *ROE*). Haugen and Baker (1996) and Cohen et al. (2002) find that more profitable firms have higher average stock returns than firms with low profitability. We follow Fama and French (2008) and use *ROA* and *ROE* to measure profitability. Net income is the sum of items *IB* and *TXDI* minus item *DVP*. *ROA* is net income scaled by average book assets (*AT*) and *ROE* is net income scaled by book equity, as defined in the *BM* ratio.

Discretionary Accruals (*DACC*). Xie (2001) find that the overpricing of operating accruals that Sloan (1996) documents is due largely to abnormal accruals (often termed "discretionary accruals" in the literature). We follow Xie (2001) and use the Jones model to estimate normal accruals and abnormal accruals in cross-section for each two-digit SIC code and year combination, formed separately for NYSE/AMEX firms and for NASDAQ firms. We denote the predicted values of the Jones model as normal accruals and the residuals as abnormal accruals (*DACC*).

Analyst forecast revision (*FRV*). Givoly and Lakonishok (1979) and Gleason and Lee (2003) document that stock prices exhibit a drift after analyst forecast revisions, namely, firms whose consensus forecast has been recently revised upward tend to earn higher abnormal returns than firms whose consensus forecast has been recently revised downward. Following Chan et al. (1996), Gleason and Lee (2003), and Zhang (2006), we define *FRV* as analyst average EPS forecast (from IBES) for the currently unreported fiscal year FY1 during month *t*, in excess of the average EPS forecast for the same fiscal year made during month *t*-6, divided by stock price at the time the average forecast of month t is measured.

Analyst forecast dispersion (*DISP*). Ackert and Athanassakos (1997) and Diether et al. (2008) find that firms with low forecast properties (dispersion or error) outperform firms with high forecast properties. We compute DISP as the standard deviation of analyst EPS forecasts (from IBES) for the unreported fiscal year FY1, divided by the absolute value of the average analyst EPS forecast for the same fiscal year, measured in month *t*.[25]

Standardized Earnings Surprise (*SUE*). Firms reporting unexpectedly high earnings subsequently outperform firms reporting unexpectedly low earnings in the next few months (e.g., Ball and Brown, 1968; Bernard and Thomas, 1989). This anomaly is referred as post earnings announcement drift (PEAD). We follow Bernard and Thomas (1997) and compute *SUE* as quarterly earnings minus earnings from four quarters ago, both split-adjusted, then scaled by the split-adjusted stock price at the end of quarter.[26]

A.2. Control variables

Firm Size (*MARKETCAP*). Size, in million dollars, is the product of number of shares outstanding and stock price in month *t*-1.

Institutional Ownership (*IO*). This variable is defined as number of shares held by institutional investors scaled by number of shares outstanding using the 13f database from the quarter that ends in or before month *t*-1.

Amihud (2002) illiquidity (*ILLIQ*). *ILLIQ* is the average ratio of the daily absolute return to the dollar trading volume (x 10^6) over the prior 12 month period ending in month *t*-1. Dollar trading volume is the product of stock price and volume. Since the dealer nature of the NASDAQ market makes the share turnover difficult to compare with the turnover observed on NYSE and AMEX, we follow Gao and Ritter (2010) by adjusting the trading volume for NASDAQ stocks.[27]

[25] We also scale by stock price to mitigate heteroscedasticity (Zhang, 2006) and find similar results.

[26] For a robustness check, we also standardize the change in earnings by the standard deviation of the earnings changes in the prior eight quarters. Our results remain qualitatively similar.

[27] Specifically, we divide NASDAQ volume by 2.0, 1.8, 1.6, and 1 for the periods prior to February 2001, between February 2001 and December 2001, between January 2002 and December 2003, and January 2004 and later years, respectively.

Convertible (*CONVERTIBLE*). A dummy that equals to one if the firm has convertible debt outstanding, which is likely subject to convertible bond arbitrageur and thus may have high short interest (Choi et al., 2010).

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