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Abstract

This paper investigates the relation between short selling and momentum. We document that a consistent momentum strategy that buys lightly shorted winners and sells heavily shorted losers exhibits strong short-term momentum and no long-term reversal. In contrast, an inconsistent momentum strategy that buys heavily shorted winners and sells lightly shorted losers experiences weak short-term momentum and persistent long-term reversal. Our results are robust after controlling for firm characteristics, proxy for short-sale constraints, and investor sentiment, as well as an exogenous shock (the Taxpayer Relief Act of 1997). These findings present a new challenge to existing theories of momentum that rely solely on investor underreaction and overreaction.

Keywords: Momentum, Reversal, Short selling, Short-sale constraints

1. Introduction

Two and half decades after its initial discovery, the momentum strategy (Jegadeesh and Titman, 1993) that buys past winners and sells past losers continues to be an intriguing financial market anomaly. It has been well documented that momentum exists both around the world (Griffin et al., 2003) and across asset classes (Asness et al., 2013). Interestingly, many studies show that momentum tends to be followed by reversals in the long run (Lee and Swaminathan, 2000, Jegadeesh and Titman, 2001), which appears to support the predictions from several behavioral models based on investor under- or overreaction to news (Daniel et al., 1998, Barberis et al., 1998, Hong and Stein, 1999).

However, some studies find that short-term momentum and long-term reversals are not necessarily linked. For example, Cooper et al. (2004) find that following market states when the prior three-year market return is negative, "long-run reversal can apparently exist without short-run momentum" (p. 1353). Conrad and Yavuz (2017) report that the stocks in a momentum portfolio, which contribute to momentum profits, do not experience significant subsequent reversals, and vice versa.

In this paper, we propose jointly considering opinions of long-side and short-side investors to better understand the relation between momentum and long-term reversal. Specifically, we use past recent returns to proxy for the opinion of

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long-side investors and the recent level of short interest (as a proxy for short selling activities) to measure the opinion of short sellers. We emphasize that the *consistency* between past returns and short interest could potentially be useful in terms of delivering a consensus *opinion* on a stock by aggregating information from both long-side and short-side investors.

Our approach is motivated by Miller's (1977) pioneering work that sheds light on the relation between divergence of opinion, short-sale constraints, and market efficiency. Miller observes that (p. 1160) "because the number of people with extremely pessimistic evaluations of a stock are likely to increase with the divergence of opinion about a stock, short sales tend to moderate the tendency for riskier stocks to be bid up to higher prices." In other words, when short-sale constraints are binding, stocks that experience recent surge in prices could be overvalued relative to their fundamentals. Consistent with Miller's prediction, both Harrison and Kreps (1978) as well as Scheinkman and Xiong (2003) show that short-sale constraints can potentially trigger a speculative bubble in asset prices as buyers are willing to overpay for an asset due to the belief that they can find another buyer who is willing to pay even more. Diamond and Verrecchia (1987) present a model where the high costs associated with short selling can hinder informational efficiency especially with respect to private bad news. From a theoretical perspective, these studies demonstrate the important role played by short sellers in curbing overvalued asset prices.

Empirically, many studies have also found that short selling activities contain useful information about future stock returns. Rapack et al. (2016) report that short interest is probably the best predictor of aggregate stock returns both in and out of sample. Moreover, its predictive power appears to stem from information related to cash flow news, which could come from either public (Engelberg et al., 2012) or private sources (Christophe et al., 2010). Massa et al. (2015) show that even when short sellers do not possess superior information, their presence can still speed up the dissemination of private information as insiders try to preempt competition from short sellers.[1] In addition to the evidence compiled from academic studies, anecdotal evidence also appears to support the notion that short-sellers are avid fundamentalists. For example, one Wall Street Journal article[2] describes how James Chanos, a famed short seller of Enron stock, discovered accounting fraud using in-depth analysis of Enron's regulatory filings.

Given the collective evidence that short sellers appear to be informed traders and their short selling activity has predictive value, it seems reasonable to assume that short sellers possess superior information than the average long-side investor. As such, we conjecture that the level of short interest could play an important role for determining the momentum-reversal pattern. To illustrate, consider the case of a past winner in a momentum portfolio, where its share price has gone up substantially because long-side investors are buying aggressively following some positive earnings news. Suppose that short sellers, after some in-depth research, conclude that the rise in stock price is unwarranted as the company' earnings growth is unsustainable. Therefore, they heavily short sell the stock. Seeing this dramatic increase in short interest, long-side investors have to pause and reevaluate their bullish outlook since they know short sellers have some superior information. As a result, the share price of this past winner stock might stall. On the other hand, if short interest level remains low even after an astronomical rise in share price, the fact that short-sellers cannot find fault with the bullish case will further embolden long-side investors, which could trigger even more aggressive buying. Similar argument can also be made in the case of past losers. Taken together, we contend that when short sellers have superior information, the short interest variable should have a signaling effect on long-side investors, who will use this variable to help confirm their views on stocks they own. Therefore, when short interest and past returns are aligned, momentum is likely to continue as long and short-side investors appear to have reached a consensus. However, when the two variables are in disagreement, momentum could falter. Thus, our empirical strategy is to first classify past winners (losers) into lightly, normally, or heavily shorted winners (losers) based on the stocks' short interest ratios at the end of a formation period. We then construct a *consistent* momentum portfolio that buys lightly shorted winners and sells heavily shorted losers. In contrast, the *inconsistent* momentum portfolio buys heavily shorted winners and sells lightly shorted losers.

We report several interesting findings regarding the relation between short selling and the momentum-reversal pattern. We show that the *consistent* momentum portfolio experiences strong and persistent momentum but no reversal. The alpha of the *consistent* portfolio is 1.07% (t-value = 4.25), which almost doubles the alpha generated by the standard momentum portfolio in the first-year holding period. Moreover, the *consistent* portfolio experiences no reversal in the subsequent 2–5 years. In contrast, the *inconsistent* portfolio records an insignificant alpha of 0.13% in the first year and witnesses significant reversals in the second (−0.56%) and third (−0.30%) years as well as negative alphas in the fourth (−0.15%) and fifth (−0.43%) years. We find similar results after controlling for various firm characteristics such as size, book-to-market ratio, idiosyncratic volatility, illiquidity, financial distress, and other fundamental variables.

In addition, we find stronger results among stocks with more binding short-sale constraints in both the short and long run. This finding confirms the insights from Diamond and Verrecchia (1987) and Miller (1977) in that when short-sale constraints are more binding or costly, short interest is likely to become more informative as only informed short sellers are willing to keep their short positions.

[1] Other studies reporting that short sellers are informative about firms' fundamentals include Curtis and Fargher (2014), Deshmukh et al. (2015), Akbas et al. (2017).

[2] https://www.wsj.com/articles/SB1004916006978550640.

Daniel et al. (2017) provide an interesting study to identify overpriced winners with past return, the *change* in short interest, and institutional ownership. Our study differs from theirs in that we rely on the *level* of short interest.[3] Empirically, we find that the level of short interest dominates the change in short interest in predicting stock returns. Moreover, we find that the incremental role of the level of short interest is robust after controlling for the change in short interest in both the short and long run in both portfolio and regression analyses. Our approach also performs well without using the institutional ownership variable, which is a key component in the DKR model. Importantly, we note that DKR's finding is confined to past winners, whereas our approach applies to both past winners and losers.

The remainder of this article is organized as follows. The next section describes our data and empirical strategy. Section 3 presents the main results as well as a battery of robustness checks. We offer some concluding remarks in Section 4.

2. Data and methodology

Our sample consists of all common stocks (share code is 10 or 11) with available monthly short interest data listed on NYSE and AMEX over the period of January 1988 to December 2016.[4] Monthly short interest data are from Compustat. Closed-end funds, REITs, trusts, and ADRs are excluded from the sample. Stock information such as price, trading volume and the number of outstanding shares is from the Center for Research in Security Prices (CRSP). Institutional ownership data is from Thomson Reuters. Our main variable of interest, the short interest ratio (SIR_t), is defined as the ratio of total number of uncovered shares shorted (SI) over the total number of shares outstanding in month t.

Following the method in Lee and Swaminathan (2000), we form 30 (10×3) portfolios based on independent sorts of past J-month cumulative returns and the recent level of short interest at month t-2. We assign all sample stocks into ten groups based on their past J-month returns. Within each decile, stocks are further independently divided into three groups based on their level of short interest at month t-2. In the robustness test, we also use the two-way dependent sort. To avoid short-term reversal (Jegadeesh, 1990), we skip one month between formation and holding periods (month t-1). Stocks with prices less than $5 at the end of formation period are excluded. Portfolios are rebalanced monthly and hold for K months. The monthly return of a specific portfolio held for K months at month t is the equal-weighted average of returns from month t to month $t+K$.

3. Empirical results

3.1. Univariate sorts on past returns and short interest

We start the empirical analysis by examining the return predictability of the recent past returns and the level of short interest respectively. Table 1 reports the results. Following Jegadeesh and Titman (1993), we assign stocks into ten portfolios based on their J-month cumulative returns and hold them for K months. We skip one month between the formation and holding periods. Portfolios are rebalanced monthly. Panel A and B in Table 1 reports the average monthly returns for the simple momentum strategies. For example, the simple momentum strategy for ($J=6$, $K=6$) generates an average monthly raw return of 0.75% (t-statistic is 2.50) and a Fama and French (1993) three-factor adjusted return of 1.02% (t-statistic is 4.07). It is expected that the average momentum profit in our sample period of 1988 to 2016 is slightly smaller than that documented in Jegadeesh and Titman (1993, 2001) due to the increases in arbitrage capital and trading activities in the recent decade (Hanson and Sunderam, 2014; Chordia et al., 2014).

Consistent with Jegadeesh and Titman (2001), the simple momentum strategy generates significant and positive returns in the subsequent first year and insignificant and even negative returns after the first year in the holding period. For example, for ($J=6$, $K=6$), the momentum strategy generates negative monthly raw returns in the subsequent years 2 to 5. After controlling for Fama-French three factors, the strategy generates negative returns in years 2 and 5, and insignificant and small positive returns in years 3 and 4. Therefore, consistent with prior studies, we find that simple momentum strategy has short-term momentum and long-term reversal.

Panels C and D in Table 1 report the average monthly returns for portfolios sorted on the level of short interest. Because we use two-way independent sorts of past return and short interest to form 30 (10×3) portfolios, we test the return predictability of short interest when sample stocks are divided into only three portfolios based on the SIR. The formation period J is one month for the short selling strategy. We skip one month between formation and holding period. The portfolio consisting of stocks with smallest level of short interest ratio (lightly shorted stocks) is denoted as S1, and the portfolio with highest level of short interest ratio (heavily shorted stocks) is denoted as S3.

Panel D shows that heavily shorted stocks (S3) experience an average alpha of −0.35% ($t=-3.64$) in the subsequent one month, consistent with prior studies. Consistent with Boehmer et al. (2010), lightly shorted stocks (S1) experience an average significantly positive abnormal return of 0.24% in the subsequent month ($t=2.67$). The return spread between lightly shorted stocks and heavily shorted stocks is quite significant and positive in the subsequent one-year horizon. Moreover, the

[3] In their NYSE/AMEX/NASDAQ sample, Daniel et al. identify only 16 "overpriced winners" with negative alphas among 825 past winners. In contrast, in our NYSE/AMEX sample, we do not find such overprice winners with negative alphas even among stocks with low institutional ownerships. We conjecture that the overpriced winners identified in the Daniel et al. study might be mainly small NASDAQ firms.

[4] Because Compustat does not cover short interest data for NASDAQ stocks before 2003, we limit our sample to stocks listed on NYSE/AMEX.

Table 1
Monthly returns of portfolios sorted on past returns or short interest.

Panel A: Raw Returns to Momentum Strategies

J	Portfolio	Monthly Returns				Monthly Returns in Event Year				
		$K=1$	$K=3$	$K=6$	$K=12$	Year 1	Year 2	Year 3	Year 4	Year 5
6	M1	0.59	0.58	0.57	0.71	0.71	1.26	1.13	1.23	1.34
		(1.37)	(1.34)	(1.27)	(1.56)	(1.56)	(2.79)	(2.59)	(2.80)	(3.23)
	M10	1.35	1.27	1.31	1.11	1.11	0.93	1.12	1.22	1.05
		(4.16)	(3.83)	(3.83)	(3.1)	(3.1)	(2.41)	(2.92)	(3.15)	(2.51)
	M10-M1	0.76	0.69	0.75	0.4	0.4	−0.33	−0.01	−0.01	−0.29
		(2.52)	(2.32)	(2.5)	(1.61)	(1.61)	(−1.92)	(−0.08)	(−0.06)	(−1.84)
11	M1	0.46	0.45	0.56	0.83	0.83	1.37	1.13	1.29	1.34
		(0.97)	(0.93)	(1.16)	(1.73)	(1.73)	(2.90)	(2.43)	(2.80)	(3.15)
	M10	1.45	1.31	1.18	1.06	1.06	1.01	1.17	1.10	0.99
		(4.08)	(3.74)	(3.33)	(2.86)	(2.86)	(2.68)	(2.96)	(2.75)	(2.31)
	M10-M1	0.98	0.86	0.62	0.23	0.23	−0.36	0.04	−0.19	−0.36
		(2.64)	(2.46)	(1.82)	(0.80)	(0.80)	(−1.67)	(0.23)	(−1.12)	(−2.07)

Panel B: FF3 Alphas to Momentum Strategies

J	Portfolio	Monthly Returns				Monthly Returns in Event Year				
		$K=1$	$K=3$	$K=6$	$K=12$	Year 1	Year 2	Year 3	Year 4	Year 5
6	M1	−0.76	−0.78	−0.81	−0.63	−0.63	−0.10	−0.23	−0.07	0.18
		(−3.81)	(−3.93)	(−4.16)	(−3.42)	(−3.42)	(−0.6)	(−1.44)	(−0.55)	(1.00)
	M10	0.32	0.19	0.20	0.01	0.01	−0.23	−0.09	0.05	−0.10
		(2.29)	(1.41)	(1.53)	(0.12)	(0.12)	(−1.56)	(−0.56)	(0.33)	(−0.56)
	M10-M1	1.08	0.97	1.02	0.64	0.64	−0.13	0.14	0.13	−0.28
		(3.82)	(3.79)	(4.07)	(3.19)	(3.19)	(−0.92)	(1.03)	(1.08)	(−1.66)
11	M1	−0.97	−0.96	−0.82	−0.58	−0.58	−0.13	−0.32	−0.03	0.19
		(−4.28)	(−4.33)	(−3.81)	(−2.87)	(−2.87)	(−0.67)	(−1.97)	(−0.18)	(1.10)
	M10	0.38	0.24	0.12	−0.03	−0.03	−0.21	−0.03	−0.06	−0.16
		(2.52)	(1.55)	(0.89)	(−0.20)	(−0.20)	(−1.50)	(−0.19)	(−0.33)	(−0.94)
	M10-M1	1.35	1.19	0.94	0.55	0.55	−0.08	0.29	−0.03	−0.35
		(3.92)	(3.95)	(3.58)	(2.61)	(2.61)	(−0.48)	(1.68)	(−0.19)	(−1.93)

Panel C: Raw Returns to Short Interest Strategy

J	Portfolio	Monthly Returns				Monthly Returns in Event Year				
		$K=1$	$K=3$	$K=6$	$K=12$	Year 1	Year 2	Year 3	Year 4	Year 5
1	S1	1.15	1.13	1.11	1.07	1.07	1.08	1.21	1.14	1.13
		(4.55)	(4.44)	(4.27)	(3.96)	(3.96)	(3.62)	(4.07)	(3.68)	(3.58)
	S3	0.87	0.88	0.90	0.94	0.94	1.07	1.17	1.13	1.13
		(2.59)	(2.6)	(2.62)	(2.65)	(2.65)	(2.86)	(3.15)	(3.00)	(2.95)
	S1-S3	0.28	0.25	0.21	0.13	0.13	0.02	0.04	0.01	0.01
		(2.61)	(2.28)	(1.91)	(1.18)	(1.18)	(0.14)	(0.36)	(0.13)	(0.06)

Panel D: FF3 Alphas to Short Interest Strategy

J	Portfolio	Monthly Returns				Monthly Returns in Event Year				
		$K=1$	$K=3$	$K=6$	$K=12$	Year 1	Year 2	Year 3	Year 4	Year 5
1	S1	0.24	0.23	0.20	0.16	0.16	0.12	0.19	0.16	0.17
		(2.67)	(2.44)	(2.11)	(1.63)	(1.63)	(1.07)	(1.36)	(1.20)	(1.55)
	S3	−0.35	−0.34	−0.32	−0.28	−0.28	−0.18	−0.15	−0.11	−0.06
		(−3.64)	(−3.44)	(−3.06)	(−2.57)	(−2.57)	(−1.64)	(−1.24)	(−0.81)	(−0.41)
	S1-S3	0.59	0.57	0.52	0.44	0.44	0.30	0.33	0.27	0.23
		(7.11)	(7.12)	(6.4)	(5.14)	(5.14)	(3.26)	(3.81)	(3.15)	(2.47)

Panel A and B present equal-weighted average monthly raw and Fama-French 3-factor adjusted returns in percentages for simple price momentum strategies for NYSE/AMEX common stocks with monthly short interest data, respectively. All sample stocks are assigned into ten portfolios in ascending order based on their past J-month cumulative returns and held for K months. M1 represents the loser portfolio and M10 represents the winner portfolio. Portfolios are rebalanced monthly. Stocks with prices less than \$5 at the end of formation period are excluded. We skip one month between formation and holding periods. Newey and West (1987) t-statistics are in parentheses. The length of lag depends on K where $K=1$, 3, 6 or 12 months. The sample period is from January 1988 to December 2016. Panel C and D present equal-weighted average monthly raw returns and Fama-French 3-factor adjusted returns in percentages for heavily and lightly shorted stock portfolios, respectively. All NYSE/AMEX common stocks with monthly short interest data are sorted based on their short interest ratios at month t and then equally assigned into ten portfolios. S1 represents lightly shorted stock portfolio and S3 represents heavily shorted stock portfolio. S1-S3 represents short selling strategy portfolio. The portfolios are rebalanced monthly and held for K months where $K=1$, 3, 6, or 12 months. Stocks with prices less than \$5 at the end of formation period are excluded. We skip one month between formation and holding periods. Newey and West (1987) t-statistics are in parentheses. The sample period is from January 1988 to December 2016.

positive return spread is significant and positive in the subsequent five years. Since we only sort stocks into three portfolios, the returns of short interest strategy are smaller than those reported in prior studies. Overall, consistent with prior studies, our findings suggest that short interest has strong return predictability.

3.2. The interaction of the past return and short interest

In this subsection, we study whether an empirical approach that conjoins the opinions from both long-side and short-side investors can help clarify the momentum-reversal pattern. We first sort stocks into ten portfolios based on their decile rankings from past J-month returns. Independently, we also sort stocks into three portfolios based on a stock's short interest ratio at month t-1. We then intersect these past return and short-interest portfolios to form 30 doubly sorted portfolios. Portfolio M1 is the past loser portfolio and M10 is the past winner portfolio. S1 is the lightly shorted stock portfolio and S3 is the heavily shorted portfolio.

To better understand the momentum-reversal pattern, we construct two modified momentum portfolios. First, the *consistent* momentum portfolio buys lightly shorted winners (M10S1) and sells heavily shorted losers (M1S3). In this case, investors with optimistic and pessimistic views seemingly agree that lightly shorted winners (heavily shorted losers) are underpriced (overpriced) and, consequently, we expect M10S1 and M1S3 to sustain their price momentum. Second, the *inconsistent* portfolio buys heavily shorted winners (M10S3) and sells lightly shorted losers (M1S1). In this case, short-side and long-side investors appear to strongly disagree about the current valuations of heavily shorted winners and lightly shorted losers. If short sellers are informed traders, we expect these stocks to experience weak momentum or even reversals.

Table 2 reports the average monthly raw and risk-adjusted returns of these portfolios. There are several important empirical findings. First, after controlling for past returns, lightly shorted stocks significantly outperform heavily shorted stocks. The return spread based on risk-adjusted returns is stronger and more persistent. For example, for ($J = 6$, $K = 6$), Panel B of Table 2 shows that after controlling for Fama-French 3-factor, lightly shorted losers outperform heavily shorted losers by 0.89% per month ($t = 4.88$), and lightly shorted winners outperform heavily shorted winners by 0.37% per month ($t = 2.99$). This outperformance is robust in different (J, K) based on factor-adjusted returns. These results are consistent with return predictability of short interest documented in prior studies. Moreover, the outperformance is asymmetric between past winner portfolio and past loser portfolio. The spread in past loser portfolio is larger than that in past winner portfolio.

Second, after controlling for the level of short interest, momentum profit is highest among heavily shorted stocks. For example, for the case where $J = 6$ and $K = 6$, Panel B of Table 2 shows that the momentum return is 1.22% per month among heavily shorted stocks and 0.70% and 0.81% among lightly and normally shorted stocks, respectively. The difference is mainly due to short leg. The spread among past losers (M1S1-M1S3) is 0.89%, while the spread among past winners (M10S1-M10S3) is only 0.37%.

Third, the *consistent* momentum portfolio generates economically and statistically significant profit, but the *inconsistent* portfolio generates economically and statistically insignificant profit in the first-year holding period. For the case where $J = 6$ and $K = 6$, the consistent portfolio earns an average monthly alpha of 1.59% ($t = 5.58$), compared with the alpha of 0.33% ($t = 1.39$) recorded by the inconsistent portfolio. In contrast, the simple momentum strategy generates an average monthly alpha of 1.02% ($t = 4.07$), which is eclipsed by the consistent momentum portfolio by 56%.

These findings have three main important implications. First, not all past winners or losers experience strong momentum even in the first year after the formation period. Only stocks with consistent opinions between optimistic and pessimistic investors experience strong momentum, but stocks with significant disagreements experience insignificant and weak momentum in the first year. Second, the joint approach proposed here could efficiently identify consistent momentum stocks and inconsistent momentum stocks in the first-year holding period. Third, the asymmetry among past winners and losers indicates that opinions of short sellers seem more important for past losers.

3.3. Controlling for firm characteristics

In this subsection, we examine whether our findings are robust after controlling for several important firm characteristics such as size, book-to-market ratio, trading volume, idiosyncratic volatility, illiquidity, distress, gross profitability, investment, and change in short interest. Prior studies show that these variables are significantly related to the profitability of momentum and short selling. First, we equally divide all sample stocks into three portfolios based on their ranks on the specific control variable. Then, within each group, we use two-way independent sorts to form 30 (10×3) portfolios based on their past returns and short interest ratio. In the unreported report, we also use the three-way independent sorts. The results are basically similar for two methods. The merit of the way we report here is that each portfolio in which we are interested has enough stocks. For brevity, Table 3 only reports the returns to consistent and inconsistent momentum portfolios.

3.3.1. Controlling for size

Many studies show that momentum profits are negative related to firm size (Jegadeesh and Titman, 1993; Hong et al., 2000). Asquith et al. (2005) find that heavily shorted stocks are mainly small- and medium-sized stocks. To examine whether the size effect subsumes the return predictability of the past return and short interest, we examine the performance of the joint approach in three different size subsamples. First, we equally divide all sample stocks into three size groups (small,

Table 2
Monthly returns of portfolios sorted on past returns and short interest.

Panel A: Raw Returns

J	Portfolio	K = 1				K = 6				K = 12			
		S1	S2	S3	S1-S3	S1	S2	S3	S1-S3	S1	S2	S3	S1-S3
6	M1	0.89	0.76	0.29	0.60	0.87	0.75	0.34	0.54	0.83	0.90	0.56	0.27
		(2.19)	(1.85)	(0.62)	(3.31)	(2.08)	(1.74)	(0.70)	(3.09)	(2.00)	(1.96)	(1.14)	(1.64)
	M10	1.53	1.39	1.22	0.32	1.40	1.32	1.25	0.15	1.14	1.18	1.04	0.09
		(4.86)	(4.32)	(3.36)	(1.87)	(4.37)	(3.91)	(3.32)	(1.15)	(3.47)	(3.32)	(2.65)	(0.68)
	M10-M1	0.64	0.63	0.93		0.53	0.57	0.91		0.31	0.28	0.48	
		(2.07)	(2.03)	(2.66)		(2.11)	(2.03)	(2.67)		(1.54)	(1.21)	(1.69)	
	Consistent	1.24				1.07				0.57			
		(3.51)				(3.10)				(1.84)			
	Inconsistent	0.32				0.38				0.21			
		(1.06)				(1.41)				(1.03)			
11	M1	0.87	0.63	0.24	0.63	0.90	0.80	0.33	0.57	1.02	1.05	0.66	0.36
		(1.91)	(1.36)	(0.46)	(3.04)	(2.00)	(1.69)	(0.65)	(3.04)	(2.36)	(2.17)	(1.29)	(1.92)
	M10	1.65	1.47	1.32	0.32	1.39	1.17	1.07	0.32	1.17	1.15	0.92	0.25
		(4.89)	(4.01)	(3.44)	(1.78)	(4.34)	(3.28)	(2.71)	(2.02)	(3.54)	(3.06)	(2.27)	(1.76)
	M10-M1	0.78	0.84	1.09		0.49	0.38	0.74		0.16	0.10	0.27	
		(1.97)	(2.23)	(2.84)		(1.72)	(1.14)	(2.00)		(0.68)	(0.34)	(0.86)	
	Consistent	1.41				1.06				0.52			
		(3.35)				(2.75)				(1.47)			
	Inconsistent	0.46				0.17				−0.09			
		(1.29)				(0.60)				(−0.41)			

Panel B: FF3 Alphas

J	Portfolio	K = 1				K = 6				K = 12			
		S1	S2	S3	S1-S3	S1	S2	S3	S1-S3	S1	S2	S3	S1-S3
6	M1	−0.27	−0.56	−1.16	0.89	−0.29	−0.58	−1.18	0.89	−0.28	−0.40	−0.91	0.63
		(−1.35)	(−2.80)	(−5.28)	(4.99)	(−1.52)	(−3.07)	(−5.14)	(4.88)	(−1.47)	(−2.25)	(−4.10)	(3.78)
	M10	0.62	0.38	0.08	0.54	0.41	0.23	0.04	0.37	0.16	0.10	−0.15	0.32
		(3.87)	(2.22)	(0.53)	(3.35)	(3.00)	(1.63)	(0.28)	(2.99)	(1.34)	(0.86)	(−1.19)	(2.62)
	M10-M1	0.89	0.94	1.25		0.70	0.81	1.22		0.44	0.49	0.75	
		(3.39)	(3.16)	(4.06)		(3.46)	(3.16)	(4.16)		(2.23)	(2.66)	(3.14)	
	Consistent	1.78				1.59				1.07			
		(6.06)				(5.58)				(4.25)			
	Inconsistent	0.36				0.33				0.13			
		(1.33)				(1.39)				(0.62)			
11	M1	−0.38	−0.78	−1.27	0.89	−0.26	−0.51	−1.15	0.89	−0.12	−0.28	−0.86	0.74
		(−1.53)	(−4.01)	(−4.6)	(4.06)	(−1.25)	(−2.46)	(−4.64)	(4.45)	(−0.63)	(−1.41)	(−3.69)	(3.99)
	M10	0.71	0.43	0.16	0.55	0.46	0.12	−0.08	0.54	0.22	0.07	−0.25	0.47
		(4.2)	(2.29)	(0.91)	(3.03)	(3.04)	(0.79)	(−0.48)	(3.69)	(1.63)	(0.55)	(−1.87)	(3.86)
	M10-M1	1.09	1.21	1.42		0.72	0.64	1.07		0.34	0.35	0.61	
		(3.15)	(3.68)	(3.93)		(3.05)	(2.19)	(3.48)		(1.50)	(1.66)	(2.48)	
	Consistent	1.97				1.61				1.08			
		(5.14)				(5.43)				(3.95)			
	Inconsistent	0.54				0.18				−0.13			
		(1.70)				(0.75)				(−0.67)			

This table presents average monthly returns of portfolios based on two-way independent sorts on past J-month returns and short interest ratio (SIR) at month t. At the beginning of each month, all NYSE/AMEX common stocks with monthly short interest data are sorted in ascending order based on their past J-month returns and then equally assigned into ten portfolios. M1 represents the loser portfolio and M10 represents the winner portfolio. The stocks are then independently sorted based on their SIRs and assigned into three portfolios. S1 represents the lightly shorted stock portfolio and S3 represents the heavily shorted stock portfolio. Ten portfolios based on past returns and three portfolios based on SIR are intersected to form 30 independently sorted portfolios. Stocks with prices less than $5 at the end of formation period are excluded. We skip one month between formation and holding periods. Newey and West (1987) t-statistics are in parentheses. The sample period is from January 1988 to December 2016. The 30 intersected portfolios are rebalanced monthly and held for K months where $K = 1$, 6, or 12 months. The consistent momentum portfolio is to buy lightly shorted winners and sell heavily shorted losers. The inconsistent portfolio is to buy heavily shorted winners and sell lightly shorted losers. Panel A reports raw returns when $J = 6$ or 11 months. Panel B reports Fama-French 3-factor adjusted returns.

middle, and big) based on their market capitalizations at the end of prior month. Then, within each size group, we form 30 portfolios independently sorted based on past returns and SIR.

Table 3 confirms that our results are robust across the various size groups. For ($J = 6$, $K = 6$), the consistent momentum stocks experience strong momentum in all three size groups (1.95%, 1.31%, 1.16%), but the inconsistent momentum stocks experience insignificantly weak momentum in all size groups (0.43%, 0.29%, 0.29%). In an unreported table, we also find that the return spread between heavily shorted losers and lightly shorted losers is economically and statistically significant in all three size groups, but the return spread for past winners is only significant in the smallest size group.

Table 3
Return predictability of the joint approach controlling for firm characteristics.

Characteristics		1				2				3			
		K = *1*	*K* = *3*	*K* = *6*	*K* = *12*	*K* = *1*	*K* = *3*	*K* = *6*	*K* = *12*	*K* = *1*	*K* = *3*	*K* = *6*	*K* = *12*
ME	Consistent	1.81	1.86	1.95	1.51	1.26	1.37	1.31	0.97	1.47	1.27	1.16	0.76
		(4.74)	(5.77)	(6.87)	(5.15)	(2.7)	(3.62)	(3.58)	(3.62)	(4.04)	(3.91)	(3.74)	(2.66)
	Inconsistent	0.71	0.60	0.43	0.08	0.14	0.06	0.29	0.07	−0.03	0.09	0.29	0.22
		(1.74)	(1.65)	(1.34)	(0.27)	(0.46)	(0.20)	(1.04)	(0.27)	(−0.07)	(0.29)	(1.02)	(0.93)
BM	Consistent	1.22	1.28	1.21	0.78	1.32	1.18	1.39	0.90	1.21	1.17	1.13	0.63
		(3.55)	(4.55)	(4.40)	(2.88)	(3.46)	(3.33)	(4.56)	(3.04)	(3.27)	(3.36)	(3.44)	(2.12)
	Inconsistent	−0.01	0.11	0.37	0.34	−0.08	0.02	0.24	0.00	0.11	0.00	0.03	0.01
		(−0.02)	(0.28)	(1.37)	(1.67)	(−0.17)	(0.07)	(0.87)	(0.01)	(0.29)	(0.01)	(0.10)	(0.05)
Turnover	Consistent	1.57	1.58	1.47	1.07	1.39	1.17	1.14	0.84	2.23	2.08	2.10	1.60
		(5.7)	(7.08)	(7.44)	(5.82)	(4.26)	(4.48)	(4.82)	(4.32)	(4.04)	(4.52)	(5.22)	(4.58)
	Inconsistent	0.10	0.47	0.49	0.31	−0.13	0.28	0.50	0.30	0.38	0.52	0.65	0.25
		(0.32)	(1.96)	(2.04)	(1.37)	(−0.4)	(1.29)	(2.40)	(1.75)	(0.87)	(1.31)	(1.69)	(0.80)
IVOL	Consistent	0.58	0.60	0.77	0.59	1.10	1.08	1.20	0.79	2.19	2.34	2.18	1.54
		(2.62)	(3.55)	(4.76)	(4.22)	(3.92)	(4.86)	(5.37)	(3.79)	(3.87)	(5.15)	(5.37)	(4.22)
	Inconsistent	0.15	0.28	0.39	0.32	0.12	0.25	0.43	0.37	0.96	0.66	0.59	0.05
		(0.58)	(1.84)	(2.31)	(2.35)	(0.37)	(1.20)	(2.27)	(2.30)	(1.96)	(1.63)	(1.80)	(0.17)
ILLIQ	Consistent	1.54	1.39	1.43	1.07	1.78	1.60	1.48	1.16	2.08	2.13	2.13	1.54
		(4.12)	(4.18)	(4.38)	(3.57)	(4.65)	(4.03)	(4.13)	(4.63)	(6.00)	(6.59)	(7.39)	(5.73)
	Inconsistent	0.07	0.07	0.32	0.24	0.00	0.03	0.26	−0.07	0.77	0.53	0.5	0.30
		(0.18)	(0.22)	(1.05)	(0.99)	(0.00)	(0.10)	(0.95)	(−0.32)	(2.04)	(1.78)	(1.76)	(1.08)
Failure Probability	Consistent	0.48	0.18	0.31	0.26	0.71	0.63	0.64	0.28	1.05	1.19	1.34	1.00
		(1.59)	(0.68)	(1.53)	(1.54)	(2.93)	(2.77)	(2.94)	(1.50)	(2.19)	(2.94)	(4.12)	(3.4)
	Inconsistent	−0.04	−0.08	−0.02	−0.10	−0.08	−0.05	0.10	−0.11	0.02	−0.20	−0.19	−0.32
		(−0.16)	(−0.37)	(−0.12)	(−0.6)	(−0.31)	(−0.2)	(0.44)	(−0.59)	(0.04)	(−0.62)	(−0.6)	(−1.38)
O-SCORE	Consistent	0.65	0.72	0.72	0.36	1.27	1.03	1.01	0.52	1.72	1.68	1.47	0.92
		(1.73)	(2.33)	(2.29)	(1.14)	(3.23)	(2.90)	(2.71)	(1.77)	(4.03)	(4.87)	(4.37)	(3.07)
	Inconsistent	0.37	0.34	0.55	0.30	−0.24	0.04	0.27	0.08	0.10	−0.07	−0.12	−0.05
		(0.93)	(1.08)	(1.85)	(1.29)	(−0.58)	(0.13)	(1.03)	(0.39)	(0.21)	(−0.17)	(−0.36)	(−0.18)
Gross Profitability	Consistent	1.41	1.70	1.73	1.20	1.34	1.23	1.19	0.81	0.93	0.95	0.96	0.52
		(3.75)	(4.81)	(5.24)	(4.22)	(3.42)	(3.63)	(3.67)	(2.76)	(2.30)	(3.01)	(3.34)	(1.59)
	Inconsistent	−0.04	0.35	0.49	0.39	−0.24	−0.04	0.06	0.00	−0.08	−0.16	0.03	−0.07
		(−0.09)	(1.13)	(1.66)	(1.66)	(−0.59)	(−0.11)	(0.18)	(−0.01)	(−0.22)	(−0.48)	(0.09)	(−0.33)
Investment to Asset	Consistent	1.52	1.42	1.39	0.70	0.82	0.87	0.92	0.66	1.30	1.36	1.12	0.75
		(4.02)	(4.58)	(4.55)	(2.36)	(2.35)	(2.88)	(3.07)	(2.4)	(3.06)	(3.68)	(3.29)	(2.40)
	Inconsistent	−0.23	0.11	0.12	0.00	0.04	0.19	0.50	0.35	0.17	−0.05	0.02	−0.14
		(−0.67)	(0.38)	(0.43)	(0.00)	(0.11)	(0.58)	(1.56)	(1.46)	(0.45)	(−0.15)	(0.05)	(−0.54)
Change in Short Interest	Consistent	1.54	1.53	1.47	0.95	1.29	0.99	1.10	0.77	2.21	1.86	1.83	1.44
		(3.42)	(5.22)	(5.09)	(3.87)	(4.78)	(4.07)	(4.79)	(3.83)	(5.06)	(4.8)	(4.75)	(4.38)
	Inconsistent	0.38	0.55	0.42	0.14	0.40	0.32	0.31	0.28	0.29	0.61	0.61	0.15
		(1.07)	(1.59)	(1.56)	(0.66)	(1.19)	(1.23)	(1.26)	(1.39)	(0.77)	(1.88)	(2.04)	(0.61)

This table presents average monthly Fama-French 3-factor alphas of portfolios independently sorted on past 6-month returns and short interest ratios in different firm characteristic subsamples. First, all sample stocks are equally divided into three groups based on the magnitude of each firm characteristic. Second, we form 30 two-way independently sorted portfolios described in Table 2. The consistent momentum portfolio is to buy lightly shorted winners and sell heavily shorted losers. The inconsistent portfolio is to buy heavily shorted winners and sell lightly shorted losers. Firm characteristics include firm size (ME), book-to-market ratio (BM), stock turnover, idiosyncratic volatility (IVOL), Amihud (2002) illiquidity measure (ILLIQ), failure probability, O-SCORE, gross profitability, investment to assets, and change in short interest over past 6-month. Stocks with prices less than $5 at the end of formation period are excluded. we skip one month between formation and holding periods. The holding period (K) is 1, 3, 6, or 12 months. Newey and West (1987) t-statistics are in parentheses. The sample period is from January 1988 to December 2016.

3.3.2. Controlling for book-to-market ratio

Sagi and Seasholes (2007) show that momentum profits are higher among firms with low book-to-market (BM) ratios. D'Avolio (2002) documents that glamour stocks are more likely to be shorted. In this subsection, we examine whether the joint approach efficiently identifies consistent momentum stocks and contrarian stocks in three different BM-ratio groups. Stocks' BM ratios in year t are calculated based on book value and market value in the previous year's annual report (year t-1).

We find consistent results in three BM subsamples. First, the return spread between lightly shorted losers and heavily shorted losers is significant in all three BM-ratio groups. The return spread for past winners is significant only among value stocks, but the sign of return spread is still positive. Second, the consistent momentum stocks experience large and significant momentum, but inconsistent momentum stocks experience weak and insignificant momentum. Third, the identification effect of the joint approach seems stronger among value stocks. Overall, the opinion joint approach could efficiently identify consistent and inconsistent momentum stocks in all three BM-ratio portfolios, although it performs best among value stocks.

3.3.3. *Controlling for trading volume*

Lee and Swaminathan (2000) document that momentum profits concentrate in high volume stocks. Hong et al. (2016) document that days to cover, the ratio of short interest to trading volume, is a better return predictor than the short interest ratio. In addition, trading volume is used to measure the divergence of opinion in the prior research. In this subsection, we examine whether the identification effect of the opinion joint approach is subsumed by trading volume.

Consistent with Lee and Swaminathan (2000), the simple momentum profit is highest among high volume stocks. Overall, the identification effect of short interest on momentum is robust in all three volume groups. The spread between lightly and heavily shorted losers is significant in all three volume groups. However, the spread between lightly shorted winners and heavily shorted winners is significant only in low volume group, though the sign of spread is expected in middle and high volume groups. The consistent portfolio generates significant momentum returns in all three volume groups, significantly outperforming the contrarian portfolio and simple momentum portfolio.

3.3.4. *Controlling for idiosyncratic volatility*

For ($J=6$, $K=6$), the consistent momentum strategy generates an average monthly alpha of 0.77%, 1.20%, and 2.18% in low, middle, and high IVOL subsamples, respectively. All alphas are economically and statistically significant. In contrast, the inconsistent momentum strategy generates an average monthly alpha of 0.39%, 0.43%, and 0.59% in low, middle, and high IVOL subsamples, respectively.

3.3.5. *Controlling for illiquidity*

We use illiquidity measure in Amihud (2002) to control for the effect of stock illiquidity (ILLIQ). For ($J=6$, $K=6$), the consistent momentum strategy generates an average monthly alpha of 1.43%, 1.48%, and 2.13% in low, middle, and high ILLIQ subsamples, respectively. All alphas are economically and statistically significant. In contrast, the inconsistent momentum strategy generates an average monthly alpha of 0.32%, 0.26%, and 0.50% in low, middle, and high ILLIQ subsamples, respectively. All alphas are statistically significant.

3.3.6. *Controlling for financial distress*

We use the failure probability in Campbell et al. (2008) and O-SCORE in Ohlson (1980) to measure the firm's financial distress. We examine whether financial distress could explain the role of short interest in identifying consistent and inconsistent momentum. For ($J=6$, $K=6$), the consistent momentum strategy generates an average monthly alpha of 0.31%, 0.64%, and 1.34% in low, middle, and high failure probability subsamples, respectively. In contrast, the inconsistent momentum strategy generates an average monthly alpha of −0.02%, 0.10%, and −0.19% in low, middle, and high failure probability subsamples, respectively. All alphas are statistically significant. Similarly, for ($J=6$, $K=6$), the consistent momentum strategy generates an average monthly alpha of 0.72%, 1.01%, and 1.47% in low, middle, and high O-SCORE subsamples, respectively. In contrast, the inconsistent momentum strategy generates an average monthly alpha of 0.55%, 0.27%, and −0.55% in low, middle, and high O-SCORE subsamples, respectively. All alphas are statistically significant. These findings are consistent with Avramov et al. (2007, 2013), suggesting that the incremental effect of short interest is stronger among stocks with high financial distress.

3.3.7. *Controlling for gross profitability*

Novy-Marx (2013) documents that the gross profitability (GP) is an important firm fundamental variable and could significantly predict the cross section of stock returns. Our results show that for ($J=6$, $K=6$), the consistent momentum strategy generates an average monthly alpha of 1.73%, 1.19%, and 0.96% in low, middle, and high GP subsamples, respectively. All alphas are statistically significant. In contrast, the inconsistent momentum strategy generates an average monthly alpha of 0.49%, 0.06%, and 0.03% in low, middle, and high GP subsamples, respectively. All alphas are statistically significant. These results suggest that the incremental effect of short interest is stronger among stocks with low gross profitability.

3.3.8. *Controlling for investment*

A firm's investment is also an important fundamental variable. Titman et al. (2004) document that firms with high past investment experience lower future stock returns. Here, we use investment to assets to control for the effect of capital investment. Our results show that for ($J=6$, $K=6$), the consistent momentum strategy generates an average monthly alpha of 1.39%, 0.92%, and 1.12% in low, middle, and high investment subsamples, respectively. All alphas are statistically significant. In contrast, the inconsistent momentum strategy generates an average monthly alpha of 0.12%, 0.50%, and 0.02% in low, middle, and high investment subsamples, respectively. All alphas are statistically significant.

3.3.9. *Controlling for change in short interest*

Daniel et al. (2017) use past winners, institutional ownership, and the change in short interest to efficiently identify overpriced winners. We examine whether the incremental effect of the level of short interest could be explained by the change in short interest.

Our results show that for ($J=6$, $K=6$), the consistent momentum strategy generates an average monthly alpha of 1.47%, 1.10%, and 1.83% in the low, middle, and high change-in-short-interest subsamples, respectively. All alphas are statistically significant. In contrast, the inconsistent momentum strategy generates an average monthly alpha of 0.42%, 0.31%, and 0.61%

Table 4
The joint approach and the short-sale constraints.

Portfolio	IO = 1 K=6				IO = 2 K=6				IO = 3 K=6			
	S1	S2	S3	S1-S3	S1	S2	S3	S1-S3	S1	S2	S3	S1-S3
M1	−0.55	−0.96	−1.85	1.30	−0.09	−0.38	−1.07	0.98	0.32	−0.01	−0.32	0.64
	(−2.46)	(−4.79)	(−8.02)	(5.02)	(−0.42)	(−1.67)	(−3.93)	(5.05)	(1.68)	(−0.05)	(−1.36)	(3.00)
M10	0.33	0.03	−0.55	0.89	0.43	−0.08	−0.11	0.54	0.98	0.77	0.66	0.33
	(1.90)	(0.14)	(−2.87)	(3.91)	(2.96)	(−0.61)	(−0.7)	(3.17)	(4.66)	(4.37)	(3.56)	(1.67)
M10-M1	0.88	0.99	1.30		0.53	0.30	0.96		0.66	0.78	0.97	
	(3.71)	(3.87)	(3.99)		(2.08)	(1.07)	(2.89)		(1.85)	(2.75)	(3.05)	
Consistent	2.18				1.51				1.30			
	(7.43)				(4.84)				(3.68)			
Inconsistent	−0.01				−0.02				0.33			
	(−0.03)				(−0.06)				(0.96)			
M1	−1.32				−0.69				−0.12			
	(−6.98)				(−2.97)				(−0.57)			
M10	−0.12				0.04				0.77			
	(−0.78)				(0.33)				(4.54)			
Simple	1.20				0.73				0.89			
	(4.90)				(2.68)				(3.09)			

This table presents the average monthly Fama-French 3-factor alphas of portfolios independently sorted on past 6-month returns and short interest ratios in three different institutional ownership subsamples. First, all sample stocks are equally divided into three groups based on the level of institutional ownership at the end of the prior quarter. Then within each IO groups, we form 30 two-way independently sorted portfolios described in Table 2. IO 1 (3) includes stocks with the lowest (highest) level of institutional ownership. Stocks with prices less than $5 at the end of formation period are excluded. We skip one month between formation and holding periods. The holding period is 6 months. The abnormal returns of the loser and winner portfolios and simple momentum strategies are also reported. The consistent momentum portfolio is to buy lightly shorted winners and sell heavily shorted losers. The inconsistent portfolio is to buy heavily shorted winners and sell lightly shorted losers. The sample period is from January 1988 to December 2016. Newey and West (1987) t-statistics are in parentheses.

in the low, middle, and high change-in-short-interest subsamples, respectively. These results suggest that the change in short interest cannot explain the incremental role of the level of short interest in improving momentum strategy.

3.4. The role of short-sale constraint

Short-sale constraints tend to increase the cost of short selling. Therefore, such constraints could help weed out relatively uninformed short sellers. Consequently, the short interest variable should be more informative when short-sale constraints are severe. Given the important role of short-sale constraints,[5] in this subsection we study whether our approach performs best among stocks with the most binding short-sale constraints.

Following Nagel (2005) and Daniel et al. (2017), we rely on institutional ownership (IO) as a proxy for the short-sale constraint. Institutional ownership data are from Thomson-Reuters 13-F filings (S34). Since IO data are reported quarterly, we use reported IO in month t for the subsequent months $t+1$ to $t+3$. We delete sample stocks without IO data.[6] We equally divide all sample stocks into three portfolios based on their levels of institutional ownership in each month. Then, within each of three IO portfolios, we use two-way independent sorts to equally assign stocks into 30 (10×3) portfolios based on their recent past returns and the current level of short interest. In the main analysis, both the formation and holding period of the momentum strategy are 6 months.

Table 4 represents the results. There are three main findings. First, the return spread between lightly shorted losers and heavily shorted losers is economically and statistically significant in all three IO portfolios, and the return spread for past winners is also significant in three IO portfolios. These findings suggest that the simple joint approach will work well for all past losers and winners, even if we do not add a measurable short-sale constraint into this approach. One potential explanation is that past losers may suffer from binding short-sale constraints even in the high IO portfolio.

Second, the return spreads for both past losers and winners are largest in low IO portfolios. Moreover, the return spreads are larger for past losers than for past winners in all three IO portfolios. The return spreads for past losers are 1.30% and 0.64% in low and high IO portfolios, respectively. The return spreads for past winners are 0.89% and 0.33% in low and high IO portfolios, respectively. These results suggest that past losers are more likely to be short-sale constrained than past winners.

Third, the consistent momentum stocks experience large and significant momentum, and the inconsistent momentum stocks experience small and insignificant momentum in the first 6-month holding period in all three IO portfolios.

[5] Asquith et al. (2005) report that institutional ownership of 95% of 5500 domestic common stocks in NYSE/AMEX/NASDAQ is greater than their short interest, and they conclude that most stocks are not short-sale constrained. However, in reality, institutions are unlikely to lend out all their shares. Moreover, besides the borrowing costs, other shorting costs such as holding costs, margin interest, the risk of being recalled, and the risk of short squeezes could deter potential short sellers.

[6] Since more than 97% of our sample stocks have IO data each month, our results are not affected by deleting those stocks without IO data.

Moreover, the return difference between the consistent momentum portfolio and the inconsistent portfolio is largest in the low IO portfolio. Overall, the simple joint approach could efficiently identify consistent momentum stocks and inconsistent momentum stocks in all three IO portfolios, but the identification effect is strongest among stocks with the most binding short-sale constraints. These findings are supportive of the signaling effect of the short interest variable, as well as the view that short-sale constraints and the informativeness of short interest are positively correlated.

3.5. Regression analysis

Our portfolio analysis indicates that the joint approach could efficiently identify consistent and inconsistent momentum stocks. However, this approach cannot control for many important variables simultaneously due to the insufficient number of stocks after N-way independent sorts. To address this concern, we rely on the Fama and MacBeth (1973) regression approach to investigate the *incremental* return predictability of short selling after controlling for variables that are known to have predictive power for stock returns. We run the following monthly firm-level cross-sectional Fama and MacBeth (1973) regressions:

$$R_{it+k} = \alpha + \beta_1 PastReturn_{it} + \beta_2 SIR_{it} + \beta_3 PastReturn_{it} * SIR_{it} + \beta_4 CV_{it} + \beta_5 PastReturn_{it} * CV_{it} + +\varepsilon_{it+1}$$

where, $R_{i\,t+k}$ is the average monthly raw return for stock *i* in the next *k* months, *PastReturn* is the past 6-month cumulative returns, *SIR* is the level of short interest in month t, and *CV* denotes a vector of control variables including size, book-market ratio (BM), institutional ownership, idiosyncratic volatility, illiquidity, turnover, gross profitability, investment to assets, failure probability, O-SCORE, and change in short interest.

Table 5 reports the estimated coefficients of interest. Model 1 is the benchmark model. Model 1 shows that the coefficient of the interaction term of past returns and short interest is significant and positive, suggesting that short interest has an incremental effect on the return predictability of past returns. We control for the firm size and BM ratio in the Model 2. The coefficient of the interaction term is still significant and positive in the Model 2. We control for more variables such as idiosyncratic volatility, turnover, illiquidity, and change in short interest in Model 3 and 4. We get consistent results. In Model 5, we control for more variables such as financial distress, gross profitability, and investment. The coefficient of the interaction term is still positive and significant. Overall, consistent with the portfolio analysis results from Tables 3 and 4, the short interest has an incremental effect on the return predictability of past returns even after controlling for a broad set of well-known firm characteristics.

3.6. Long-term performance

In this subsection, we explicitly examine whether momentum and long-term reversals are inherently linked. We study whether the joint approach could identify consistent momentum stocks that experience persistent momentum and inconsistent momentum stocks that experience persistent reversals *in the long run*. Table 6 reports the results.

Panel A reports the average monthly Fama-French 3-factor adjusted returns of portfolios sorted on past returns and short interest in the five years after the formation period. First, the average monthly return spread between lightly shorted stocks and heavily shorted stocks is significant in the first four years for past losers and in the first two years for past winners. The average monthly return spread is 0.63% ($t = 3.78$), 0.40% ($t = 2.48$), 0.60% ($t = 3.45$), and 0.30% ($t = 2.09$) for past losers in the first-, second-, third-, and fourth- years respectively. The monthly return spread is 0.32% ($t = 2.62$) and 0.28% ($t = 2.26$) for past winners in the first- and second- years. The sign of return spread is also as expected (positive) for other years, though the return spread is insignificant. Second, the simple momentum strategy experiences weak reversals in the second and fifth years, consistent with Jegadeesh and Titman (2001). The magnitude of reversals is relatively small because our sample stocks are from NYSE/AMEX and the sample period is from 1988 to 2016. By comparison, the consistent momentum portfolio experiences significant monthly returns in the first year (1.07%) and positive returns in the second (0.12%), third (0.41%) and fourth years (0.32%). In contrast, the inconsistent portfolio experiences insignificant monthly positive returns (0.13%) in the first year and strong reversals in the next four years. The monthly alphas for contrarian portfolio are −0.56% (t=−3.28), −0.30% (t=−1.82), −0.15% (t=−0.92), and −0.43% (t=−2.30) in the second to fifth years, respectively.

Panel B reports the long-term performance of the consistent momentum portfolio and inconsistent momentum portfolio after controlling for firm characteristics documented in Table 3. The consistent portfolio experiences significant momentum in the first years and no reversal in the long run in almost all three size, BM ratio, turnover, idiosyncratic volatility, illiquidity, financial distress, gross profitability, investment, and change in short interest subsamples. In contrast, the inconsistent momentum portfolio experiences zero or weak momentum in the first year and persistent reversals in the long run in most firm-characteristic subsamples. We note that these results are consistent with Conrad and Yavuz (2017) who only control for size and BM ratio. In comparison, we obtain consistent results after controlling for many other well-known firm characteristics.

Panel C reports the long-run results using IO as a proxy for short-sale constraints. First, the return spreads between lightly shorted losers and heavily shorted losers are significant for five years in the low IO portfolio. The magnitude and significance of the return spread decrease from low to high IO portfolio for past losers. We get similar results for past winners. Though the magnitude and significance decrease after the first holding year, the incremental effect of short interest

Table 5
Fama and MacBeth (1973) regressions.

	1	2	3	4	5
Intercept	0.9802	1.2890	1.4277	1.3868	1.2164
	(7.59)	(4.27)	(2.63)	(2.56)	(2.15)
PastReturn	0.3057	1.1757	−0.8815	−0.9740	−1.5171
	(1.75)	(2.52)	(−0.59)	(−0.64)	(−1.07)
SIR	−4.9933	−2.9368	−4.1769	−3.3575	−2.4347
	(−5.86)	(−3.76)	(−6.82)	(−5.03)	(−3.63)
ME		−0.0172	−0.1063	−0.1066	−0.0793
		(−0.93)	(−1.66)	(−1.65)	(−1.11)
BM		0.0167	0.0419	0.0433	0.0312
		(0.47)	(1.32)	(1.34)	(1.01)
IO			0.4887	0.4861	0.4498
			(17.25)	(17.13)	(16.15)
TO			−0.0273	−0.0353	−0.0638
			(−0.36)	(−0.46)	(−0.75)
IVOL			−0.0770	−0.0733	0.0042
			(−1.60)	(−1.53)	(0.09)
ILLIQ			−0.0426	−0.0432	−0.0377
			(−0.72)	(−0.73)	(−0.57)
Distress					0.0192
					(2.07)
GP					0.1045
					(1.00)
IA					−0.0318
					(−0.27)
CSIR				−3.0414	−2.9954
				(−3.1)	(−2.97)
PastReturn*SIR	5.5726	3.4197	5.7230	4.8468	4.9565
	(3.60)	(2.10)	(3.18)	(2.38)	(2.32)
PastReturn*ME		−0.0798	0.0086	0.0414	0.1017
		(−2.01)	(0.04)	(0.19)	(0.52)
PastReturn*BM		−0.1364	−0.1012	−0.1280	−0.2416
		(−1.60)	(−1.18)	(−1.44)	(−2.51)
PastReturn*IO			−0.0587	−0.0600	0.0851
			(−0.53)	(−0.54)	(0.72)
PastReturn*TO			−0.1481	−0.0931	−0.0057
			(−0.69)	(−0.44)	(−0.03)
PastReturn*IVOL			−0.1796	−0.2256	−0.4021
			(−1.07)	(−1.30)	(−2.35)
PastReturn*ILLIQ			0.1085	0.1537	0.2139
			(0.57)	(0.82)	(1.23)
PastReturn*Distress					0.0770
					(1.81)
PastReturn*GP					−0.4899
					(−1.56)
PastReturn*IA					−0.2215
					(−0.51)
PastReturn*CSIR				6.1288	0.3386
				(1.90)	(0.10)

This table presents the results of Fama and MacBeth (1973) cross-section regressions. The dependent variable is the average monthly return over the 6-month holding period. The independent variables include the past 6-month cumulative return (PastReturn), the short interest ratio (SIR), the interaction term of past returns and SIR, and control variables include the natural logarithm of firm market capitalization (ME) at the end of month t-1, the natural logarithm of book-to-market ratio measured at the end of prior year (BM), the trading volume scaled by outstanding shares (TO), institutional ownership (IO), idiosyncratic volatility (IVOL), Amihud (2002) illiquidity measure (ILLIQ), financial distress measured by O-SCORE, gross profitability (GP), capital investment to assets (IA), and the change in short interest over past 6-month, and the interaction terms of past returns and control variables. The sample period is from January 1988 to December 2016. Newey and West (1987) t-statistics are in parentheses.

seem quite robust in the long run. Second, the magnitude and significance are larger for past losers than for past winners even in the long run. Third, the consistent momentum portfolio experience persistent momentum in the long run in all three IO portfolios, which is more pronounced in low and middle IO portfolios. In contrast, the inconsistent portfolio experience persistent reversals in the long run in all three IO portfolios.

To summarize, the long-short joint approach appears to work well both in the short and long run, even after controlling for a set of well-known firm characteristics. Moreover, the identification of the joint approach on the momentum-reversal pattern is more effective among stocks with more binding short-sale constraints. Importantly, we find that short-term momentum and long-run reversal patterns are not necessarily linked in a manner consistent with the predictions of several well-known behavioral models. In addition, these patterns vary across portfolios with different levels of short interest.

Table 6
Long-term performance.

Panel A

	Year 1			Year 2			Year 3			Year 4			Year 5		
	S1	S3	S1-S3	S1	S3	S1-S3	S1	S3	S1-S3	S1	S3	S1-S3	S1	S3	S1-S3
M1	−0.28	−0.91	0.63	0.14	−0.26	0.40	0.20	−0.40	0.60	0.12	−0.18	0.30	0.24	0.09	0.14
	(−1.47)	(−4.1)	(3.78)	(0.91)	(−1.39)	(2.48)	(1.02)	(−2.21)	(3.45)	(0.72)	(−1.12)	(2.09)	(1.40)	(0.46)	(0.97)
M10	0.16	−0.15	0.32	−0.13	−0.42	0.28	0.01	−0.11	0.12	0.14	−0.03	0.17	0.03	−0.19	0.22
	(1.34)	(−1.19)	(2.62)	(−0.85)	(−2.47)	(2.26)	(0.04)	(−0.65)	(0.85)	(0.66)	(−0.19)	(1.30)	(0.22)	(−0.89)	(1.61)
M10-M1	0.44	0.75		−0.27	−0.16		−0.19	0.29		0.02	0.15		−0.21	−0.29	
	(2.23)	(3.14)		(−1.86)	(−0.97)		(−1.18)	(1.82)		(0.13)	(1.04)		(−1.27)	(−1.62)	
Consistent	1.07			0.12			0.41			0.32			−0.06		
	(4.25)			(0.59)			(1.95)			(1.82)			(−0.35)		
Inconsistent	0.13			−0.56			−0.30			−0.15			−0.43		
	(0.62)			(−3.28)			(−1.82)			(−0.92)			(−2.30)		

Panel B

		Characteristic=1					Characteristic=2					Characteristic=3				
		Year 1	Year 2	Year 3	Year 4	Year 5	Year 1	Year 2	Year 3	Year 4	Year 5	Year 1	Year 2	Year 3	Year 4	Year 5
ME	Consistent	1.51	0.11	0.58	0.48	−0.15	0.97	0.26	0.53	0.20	−0.10	0.76	−0.19	0.12	0.26	−0.22
		(5.15)	(0.37)	(2.37)	(2.15)	(−0.72)	(3.62)	(1.34)	(2.01)	(1.07)	(−0.44)	(2.66)	(−0.97)	(0.52)	(1.52)	(−1.15)
	Inconsistent	0.08	−1.16	−0.16	0.03	−0.37	0.07	−0.50	0.09	−0.18	−0.30	0.22	−0.24	−0.20	−0.07	−0.40
		(0.27)	(−3.94)	(−0.66)	(0.16)	(−1.35)	(0.27)	(−2.61)	(0.48)	(−0.88)	(−1.12)	(0.93)	(−1.29)	(−1.02)	(−0.38)	(−2.12)
BM	Consistent	0.78	0.27	0.35	0.50	−0.03	0.90	−0.01	0.21	0.02	−0.16	0.63	−0.05	0.25	−0.06	0.01
		(2.88)	(1.25)	(1.55)	(1.86)	(−0.14)	(3.04)	(−0.05)	(0.70)	(0.08)	(−0.60)	(2.12)	(−0.17)	(0.93)	(−0.22)	(0.02)
	Inconsistent	0.34	−0.16	−0.18	−0.11	−0.07	0.00	−0.39	−0.45	−0.11	−0.29	0.01	−0.25	−0.04	−0.05	−0.71
		(1.67)	(−0.81)	(−0.82)	(−0.49)	(−0.21)	(0.01)	(−1.97)	(−2.10)	(−0.41)	(−1.05)	(0.05)	(−0.91)	(−0.17)	(−0.22)	(−2.53)
TO	Consistent	1.07	0.18	0.31	0.39	−0.08	0.84	0.21	0.08	−0.03	−0.18	1.60	0.15	0.38	0.44	−0.19
		(5.82)	(1.06)	(1.59)	(2.12)	(−0.43)	(4.32)	(1.34)	(0.42)	(−0.19)	(−0.98)	(4.58)	(0.53)	(1.30)	(2.01)	(−0.73)
	Inconsistent	0.31	−0.52	−0.29	0.08	−0.39	0.30	0.06	−0.07	−0.02	−0.19	0.25	−0.72	0.05	0.10	−0.58
		(1.37)	(−2.93)	(−1.77)	(0.42)	(−1.83)	(1.75)	(0.36)	(−0.42)	(−0.15)	(−1.09)	(0.80)	(−2.77)	(0.21)	(0.51)	(−1.73)
IVOL	Consistent	0.59	0.02	0.29	0.24	−0.04	0.79	0.21	0.44	0.27	0.06	1.54	0.12	0.49	0.34	0.05
		(4.22)	(0.10)	(2.22)	(1.60)	(−0.28)	(3.79)	(1.19)	(2.75)	(1.87)	(0.32)	(4.22)	(0.46)	(1.70)	(1.39)	(0.20)
	Inconsistent	0.32	−0.10	−0.36	−0.15	−0.40	0.37	−0.24	−0.22	−0.02	−0.41	0.05	−0.70	−0.12	−0.47	−0.50
		(2.35)	(−1.05)	(−3.65)	(−1.13)	(−3.2)	(2.3)	(−1.65)	(−1.39)	(−0.12)	(−2.78)	(0.17)	(−2.54)	(−0.53)	(−2.17)	(−1.54)
ILLIQ	Consistent	1.07	0.11	0.39	0.37	−0.10	1.16	0.24	0.53	0.30	−0.39	1.54	0.14	0.38	0.22	−0.08
		(3.57)	(0.5)	(1.66)	(1.98)	(−0.41)	(4.63)	(1.06)	(2.16)	(1.49)	(−1.88)	(5.73)	(0.60)	(1.63)	(0.99)	(−0.37)
	Inconsistent	0.24	−0.32	−0.32	−0.29	−0.41	−0.07	−0.60	0.33	0.02	−0.44	0.30	−0.69	−0.20	0.06	−0.16
		(0.99)	(−1.63)	(−1.72)	(−1.45)	(−1.81)	(−0.32)	(−3.2)	(1.64)	(0.08)	(−1.77)	(1.08)	(−2.67)	(−1.03)	(0.31)	(−0.65)
FP	Consistent	0.26	−0.04	−0.07	−0.14	0.12	0.28	0.09	0.08	−0.07	−0.40	1.00	0.20	0.59	0.12	−0.13
		(1.54)	(−0.25)	(−0.38)	(−0.82)	(0.62)	(1.50)	(0.56)	(0.43)	(−0.37)	(−1.78)	(3.40)	(0.79)	(2.29)	(0.47)	(−0.51)
	Inconsistent	−0.10	−0.22	−0.20	−0.15	−0.20	−0.11	−0.43	−0.32	−0.12	−0.36	−0.32	−0.92	−0.16	−0.02	−0.23
		(−0.6)	(−1.44)	(−1.48)	(−0.78)	(−0.81)	(−0.59)	(−3.23)	(−2.29)	(−0.76)	(−1.58)	(−1.38)	(−3.62)	(−0.74)	(−0.07)	(−0.77)
O-SCORE	Consistent	0.36	−0.05	0.33	0.15	0.35	0.52	−0.14	0.38	0.30	−0.04	0.92	0.17	0.34	−0.06	−0.25
		(1.14)	(−0.19)	(1.44)	(0.72)	(1.39)	(1.77)	(−0.51)	(1.55)	(1.11)	(−0.15)	(3.07)	(0.56)	(1.12)	(−0.20)	(−1.06)
	Inconsistent	0.30	0.06	−0.43	0.14	−0.14	0.08	0.01	−0.45	−0.10	−0.17	−0.05	−0.69	−0.21	0.05	0.03
		(1.29)	(0.29)	(−2.22)	(0.55)	(−0.40)	(0.39)	(0.03)	(−1.62)	(−0.38)	(−0.67)	(−0.18)	(−2.75)	(−0.77)	(0.15)	(0.06)
GP	Consistent	1.20	0.12	0.45	0.23	−0.05	0.81	−0.03	0.39	0.11	−0.36	0.52	0.14	0.26	0.18	0.22
		(4.22)	(0.43)	(1.65)	(0.78)	(−0.17)	(2.76)	(−0.12)	(1.4)	(0.44)	(−1.5)	(1.59)	(0.61)	(1.2)	(0.64)	(0.89)
	Inconsistent	0.39	−0.07	−0.24	−0.37	−0.32	0.00	−0.45	−0.06	0.18	−0.29	−0.07	−0.24	−0.66	−0.27	−0.50
		(1.66)	(−0.29)	(−1.22)	(−1.43)	(−1.14)	(−0.01)	(−1.97)	(−0.25)	(0.70)	(−0.98)	(−0.33)	(−0.74)	(−2.35)	(−1.05)	(−1.91)
IA	Consistent	0.70	−0.18	0.16	0.36	−0.18	0.66	0.02	0.22	0.23	−0.03	0.75	0.23	0.65	−0.25	0.02
		(2.36)	(−0.63)	(0.59)	(1.13)	(−0.63)	(2.4)	(0.09)	(0.89)	(1.01)	(−0.14)	(2.4)	(0.75)	(2.28)	(−0.87)	(0.07)
	Inconsistent	0.00	−0.20	−0.08	−0.20	−0.48	0.35	−0.43	−0.50	0.09	−0.34	−0.14	−0.17	−0.15	−0.22	−0.30
		(0.00)	(−0.79)	(−0.42)	(−0.90)	(−2.20)	(1.46)	(−1.63)	(−1.96)	(0.39)	(−1.57)	(−0.54)	(−0.77)	(−0.67)	(−0.82)	(−0.71)
CSIR	Consistent	0.95	0.03	0.34	0.23	−0.07	0.77	0.06	0.18	0.18	−0.23	1.44	0.19	0.53	0.34	−0.04
		(3.87)	(0.16)	(1.65)	(1.10)	(−0.31)	(3.83)	(0.25)	(0.85)	(1.02)	(−1.43)	(4.38)	(0.80)	(2.09)	(1.63)	(−0.16)
	Inconsistent	0.14	−0.50	−0.24	−0.16	−0.30	0.28	−0.33	−0.23	−0.21	−0.39	0.15	−0.63	−0.02	−0.07	−0.37
		(0.66)	(−2.76)	(−1.37)	(−0.86)	(−0.99)	(1.39)	(−1.88)	(−1.23)	(−1.25)	(−1.81)	(0.61)	(−2.83)	(−0.07)	(−0.39)	(−1.54)

Panel C

	IO=1					IO=2					IO=3				
	Year 1	Year 2	Year 3	Year 4	Year 5	Year 1	Year 2	Year 3	Year 4	Year 5	Year 1	Year 2	Year 3	Year 4	Year 5
	S1-S3	S1-S3	S1-S3	S1-S3	S1-S3	S1-S3	S1-S3	S1-S3	S1-S3	S1-S3	S1-S3	S1-S3	S1-S3	S1-S3	S1-S3
M1	1.15	0.83	0.85	0.41	0.38	0.64	0.48	0.68	0.19	0.00	0.46	0.23	0.12	0.11	−0.01
	(4.69)	(3.26)	(3.13)	(2.00)	(1.65)	(3.06)	(2.52)	(3.41)	(1.03)	(−0.02)	(1.83)	(1.20)	(0.83)	(0.56)	(−0.06)
M10	0.93	0.53	0.20	0.46	0.55	0.56	0.42	0.48	0.22	0.38	0.24	0.47	0.30	0.31	0.13
	(4.64)	(3.36)	(0.94)	(2.27)	(2.54)	(4.11)	(2.68)	(3.00)	(1.24)	(2.54)	(1.53)	(3.6)	(2.10)	(2.18)	(0.70)

(*continued on next page*)

Table 6 (*continued*)

Consistent	1.63	0.24	0.53	0.42	0.08	1.07	0.25	0.73	0.45	−0.08	0.91	0.02	0.25	0.41	−0.15
	(6.14)	(0.92)	(1.81)	(1.67)	(0.33)	(4.08)	(1.19)	(3.69)	(2.06)	(−0.36)	(2.93)	(0.09)	(1.10)	(2.04)	(−0.79)
Inconsistent	−0.45	−1.12	−0.52	−0.44	−0.85	−0.13	−0.65	−0.43	0.04	−0.42	0.20	−0.68	−0.17	−0.01	−0.25
	(−1.49)	(−4.26)	(−2.15)	(−1.93)	(−2.89)	(−0.71)	(−2.96)	(−2.3)	(0.19)	(−1.82)	(0.82)	(−3.67)	(−0.81)	(−0.06)	(−0.99)
M1	−1.10	−0.36	−0.36	−0.16	0.07	−0.56	−0.17	−0.32	−0.17	0.17	0.04	0.52	0.16	0.13	0.33
	(−5.45)	(−2.25)	(−1.89)	(−1.29)	(0.36)	(−2.56)	(−1.01)	(−1.87)	(−1.16)	(0.85)	(0.23)	(3.03)	(1.06)	(0.69)	(1.79)
M10	−0.40	−0.55	−0.27	−0.12	−0.24	−0.09	−0.35	−0.14	−0.06	−0.18	0.61	0.27	0.19	0.24	0.07
	(−2.96)	(−3.44)	(−1.48)	(−0.54)	(−1.52)	(−0.83)	(−2.34)	(−0.91)	(−0.42)	(−1.24)	(4.28)	(1.70)	(1.16)	(1.81)	(0.37)
Simple	0.71	−0.19	0.10	0.03	−0.31	0.47	−0.19	0.18	0.11	−0.35	0.56	−0.24	0.03	0.12	−0.26
	(3.05)	(−1.04)	(0.55)	(0.22)	(−1.69)	(2.39)	(−1.27)	(1.26)	(0.86)	(−2.06)	(2.37)	(−1.57)	(0.14)	(0.81)	(−1.76)

Panel A presents average monthly Fama-French 3-factor adjusted returns of portfolios independently sorted on past 6-month returns and short interest ratio in the first, second, third, fourth and fifth years. Panel B reports the performance of consistent and inconsistent portfolios after controlling for firm characteristics. Panel C reports the results after controlling for intuitional ownerships. Stocks with prices less than $5 at the end of formation period are excluded. We skip one month between formation and holding periods. The sample period is from January 1988 to December 2016. Newey and West (1987) t-statistics are in parentheses.

Table 7
Investor sentiment.

	High Sentiment				Low Sentiment				High - Low Sentiment			
	S1	S2	S3	S1-S3	S1	S2	S3	S1-S3	S1	S2	S3	S1-S3
M1	−0.52	−0.50	−1.06	0.55	−0.02	−0.66	−1.32	1.30	−0.49	0.16	0.26	−0.76
	(−2.49)	(−2.68)	(−3.73)	(2.11)	(−0.06)	(−1.86)	(−3.38)	(5.26)	(−1.17)	(0.4)	(0.52)	(−1.98)
M10	0.99	0.82	0.34	0.65	0.31	−0.04	−0.12	0.43	0.68	0.86	0.46	0.22
	(3.9)	(4.05)	(1.62)	(3.01)	(1.50)	(−0.18)	(−0.47)	(1.9)	(2.02)	(2.77)	(1.31)	(0.70)
M10-M1	1.51	1.32	1.40		0.33	0.62	1.20		1.17	0.70	0.20	
	(4.41)	(5.15)	(3.95)		(0.72)	(1.20)	(2.12)		(1.82)	(1.16)	(0.28)	
Consistent	2.05				1.63				0.42			
	(4.95)				(3.34)				(0.60)			
Inconsistent	0.86				−0.10				0.96			
	(2.87)				(−0.19)				(1.39)			
M1	−0.75				−0.82				0.07			
	(−3.60)				(−2.27)				(0.17)			
M10	0.65				0.02				0.63			
	(3.37)				(0.09)				(2.11)			
M10-M1	1.40				0.84				0.56			
	(4.80)				(1.61)				(0.86)			

This table presents average monthly Fama-French 3-factor alphas of interacted portfolios described in Table 2 following high and low investor sentiment periods. A month t is classified as a high (low) sentiment month if the Baker and Wurgler (2006) sentiment index in month t is above (below) the sample median value. The holding period is 1-month. The sample period is from January 1988 to September 2015. Newey and West (1987) t-statistics are in parentheses.

3.7. Robustness tests

3.7.1. Investor sentiment

Based on the behavioral model of Hong and Stein (1999), Antoniou et al. (2013) show that momentum profits arise following high sentiment periods and are small and insignificant following low sentiment periods. Stambaugh et al. (2012) also find that momentum profit is higher following high sentiment periods. Short-sale constraints play an important role in their arguments because the difference in short-leg returns explains most of the difference in momentum profits following high vs. low sentiment periods. They attribute this finding to the observation that short-sale constraints effectively prohibit arbitraging the overpricing of past losers during high sentiment period, and subsequent correction of mispricing following high sentiment leads to high short-leg profits.

In this subsection, we examine whether our results are robust to variations in investor sentiment. We use the monthly sentiment index created by Baker and Wurgler (2006, 2007) to define high and low sentiment periods. Following Stambaugh et al. (2012), we classify month t as a high (low) sentiment month if the Baker and Wurgler (2006) sentiment index in month t is above (below) the sample median value. In the portfolio analysis, we then examine the returns of portfolios following high or low sentiment periods (i.e., month $t+1$).

Table 7 reports the Fama-French 3-factor adjusted returns of various portfolios. First, the return spreads between lightly shorted losers and heavily shorted losers are significant following both high and low sentiment periods. However, the return spread is significantly larger following low sentiment periods. Second, the return spreads between lightly shorted winners and heavily shorted winners are significant following both high and low sentiment periods. Moreover, there is no significant difference on the return spread between high and low sentiment periods. Third, consistent with prior studies, simple momentum strategy generates a significant and higher profit following high sentiment periods and no profit following low sentiment periods. The *consistent* momentum portfolio generates an average monthly alpha of 2.05% ($t=3.55$) and 1.63%

Table 8
Exogenous shock.

	Before TRA97				Post TRA97			
	S1	S2	S3	S1-S3	S1	S2	S3	S1-S3
M1	0.15	−0.18	−0.59	0.74	−0.02	−0.18	−0.89	0.86
	(0.7)	(−0.7)	(−2.48)	(2.09)	(−0.09)	(−0.62)	(−3.09)	(3.06)
M10	0.90	0.76	0.41	0.49	0.80	0.50	0.27	0.53
	(4.29)	(3.38)	(2.15)	(2.21)	(3.70)	(2.01)	(1.24)	(2.60)
M10-M1	0.75	0.93	1.00		0.82	0.68	1.16	
	(2.43)	(2.44)	(2.96)		(2.34)	(1.63)	(2.64)	
Consistent	1.49				1.68			
	(4.21)				(4.17)			
Inconsistent	0.26				0.29			
	(0.87)				(0.76)			
M1	−0.26				−0.47			
	(−1.45)				(−1.78)			
M10	0.68				0.47			
	(4.40)				(2.50)			
Simple	0.94				0.94			
	(3.45)				(2.37)			

This table presents the average monthly Fama-French 3-factor alphas of the double-sorted portfolios (as described in Table 2) before and after the Taxpayer Relief Act of 1997 (TRA97). We use June 1997 as the cutoff date. Since TRA97 was implemented in the middle of that month, we exclude the observation from June of 1997. The holding period is 1-month. The whole sample period is from 1988 to 2016. Newey and West (1987) t-statistics are in parentheses.

($t = 3.34$) following high and low sentiment periods respectively. In contrast, the *inconsistent* portfolio generates an alpha of 0.86% ($t = 2.87$) and −0.10% ($t = -0.19$) following high and low sentiment periods, respectively. Overall, the incremental effect of short interest on momentum is significant following both high and low sentiment periods.

These findings suggest that investor sentiment has no significant impact on the identification of the joint approach on the momentum-reversal pattern. The joint approach could identify *ex ante* consistent momentum stocks following both high and low sentiment periods. These results are consistent with the interpretation that short sellers are informed traders and consequently not influenced by the shifts in investor sentiment.

3.7.2. Exogenous shock

To address the concern that short interest could be an endogenous variable and can affect stock return distributions, in this subsection we probe the robustness of the long-short joint approach using an exogenous shock — the Taxpayer Relief Act of 1997 (TRA97). This exogenous shock on short selling was first identified by Arnold et al. (2005), who note that prior to the enactment of TRA97, investors were allowed to hold both long and short positions in the same stocks to minimize their tax liabilities. TRA97 banned this practice in June 1997 and therefore makes short-selling more informative afterwards. Following Arnold et al. (2005), we divide our sample into to two subsamples: before and after June 1997. We throw out the June 1997 observation because TRA97 was implemented in the middle of that month.

Table 8 reports the results. First, we find that the simple momentum strategy generates same return before and after TRA97. Second, the return spreads between lightly shorted losers and heavily shorted losers are economically and statistically significant before and after TRA97. The return spread is 0.74% ($t = 2.09$) and 0.86% ($t = 3.06$) before and after TRA97, respectively. Interestingly, we do find that the consistent momentum portfolio performance slightly better after TRA97 (1.68% vs. 1.49%), which appears consistent with the interpretation that short selling could be more informative after the implementation of TRA97.

3.7.3. Momentum crashes

Daniel and Moskowitz (2016) document that momentum suffers from infrequent but extremely large crashes. For example, they find that during the two-month period in July and August of 1932, a momentum portfolio would lose 90% of its total value. Fig. 1 shows that, even though the consistent momentum strategy earns significantly higher average return than the simple momentum strategy, it could still suffer from such infrequent but large crashes (e.g. during 2008–2009 financial crisis). This finding is not surprising because as shown by Daniel and Moskowitz (2016), momentum crashes usually occur when there is a transition in market cycles. But outperformance from the consistent momentum strategy is largely due to the information content of short interest on individual firms. In other words, the short-interest based consistent momentum strategy is successful at improving the mean but not the volatility of momentum profits. To further dampen the volatility of the consistent momentum, we adopt the risk-managed momentum strategy first proposed by Barros and Santa-Clara (2015), which scales the long-short momentum portfolio using a ratio of its realized past 6-month return volatility and a target volatility. We call this new strategy – risk-managed consistent momentum. We find that this new strategy outperforms even the risk-managed simple momentum. For example, the risk-managed consistent momentum has a higher mean (1.21% vs. 1.08%), lower volatility (4.2% vs. 4.4%), and smaller kurtosis (0.60 vs. 2.02) than the risk-managed simple momentum. Its

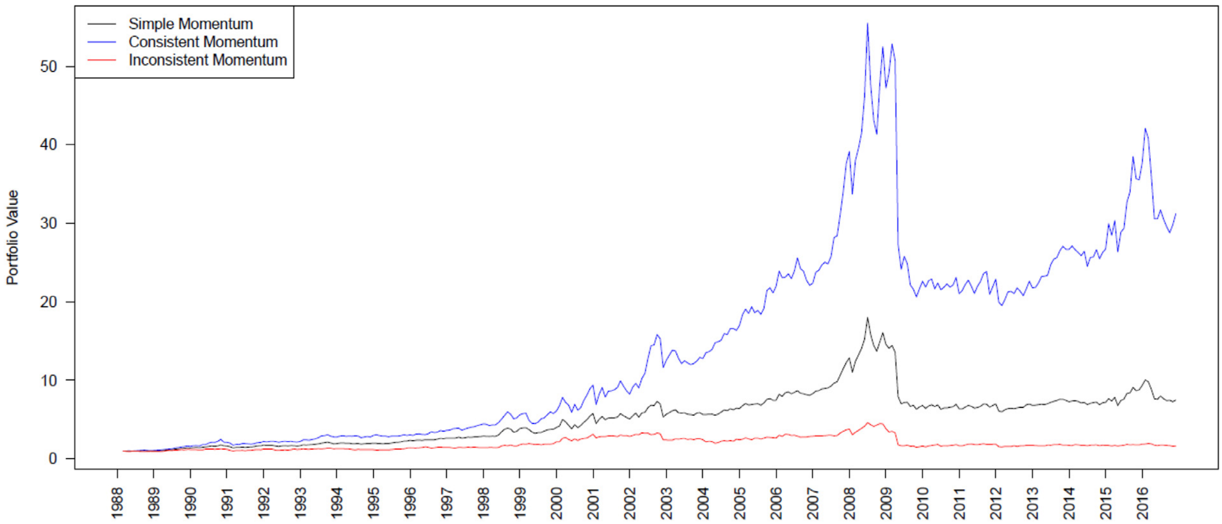

Fig. 1. Performance of simple, consistent, and inconsistent momentum strategies.

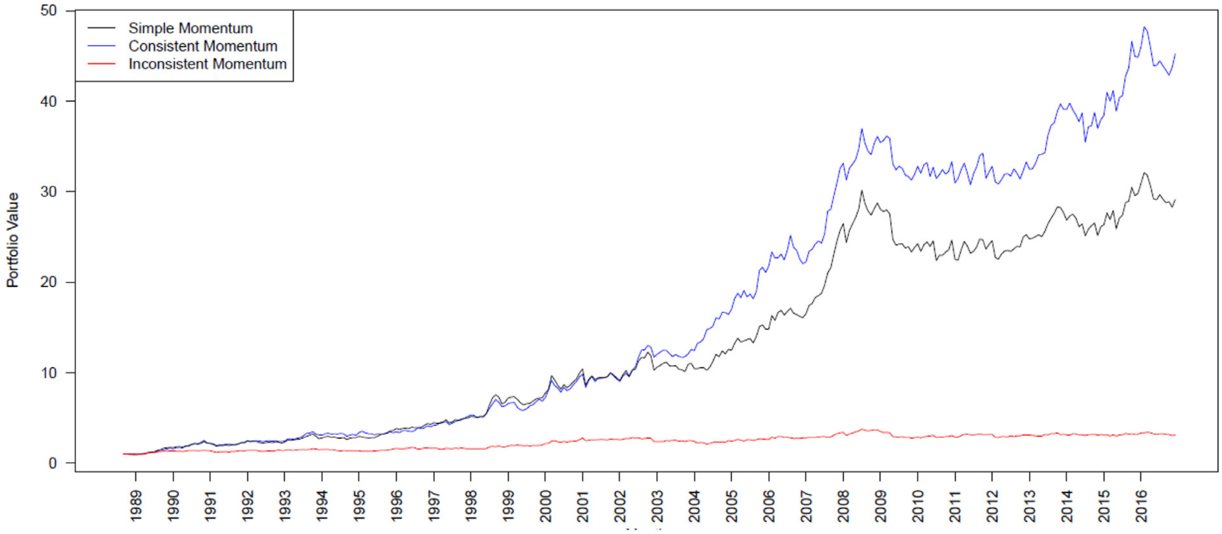

Fig. 2. Risk-managed momentum strategies.

worst monthly return is −14.8%, which is still better than the −17.2% registered by the risk-managed simple momentum. In Fig. 2, we plot the time series of cumulative profits of the three risk-managed strategies: simple, consistent, and inconsistent momentum. Compared with similar plots from Fig. 1, we find that the risk-managed consistent momentum strategy no longer suffers from large crashes.

4. Conclusion

This paper studies the role of short selling on momentum-reversal pattern. We use the current level of short interest as a proxy for opinion of short sellers. Under the assumption that short sellers are informed traders, we conjecture that the level of short interest sends a strong signal to long-side investors, who could become more aggressive (cautious) buyers when the signal is consistent (inconsistent) with their prior views. We argue that our approach can shed light on the complex momentum-reversal pattern observed in the data.

We report that our long-short joint approach can successfully identify momentum stocks that exhibit persistent momentum and those that experience no momentum. A consistent momentum portfolio that buys lightly shorted winners and sells heavily shorted losers exhibits strong short-term momentum and no long-term reversal. In contrast, the inconsistent momentum portfolio that buys heavily shorted winners and sells lightly shorted losers experience weak short-term momentum and long-term reversal. Our results are robust after controlling for firm characteristics, seasonality, and sentiment. The documented effect is stronger among stocks with more binding short-sale constraints. Moreover, a risk-managed version of the consistent momentum appears to be crash-proof.

Our findings provide new evidence that short-term momentum and long-term reversals are not necessarily linked. These results confirm that underreaction and overreaction theories seem to apply to different sets of momentum stocks. In our humble opinion, existing models of momentum are inadequate in terms of explaining the empirical findings documented in this paper. Specifically, any new models of momentum need to consider the important role played by short sellers.

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