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The big picture: The industry effect of short interest

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ABSTRACT

We examine whether industry-level short interest predicts industry stock returns and find that the former is negatively associated with the latter. Furthermore, this predictive ability is more pronounced in industries with higher information asymmetry surrounding firms, suggesting that either short sellers' access to private information or their superior information processing skills are important. We also find that this predictive ability is stronger when the short-sale constraint is more binding and when the economic condition is challenging. Overall, our results imply that short sellers' collective activities convey important industry information, leading to predictable and profitable industry portfolios.

1. Introduction

Short interest, measured as the percentage of a firm's shares sold short, has increased substantially in the US in recent decades and is receiving greater attention from both practitioners and academics. Although some regulators are concerned that short sales have a destabilizing effect during market downturns, proponents argue that they are conducive to price discovery and market efficiency (Boehmer, Jones, & Zhang, 2013; Boehmer & Wu, 2013). Given the constraints and costs faced by short sellers, high levels of short interest typically indicate that sophisticated investors hold bearish views. Short interest's ability to predict subsequent stock returns is well documented, particularly at the *individual stock* and *aggregate market* levels (Arnold, Butler, Crack, & Zhang, 2005; Boehmer, Huszar, & Jordan, 2010; Boehmer, Jones, & Zhang, 2008; Desai, Ramesh, Thiagarajan, & Balachandran, 2002; Diamond & Verrecchia, 1987; Rapach, Ringgenberg, & Zhou, 2016).

However, anecdotal evidence suggests that investors are increasingly making short sales at the *industry* or *sector* levels. For example, the rapid rise of e-commerce has prompted short sellers to target traditional brick-and-mortar retailers.[2] Fig. 1 confirms this trend and shows that, in the universe of US stocks, investors' short positions are indeed becoming more concentrated at the industry level and less concentrated in individual stocks within a given industry over time. Specifically, Panel A of Fig. 1 shows the Herfindahl–Hirschman index, which is calculated as the sum of the squared percentages of the total cross-sectional volume of short sales accounted for by individual firms. This index generally trends downward, indicating that short positions are becoming more spread out across firms over time, consistent with a reduced concentration in individual stocks. Panel B shows an alternative Herfindahl–Hirschman index, which we calculate to address the concern that the index in Panel A may be decreasing simply because the number of firms is gradually increasing. We present both the mean and the median of this alternative index, which is calculated as the short sales volume for each firm in an industry as a percentage of the industry's total short sales volume, for each of the 48 Fama–French (FF48) industries. Both series exhibit a downward trend, supporting the results in Panel A. Lastly, we present an index of the *cross-industry* short concentration, which is calculated as the volume of short sales for all firms in an FF48 industry as a percentage of the total short sales volume in the market. This index exhibits a clear upward trend, especially after 2000. The industry-level short concentration is particularly pronounced during three crisis periods—the oil crisis in 1979, the dot-com crash in the early 2000s, and the more recent financial crisis in 2008—suggesting that aggregate short sellers may have targeted certain industries, as these crises each had different causes.

There are several possible explanations for the shift to more

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2 https://www.wsj.com/articles/investors-bet-on-more-pain-for-retailers-11575196206

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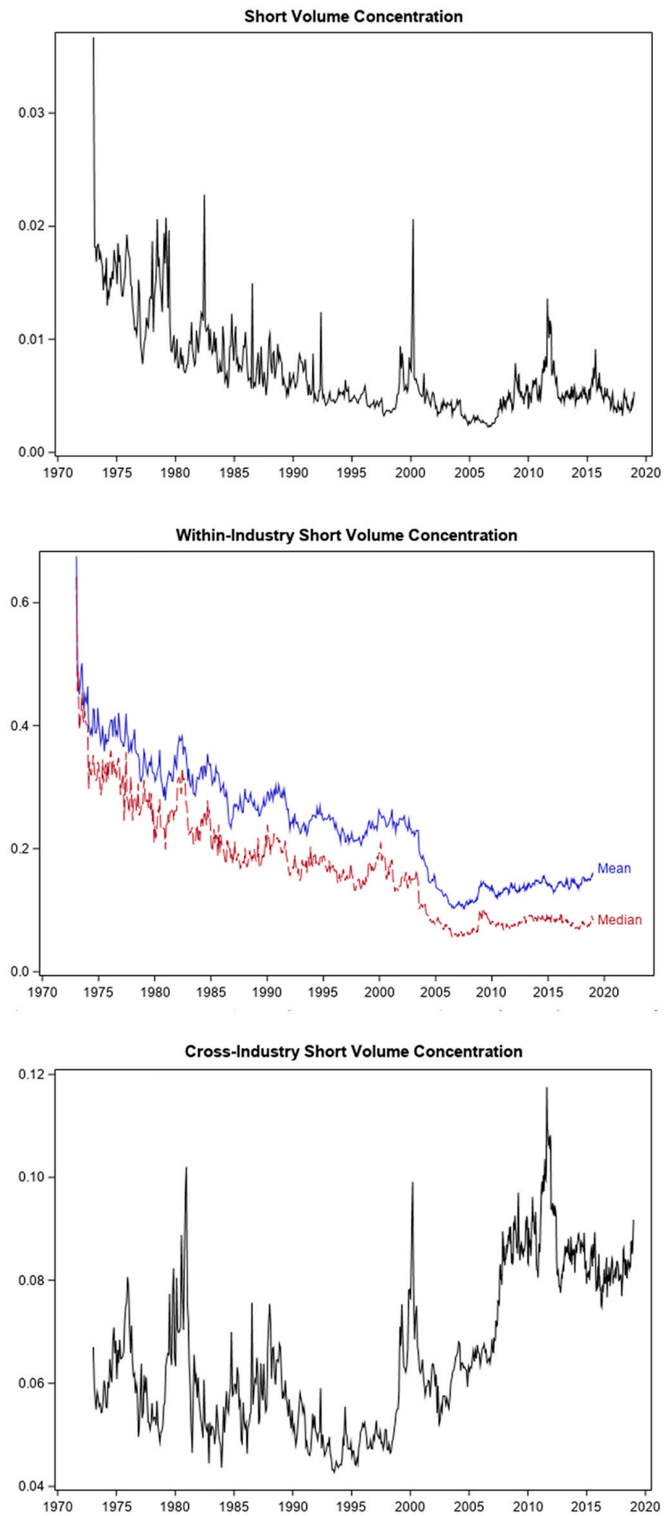

Fig. 1. Evolution of short-interest concentration.
Panel A: This panel shows the time-series of the Herfindahl–Hirschman index that is calculated as the sum of the squared percentages of the total cross-sectional short sales volume accounted for by individual firms.
Panel B: This panel shows the time-series of the mean and median of the Herfindahl–Hirschman index that is calculated as the sum of the squared percentages of each FF48 industry short sales volume accounted for by individual firms in the industry.
Panel C: This panel shows the time-series of the Herfindahl–Hirschman index that is calculated as the sum of the squared percentages of the total cross-sectional short sales volume accounted for by each FF48 industry.

concentrated industry short positions. On the one hand, this trend is consistent with an increasingly efficient financial market in which securities are appropriately priced in general. Chordia, Roll, and Subrahmanyam (2008) show that the US stock market has become more efficient over time owing to improved liquidity. Busse and Green (2002) find that US stock prices respond to CNBC reports in under one minute. Given this high market efficiency, average investors are better off tracking systematic risk factors and adjusting their exposures to those factors accordingly. For example, many investors follow sector rotation strategies. These strategies avoid individual stock bets and are based largely on industries' different cyclicalities and responses to macroeconomic shocks. On the other hand, a behavioral argument proposed by Peng and Xiong (2006) may also explain investors' increased focus on broad economic factors. Specifically, psychology theory suggests that attention is a scarce cognitive resource (Kahneman, 1973). Consequently, investors usually exhibit category-learning behavior and tend to allocate more of their limited attention to market- and sector-level factors rather than to firm-specific factors. Froot and Teo (2008) present empirical evidence that asset reallocations by institutional investors are more intensive across groupings based on investment styles and industry sectors than they are across random stock groupings. Beber and Kavajecz (2011) also find evidence consistent with equity sector rotation in their study of aggregate investor portfolio rebalancing.

This study investigates the relationship between short interest and stock returns at the industry level, which is important for at least two reasons. First, it is beneficial to understand whether and how industry-level information is priced into both time-series and cross-sectional stock returns. Various industry characteristics such as technological shocks, innovation, and competition have been theoretically shown to affect industry fundamentals. Thus, they are expected to affect asset prices as well (Gârleanu, Kogan, & Panageas, 2012; Hoberg & Phillips, 2010; Kogan, Papanikolaou, & Stoffman, 2013; Pástor & Veronesi, 2009). However, many empirical studies of industry-level data focus only on industry portfolio returns, possibly because industry-level information disclosures in the market are much less frequent than macroeconomic and firm-specific news releases are. For example, studies show that industry portfolio returns predict stock market returns both in the US (Hoberg & Phillips, 2010; Hong, Torous, & Valkanov, 2007; Makarov & Papanikolaou, 2008; Menzly & Ozbas, 2010; Pönkä, 2017) and internationally (Bannigidadmath & Narayan, 2016; Lee, Chen, & Chang, 2013; Narayan & Bannigidadmath, 2015; Zhang, Zhang, Zhang, Han, & Chen, 2020). However, these studies either provide limited insight into the underlying economic relationship between industry information and stock returns or face empirical issues, such as the time-series mismatch between volatile stock returns and less volatile industry returns (Huszár, Tan, & Zhang, 2017). We overcome these concerns by using industry-level short interest as a proxy for industry information and examine this proxy's ability to predict industry stock returns.

More importantly, our findings may provide investment insights for practitioners (e.g., top-down investors), who are increasingly focusing on broad economic factors that affect entire industries rather than on idiosyncratic factors that affect individual firms, as Fig. 1 shows. Investors' preferences for industry (re)allocations are facilitated by industry recommendations made by sell-side analysts, who usually specialize in one industry (Kadan, Madureira, Wang, & Zach, 2012), as well as by the sector exchange traded funds offered by major investment companies, which are portfolios of securities for specific industries (e.g., energy, biotechnology, chemicals, etc.). Since sector exchange traded funds are traded on exchanges in the same manner as stocks are, they offer a convenient way for investors to short overall industries.

We begin our empirical analysis by testing whether industry short interest predicts future industry stock returns. Using a sample spanning the period from July 2003 to December 2018, we find that short interest is negatively related to stock returns at the industry level. This finding is consistent with the decline in sales and operating profits that is predicted by a high industry-level short value, as in Huszár et al. (2017). In addition, we examine the profitability of a trading strategy based on industry short interest. We show that such a strategy outperforms both a benchmark strategy and the broad market. This finding remains valid despite the persistence of short interest (Asquith, Pathak, & Ritter, 2005) and the presence of noninformation factors, such as the growing participation of hedge funds and the development of equity lending markets, in short-interest activities.

Furthermore, we consider empirical settings in which short sellers have greater incentives to exploit their private information and information processing skills when investing in industry portfolios. In particular, we find that the negative relationship between industry short interest and industry stock returns is more evident for industries that exhibit high information asymmetry, thus confirming the hypothesis that short sellers have superior information. In addition, consistent with previous findings (e.g., Chi, Pincus, & Teoh, 2014), industry short interest's ability to predict industry returns is more pronounced when short selling is more likely to be constrained and when the economic condition is challenging. Taken together, these findings corroborate the notion that short sellers' collective behavior in an industry conveys meaningful information about the industry and that this information is incorporated in the relevant stock prices.

This study contributes to the literature in several ways. First, it adds to the growing body of research on industry-level pricing signals. For example, Hou and Robinson (2006) show that industry concentration is negatively related to future industry returns. DellaVigna and Pollet (2007) find that predictable shifts in demographic cohorts can successfully predict returns for age-sensitive industries. Akhigbe and Madura (2008) provide evidence that firm-level earnings restatements have industry-wide valuation effects. A closely related study to ours is that of Huszár et al. (2017). However, they focus on how industry short interest explains firm-level stock performance. By contrast, we relate industry short interest to industry performance and study the information content of short interest in that context.[3] Hence, our findings are applicable specifically to practitioners with interest in sector rotation and industry portfolio balancing. Second, we provide more granular evidence regarding the ability of industry-level short interest to predict returns by identifying the conditions under which short sellers' collective information is most useful. Finally, we present an applicable trading strategy that highlights the usefulness of incorporating short interest signals at the industry level, which can benefit investors interested in sector rotation and industry portfolio balancing.

2. Sample and descriptive statistics

The data used in this study come from three sources. Data on short interest and firm characteristics are taken from Compustat.[4] Data on returns are taken from the Center for Research in Security Prices (CRSP).[5] The institutional holding data are provided by the Thomson Reuters s34 Holdings Database.[6] For the period from 1981 through September 2007, short interest is reported on the 15th of each month. After September 2007, short interest is reported on both the 15th and the final trading day of each month. In our analysis, we use the most recent data on short interest in each month. We use FF48 industry classifications to group firms into industries.[7] Then, we calculate the equally weighted short interest for the firms within each industry, which we use as a measure of industry-level short interest.

To determine whether industry-level short interest represents short sellers' opinions about an industry, we plot the average fraction of firms sold short in an industry over time for the full sample of short interest in Fig. 2. We find that when short interest data were introduced in January 1973, only 2% of the firms in an industry were included. This figure increased steadily to nearly 51% by June 2003, and it has remained at over 90% since July of that year.[8] The more comprehensive coverage of short interest data starting in July 2003 provides a more accurate representation of industry-level short interest. Thus, we frame our analysis using the sample period from July 2003 to December 2018.

In Panel A of Table 1, we report the mean, standard deviation, 10th percentile, 25th percentile, median, 75th percentile, and 90th percentile values for monthly short interest at the firm level. On average, 3.7% of a firm's shares are sold short, and the median short interest is 1.7%. Panel B reports these statistics for monthly short interest and the variables for firm characteristics at the industry level. The equally weighted short interest for an average industry is 9.0%. Furthermore, the average industry has 80 firms, 93% of which are sold short. Aggregating the firm characteristics at the industry level, we find that the average industry has a total market capitalization exceeding USD 351 billion, an equally weighted book-to-market ratio of 0.76, a firm age of 263 months, and a share turnover ratio of 0.86%. In addition, 13.6% of firms in the average industry are included in the S&P 500 index. The average industry earns a monthly return of 1.00% and has a cumulative return over the prior twelve months of 16.64%.

3. Empirical analysis

We begin our empirical analysis by examining whether short interest predicts performance at the industry level. If the collective wisdom of short sellers in an industry is valuable, we expect an industry to perform better (worse) following lower (higher) industry-level short interest. To validate this hypothesis, we use the following panel regression:

$$Ret_{i,t+1,t+T} = \beta_0 + \beta_1 \cdot Short\ Interest_{i,t} + \boldsymbol{X}_{i,t} \cdot \boldsymbol{B}' + \gamma_t + \varepsilon_{t+1,t+T}, \tag{1}$$

where $Ret_{i,\ t+1,\ t+T}$ is the equally weighted future performance of industry i over holding period T and $Short\ Interest_{i,\ t}$ is the equally weighted short interest of industry i measured at the end of month t. Additionally, $\mathbf{X}_{i,\ t}$ is a vector of industry characteristics, including the number of firms, the fraction of firms with short interest, the total market capitalization, the average book-to-market ratio, the average firm age, the average share turnover ratio, the fraction of firms that are components of the S&P 500 index, and momentum, as measured by the cumulative return over the prior twelve months.[9] Lastly, γ_t is the time fixed effect. All of the regressors except S&P 500 membership and momentum are expressed as natural logarithms, and we follow Rapach et al. (2016) in standardizing short interest to have a mean of zero and a standard deviation of one.

We estimate the model using the two-way clustered standard error

[3] In addition, we examine the relationship between industry short interest and industry performance in both cross-sectional and time-series settings, whereas Huszár et al. (2017) only focus on the cross-sectional relationship between industry short interest and firm-level performance. Additional differences between our study and that of Huszár et al. (2017) are that we consider the trending nature of short interest data and that we perform sensitivity analyses related to information asymmetry, short-sale constraints, and the short interest concentration at the industry level.

[4] http://www.spglobal.com/marketintelligence

[5] http://www.crsp.org/

[6] http://thomson.com

[7] The FF48 classification is a common method of grouping firms into 48 industry groups based on their four-digit Standard Industry Classification codes. More details are provided at: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/det_48_ind_port.html.

[8] The structural break in the short interest data is due to the jump in short interest coverage in Compustat caused by the inclusion of NASDAQ stocks. Specifically, 2679 firms have short interest information in June 2003, whereas 5793 firms have short interest information in July 2003. After July 2003, the number of firms with short interest information in a given month ranges from 4716 to 5818.

[9] We follow the literature on equity performance determinants (e.g., Gompers & Metrick, 2001) to select these control variables.

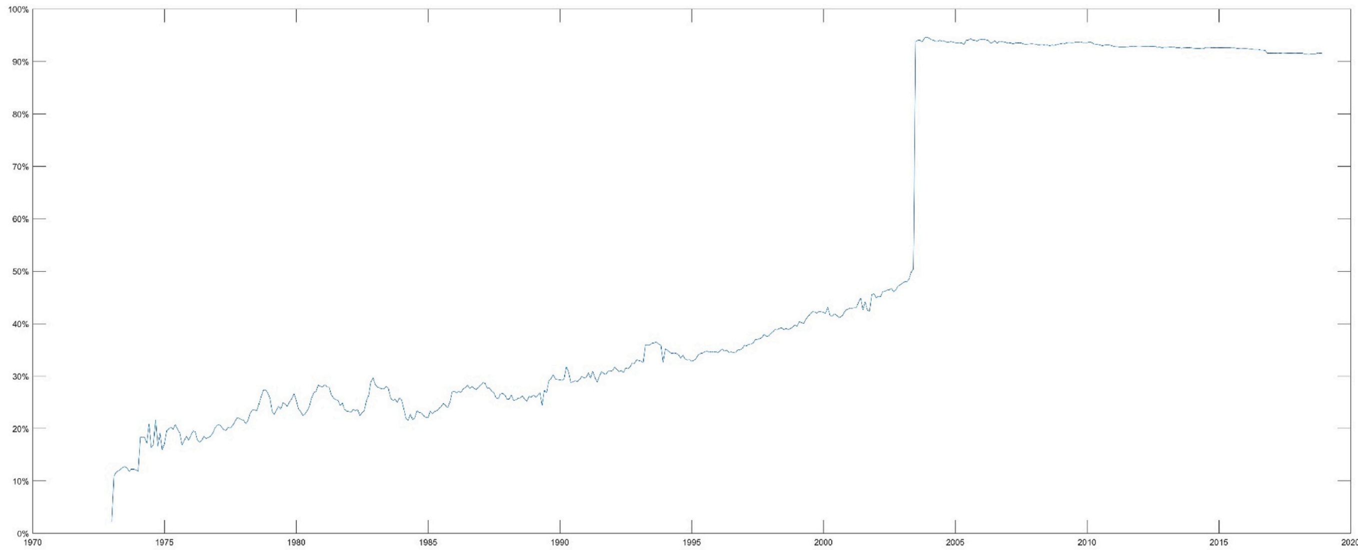

Fig. 2. Average percentage of firms sold short in an industry.
This figure plots the average number of firms sold short in an industry in each month. The sample period is from January 1973 to December 2018.

Table 1
Descriptive statistics.

Variable	Mean	Std. Dev.	P10	P25	Median	P75	P90
Panel A: Firm-Month Observations							
Short Interest (%)	3.74	6.06	0.04	0.21	1.69	4.68	9.80
Panel B: Industry-Month Observations							
Short Interest (%)	9.04	32.00	2.28	3.06	4.30	6.23	10.15
Num Firms	79.96	106.26	9.00	19.00	46.00	101.00	167.00
Short Intensity (%)	92.95	5.78	85.37	90.00	93.55	97.13	100.00
MktCap ($billions)	351.50	501.24	16.11	45.23	134.95	461.03	977.13
BM	0.76	0.39	0.43	0.54	0.66	0.88	1.17
Age (Months)	262.82	83.59	160.88	197.86	257.37	309.09	376.11
Turnover (%)	0.86	0.46	0.45	0.60	0.79	1.01	1.26
SP500 (%)	13.59	9.60	1.92	7.50	11.81	18.46	25.00
Ret (%)	1.00	7.14	−6.91	−2.51	1.23	4.60	8.23
Momentum (%)	16.64	33.54	−20.43	−1.55	14.38	30.61	53.15

Notes: This table presents the mean, standard deviation, 10th percentile, 25th percentile, median, 75th percentile, and 90th percentile values of the variables in the sample for the period from July 2003 to December 2018. Panel A reports statistics based on 967,406 firm-month observations, and Panel B reports statistics based on 8928 industry-quarter observations. The variables are defined in Appendix A.

approach presented by Petersen (2009); the results are provided in Table 2. In the first three columns, the dependent variable is the industry market-adjusted return, calculated as the difference between the raw industry return and the CRSP market return. We find that the coefficients of short interest are negative and statistically significant at the 1% level across all holding periods (from post one month to post twelve months), suggesting that short interest at the industry level has strong predictive ability; industries with higher short interest underperform those with lower short interest. In addition, conditional on short interest, industries with fewer firms, larger total market capitalizations, and longer trading histories earn higher future returns. The last three columns report similar statistics when industry performance is measured using the risk-adjusted returns of Daniel, Grinblatt, Titman, and Wermers (1997) (DGTW, henceforth). These results are highly comparable to those based on market-adjusted returns, reinforcing our finding that short interest can differentiate between industries based on their risk-adjusted performance. From a practical viewpoint, investors interested in industry sector selection should include industry short interest as a signal for their decisions.

To determine whether the dynamics of industry-level short interest affect an industry's performance over time, we extend Eq. (1) by including an industry fixed effect. The results of estimating this regression are shown in Table 3. We find that the coefficients of short interest are all significantly negative, providing strong evidence that an industry with higher short interest will underperform the market to a greater extent in the future. This finding implies that investors who are restricted to investing in certain industries can use industry short interest to overweight or underweight certain industries when performing portfolio rebalancing.

The literature shows that short interest is persistent over time (Asquith et al., 2005). Given this aspect of the data, we examine whether our previous findings are driven by the persistence of or changes in short interest, where the latter reflects short sellers' changing beliefs about industry value. We decompose the short interest term in Eq. (1) into lagged short interest and the change in short interest.[10] The model specification is:

[10] Note that the two terms in this decomposition sum to the concurrent short interest. This specification helps us to pinpoint the source of short interest's predictive ability.

Table 2
Ability of industry short interest to predict industry performance.

	Mkt-adj. Ret_{m+1}	*Mkt-adj.* $Ret_{m+1,m+3}$	*Mkt-adj.* $Ret_{m+1,m+12}$	*DGTW* Ret_{m+1}	*DGTW* $Ret_{m+1,m+3}$	*DGTW* $Ret_{m+1,m+12}$
Short Interest	−0.002***	−0.006***	−0.017***	−0.002***	−0.005***	−0.017***
	(−3.36)	(−3.76)	(−2.82)	(−3.41)	(−3.50)	(−3.30)
Num Firms	−0.004***	−0.013***	−0.034***	−0.004***	−0.013***	−0.034***
	(−2.85)	(−3.02)	(−2.73)	(−2.90)	(−2.77)	(−2.62)
Short Intensity	0.013	0.033	0.029	0.005	0.011	−0.023
	(1.24)	(1.15)	(0.31)	(0.49)	(0.40)	(−0.25)
MktCap	0.003***	0.011***	0.029***	0.003***	0.010**	0.030***
	(2.74)	(2.62)	(2.83)	(2.84)	(2.51)	(2.70)
BM	0.002	0.005	0.000	0.001	0.003	−0.007
	(0.47)	(0.53)	(0.00)	(0.23)	(0.41)	(−0.22)
Age	0.008**	0.026***	0.100***	0.008**	0.024***	0.093***
	(2.35)	(2.81)	(3.55)	(2.42)	(2.84)	(3.82)
Turnover	−0.004	−0.011	−0.048**	−0.003	−0.008	−0.039**
	(−1.18)	(−1.40)	(−2.21)	(−1.14)	(−1.32)	(−1.96)
SP500	−0.033**	−0.102**	−0.312***	−0.031*	−0.103*	−0.327**
	(−2.07)	(−2.14)	(−2.93)	(−1.91)	(−1.95)	(−2.47)
Momentum	0.004	0.004	−0.073***	0.005	0.009	−0.050*
	(1.07)	(0.54)	(−2.92)	(1.39)	(1.22)	(−1.90)
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.2296	0.2834	0.3204	0.0550	0.0664	0.0939

Notes: This table presents the estimation results of regressing industry future returns on industry-level short interest. The first (last) three columns report the results for market-adjusted returns (DGTW returns). Standard errors are adjusted for both industry and year clustering, and the related *t*-statistics are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 3
Ability of industry short interest to predict industry performance, industry fixed-effect model.

	Mkt-adj. Ret_{m+1}	*Mkt-adj.* $Ret_{m+1,m+3}$	*Mkt-adj.* $Ret_{m+1,m+12}$	*DGTW* Ret_{m+1}	*DGTW* $Ret_{m+1,m+3}$	*DGTW* $Ret_{m+1,m+12}$
Short Interest	−0.004***	−0.012***	−0.023***	−0.002***	−0.005***	−0.012***
	(−6.45)	(−10.95)	(−9.74)	(−3.48)	(−5.26)	(−6.11)
Num Firms	−0.002	0.004	0.068***	−0.007	−0.008	0.010
	(−0.44)	(0.43)	(3.66)	(−1.57)	(−1.05)	(0.66)
Short Intensity	0.125***	0.344***	0.955***	0.077***	0.204***	0.626***
	(7.08)	(11.16)	(15.22)	(5.03)	(7.84)	(11.83)
MktCap	−0.008***	−0.030***	−0.170***	−0.003*	−0.011***	−0.071***
	(−4.53)	(−9.32)	(−25.64)	(−1.96)	(−4.03)	(−12.75)
BM	0.013***	0.038***	0.036***	0.000	0.003	−0.008
	(6.98)	(11.70)	(5.52)	(0.26)	(1.05)	(−1.38)
Age	0.007	0.032***	0.176***	0.007	0.033***	0.173***
	(1.03)	(2.67)	(7.27)	(1.11)	(3.25)	(8.49)
Turnover	−0.006**	−0.013***	−0.065***	−0.005**	−0.014***	−0.091***
	(−2.33)	(−3.13)	(−7.56)	(−2.19)	(−3.96)	(−12.65)
SP500	−0.016	−0.055*	−0.150**	−0.056***	−0.187***	−0.536***
	(−0.89)	(−1.71)	(−2.30)	(−3.53)	(−6.90)	(−9.72)
Momentum	0.000	−0.011***	−0.089***	0.003*	0.006**	−0.017***
	(0.26)	(−3.60)	(−14.31)	(1.89)	(2.16)	(−3.28)
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.0316	0.0891	0.1963	0.0105	0.0296	0.0997

Notes: This table presents the estimation results of regressing industry future returns on industry-level short interest with industry fixed effects. The first (last) three columns report the results for market-adjusted returns (DGTW returns). The related *t*-statistics are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

$$Ret_{i,t+1,t+T} = \beta_0 + \beta_1 \cdot Short\ Interest_{i,t-1} + \beta_2 \cdot \Delta Short\ Interest_{i,t} + \boldsymbol{X}_{i,t} \cdot \boldsymbol{B}' + \gamma_t + \varepsilon_{t+1,t+T}. \tag{2}$$

We repeat the analysis shown in Table 2 for this equation, and the results are presented in Table 4. We find that both lagged short interest and the change in short interest are negatively related to future industry performance. In particular, the coefficients of lagged short interest are uniformly significant at the 1% level, whereas those of the change in short interest are significant at the 10% level and above in four out of six cases. This result suggests that short interest's ability to predict industry-level returns arises from both the historical level of and the shock to short interest.

Rapach et al. (2016) study the predictive ability of market-wide short interest and find an upward trend in aggregate market short interest. They attribute this finding to the growing popularity of hedge funds and the development of equity lending markets. Clearly, these systematic increases in short interest are not related to short sellers' information sets. To ensure that our results are robust to this noninformation effect, we examine detrended industry-level short interest and its relation to future industry performance. Here, we follow Rapach et al. (2016) and

Table 4
Ability of the change in industry short interest to predict industry performance.

	Mkt-adj. Ret$_{m+1}$	*Mkt-adj. Ret*$_{m+1,m+3}$	*Mkt-adj. Ret*$_{m+1,m+12}$	*DGTW Ret*$_{m+1}$	*DGTW Ret*$_{m+1,m+3}$	*DGTW Ret*$_{m+1,m+12}$
Lagged Short Interest	−0.002***	−0.006***	−0.017***	−0.002***	−0.005***	−0.017***
	(−3.23)	(−3.62)	(−2.61)	(−3.25)	(−3.56)	(−3.07)
Δ Short Interest	−0.003	−0.005*	−0.019***	−0.003*	−0.004	−0.018***
	(−1.62)	(−1.83)	(−3.77)	(−1.77)	(−1.42)	(−3.93)
Num Firms	−0.004***	−0.013***	−0.034***	−0.004***	−0.013***	−0.034***
	(−2.83)	(−3.09)	(−2.74)	(−2.83)	(−2.81)	(−2.62)
Short Intensity	0.013	0.033	0.026	0.005	0.011	−0.026
	(1.27)	(1.14)	(0.28)	(0.50)	(0.39)	(−0.28)
MktCap	0.003***	0.011***	0.029***	0.003***	0.011**	0.029***
	(2.74)	(2.67)	(2.85)	(2.80)	(2.53)	(2.71)
BM	0.002	0.005	−0.001	0.001	0.003	−0.007
	(0.47)	(0.52)	(−0.02)	(0.24)	(0.41)	(−0.24)
Age	0.008**	0.026***	0.099***	0.007**	0.024***	0.092***
	(2.29)	(2.84)	(3.55)	(2.33)	(2.85)	(3.83)
Turnover	−0.004	−0.011	−0.049**	−0.003	−0.009	−0.040**
	(−1.30)	(−1.46)	(−2.26)	(−1.29)	(−1.39)	(−2.00)
SP500	−0.032**	−0.103**	−0.311***	−0.030*	−0.104**	−0.325**
	(−2.04)	(−2.17)	(−2.97)	(−1.87)	(−1.97)	(−2.49)
Momentum	0.004	0.003	−0.072***	0.005	0.008	−0.050*
	(1.05)	(0.39)	(−2.87)	(1.36)	(1.08)	(−1.87)
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.2298	0.2822	0.3182	0.0553	0.0668	0.0925

Notes: This table presents the estimation results of regressing industry future returns on lagged industry short interest and the change in short interest. The first (last) three columns report the results for market-adjusted returns (DGTW returns). The related *t*-statistics are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 5
Ability of detrended industry short interest to predict industry performance, regression approach.

	Mkt-adj. Ret$_{m+1}$	*Mkt-adj. Ret*$_{m+1,m+3}$	*Mkt-adj. Ret*$_{m+1,m+12}$	*DGTW Ret*$_{m+1}$	*DGTW Ret*$_{m+1,m+3}$	*DGTW Ret*$_{m+1,m+12}$
Short Interest	−0.002***	−0.005***	−0.014**	−0.002***	−0.004***	−0.014***
	(−2.95)	(−3.41)	(−2.27)	(−3.36)	(−3.06)	(−2.64)
Num Firms	−0.004***	−0.012***	−0.033***	−0.004***	−0.012***	−0.033**
	(−2.79)	(−2.96)	(−2.67)	(−2.83)	(−2.71)	(−2.53)
Short Intensity	0.013	0.032	0.024	0.004	0.010	−0.028
	(1.22)	(1.12)	(0.26)	(0.45)	(0.35)	(−0.31)
MktCap	0.003***	0.010**	0.028***	0.003***	0.010**	0.029***
	(2.67)	(2.55)	(2.75)	(2.79)	(2.46)	(2.62)
BM	0.002	0.005	−0.001	0.001	0.003	−0.007
	(0.44)	(0.50)	(−0.02)	(0.21)	(0.38)	(−0.25)
Age	0.008**	0.025***	0.099***	0.007**	0.024***	0.091***
	(2.34)	(2.80)	(3.55)	(2.40)	(2.83)	(3.82)
Turnover	−0.004	−0.011	−0.049**	−0.003	−0.009	−0.041**
	(−1.22)	(−1.45)	(−2.26)	(−1.20)	(−1.40)	(−2.03)
SP500	−0.032**	−0.099**	−0.305***	−0.030*	−0.101*	−0.320**
	(−2.02)	(−2.09)	(−2.87)	(−1.88)	(−1.92)	(−2.43)
Momentum	0.004	0.005	−0.071***	0.005	0.009	−0.048*
	(1.11)	(0.60)	(−2.84)	(1.44)	(1.30)	(−1.84)
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.2294	0.2829	0.3191	0.0548	0.0656	0.0920

Notes: This table presents the estimation results of regressing industry future returns on detrended industry-level short interest. Detrended industry-level short interest is given by the residual term of a linear time trend model that regresses industry short interest on time *t*. We then standardize the detrended industry short interest series to have a mean of zero and a standard deviation of one. The first (last) three columns report the results for market-adjusted returns (DGTW returns). The related *t*-statistics are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

consider two methods for removing the short interest trend. First, we use a linear time trend model with the following specification:

$$Short\ Interest_{i,t} = \alpha_i + \beta_i \cdot t + \widehat{u_{i,t}}, \tag{3}$$

where short interest takes the form of a natural logarithm and $\widehat{u}_{i,t}$ is detrended short interest for industry *i* in month *t*. We then standardize $\widehat{u}_{i,t}$ to have a mean of zero and a standard deviation of one. By design, this detrended short interest series captures short sellers' actions outside of any systematic trends.

We replicate the analysis shown in Table 2 using this detrended short interest series and report the results in Table 5. The coefficients of short interest are negative and statistically significant at the 1% level for the models with post-one-month and post-three-month industry performance. In the case of post-twelve-month performance, the coefficients are statistically significant at the 5% level and above. These results are robust to using the market-adjusted and DGTW risk-adjusted performance measures.

To ensure robustness, we use a second stochastic detrending method, following that of Rapach et al. (2016). Specifically, we calculate detrended short interest as the difference between the log short interest in month *t* and the average log short interest from month *t* – 35 to month *t*.[11] We re-estimate the models shown in Table 2 and present the

[11] To ensure robustness, we also consider calculating the average short interest using other moving window sizes, such as the prior 24 and the prior 60 months. The results using these window sizes are not materially different.

Table 6
Ability of detrended industry short interest to predict industry performance, moving average approach.

	Mkt-adj. Ret$_{m+1}$	*Mkt-adj. Ret*$_{m+1,m+3}$	*Mkt-adj. Ret*$_{m+1,m+12}$	*DGTW Ret*$_{m+1}$	*DGTW Ret*$_{m+1,m+3}$	*DGTW Ret*$_{m+1,m+12}$
Short Interest	−0.003**	−0.007**	−0.017	−0.003**	−0.008*	−0.026**
	(−2.44)	(−2.06)	(−1.24)	(−2.56)	(−1.90)	(−2.05)
Num Firms	−0.004***	−0.011***	−0.024*	−0.003***	−0.011***	−0.024**
	(−2.72)	(−2.84)	(−1.72)	(−2.89)	(−2.69)	(−1.97)
Short Intensity	0.002	−0.000	−0.048	−0.006	−0.020	−0.090
	(0.19)	(−0.01)	(−0.58)	(−0.92)	(−1.04)	(−1.17)
MktCap	0.003***	0.011***	0.025**	0.003***	0.010***	0.024**
	(3.36)	(2.94)	(2.53)	(3.48)	(2.68)	(2.33)
BM	0.000	−0.000	−0.017	−0.001	−0.001	−0.024
	(0.05)	(−0.02)	(−0.58)	(−0.19)	(−0.18)	(−0.85)
Age	0.007**	0.022***	0.084***	0.006**	0.020***	0.074***
	(2.14)	(2.72)	(3.14)	(2.02)	(2.60)	(3.24)
Turnover	−0.006*	−0.018**	−0.063***	−0.005**	−0.015**	−0.056***
	(−1.96)	(−2.16)	(−2.84)	(−2.07)	(−2.17)	(−2.69)
SP500	−0.030**	−0.095**	−0.254***	−0.027**	−0.095**	−0.263***
	(−2.55)	(−2.57)	(−3.01)	(−2.34)	(−2.33)	(−2.61)
Momentum	0.002	−0.002	−0.074**	0.003	0.004	−0.053**
	(0.46)	(−0.15)	(−2.13)	(0.74)	(0.43)	(−2.05)
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.2295	0.2750	0.3270	0.0542	0.0591	0.0759

Notes: This table presents the estimation results of regressing industry future returns on detrended industry-level short interest. Detrended industry short interest in a particular month is given by the difference between industry short interest in that month and the three-year backward-looking moving average. The first (last) three columns report the results for market-adjusted returns (DGTW returns). The related *t*-statistics are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

coefficient estimates in Table 6. Overall, the results are similar to those in Table 5; except in one case, all coefficients of short interest are significantly negative at the 10% level and above. Taken together, Tables 5 and 6 show that our findings on industry short interest's ability to predict industry returns are not entirely due to secular short interest changes in some industries relative to others. Rather, this predictive power stems from shocks to short sellers' views on an industry's valuation. This result echoes our finding in Table 4, in which we examine the ability of changes in short interest to forecast industry returns.

4. Additional evidence

In this section, we present additional tests that confirm short interest's ability to predict industry-level returns. Specifically, we identify the conditions under which short interest is likely to demonstrate a stronger ability to predict returns. In addition, we discuss a trading strategy based on industry-level short interest signals.

We start by exploring the economic reasons that industry aggregate short interest predicts industry performance. If this predictive ability is due to short sellers' superior information about the industry's valuation, we expect stronger results when such information is more useful (e.g., when industries have high information asymmetry) and, thus, harder to evaluate. To test this hypothesis, we group industries into tercile portfolios based on their levels of aggregate information asymmetry, as measured by the average return volatility or idiosyncratic volatility.[12] We then re-estimate our baseline model, given by Eq. (1), for the lowest and highest asymmetry terciles. Panel A of Table 7 reports the results when the information asymmetry groupings are based on return volatility. To conserve space, we report only the coefficients of short interest. We find that short interest in industries with low information asymmetry exhibits weaker predictive ability than that in industries with high information asymmetry. For instance, among industries with the lowest information asymmetry (the first three columns), the coefficients are all statistically insignificant. In comparison, among industries with the highest level of information asymmetry (the last three columns), the coefficients are significant at the 1% level across all specifications. Panel B shows that when information asymmetry is measured by idiosyncratic volatility, short interest predicts industry performance only for the highest information asymmetry tercile. These results are consistent with the hypothesis that short interest predicts industry-level returns owing to short sellers' superior collective information.

A strand of the literature on short interest relates the predictability of returns to constraints on obtaining shares for short sales. For instance, Asquith et al. (2005) use institutional ownership as a proxy for the short selling supply, and they use the short interest ratio as a proxy for the short selling demand. They find that when institutions cannot provide enough loanable shares to short sellers, short interest predicts lower abnormal returns more significantly. Motivated by this literature, we examine whether short-sale constraints, measured by the interaction between institutional ownership and short interest, affect the predictive power of industry-level short interest. To do so, we sort industries into tercile portfolios based on their average institutional ownership and then re-estimate our baseline models for the two extreme terciles. The results are presented in Panel C of Table 7. We find that industry short interest predicts industry performance only for the lowest tercile of industry institutional ownership, consistent with the findings of prior research on short-sale constraints.

Next, we relate the predictive ability of industry short interest to changing macroeconomic conditions. Based on the findings in Panels A and B of Table 7, we further hypothesize that industry short interest is a better predictor of industry performance when the economy is under stress and the entire market faces high uncertainty. To test this hypothesis, we extend the analysis in Table 2 by including an additional recession dummy and the interaction between the recession dummy and industry short interest in the model.[13] Table 8 presents the results. To conserve space, we report only the coefficients of short interest, the recession dummy, and the interaction term. We find that all of the coefficients of the interaction term are negatively and statistically significant except in one case. These results support our hypothesis that industry short interest has stronger predictive power during challenging economic conditions in which information processing and evaluation

[12] The definitions of these variables for information asymmetry are presented in the appendix.

[13] We use National Bureau of Economic Research business cycle data to identify macroeconomic recessions. The data can be found at http://www.nber.org/cycles.html. To capture the effects of recessions on industry performance, we do not include a time fixed effect in the model.

Table 7
Ability of industry short interest to predict industry performance conditional on information asymmetry or institutional ownership.

Panel A: Information asymmetry measured by return volatility (RVOL)						
	Low RVOL			High RVOL		
	Mkt-adj. Ret$_{m+1}$	*Mkt-adj. Ret*$_{m+1,m+3}$	*Mkt-adj. Ret*$_{m+1,m+12}$	*Mkt-adj. Ret*$_{m+1}$	*Mkt-adj. Ret*$_{m+1,m+3}$	*Mkt-adj. Ret*$_{m+1,m+12}$
Short Interest	0.000	−0.001	−0.012	−0.005***	−0.015***	−0.033***
	(0.07)	(−0.33)	(−1.42)	(−3.55)	(−3.90)	(−3.11)
R^2	0.2320	0.2342	0.2625	0.3270	0.4003	0.4566
Panel B: Information asymmetry measured by idiosyncratic volatility (IVOL)						
	Low IVOL			High IVOL		
	Mkt-adj. Ret$_{m+1}$	*Mkt-adj. Ret*$_{m+1,m+3}$	*Mkt-adj. Ret*$_{m+1,m+12}$	*Mkt-adj. Ret*$_{m+1}$	*Mkt-adj. Ret*$_{m+1,m+3}$	*Mkt-adj. Ret*$_{m+1,m+12}$
Short Interest	−0.001	−0.002	−0.013	−0.003***	−0.010***	−0.025***
	(−0.81)	(−0.64)	(−1.30)	(−3.01)	(−3.70)	(−3.12)
R^2	0.2340	0.2298	0.2229	0.3234	0.4112	0.4625
Panel C: Conditioning on institutional ownership (IO)						
	Low IO			High IO		
	Mkt-adj. Ret$_{m+1}$	*Mkt-adj. Ret*$_{m+1,m+3}$	*Mkt-adj. Ret*$_{m+1,m+12}$	*Mkt-adj. Ret*$_{m+1}$	*Mkt-adj. Ret*$_{m+1,m+3}$	*Mkt-adj. Ret*$_{m+1,m+12}$
Short Interest	−0.003**	−0.009***	−0.018**	−0.001	−0.003	−0.009
	(−2.39)	(−2.83)	(−2.09)	(−1.14)	(−1.06)	(−0.98)
R^2	0.1957	0.2404	0.2933	0.3554	0.3845	0.4304

Notes: This table presents the estimation results of regressing industry future returns on industry-level short interest, conditional on industry-level information asymmetry or institutional ownership. At the beginning of each month, industries are sorted into terciles based on the average return volatility (Panel A), idiosyncratic volatility (Panel B), or institutional ownership (Panel C). The first (last) three columns in each panel report the results for the lowest (highest) tercile. The related *t*-statistics are reported in parentheses. To conserve space, only the coefficients on industry short interest are reported. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 8
Ability of industry short interest to predict industry performance conditional on macroeconomic conditions.

	Mkt-adj. Ret$_{m+1}$	*Mkt-adj. Ret*$_{m+1,m+3}$	*Mkt-adj. Ret*$_{m+1,m+12}$	*DGTW Ret*$_{m+1}$	*DGTW Ret*$_{m+1,m+3}$	*DGTW Ret*$_{m+1,m+12}$
Short Interest	−0.004***	−0.010***	−0.032***	−0.002***	−0.005***	−0.019***
	(−3.84)	(−4.47)	(−4.69)	(−2.91)	(−3.38)	(−3.75)
Recession	0.021*	0.070***	0.256***	0.007	0.019*	0.056***
	(1.93)	(3.59)	(7.15)	(1.43)	(1.76)	(2.68)
Short Interest × Recession	−0.012**	−0.043***	−0.055**	−0.005*	−0.013**	−0.022
	(−2.44)	(−4.71)	(−2.50)	(−1.83)	(−2.14)	(−1.59)
R^2	0.0299	0.0892	0.1763	0.0079	0.0190	0.0460

Notes: This table presents the results of regressing industry future returns on industry-level short interest, controlling for macroeconomic conditions. Recession is a dummy variable that equals one if month *m* is classified as a recession by the National Bureau of Economic Research. The first (last) three columns report the results for market-adjusted returns (DGTW returns). Standard errors are adjusted for both industry and year clustering, and the related *t*-statistics are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

are obstructed.

Finally, we propose a trading strategy based on our findings. Given the trend in short interest, we detrend industry short interest using the stochastic detrending method with a three-year window to formulate our strategy. Our analysis uses monthly short interest data. Although this frequency allows for more observations and, thus, greater testing power, a strategy that requires monthly portfolio rebalancing may incur high transaction costs. To overcome this problem, we consider a quarterly portfolio rebalancing strategy in which we sort industries according to detrended short interest at the beginning of each quarter and hold the portfolios over the quarter.[14]

Fig. 3 plots the accounting balance of this strategy in the case of a $1 initial investment. We present two portfolio series; one is based on the lowest detrended short interest, and the other is based on the highest detrended short interest. The upper panel shows the results when industry performance is measured by market-adjusted returns. We find that a portfolio based on industries with low short interest outperforms a portfolio based on industries with high short interest over time. Specifically, the former portfolio turns the $1 investment into $1.36, whereas the latter yields only $0.66. The lower panel reports the results when industry performance is gauged by DGTW risk-adjusted returns. Again, we find that a strategy based on low (high) detrended short interest performs better (worse) than its respective benchmark. Specifically, the low short interest portfolio earns 58% higher returns relative to the benchmark, whereas the high short interest portfolio underperforms the benchmark by 25%.

5. Conclusion

This study bridges the literature on industry pricing signals with that on short selling. We examine whether industry-level short interest, which represents short sellers' aggregate sentiment regarding industry valuation and is easily measurable and obtainable, predicts industry stock returns. We find strong evidence that industries with lower short interest outperform those with higher short interest after properly adjusting for risk. This predictive ability is evident in both cross-sections and time series and is robust to the persistence of short interest and the increase in the popularity of the short-sale market.

To provide more granular results, we examine the conditions under

[14] For robustness, we also consider other specifications of the strategy, such as performing monthly portfolio rebalancing or alternating the moving window sizes in calculating the detrended industry short interest. The results of these specifications are not materially different.

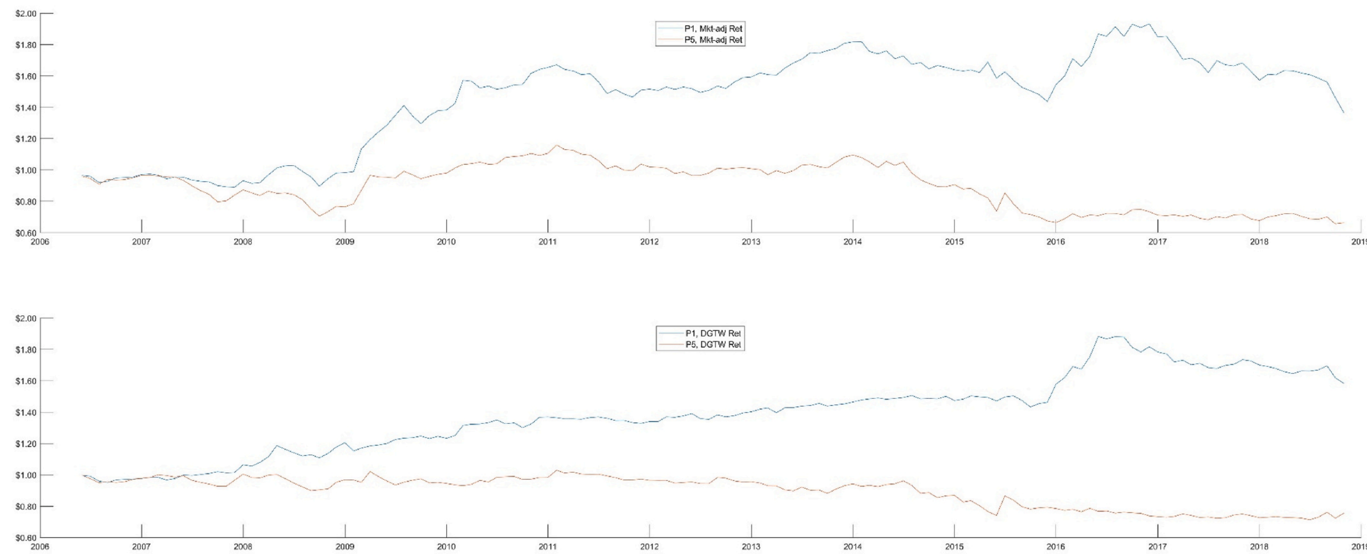

Fig. 3. Accounting balances of portfolios sorted on industry short interest.
P1 (P5) represents the portfolio of industries with the lowest (highest) detrended short interest. Detrended industry short interest is estimated as the difference between industry short interest in a month and the three-year backward-looking moving average. Each portfolio starts with a $1 balance and is rebalanced at the beginning of each quarter. The portfolio returns used in the top (bottom) panel are market-adjusted (DGTW risk-adjusted) returns.

which the industry information conveyed by aggregate short selling is more valuable. We find that the negative relationship between industry short interest and industry portfolio performance is more pronounced for industries with higher information asymmetry. Moreover, the relationship within an industry becomes stronger as short-sale conditions become more restrictive and during more challenging economic conditions.

Our findings are important given the ongoing trends in broad market investing. Investors who use industry category strategies can extract useful information about valuations from sophisticated traders, such as short sellers. We propose and present a trading strategy based on industry short interest signals that earns a higher risk-adjusted return relative to a benchmark and the market. This result offers novel and practical insights for investors interested in sector rotation and industry portfolio rebalancing strategies.

Declaration of Competing Interest

The authors of this research paper have no competing interests to declare.

Appendix A. Variable definitions

Variable	Definition
Short Interest	Number of shares sold short divided by number of shares outstanding, averaged across firms within an industry
Num Firms	Number of firms in an industry
Short Intensity	Fraction of firms in an industry with nonnegative short interest
MktCap	Aggregate market capitalization of firms in an industry
BM	Average book-to-market ratio of firms in an industry. A firm's book-to-market ratio is the book value of equity divided by the market capitalization at year end
Age	Number of months since the return data appeared in CRSP
Turnover	Average share turnover of firms in an industry. A firm's share turnover is the average daily trading volume divided by the number of shares outstanding over the previous 250 trading days
SP500	Fraction of firms in an industry that are S&P 500 components
Ret	Equally weighted return of firms in an industry over a specified period
Momentum	Buy-and-hold industry return over the previous twelve months
Mkt-adj. Ret	Difference between the industry return and the CRSP market return
DGTW Ret	Equally weighted DGTW return of firms in an industry over a specified period. A firm's DGTW return is the difference between the raw return and the stock's characteristic-based benchmark return using 125 triple-sorted quintile portfolios based on size, the book-to-market ratio, and momentum (Daniel et al., 1997)
RVOL	Average return volatility of firms in an industry. A firm's return volatility is the standard deviation of its daily returns over the previous 250 trading days
IVOL	Average idiosyncratic volatility of firms in an industry. A firm's idiosyncratic volatility is the sum of the squared residuals from a regression of daily excess returns on the five Fama–French factors (Fama & French, 2015) and the momentum factor (Carhart, 1997) over the previous 250 trading days, the standard deviation of daily returns over the past 250 trading days
IO	Average institutional ownership of firms in an industry. Firm institutional ownership is number of shares held by institutional investors divided by number of shares outstanding

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