Do short sellers exploit industry information?

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Abstract

This study provides new evidence that short sellers have superior skills in processing industry information. In industries with the highest aggregate shorted values, the most-shorted stocks earn –2.76% abnormal returns over the next six months. These results are likely driven by short sellers' preference for complex industries with the highest profit potential. In the targeted industries, firm-level shorting predicts an increase in default risk, suggesting that short sellers successfully identify firms with fundamental problems. Overall, our results suggest that short sellers help to reduce information complexity and improve economic efficiency at the industry level.

JEL classification: G10, G12, G14

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Abstract

This study provides new evidence that short sellers have superior skills in processing industry information. In industries with the highest aggregate shorted values, the most-shorted stocks earn –2.76% abnormal returns over the next six months. These results are likely driven by short sellers' preference for complex industries with the highest profit potential. In the targeted industries, firm-level shorting predicts an increase in default risk, suggesting that short sellers successfully identify firms with fundamental problems. Overall, our results suggest that short sellers help to reduce information complexity and improve economic efficiency at the industry level.

"Investors are using Australia's stock market to bet that an iron-ore rout has further to run. Two of the five most-shorted companies in the nation's benchmark equity index are producers of the commodity, according to data compiled by Markit Group Ltd. and Bloomberg. Bearish bets on Atlas Iron Ltd. (AGO) this month hit a record, the data show. A gauge of iron-ore prices in China tumbled 41 percent this year to the lowest since 2009, falling below $80 a dry ton this week."

- Haigh and Stringer, *Bloomberg*, September 25, 2014

1. Introduction

Conventional wisdom in finance suggests that stock returns are influenced by three sources of information: macroeconomics, industry, and firm specific information. The extant asset pricing literature has mainly focused on macroeconomic news (such as interest rates, recession, and more recently the global financial crisis) and firm-specific information (such as earnings news, mergers and acquisitions, financial statement revision, CEO death, and fraud). Unlike for macroeconomic and firm-specific news, there are no systematic industry-specific news releases, and this lack of information availability hinders the analysis of the relation between industry information and stock returns.

A few empirical industry studies aggregate firm-level returns by industry to proxy for industry information. For example, Makarov and Papanikolaou (2007) create four factors from U.S. industry-level returns to predict market returns. Hong, Torous, and Valkanov (2007) document a strong relation between industry portfolio returns (such as retail, services, commercial real estate, and the metal and petroleum industries) and aggregate market returns in the U.S. and in eight other countries. Hoberg and Philips (2010) use industry returns to proxy for industry booms and busts to study the externality of industry competition on firms' cash flow and stock return.

The limitations of using industry returns to proxy for industry information are twofold. First, since in these studies both the explanatory and the dependent variables are based on stock returns, albeit with some lags, to some extent the relation between lagged industry and future market returns is mechanical. Second, stock returns may be too volatile to capture the slowly changing nature of an industry. For example during the industrial revolution, the transition to new manufacturing processes took about 80 years, from 1760 to 1840. Technological advancements may result in new industries, such as the information technology (IT) industry, or foster major restructurings in traditional industries (see, e.g., Kliesen, 1993; Foster, Haltiwanger, and Krizan, 2006). Hence we need a better measure to capture the gradual but irreversible structural shifts or breaks at the industry level.[2]

In this study, we introduce a new measure of industry information: the aggregate shorted value at the industry level. Short sellers are considered to be relatively informed traders who either have material private information or have superior information processing skills (Engelberg, Reed, and Ringgenberg, 2012). Therefore their aggregate positions in all listed firms within an industry are likely to convey new material information about a specific industry. Moreover, anecdotal evidence suggests that short sellers have industry preferences. For example, well-known short sellers, such as George Soros, reportedly targeted the IT sector in the early 2000s. In 2007, short sellers focused on firms in the renewable energy industry (Hauck and Tsang, 2007), likely because of the increased competition in the industry, restructuring, and the faltering government support for low-polluting industries. More recently, short sellers shifted into mining- and oil-related stocks as global iron ore and oil prices declined in 2014 (Haigh and Stringer 2014; Holm 2014).

[2] A United Nation's report (UN, 2009) refers to the following definition for structural changes: "the different arrangements of productive activity in the economy and different distributions of productive factors among various sectors of the economy, various occupations, geographic regions, types of product, etc …". While there is an extensive literature on industry growth (e.g., Beck, Levine, and Loayza, 2000; Fogel, Morck, and Yeung, 2008; Gupta and Yuan, 2009; King and Levine, 1993; Levine 2004; Rajan and Zingales, 1998) those studies generally do not specifically examine industry information over time and pay little attention to industry restructuring in a developed-country setting.

Our first empirical analysis shows that short sellers' industry preference contains material information. In a portfolio setting, we find that stocks with high short interest ratio (SIR) (from the top sextile) within the most-shorted industry (from the top sextile based on aggregate shorted value) earn abnormal value-weighted returns of –2.76% in the next six months.[3] However, stocks with similarly high SIR in the least-shorted industries earn insignificant abnormal returns over the same time horizon. The traditional long-short strategy (i.e., shorting the most-shorted stocks and longing the least-shorted stocks) within the most-shorted industries generates the highest value-weighted returns of 4.74% in the next six months. We also confirm that our portfolio results are robust, using findings from firm level regression analyses.

Our second analysis explores the characteristics of industries in which short sellers have concentrated interests (i.e., industries with the highest aggregate shorted value). This helps us to understand the source of the new industry information revealed by short sellers. We find that these highly shorted industries are more complex in that they are associated with greater diversity in growth opportunities and leverage across firms. This suggests that short sellers strategically position themselves in industries where they are likely to maximize profits by using their superior information processing skills.

Last, we examine the economic implications of short sellers having superior industry information. We find that firm-level short selling forecasts a change in firm-level default risk in the most-shorted industries, but not in others. This implies that aggregate short selling helps industries to achieve better economic efficiency by identifying firms with fundamental problems, not only firms with temporary misvaluations.

[3] At the firm level, to measure short sellers' interest in a specific stock, we use the traditional short interest ratio (SIR), the ratio of the shares shorted relative to the shares outstanding (see, among others, Desai et al. 2002).

Our study makes two contributions to the literature. First, we propose a new measure of industry information based on the industry preferences of so-called relatively informed traders, short sellers. This measure can be a convenient industry level information proxy for retail investors to use in overcoming their information disadvantage. Second, we find that short sellers' information advantage in specific industries benefits those industries by reducing information complexity and improving the industry's economic efficiency. To our knowledge, this is the first study showing that short sellers create a positive externality at the industry level.

The rest of this study is organized as follows. Section 2 reviews the relevant literature and the testable hypotheses. Section 3 presents the data and the main empirical findings. Section 4 discusses the relevant robustness test results. Section 5 concludes.

2. Literature review and hypothesis development

2.1. Literature review on industry information

The theoretical literature suggests that industry-specific information, such as information about technological innovation, is priced in the time-series and cross-sectional stock returns. For example, Pastor and Veronesi (2009) and Garleanu, Kogan, and Panageas (2012) examine stock pricing of technological risk and innovation in conjunction with life-cycle adaptation and in incomplete market settings, respectively. Hoberg and Phillips (2010) claim that industry booms and busts are strongly linked to industry competition. Specifically, the high market valuations in competitive industries are more likely to be followed by a decline in operating profits and stock returns than those in less-competitive industries. These findings are consistent with Schumpeter's (1942) creative destruction theory, which posits that increasing competition in booming industries can cause less-adaptive firms to fail. Subsequently, industry competition is reduced and the industry is returned to a steady state.

Recently, Kogan, Papanikolaou, and Stoffman (2015) provided a general equilibrium model, which predicts uneven distribution of profitability in response to innovation across firms within an industry. They show that in industries undergoing restructuring and embodied or disembodied innovation, estimating future profitability systematically may require sophisticated skills. According to Berndt (1990), because embodied innovations require completely new technology, existing capital investments cannot be applied effectively. On the other hand, disembodied technological developments provide tools and new procedures for using existing capital (and even old capital) more effectively. Hence, value firms may benefit more from disembodied technological progress, but growth firms are likely to profit more from embodied technological improvement because they have less existing invested capital.

Despite the above mentioned theories, numerous case studies, and industry reports emphasizing the economic importance of structural changes in industries (e.g., Kliesen, 1993; Foster, Haltiwanger, and Krizan, 2006; Klier and Ribenstein, 2012), only a limited number of comprehensive empirical studies link industry information to asset prices. Two notable exceptions are studies by Makarov and Papanikolaou (2007) and Hong, Torous, and Valkanov (2007), who use aggregate stock returns at the industry level to capture industry information. Makarov and Papanikolaou (2007) propose four new industry pricing factors to capture the time dynamics of the changing industry landscape in the U.S. Their first factor captures aggregate market returns; the second and third factors capture the relative productivity of capital versus consumption goods industries and business cycles, respectively.[4] Hong, Torous, and Valkanov (2007) also find that industry portfolio returns predict the market, which they attribute to investors' limited attention.

[4] The second factor is the portfolio return of stocks from industries that produce investment goods minus the portfolio return of stocks from industries that produce consumption goods. The third factor is the portfolio returns of stocks from cyclical industries minus the portfolio returns of stocks from noncyclical industries.

2.2 Literature review on short sellers and hypotheses development

Short sellers are generally considered to be relatively well informed institutional traders. Among others, Desai et al. (2002) find evidence of short sellers' information advantage in NASDAQ stocks. Many studies also find that high firm-level shorting predicts negative returns, and vice versa (e.g., Boehmer, Jones, and Zhang, 2008; Diether, Lee, and Werner, 2009a; 2009b; Boehmer, Huszár, and Jordan, 2010). Traditionally, SIR is used as a good proxy for short sellers' information at the firm level in conjunction with controls for short-sale constraints and liquidity (Asquith, Pathak, and Ritter, 2005; Boehmer et al. 2010).

Since industry information is shown to influence stock returns, relatively well informed short sellers may capture industry information first, before other traders. Short sales are expensive and risky, especially in bubbling industries (Lamont and Stein, 2004); thus large aggregate exposure of short sellers to a specific industry may be a proxy for industry-specific information (e.g., Hauck and Tsang, 2007; Haigh and Stringer, 2014). If an industry's high aggregate short interest is significantly related to future abnormal stock returns, short sellers may have superior industry information in addition to firm-level information. This leads to our first testable hypothesis:

H1: Industry-level short interest is related to future abnormal returns, ceteris paribus.

If we find supporting evidence for the first hypothesis, a natural follow-up question is, what is the source of the short seller's superior industry information? Some studies suggest that short sellers obtain information through tips or connections (e.g., Anderson, Reeb, and Zhao, 2012; 2013; and Berkman, McKenzie, and Verwijmeren, 2013); others propose that short sellers process new information more efficiently (Engelberg, Reed, and Ringgenberg, 2010). We use the nature of information in each industry to separate the two explanations. In a complex industry, short sellers may make more profits if they can process information more efficiently. When short sellers rely on tips and connections, they should be able to profit no matter which industry they target. Following the arguments by Kogan and Papanikolaou (2010) and Pastor and Veronesi (2003), we use within-industry variation in the uncertainty about future profit opportunities to proxy for complexity. This measure captures that, in complex industries, the adaptation to new technology has uneven effects across firms, thereby creating mis-valuation opportunities for short sellers. This gives us the second testable hypothesis:

H2: Short sellers make more profits in more complex industries.

Last, we want to verify whether short sellers' superior skills in processing industry information have any economic implications for the targeted industries and firms within an industry. Short sellers are often accused of targeting vulnerable firms in distressed or sensitive industries. Nevertheless, from the perspective of an industry, short sellers may help to improve economic efficiency by identifying firms with fundamental problems beyond temporary overvaluation, thereby revealing new information about future distress. Our third testable hypothesis addresses how short sellers influence the economic consequences at the firm and industry level as follows,

H3: Short sellers contribute to the economic efficiency of the targeted industries by identifying firms with fundamental problems (e.g., firms with high default risk).

We test the above three empirical hypotheses in the following sections.

3. Empirical findings

3.1. Data and summary statistics

We use monthly CRSP stock returns from January 1990 to December 2013. We obtain the firms' financial information from the annual Compustat database and institutional ownership information from 13f filings. When institutional ownership data are missing, we replace the missing values with zero. In the robustness test, we exclude those firms without institutional ownership information. The short-sale information is obtained from Compustat monthly securities files, which include the number of shares shorted as of the middle of the month. Since the data are somewhat limited before July 2003, we also perform robustness tests using the data only after July 2003. We collect information about the monthly Fed Fund rates and the corporate bond yield spread (i.e., the spread between the BAA and AAA rated corporate bonds) from the Federal Reserve Bank of St. Louis economic data series.

Following standard data cleaning procedures, we exclude monthly stock observations with any of the following information missing: book-to-market ratio (from the monthly file), closing price for the last day of the previous month, trading volume, return, share volume, and bid-ask prices for the previous month. In the case of delisting, we use the delisting returns if they are available from the CRSP or delete the stock observation in the month of delisting. After the data cleaning, we have 755,325 stock-month observations, an average of about 2,500 observations per month. Table 1 provides the relevant summary statistics for the full sample.

[Table 1 about here]

In Figure 1, we show the time trends of shorting for four key GICS industry groups (from the 24 GICS industry groups) based on the GICS from 1990 to 2013.[5] We depict the industry cumulative returns on the left axis and the corresponding period's total shorted values in millions of dollars on the right axis. The industry cumulative holding returns are based on the monthly value-weighted average industry returns, including all stocks from the industry with valid stock returns, market capitalization, and trading volumes. The co-movement of the aggregate shorted value and the industry returns suggests that short sellers hold large positions in booming industries as their position values continue to increase with the rising prices in the industry, implying losses

[5] The relevant graphs for all 24 industries are available in the online appendix.

for them in the short run. This result indicates that short sellers seem to have good reasons to hold on to their short positions despite rising prices, possible due to their information advantage at the industry level.

[Figure 1 about here]

Interestingly, short sellers increase their positions before an industry experiences a significant decline in prices. Panel A shows that the shorted value increased with the industry run-up in 2006; see diversified financials (GICS 4020) and finance-real estate groups (GICS 4040). Panel B shows that there was a peak in shorted value just before 2008, suggesting that short sellers held on to their position when the market experienced a price correction. The contrarian trend is clearer in Panels C and D, with the IT and utilities industries, respectively. It is important to note that while there was governmental intervention in the first industry, there was none in the latter two industries; thus Panels C and D may provide a better picture of market forces and short sellers' trading strategies without government intervention.

To gain a more direct understanding of short sellers' industry dynamics, we plot the industry rank of total industry shorted value over time in Figure 2. It shows that the IT industry did not attract much interest from short seller before 1999, possibly due to its infancy. The aggregate shorted value significantly increased in real estate financials (GICS 4040) already around 2004, suggesting that some short sellers might have realized that there was significant mispricing or shortage in the industry long before the global financial crisis.

[Figure 2 about here]

3.2. Short sellers' industry information

In this section, we test the first empirical hypothesis (*H1*): whether short sellers have superior industry information. We perform the tests both in portfolio settings and in cross-sectional analyses.

3.2.1. Portfolio analysis

Following standard empirical asset pricing and short-sale studies (e.g., Desai et al. 2002; Asquith, Pathak, and Ritter, 2005), we examine the industry information advantage of short sellers by testing whether stocks in industries targeted by short sellers earn abnormal returns. In each month, we first sort all industries based on the industry aggregate shorted value into six groups. We rely on the MSCI global industry classification standard (GICS) for our industry classification and adopt the 24-industry GICS grouping to identify firms that are comparable in their business focus and structure and can be considered competitors (Bhojraj, Lee, and Oler, 2003).[6] As it is problematic to establish quintile groups with 24 industries, we use sextile groups, where each sextile includes four GICS industries. These sextiles are formed by ranking the industries based on the total shorted value (i.e., the sum of the shorted value for each stock in a specific industry and the shorted value is the number of shares shorted times the corresponding share price). Then we sort all firms within each industry group into six groups based on the stock's own level of short interest ratio, SIR.

For each of the 36 double-sorted (DS) portfolios, we use the Fama-French-Carhart (Fama and French, 1996; Carhart, 1997) factor model to test for abnormal returns using the following specification:

Double-sorted portfolios: $$\text{PortfRet-RF} = \alpha + \beta\, MKT + \delta\, HML + \gamma\, SMB + \varphi MOM + \varepsilon \qquad (1)$$

[6] The industry definitions are provided in Table 1 of the online Appendix.

If short sellers have superior industry information, then stocks with high SIR in the most-shorted industries should be associated with the most negative abnormal returns. Since active traders usually use hedged trading strategy to remove unnecessary exposure to other sources of risk, we also examine the performance of hedge portfolios using the following specifications:

Within industry: $$\text{(Long-Short)PortfRet} = \alpha + \beta\ MKT + \delta\ HML + \gamma\ SMB + \varphi MOM + \varepsilon \qquad \text{(2A)}$$

Across industries: $$\text{(Long-Short)PortfRet} = \alpha + \beta\ MKT + \delta\ HML + \gamma\ SMB + \varphi MOM + \varepsilon \qquad \text{(2B)}$$

In model specification 2A, we create hedge portfolios of high- and low-SIR stocks within industry sextiles and test the abnormal returns on these long-short portfolios. We expect that within each industry sextile group, stocks with low SIR will outperform stocks with high SIR because short sellers are known to possess firm-specific information.

To directly measure the cross-industry information, we also consider hedge portfolio returns with model specification 2B. That is, we long stocks in the least-shorted industries (sextile) and short stocks in the most-shorted industries (sextile) within the same firm SIR sextile group. If the distribution of firm SIR is relatively even and high-SIR stocks are not explicitly concentrated in highly shorted industries, this portfolio strategy would capture the industry information beyond the firm information.

In Table 2, we report the equal- and value-weighted averages of excess stock returns for 36 double-sorted short portfolios. The portfolios are established at the end of the month, and returns are measured over the next one month and the next six months. In the second column in Table 2, we report the time-series average of the number of stocks and average returns for the 36 portfolios. We find that among the portfolios, those in the most-shorted industries (where the portfolio rank first digit is 6) are the largest groups. We report the arithmetic average and the value-weighted average SIR for each portfolio under headings *AveSIR* and *vwSIR* respectively in columns 3 and

4. The time-series average numbers reveal that even in the least-shorted industries, the firm-level SIR can be very high. For portfolios 16 and 66, the value-weighted average SIRs are 7.8% and 10%. More importantly, for portfolios 46, 56, and 66, the *vwSIR* is about 10% across all three portfolios, suggesting that firm-level shorting can be excessively high even in the less-shorted industries.

[Table 2 about here]

First, we find that there is little variation in returns across the portfolios in the least-shorted industries. Columns 5 and 6 in Table 2 show that in the least-shorted industries (where the first digit of *Portfrank*=1), value-weighted excess returns range from 0.78% to 0.54%. In contrast, in the most-shorted industries (where the first digit of *Portfrank*=6), the value-weighted excess returns range from 1.19% to 0.24%, suggesting a much larger difference between the least-shorted and the most-shorted stocks. On average, within each industry sextile, portfolios with a higher firm-level SIR have lower returns, consistent with Desai et al. (2002).

[Table 3 about here]

In Table 3, we examine the future performance of 36 double-sorted portfolios using the four-factor adjusted portfolio returns over a six-month horizon (Fama and French, 1993; Carhart, 1997). We focus on longer-term returns because industry information is expected to be slowly incorporated and shorter-term returns can be affected by temporary mispricing or noise in the market. For example, large short sales may result in transient price effects, but only the permanent price effect is expected to provide evidence of information (Madhavan, 2000; Brogaard, Hendershott, and Riordan, 2014).

We report future abnormal returns of the 36 double-sorted portfolios in Table 3, Panels A and B. Focusing on the most-shorted stocks (sextile 6 based on firm SIR) in the most-shorted industries, we find significant abnormal –2.91% equal-weighted returns in Panel A, and –2.76% value-weighted returns in Panel B. However, we find no significant negative returns on high firm SIR stock portfolios in the least-shorted industries. Comparing the abnormal returns on the highly shorted stock portfolios across industries, we report a return difference of 2.8% (on the right side of the table under the heading "Hedge portfolios"). Overall, the persistence of negative information in the most-shorted stocks in the highly shorted industries suggests that short sellers trade on firm-specific information and industry information in the medium term (six-month horizon).[7]

To ensure that our results are not driven by small stocks, we exclude penny stocks (stocks with a share price of less than $5) and repeat the same portfolio analyses as in Table 3 for the full sample period. The relevant results, reported in Table 4, Panel A, provide even stronger evidence that short sellers possess industry information. The negative information in the high-SIR stocks is again the most significant in the highly shorted industry, generating a return of –3.16%. It is largely insignificant in the least-shorted industries. In Panel B, the results with value-weighting are statistically and economically similar. Thus, taken together, the results shown in Tables 2 and 4 support our first hypothesis that short sellers have superior industry information.

[Table 4 about here]

Considering realizable long-short trading strategies, we find that short sellers can generate an abnormal return of 4.96% within the most-shorted industries in six months (as shown in column *HighInd SV=6* in Table 3, Panel A). In Panel A of Table 4, excluding penny stocks, we find that the same portfolio has an abnormal return of 5.12% over the next six months.

[7] For reference, in Appendices A, B, and C we also show the one-month returns on the portfolios. The results in Appendix A show that highly shorted stocks even in the least-shorted industries underperform at the one-month horizon, which is consistent with the findings of prior studies that short sellers have firm-specific information. Here, we only suggest that not only do short sellers have firm-specific information but they also consider more macro-information by taking into account industry trends and structural changes.

Overall, we find strong evidence supporting our first hypothesis (*H1*).

3.2.2. Cross-sectional analyses

To confirm our finding with the portfolio analysis, we perform robustness tests using cross-sectional analyses. We use the Fama-MacBeth regression framework to test the link between industry-level short interests and future returns after controlling for the usual firm characteristics as well as firm-level SIR. Our model specification is given in the following equation:

$$\mathrm{Ret}_{1,6} = \alpha + \beta \text{ HighfirmSIR} + \delta \text{ HighIndSV} + \varphi \text{ FirmControls} + \varepsilon \tag{3}$$

$$\begin{aligned}\mathrm{Ret}_{1,6} = \alpha + \beta \text{ HighfirmSIR} + \delta_1 \text{HighIndSV} + \lambda_1 \text{HighIndSV} * \text{HighfirmSIR} \\ + \varphi \text{ FirmControls} + \varepsilon\end{aligned} \tag{3A}$$

$$\begin{aligned}\mathrm{Ret}_{1,6} = \alpha + \beta \text{ HighfirmSIR} + \delta_2 \text{HighIndSV} + \lambda_2 \text{HighIndSV*HighfirmSIR} \\ + \upsilon \text{ LowIndSV} + \nu \text{ LowIndSV*HighfirmSIR} + \varphi \text{ FirmControls} + \varepsilon\end{aligned} \tag{3B}$$

where the dependent variable is the stock's future six-month cumulative holding period return with dependent variables such as firm controls (e.g., firm size, market-to-book, and turnover) and key shorting measure such as the *HighfirmSIR*, which takes on the value of one for stocks with an SIR from the top decile of the distribution. In addition, we include dummy variables to capture high and low industry-level shorting. *HighIndSV* and *LowIndSV* variables take on the value of one if the industry is within the top sextile or bottom sextile based on the aggregate industry shorted value in the specific month, and zero otherwise. To test the interconnectivity of firm and industry information by short sellers, we also include interaction variables for firm-level and industry-level shorting (*HighfirmSIR*HighIndSV* and *HighfirmSIR*LowIndSV*). If the industry information is not relevant, we would expect insignificant coefficient estimates of δ and λ. If short sellers effectively exploit industry information in conjunction with firm information, we would expect the coefficient estimate of λ, on the interaction term, to be significantly negative.

[Table 5 about here]

We find robust evidence in support of our first hypothesis, as shown in Table 5, Panel A. Model 1 shows a significant negative coefficient estimate of –1.61 on the *HighFirmSIR* dummy measure, implying that highly shorted stocks experience about –1.61% lower returns over the next six months. In Models 2 and 3, we include the industry shorting measure, specifically, a dummy variable that equals one for industries from the highest sextile for the *HighIndSV* dummy, and zero otherwise. The significant coefficient estimate on the interaction variable of the high industry-level shorting and the high firm-level shorting (*HighIndSV*HighfirmSIR*) suggests that industry information is used in conjunction with firm-level shorting. It is important to note that the coefficient estimate on the *HighfirmSIR* is economically similar across Models 1 and 3, suggesting that the interaction does not weaken the primary effect, which is the superior firm information of short sellers.

On the right side of Table 5, Panel A, we replicate the same analyses with a reduced sample by excluding penny stocks. The results are similar with the reduced sample, if not stronger. We include additional analyses in Table 5, Panel B, by using previous one-month and six-month returns as additional control variables for return momentum or reversal. The results in Table 5, Panel B, are economically and statistically similar to those reported in Panel A, confirming that our findings are robust.

Overall, we find supporting evidence for *H1*, that short sellers profit from their superior industry information *ceteris paribus*, in both the portfolio setting and the cross-sectional analysis.

3.3. Analyses of short sellers' industry preference

Given that short sellers profit from superior industry information, we investigate the characteristics of industries targeted by short sellers. Following the literature, we focus on industry characteristics such as market-to-book ratio, liquidity, and idiosyncratic risk (Desai et al. 2002; Au, Doukas, and Onayev, 2009; Boehmer et al. 2010) to proxy for the complexity of an industry. We use the following baseline regression model specification to test our second hypothesis,

$$\text{LogIndSV} = \alpha + \beta \text{ IndChar} + \delta \text{ IndHetero} + \phi \text{ LogMcap} + \theta \text{ LogFirms} + \varepsilon \tag{4}$$

where *LogIndSV* is the natural logarithm of the total industry shorted value in millions. Industry value-weighted average book-to-market ratio (*vwBtoM*), value-weighted lagged one-month returns ($vwLagRet_{-1m}$), value-weighted lagged six-month returns ($vwLagRet_{-6m}$), lagged one-month value-weighted average turnover ($vwTurn_{-1m}$), lagged one-month value-weighted average price spread ($vwHLspread_{-1m}$), and the value-weighted market leverage (*vwMLever*) of all listed firms within an industry. The industry heterogeneity vector (*IndHetero*) includes two measures to capture the degree of variation in firm characteristics within the industry, namely the industry standard deviation of the firm's book-to-market ratio (*Indstd_BtoM*) and the industry standard deviation of the firm's market leverage ratio (*Indstd_MLever*).

In addition, we control for industry size since the number of shorted shares and the shorted value are likely to be affected by the size of the firms and the size of the industry (i.e., the number of firms in the industry). Specifically, we include two control variables, *vwLogMcap* and *LogFirms*, which are value-weighted averages of all firms' market capitalization in millions of USD in the industry and the natural logarithm of the number of firms in the industry, respectively. In the regression framework, we include time fixed effect and cluster the standard errors by year.

[Table 6 about here]

Table 6 shows that short sellers concentrate on complex industries with higher past returns and greater liquidity. The significant positive coefficients on the *Indstd_BtoM* and *Indstd_Mlever* variables suggest that more shorting occurs in industries where there is a large variation in book-to-market and leverage ratios, respectively. These findings support *H2* by revealing that short sellers focus on heterogeneous industries with greater information complexity (e.g., the dispersion in the book-to-market ratios indicates dispersion and uncertainty about future profit expectations within the industry) where they can exploit their private information or superior information-processing skills for more gains.

3.4. The economic implications of short sellers' industry information

Given that we find supporting evidence that short sellers exploit industry information and choose to target certain industries, it is important to understand the economic implications of their information. To address the information content in short sellers' industry concentration, we examine whether short sellers' concentration at the industry level are related to the firm's future default risk. This question is important because the firm's ongoing concern has significant economic implications. To test our third hypothesis (*H3*), that short sellers provide new economic information in the targeted industries, we examine the relationship between firm-level shorting and the change in the distance-to-default (DtoD) measure over the next six months.

Our DtoD measure is based on Duan et al. (2012)'s transformed-data MLE method calculation of the Merton (1974)'s model of default.[8] This method is considered to be superior relative to the volatility restriction model (Jones et al. 1984; Ronn and Verma, 1986) and KMV method (Crosbie and Bohn, 2003) to extreme high leverage for financial related firms, such as real estate investment firms, banks and insurance companies in our sample.

We use a Fama-MacBeth regression model specified as follows,

[8] The distance to default data is obtained from the Credit Research Initiate at the Risk Management Institute (RMI) of the National University of Singapore. The technical documentation and the data available through the RMI at http://rmicri.org/cms/about/techreport/.

$$\mathrm{ChngDtoD}_{t+6} = \alpha + \vartheta_1 \mathrm{firmSIR} + \vartheta_2 \mathrm{HighIndSV} + \vartheta_3 \mathrm{HighIndSV*firmSIR} + \omega_i \sum_{i=0}^{k} \mathrm{FirmControl}_i + \zeta \tag{5}$$

where the dependent variable is the change in the distance-to-default measure from time *t* to time *t*+6, where the shorting and the control measures are established at time *t*. The key explanatory variables are the firm-level short interest (*firmSIR*) and the high level of industry short dummy variable (*HighIndSV*), which equals one if the industry level total shorted value is in the top sextile, as discussed earlier in the portfolio analysis. We also include an interaction measure for the latter two variables to test our *H3* in the pooled sample. In addition, we examine the short interest default predictability in the subsample setting, separately in the sample of firms from highly shorted industries and sample of firms from lightly shorted industries. Other firm control variables include traditional stock market controls, such as market capitalization, book-to-market ratio, bid-ask spread, high-low price spread, turnover, and a number of corporate controls such as: cash-to-sales ratio, rollover risk (i.e., ratio of short-term debt to long-term debt adopted from Almeida, 2012) and the traditional financial constraint measure (*KZfirm*) (Kaplan and Zingales, 1997).

Specifically, the rollover risk is expected to control for an increase in refinancing in the presence of deteriorating debt market liquidity. In the cross-section, firms with high rollover risk are expected to be closer to default (He and Xiong, 2012), while cash holdings may be important in dealing with competition, especially in industries with changing technologies (Lyandres and Palazzo, 2015). Table 7 reports the findings. For this analysis the sample period is slightly smaller because we need to have valid distance-to-default information continuously for six months to be able to perform the change-in-default-risk analysis.

[Table 7 about here]

Panel A of Table 8 shows that stocks with higher shorting in highly shorted industries are associated with a future decline in the distance-to-default measure. However, in itself the shorting measure, the *FirmSIR*, has an insignificant relation to the change in the distance-to-default measures in industries with a low concentration of short sellers. This result implies that the firm-level SIR and default link is only manifested in those industries that are highly shorted. In industries that are not highly shorted, the high firm-level SIR likely captures only temporary overvaluation rather than serious ongoing concern issues about the targeted firms.

In Panel B of Table 8, we further confirm these results with subsample analyses. We find that the significant relation between *FirmSIR* and *ChngDtoD* exists only in industries with a high level of shorting. This finding supports our third hypothesis (*H3*). Overall, we find that short sellers help to improve the economic efficiency of the targeted industries by identifying firms that may have future ongoing concern issues. To our knowledge, this is the first time in the literature that short sellers have been shown to create economic information at the industry level.

4. Robustness tests

We perform several robustness tests to ensure that our portfolio results are not driven by a small group of extreme stocks in supporting *H1*.[9] First, to address the concern that our results might be driven by financial stocks, or by stocks from regulated industries, we replicate our analysis without regulated industries, excluding all financial firms and utilities industries (GICS groups 4010, 4020, 4030, and 5010). We find that our main results remain the same (see Table 3) and are not a manifestation of the global financial crisis.

Next we consider whether our results could be a manifestation of high short-sale costs or binding short-sale constraints. To address this shorting cost/constraint endogeneity issue, we first

[9] All robustness results are available in the online appendix.

replicate our main analysis without illiquid stocks. Next we replicate our analysis by excluding penny stocks and stocks with a low level of institutional ownership. These subsample analyses are motivated by prior empirical evidence that small, illiquid stocks may be difficult or costly to short (D'Avolio 2002). However, in all three analyses with the reduced sample containing only larger, more liquid stocks with non-trivial institutional ownership, we still find consistent results.

Lastly, we consider whether the results are driven by insiders. We exclude family firms based on the definition of Anderson. Reeb, and Zhao (2013) and find that the results remain economically and statistically similar. All relevant results are available in the online appendix.

5. Conclusion

Our study explores the information advantage possessed by short sellers at the industry level. First, we provide evidence that short sellers earn significant profits by exploiting superior industry information. In both portfolio and cross-sectional analyses, we show that stocks with high SIR within the most-shorted industries earn significantly more negative abnormal returns in the next six months than similarly highly shorted stocks in less-shorted industries. Within the most-shorted industries (industries from the top sextile based on the aggregate shorted value), the portfolio of the most-shorted stocks (top-sextile stocks based on SIR) earns –2.76% value-weighted abnormal returns over the next six months. In contrast, the portfolio of the most-shorted stocks in the least-shorted industries earns insignificant abnormal returns during the same period. We find even more striking results with industry-adjusted high-low short hedge portfolios. Hedge portfolios within the most-shorted industries, created by longing the least-shorted stocks and shorting the most-shorted stocks, generate 4.74% value-weighted abnormal returns. Second, we find that short sellers focus on more complex industries where they can benefit more from their superior information-processing skills. In these targeted industries, short sellers aid information efficiency and economic efficiency by identifying not just temporarily overpriced stocks but firms with fundamental problems.

Overall, our study provides new evidence about short sellers' superior information beyond specific firms. We suggest that short sellers' industry preferences may signal valuable information to retail traders as well as to regulators. Specifically, the industry concentration of these relatively informed active traders likely captures important ongoing changes in the industry. These changes, in combination with strong competition and industry diversity are associated with increase in uncertainty about future profitability, resulting in higher default risk for some firms. Thus, short sellers' industry concentration conveys important economic information to all market participants and may warrant further attention.

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Table 1. Summary statistics for US firms from 1990 to 2013

Lead1mret (*Lead6mret*) is the next month (next six-month) holding period return. *SIR* (in %) is the number of shares shorted relative to the number of shares outstanding as a percentage; *MillSV* is the total value of shorted shares in million USD for a specific stock. *Mcapmill* is the month-end share price times the number of total shares in million USD. *BAspread* is the ask-bid price difference relative to the average bid-ask price, while *HLspread* is the monthly price spread, as the difference between the monthly highest and lowest price relative to the average of the highest and the lowest price in the month. *Turn* (in %) is the number of shares traded in the month relative to the total number of shares outstanding as a percentage. *BtoM* is the firm's book value of equity relative to stock market capitalization. *Mlever* is the market leverage where the total debt (short-term plus long-term debt) is measured relative to the ratio of the total debt plus market capitalization.

Variable	**Mean**	**Std Dev**	**Minimum**	**Maximum**
Lead1mret	0.010	0.141	-0.981	7.007
Lead6mret	0.064	0.378	-0.995	41.429
SIR (in %)	3.334	5.305	0.000	99.954
MillSV	73.545	210.532	0.000	18414.990
Mcapmill	3473.190	14625.530	0.048	626550.330
BAspread	0.011	0.022	0.000	1.290
HLspread	0.155	0.123	0.000	1.947
Turn (in %)	14.650	29.432	0.000	4914.010
BtoM	0.671	0.540	0.018	8.133
Mlever	0.201	0.167	0.000	0.822
EFD	-2.753	12.276	-290.661	187.443
Rollover	0.246	0.299	0.000	1.000

Table 2. Summary of statistics of portfolio returns and shorting activity for the double-sorted portfolios

The table summarizes the time-series averages of number of stocks in a portfolios (*#Firms*), the time series means and the value weighted averages of the firm's SIR in the portfolios (with *AveSIR* and *vwSIR*)**,** the future equal- and value-weighted one-month ($EqExcRet_{1m}$ and $VwExcRet_{1m}$) and six-month ($EqExcRet_{6m}$ and $VwExcRet_{6m}$) excess returns on the 66 double-sorted portfolios, where the excess returns are in excess of the risk-free rate. The 66 portfolios are established using industry-level shorted value to establish industry sextiles and then within each industry group, firm sextiles based on firm-level shorting. The portfolio with *Portfrank*=11 includes firms from industries with the lowest aggregate shorted value (*IndSV*) where the stock itself has also been in the lowest quintile based on its SIR. In the portfolio rank, the first digit refers to the industry rank, while the second digit refers to the stock's rank based on the firm SIR within the industry. *Portfrank*=11-61 reflects a long-short hedge portfolio where the long position is in the portfolio with *Portfrank*=11 and the short position is in the portfolio with *Portfrank*=61.

Panel A. Summary of return of double-sorted portfolios, using GICS 24-industry group

Portfrank	#Firms	AveSIR	vwSIR	$EqExcRet_{1m}$	$VwExcRet_{1m}$	$EqExcRet_{6m}$	$VwExcRet_{6m}$
11	34.673	0.026	0.027	0.910	0.781	6.241	5.934
12	35.214	0.254	0.267	0.744	0.746	5.648	5.770
13	35.206	0.810	0.810	0.792	0.758	5.807	5.555
14	35.335	1.535	1.534	0.759	0.798	6.802	6.611
15	35.381	2.722	2.729	0.695	0.729	5.658	5.707
16	34.851	8.093	7.849	0.489	0.541	4.786	5.190
21	47.359	0.053	0.057	0.968	0.995	5.778	5.968
22	47.858	0.379	0.387	0.738	0.756	4.422	4.633
23	47.854	0.952	0.952	0.786	0.828	4.531	4.631
24	48.018	1.776	1.774	0.915	0.919	5.940	5.713
25	48.028	3.190	3.188	0.918	0.864	5.398	5.209
26	47.523	9.455	9.190	0.418	0.435	3.435	3.507
31	58.125	0.049	0.052	0.814	0.797	5.989	6.101
32	58.605	0.407	0.420	0.838	0.864	6.469	6.407
33	58.637	1.033	1.032	0.971	0.943	6.101	6.005
34	58.758	1.890	1.887	1.042	0.999	6.456	5.974
35	58.801	3.401	3.399	0.806	0.835	5.740	5.730
36	58.285	10.358	10.032	0.419	0.462	4.490	4.538
41	73.249	0.050	0.052	0.939	0.918	6.159	5.811
42	73.698	0.459	0.479	1.103	1.050	6.276	6.057
43	73.737	1.193	1.192	0.913	0.906	5.283	5.116
44	73.861	2.099	2.099	0.793	0.792	5.740	5.533
45	73.893	3.581	3.578	0.856	0.837	4.607	4.577
46	73.363	10.047	9.725	0.332	0.401	3.271	3.421
51	102.381	0.054	0.057	1.070	1.001	5.870	5.489
52	102.879	0.471	0.489	0.811	0.810	5.270	5.137
53	102.918	1.243	1.245	0.789	0.833	5.452	5.507
54	103.050	2.232	2.232	1.005	0.963	5.517	5.330
55	103.068	3.813	3.810	0.645	0.623	4.512	4.484
56	102.552	10.100	9.807	0.512	0.521	3.202	3.420
61	123.420	0.067	0.073	1.236	1.191	6.681	6.401
62	123.982	0.455	0.464	1.014	0.982	5.842	5.432
63	123.918	1.150	1.151	0.767	0.720	4.811	4.616
64	124.139	2.123	2.121	0.675	0.663	4.173	4.195
65	124.139	3.721	3.717	0.579	0.592	3.956	4.098
66	123.605	10.319	9.998	0.248	0.244	1.749	1.857

Table 2 (continued)

Panel B. Summary statistics of hedge portfolios

The table summarizes the future equal- and value-weighted one-month (*$EqExcRet_{1m}$* and *$VwExcRet_{1m}$*) and six-month (*$EqExcRet_{6m}$* and *$VwExcRet_{6m}$*) excess returns on hedge portfolios based on the 66 double-sorted portfolios. For illustration, the portfolio with *Portfrank*=1161 includes a long position in the stocks from portfolio with *Portfrank*=11 and short position in the stocks from the portfolio with *Portfrank*=61, effectively including the least shorted stock across the least and most shorted industries.

Portfrank	**$EqExcRet_{1m}$**	**$VwExcRet_{1m}$**	**$EqExcRet_{6m}$**	**$VwExcRet_{6m}$**
1161	-0.325	-0.410	-0.440	-0.467
1162	-0.270	-0.236	-0.193	0.338
1163	0.025	0.039	0.996	0.940
1164	0.084	0.134	2.629	2.415
1165	0.116	0.137	1.702	1.609
1166	0.241	0.296	3.037	3.333
2161	0.421	0.240	1.455	0.745
2162	0.550	0.560	2.344	2.461
2163	0.395	0.335	1.499	1.563
2164	0.607	0.517	2.888	2.391
2165	0.558	0.480	2.668	2.069
2166	0.987	0.947	4.932	4.544

Table 3. Summary of future one-month and six-month abnormal returns on double-sorted portfolios, sorting on industry aggregate shorting and firm-level short interest ratio, using GICS 24-industry classification

The table summarizes portfolio abnormal returns, from the Fama-French-Carhart four-factor model, where the portfolio excess returns are the future one-month (in Panels A and B) and six-month (in Panels C and D) equal- or value-weighted excess returns, as a percentage, on double-sorted portfolios since portfolio creation. In establishing the double-sorted portfolios, at the end of each month, industries are ranked based on the industry aggregate shorted value (*IndSV*). Then, within each industry (sextile) group, stock portfolios are established based on the individual firm-level SIR, where SIR is the number of shares shorted relative to the total number of shares outstanding in the previous month. To save space, only the portfolio abnormal returns (the intercepts from the portfolio return regressions) are reported with the relevant *p*-values (in italics), where <0.001 reflects that the values are significant at the 0.1% level. For each portfolio, 281 months of data are used, from January 1990 to April 2013.

Panel A. Future six-month abnormal portfolio returns on equal-weighted double-sorted portfolios

	Low IndSV=1	**Low IndSV=2**	**Mid-low IndSV=3**	**Mid-high IndSV=4**	**High IndSV=5**	**High IndSV=6**	**Hedge portfolios**
Low Firm SIR=1	3.052	1.848	1.338	2.133	1.320	2.055	0.998
	<.001	*0.001*	*0.019*	*<.001*	*0.018*	*0.002*	*0.195*
Low Firm SIR=2	1.897	0.652	0.806	2.717	0.849	1.314	0.583
	<.001	*0.177*	*0.215*	*<.001*	*0.067*	*0.022*	*0.368*
Mid-Low Firm SIR=3	2.064	0.724	1.831	1.775	1.374	0.357	1.707
	<.001	*0.108*	*<.001*	*<.001*	*0.002*	*0.489*	*0.007*
Mid-High Firm SIR=4	2.881	1.633	1.538	1.991	1.192	-0.663	3.544
	<.001	*0.001*	*0.004*	*<.001*	*0.008*	*0.166*	*<.001*
High Firm SIR=5	0.997	0.981	0.714	0.759	0.264	-1.004	2.000
	0.078	*0.050*	*0.226*	*0.119*	*0.529*	*0.068*	*0.011*
High Firm SIR=6	-0.127	-1.463	-0.615	-0.562	-1.529	-2.906	2.779
	0.855	*0.016*	*0.265*	*0.272*	*0.002*	*<.001*	***0.001***
Hedge portfolios	3.180	3.311	1.953	2.694	2.849	4.961	
	<.001	*<.001*	*0.004*	*<.001*	*<.001*	*<.001*	

Panel B. Future six-month abnormal portfolio returns on value-weighted double-sorted portfolios

	Low IndSV=1	**Low IndSV=2**	**Mid-low IndSV=3**	**Mid-high IndSV=4**	**High IndSV=5**	**High IndSV=6**	**Hedge portfolios**
Low Firm SIR=1	2.528	2.085	1.646	1.974	1.153	1.974	0.555
	<.001	*<.001*	*0.002*	*<.001*	*0.030*	*0.002*	*0.447*
Low Firm SIR=2	2.239	0.931	0.940	2.815	1.197	1.146	1.093
	<.001	*0.039*	*0.116*	*<.001*	*0.006*	*0.029*	*0.063*
Mid-Low Firm SIR=3	1.776	1.002	1.763	1.696	1.691	0.308	1.468
	<.001	*0.015*	*<.001*	*<.001*	*<.001*	*0.511*	*0.009*
Mid-High Firm SIR=4	2.532	1.509	1.465	1.885	1.246	-0.467	2.998
	<.001	*0.001*	*0.001*	*<.001*	*0.003*	*0.304*	*<.001*
High Firm SIR=5	0.945	0.809	0.894	0.828	0.287	-0.780	1.724
	0.083	*0.079*	*0.107*	*0.075*	*0.477*	*0.142*	*0.028*
High Firm SIR=6	0.333	-1.336	-0.684	-0.269	-1.310	-2.762	3.096
	0.633	*0.020*	*0.198*	*0.597*	*0.005*	*<.001*	***<.001***
Hedge portfolios	2.195	3.421	2.330	2.243	2.463	4.736	
	0.003	*<.001*	*<.001*	*<.001*	*<.001*	*<.001*	

Table 4. Future six-month abnormal returns on double sorted portfolios, excluding penny stocks

The table summarizes portfolio abnormal returns, from the Fama-French-Carhart four factor model, where the portfolio excess returns are the future one-month (in Panels A and B) and six-months (in Panels C and D) equal or value-weighted excess returns in percentage on double-sorted portfolios since portfolio creation. In establishing the double-sorted portfolios, first we exclude at the end of each month all penny stocks (stcokc with a share price of less than $5); then the industries are ranked based on the industry aggregate shorted value (*IndSV*). Then, within each industry (sextile) group, stock portfolios are established based on the individual firm-level SIR, where SIR is the number of shares shorted relative to the total number of shares outstanding in the previous month. To save space only the portfolio abnormal returns (the intercepts from the portfolio return regressions) are reported with the relevant *p*-values (in italics), where <0.001 reflects that the values are significant at the 0.1% level. For each portfolio, 281 months of data are used, from January 1990 to April 2013.

Panel A. Future six-month abnormal returns on equal-weighted double-sorted portfolios, excluding penny stocks

	Low IndSV=1	**Low IndSV=2**	**Mid-low IndSV=3**	**Mid-high IndSV=4**	**High IndSV=5**	**High IndSV=6**	**Hedge portfolios**
Low Firm SIR=1	2.433	1.750	1.201	2.044	1.354	1.958	0.475
	<.001	*<.001*	*0.015*	*<.001*	*0.003*	*<.001*	*0.426*
Low Firm SIR=2	1.605	0.875	0.558	1.906	1.388	1.128	0.477
	<.001	*0.056*	*0.389*	*<.001*	*0.001*	*0.030*	*0.421*
Mid-Low Firm SIR=3	1.485	1.164	1.474	1.514	1.352	0.147	1.338
	0.001	*0.011*	*0.003*	*<.001*	*0.001*	*0.758*	*0.024*
Mid-High Firm SIR=4	1.508	0.771	1.154	1.306	0.798	-0.518	2.025
	0.003	*0.071*	*0.010*	*0.002*	*0.053*	*0.264*	*0.002*
High Firm SIR=5	0.561	0.523	0.094	0.717	-0.047	-0.856	1.417
	0.348	*0.264*	*0.858*	*0.130*	*0.910*	*0.124*	*0.092*
High Firm SIR=6	-0.316	-1.590	-1.224	-0.493	-1.738	-3.161	**2.845**
	0.645	*0.005*	*0.029*	*0.330*	*<.001*	*<.001*	***0.001***
Hedge portfolios	2.748	3.339	2.426	2.538	3.092	5.118	
within industry	*<.001*	*<.001*	*<.001*	*<.001*	*<.001*	*<.001*	

Panel B. Future six-month abnormal returns on value-weighted double-sorted portfolios, excluding penny stocks

	Low IndSV=1	**Low IndSV=2**	**Mid-low IndSV=3**	**Mid-high IndSV=4**	**High IndSV=5**	**High IndSV=6**	**Hedge portfolios**
Low Firm SIR=1	2.018	1.842	1.282	2.005	1.344	1.852	0.166
	<.001	*<.001*	*0.006*	*<.001*	*0.002*	*<.001*	*0.783*
Low Firm SIR=2	1.766	1.000	0.865	1.998	1.545	0.908	0.858
	<.001	*0.022*	*0.137*	*<.001*	*<.001*	*0.057*	*0.117*
Mid-Low Firm SIR=3	1.329	1.161	1.476	1.420	1.475	0.156	1.173
	0.002	*0.007*	*0.001*	*<.001*	*<.001*	*0.730*	*0.034*
Mid-High Firm SIR=4	1.424	0.781	1.218	1.260	0.890	-0.346	1.770
	0.003	*0.063*	*0.005*	*0.002*	*0.026*	*0.442*	*0.005*
High Firm SIR=5	0.494	0.579	0.337	0.759	0.004	-0.740	1.233
	0.404	*0.209*	*0.525*	*0.097*	*0.992*	*0.170*	*0.141*
High Firm SIR=6	-0.048	-1.537	-1.163	-0.341	-1.480	-3.012	**2.964**
	0.944	*0.006*	*0.038*	*0.501*	*0.001*	*<.001*	***0.001***
Hedge portfolios	2.067	3.379	2.445	2.346	2.824	4.865	
within industry	*0.004*	*<.001*	*<.001*	*<.001*	*<.001*	*<.001*	

Table 5. Fama-MacBeth analysis of future stock returns in relation to industry-level shorting

The dependent variable is the future six-month cumulative holding period return on the stock. *LogMcap* and *BtoM* are the market capitalization and the book-to-market ratios, where the market cap is the total shares outstanding in millions times the share price at the end of the previous month; *BtoM* definition follows Fama and French (1997). $Turn_{-1m}$ is the monthly turnover as a percentage. *HighSIRfirm* is a dummy that takes on the value of 1 for the specific firm-month observation where the firm's short interest ratio is in the top sextile of the distribution. *HighIndSV (LowIndSV*) is a dummy that takes on the value of 1 for industries where the industry total shorted value *(IndSV*) in millions of USD is among the top 4 (bottom 4) industry groups (from the 24 GICS industry groups). In Panel B as additional controls, lagged one-month (Ret_{-1m}) and six-month returns (Ret_{-6m}) are also included. The coefficient estimates are displayed with the corresponding *t*-stats in brackets, from a Fama-MacBeth regression, with Newey-West robust standard errors with 5 lags.

Panel A. Fama-MacBeth analysis of future stock returns and industry short selling

	$\mathbf{Ret_{6m}}$	$\mathbf{Ret_{6m}}$	$\mathbf{Ret_{6m}}$	$\mathbf{Ret_{6m}}$	$\mathbf{Ret_{6m}}$	$\mathbf{Ret_{6m}}$
	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
		Full sample		Subsample, excluding penny stocks		
Intercept	5.332**	5.275**	5.208**	5.721***	5.668***	5.584***
	[2.09]	[2.07]	[2.04]	[2.79]	[2.77]	[2.74]
$LogMcap_{-1m}$	0.031	0.032	0.033	0.021	0.020	0.024
	[0.13]	[0.14]	[0.14]	[0.12]	[0.12]	[0.14]
$BtoM_{-1m}$	2.217***	2.215***	2.223***	1.518**	1.512**	1.523**
	[3.80]	[3.79]	[3.83]	[2.55]	[2.55]	[2.58]
$Turn_{-1m}$	0.004	0.004	0.004	0.002	0.003	0.002
	[0.14]	[0.17]	[0.15]	[0.08]	[0.09]	[0.07]
HighfirmSIR	-1.606***	-1.295***	-1.302***	-1.518***	-1.145**	-1.174**
	[-4.25]	[-2.83]	[-2.94]	[-3.75]	[-2.36]	[-2.51]
HighIndSV	-0.397	-0.213	-0.155	-0.447	-0.207	-0.156
	[-0.54]	[-0.28]	[-0.21]	[-0.63]	[-0.29]	[-0.22]
HighIndSV*HighfirmSIR		-1.041	-1.036*		-1.313**	-1.285**
		[-1.64]	[-1.66]		[-2.19]	[-2.19]
LowIndSV			0.500			0.353
			[0.96]			[0.78]
LowIndSV*HighfirmSIR			0.302			0.593
			[0.30]			[0.62]
R-square	0.032	0.033	0.036	0.034	0.035	0.038
Adjusted R-square	0.030	0.031	0.032	0.032	0.032	0.034
Observations	744,220	744,220	744,220	632,164	632,164	632,164

Table 5. continued

Panel B. Fama-MacBeth analysis of future stock returns and industry short selling, including past return controls

	Ret_{6m}	**Ret_{6m}**	**Ret_{6m}**	**Ret_{6m}**	**Ret_{6m}**	**Ret_{6m}**
	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
		Full sample		Subsample, excluding penny stocks		
Intercept	4.790**	4.739**	4.654**	5.152***	5.105***	4.996***
	[2.19]	[2.17]	[2.13]	[2.74]	[2.72]	[2.66]
$LogMcap_{-1m}$	-0.020	-0.020	-0.018	-0.003	-0.003	0.002
	[-0.10]	[-0.10]	[-0.09]	[-0.02]	[-0.02]	[0.01]
$BtoM_{-1m}$	1.845***	1.843***	1.852***	1.130*	1.125*	1.134*
	[3.10]	[3.10]	[3.13]	[1.88]	[1.87]	[1.90]
$Turn_{-1m}$	-0.025	-0.024	-0.024	-0.027	-0.027	-0.027
	[-1.21]	[-1.16]	[-1.20]	[-1.29]	[-1.26]	[-1.30]
HighfirmSIR	-1.396***	-1.103***	-1.103***	-1.297***	-0.945**	-0.963**
	[-3.83]	[-2.59]	[-2.68]	[-3.31]	[-2.06]	[-2.16]
HighIndSV	-0.451	-0.274	-0.210	-0.529	-0.300	-0.236
	[-0.70]	[-0.41]	[-0.31]	[-0.86]	[-0.48]	[-0.37]
HighIndSV*HighfirmSIR		-0.980	-0.985*		-1.239**	-1.225**
		[-1.63]	[-1.68]		[-2.20]	[-2.24]
LowIndSV			0.535			0.408
			[1.01]			[0.90]
LowIndSV*HighfirmSIR			0.212			0.500
			[0.21]			[0.53]
Ret_{-1m}	-1.337	-1.341	-1.282	-1.733	-1.732	-1.671
	[-1.37]	[-1.37]	[-1.31]	[-1.56]	[-1.56]	[-1.50]
Ret_{-6m}	4.023**	4.029**	4.002**	4.487**	4.493**	4.457**
	[1.99]	[1.99]	[1.98]	[2.45]	[2.46]	[2.43]
R-square	0.046	0.047	0.049	0.051	0.052	0.055
Adjusted R-square	0.043	0.044	0.045	0.048	0.048	0.051
Observations	744,220	744,220	744,220	632,164	632,164	632,164

Table 6. Determinants of industry concentration of short selling

The dependent variable is the natural logarithm of total shorted value in millions of USD in the specific GICS sector (*IndSV*). *LogFirm* is the natural logarithm of the number of firms in the industry. The *vwLogMcap* and v*wBtoM are* the value-weighted average market capitalization in the industry and the value-weighted average book-to-market ratio, where value-weighted is based on the firm's market capitalization. The $vwLagRet_{-1m}$ and $vwLagRet_{-6m}$ are the value-weighted average last-month returns and last six-month returns in the industry respectively. The $vwTurn_{-1m}$ and $vwHLspread_{-1m}$ are the value-weighted average turnover as a percentage and price spread (*HLspread*) in the previous month, where turnover is the ratio of the total shares traded and the price spread is the highest and lowest price differential in the previous month relative to the average of the highest and lowest price. The *vwMLever* is the value-weighted market leverage, where market leverage is the ratio of total debt relative to total debt plus the market capitalization. Industry heterogeneity is measured by the cross-industry standard deviation in book-to-market (*Indstd_BtoM*) and in market leverage (*Instd_MLever*). The coefficient estimates are reported with the corresponding t-stats in parentheses from an industry-level panel regression including year fixed effects. The total number of observations is 6,774, as 281 monthly observations are available for each of the 24 sectors from January 1990 to April 2013.

	IndSV	**IndSV**	**IndSV**	**IndSV**	**IndSV**	**IndSV**	**IndSV**
	Model 1	Model2	Model3	Model4	Model5	Model6	Model7
vwBtoM	-0.437	-0.466	-0.258	-0.209	-1.114	-0.187	-0.950
	[-5.4]	[-6.49]	[-4.04]	[-3.25]	[-24.24]	[-3.20]	[-19.01]
$vwLagRet_{-1m}$	0.865	0.652	0.522	0.508	0.020	0.022	0.020
	[2.61]	[1.74]	[1.72]	[1.67]	[6.97]	[7.00]	[7.08]
$vwLagRet_{-6m}$		0.222	0.048	0.042	-0.453	-0.250	-0.494
		[1.48]	[0.37]	[0.33]	[-1.22]	[-0.65]	[-1.36]
$vwTurn_{-1m}$			0.023	0.022	0.389	0.429	0.367
			[6.91]	[6.80]	[1.52]	[1.50]	[1.44]
$vwHLspread_{-1m}$			0.052	-0.037	-0.098	-0.022	-0.108
			[0.13]	[-0.09]	[-0.86]	[-0.19	[-0.96]
vwMLever				-0.316	-0.067	-1.383	-0.662
				[-3.74]	[-0.77]	[-10.85]	[-5.27]
Indstd_BtoM					1.199		1.907
					[13.44]		[7.54]
Indstd_MLever						3.679	0.998
						[15.13]	[9.95]
LogFirms	0.981	0.976	0.934	0.928	0.982	0.987	1.003
	[45.71]	[47.03]	[65.67]	[63.90]	[68.76]	[73.69]	[75.31]
vwLogMcap	0.893	0.885	0.864	0.865	0.912	0.936	0.941
	[22.64]	[22.90]	[26.99]	[27.31]	[30.75]	[28.82]	[31.62]
Intercept	-2.109	-2.027	-2.192	-2.12	-2.657	-3.136	-3.093
	[-4.93]	[-4.88]	[-5.66]	[-5.41]	[-7.35]	[-8.24]	[-9.07]
Time fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-square	0.852	0.853	0.866	0.866	0.878	0.873	0.880

Table 7. Cross-section analysis of changes in distance-to-default in relation to short selling

The dependent variable is the change in the distance-to-default (*ChngDtoD*) measure over the next six months. The firm-level SIR (*FirmSIR*) is the number of shorted as the percentage of total shares outstanding. *HighIndSV* is a dummy that takes on the value of 1 for firms from industries from the top sextile based on the total shorted value in the industry. *HighIndSV*FirmSIR* is an interaction variable of the firm's SIR and the industry high shorting dummy. The other firm controls: natural logarithm of the stock's total market capitalization (*LogMcap*), book-to-market (*BtoM*), *Turnover*, Lagged six-month returns (Ret_{-6m}), Bid-Ask spread (*BAspread*), High-Low price spread (*HLspread*), cash-to-sales ratio (*Cash/Sales*), rollover risk (*Rollover*) adopted from Almeida et al. (2012) and Kaplan and Zingales's financial constraint measure (*KZfirm*). The coefficient estimates are reported with the corresponding t-stats in brackets from a Fama-MacBeth regression with robust Newey West standard errors with 5 lags based on the time-series averages of the 281 monthly cross-sectional regressions for the 24 GICS sectors from January 1990 to April 2013.

Panel A. Cross-section analysis of changes in distance- to-default in relation to short selling in pooled sample

	ChngDtoD	**ChngDtoD**	**ChngDtoD**	**ChngDtoD**	**ChngDtoD**	**ChngDtoD**
FirmSIR	-0.001	0.002	0.000	0.000	0.000	0.000
	[-0.37]	[1.18]	[0.08]	[0.08]	[0.25]	[0.16]
HighIndSV		0.010	0.014	0.013	0.015	0.016
		[0.44]	[0.64]	[0.63]	[0.72]	[0.74]
HighIndSV*FirmSIR		-0.008***	-0.008***	-0.007***	-0.007***	-0.007***
		[-2.96]	[-2.88]	[-2.74]	[-2.75]	[-2.73]
LogMcap	-0.015	-0.015	-0.012	-0.012	-0.012	-0.012
	[-1.21]	[-1.20]	[-1.02]	[-1.03]	[-1.00]	[-0.99]
BtoM	0.011	0.013	0.026	0.026	0.027	0.026
	[0.58]	[0.73]	[1.46]	[1.44]	[1.53]	[1.47]
BAspread	-0.253	-0.262	-0.544	-0.541	-0.563	-0.565
	[-0.50]	[-0.52]	[-1.10]	[-1.09]	[-1.15]	[-1.16]
HLspread	-0.608***	-0.606***	-0.609***	-0.608***	-0.610***	-0.612***
	[-7.32]	[-7.40]	[-7.98]	[-7.97]	[-8.02]	[-8.03]
Turnover	-0.001	-0.001	-0.000	-0.000	-0.000	-0.000
	[-0.82]	[-0.83]	[-0.13]	[-0.12]	[-0.17]	[-0.17]
Ret_{-6m}			-0.225***	-0.225***	-0.225***	-0.225***
			[-9.34]	[-9.34]	[-9.39]	[-9.42]
Cash/Sales				0.067**	0.066**	0.071**
				[2.14]	[2.13]	[2.12]
Rollover					0.029*	0.030*
					[1.84]	[1.90]
KZfirm						0.002*
						[1.86]
Intercept	0.216***	0.213***	0.201***	0.201***	0.190***	0.191***
	[3.75]	[3.73]	[3.49]	[3.48]	[3.32]	[3.32]
R-square	0.036	0.040	0.045	0.046	0.047	0.048
Adjusted R-square	0.032	0.035	0.039	0.039	0.040	0.040
Observations	410,287	410,287	410,287	410,287	410,287	410,287

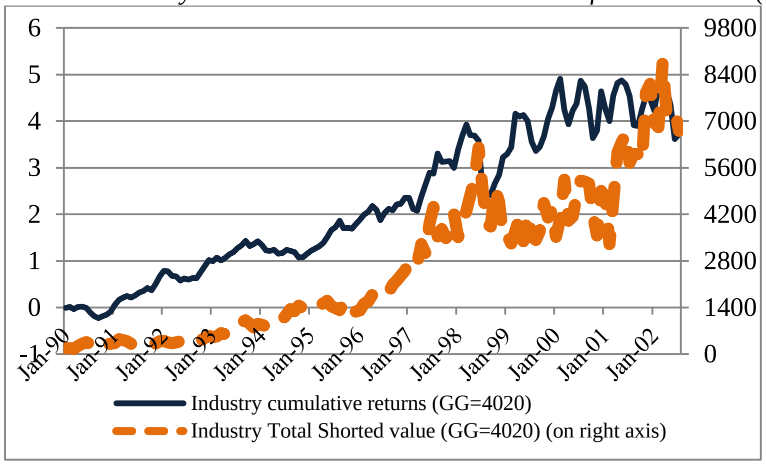
Table 7. continued

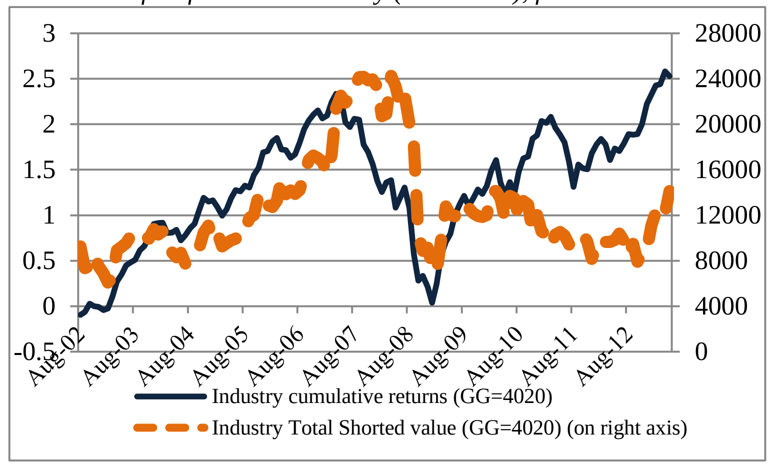
Panel B. Cross-section analysis of changes in distance-to-default in relation to short selling in sub-sample

	ChngDtoD Sample: Industries with high SV			ChngDtoD Sample: Industries with low SV		
	Model 1A	Model 2A	Model 3A	Model 1B	Model 2B	Model 3B
FirmSIR	-0.007**	-0.007**	-0.007**	-0.000	0.000	-0.000
	[-2.16]	[-2.19]	[-2.27]	[-0.14]	[0.08]	[-0.01]
LogMcap	-0.018	-0.019	-0.018	-0.010	-0.010	-0.010
	[-1.36]	[-1.40]	[-1.36]	[-0.82]	[-0.78]	[-0.78]
BtoM	0.061*	0.058	0.057	0.021	0.022	0.020
	[1.76]	[1.64]	[1.59]	[1.09]	[1.19]	[1.09]
BAspread	-0.196	-0.147	-0.161	-0.524	-0.545	-0.556
	[-0.35]	[-0.26]	[-0.28]	[-1.06]	[-1.11]	[-1.15]
HLspread	-0.723***	-0.712***	-0.713***	-0.606***	-0.609***	-0.610***
	[-7.45]	[-7.41]	[-7.48]	[-6.83]	[-6.89]	[-6.89]
Turnover	0.000	0.000	0.000	0.000	-0.000	-0.000
	[0.24]	[0.30]	[0.29]	[0.01]	[-0.05]	[-0.05]
Ret_{-6m}	-0.253***	-0.251***	-0.253***	-0.219***	-0.220***	-0.219***
	[-7.47]	[-7.33]	[-7.45]	[-8.98]	[-9.07]	[-9.01]
Cash/Sales	-0.233	-0.292	0.002	0.133**	0.131**	0.141**
	[-0.82]	[-0.95]	[0.01]	[2.44]	[2.40]	[2.54]
Rollover		-0.018	-0.014		0.040**	0.041**
		[-0.71]	[-0.55]		[2.21]	[2.29]
KZfirm			0.008			0.002
			[1.64]			[1.22]
Intercept	0.245***	0.258***	0.252***	0.191***	0.173***	0.175***
	[3.51]	[3.62]	[3.55]	[3.13]	[2.85]	[2.87]
R-square	0.060	0.063	0.067	0.043	0.045	0.046
Adjusted R-square	0.038	0.039	0.040	0.036	0.036	0.037
Observations	113,421	113,421	113,421	296,866	296,866	296,866

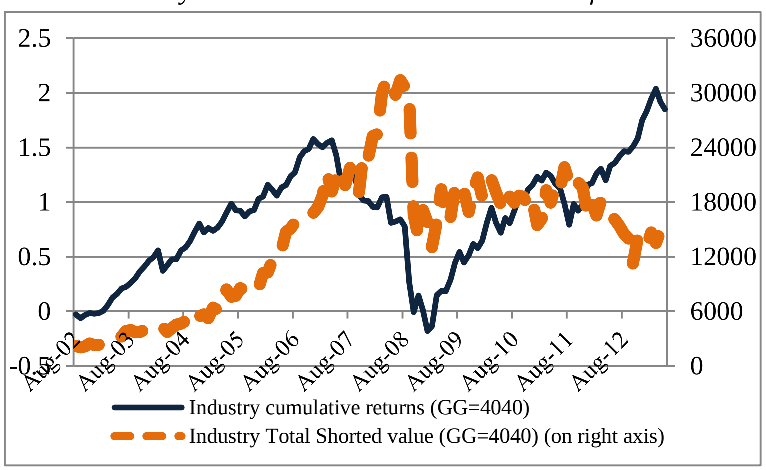
Figure 1. Time series of industry short selling in four key GICS industries.
GICS 4020 and 4040 are Diversified financials, and Financials-Real Estate GICS industry groups, respectively, while GICS 4510 and GCS 5510 are the Software and Services industry and the Utilities industry.

Panel A. Industry cumulative returns and time-series of shorted value (in $Mill) in the diversified financials industry (GG=4020), for 1990–2002 and 2002–2013





Panel B. Industry cumulative returns and time-series of shorted value in the financials-real estate industry (GG=4040), for 1990–2002 and 2002–2013



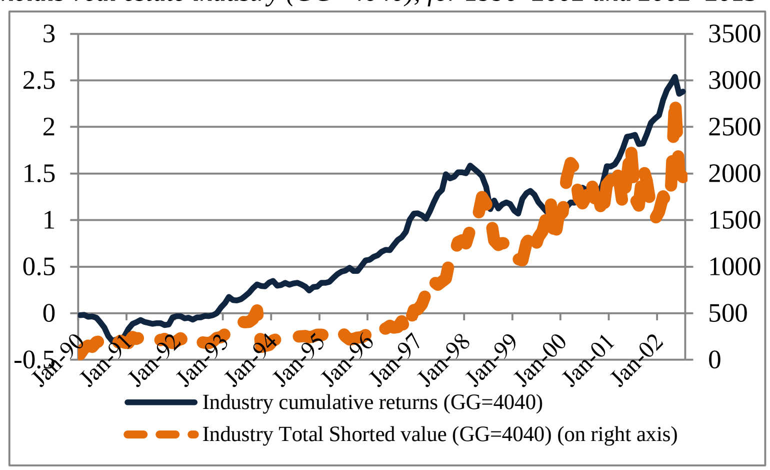
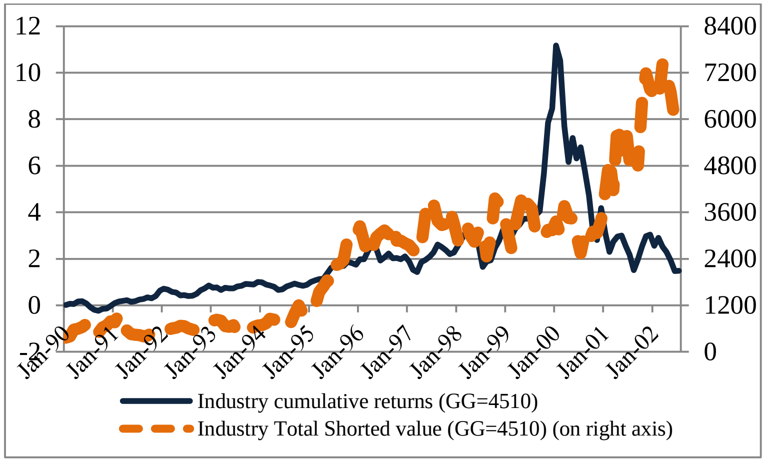
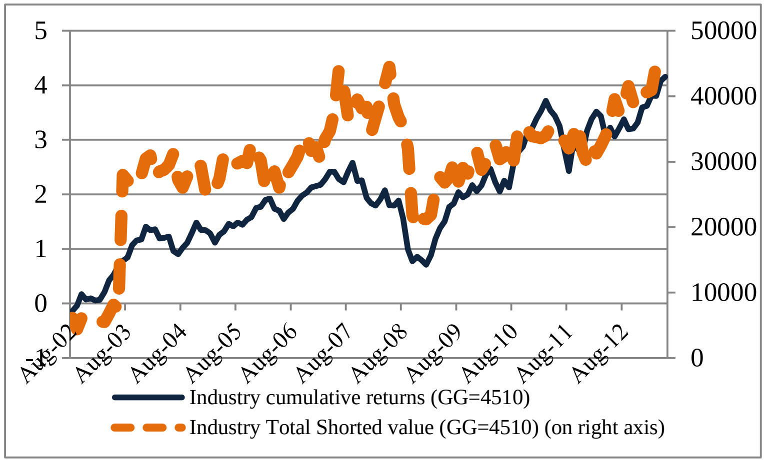


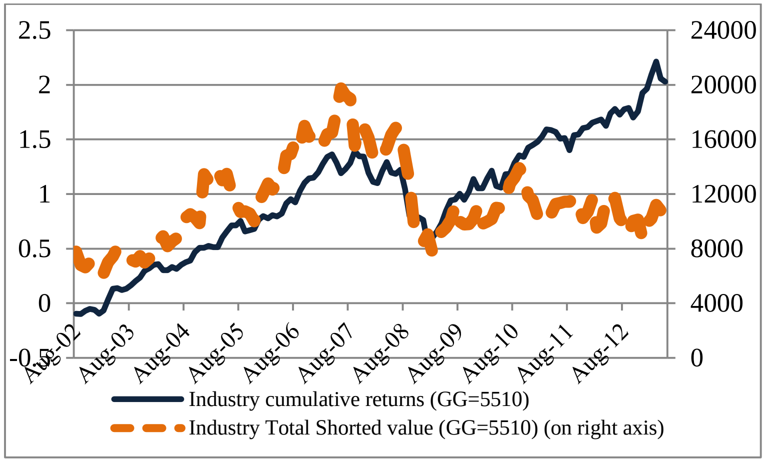
Figure 1. continued

Panel C. Industry cumulative returns and time-series of shorted value in the software and services industry (GG=4510), for 1990–2002 and 2002–2013





Panel D. Industry cumulative returns and time-series of shorted value in the utilities industry (GG=5510), for 1990–2002 and 2002–2013



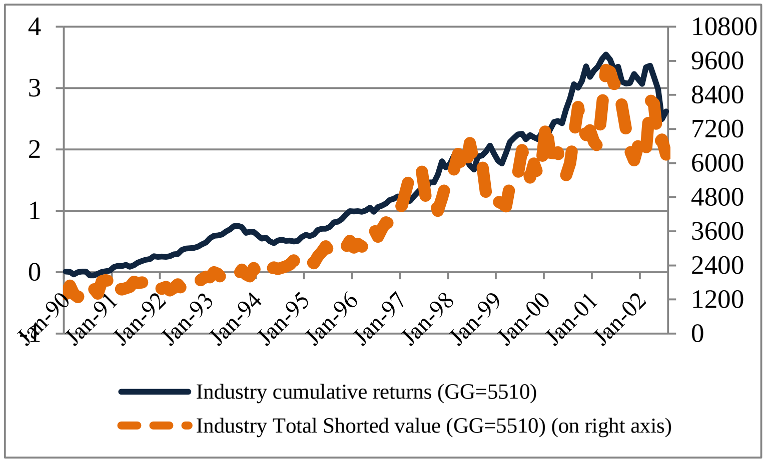
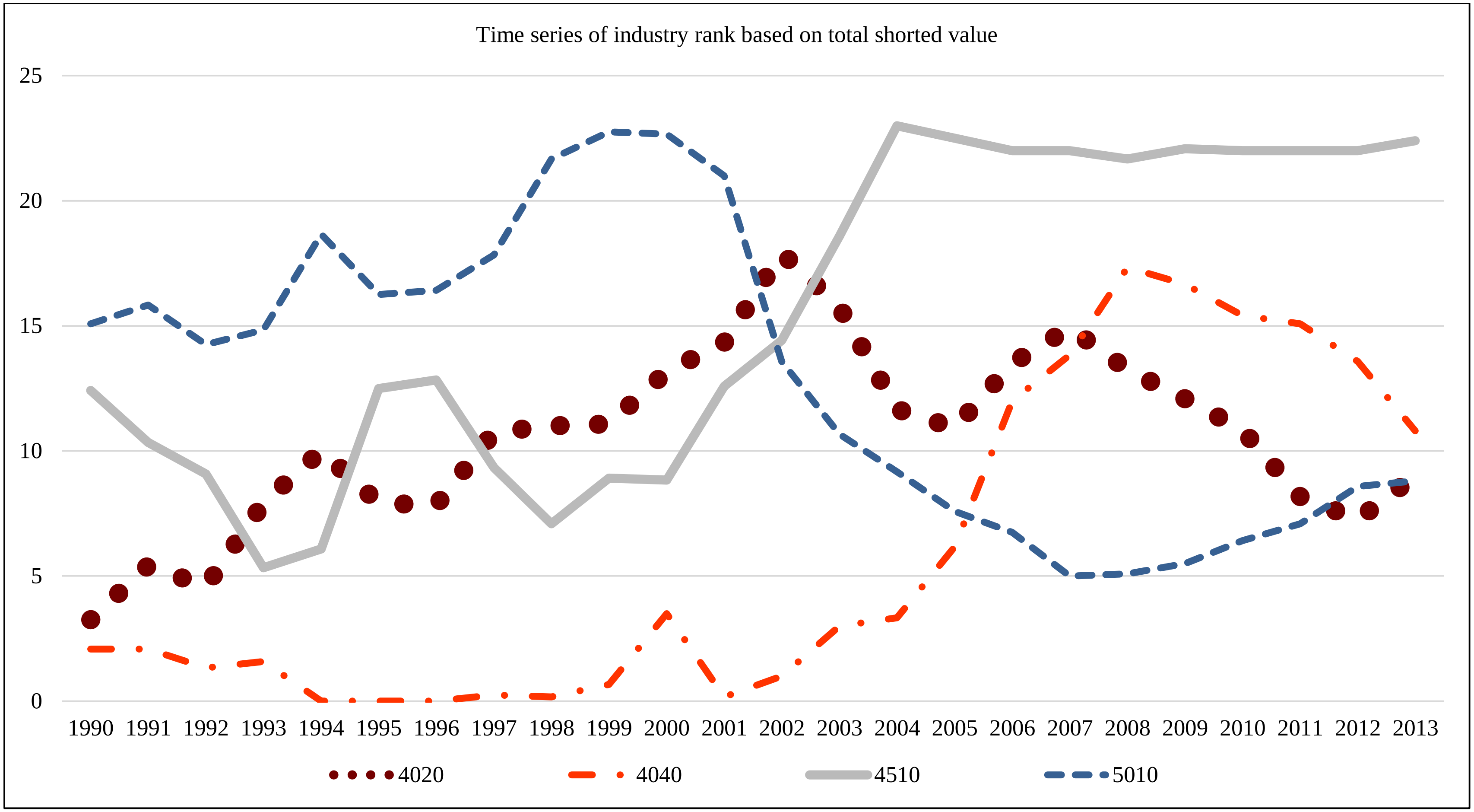


Figure 2. Time series of the industry rank of four key GICS industry groups

On the left axis, 1 through 24 shows the industry rank for a specific month based on the total shorted value of all stocks in a GICS industry group relative to the other industries. GICS 4020 and 4040 are Diversified financials, and Financials-Real Estate GICS industry groups, respectively, while GICS 4510 and GCS 5510 are the Software Services industry and the Utilities industry



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Appendix A. Summary of future one-month abnormal returns on double-sorted portfolios, sorting on industry aggregate shorting and firm-level short interest ratio, using GICS 24-industry classification (Table 4 replicated with one-month results)

The table summarizes portfolio abnormal returns, from the Fama-French-Carhart four-factor model, where the portfolio excess returns are the future one-month equal- or value-weighted excess returns, as a percentage, on double-sorted portfolios since portfolio creation. In establishing the double-sorted portfolios, at the end of each month, industries are ranked based on the industry aggregate shorted value (*IndSV*). Then, within each industry (sextile) group, stock portfolios are established based on the individual firm-level SIR, where SIR is the number of shares shorted relative to the total number of shares outstanding in the previous month. To save space, only the portfolio abnormal returns (the intercepts from the portfolio return regressions) are reported with the relevant *p*-values (in italics). For each portfolio, 281 months of data are used from January 1990 to April 2013.

Panel A. Future one-month abnormal portfolio returns on equal-weighted double-sorted portfolios

	Low IndSV=1	**Low IndSV=2**	**Mid-low IndSV=3**	**Mid-high IndSV=4**	**High IndSV=5**	**High IndSV=6**	**Hedge portfolios**
Low Firm SIR=1	0.423	0.395	0.272	0.356	0.479	0.643	-0.220
	0.029	*0.049*	*0.153*	*0.037*	*0.008*	*0.002*	*0.378*
Low Firm SIR=2	0.133	0.106	0.265	0.493	0.124	0.322	-0.189
	0.445	*0.503*	*0.091*	*0.002*	*0.406*	*0.069*	*0.385*
Mid-Low Firm SIR=3	0.141	0.133	0.312	0.245	0.056	0.006	0.135
	0.394	*0.371*	*0.044*	*0.078*	*0.684*	*0.970*	*0.533*
Mid-High Firm SIR=4	-0.030	0.192	0.408	0.063	0.266	-0.152	0.122
	0.865	*0.233*	*0.008*	*0.679*	*0.100*	*0.384*	*0.569*
High Firm SIR=5	-0.090	0.190	0.028	0.085	-0.075	-0.301	0.212
	0.637	*0.248*	*0.865*	*0.606*	*0.642*	*0.107*	*0.429*
High Firm SIR=6	-0.314	-0.255	-0.285	-0.461	-0.320	-0.624	0.311
	0.134	*0.152*	*0.140*	*0.006*	*0.074*	*0.001*	*0.269*
Hedge portfolios	0.736	0.650	0.557	0.816	0.799	1.268	
	0.004	*0.010*	*0.021*	*<.001*	*<.001*	*<.001*	

Panel B. future one-month abnormal portfolio returns on value-weighted double-sorted portfolios

	Low IndSV=1	**Low IndSV=2**	**Mid-low IndSV=3**	**Mid-high IndSV=4**	**High IndSV=5**	**High IndSV=6**	**Hedge portfolios**
Low Firm SIR=1	0.235	0.394	0.234	0.335	0.391	0.583	-0.348
	0.184	*0.032*	*0.167*	*0.035*	*0.017*	*0.003*	*0.136*
Low Firm SIR=2	0.162	0.120	0.277	0.445	0.138	0.304	-0.142
	0.302	*0.407*	*0.066*	*0.002*	*0.334*	*0.065*	*0.486*
Mid-Low Firm SIR=3	0.118	0.189	0.285	0.252	0.125	-0.020	0.138
	0.430	*0.179*	*0.049*	*0.056*	*0.342*	*0.900*	*0.496*
Mid-High Firm SIR=4	0.017	0.199	0.371	0.077	0.242	-0.170	0.186
	0.920	*0.207*	*0.011*	*0.601*	*0.123*	*0.311*	*0.362*
High Firm SIR=5	-0.054	0.145	0.074	0.070	-0.093	-0.279	0.226
	0.771	*0.377*	*0.626*	*0.652*	*0.550*	*0.130*	*0.393*
High Firm SIR=6	-0.265	-0.242	-0.258	-0.389	-0.313	-0.623	0.358
	0.201	*0.170*	*0.169*	*0.024*	*0.077*	*0.001*	*0.201*
Hedge portfolios	0.500	0.636	0.491	0.724	0.705	1.205	
	0.037	*0.008*	*0.030*	*<.001*	*0.001*	*<.001*	

Appendix B. Future one-month abnormal returns on double sorted portfolios, excluding penny stocks (Table 5 replicated)

The table summarizes portfolio abnormal returns, from the Fama-French-Carhart four-factor model, where the portfolio excess returns are the future one-month (in Panels A and B) and six-month (in Panels C and D) equal- or value-weighted excess returns as a percentage on double-sorted portfolios since portfolio creation. In establishing the double-sorted portfolios, first we exclude at the end of each month all penny stocks (stock with a share price of less than $5); then the industries are ranked based on the industry aggregate shorted value (*IndSV*). Then, within each industry (sextile) group, stock portfolios are established based on the individual firm-level SIR, where SIR is the number of shares shorted relative to the total number of shares outstanding in the previous month. To save space only the portfolio abnormal returns (the intercepts from the portfolio return regressions) are reported with the relevant *p*-values (in italics). For each portfolio, 281 months of data are used, from January 1990 to April 2013.

Panel A. Future one-month abnormal returns on equal-weighted double-sorted portfolios, excluding penny stocks

	Low IndSV=1	**Low IndSV=2**	**Mid-low IndSV=3**	**Mid-high IndSV=4**	**High IndSV=5**	**High IndSV=6**	**Hedge portfolios**
Low Firm SIR=1	0.230	0.296	0.210	0.336	0.294	0.431	-0.201
	0.182	*0.065*	*0.156*	*0.015*	*0.039*	*0.010*	*0.328*
Low Firm SIR=2	0.193	0.056	0.191	0.411	0.086	0.355	-0.162
	0.210	*0.700*	*0.214*	*0.003*	*0.506*	*0.022*	*0.424*
Mid-Low Firm SIR=3	0.073	0.211	0.163	0.160	0.245	-0.097	0.170
	0.640	*0.181*	*0.293*	*0.246*	*0.081*	*0.555*	*0.409*
Mid-High Firm SIR=4	0.003	0.051	0.350	0.013	0.127	-0.203	0.206
	0.988	*0.758*	*0.028*	*0.931*	*0.417*	*0.240*	*0.338*
High Firm SIR=5	-0.165	0.035	0.081	0.096	-0.142	-0.310	0.145
	0.377	*0.842*	*0.623*	*0.555*	*0.363*	*0.099*	*0.580*
High Firm SIR=6	-0.280	-0.159	-0.296	-0.441	-0.362	-0.691	0.411
	0.173	*0.368*	*0.105*	*0.012*	*0.036*	*<.001*	*0.140*
Hedge portfolios	0.509	0.455	0.506	0.777	0.656	1.122	
within industry	*0.030*	*0.033*	*0.017*	*<.001*	*<.001*	*<.001*	

Panel B. Future one-month abnormal returns on value-weighted double-sorted portfolios excluding penny stocks

	Low IndSV=1	**Low IndSV=2**	**Mid-low IndSV=3**	**Mid-high IndSV=4**	**High IndSV=5**	**High IndSV=6**	**Hedge portfolios**
Low Firm SIR=1	0.116	0.306	0.182	0.332	0.242	0.404	-0.289
	0.488	*0.049*	*0.210*	*0.014*	*0.085*	*0.015*	*0.168*
Low Firm SIR=2	0.244	0.110	0.272	0.378	0.119	0.308	-0.064
	0.098	*0.430*	*0.078*	*0.005*	*0.352*	*0.040*	*0.743*
Mid-Low Firm SIR=3	0.066	0.243	0.162	0.147	0.242	-0.094	0.160
	0.662	*0.108*	*0.279*	*0.270*	*0.078*	*0.559*	*0.426*
Mid-High Firm SIR=4	<.001	0.066	0.347	0.015	0.130	-0.208	0.207
	0.998	*0.684*	*0.025*	*0.920*	*0.397*	*0.213*	*0.313*
High Firm SIR =5	-0.141	0.040	0.095	0.093	-0.154	-0.277	0.136
	0.457	*0.817*	*0.550*	*0.550*	*0.315*	*0.137*	*0.606*
High Firm SIR =6	-0.233	-0.176	-0.267	-0.412	-0.338	-0.667	0.434
	0.259	*0.318*	*0.149*	*0.022*	*0.050*	*<.001*	*0.121*
Hedge portfolios	0.348	0.482	0.449	0.744	0.580	1.071	
within industry	*0.132*	*0.019*	*0.035*	*<.001*	*0.001*	*<.001*	

Appendix C. Fama-Macbeth return regression with one-month returns

The dependent variable is the future one-month cumulative holding period return on the stock. *LogMcap* and *BtoM* are the market capitalization and book-to-market ratios, where the market cap is the total shares outstanding in millions times the share price at the end of the previous month; the *BtoM* definition follows Fama and French (1997). $Turn_{-1m}$ is the monthly turnover as a percentage. *HighSIRfirm* is a dummy that takes on the value of 1 for the specific firm-month observation where the firm's short interest ratio is in the top sextile of the distribution. *HighIndSV (LowIndSV*) is a dummy that takes on the value of 1 for industries where the industry total shorted value *(IndSV*) in millions of USD is among the top 4 (bottom 4) industry groups (from the 24 GICS industry groups). In Panel B as additional controls, lagged one-month (Ret_{-1m}) and six-month returns (Ret_{-6m}) are also included. The coefficient estimates are displayed with the corresponding *t*-stats in parentheses, from a Fama-MacBeth regression, with Newey-West robust standard errors with 5 lags.

Panel A. Fama-MacBeth analysis of future stock returns and industry short selling

	Ret_{1m}	**Ret_{1m}**	**Ret_{1m}**	**Ret_{1m}**	**Ret_{1m}**	**Ret_{1m}**
	Full sample			Subsample, excluding penny stocks		
Intercept	0.909*	0.904*	0.920*	0.918**	0.913**	0.928**
	(1.75)	(1.75)	(1.77)	(2.23)	(2.23)	(2.26)
$LogMcap_{-1m}$	0.000	-0.000	-0.001	0.007	0.006	0.006
	(0.00)	(-0.01)	(-0.02)	(0.21)	(0.19)	(0.17)
$BtoM_{-1m}$	0.010*	0.010*	0.010*	0.007	0.007	0.007
	(1.71)	(1.72)	(1.72)	(1.14)	(1.15)	(1.14)
$Turn_{-1m}$	0.226*	0.224*	0.225*	0.157	0.155	0.156
	(1.78)	(1.77)	(1.78)	(1.22)	(1.21)	(1.21)
HighfirmSIR	-0.429***	-0.382***	-0.394***	-0.392***	-0.335***	-0.350***
	(-4.51)	(-3.46)	(-3.68)	(-4.15)	(-3.05)	(-3.28)
HighIndSV	-0.018	0.005	-0.005	-0.044	-0.012	-0.023
	(-0.10)	(0.03)	(-0.03)	(-0.27)	(-0.08)	(-0.14)
HighIndSV*HighfirmSIR		-0.142	-0.131		-0.191	-0.176
		(-1.00)	(-0.94)		(-1.36)	(-1.28)
LowindSV			-0.110			-0.109
			(-1.23)			(-1.21)
LowindSV*HighfirmSIR			0.022			0.097
			(0.09)			(0.41)
R-square	0.028	0.029	0.032	0.031	0.032	0.035
Adjusted R-square	0.026	0.027	0.028	0.029	0.029	0.031
Observation	744,211	744,211	744,211	632,159	632,159	632,159

Appendix C. continued

Panel B. Fama-MacBeth analysis of future stock returns and industry short selling with past return controls

	Ret_{1m}	**Ret_{1m}**	**Ret_{1m}**	**Ret_{1m}**	**Ret_{1m}**	**Ret_{1m}**
	Full sample			Subsample, excluding penny stocks		
Intercept	0.820*	0.816*	0.827*	0.824**	0.819**	0.828**
	(1.76)	(1.76)	(1.78)	(2.13)	(2.13)	(2.15)
$LogMcap_{-1m}$	-0.012	-0.013	-0.013	0.000	-0.000	-0.001
	(-0.29)	(-0.30)	(-0.32)	(0.01)	(-0.01)	(-0.03)
$BtoM_{-1m}$	0.006	0.006	0.006	0.003	0.003	0.003
	(1.05)	(1.07)	(1.06)	(0.60)	(0.61)	(0.60)
$Turn_{-1m}$	0.188	0.187	0.188	0.123	0.121	0.121
	(1.48)	(1.47)	(1.48)	(0.95)	(0.94)	(0.93)
HighfirmSIR	-0.411***	-0.365***	-0.374***	-0.366***	-0.311***	-0.321***
	(-4.48)	(-3.47)	(-3.67)	(-4.09)	(-2.99)	(-3.18)
HighIndSV	-0.013	0.010	0.004	-0.033	-0.002	-0.006
	(-0.08)	(0.06)	(0.03)	(-0.21)	(-0.02)	(-0.04)
HighIndSV*HighfirmSIR		-0.139	-0.130		-0.181	-0.171
		(-1.01)	(-0.97)		(-1.34)	(-1.31)
LowindSV			-0.092			-0.088
			(-1.07)			(-1.01)
LowindSV*HighfirmSIR			0.023			0.081
			(0.10)			(0.35)
Ret_{-1m}	-0.419	-0.418	-0.425	-0.693	-0.692	-0.704
	(-1.04)	(-1.05)	(-1.06)	(-1.48)	(-1.48)	(-1.50)
Ret_{-6m}	0.640**	0.639**	0.641**	0.689**	0.688**	0.690**
	(2.06)	(2.06)	(2.06)	(2.54)	(2.54)	(2.55)
R-square	0.040	0.041	0.043	0.046	0.047	0.049
Adjusted R-square	0.037	0.038	0.039	0.042	0.043	0.045
Observation	744,211	744,211	744,211	632,159	632,159	632,159