Do short sellers exploit industry information?

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This draft: November 15, 2015

Abstract

This study provides new evidence about short sellers' 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' focus on complex industries with the highest profit potentials. In the targeted industries, firm level shorting predicts increase in default risk, suggesting that short sellers successfully identify firms with fundamental issues. Overall, in addition to aiding information discovery at the firm level, short sellers also reduce information complexity and improve economic efficiency at the industry level.

JEL classification: G10, G12, G14

Keywords: Industry information; Industry restructuring; Pricing efficiency; Short selling

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[1] We thank Sumit Agarwal, Brent W. Ambrose, Duan Jin-Chuan, Allaudeen Hameed, Robert L. Kimmel, Julia Kiraly, David M. Reeb, Mathew Ringgenberg, and Noah Stoffman and all seminar participants at NUS Business School, at the Risk Management Institute (RMI) at NUS, and at the Annual Summer Research Camp at Economics Research Institute of the Hungarian Academy of Science (KTI-MTA) for helpful discussions and comments. We gratefully acknowledge generous financial support from NUS, under the research grant WBS-R315000110112.

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“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.”

- *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 firm specific information (such as earnings news, M&A, financial statement revision, CEO death, and fraud) and macroeconomic news (such as interest rate, recession, and more recently the global financial crises). Unlike macroeconomic and firm-specific news, there are no systematic industry specific news announcements and this lack of information availability generally hinders the analysis of the relation between the industry information and stock returns.

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

The limitations of using the industry returns to proxy for industry information are twofold. First, since in these studies the explanatory variables as well as the dependent variables are based on stocks returns albeit with some lags, to some extant the relation between lagged industry and future market returns are mechanical. Second, stock returns may be too volatile to capture the slow changing nature of industry information. For example during the industrial revolution, the transition of new manufacturing processes took about 80 years from 1760 to 1840. Technological advancements may result in new industries, such as the IT industry, or foster major restructurings in traditional industries (e.g., Kliesen, 1983; Foster, Haltiwanger, 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 relatively informed traders who either have material private information or are able to process public information faster (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 also suggests that short sellers have industry preferences. For example, well-known short sellers, such as George Soros, reportedly targeted the IT sector in early 2000s. In 2007, short sellers focused on firms in the renewable energy industry (Bloomberg, 2007), likely because of the increased competition in the industry, restructuring and the faltering government

[2] Pianta and Vivarelli (2003) provide a comprehensive study on the impact of technological innovation and globalization on employment with some policy implications, while a UN report provide a general 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 …”. Even the traditional industries such as mining and utilities have also been reinvented with offshore mining and alternative energy production and storage. In addition, we also note the extensive literature on industry growth but those studies generally consider industry growth in relation with financial development and liberalization (e.g., Beck, Levine and Loayza, 2010; Fogel, Morck and Yeong, 2008; Gupta and Yuan, 2010; King and Levine, 1993; Levine, 2004; Rajan and Zingales, 1998) and do not specifically examine the industry information over time in a developed country setting.

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 (Bloomberg, 2014; Wall Street Journal, 2014).

Our first empirical analysis verifies that short sellers' industry preference contains material information. In a portfolio setting, we find that stocks with high 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 during 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 Fama-MacBeth regression analyses.

Our second analysis explores the characteristics of the industries where 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 from superior information processing skills.

Lastly, we examine the economic implication of short sellers having superior industry information. We address regulatory views on industry shorting and the economic information in short sales within the targeted industries. We alleviate the regulatory concerns raised during the

[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 Ramesh, Thiagarajan, and Balachandran, 2002).

global financial crisis by showing that short sellers do not target vulnerable industries with high external finance dependence or extensive recent price declines. We find that firm level short selling forecasts change in firm-level default risk in the most shorted industries but not in others. This implies that aggregate short selling aid industries to achieve better economic efficiency by identifying firms with fundamental issues not only firms with temporary misvaluations.

Our study makes two contributions to the literature. First, we propose a new measure of industry information based on the relatively informed short sellers' industry preferences. This measure can be used as a convenient industry-level information proxy for retail investors to overcome their information disadvantage. Secondly, we find that short sellers' information advantage in specific industries benefits these industries by reducing information complexity and improving the industry's economic efficiency. To our knowledge, this is the first time in the literature that short sellers are found to create 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

Theoretical literature suggests that industry specific information such as technological innovation are 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 (2015) 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 decline in operating profits and stock returns than those in less competitive industries. These findings are consistent with Schumpeter's (1942) creative destruction theory where increasing competition in the 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, Papanikolau and Stoffman (2015) provide a general equilibrium model, which predicts uneven distribution of profitability in response to innovation across firms within the industry. They show that in industries undergoing restructuring and embodied or disembodied innovation, estimating the future profitability systematically may require sophisticated skills. According to Berndt (1990), as embodied innovations require completely new technology, the existing capital investments cannot be applied effectively. On the other hand, disembodied technological developments provide tools and new procedures to use existing capital (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 as 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 Makarov and Papanikolaou (2007)'s and Hong, Torous, and Valkanov (2007)'s studies which 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 while the second and third factors capture the relative productivity of capital versus consumption goods industries and business cycles, respectively.[4] Hong et al. (2007) also find that industry portfolio returns predict the market which they attribute to investors' limited attention.

2.2 Literature review of short sellers and hypotheses development

Short sellers are generally considered to be relatively informed institutional traders. Among others, Desai et al. (2002) find evidence of short sellers' information advantage in NASDAQ stocks. Many studies (e.g., Boehmer, Jones and Zhang, 2008; Diether, Lee, and Werner, 2009; Boehmer, Huszar and Jordan, 2010) also find that high firm level shorting predicts negative returns and vice versa. 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 et al, 2005; Boehmer et al. 2010).

Since industry information is shown to influence stock returns, the relatively informed short sellers may capture the 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., Bloomberg, 2007; 2014). If industry 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 interests are related to future abnormal returns ceteris paribus.

[4] The second factor is the portfolio return of stocks from industries that produces 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.

If we find supporting evidence for the first hypothesis, a natural follow up question is to understand the source of short seller's superior industry information. Some studies suggest that short sellers obtain information through tipping or connection (e.g., Anderson, Reeb, and Zhao, 2012; 2013; and Berkman, McKenzie, and Verwijmere, 2013) while others propose that short sellers are more efficient in processing new information (Engelberg, Reed and Ringgenberg, 2010). We use the information nature of the industry to separate the two explanations. If an industry is more complex, short sellers may make more profits if they can process information more efficiently. Under the tipping/connection explanation, short sellers should be able to make profits 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 of new technology have uneven effects across firms thereby creating misvaluation opportunities for short sellers. This gives us the second testable hypothesis:

H2: Short sellers make more profits in a complex industry than a less complex industry.

Lastly, we want to verify whether the short sellers' superior skills in processing industry information have any economic implications for the targeted industries and firms within the 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 the economic efficiency by identifying firms with fundamental issues beyond temporary overvaluations, revealing new information about future distress. Our third testable hypothesis addresses the economic consequence of the short sellers at the industry and the firm level as follows, *H3: Short sellers aid economic efficiency of the targeted industries by identifying firms with fundamental issues (where the future of the firm as a going concern may be an issue).*

We test the 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 firm's financial information from annual Compustat database and institutional ownership information from13f filings. When institutional ownership data is 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 coverage is somewhat limited before July 2003, we also perform robustness test using the data only after July 2003. We also 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. Luis 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 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 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 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 suggest that short sellers are holding large positions in booming industries as their position values continue to increase with the rising prices in the industry, implying loss 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 the rising price, possible due to their information advantage at the industry level.

[Figure 1 about here]

Interestingly, short sellers increase their positions before the industry experiences 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 hold on to their position when the market experienced price correction. The contrarian trend is clearer in Panels C and D, with the IT and utilities industry respectively. Is important to note that while there was governmental intervention with the first industry, there was none with the latter two industries, thus the Panel C and D may provide a better picture of the market forces and short sellers trading strategies without government intervention.

To have 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

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

attract much of short sellers' interests before 1999, plausibly due to its infancy. The aggregate shorted value significantly increased in the real estate financials (GICS 4040) already around 2004, suggesting that some short sellers might have realized significant mispricing or unattainability 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 et al. 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 GICS industry grouping to identify firms that are comparable in their business focus, 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 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

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

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:

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

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 the unnecessary exposure to other sources of risk, we also examine the performance of hedge portfolios using the following specifications:

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

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

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 groups, stocks with low SIR outperform stocks with high SIR as short sellers known to possess firm specific information.

To directly measure the across 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 groups. 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 column 3 and 4. The time series average numbers reveal that even in the least shorted industries, the firm level SIR can be very high. Comparing Portfolios 16 and 66, the value-weighted average SIR are 7.8% versus 10%. More importantly comparing portfolios 46, 56, and 66, the *vwSIR* are 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 in 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 (Madhaven 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% (in the right side of the table under the heading of 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 share price 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 of industry information of short sellers. The negative information in the high SIR stocks is again the most significant in the highly shorted industry, generating a return of -3.2%. It is largely insignificant in the least shorted industries. In Panel B, the results with value-weighting are

[7] For reference in Appendix 1 we also show the 1-month returns on the portfolios. The results in Appendix I. show that highly shorted stocks even in the least shorted industries underperform at the one month horizon, which is consistent with prior studies that short sellers have firm specific information. Here, we only suggest that not only short sellers have firm specific information but they also consider more macro information by taking into account industry trends and structural changes.

statistically and economically similar. Thus taken together, the results from Tables 2 and 4 provide support for 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 shown in Table 3 (as shown in column *HighInd SV=6* in Table 3 Panel A). In Panel A of Table 4, excluding penny stocks, the same portfolio generates 5.12% abnormal returns over the next six months.

Overall, we find strong evidence supporting our first hypothesis.

3.2.2. Cross-sectional analyses

To confirm our finding with the portfolio analysis, we perform robustness tests using cross-sectional analyses. We use 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:

$$Ret_{1,6} = \alpha + \beta \ HighfirmSIR + \delta \ HighIndSV + \phi \ FirmControls + \varepsilon \tag{3}$$

$$\begin{aligned} Ret_{1,6} = \alpha &+ \beta \ HighfirmSIR + \delta_1 HighIndSV + \lambda_1 HighIndSV * HighfirmSIR \\ &+ \phi \ FirmControls + \varepsilon \end{aligned} \tag{3A}$$

$$\begin{aligned} Ret_{1,6} = \alpha &+ \beta \ HighfirmSIR + \delta_2 HighIndSV + \lambda_2 HighIndSV * HighfirmSIR \\ &+ \upsilon \ LowIndSV + \nu \ LowIndSV * HighfirmSIR + \phi \ FirmControls + \varepsilon \end{aligned} \tag{3B}$$

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 stock with SIR from the top decile of the distribution. In addition, we also include dummy variables to capture high and low industry level shorting. *HighIndSV* and *LowIndSV* variables take on the value of one if the industry if within the top sextile or bottom sextile based on the aggregate industry shorted value in the specific month. To test the interconnectivity of firm and industry information by short sellers, we also include interaction variables for the frim level and industry level shorting (e.g., *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 expect the coefficient estimate of λ, on the interaction term, to be significantly negative.

[Table 5 about here]

We find robust evidence in Table 5 Panel A. Model 1 shows 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 6 months. In Model 2 and 3, we include the industry shorting measure, specifically, a dummy variable that takes on the value of 1 for industries from the highest sextile for the *HighIndSV* dummy. The significant coefficient estimate on the interaction variable of the high industry shorting and the high firm level shorting (*HighIndSV*HighfirmSIR*) suggests that the industry information is used in conjunction with the firm level shorting. It is important to note that the coefficient estimate on the *HighfirmSIR* is not economically across Models 1 and 3, suggesting that the interaction does not weaken the primary effect which is the superior firm information from 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 also include additional analyses in Table 5 Panel B by including previous one month and six month returns as additional control variables for return momentum or reversal. The results from

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 in both portfolio setting and cross-sectional analysis: short sellers profit from their superior industry information *ceteris paribus*.

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 the industry characteristics such as market-to-book ratios, liquidity and idiosyncratic risk (Desai et al, 2002; Au et al. 2009; Boehmer et al. 2010) to proxy for complexity of an industry. We use the following baseline regression model specification to test our second hypothesis,

$$LogIndSV = \alpha + \beta\ IndChar + \delta\ IndHetero + \varphi\ LogMcap + \theta\ LogFirms + \varepsilon \quad (4)$$

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 ($vwLagRet_{-1m}$) and 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 ratios (*Indstd_BtoM*) and industry standard deviation of firm's market leverage ratios (*Indstd_MLever*).

In addition we control for the industry size since the number of shorted shares and the shorted value is likely to be affected by the size of the firms and the industry size (i.e., the number of firms in the industry). Specifically, we include two control variables *vwLogMcap* and

LogFirms which are value-weighted averages of the natural logarithm of the value-weighted industry average 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 use time fixed effect and allow clustering of 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 occur 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 uncertainty (e.g., the dispersion in the book-to-market ratios indicate dispersion and uncertainty about future profit expectation within the industry) where they can exploit their private information or superior information processing skills for maximum profit.

3.4. The economic implication 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 advantage. The first concern is whether short sellers are targeting vulnerable industries. Second, we want to find out how the firms within the targeted firms perform in the medium horizon.

In the first test, we focus on the industry distress measures, which capture industry-level external finance dependence (e.g., Rajan and Zingales, 1998) and rollover or refinancing risk (e.g., Acharya, Gale and Yorulmazer, 2011; Almeida, Campello, Larajeira, and Weisbenne, 2012). The industry external finance dependence measure captures the industry's capital intensity, *i.e.,* whether the internal operating cash flows are sufficient to cover capital expenditures, while the rollover risk measure quantifies the fraction of the total debt which needs to be refinanced within the next year. In normal market conditions when capital is plentiful and cheap, these measures are unlikely to capture significant risk for an industry.

However, when credit supply is restricted and the cost of external funding is expensive, these measures will capture significant industry risk. In industries that are heavily reliant on external funding for investment, even a small shock in the cost and availability of external capital can significantly reduce future cash flows hindering firms to finance new investment opportunities or refinance existing outstanding debt. Empirically, we use the fed fund rate and the yield spread to proxy for financing risk. Our regression model is specified as follows:

$$LogIndSV = \alpha + \beta \ IndChar + \delta \ IndHetero + \gamma \ IndFinRisk + \varphi \ LogMcap + \theta \ LogFirm + \varepsilon \quad \text{(4A)}$$

$$\begin{aligned} LogIndSV = \alpha + \beta \ IndChar + \delta \ IndHetero + \gamma \ IndFinRisk + \rho \ IndFinRisk * ExtFin + \\ + \varpi \ ExtFin + \varphi \ LogMcap + \theta \ LogFirm + \varepsilon \end{aligned} \quad \text{(4B)}$$

where the dependent variable, *LogIndSV*, and the explanatory variables: *IndChar*, *IndHetero*, *LogMcap*, and *LogFirms* are as defined in equation 4. The additional new explanatory variables are the industry financial risk measures (*IndFinRisk*), namely the industry value-weighted average external finance dependence (*vwEFD*) and the industry value-weighted average rollover risk (*vwRollover*).

Table 7 reports the relation between industry-level short interests and industry external finance dependence (Rajan and Zingales, 1998) and rollover risk (see Almeida, Campello, Larajeira, and Weisbenne, 2012) measures. We adopt the external finance dependence measure in Models 1 through 3, and then the rollover risk measure in Models 4 through 6.

[Table 7 about here]

Models 1 through 3 report the relevant results about the industry external finance dependence and show that short sellers focus on industries with high external finance dependence.[8] The results imply that short sellers prefer capital intensive industries. Perhaps, because these industries are more difficult to value, short sellers can benefit more from their superior information processing skills. However, once we consider the external financing costs in interaction with industry external finance dependence (*vwEFD*) in Models 2 and 3, we do not find that short sellers specifically target capital intensive industries when funding is expensive.

From Models 4 through 6, the results with the rollover risk are similarly inconclusive. The significant negative coefficients on the *vwRollover* measures in Models 4 through 6 suggest that short sellers do not specifically target industries with high refinancing risk. However, the significant positive coefficient estimate on the interaction variable between rollover risk and yieldspread (*vwRollover*yieldspread*) does provide some evidence that short sellers consider refinancing risk in relation to external financing costs. Overall, we do not find strong evidence that short sellers target financially vulnerable industries or industries in already distress.

Next, we examine how short sellers' concentration at the industry level affects the underlying firm's future default risk. This question is important as the firm's going concern status has significant economic implications. To test our third hypothesis (H3) whether short sellers provide any new economic information in the targeted industries, we examine the relationship between firm level shorting and the change in the distance to default measure over the next six month. We use Fama-MacBeth regression model specified as follows,

$$ChngDtoD_{t+6} = \alpha + \vartheta_1 firmSIR + \vartheta_2 HighIndSV + \vartheta_2 HighIndSV * firmSIR + \omega_i \sum_{i=0}^{k} FirmControl_i + \zeta \quad (5)$$

[8] The *vwEFD* is the value weighted average firm *EFD*, where the firm *EFD* is the ratio of the capital expenditure minus operating income to the capital expenditure as defined by Rajan and Zingales (1998). The higher EFD captures the excess capital investment, the amount of Capital that could not have been financed by just the usual operating income.

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 takes on the value of one if the industry level total shorted value is in the top sextile as discussed earlier with 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 also examine the short interest default predictability in the subsample setting, separately in the sample of firms from highly shorted industries and sample of firm 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 and long term debt,) and Kaplan and Zingales (Kaplan and Zingales, 1997), and financial constraint measure (*KZfirm*). Specifically, the rollover risk is expected to control for increase in refinancing in the presence of deteriorating debt market liquidity. In the cross-section, firms with high rollover risk expected to be closer to default (He and Xiong, 2012) while cash holding may be important to deal with competition especially in industries with changing technologies (Lyandres and Palazzo, 2015). Table 8 reports the findings.

[Table 8 about here]

Panel A of Table 8 shows that stocks with higher shorting are associated with a future decline in the distance to default measure. However, in itself the shorting measure, the *FirmSIR*, has insignificant relation with the change in the distance to default measures in industries with low concentration of short sellers. This result implies that in complex industries where short sellers strategically position themselves, the high firm level SIR reveals important future default risk concerns about specific firms. On the other hand, in industries which are generally not shorted, the high firm level SIR likely captures only temporary overvaluation rather than serious going concern issues about the firm.

In Panel B of Table 8, we further confirm these results with subsample analyses. We show that the significant relation between *FirmSIR* and *ChngDtoD* exists only in industries with high level of shorting, providing support for 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 going concern issues. To our knowledge, this is the first time in the literature that short sellers are 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 may be driven by financial stocks, or 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 in Table 3 remain the same, 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 replicate our main analysis without illiquid stocks. Next, we replicate our analysis by excluding penny stocks and stocks with low level of institutional ownership. These subsample analyses are motivated by prior empirical evidence (D'Avolio, 2002) which find that small, illiquid stocks may be difficult or costly to short. However, in all three analyses with the reduced sample

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

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 et al. (2013) and find that the results remain economically and statistically similar. All relevant results are available in the online appendix.

5. Conclusion

Our study aims to explore the information advantage of short sellers at the industry level. First, we find confirming 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 (from top sextile) within the most shorted industries earn significantly more negative abnormal returns in the next six months than the highly shorted stocks in less shorted industries. Within the most shorted industry (industries from top sextile), the portfolio of 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 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. Lastly, short sellers do not seem to target financially vulnerable industries. Instead they improve the economic efficiency of the specific industries by identifying firms with fundamental problems within the targeted industries. These results imply that short sellers help to improve the information efficiency and economic efficiency at the industry level.

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Table 1.

Summary statistics of 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 in percentage while *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 in 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. *CDSpread1yr* is the credit-default-spread from Markit for the 1-year horizon if available at the entity level. *Recoveryrate* is the entity level recovery rates available from credit default contracts.

Panel A. Summary Statistics for the full sample, from January 1990 to May 2013

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

Panel B. Summary Statistics for the full sample, from July 2003 1990 to May 2013

Variable	Mean	Std Dev	Minimum	Maximum
Lead1mret	0.010	0.147	-0.964	7.007
Lead6mret	0.066	0.394	-0.994	20.198
SIR (in %)	4.363	5.887	0.000	99.954
MillSV	93.094	237.060	0.000	18414.990
Mcapmill	3668.470	15531.400	0.106	626550.330
BAspread	0.007	0.017	0.000	1.290
HLspread	0.161	0.129	0.000	1.947
Turn (in %)	19.180	35.525	0.000	4914.010
BtoM	0.661	0.554	0.029	8.133
Mlever	0.183	0.164	0.000	0.802
EFD	-2.850	14.685	-290.661	187.443
Rollover	0.259	0.318	0.000	1.000
CDSpread1yr	1.911	4.236	0.010	255.274
Recoveryrate	0.365	0.053	0.000	0.950

Table 2.
Summary of return of double-sorted portfolios, using GICS 24 industry group

The table summarizes the time-series averages of 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 lowest aggregate shorted value (IndSV) where the stock itself have 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 portfolio with *Portfrank*=11 and the short position is in portfolio with *Portfrank*=61. #Firms show the time series average of the number of firms in the specific portfolio.

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. Hedge portfolios

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-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, 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 (the last return data is available for May 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 share price less than $5) then the industries are ranked based on the industry aggregate shorted value (*IndSV*). Then, within each industry (sextile) group, stock portfolios 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 used from January 1990 to May 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 with firm level shorting and industry shorting

The dependent variable is the future six-month cumulative holding period return on the stock. *LogMcap* and *BtoM* 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 is following Fama and French (1997). $Turn_{-1m}$ is the monthly turnover in percentage. *HighSIRfirm* is a dummy that takes on the value of one 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 one 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 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	744220	744220	744220	632164	632164	632164

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	744220	744220	744220	632164	632164	632164

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 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 in percentage and pricespread (*HLspread*) in the previous month, where turnover is the ratio of the total shares traded and the pricespread 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 across 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 parenthesis from industry level panel regression including year fixed effects. The total number of observations is 6774, as 281 monthly observations are available for each of the 24 sectors from January 1990 to April 2013 (May, 2013 is the last return observation).

	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	0.8784	0.8731	0.8798

Table 7

Determinants of industry concentration of short selling: External financing conditions

The dependent variable is the natural logarithm of total shorted value in millions of USD in the specific GICS sector (*IndSV*). The *vwEFD* the industry average value-weighted external finance dependence adopted from Rajan and Zingales (1998). The *vwRollover* as the industry value-weighted rollover risk measure is adopted from Almedia et al. (2012). Interaction of the latter two variables with fedfund rate (*vwEFD*fedfund* and *vwRollover*fedfund*) and corporate yieldspread (*vwEFD*yieldspread* and *vwRollover *yielspread*) are also included. The additional industry controls are defined in Table 6. The coefficient estimates are reported with the corresponding t-stats in parenthesis from industry level panel regression including year fixed effects. The total number of observations is 6774, as 281 monthly observations are available for each of the 24 sectors from January 1990 to April 2013 (May, 2013 is the last return observation).

	IndSV	**IndSV**	**IndSV**	**IndSV**	**IndSV**	**IndSV**
	Model1	Model2	Model3	Model4	Model5	Model6
vwEFD	0.017	0.017	0.041			
	[8.82]	[6.85]	[9.53]			
vwEFD*fedfund		0.001				
		[1.71]				
vwEFD*yieldspread			-0.020			
			[-6.55]			
vwRollover				-0.642	-0.769	-1.217
				[-9.83]	[-7.90]	[-6.39]
vwRollover*fedfund					0.014	
					[0.43]	
vwRollover *yielspread						0.491
						[2.99]
Fedfundrate		-0.090			-0.092	
		[-9.31]			[-7.51]	
Yieldspread			0.364			0.273
			[7.98]			[6.02]
vwBtoM	-0.662	-0.496	-0.600	-0.967	-0.863	-0.982
	[-9.93]	[-6.05]	[-6.80]	[-19.63]	[-14.51]	[-16.09]
$vwLagRet_{-1m}$	0.359	-0.137	-0.223	0.394	-0.076	-0.148
	[1.40]	[-0.69]	[-1.04]	[1.60]	[-0.39]	[-0.70]
$vwLagRet_{-6m}$	-0.136	-0.366	-0.337	-0.094	-0.307	-0.284
	[-1.20]	[-4.91]	[-4.85]	[-0.86]	[-4.11]	[-3.93]
$vwTurn_{-1m}$	0.018	0.030	0.033	0.021	0.032	0.036
	[6.18]	[12.06]	[12.90]	[7.54]	[13.47]	[14.82]
$vwHLspread_{-1m}$	-0.422	-0.960	-2.074	-0.274	-0.807	-1.800
	[-1.17]	[-3.42]	[-7.09]	[-0.74]	[-3.02]	[-6.42]
vwMLever	-1.119	-1.692	-2.064	-1.036	-1.580	-1.871
	[-6.74]	[-9.15]	[-10.68]	[-6.96]	[-9.06]	[-10.70]
Indstd_Mlever	2.895	4.879	5.411	2.385	4.205	4.587
	[9.71]	[12.8]	[14.40]	[8.41]	[12.36]	[14.00]
Indstd_BtoM	0.816	0.110	0.299	1.032	0.396	0.586
	[7.68]	[1.49]	[3.02]	[10.47]	[5.80]	[6.73]
LogFirms	0.995	1.094	1.131	0.971	1.072	1.109
	[74.43]	[101.37]	[111.46]	[81.42]	[86.72]	[92.42]
vwLogMcap	0.982	1.228	1.296	0.938	1.176	1.234
	[34.89]	[46.74]	[61.27]	[33.46]	[49.89]	[57.98]
Intercept	-3.388	-4.88	-6.060	-2.803	-4.216	-5.254
	[-10.40]	[-17.04]	[-28.53]	[-8.80]	[-15.97]	[-21.18]
Time fixed-effect	Yes	No	No	Yes	No	No
R-square	0.88	0.84	0.83	0.88	0.84	0.83

Table 8

Cross-section analysis of changes in distance to default in relation with 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 percentage of total shares outstanding shorted. *HighIndSV* is a dummy that takes on the value of one 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 6-month returns (Ret_{-6m}), Bid-Ask spread (*BAspread*) and High-Low price spread (*HLspread*), cash-to-sales ratio (Cash/Sales), rollover risk (Rollover) adopted from Almedia 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 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 (May, 2013 is the last return observation).

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

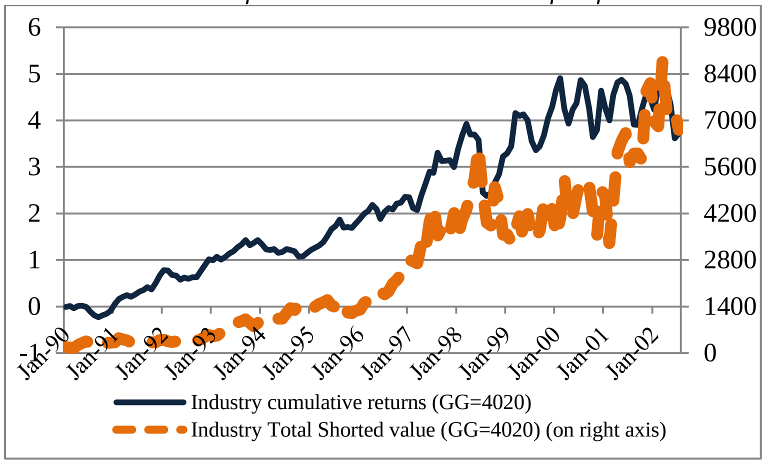
	ChngDtoD	**ChngDtoD**	**ChngDtoD**	**ChngDtoD**	**ChngDtoD**	**ChngDtoD**
FirmSIR	-0.001	0.002	0.000	0.000	0.000	0.000
	[-0.37]	[1.18]	[0.08]	[0.08]	[0.25]	[0.16]
HighIndSV		0.010	0.014	0.013	0.015	0.016
		[0.44]	[0.64]	[0.63]	[0.72]	[0.74]
HighIndSV*FirmSIR		-0.008***	-0.008***	-0.007***	-0.007***	-0.007***
		[-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-Squared	0.036	0.040	0.045	0.046	0.047	0.048
Adj. R-squared	0.032	0.035	0.039	0.039	0.040	0.040
Observations	410287	410287	410287	410287	410287	410287

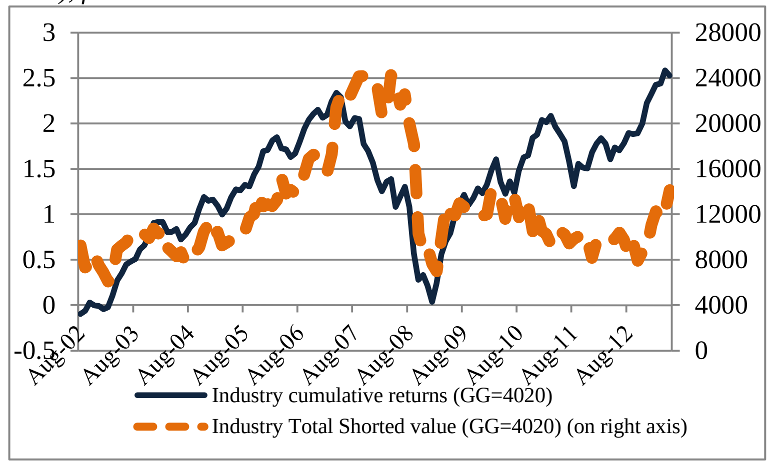
Table 8 continued

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

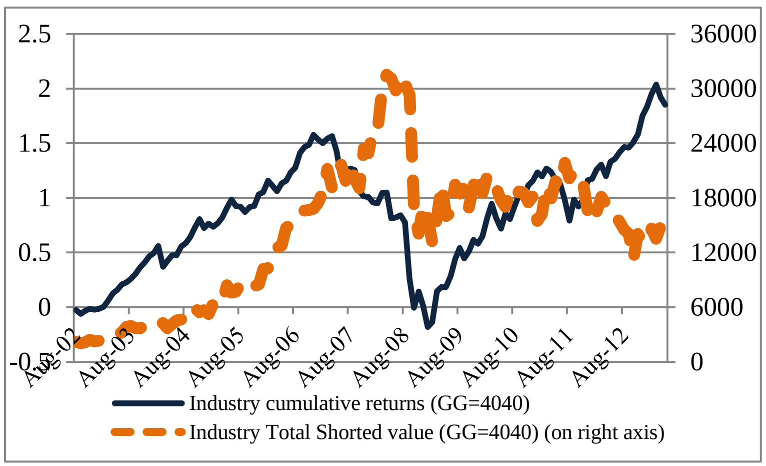
	ChngDtoD Sample: Industries with high SV			ChngDtoD Sample: Industries with low SV		
	Model 1A	Model 2A	Model 3A	Model 1B	Model 2B	Model 3B
FirmSIR	-0.007**	-0.007**	-0.007**	-0.000	0.000	-0.000
	[-2.16]	[-2.19]	[-2.27]	[-0.14]	[0.08]	[-0.01]
LogMcap	-0.018	-0.019	-0.018	-0.010	-0.010	-0.010
	[-1.36]	[-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-Squared	0.060	0.063	0.067	0.043	0.045	0.046
Adj. R-squared	0.038	0.039	0.040	0.036	0.036	0.037
Observations	113421	113421	113421	296866	296866	296866

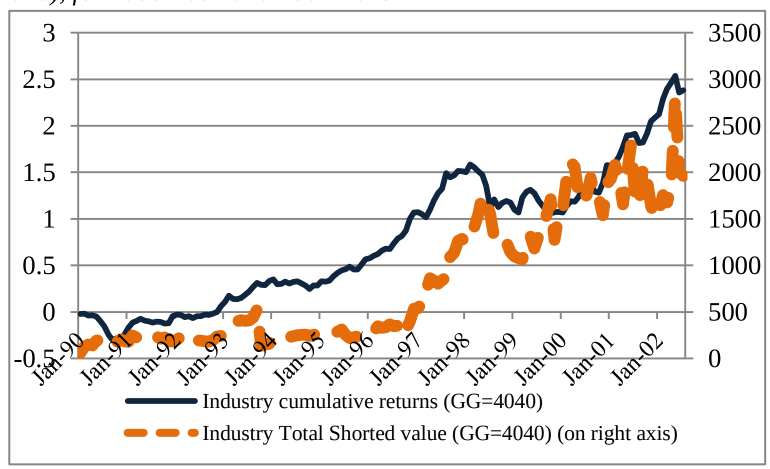
Panel A. Time series of shorted value in the diversified financials industry (GG=4020), for 1990-2002 and 2002-2013



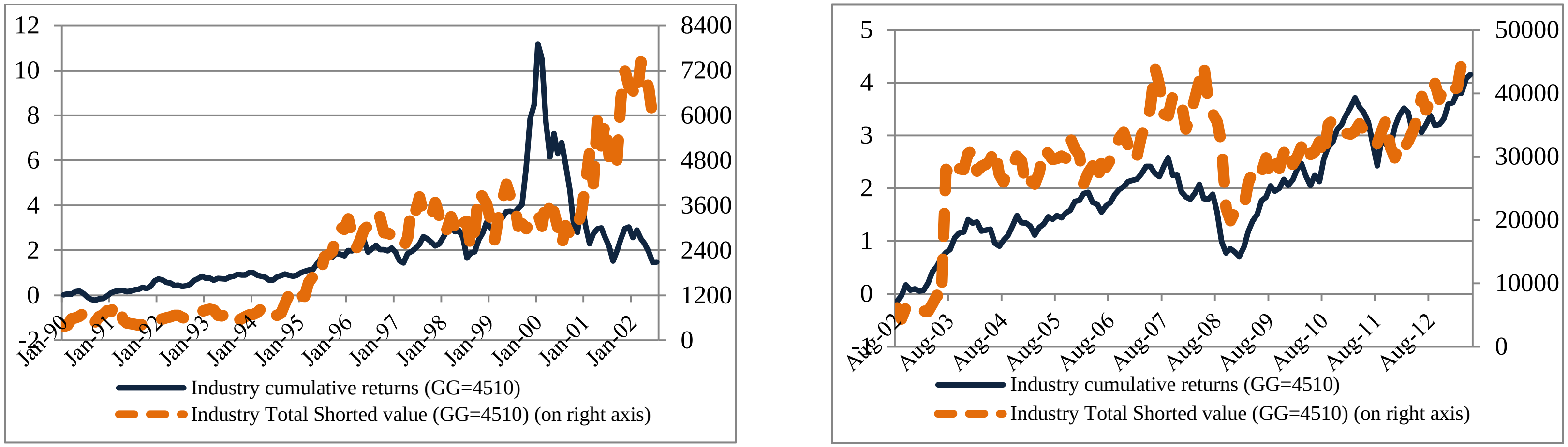


Panel B. Time series of shorted value in the financial-real estate industry (GG=4040), for 1990-2002 and 2002-2013





Panel C. Time series of shorted value in the software & services industry (GG=4510), for 1990-2002 and 2002-2013



Panel D. Time series of shorted value in the utilities industry (GG=5510), for 1990-2002 and 2002-2013

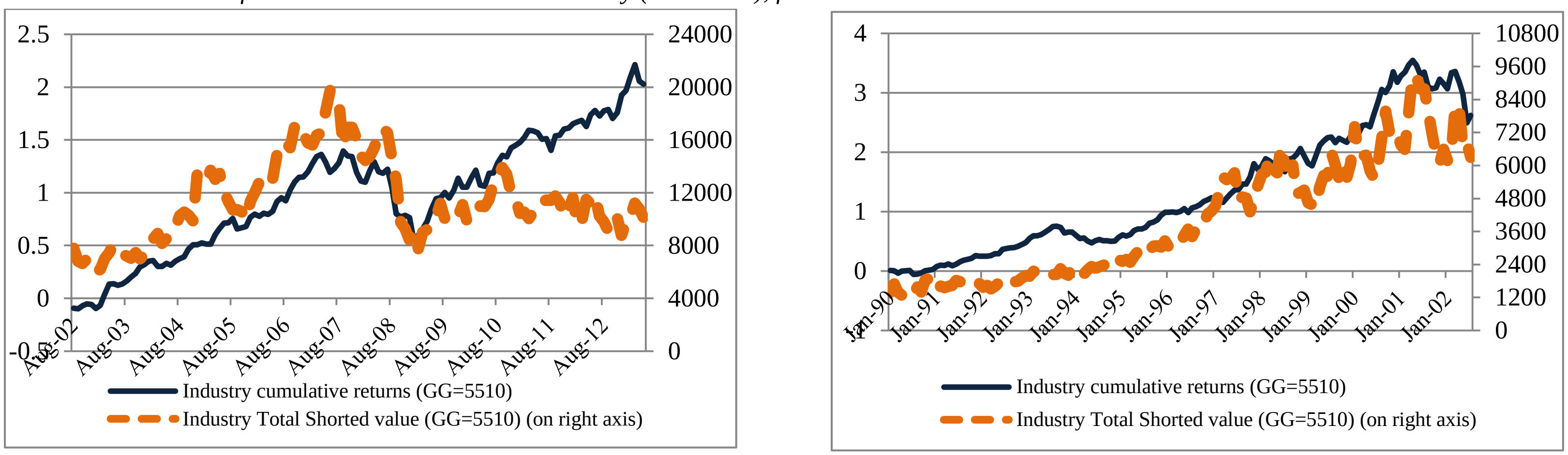


Figure 1
Time-series of the industry short selling in four key GICS industries.
GICS 4020 and 4040 are Diversified financials, and Financials-Real Estate GICS industry groups, respectively while GICS 4510 and GCS 5510 are the Software Services industry and the Utilities industry.

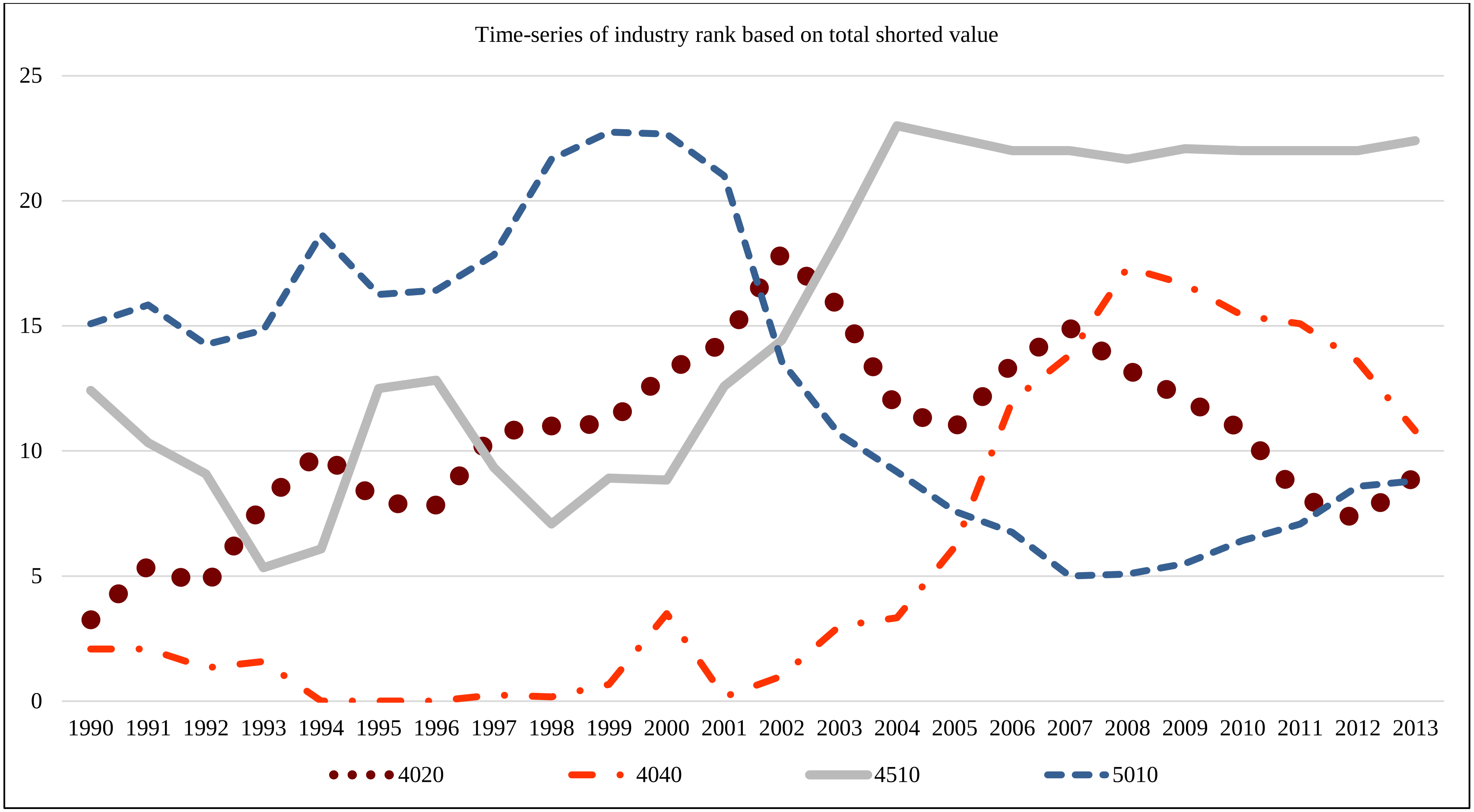


Figure 2

Time-series of the industry rank of four key GICS industry groups

On the left axis 1 through 24 depicts the industry ranks 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.

Appendix 1.

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 replicate 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, in 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 (the last return data is available for May 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 Table 2.

Future one-month abnormal returns on double sorted portfolios, excluding penny stocks (Table 5 replicate)

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 (stock with share price less than $5) then the industries are ranked based on the industry aggregate shorted value (*IndSV*). Then, within each industry (sextile) group, stock portfolios 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 used from January 1990 to May 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 Table 3.

FMB return regression with one-month returns

The dependent variable is the future one-month cumulative holding period return on the stock. *LogMcap* and *BtoM* 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 is following Fama and French (1997). $Turn_{-1m}$ is the monthly turnover in percentage. *HighSIRfirm* is a dummy that takes on the value of one 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 one 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 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
Adj R square	0.026	0.027	0.028	0.029	0.029	0.031
Observation	744211	744211	744211	632159	632159	632159

Appendix Table 3. Continued

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

	$\mathbf{Ret_{1m}}$	$\mathbf{Ret_{1m}}$	$\mathbf{Ret_{1m}}$	$\mathbf{Ret_{1m}}$	$\mathbf{Ret_{1m}}$	$\mathbf{Ret_{1m}}$
	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
Adj R square	0.037	0.038	0.039	0.042	0.043	0.045
Observation	744211	744211	744211	632159	632159	632159