Industry Concentration of Short Sellers: Cash Flow or Distress news?

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Abstract

In this study, we provide new empirical evidence that short sales convey both industry information and firm-specific information. We report significant negative (positive) abnormal returns of -0.6% (+0.6%) over one month and -2.9% (2.0%) over six months on stocks with a high (low) short interest ratio within highly shorted industries. These relatively symmetric returns on long-short portfolios suggest that short sellers are informed on both the long and the short side within specific industries. We show that short sellers target heterogeneous industries with price run-ups where superior information processing skills can be best used to maximize profits. Our analyses also reveal that short sellers convey future negative industry cash flow news, they front run rather than ex-post react to industry distress. Overall our findings alleviate regulatory concerns that short sellers ride on industry distress.

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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, Sept. 25, 2014

1. Introduction

Short sellers are generally considered essential to ensure pricing efficiency (Harrison and Kreps, 1978; Hong and Stein, 2003) because they convey new information to the market. A number of empirical studies (e.g., Boehmer and Wu, 2013; Bris, Goetzman, and Zhu, 2007; Saffi and Sigurdsson, 2011) support this theoretical claim. Interestingly, despite the consensus that short sellers promote efficient pricing, the source of their information is still debated. Engelberg, Reed, and Ringgenberg (2012) suggest that short sellers are efficient information processors who react to public information faster. Anderson, Reeb, and Zhao (2012; 2013) and Berkman, McKenzie, and Verwijmeren (2013) take a different view. They suggest that short sellers are insiders or use information from insiders, which is obtained through family, regulatory work or brokerage connections. Berkman et al. (2014) show evidence of widespread short selling, involving hedge funds before private placements, that is consistent with information leakage.

Overall, regulators tend to be skeptical about the beneficial role played by short sellers, especially during market and industry downturns. During the Great Depression and the 2008 Global Financial Crisis (GFC), shorts sellers were often linked with increasing share price volatility and industry distress. The concern is that large-scale shorting in distressed industries may overly depress stock prices and thereby hinder fund raising and firm recovery (Scharpino, 2009). Extensive media coverage also suggests that short sellers have industry preferences. In

2007, short sellers targeted the renewable energy industry (Bloomberg, 2007) and traded on the expected industry decline following the faltering government support for low-polluting industries. More recently, short sellers focused on mining- and oil-related stocks as global iron ore and oil prices declined in 2014 (Bloomberg, 2014; Wall Street Journal, 2014).

Although there is ample anecdotal evidence and media coverage that short sellers focus on specific industries, to the best of our knowledge there is no direct empirical evidence. The empirical question of whether short sellers discover or provide new information or merely exploit industry distress is of major regulatory concern. If we find that short sellers ride on industry distress (i.e., short sales ex-post react to distress signal), then our findings provide guidance to regulators to implement more effective short sale restrictions at the industry level than just ad-hoc circuit breakers. Conversely, if we find that industry short sales provide new information about future industry distress then the regulatory concerns regarding industry and market shorting may be alleviated.

We provide robust portfolio analyses showing that short sellers trade on industry information. Specifically, we show that within-industry equal-weighted (value-weighted) long-short portfolios earn significant future abnormal returns ranging from 0.7% to 1.3% (0.5% to 1.2%) over one month or 3.2% to 5% (2.2% to 4.7%) over six months. Among the within industry long-short portfolios, those in industries with the largest shorted values are associated with the highest abnormal returns, suggesting that there is industry information in short selling. Specifically, at the six month level, we find that in the most shorted industries, the equal-weighted (value-weighted) hedge portfolio earns 1.7% (2.5%) higher return than similar hedge portfolio in the least shorted industries. Our finding that short sellers, as active fund managers, trade on within industry mispricing is consistent with recent reversal studies (e.g., Hameed and Mian, 2014) that document stronger within industry price reversals.

Next, we examine the determinants of industry concentrated short selling. We show that short sellers concentrate on heterogeneous industries with past price run-up, where their contrarian trading strategies and superior information processing skills can generate the greatest profit. We also address regulatory concerns that short sellers may only exploit distress news and do not provide new information at the industry level. We use two proxies for financial distress, namely industry external finance dependence and rollover risk, and also make use of direct distress measures from credit default swap (CDS) contracts. We do not find evidence that concentrated industry shorting is associated with increased industry credit risk, rollover risk or financial constraints. Rather, we provide robust evidence that concentrated industry short selling is an important predictor of industry cash flow news, as it signals significant decline in the average sales.

Overall, we provide new insights into short sellers' trading strategies. Specifically, we show that short sellers, as regulators claim, do trade on both industry and firm information. We also show that short sellers are informed contrarian traders at the industry level, thereby alleviating regulatory concerns that short sellers target distressed industries. Taken together, our findings suggest that aggregate industry shorting is an important industry barometer which may help in forecasting industry corrections.

2. Review of short sellers' role in conjunction with market efficiency

2.1. Short sellers' beneficial role in the market: The academic view

Short selling has been widely investigated using the reported monthly total shorted shares relative to the total number of shares outstanding, or the short interest ratio (SIR). Among others, Desai, Ramesh, Thiagarajan, and Balachandran (2002) show that stocks with high SIR or large increase in SIR subsequently underperform stocks with a low SIR. This evidence is consistent with the model of Diamond and Verrecchia (1987), which suggests that because of the higher costs and risks in short sales the concentration of informed traders is higher among short sellers short. Miller (1977) also stresses that overvaluation is unlikely to occur if there is no information dispersion in the market; therefore, short sellers are essential for correcting or restricting overvaluations only when there is disagreement among investors in the market.

Earlier studies (for example, Deschow, Hutton, Meulbroek, Sloan, 2001; Desai et al. 2002) find that short sellers focus on temporarily overpriced stocks, such as high market-to-book. Christophe, Ferri, and Angel (2004) and Christophe, Ferri and Hsieh, (2010) show that short sellers are especially active around earnings news and target stocks with future bad earnings news and/or analyst recommendation downgrades. Using short sale trade-level data, Diether, Lee, and Werner (2009a; 2009b) reveal the economic importance of short selling by showing that short sales account for 24% of NYSE and 31% of NASDAQ trading volume. The authors also show that large short volumes predict future negative returns, and short sellers are predominantly contrarian traders who aim to profit from correcting temporary overvaluation. In complementary study, Au, Doukas, and Onayev (2006) find that short sellers avoid high idiosyncratic risks stocks.

Overall, although short sellers are deemed to be important information providers, insights about the source of their information and their trading strategies are still relatively limited. With the notable exception of Diether et al. (2009), who show that short sellers are contrarians and profit from temporary overvaluation and liquidity provision, the rest of the short sale literature links extensive short selling to specific negative firm events. To the best of our knowledge, there is very limited information about how short sellers identify stocks, and whether they consider market trends or industry information.

2.2. Aggressive short sellers: The regulatory view since the global financial crisis

During the 2008 global financial crisis, disclosure requirements were introduced worldwide in an attempt to better understand the effects and potential harm due to large short positions. The fear of aggressive industry or market-wide short selling resulted in restrictions on short selling of financial stocks and stocks in key industries on numerous exchanges.

Recent empirical studies (e.g., Goldstein and Gumbel, 2008; Khanna and Mathews, 2012) find that short sellers target firms thereby distressing share prices and reducing price informativeness. As a results firms may engage in inefficient investment our could suffer because of high financing costs, which in turn would further reduce share prices making the short position profitable. While Khanna and Mathews (2012) focus on the interaction of block holders and short sellers, Brunnermeier and Oehmke (2013) concentrate on inefficient termination of short sales in the context of financial institutions. They especially focus on financial institutions because short selling can result in self-fulfilling death spiral for financial institutions. And the large scale failure of financial institutions is of a major concern because of the crucial role of the financial system in the global economy.

While a handful of careful academic studies (e.g., Boehmer, Jones, and Zhang, 2013; Beber and Pagano, 2013) show that the short sale bans were ineffective in protecting prices and stabilizing the market, regulators still advocate intervention on the gounds that short sellers target distressed industries.

In this study, we address this regulatory concern using time series data over a long period from 1990 to 2013, and examine whether short sellers target distressed industries and whether they have access to industry information. If short sellers possess industry information and effectively identify overvalued industries, then short selling at the industry level should be encouraged. However, if short sellers are momentum traders at the industry level and exploit industry distress, then their trades should be prohibited or heavily regulated.

3. Data and Research Methods

3.1. Data

We use data from January 1990 to December 2013, based on monthly stock return observations from the monthly CRSP securities file. We complement the stock return data with financial information from the Compustat annual files and 13f filings for institutional ownership. For stocks with missing institutional ownership data, we assume zero institutional ownership. In the robustness analyses, we exclude observations without institutional ownership.

We collect short sale information from the 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, in the robustness analyses we replicate the results using data only after July 2003. We also collect information about the monthly fedfund rates and the corporate bond yieldspread (i.e., the spread between the BAA and AAA rated corporate bonds) from the Federal Reserve Bank of St. Luis FRED 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. The short sale data coverage dramatically increases in the monthly securities files after 2003. Table 1 provides the relevant summary statistics for the full sample.

[Table 1 about here]

3.2. Research methods

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 perform portfolio analyses to examine the firm- and industry-specific information in short selling. Specifically, for each month, we rank industries based on the industry aggregate shorted value, then within industry groups we differentiate across stocks based on the stock's own level of shorting. We adopt 24 GICS industry groupings to identify firms that are comparable in their business focus and are considered competitors and active in the same industry by industry professionals (Bhojraj, Lee and Oler, 2003). [2] As it is problematic to establish quintile groups with 24 industries, we use sextile groups, where each sextile includes four 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, where the total shorted value at the stock level is the number of shares shorted times the corresponding share price). Then, within each industry sextile, we group stocks into sextile groups based on the firm-level 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:

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

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

If we assume that short sellers have private firm information, stocks with a high SIR should underperform. Similarly, if we assume short sellers have industry information, then stocks with a high SIR in the most shorted industries should experience the most negative abnormal returns. Thus, for stocks with a high SIR in highly shorted industries, the negative abnormal returns reflect the negative views regarding both the specific firm and the industry.

To further validate the evidence of short sellers' information, we examine the performance of hedge portfolios using the following specification:

$$\textit{Hedge portfolios: (Long - Short)PortfRet} = \alpha + \beta\ MKT + \delta\ HML + \gamma\ SMB + \phi MOM + \varepsilon \qquad (2)$$

Within each industry sextile, we create hedge portfolios of high and low SIR stocks. We expect hedge portfolios to have the most significant abnormal returns within the most shorted industries, where short sellers' firm specific information is combined with industry information. If there is no industry information in short selling, then the stocks with high SIR in the least- and most-shorted industries will have similar negative returns. We also expect that within industry groups, stocks with low SIR outperform stocks with high SIR. But with lightly shorted stocks, we do not expect that stocks with low SIR in highly shorted outperform stocks with low SIR in less shorted industries.

3.2.2. Determinants of industry concentrated shorting

At the industry level, we want to understand what drives industry concentrated shorting. As a starting point, we revisit prior short sale studies (e.g., Desai et al., 2002) which find that short sellers target temporary overvalued stocks, such as stocks with high market-to-book ratios. Other studies find that short sellers are aware of the risk and costs of shorting and target stocks where shorting is more feasible, such as liquid stocks with low idiosyncratic volatility (Au et al. 2009;

Boehmer et al. 2010). We consider the following model specification to examine the determinant of industry short selling:

$$LogIndSV = \alpha + \beta \ IndChar + \delta \ IndHetero + \varphi LogMcap + \theta LogFirms + \varepsilon \qquad (3)$$

where *LogIndSV* is the natural logarithm of the total industry shorted value in millions. Since the number of shorted shares and the shorted value is likely to be affected by the size of the firms (how many shares are traded) and the industry size (how many firms are in the industry), we include control variables *vwLogMcap* and *LogFirms* which are value-weighted averages of the natural logarithm of the firm's total market capitalization in millions and the natural logarithm of the number of firms in the industry, respectively. The variables of interest in the *IndChar* vector are: 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*).

With the exception of the last two variables, all are standard measures as used in earlier short sale studies (see for example, Boehmer et al, 2008; 2010 and Diether et al, 2008). The *HLspread* is the monthly highest and lowest price difference relative to the highest recorded price, while the market leverage (*Mlever*) is the ratio of total debt relative to the sum of total debt and total market capitalization. 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 the regression framework we use time fixed effect and allow clustering of the standard errors by year.

Next, we extend our analysis to examine the role of industry distress in industry concentration of short sales. We introduce two indirect distress measures, namely industry external finance dependence (see Rajan and Zingales, 1998) and rollover or refinancing risk (see 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 the 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 a specific company or industry. However, when the credit supply is restricted and the cost of external funding is expensive, these measures will capture significant risk. Thus, in the empirical analyses, we introduce the degree of external finance dependence and rollover risk measures in conjunction with external financing costs. Our two alternative measures for financing costs are the fed fund rate and the yield spread. We test whether short sellers target industries more exposed to financing risk, where we measure financing risk with external finance dependence and rollover risk, with the following model specifications:

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

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

where the dependent variable, *LogIndSV*, and the explanatory variables: *IndChar*, *IndHetero*, *LogMcap*, and *LogFirms* are as defined in equation 3. 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*). In model 4B, we interact these financing risk measures with external financing costs (*ExtFin*), captured by the fed fund rate and the yield spread. For Model 4A in the regression framework, we use time fixed effect and allow clustering of the standard errors by year, while for Model4B, we still allow for the clustering of the standard error but we use the external finance dependence measure to capture the market conditions.

We are aware that the above measures, external finance dependence and rollover risks, may not fully capture distress risk. To address this measurement issue, we adopt direct firm's financial distress measures from credit default swap (CDS) contracts, namely the spread and the recovery rates. We do not want to explicitly rely on CDS data for testing distress because the data from Markit is only available from 2003. However, we want to test whether our findings with the above proxies for distress are consistent with the findings using direct distress measures. We examine the relationship between industry concentrated short selling and distress for the subsample period from 2003 to 2013 using CDS data with the following model specification:

$$\begin{aligned} LogIndSV = {} & \alpha + \beta\, IndChar + \delta\, IndHetero + \gamma IndCDSspread + \rho \Delta IndCDSspread \\ & + \varphi LogMcap + \theta LogFirm + \varepsilon \end{aligned} \tag{5A}$$

$$\begin{aligned} LogIndSV = {} & \alpha + \beta\, IndChar + \delta\, IndHetero + \gamma Ind\,Recovrate + \rho \Delta Ind\,Recovrate \\ & + \varphi LogMcap + \theta LogFirm + \varepsilon \end{aligned} \tag{5B}$$

where the dependent variable, *LogIndSV*, and the explanatory variables: *IndChar*, *IndHetero*, *LogMcap*, and *LogFirms* are as defined in equation 3. The additional new explanatory variables are the industry distress measures. In Model 5A, we use one-year spread information from CDS contracts, the spread level (*IndCDSspread*), and the change in the spread level since last month (*ΔIndCDSspread*). In Model 5B, we use the average recovery rate information from CDS contracts, the recovery rate level (*IndRecovrate*), and the change in the recovery rate level since last month (*ΔIndRecovrate*).

3.2.3. Industry information content in industry concentrated shorting

An ever growing literature explains stock price movements with cash flow news and discount rate news. Numerous studies argue that cash flow news is more important than previously suggested (see for example, Chen, Da, and Priestly, 2012; Chen, Da, and Zhao 2013; Koijen and Van Nieuwerburgh, 2011). Motivated by this cash flow news literature, we test whether short sellers are able to predict the changes in earnings, changes in industry sales, which in turn could reveal new insight about the type of information they are trading on. In testing short sellers' industry cash flow predictability, we use the following three alternative model specifications:

$$\Delta IndSales = \alpha + \beta\ IndChar + \varepsilon \tag{6A}$$

$$\Delta IndSales = \alpha + \beta\ IndChar + \delta\ IndHetero + \varepsilon \tag{6B}$$

$$\Delta IndSales = \alpha + \beta\ IndChar + \delta\ IndHetero + \gamma IndFinRisk + \varepsilon \tag{6C}$$

where the dependent variable, *ΔIndSales* is the change in the total industry sales. Since we need to control for the number of firms in the industry, the change measure is the change in the average sales in the industry. The control variables, such as the industry characteristic (*IndChar*) and industry diversity (*IndHetero*) are defined in equation 3. We also control for financing risk with the *IndFinRisk* measures, industry external finance dependence and rollover risk as defined in equation 4.

4. Empirical results

In this section, we first explain our approach to measure industry concentration. While traditionally, the SIR is considered a good measure of shorting demand at the firm level, we suggest that aggregate shorting activity may be more important at the industry level. If short sellers, as active institutional traders, are individually informed, then their aggregate exposure to a specific industry may combine the group-level information and thus provide an indication of future returns. The extensive exposure of short sellers to a specific industry is considered to reflect their combined opinion about the industry, as the media suggests (e.g., Bloomberg, 2007; 2014).

In the absence of naked short selling, generally, a short seller who wants to short shares of XXX trading at $100 needs to borrow the shares and post collateral of 102%, and also needs to post a 50% margin. Taken together, shorting XXX shares trading at $100 requires a cash outlay of about $150 per share from the short seller. In addition, to correct overpricing in a bullish market environment, the short seller may encounter capital constraints because any share price increase may likely result in margin calls. If a downward share price correction does not take place soon, the short seller may need to prematurely terminate his or her position to limit the losses (Lamont and Stein, 2004). Overall, short selling is expensive and costly for investors, especially in overoptimistic market environments.

More importantly, if short sellers prefer a neutral market position, then they can best exploit their firm-specific information by trading within the industry, holding both long and short positions, to hedge not only the market but also the industry risk. Unfortunately, we do not have information about the long positions of the short sellers, but we can assume that, on average, they are likely to be long in stocks with no or low level of shorting. If we find that short sales are indeed more informative when analyzed together with industry information, then we can explain the previous inconclusive evidence about short selling (for example, Boehmer et al. (2010)'s findings that stocks with high SIR are not generally overpriced).

4.1. Summary statistics and time trends in industry short selling

In Figure 1, we show the time trends of shorting for three key GIC industry groups (from the 24 GIC industry groups) based on the GIC from 1990 to 2013[3]. 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. While the co-movement of the aggregate shorted value and the industry returns are partly a construction, as the aggregate position is a function of the share price, the short sellers' large capital exposure to a specific industry is expected to be a signal of industry information.

[Figure 1 about here]

The graphs also indicate that short sellers increase their positions before an industry experiences significant decline in prices, suggesting that regulatory concerns about short sellers' trading on distress signals are unwarranted. Next, we perform more direct tests to establish the determinants of short sale concentration, whether short sellers' trades are contrarian trades driven by industry run-up, or whether their trades are a momentum strategy based on industry distress.

4.2. Performance analysis of double-sorted portfolios based on industry and firm shorting

Following standard empirical asset pricing and short sale studies (e.g., Desai et al. 2002; Asquith, Pathak and Ritter, 2005), we perform portfolio analyses to examine the firm- and industry-specific information in short selling. As discussed earlier (in Section 3.2), adopting the 24 GICS industry group classification, we establish industry sextiles based on the total shorted value in the industry. Then, within each industry sextile group, we establish sextile groups based on the firm level shorting. ,

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

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 beginning of each calendar month by establishing industry sextiles, each consisting of two industries (GIC industry groups) based on the aggregate shorted value in the specific industry. Then, within each industry group, we establish stock portfolio sextiles based on firms' individual shorting levels.

[Table 2 about here]

The first interesting finding is that there is very little variation in returns across the portfolios in the least-shorted industries. Within the least-shorted industry (where the first digit of *Portfrank*=1), excess returns with equal-weighting (value-weighting) range from 0.91% (0.78%) to 0.49% (0.54%). In contrast, in the most-shorted industries (where the first digit of *Portfrank*=5), the excess returns with equal-weighting (value-weighting) range from 1.24% (1.19%) to 0.25% (0.24%), suggesting a much larger difference between the least-shorted and the most-shorted stocks. On average, within each industry sextile, we find some evidence of a trend that portfolios with a higher firm-level SIR have lower returns, consistent with earlier short sale studies (Desai et al. 2002).

4.2.1. One-month and six-month double-sorted portfolio returns, full sample

In Table 3 we examine the performance of 36 double-sorted portfolios, over the following month in Panels A and B, and over the following six months in Panels C and D. We are especially interested in whether the longer-term returns show evidence of information, while the shorter-term returns could be the result of temporary mispricing due to active or aggressive trading. 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, 2013).

[Table 3 about here]

Panel A of Table 3 shows that the abnormal returns for highly shorted stocks in the least-shorted industries (in column *LowIndSV*=1, 2, and 3) are generally insignificant, whereas they are significant in the most-shorted industries. We find significant abnormal returns across all six industry groups for the hedge portfolios. However, the monthly 1.27% abnormal return on the hedge portfolio in the most-shorted industry (in column *HighIndSV*=6) is significantly higher than the 0.74% on the hedge portfolio in the least shorted industry sextile, suggesting that the profits are more significant when firm level information is combined with industry information. The value-weighted portfolio results in Panel B of Table 3 are statistically and economically similar to the equal-weighted results reported in Panel A of Table 3.

In Panels C and D of Table 3 we examine the performance of the same double-sorted portfolios, but over a longer six-month horizon. We find no evidence of negative returns on highly shorted stock portfolios in the least-shorted industries, but find significant negative abnormal returns of -2.91% and -2.76% on the equal- and value-weighted highly shorted stock portfolio within the most-shorted industry. The industry information is also more prevalent in the longer term analysis. In comparing the abnormal returns on highly shorted stock portfolios across industries, we report 2.8% difference given that the highly shorted stocks in highly shorted industries are associated with -2.9% significant abnormal returns while the highly shorted stocks in lightly shorted industries are associated with -0.1% insignificant abnormal returns. Overall, the persistence of negative information in the highly shorted industries suggests that the industry information provided by short sellers is of a more permanent nature.

4.2.2. One-month and six-month double-sorted portfolio returns, subsample analysis

As the short sale data are relatively sparse before July 2003 (due to the limited Compustat coverage), we repeat our analysis in Table 3 using the data post July 2003. In Table 4, we show that the industry information is still prevalent. In Panels A and B of Table 4, we find that the negative abnormal returns on the highly shorted stocks are significant in both the least- and the most-shorted industries over the one-month horizon. Over the longer six-month horizon, in terms of economic magnitude, we report that the largest negative information in highly shorted stocks in the most-shorted industries dominates. In Panels C and D, we find that equal- (value) weighted portfolios of stocks with a high SIR in the most-shorted industry earn -3.85% (-3.43%) compared with -2.22% (-1.85%) in the least-shorted industries. These results again suggest that the short-sellers' industry information is more permanent.

[Table 4 about here]

4.3. Industry concentration of short selling: Distress or cash flow news?

Figure 1 provides some indication that short sellers have strong industry preferences. Next, we address regulatory concerns over whether short sellers exploit industry distress signals in a more controlled setting. We examine industry concentration in a regression framework to determine whether short sellers are momentum traders who exploit distress information or are contrarian traders who predict future news.

In Table 5, we examine short sellers' industry concentration in relation to industry characteristics. The dependent variable is the natural logarithm of next month's total shorted value, which is the aggregate exposure of short sellers to a specific industry. In Table 5, we consider key stock characteristics such as firm size, liquidity, leverage, and industry diversity. The results in Table 5 show that short sellers load up on industries with higher past returns and greater liquidity. Thus, short sellers are contrarians at the industry level and prefer industries with more liquid stocks to minimize trading costs and risks. The results from Models 5 to 7 show that greater diversity in relative firm valuation encourages shorting. The significant positive coefficients on the *Indstd_BtoM* and *Indstd_Mlever* variables suggest that industry shorted value is higher in industries where there is a large variation in book-to-market and leverage ratios, respectively. These findings suggest that short sellers focus on industries in which firms are very different, and in which they can exploit their private information or superior information processing skills for maximum profit.

[Table 5 about here]

In Table 6, in addition to general stock characteristics, we also include measures to capture industry distress. Since we do not have direct distress measure from CDS data, for the entire sample period, we use well established measures from the corporate finance literature which can capture financing risk for the industry. Specifically, we include measures such as industry external financial dependence (Rajan and Zingales, 1998) and rollover or refinancing risk (see Almeida, Campello, Larajeira, and Weisbenne, 2012). The value-weighted average external finance dependence, as an industry specific measure captures the importance of the external capital market for the industries. The second measure, the rollover risk captures the relative importance of short term funding, and calculated as the percentage of short term debt relative to long term debt. For industries, that are heavily reliant on external funding for investment, even a small adverse change in the cost and availability of external capital can reduce future cash flow significantly if the firms are unable to finance new investment opportunities because of high cost. Since both measures are especially informative in conjunction with external financing costs, we examine them in conjunction with the fedfund rate and the yieldspread, both of which capture the cost of external financing in the U.S. market.

[Table 6 about here]

In Panel A of Table 6, we first adopt the external finance dependence measure in Models 1 through 3, then the rollover risk measure in Models 4 through 6. In Models 1 through 3, we find that short sellers focus on industries with high external finance dependence.[4] These 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 Models 2 and 3 in interaction with industry external finance dependence (*vwEFD*), we do not find that short sellers specifically target capital intensive industries when funding is expensive. The results with the rollover risk measure are consistent. The significant negative coefficient 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 (*vwRolloevr*yieldspread*) suggest that short sellers consider the importance of refinancing risk in relation with external financing costs. Overall the results from Panel A of Table 6 suggest that short sellers may consider financing risk but that is not their primary concern.

Next, in Panel B of Table 6, we use direct distress measures, namely the reported one-year spread from CDS contracts and the firm level recovery rate. Specifically we test the regulatory concern whether short sellers target distressed industries, and potentially hinder or delay firm recovery in distressed industries. We examine short sellers' industry concentration in conjunction with the level of and change in credit risk, relying on the CDS and recovery rate information

[4] 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.

from Markit. Because the CDS market data are only available after 2003, our sample period is from 2003 to 2013. If short sellers target industries with declining credit quality, we would expect to find a positive relationship between industry shorting and an increase in credit risk and credit default spreads, or a decline in the recovery rate (Daniels and Malene, 2005).

We find no significant relationship between the aggregate industry shorted value and the industry average CDS, or changes in the CDS level. In Models 1 to 3 of Panel B of Table 6, we use the 1-year CDS rates and in Models 4 to 6 we use the five-year CDS rates. We expect the first measure to be more sensitive to short-term market information or new information. Lastly, in Models 7 to 9, we rely on the recovery rates, which are the most widely available entity-level information from Markit, where high recovery rates signal a low credit risk. Regulatory concerns suggest that we find positive relation between shorting and decreasing recovery rates but we find no evidence that short sellers *only* react to the distress signals.

Overall, our results from Tables 5 and 6 suggest that short sellers trade on industry information because some of the industry concentration can be explained by industry characteristics. Contrary to regulatory claims that short sellers target distressed industries, we actually find that short sellers are contrarian and concentrate on heterogeneous industries with recent price run-up. But we do not know the source or type of the information which is essential to better understand how the short sales trades predict stock returns.

An extensive literature documents the importance of cash flow news and discount rate news in understanding the variation in stock prices. While, we do not directly test discount rate news, we examine industry short selling in relation to distress where distress and discount rates at the firm level are strongly related. We do not find strong evidence that short sellers trade on the distress information. Since extant short sale studies suggest that short sellers are able to identify overvaluation, we will examine cash flow news, namely changes in future industry earnings in relation to industry concentrated short selling.

[Table 7 about here]

In Table 7, the cash flow news is measured by the changes in the average sales in the industry. Overall, results from Models 1 through 6 show that large industry shorting is associated with significant decline in sales as reflected by the negative coefficient estimate on the $LogIndSIV_{-1m}$ variable. Even after controlling for all important industry characteristics, such as industry diversity and financial risk, in Model 6, we still find that a 1 unit increase in the natural logarithm of total shorted value is associated with 4.8% decline in average industry sales. We can conclude that short sellers are likely to trade on expected cash flow news.

5. Robustness tests

We perform numerous robustness tests to ensure that our portfolio results, documenting the industry information in short selling, are not driven by a small group of extreme stocks.[5] 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 (i.e., excluding GICS groups 4010, 4020, 4030, and 5010). We find that our main results (Table 3) remain the same and the results 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 replicate our main analysis without illiquid stocks. Next, we also replicate our analysis by excluding penny stocks and stocks with low level of institutional ownership. These subsample

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

analyses are motivated by prior empirical evidence (e.g., D'Avolio, 2002) who found that small, illiquid stocks may be difficult or very costly to short. 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. As a rough approach, we exclude family firms based on the definition of Anderson et al. (2013) and find that the results remain economically and statistically similar.

5. Conclusion

To the best of our knowledge, this study is the first to document evidence on the return predictability of short sales at the industry level. We report robust empirical evidence of industry information in short selling. We document that highly (lightly) shorted stocks in the most targeted industries experience significant -0.6% (0.6%) abnormal returns over the next one month from 1990 to 2013.

We show that short sellers prefer more complex industries, in which there is greater heterogeneity across stocks and where they can benefit more from their superior information processing skills. More importantly, we find that short sellers are contrarians at the industry level. We also disentangle the information content in industry shorting into distress and cash flow news. We find significant evidence that short sellers do not target industries with increasing credit risk or distress. Rather, short sellers tend to front-run industry distress and signal future cash flow problems measured by the decline in future sales.

Overall, we find that short sellers trade on both firm and industry information. We conclude that the concentration of short sellers reflects industry opaqueness and predicts future industry problems. These findings suggest that industry-wide short sale bans may not be warranted because, on average, short sellers help information discovery 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 *MillSIval* is the total value of shorted shares in million USD. *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
MillSIval	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
MillSIval	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 one-month (*ExcessRet_1m*) and six-month (*ExcessRet_6m*) equal and value-weighted excess returns on the 66 double-sorted portfolios, using industry level shorting in the GICS 24 industry groups for the first level shorting and then firm level short interest ratio within industries. The Portfolio with *Portfrank*=11 includes firms from industries with lowest aggregate shorted value 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. *Excessret1m_eq* and *Excessret1m_vw* are the monthly equal and value-weighted portfolio returns in excess of the risk free rate. *Excessret6m_eq* and *Excessret6m_vw* are the six-month equal and value-weighted portfolio returns in excess of the prevailing risk free rate.

Portfrank	#Firms	Equal-weighted: ExcessRet_1m	Value-weighted: ExcessRet_1m	Equal-weighted: ExcessRet_6m	Value-weighted: ExcessRet_6m
11	34.673	0.910	0.781	6.241	5.934
12	35.214	0.744	0.746	5.648	5.770
13	35.206	0.792	0.758	5.807	5.555
14	35.335	0.759	0.798	6.802	6.611
15	35.381	0.695	0.729	5.658	5.707
16	34.851	0.489	0.541	4.786	5.190
21	47.359	0.968	0.995	5.778	5.968
22	47.858	0.738	0.756	4.422	4.633
23	47.854	0.786	0.828	4.531	4.631
24	48.018	0.915	0.919	5.940	5.713
25	48.028	0.918	0.864	5.398	5.209
26	47.523	0.418	0.435	3.435	3.507
31	58.125	0.814	0.797	5.989	6.101
32	58.605	0.838	0.864	6.469	6.407
33	58.637	0.971	0.943	6.101	6.005
34	58.758	1.042	0.999	6.456	5.974
35	58.801	0.806	0.835	5.740	5.730
36	58.285	0.419	0.462	4.490	4.538
41	73.249	0.939	0.918	6.159	5.811
42	73.698	1.103	1.050	6.276	6.057
43	73.737	0.913	0.906	5.283	5.116
44	73.861	0.793	0.792	5.740	5.533
45	73.893	0.856	0.837	4.607	4.577
46	73.363	0.332	0.401	3.271	3.421
51	102.381	1.070	1.001	5.870	5.489
52	102.879	0.811	0.810	5.270	5.137
53	102.918	0.789	0.833	5.452	5.507
54	103.050	1.005	0.963	5.517	5.330
55	103.068	0.645	0.623	4.512	4.484
56	102.552	0.512	0.521	3.202	3.420
61	123.420	1.236	1.191	6.681	6.401
62	123.982	1.014	0.982	5.842	5.432
63	123.918	0.767	0.720	4.811	4.616
64	124.139	0.675	0.663	4.173	4.195
65	124.139	0.579	0.592	3.956	4.098
66	123.605	0.248	0.244	1.749	1.857

Table 2 continued

Panel B. Hedge portfolios

Portfrank	#Firms	Equal-weighted: ExcessRet_1m	Value-weighted: ExcessRet_1m	Equal-weighted: ExcessRet_6m	Value-weighted: ExcessRet_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). 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*	*0.000*	*0.000*	*0.000*	

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*	*0.000*	*0.001*	*0.000*	

Table 3 continued

Panel C. 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
	0.000	*0.001*	*0.019*	*0.000*	*0.018*	*0.002*	*0.195*
Low Firm SIR=2	1.897	0.652	0.806	2.717	0.849	1.314	0.583
	0.000	*0.177*	*0.215*	*0.000*	*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
	0.000	*0.108*	*0.000*	*0.000*	*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
	0.000	*0.001*	*0.004*	*0.000*	*0.008*	*0.166*	*0.000*
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*	*0.000*	*0.001*
Hedge portfolios	3.180	3.311	1.953	2.694	2.849	4.961	
	0.000	*0.000*	*0.004*	*0.000*	*0.000*	*0.000*	

Panel D. 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
	0.000	*0.000*	*0.002*	*0.000*	*0.030*	*0.002*	*0.447*
Low Firm SIR=2	2.239	0.931	0.940	2.815	1.197	1.146	1.093
	0.000	*0.039*	*0.116*	*0.000*	*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
	0.000	*0.015*	*0.000*	*0.000*	*0.000*	*0.511*	*0.009*
Mid-High Firm SIR=4	2.532	1.509	1.465	1.885	1.246	-0.467	2.998
	0.000	*0.001*	*0.001*	*0.000*	*0.003*	*0.304*	*0.000*
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*	*0.000*	*0.000*
Hedge portfolios	2.195	3.421	2.330	2.243	2.463	4.736	
	0.003	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	

Table 4.

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, after July 2003

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 return 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, 118 months of data are used from July 2003 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, after July 2003

	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	0.441	0.724	0.398	0.567	0.656	0.871	-0.429
	0.152	*0.015*	*0.189*	*0.023*	*0.033*	*0.008*	*0.258*
Low Firm SIR=2	0.281	0.509	0.137	0.397	0.149	0.401	-0.120
	0.311	*0.008*	*0.511*	*0.066*	*0.553*	*0.143*	*0.707*
Mid-Low Firm SIR=3	0.497	0.370	0.217	0.173	0.147	0.137	0.360
	0.051	*0.013*	*0.178*	*0.305*	*0.367*	*0.549*	*0.291*
Mid-High Firm SIR=4	-0.044	0.285	0.120	0.237	0.204	-0.153	0.109
	0.840	*0.157*	*0.486*	*0.189*	*0.213*	*0.460*	*0.711*
High Firm SIR =5	-0.404	0.285	-0.205	0.031	-0.105	-0.176	-0.227
	0.093	*0.140*	*0.223*	*0.862*	*0.587*	*0.360*	*0.481*
High Firm SIR =6	-0.873	-0.173	-0.601	-0.482	-0.320	-0.843	-0.030
	0.008	*0.410*	*0.003*	*0.018*	*0.130*	*0.000*	*0.943*
Hedge portfolios	1.314	0.896	0.999	1.048	0.975	1.714	
	0.002	*0.020*	*0.004*	*0.001*	*0.007*	*0.000*	

Panel B. Future one-month abnormal portfolio returns on value-weighted double-sorted portfolios after July 2003

	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	0.162	0.729	0.431	0.548	0.619	0.815	-0.652
	0.561	*0.004*	*0.103*	*0.015*	*0.029*	*0.010*	*0.071*
Low Firm SIR=2	0.322	0.472	0.166	0.492	0.207	0.443	-0.121
	0.161	*0.003*	*0.400*	*0.008*	*0.367*	*0.079*	*0.682*
Mid-Low Firm SIR=3	0.440	0.470	0.185	0.187	0.188	0.166	0.274
	0.044	*0.001*	*0.190*	*0.238*	*0.209*	*0.470*	*0.393*
Mid-High Firm SIR=4	0.003	0.275	0.095	0.237	0.219	-0.126	0.129
	0.989	*0.151*	*0.552*	*0.171*	*0.164*	*0.544*	*0.654*
High Firm SIR =5	-0.426	0.308	-0.144	-0.003	-0.119	-0.163	-0.263
	0.063	*0.096*	*0.373*	*0.986*	*0.521*	*0.395*	*0.412*
High Firm SIR =6	-0.829	-0.122	-0.579	-0.463	-0.272	-0.765	-0.064
	0.010	*0.551*	*0.004*	*0.021*	*0.176*	*0.000*	*0.876*
Hedge portfolios	0.991	0.852	1.010	1.011	0.891	1.579	
	0.009	*0.014*	*0.001*	*0.001*	*0.007*	*0.000*	

Table 4 continued

Panel C. Future six-month abnormal portfolio returns on equal-weighted double-sorted portfolios after July 2003

	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	3.712	2.760	1.412	2.901	2.257	3.001	0.711
	0.000	*0.000*	*0.105*	*0.000*	*0.005*	*0.000*	*0.503*
Low Firm SIR=2	1.378	2.100	0.873	2.180	0.702	0.932	0.446
	0.053	*0.000*	*0.136*	*0.000*	*0.269*	*0.178*	*0.582*
Mid-Low Firm SIR=3	3.297	2.318	1.568	0.768	1.859	-0.262	3.559
	0.000	*0.000*	*0.001*	*0.099*	*0.001*	*0.673*	*0.000*
Mid-High Firm SIR=4	2.674	1.700	0.943	1.324	0.870	-0.548	3.222
	0.009	*0.002*	*0.039*	*0.004*	*0.068*	*0.270*	*0.002*
High Firm SIR =5	-1.350	0.987	0.639	-0.174	-0.024	-1.250	-0.100
	0.034	*0.109*	*0.250*	*0.746*	*0.957*	*0.031*	*0.899*
High Firm SIR =6	-2.221	-1.218	-1.425	-1.099	-1.546	-3.845	1.623
	0.013	*0.103*	*0.021*	*0.073*	*0.006*	*0.000*	*0.119*
Hedge portfolios	5.933	3.979	2.836	4.000	3.804	6.845	
	0.000	*0.000*	*0.002*	*0.000*	*0.000*	*0.000*	

Panel D. Future six-month abnormal portfolio returns on value-weighted double-sorted portfolios after July 2003

	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	3.061	3.016	1.763	2.598	2.143	2.625	0.436
	0.000	*0.000*	*0.028*	*0.000*	*0.005*	*0.001*	*0.655*
Low Firm SIR=2	2.149	2.312	1.198	2.614	1.373	1.076	1.074
	0.001	*0.000*	*0.027*	*0.000*	*0.023*	*0.097*	*0.149*
Mid-Low Firm SIR=3	2.649	2.525	1.748	0.848	2.221	0.149	2.500
	0.000	*0.000*	*0.000*	*0.049*	*0.000*	*0.800*	*0.002*
Mid-High Firm SIR=4	2.118	1.495	0.930	1.296	0.972	-0.286	2.404
	0.005	*0.003*	*0.030*	*0.003*	*0.034*	*0.570*	*0.003*
High Firm SIR =5	-1.672	0.924	0.634	-0.157	-0.026	-0.962	-0.709
	0.004	*0.080*	*0.177*	*0.747*	*0.951*	*0.092*	*0.363*
High Firm SIR =6	-1.855	-0.992	-1.513	-1.000	-1.336	-3.430	1.575
	0.041	*0.144*	*0.006*	*0.085*	*0.010*	*0.000*	*0.135*
Hedge portfolios	4.917	4.008	3.276	3.598	3.479	6.055	
	0.000	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	

Table 5.

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. *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_Lever*). 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).

Panel A. Determinants of industry concentration of short selling: Firm Characteristics

	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_Lever						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 6

Determinants of industry concentration of short selling: Industry distress

The dependent variable is the natural logarithm of total shorted value in millions of USD in the specific GICS sector. 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). $AveCDSpread1yr_{-1m}$ and $\Delta AveCDSpread1yr$ are the lagged one month industry average credit-default-spread and the change in this measure from the previous month. *AveRecoveryrate* and Δ*AveRecoveryrate* are the industry average recovery rates and the change in this measure. The additional industry controls are defined in Table 5. 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).

Panel A. Industry concentration in relation with industry external finance dependence and rollover risk

	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 6. continued.

Panel B. Determinants of industry concentration of short selling, considering credit risk

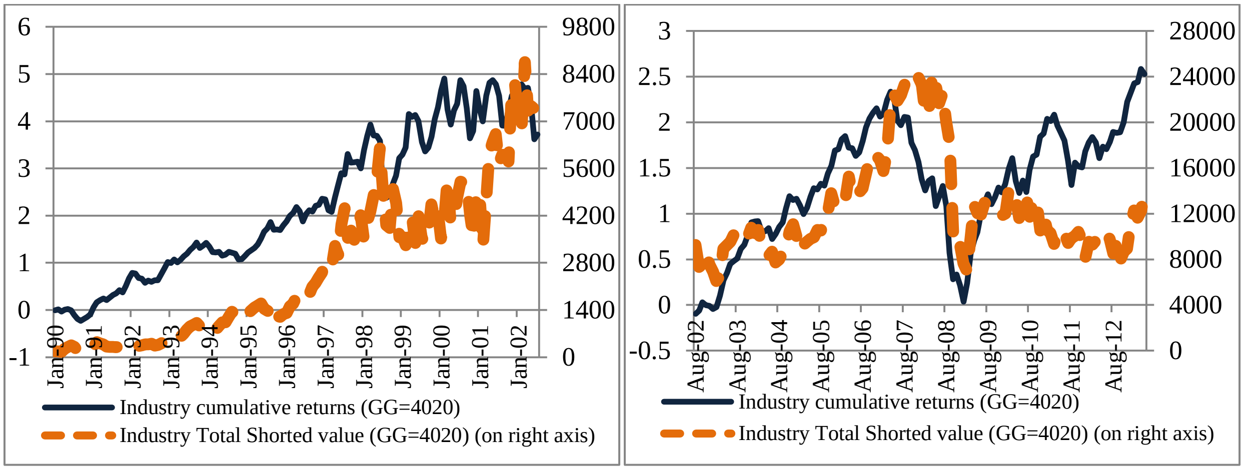
	Model1	**Model2**	**Model3**	**Model4**	**Model5**	**Model6**
ΔIndCDSpread	0.001	0.001	0.001			
	[0.35]	[0.19]	[0.32]			
$IndCDSpread_{-1}$	-0.002	-0.002	-0.002			
	[-1.15]	[-0.99]	[-1.45]			
ΔIndRecoveryrate				-0.102	-0.151	-0.176
				[-0.44]	[-0.65]	[-0.78]
$IndRecoveryrate_{-1m}$				0.861	0.967	0.843
				[1.9]	[2.12]	[1.96[
vwMlever		-0.979	-1.401		-1.006	-1.410
		[-11.97]	[-11.58]		[-12.54]	[-11.81]
Indstd_MLever		2.209	3.106		2.260	3.136
		[12.38]	[14.51]		[12.82]	[15.01]
Indstd_BtoM		0.322	0.184		0.324	0.183
		[7.31]	[3.47]		[7.51]	[3.56]
vwEFD			0.013			0.013
			[9.76]			[9.7]
vwRollover			-0.134			-0.108
			[-2.41]			[-2.05]
vwBtoM	-0.333	-0.571	-0.343	-0.341	-0.577	-0.351
	[-10.42]	[-11.58]	[-5.35]	[-10.84]	[-11.68]	[-5.5]
$vwLagRet_{-1m}$	0.042	-0.081	-0.110	0.102	-0.015	-0.047
	[0.27]	[-0.57]	[-0.8]	[0.67]	[-0.11]	[-0.35]
$vwLagRet_{-6m}$	0.175	0.066	0.022	0.165	0.052	0.009
	[4.04]	[1.6]	[0.55]	[3.65]	[1.18]	[0.21]
$vwTurn_{-1m}$	0.017	0.016	0.014	0.017	0.016	0.014
	[12.25]	[11.79]	[9.89]	[12.45]	[12.1]	[10.26]
$vwHLspread_{-1m}$	-0.604	-1.164	-1.107	-0.576	-1.130	-1.118
	[-2.45]	[-4.73]	[-4.61]	[-2.29]	[-4.54]	[-4.68]
LogFirms	0.843	0.887	0.887	0.844	0.889	0.890
	[87.43]	]113.25]	[110.22]	[91.48]	[115.08]	[112.13]
vwLogMcap	0.454	0.504	0.541	0.457	0.508	0.543
	[43.57]	[50.89]	[43.91]	[43.11]	[49.49]	[42.89]
Intercept	2.131	1.563	1.328	1.775	1.150	0.971
	[18.73]	[15.86]	[13.05]	[8.21]	[5.19]	[4.52]
Time fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
R-square	0.833	0.85	0.856	0.83	0.85	0.86

Table 7.
Industry sales forecast, industry cash flow news in short selling

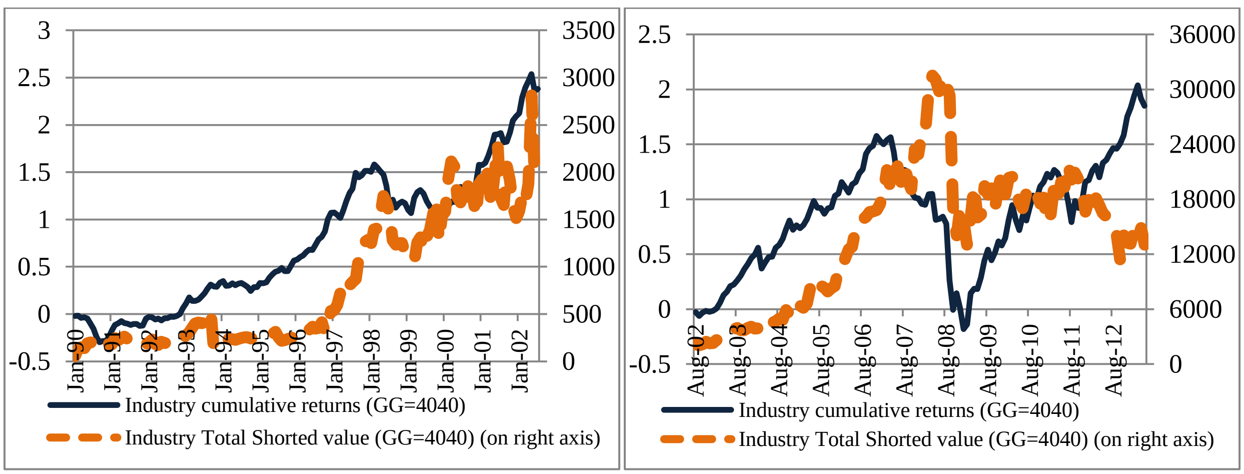
The dependent variable is the change in average sales in the industry, the (total sales / number of firms)/(total sales / number of firms)-1. The explanatory variables include: firm controls, *vwBtoM*, $vwTurn_{-1m}$, $vwHLspread_{-1m}$, $vwLagRet_{-1m}$, $vwLagRet_{-6m}$, *vwMlever*, *Indstd_BtoM*, *LogFirms* and *vwLogMcap* and the two industry heterogeneity measures, *Indstd_Mlever* and *Indstd_BtoM* as defined in Table 5. The financing risk measures, *vwEFD* and the *vwRollover* are defined in Table 6. The coefficient estimates with the corresponding t-stats in parenthesis from industry level panel regression including year fixed effects.

	Model1	**Model2**	**Model3**	**Model4**	**Model5**	**Model6**
$LogIndSV_{-1m}$	-0.040	-0.038	-0.044	-0.044	-0.045	-0.048
	[-2.82]	[-2.61]	[-2.86]	[-2.90]	[-3.13]	[-3.19]
vwBtoM	-0.162	-0.170	-0.167	-0.161	0.062	0.099
	[-3.25]	[-2.96]	[-3.09]	[-2.76]	[0.71]	[0.93]
$vwTurn_{-1m}$		0.003	0.004	0.004	0.003	0.003
		[1.68]	[1.93]	[1.96]	[1.82]	[1.73]
$vwHLspread_{-1m}$		-0.509	-0.428	-0.473	-0.270	-0.378
		[-1.32]	[-1.12]	[-1.31]	[-0.79]	[-1.08]
$vwLagRet_{-1m}$			-1.359	-1.373	-1.292	-1.356
			[-1.76]	[-1.83]	[-1.74]	[-1.95]
$vwLagRet_{-6m}$			-0.018	-0.017	-0.010	-0.011
			[-0.11]	[-0.11]	[-0.07]	[-0.08]
vwMlever				-0.046	-0.356	-0.384
				[-0.68]	[-4.65]	[-3.98]
Indstd_Mlever					0.947	1.034
					[3.79]	[3.41]
Indstd_BtoM					-0.338	-0.369
					[-2.53]	[-2.55]
vwEFD						0.002
						[1.33]
vwRollover						0.087
						[1.22]
LogFirms	0.040	0.035	0.039	0.038	0.037	0.042
	[3.00]	[2.60]	[2.89]	[2.87]	[3.43]	[3.63]
vwLogMcap	0.067	0.057	0.061	0.061	0.063	0.068
	[4.02]	[3.03]	[2.96]	[2.96]	[3.49]	[3.70]
Intercept	-0.111	-0.004	0.057	0.076	0.025	0.000
	[-1.05]	[-0.02]	[0.30]	[0.42]	[0.19]	[0.00]
R-square	0.60	0.60	0.61	0.61	0.63	0.63

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