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Short interest and stock price crash risk

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ABSTRACT

Using a large sample of U.S. public firms, we find robust evidence that short interest is positively related to one-year ahead stock price crash risk. The evidence is consistent with the view that short sellers are able to detect bad news hoarding by managers. Additional findings show that the positive relation between short interest and future crash risk is more salient for firms with weak governance mechanisms, excessive risk-taking behavior, and high information asymmetry between managers and shareholders. Empirical support is provided showing that the relation between short interest and crash risk is driven by bad news hoarding.

1. Introduction

Recent academic studies argue that bad news hoarding leads to stock price crash risk. These studies maintain that managers withhold bad news from investors because of career and short-term compensation concerns and that when a sufficiently long-run of bad news accumulates and reaches a critical threshold level, managers tend to give up. At that point, all of the negative firm-specific shocks become public at once leading to a crash—a large negative outlier in the distribution of returns (Jin and Myers, 2006; Kothari et al., 2009; Hutton et al., 2009). Empirical evidence supports the bad news hoarding theory of stock price crash risk by showing that accrual manipulation, corporate tax avoidance activities, institutional investor instability and a less-religious head-office milieu act to increase future firm-specific crash risk (Hutton et al., 2009; Kim et al., 2011a; Callen and Fang, 2013a,b).

Anecdotal evidence suggests that short sellers are skilled in identifying firms that hoard bad news and suffer from stock price crashes as a consequence. Former short-selling expert Kathryn Staley (1997), author of the book "the Art of Short Selling" writes: "Short sellers accumulate volumes of disparate facts and observations then they make an intuitive leap based on the information at hand. Frequently, the signs point to large problems that will not be revealed in total until after the collapse." She also emphasizes that "to piece together the story of a corporation", short sellers collect and analyze information from a variety of channels, including financial statement, proxy and insider filings, marketplaces, trading patterns, media and others. Similarly, in testimony before the Securities and Exchange Commission (*SEC*) Roundtable on Hedge Funds, Chanos (2003) states that his firm's (Kynikos Associates)'s decision to short sell *Enron* well before Enron's bankruptcy was based on their investigation of problems at *Enron*, including (1) materially overstated earnings; (2) hidden assets that were losing money; (3) the sudden departure of the CEO for "personal reasons"; and (4) significant insider selling by senior executives.[1] This "labor-intensive work" provides a framework for short sellers to identify short-sale candidate firms in which management mislead investors and mask events that will affect future performance.

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[1] On the relation between insider sales and short sales, see Khan and Lu (2013).

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We conjecture that short sellers are sophisticated investors who are able to detect news hoarding activities by firms whose stock they short in anticipation of price crashes. If so, the level of short interest should reflect the potential for bad news hoarding behavior in firms and, as a result, short interest should be positively associated with future stock price crash risk. This study examines the empirical link between short selling and future stock price crash risk with reference to a large sample of U.S. public firms. Consistent with the view that short sellers are able to identify bad news hoarding by managers, we find robust evidence that short selling is significantly positively associated with future (i.e., one-year-ahead) stock price crash risk. The effect is economically as well as statistically significant. On average, an increase of one standard deviation in short interest is associated with an increase in crash risk equal to 12.25% of the sample mean. Our findings are robust to a battery of sensitivity tests including alternative empirical specifications, additional controls, and different forecasting windows.

We further investigate whether the positive relation between short selling and future stock price crash is mediated by the severity of the firm's agency conflicts and governance mechanisms. Ultimately, the relation between short selling and future firm-specific crash risk is motivated by agency conflicts between managers and shareholders that bring about managerial bad news hoarding behavior (Jin and Myers, 2006; Kothari et al., 2009; Hutton et al., 2009). The severity of agency conflicts should help short sellers in identifying firms with bad news hoarding in anticipation of future stock price crash. Furthermore, empirical evidence suggests that firms with weaker external monitoring mechanisms are more likely to suffer crash risk (Callen and Fang, 2013a). Thus, we expect that the positive association between short selling and future firm-specific crash risk is more salient for firms with severe agency conflicts. Consistent with expectation, we find that the observed relation between short selling and future crash risk is more pronounced for firms with weaker external monitoring mechanisms, firms with greater risk-taking, and firms with higher level of information asymmetry. These findings shed light on agency theory explanations for the positive relation between short selling and future crash risk.

Other studies have found increased short selling prior to public announcements of accounting irregularities, and poor subsequent stock performance. Desai et al. (2006) provide evidence that the accumulation of short interest in restating firms prior to the restatement is large compared to non-restating firms, especially for restating firms with high levels of accrual manipulation. Similarly, Karpoff and Lou (2010) find that the build-up of short interest before public revelation of accounting misconduct is more pronounced in firms with severe reporting issues, especially large total accrual manipulation.

Distinct from the latter two studies, we employ a market-based measure, stock price crash risk, to test whether short sellers, on average, can detect managerial bad news hoarding. This market-based risk measure offers several unique features relative to the conventional measures of accounting irregularities (i.e., restatements and SEC enforcement actions) that are the focus of these prior studies. First, restatements and SEC enforcement actions are extreme cases, and are not necessarily indicative of a general policy of managerial bad news hoarding. By focusing on exceptional cases, these prior studies may not generalize. Compared with these extreme cases, our market-based risk measure provides potential insights into managerial bad news hoarding for a broad sample of firms.

Second, accrual manipulation documented in the two prior studies is only one of many ways for short sellers to identify firms that conceal bad news (Hutton et al., 2009; Kim et al., 2011a). For example, *Enron* and *Lehman* concealed bad news prior to their bankruptcies by using complex off-balance-sheet mechanisms. These off-balance-sheet mechanisms are under the scope of professional auditing but precisely because they are off-balance sheet, they cannot be captured by accrual manipulation metrics. Similarly, a series of channels, including classification shifting, opaqueness of notes accompanying financial statements, conference call and press release, also provide opportunities for managers to mask bad economic news but are not reflected in accrual manipulation. Indeed, after explicitly controlling for accrual manipulation, our study still finds a significant relation between short interest and future crash risk consistent with the claims by Staley (1997) and Chanos (2003) that short sellers use multiple channels beyond accruals to identify candidate firms with bad news hoarding.

Third, an important and as yet unexplored feature of our study is to show that, after controlling for accrual manipulation, the predictive power of short selling for future crash risk is conditional on external governance mechanisms, corporate risk-taking levels, and information asymmetry. These findings also help to alleviate the concern that short sellers cause stock price crashes in the first place rather than predicting them based on their informational advantage regarding managerial bad news hoarding. We would be unlikely to observe that the relation between short selling and future crash risk varies systematically with a series of firm characteristics reflecting agency conflicts if in fact short sellers are the underlying cause of stock price crashes.

Our study contributes to the literature in a number of additional ways. By emphasizing a unique perspective—the higher moments of the stock return distribution—this study provides further empirical evidence regarding the superior ability of short sellers in detecting managerial manipulation of information flows.[2] More importantly, our contextual findings regarding interactions of short interest with agency conflicts not only contribute to the ongoing debate about whether short selling truly reflects informed trading but also contribute to our understanding of the kinds of information that short sellers act upon. These findings indicate the ways in which agency problems help short sellers identify crash-prone firms and corroborate the agency perspective of our main finding, namely, that the positive relation between short selling and future crash risk is driven by managerial opportunism behavior in the form of bad news hoarding. Thus, such contextual evidence buttresses and enriches our understanding of the linkage between short interest and future stock price crash risk.

Our study also potentially benefits shareholders by helping them understand the role that short sellers play in detecting bad news hoarding activities by managers that may result in future stock price crashes. As noted by Xing et al. (2010) and Yan (2011), extreme outcomes in the equity market have a material impact on the welfare of investors and investors are concerned about the occurrence of these outcomes.[3] In addition, our findings complement the recent strand of literature investigating the economic determinants of short selling in the framework of accounting irregularities (e.g., Desai et al., 2006; Karpoff and Lou, 2010) by showing that short interest portends bad news hoarding in large samples beyond cases involving restatements and other egregious public accounting irregularities.

The paper proceeds as follows. Section 2 reviews prior literature and develops our hypotheses. Section 3 describes the sample, variable measurement, and research design. Section 4 presents the empirical results. Section 5 concludes.

[2] Prior studies on short selling investigate the relation between short selling and subsequent stock returns (e.g., Figlewski, 1981; Brent et al., 1990; Woolridge and Dickinson, 1994; Asquith and Meulbroek, 1996; Desai et al., 2002; Boehmer et al., 2008; Drake et al., 2011).

[3] Recent studies (e.g., Gabaix, 2012; Kelly and Jiang, 2014) provide empirical evidence that tail risk significantly increases firms' costs of equity capital.

2. Literature review and hypotheses development

Theoretical research (e.g., Miller, 1977; Diamond and Verrecchia, 1987) suggests that, because short sales are more costly and riskier than long transactions, short sellers will not choose to sell stock short absent strong beliefs that stock price will decline in the future to cover at least the additional costs and risks associated with shorting.[4] Early studies fail to document a strong and consistent relation between short interest and subsequent stock returns (e.g., Figlewski, 1981; Woolridge and Dickinson, 1994; Brent et al., 1990; Figlewski and Webb, 1993).[5] In contrast, more recent literature shows a strong empirical link. Asquith and Meulbroek (1996) and Desai et al. (2002) find significant, negative abnormal return for stocks with high short interest. Similarly, Boehmer et al. (2008) find that heavily shorted stocks underperform lightly shorted stocks by an annualized risk-adjusted average return of 15.6%. Diether et al. (2009) find that short sellers increase trading following positive returns and correctly predict future negative abnormal returns. In sum, these studies are supportive of the notion that short sellers actively exploit overpriced stocks and are informed about upcoming bad news regarding firms whose stocks they short.[6] However, this stream of literature is silent on whether managerial self-interested incentive is related to contemporaneous equity overpricing or whether managers deliberately withhold bad news from the public before it is released.

Another stream of literature focuses on short selling activities in the context of accounting irregularities, and concludes that short sellers can identify firms engaged in manipulative, even illicit accounting practices before their public revelation. Dechow et al. (1996) find an increase in short interest in the two months leading up to SEC announcements of Accounting and Auditing Enforcement Releases (*AAERs*) and in the subsequent six months. Similarly, Efendi et al. (2005) and Desai et al. (2006) investigate short selling around the accounting restatements for a sample compiled by the Government Accountability Office (GAO). Both studies find an increase in short interest in the months preceding the restatement announcements. Karpoff and Lou (2010) examine short interest in firms that are investigated by SEC for financial misrepresentation, and find that abnormal short sales increase in the 19 months before the public revelation of misrepresentation. They also provide evidence suggesting that short sellers anticipate the ultimate discovery and severity of financial misrepresentation. Further, the latter three studies suggest that short sellers are proficient at using the information conveyed by accruals to identify firms with accounting irregularities.[7] But, these studies do not address whether short sellers are informed about managerial manipulative behavior beyond accounting irregularities nor do they clarify whether short sellers can identify managerial manipulative behavior through channels other than accounting information (i.e., accruals). Also, focusing on exceptional accounting cases makes these studies vulnerable to the criticism of lack of generalizability.[8]

This paper extends prior research by examining the relation between short selling and future stock price crash risk induced by managerial bad news hoarding activities in a broad sample. Recent studies maintain that managers withhold bad news as long as possible from investors because of career and short-term compensation concerns.[9] Consistent with this idea, Graham et al.'s (2005) survey finds that managers with bad news tend to delay disclosure more than those with good news. Focusing on dividend changes and management earnings forecasts, Kothari et al. (2009) provide evidence consistent with the view that managers, on average, delay the release of bad news to investors.

Anecdotal evidence during the past two decades highlights the issue of bad news hoarding in public firms. *Enron* set up off-balance-sheet *Special Purpose Vehicles* to hide assets that were losing money until accumulated losses were no longer sustainable. (*Report of Investigation by the Special Investigative Committee of the Board of Directors of Enron Corp.*, February 2002). New Century failed to disclose dramatic increases in early default rates, loan repurchases and pending loan repurchase requests until this was no longer sustainable with the collapse of the subprime mortgage business (Schapiro, M. L. Testimony Concerning the State of the Financial Crisis before the Financial Crisis Inquiry Commission. 2010, SEC).

Jin and Myers (2006) provide a theoretical analysis linking bad news hoarding to stock price crash risk. They maintain that managers control the disclosure of information about the firm to the public, and that a threshold level exists at which managers will stop withholding bad news. They argue that lack of full transparency concerning managers' investment and operating decisions and firm performance allows managers to capture a portion of cash flows in ways not perceived by outside investors. Managers are willing to personally absorb limited downside risk and losses related to temporary bad performance by hiding firm-specific bad news. However, if a sufficiently long run of bad news accumulates to a critical threshold level, managers choose to give up, and all of the negative firm-specific shocks become public at once. This disclosure brings about a corresponding crash—a large negative outlier in the distribution of returns, generating long left tails in the distribution of stock returns.

The empirical evidence supports the bad news hoarding theory. Jin and Myers's (2006) cross-country evidence indicates that firms in more opaque countries are more likely to experience stock crashes (i.e., large negative returns). Hutton et al. (2009) find firm-level evidence of a positive relation between accrual manipulation and crash risk.[10] Kim et al. (2011a,b) show that corporate tax avoidance and CFO's equity incentives are positively related to firm-specific stock price crash risk.[11] Callen and Fang (2013a) find that equity ownership by transient institutions is positively related to future crash risk. Callen and Fang (2013b) provide evidence that firms headquartered in locations with higher levels of religiosity

[4] Examples of the costs and risks of short selling are the uptick rule, restrictions on access to proceeds from short sales, unlimited loss with increases in stock price, legal constraints on short selling by certain institutions, and negative rebate rates.

[5] This is possibly due to sample selection issues including (1) the use of small samples reported by the media and (2) the exclusion of firms with material short positions (Desai et al., 2002).

[6] See also Dechow et al. (2001), Christophe et al. (2004, 2010), Engelberg et al. (2012).

[7] Using a sample of U.S. traded firms for the period of 1990–1998, Richardson (2003) fails to document evidence that short sellers trade on the information contained in accruals.

[8] Desai et al. (2006) and Karpoff and Lou (2010) acknowledge this issue.

[9] Basu (1997) claims that managers often possess valuable inside information about firm operations and asset values, and that if their compensation is linked to earnings performance, then they are inclined to hide any information that will negatively affect earnings and, hence, their compensation. Ball (2009) argues that empire building and maintaining the esteem of one's peers motivate managers to conceal bad news. Kothari et al. (2009) contend that managers will leak or reveal good news immediately to investors but they will act strategically with bad news by considering the costs and benefits of disclosing bad news, e.g., litigation risk, career concern, compensation plan, and other considerations. Kim et al. (2011b) maintain that the linking of compensation to equity incentives (e.g., stock holdings and option holdings) induces managers to hide poor performance from investors in order to maintain equity prices.

[10] The prior literature also documents that future stock price crash risk is associated with divergence of investor opinion (Chen et al., 2001); and political incentives in state-controlled Chinese firms (Piotroski et al., 2010).

[11] Kothari et al. (2009) use stock market responses to voluntary disclosure of specific information to infer bad news hoarding. In contrast, the crash risk literature uses firm-specific return distributions to detect bad news hoarding. We would argue that crash risk measures are better at capturing bad news hoarding because concealed bad news is revealed through a variety of information channels over the time, not just firm-specific voluntary disclosure at a specific point in time.

exhibit lower levels of future stock price crash risk, consistent with the view that religion, as a set of social norms, helps to curb bad news hoarding activities by managers.

Based on the above considerations, we conjecture that firms engaged in bad news hoarding will be an ideal target for short sellers, since potential stock price crashes offer ample profits. As noted by Staley (1997) and Chanos (2003), short sellers base their decisions on a comprehensive set of information channels, including financial statement, proxy and insider filings, marketplaces, trading patterns, media and others. Hence, we expect that, as sophisticated market participants, short sellers are able to identify firms that hoard bad news and short them in anticipation of a price crashes, leading to a positive relation between short interest and stock price crash risk. These considerations lead to our first hypothesis (stated in the alternative form):

H1. Firms with higher levels of short interest are associated with higher levels of future stock price crash risk.

The link between short interest and future stock price crash risk expressed by H1 might be weaker than the above arguments suggest. The extant literature (e.g., Bris et al., 2007; Karpoff and Lou, 2010) indicates that short selling improves price efficiency. Focusing on a cross-country setting, Bris et al. (2007) provide evidence supporting the view that prices incorporate negative information faster when short sales are allowed. In a sample of SEC enforcement actions, Karpoff and Lou (2010) find that short selling is positively associated with a time-to-discovery of financial misconduct and short selling dampens the amount of price inflation when firms misstate earnings. These results suggest that short sellers keep equity prices closer to fundamental values by uncovering the misconduct. Indeed, in the absence of short-sale constraints and other frictions, if short sellers are perfectly informed, equity prices will be kept in line with fundamental values and there should be no association between short interest and future stock price crash risk.

However, in reality, the situation is more complicated due to the presence of short-sale constraints and the features of realistic arbitrage trades. There are a variety of costs and risks (e.g., lending fees, recall risk, and regulatory restrictions) associated with short selling, which lead to significant limits to arbitrage and potential price inefficiency (e.g., Shleifer and Vishny, 1997; Jones and Lamont, 2002; Engelberg et al., 2014). Shleifer and Vishny (1997) also suggest that professional arbitrage activities, including short selling, might be ineffective in bringing security prices to fundamental values, especially when prices diverge far from fundamental values.[12] As result, informed short sellers, despite their ability to identify and target firms engaging in bad news hoarding with their superior information, may not be able to fully arbitrage the overpricing.[13] Moreover, market frictions such as short sales constraints, asymmetric information, incomplete (accounting) information, parameter uncertainty, and illiquidity are known to cause price delay (Hou and Moskowitz, 2005; Callen et al., 2013). Therefore, even if prices move towards efficiency driven by short selling, they will only do so with delay, thereby allowing the researcher to perceive and empirically test for an overall positive relation between short interest and future price crash risk as posited in H1.

There are other potential countervailing forces as well that work in opposition to H1 such as uninformed trading. Factors contributing to uninformed shorting include hedging and tax-based trading (Brent et al., 1990). Short positions taken for the latter reasons are not motivated by short seller's knowledge of managerial bad news hoarding and, if uninformed investors dominate short interest, we might not necessarily observe a systematic relation between short interest and future crash risk. Moreover, if informed investors are deterred from engaging in short-selling to exploit their informational advantage because of legal or regulatory constraints, we may also not find such a systematic relation (Christophe et al., 2010). Nevertheless, to the extent that these factors add noise rather than bias, H1 is still be testable.

Our test of the relation between short selling and future firm-specific crash risk (*H1*) is based on agency conflicts between managers and shareholders, which brings about managerial bad news hoarding behavior (Jin and Myers, 2006; Kothari et al., 2009; Hutton et al., 2009). Thus, the severity of agency conflicts should aid short sellers in identifying firms with bad news hoarding in anticipation of future stock price crash. Furthermore, empirical evidence suggests that firms with weaker external monitoring mechanisms are more likely to suffer crash risk (Callen and Fang, 2013a). Thus, we expect that short sellers perceive managers in firms with more agency problems to be more likely to withhold bad news from investors and, as a result, such firms are more likely to be shorted in anticipation of a crash. Here, we predict that the sensitivity of future firm-specific crash risk to short interest is more pronounced for firms with severe agency conflicts.

These considerations lead to our next hypothesis:

H2. The relation between short interest and future stock price crash risk is more pronounced (more positive), the more severe the agency conflict.

3. Sample, variables, and descriptive statistics

3.1. Data sources and sample

The initial sample comprises firm-year observations for which short interest information is available on *Compustat Supplemental Short Interest File*. Consistent with prior studies (e.g., Brent et al., 1990; Dechow et al., 2001; Desai et al., 2006; Boehmer et al., 2010), we measure the *Short Interest Ratio* (*SIR*) as the number of shares sold short divided by total shares outstanding from the last month of the fiscal year. In addition, we collect: (1) *CRSP* daily stock files to estimate our measures of firm-specific crash risk; (2) firm-level accounting data from *Compustat* annual files; (3) *I/B/E/S* for financial analyst data; (4) *American Religion Data Archive* database to estimate state-level religious norms; and (5) *Thompson-Reuters Institutional Holdings Database* for institutional ownership.[14] We restrict our *CRSP* sample to share codes of 10 and 11 to exclude securities which are not common stocks, such as certificates, trust components, shares of closed-end funds, REITs, and depositary units.

Our final sample consists of 40,660 firm-year observations for the years 1981–2011.

3.2. Measurement of firm-specific crash risk

Following prior literature (Chen et al., 2001; Jin and Myers, 2006; Hutton et al., 2009), we employ three firm-specific measures

[12] Shleifer and Vishny (1997) note that when investors allow professional arbitrageurs to manage their money, they might be mistaken about the competency of arbitrageurs due to the lack of knowledge or understanding of what arbitrage entails. This may limit the capital available to competent arbitrageurs. Thus, when arbitrage requires capital, competent arbitrageurs may be the most constrained, which further limits the effectiveness of arbitrage in achieving market efficiency.

[13] Alternatively, if short sellers have incomplete information, it may be difficult, or even impossible, for them to arbitrage away the overpricing.

[14] Data on corporate ownership for transient institutional investors starting from 1981 are available from Brian Bushee's website at http://acct3.wharton.upenn.edu/faculty/bushee/.

of (ex post) stock price crash risk for each firm-year observation: (1) the negative coefficient of skewness of firm-specific daily returns (*NCSKEW*); (2) the down-to-up volatility of firm-specific daily returns (*DUVOL*); (3) the difference between the number of days with negative extreme firm-specific daily returns and the number of days with positive extreme firm-specific daily returns (*CRASH_COUNT*).

To calculate firm-specific measures of stock price crash risk, we first estimate firm-specific daily returns from the following expanded market and industry index model regression for each firm and year (Hutton et al., 2009):

$$r_{j,t} = \alpha_j + \beta_{1,j} r_{m,t-1} + \beta_{2,j} r_{i,t-1} + \beta_{3,j} r_{m,t} + \beta_{4,j} r_{i,t} + \beta_{5,j} r_{m,t+1} + \beta_{6,j} r_{i,t+1} + \varepsilon_{j,t}, \quad (1)$$

where $r_{j,t}$ is the return on stock j in day t, $r_{m,t}$ is the return on the CRSP value-weighted market index in day t, and $r_{i,t}$ is the return on the value-weighted industry index based on the two-digit SIC code. We correct for non-synchronous trading by including the lead and lag terms for the value-weighted market and industry indices (Dimson, 1979).

We define the firm-specific daily return, $R_{j,t}$, as the natural log of one plus the residual return from Eq. (1). We log transform the raw residual returns to reduce the positive skew in the return distribution and help ensure symmetry (Chen et al., 2001). We also estimate these measures of crash risk based on raw residual returns, and obtain robust (untabulated) results.

Our first firm-specific measure of stock price crash risk is the negative coefficient of skewness of firm-specific daily returns (*NCSKEW*). It is the negative of the third moment of each stock's firm-specific daily returns, divided by the cubed standard deviation. Thus, for any stock j over the fiscal year T,

$$NCSKEW_{j,T} = -\left(n(n-1)^{\frac{3}{2}} \sum R_{j,t}^3\right) \Big/ \left((n-1)(n-2)\left(\sum R_{j,t}^2\right)^{\frac{3}{2}}\right) \quad (2)$$

where n is the number of observations of firm-specific daily returns during the fiscal year T. The denominator is a normalization factor (Greene, 1993). This study adopts the convention that an increase in *NCSKEW* corresponds to a stock being more "crash prone," i.e., having a more left-skewed distribution, hence, the first minus sign in Eq. (2).

The second measure of firm-specific crash risk is called "down-to-up volatility" (*DUVOL*) calculated as follows:

$$DUVOL_{j,T} = \log\left\{(n_u - 1)\sum\nolimits_{DOWN} R_{j,t}^2 \Big/ (n_d - 1)\sum\nolimits_{UP} R_{j,t}^2\right\} \quad (3)$$

where n_u and n_d are the number of up and down days over the fiscal year T, respectively. For any stock j over a one-year period, we separate all the days with firm-specific daily returns above (below) the mean of the period and call this the "up" ("down") sample. We further calculate the standard deviation for the "up" and "down" samples separately. We then compute the log ratio of the standard deviation of the "down" sample to the standard deviation of the "up" sample. Similar to *NCSKEW*, a higher value of *DUVOL* corresponds to a stock being more "crash prone." This alternative measure does not involve the third moment and hence is less likely to be excessively affected by a small number of extreme returns.

The last measure, *CRASH_COUNT*, is based on the number of firm-specific daily returns exceeding 3.09 standard deviations above and below the mean firm-specific daily return over the fiscal year, with 3.09 chosen to generate frequencies of 0.1% in the normal distribution (Hutton et al., 2009). *CRASH_COUNT* is the downside frequencies minus the upside frequencies. A higher value of *CRASH_COUNT* corresponds to a higher frequency of crashes. Like Hutton et al. (2009) and Kim et al. (2011a), we use the 0.1% cut-off of the normal distribution as a convenient way of obtaining reasonable benchmarks for extreme firm-specific daily returns to calculate the stock price crash risk measure *CRASH_COUNT*.[15]

We employ one-year-ahead *NCSKEW* ($NCSKEW_{T+1}$), *DUVOL* ($DUVOL_{T+1}$), and *CRASH_COUNT* ($CRASH\_COUNT_{T+1}$) as dependent variables in our empirical tests below.

3.3. Control variables

Following prior literature (Chen et al., 2001; Jin and Myers, 2006; Hutton et al., 2009), we control for the following variables: prior period price crash risk measured by $NCSKEW_T$; KUR_T defined as the kurtosis of firm-specific daily returns in the fiscal year T; $SIGMA_T$ defined as the standard deviation of firm-specific daily returns in the fiscal year T; RET_T defined as the cumulative firm-specific daily returns in the fiscal year T; MB_T defined as the market-to-book ratio at the end of the fiscal year T; LEV_T defined as the book value of all liabilities divided by the total assets at the end of the fiscal year T; ROA_T defined as the income before extraordinary items divided by total assets at the end of the fiscal year T; $LNSIZE_T$ defined as the log of market value of equity at the end of the fiscal year T; and $DTURNOVER_T$ defined as the average monthly share turnover over the fiscal year T minus the average monthly share turnover over the previous year $T-1$, where monthly share turnover is calculated as the monthly share trading volume divided by the number of shares outstanding over the month.

Following Hutton et al. (2009), we further control for a firm-level earnings manipulation measure of financial reporting quality ($ACCRM_T$), measured as the three-year moving sum of the absolute value of annual performance-adjusted discretionary accruals – as developed by Kothari et al. (2005) – from the fiscal year $T-2$ to T. We also use analysts' forecast errors ($FERROR_T$), defined as the absolute difference between actual annual earnings per share and the median earnings forecast standardized by the absolute value of the median earnings forecast, to capture overall corporate information environment. In addition, we control for the number of analysts following the firm (ANA_T) in order to capture short-term earnings pressures from analysts. Chen et al. (2001) find that firms with more analysts following have more crashes in the future. Based on Callen and Fang (2013a), we control for institutional ownership stability measured by the percentage of a firm's shares held by transient institutional investors (TRA_T). Following Callen and Fang (2012), we control for the term of audit-firm-client relationship, i.e., auditor tenure ($TENURE_T$). Finally, based on Callen and Fang (2013b), we control for the number of religious adherents to the total population in the state (REL_T) where the firm's headquarter is located as a measure of religious social norms.

An Appendix summarizes the variable definitions used in this study.

4. Empirical tests

4.1. Descriptive statistics

Table 1, Panel A presents descriptive statistics for the variables used in our regression models. The mean values of the future price cash risk measures, $NCSKEW_{T+1}$, $DUVOL_{T+1}$, and $CRASH\_COUNT_{T+1}$ are −0.1383, −0.1699, and −0.4328, respectively. The means and standard deviations of $NCSKEW_{T+1}$ and $DUVOL_{T+1}$ are similar to

[15] We also estimated all of our regressions with measures of crash risk based on market-adjusted returns and beta adjusted returns, and our (untabulated) results remain qualitatively similar.

those obtained using daily market-adjusted returns as in Chen et al. (2001). The mean value and standard deviation of SIR_T are 0.0371 and 0.0517, comparable to the statistics reported in prior studies (e.g., Dechow et al., 2001; Drake et al., 2011; Hirshleifer et al., 2011).

Table 1 Panel B presents a Pearson correlation matrix for the variables used in our study. Our future cash risk measures, $NCSKEW_{T+1}$, $DUVOL_{T+1}$, and $CRASH\_COUNT_{T+1}$ are all significantly and positively correlated with each other. While these measures are constructed differently from firm-specific daily returns, they seem to be picking up much the same information. The correlation coefficient between $NCSKEW_{T+1}$ and $DUVOL_{T+1}$, 0.92, is comparable to that reported in Chen et al. (2001). In addition, consistent with prior literature, all future crash risk measures are significantly positively correlated with the control variables $NCSKEW_T$, RET_T, MB_T, $LNSIZE_T$, $DTURNOVER_T$, ANA_T, and TRA_T. Importantly, SIR_T is significantly positively correlated with each of $NCSKEW_{T+1}$, $DUVOL_{T+1}$, and $CRASH\_COUNT_{T+1}$ at less than 1% significance level (two-tailed). The univariate results are consistent with our expectation that firms with higher levels of short interest display higher levels of future stock price crash risk.

4.2. Portfolio analysis

To further preview the relation between short interest and stock price crash risk, we implement a portfolio analysis. Specifically, we first sort our sample firms into four short interest portfolios based on the values of short interest in year *T*. Then, for each portfolio, we calculate the average value of stock price crash risk in year *T* + 1. Table 2 Column 1 shows that the price crash risk measure, $NCSKEW_{T+1}$, increases monotonically with short interest. Columns 2 and 3 report similar patterns for $DUVOL_{T+1}$ and $CRASH\_COUNT_{T+1}$, respectively. We conduct additional tests to compare the differences in means across the *SIR* quartiles. And most of *t*-statistics in parentheses are significant at the less than 10% level. These results are consistent with our first hypothesis that short interest is positively associated with future stock price crash risk.

4.3. Regression results

We examine the effect of short interest on future firm-specific stock price crash risk (H1) with reference to the regression equation:

$$CRASHRISK_{j,T+1} = \alpha_0 + \alpha_1 SIR_{j,T} + \sum_k \alpha_k Controls^k_{j,T} + YearDummies + FirmDummies + \varepsilon_{j,T}, \quad (4)$$

where $CRASHRISK_{T+1}$ is measured by one of $NCSKEW_{T+1}$, $DUVOL_{T+1}$, or $CRASH\_COUNT_{T+1}$. All regressions control for year and firm fixed-effects. To control for potential outliers, we winsorize top and bottom 1% of each regressor—but not the dependent variables following Jin and Myers (2006) and Hutton et al. (2009).[16] Regression equations are estimated using pooled ordinary least squares (*OLS*) with White standard errors corrected for firm clustering. Our focus is on the effect of SIR_T on future stock price crash risk, that is, on the coefficient α_1.

When analyzing the effect of short interest on future stock price crash risk, it is possible that short interest and stock price crash risk are simultaneously determined by other exogenous variables. In particular, endogeneity concerns arise because of potential omitted unobservable firm characteristics. Omitted variables affecting the short interest by short sellers and future stock price crash risk could lead to spurious correlations between short interest and future stock price crash risk.[17] Hence, we implement firm fixed-effect regressions to help mitigate the concern that omitted time-invariant firm characteristics may be driving the results.

Reverse causality, namely that the increase in short interest is due to realized (i.e., *ex post*) firm-specific stock price crashes, seems unlikely. We are also unaware of any theory suggesting a reverse relation. In addition, using current SIR_T to predict future crash risk in the main regression analyses helps to rule any concern of reverse causality. Finally, our focus further below on the interaction effects for *H2* makes it hard to argue for reverse causality.

Table 3 shows the results of our regression analysis of Eq. (4), where we measure future firm-specific crash risk by $NCSKEW_{T+1}$, $DUVOL_{T+1}$, and $CRASH\_COUNT_{T+1}$ in columns 1–3, respectively. Across all three models, the estimated coefficients for SIR_T are significantly positive at less than 5% significance levels (*t*-statistics = 2.62, 2.71, and 2.16). The results indicate that short interest is positively associated with future stock price crash risk, consistent with *H1*. These findings are consistent with the view that short sellers are informed *ex ante* about managerial bad news hoarding activities in the firms that they sell short.

To further examine the economic significance of the results, we followed Hutton et al. (2009) by setting SIR_T to their 25th and 75th percentile values, respectively, and comparing crash risk at the two percentile values while holding all other variables at their mean values. The increase in stock price crash risk corresponding to a shift from the 25th to the 75th percentile of the distribution of short interest is 12.25% of the sample mean averaged across alternative measures of crash risk. The specific percentages for $NCSKEW_{T+1}$, $DUVOL_{T+1}$, and $CRASH\_COUNT_{T+1}$ are 22.28%, 7.96%, and 6.50%, respectively. Comparing these results to evidence provided further below indicates that the estimated impact of short sales on firm-specific crash risk is at least similar in economic significance to the impact of accrual manipulation on crash risk.

Prior studies (i.e., Efendi et al., 2005; Desai et al., 2006; Karpoff and Lou, 2010) suggest that short sellers use accrual information to identify firms with a high risk of accounting irregularities. Hutton et al. (2009) find a positive relation between accrual manipulation and stock price crash risk in the future. Thus, we explicitly control for *ACCRM* to make sure that the relation between short interest and future crash risk is not simply driven by accrual manipulation. Consistent with Hutton et al. (2009), the coefficients on *ACCRM* are positive across all regressions, and significant for $NCSKEW_{T+1}$ (*p-value* = 0.096) and marginally significant for $DUVOL_{T+1}$ (*p-value* = 0.183). We also calculate the change in crash risk corresponding to a shift from the 25th to the 75th percentile of the distribution of *ACCRM*, while holding all other variables at their mean values. On average, the resulting estimate of the economic impact of *ACCRM* across alternative measures of crash risk is 7.72%. Untabulated results show that if *ACCRM* is excluded from the regression equation, the results for the estimated coefficient of SIR_T are even stronger, suggesting that accrual manipulation is only one of a multiple number of ways to hide bad news.[18]

Turning to the other control variables, we find that the coefficients on *NCSKEW*, *LNSIZE*, *MB*, *LEV*, *DTURNOVER*, *ANA*, and *TRA* are highly significant across at least two out of three crash risk specifications. More specifically, in consonance with the findings

[16] The regression results are qualitatively similar (untabulated) without winsorization.

[17] For instance, some firms might be more open to the public than others, and thus they are less likely to be sold short as well as suffer firm-specific stock price crashes. Under the assumption that corporate culture does not vary over the time period, we use firm fixed effects to address the concern that omitted culture (or any other time-invariant firm characteristic) is driving our results.

[18] Untabulated results show that the estimated coefficients (*t-statistics*) on SIR_T are 0.824 (3.44), 0.356 (3.49), and 0.671 (2.53) for $NCSKEW_{T+1}$, $DUVOL_{T+1}$, and $CRASH\_COUNT_{T+1}$, respectively.

Table 1
Descriptive statistics and correlation matrix.

Variables	N	Mean	Std. dev.	25th Pctl.	Median	75th Pctl.
Panel A. Descriptive statistics						
$NCSKEW_{T+1}$	40658	−0.1383	1.5865	−0.6220	−0.1767	0.2785
$DUVOL_{T+1}$	40657	−0.1699	0.6643	−0.5138	−0.1792	0.1740
$CRASH\_COUNT_{T+1}$	40660	−0.4328	1.6819	−2.0000	0.0000	1.0000
SIR_T	40660	0.0371	0.0517	0.0039	0.0176	0.0478
$NCSKEW_T$	40660	−0.0359	1.3404	−0.5710	−0.1619	0.2749
KUR_T	40660	6.6176	9.8140	1.5874	3.1583	6.9557
$SIGMA_T$	40660	0.0249	0.0135	0.0159	0.0217	0.0302
RET_T	40660	−0.0400	0.0555	−0.0454	−0.0234	−0.0126
MB_T	40660	2.7812	3.5803	1.2932	1.9990	3.2574
LEV_T	40660	0.5207	0.2277	0.3624	0.5252	0.6613
ROA_T	40660	0.1120	0.1599	0.0824	0.1291	0.1818
$LNSIZE_T$	40660	20.3859	1.7624	19.1279	20.3098	21.5611
$DTURNOVER_T$	40660	0.0034	0.0795	−0.0186	0.0017	0.0248
$ACCRM_T$	40660	0.1680	0.1440	0.0789	0.1280	0.2085
$FERROR_T$	40660	0.4180	1.3524	0.0200	0.0654	0.2241
ANA_T	40660	1.9236	0.7953	1.3863	1.9459	2.5649
TRA_T	40660	0.1341	0.1088	0.0467	0.1095	0.1980
$TENURE_T$	40660	11.1909	7.9162	5.0000	9.0000	16.0000
REL_T	40660	0.5268	0.0866	0.4533	0.5530	0.5895

	$NCSKEW_{T+1}$	$DUVOL_{T+1}$	$CRASH\_COUNT_{T+1}$	SIR_T	$NCSKEW_T$	KUR_T	$SIGMA_T$
Panel B. Correlation matrix							
$DUVOL_{T+1}$	0.92						
	0.00						
$CRASH\_COUNT_{T+1}$	0.46	0.65					
	0.00	*0.00*					
SIR_T	0.06	0.06	0.05				
	0.00	*0.00*	*0.00*				
$NCSKEW_T$	0.03	0.05	0.03	0.07			
	0.00	*0.00*	*0.00*	*0.00*			
KUR_T	0.01	0.00	0.00	0.12	0.36		
	0.01	*0.82*	*0.78*	*0.00*	*0.00*		
$SIGMA_T$	−0.02	−0.06	−0.07	0.06	0.08	0.26	
	0.00	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*	
RET_T	0.04	0.06	0.07	−0.02	−0.03	−0.23	−0.93
	0.00	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*
MB_T	0.05	0.05	0.05	0.10	−0.03	0.01	−0.04
	0.00	*0.00*	*0.00*	*0.00*	*0.00*	*0.05*	*0.00*
LEV_T	−0.02	−0.01	0.00	−0.03	−0.02	−0.01	0.03
	0.00	*0.01*	*0.33*	*0.00*	*0.00*	*0.01*	*0.00*
ROA_T	0.03	0.06	0.08	−0.01	0.00	−0.10	−0.44
	0.00	*0.00*	*0.00*	*0.05*	*0.85*	*0.00*	*0.00*
$LNSIZE_T$	0.10	0.14	0.15	0.10	0.03	−0.04	−0.50
	0.00	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*
$DTURNOVER_T$	0.03	0.04	0.04	0.13	0.04	0.11	0.12
	0.00	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*
$ACCRM_T$	0.01	0.00	−0.01	0.07	0.00	0.03	0.28
	0.00	*0.76*	*0.01*	*0.00*	*0.83*	*0.00*	*0.00*
$FERROR_T$	−0.02	−0.04	−0.05	−0.03	0.00	0.03	0.22
	0.00	*0.00*	*0.00*	*0.00*	*0.35*	*0.00*	*0.00*
ANA_T	0.08	0.10	0.10	0.16	0.08	−0.03	−0.36
	0.00	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*
TRA_T	0.08	0.09	0.08	0.40	0.03	0.10	0.03
	0.00	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*
$TENURE_T$	0.00	0.01	0.02	−0.01	0.00	−0.02	−0.21
	0.62	*0.01*	*0.00*	*0.06*	*0.86*	*0.00*	*0.00*
REL_T	−0.01	−0.01	0.00	−0.10	−0.02	−0.07	−0.10
	0.18	*0.08*	*0.36*	*0.00*	*0.00*	*0.00*	*0.00*

	RET_T	MB_T	LEV_T	ROA_T	$LNSIZE_T$	$DTURNOVER_T$	$ACCRM_T$	$FERROR_T$	ANA_T	TRA_T	$TENURE_T$
MB_T	0.03										
	0.00										
LEV_T	−0.07	−0.02									
	0.00	*0.00*									
ROA_T	0.42	0.05	−0.04								
	0.00	*0.00*	*0.00*								
$LNSIZE_T$	0.42	0.20	0.07	0.33							
	0.00	*0.00*	*0.00*	*0.00*							
$DTURNOVER_T$	−0.12	0.04	0.04	0.03	0.05						
	0.00	*0.00*	*0.00*	*0.00*	*0.00*						
$ACCRM_T$	−0.22	0.09	−0.03	−0.13	−0.24	0.00					
	0.00	*0.00*	*0.00*	*0.00*	*0.00*	*0.98*					

(*continued on next page*)

Table 1 (*continued*)

	RET_T	MB_T	LEV_T	ROA_T	$LNSIZE_T$	$DTURNOVER_T$	$ACCRM_T$	$FERROR_T$	ANA_T	TRA_T	$TENURE_T$
$FERROR_T$	−0.19	−0.06	0.08	−0.13	−0.22	−0.03	0.07				
	0.00	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*				
ANA_T	0.30	0.11	0.04	0.24	0.66	0.01	−0.17	−0.18			
	0.00	*0.00*	*0.00*	*0.00*	*0.00*	*0.02*	*0.00*	*0.00*			
TRA_T	0.02	0.10	−0.06	0.03	0.16	0.08	0.00	−0.08	0.22		
	0.00	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*	*0.96*	*0.00*	*0.00*		
$TENURE_T$	0.16	0.02	0.08	0.13	0.26	0.02	−0.16	−0.05	0.19	−0.01	
	0.00	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*	*0.07*	
REL_T	0.08	0.00	0.02	0.09	0.07	−0.01	−0.02	−0.01	−0.01	−0.18	0.00
	0.00	*0.51*	*0.00*	*0.00*	*0.00*	*0.06*	*0.00*	*0.00*	*0.02*	*0.00*	*0.75*

This table presents descriptive statistics and a correlation matrix of key variables of interest for the sample of firms included in our study. The sample covers firm-year observations with non-missing values for all control variables for the period 1981–2011. Panel A presents descriptive statistics. Panel B presents a Pearson correlation matrix. The two-tailed *p*-values are below the correlation coefficients in Panel B. All variables are defined in the Appendix.

Table 2
Portfolio analysis: short interest and crash risk.

Sorting variables SIR_T		$NCSKEW_{T+1}$ Column 1	$DUVOL_{T+1}$ Column 2	$CRASH\_COUNT_{T+1}$ Column 3
1	*Lowest*	−0.3455	−0.2667	−0.6665
		(10.99)	(12.21)	(11.36)
2		−0.1253	−0.1605	−0.4034
		(1.92)	(1.35)	(1.72)
3		−0.0948	−0.148	−0.3686
		(4.50)	(4.49)	(3.31)
4	*Highest*	−0.0138	−0.1041	−0.2906

This table presents the average stock price crash risk in portfolios sorted by short interest. The sample covers firm-year observations with non-missing values for all variables for the period 1981 to 2011. *t*-Statistics reported in parentheses are for comparisons of differences in means across the *SIR* quartiles. All variables are defined in the Appendix.

of Chen et al. (2001), the positive coefficients on firm size are consistent with their conjecture that small companies face less scrutiny from equity analysts and have more scope for hiding bad news from the public. This in turn allows bad news to dribble out slowly and imparts a more positive skewness to returns. The negative coefficients on *NCSKEW* indicate that crash risk is negatively autocorrelated over adjacent time periods. Consistent with the finding by Harvey and Siddique (2000) and Chen et al. (2001) that growth stocks are more likely to crash, the coefficients on *MB* are significantly positive across two out of three crash risk specifications. We also observe significantly positive coefficients on *LEV* across all specifications suggesting that leverage increases managerial bad news hoarding and thus stock price crash risk. In addition, consistent with Chen et al. (2001) that stocks with differences of opinion among investors or with more analysts following are more likely to crash, the coefficients on *DTURNOVER* and *ANA* are significantly positive across all three crash risk specifications. Lastly, in line with the monitoring theory of institutional investors in Callen and Fang (2013a), the coefficients on *TRA* are significantly positive across all three crash risk specifications.

The findings in Table 3 uniformly support hypothesis *H1* that short interest is positively associated with future stock price crash risk. These findings are consistent with the view that short sellers are able to detect bad news hoarding activities in the firms that they short. The results are robust to multiple measures of firm-specific crash risk, after controlling for a variety of determinants of crash risk.

Table 3
Impact of short interest on crash risk.

Dependent variable	$NCSKEW_{T+1}$	$DUVOL_{T+1}$	$CRASH\_COUNT_{T+1}$
Test variables			
SIR_T	0.7023***	0.3083***	0.6411**
	(2.62)	(2.71)	(2.16)
Control variables			
$NCSKEW_T$	−0.1338***	−0.0420***	−0.0583***
	(−13.25)	(−10.81)	(−7.34)
KUR_T	0.0002	−0.0008	−0.0015
	(0.16)	(−1.38)	(−1.28)
$SIGMA_T$	7.8794**	2.5110*	6.2629*
	(2.25)	(1.76)	(1.72)
RET_T	1.6013**	0.5262*	1.0349
	(2.36)	(1.91)	(1.41)
MB_T	0.0072*	0.0026*	0.0037
	(1.82)	(1.65)	(1.06)
LEV_T	0.2413**	0.0929**	0.1576*
	(2.48)	(2.42)	(1.70)
ROA_T	0.2133	0.1503**	0.4501***
	(1.40)	(2.56)	(3.26)
$LNSIZE_T$	0.3610***	0.1831***	0.3941***
	(15.74)	(19.06)	(16.16)
$DTURNOVER_T$	0.2347*	0.1150**	0.2981**
	(1.84)	(2.19)	(2.21)
$ACCRM_T$	0.1748*	0.0566	0.0789
	(1.66)	(1.33)	(0.76)
$FERROR_T$	0.0143*	0.0056*	0.0021
	(1.93)	(1.75)	(0.25)
ANA_T	0.1469***	0.0567***	0.0959***
	(5.13)	(4.70)	(3.05)
TRA_T	0.3492**	0.2224***	0.7289***
	(2.28)	(3.59)	(4.67)
$TENURE_T$	−0.0026	−0.0009	−0.0002
	(−1.11)	(−0.98)	(−0.08)
REL_T	−1.5766***	−0.5719**	−0.4968
	(−3.11)	(−2.53)	(−0.83)
Intercept	−7.8402***	−4.0703***	−9.0812***
	(−14.18)	(−17.36)	(−15.27)
Year fixed effects	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes
N	40658	40657	40660
Adj. *R*-sq	0.1303	0.1524	0.0874

This table estimates the cross-sectional relation between short interest and future stock price crash risk. The sample covers firm-year observations with non-missing values for all variables for the period 1981–2011. *t*-Statistics reported in parentheses are based on White standard errors corrected for clustering by firm. Year and firm fixed effects are included. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. All variables are defined in the Appendix.

4.4. Robustness checks for the main results

We perform a set of robustness checks of our main results including but not limited to alternative measures, additional controls, and different forecasting windows. To economize on the space, we report results only when future stock price crash risk is measured by $NCSKEW_{T+1}$. The regression analyses using one-year-ahead *DUVOL* and *COUNT* (untabulated) are qualitatively similar.

First, high-frequency daily returns could introduce noise in measuring crash risk. Therefore, as a robustness check, we estimate crash risk based on weekly firm-specific returns, and replicate our regressions. The result in Column (1) of Table 4 is consistent with our main findings. The sign of the *SIR* coefficient is unchanged, and the *t*-statistic remains high.

Second, we estimate our regressions annually from 1981 to 2011 using the approach of Fama and MacBeth (1973). Column (2) reports the means of the annual coefficient estimates, and assesses statistical significance using the time-series standard errors of these estimates, adjusted for serial correlation. The coefficient on *SIR* remains significantly positive at less than a 5% significance level (*t*-statistic = 2.02).

Third, Henry and Koski (2010) and Edwards and Hanley (2010) document a spike of short selling volume around seasoned equity offerings or IPOs. Also, the finance literature provides extensive evidence that the issuance of security leads to subsequent under-performance of equity prices. Thus, we conduct additional robustness tests to make sure that the relation between short interest and future crash risk is not simply driven by firms issuing new securities. Specifically, we re-estimate regression Eq. (4), after excluding firms with large changes in number of shares outstanding (i.e., at least 10%).[19] Column (3) shows that *SIR* is significantly and positively associated with *NCSKEW* in year $T+1$ (*t*-statistic = 2.21).

Fourth, thus far we examined the impact of short interest on future stock price crash risk for a one-year-ahead forecast window. We now check if this relation holds for alternative time intervals. On one hand, shorter time intervals would be of interest if the information advantage that short sellers possess is short-lived. On the other hand, Hutton et al. (2009) and Kim et al. (2011a) show that managers hide bad news up to time horizons of three years. Also, crash risk could manifest over a long period, as in the case of Mexican peso (Sill, 2000). Thus, we investigate alternative forecast windows of future crash risk. Specifically, columns (4), (5), (6) and (7) of Table 4 provide the regression results for equation (4) with three-month-ahead, six-month-ahead, two-year-ahead, and three-year-ahead *NCSKEW* as the dependent variables, respectively.[20] The positive coefficients on *SIR* are significant across the first three models (*t*-statistics = 5.33, 4.30, and 2.70, respectively). The evidence suggests that short interest has predictive power for future stock price crash risk of at least two years ahead in the future.

Fifth, in July, 2004, the SEC passed Regulation (Reg) SHO, which mandated temporary suspension of short-sale price tests (i.e., the tick test for the exchange-listed securities and the bid test for the NASDAQ National Market securities) for a set of randomly selected pilot stocks from the Russell 3000 Index.[21] Thus, short interest during this pilot program might reflect more informed trading by short sellers. The Trade and Quote (TAQ) database provides the Reg SHO – NYSE Short Sales data on a monthly basis for trade dates beginning January 2005 through June 2007. We conduct a robustness test based on the beginning-year short volume level (i.e., the first-week total short volume) for each of the three years, and re-estimate regression Eq. (4).[22] Here, we use trade-adjusted short volume, that is, short volume scaled by total trading volume, to make sure that the documented relationship between short sales and negative skewness is not simply due to the fact that both are related to trading volume (Chen et al., 2001; Xu, 2007). In Column (8) of Table 4, the coefficient on *SIR* remains significantly positive (*t*-statistics = 1.72), consistent with our main findings.

4.5. Testing the second hypothesis

In order to test the hypothesis (*H2*) that the relation between short interest and future stock price crash risk is contingent on the severity of agency conflict in the firm, we focus on three aspects of agency conflict: (1) external monitoring mechanisms; (2) risk-taking behavior; and (3) information asymmetry between managers and outsiders (i.e., shareholders). To economize on space, we present the regression results, using 1-year-ahead *NCSKEW* as the dependent variable. The other crash risk metrics yield very similar results (untabulated).

4.5.1. Governance monitoring mechanisms

We utilize investment by transient institutions, auditor–client relationship, and product market competition to proxy for external governance monitoring mechanisms. A larger percentage of transient institutional ownership (TRA_T) suggests weak investor oversight and poor corporate governance. Bushee (1998, 2001) provides evidence suggesting that transient institutional investors effectively encourage managerial opportunistic behavior because they focus on the short term and invest based on the likelihood of short-term trading profits. In a similar vein, Gaspar et al. (2005) argue that weak monitoring by short-term investors allows managers to trade off shareholder interests for personal benefits at the expense of shareholder returns. Consistent with their argument, Gaspar et al. (2005) provide evidence that firms held by transient institutions are associated with poorer equity performance in merger and acquisition activities. Callen and Fang (2013a) show that institutional investor instability as measured by transient institutional holdings is positively related to future crash risk.

Developing client-specific knowledge creates a significant learning curve for auditors in the early years of an engagement (Knapp, 1991; PricewaterhouseCoopers, 2002; Johnson et al., 2002). Over time, auditors obtain a deeper understanding of their client's industry and business and learn about critical issues that require particular attention. Empirical evidence shows that longer auditor tenure ($TENURE_T$) facilitates effective monitoring by auditors of managerial manipulative behavior in the context of financial reporting decisions (Palmrose, 1991; Geiger and Raghunandan, 2002; Carcello and Nagy, 2004). Callen and Fang (2012) suggest that shorter $TENURE_T$ is associated with more severe agency problems leading to future stock price crash.

Giroud and Mueller (2010, 2011) argue that product market competition serves as an important disciplining force on managers, and should be taken into account as substitute for conventional governance mechanisms in monitoring managerial manipulative behavior. Consistent with the argument in Giroud and Mueller (2010, 2011), Kim et al. (2011b) show that the positive relation between CFO option incentives and future crash risk is especially pronounced for firms in non-competitive industries. Following the literature above, we measure product market competition using the Herfindahl–Hirschman index (HHI_T), which is computed as the sum of squared market shares for firms in each industry for each year. Market shares are computed based on firm sales. We classify industries using the Fama–French 48 industry classification.

Overall, weaker external monitoring mechanisms, as measured by larger TRA_T, shorter $TENURE_T$, and higher HHI_T, are likely to bring about severe agency conflicts between managers and shareholders and bad news hoarding activities with concomitant stock price crashes.

To provide for a more nuanced interpretation of the coefficients and to mitigate measurement problems, we split the sample into

[19] Our results are robust to different choices of change percentage between 1% and 20%.

[20] We estimate the regressions using non-overlapping forecast windows of 3 and 6 months, respectively, for the first two negative skewness specifications.

[21] http://www.sec.gov/rules/other/34-50104.htm.

[22] It is highly unlikely that earnings announcement for public firms occur during the first week of the year.

Table 4
Robustness checks.

DEP. variable:	$NCSKEW_{T+1}$							
TEST variable	Column (1) Weekly-return-based $NCSKEW_{T+1}$	Column (2) Fama–MacBeth approach	Column (3) Excluding firms with increase in # shares (⩾10%)	Column (4) 3-month-ahead regression	Column (5) 6-month-ahead regression	Column (6) 2-year-ahead regression	Column (7) 3-year-ahead regression	Column (8) Reg SHO (trade-adjusted short vol.)
SIR_T	0.3254**	0.4607**	0.5662**	0.6260***	0.8657***	0.4942***	0.2003	0.8384*
	(2.14)	(2.02)	(2.21)	(5.33)	(4.30)	(2.70)	(1.03)	(1.72)
N	40658	40658	33113	153881	77163	36138	31191	2908
Adj. R-sq	0.1083	0.0279	0.142	0.0654	0.1314	0.1345	0.1403	0.0443

This table provides the robustness checks for the cross-sectional relation short interest and future stock price crash risk ($NCSKEW_{T+1}$). The sample covers firm-year observations with non-missing values for all variables for the period 1981–2011. Model 1 provides the estimation results using weekly-return-based negative skewness in year $T+1$ as dependent variable. Model 2 presents the regression results based on Fama–MacBeth approach. Model 3 provides the regression results after excluding firms with significant increase in the number of shares (i.e., at least 10%). Models 4–7 estimate the cross-sectional regressions for stock price crash risk in 3 months, 6 months, 2 years and 3 years ahead, respectively. Model 8 provides the regression results using the sample of the Reg SHO program. To economize on space, all the control variables (see Table 3) are suppressed. t-Statistics reported in parentheses are based on White standard errors corrected for firm clustering. Year and firm fixed effects are included. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. All variables are defined in the Appendix.

two subsamples based on the median value of each of governance monitoring measures and estimate the sub-samples separately.[23] Table 5, Panel A shows that the coefficients on SIR_T are significantly positive only for the above-median *TRA* group, the below-median *TENURE* group, and the above-median *HHI* group (t-statistics = 2.75, 2.71, and 2.52). Further, the coefficients on SIR_T are much larger in absolute value for the groups with weak external monitoring than for those with strong external monitoring. We also conduct F-tests to compare the coefficients between two subsamples based on each of governance monitoring mechanisms. The results show that the differences between the coefficient estimates for the groups with strong and weak external monitoring are significantly positive across all three governance specifications (p values = 0.0153, 0.0193, and 0.0910).

Overall, the findings in Panel A of Table 5 are consistent with *H2*, namely, that the positive relation between short interest and future stock price crash risk is stronger for firms with more severe agency conflicts.[24] The results suggest that short sellers are more likely to be well informed of managerial bad news hoarding behavior by focusing on firms with weaker external governance monitoring mechanisms.

4.5.2. Risk-taking behavior

Research studies and anecdotal evidence suggest that managers try to reduce investors' perception of high firm risk taking behavior. For example, Lambert (1984), Dye (1988), and Trueman and Titman (1988) show that managers will rationally try to reduce investor's estimates of the volatility of the firm's underlying earnings process by income smoothing. Kim et al. (2011b) contend that managers of firms with high levels of risk-taking are concerned about investor's perception of firm riskiness and will hide risk-taking information in order to support share price. Callen and Fang (2013b) also argue that managers of firms with high levels of risk-taking are more likely to conceal and hoard bad news information from investors because bad news may be perceived by investors to be the realization of excessive risk taking behavior by managers. These studies are consistent with the report of Wall Street Journal (2010) that "major banks have masked their risk levels in the past five quarters ... worried that their stocks and credit ratings could be punished".[25] Thus, excessive risk-taking behavior by managers will exacerbate agency problem in the firm by prompting managers to selectively hoard bad news information from investors.

We investigate whether the riskiness of the firm has an impact on the relation between short interest and future stock price crash risk. Empirically, we use stock return volatility ($RETURN\_VOL_T$) and earnings volatility ($EARNINGS\_VOL_T$) to proxy for the riskiness of the firm. $RETURN\_VOL_T$ is the standard deviation of daily stock returns over the current fiscal year. $EARNINGS\_VOL_T$ is measured by the standard deviation of earnings excluding extraordinary items and discontinued operations, deflated by the lagged total assets over the current and prior four years. We also use Altman's $Z\text{-}SCORE_T$ (Altman, 1968), based on the information from income statement and balance sheet, to measure the financial risk of a company. The smaller the $Z\text{-}SCORE_T$, the higher is the financial risk of a company.[26]

Table 5, Panel B estimates regression Eq. (4) separately for subsamples with above- and below-median value of each risk measure. We find that the coefficients on SIR_T are significant only for firms with above-median value of $RETURN\_VOL_T$, above-median value of $EARNINGS\_VOL_T$, and below-median value of $Z\text{-}SCORE_T$ (t-statistics = 2.80, 2.90, and 3.15). Further, the coefficients on SIR_T are at least twice as large in absolute value for the subsamples with high risk-taking level as for those with low risk-taking level. We also conduct F-tests comparing the coefficients for *SIR* across the subsamples. The results show that the differences between the coefficient estimates for the groups with high and low risk-taking levels are significant, positive across all three risk specifications (p values = 0.0068, 0.0152, and 0.0503, respectively).

[23] Another advantage is to avoid having to discuss whether 6% transient institutional ownership is "very different" from 5% transient ownership, or whether a *TENURE* of 10 is "very different" from 13.

[24] Hutton et al. (2009) show that the relation between opacity and stock price crashes decreases after the passage of SOX. We separated our sample into pre- and post-SOX and re-estimated the regression for each sample. We did not observe a weaker relationship between short interest and stock price crash risk after the passage of SOX.

[25] Wall Street Journal, "Big banks mask risk levels" (April 9, 2010). In a similar vein, *Lehman* employed off-balance-sheet "Repo 105" transactions to temporarily remove securities inventory from its balance sheet and reduce its publicly reported net leverage, thereby creating a materially misleading picture of its financial condition (*Lehman Brothers Holdings Inc. Chapter 11 Proceedings Examiner's Report*, March 2010). Similarly, part of the SEC probe of JPMorgan Chase's trading scandal in 2012 was related to the latter's failure to disclose a major change to a risk metric in a timely fashion. By omitting any mention of the change from its earnings release in April, the bank disguised a spike in the riskiness of a particular trading portfolio by cutting in half its value-at-risk number. (See http://www.cnbc.com/id/47776292 and http://www.reuters.com/article/2012/06/19/us-jpmorgan-loss-schapiro-idUSBRE85I12Y20120619).

[26] Kim et al. (2011b) find that that the relationship between equity incentives and subsequent stock prices crashes is stronger in firms with higher leverage. We separated our sample into high and low leverage groups, but we did not find stronger results for high-leverage group. This could be due to the fact that higher leverage also reflects stronger monitoring by debt holders, and not necessarily *ex ante* incentive to mask risk taking.

Table 5
Differential impact of short interest on crash risk.

Dependent variable	$NCSKEW_{T+1}$		$NCSKEW_{T+1}$		$NCSKEW_{T+1}$	
Test variables	TRANSIENT INST.		TENURE		HHI	
	High	*Low*	*High*	*Low*	*High*	*Low*
Panel A: Governance monitoring mechanisms						
SIR_T	1.0319***	−0.1165	−0.0079	1.2439***	0.7271**	0.0321
	(2.75)	(−0.27)	(−0.02)	(2.71)	(2.52)	(0.11)
N	20330	20328	19536	21122	20289	20369
Adj. *R*-sq	0.1246	0.1884	0.1365	0.1446	0.2008	0.1984
Difference in sample coefficients:						
SIR_T	Chi squared = 5.88		Chi squared = 5.48		Chi squared = 2.86	
	p value = 0.0153		*p* value = 0.0193		*p* value = 0.0910	
Dependent variable	$NCSKEW_{T+1}$		$NCSKEW_{T+1}$		$NCSKEW_{T+1}$	
Test variables	RETURN VOLATILITY		INCOME VOLATILITY		Altman *Z*-SCORE	
	High	*Low*	*High*	*Low*	*High*	*Low*
Panel B: Risk-taking behavior						
SIR_T	1.1092***	−0.4189	1.1885***	−0.0487	0.2393	1.4637****
	(2.80)	(−1.08)	(2.90)	(−0.12)	(0.67)	(3.15)
N	20328	20330	20328	20330	20330	20328
Adj. *R*-sq	0.1354	0.1747	0.1407	0.1499	0.1539	0.1455
Difference in sample coefficients:						
SIR_T	Chi squared = 7.32		Chi squared = 5.90		Chi squared = 3.83	
	p value = 0.0068		*p* value = 0.0152		*p* value = 0.0503	

Dependent variable	$NCSKEW_{T+1}$		$NCSKEW_{T+1}$	
Test variables	FORECAST ERROR		FORECAST DISPER.	
	High	*Low*	*High*	*Low*
Panel C: Information asymmetry				
SIR_T	1.4729***	0.0506	1.0308**	−0.0541
	(3.47)	(0.13)	(2.42)	(−0.13)
N	20328	20330	17393	17336
Adj. *R*-sq	0.1546	0.1541	0.1634	0.1445
Difference in sample coefficients:				
SIR_T	Chi squared = 6.23		Chi squared = 5.29	
	p value = 0.0126		*p* value = 0.0214	

This table estimates the cross-sectional relation between short interest, agency conflict, and future stock price crash risk ($NCSKEW_{T+1}$). The sample covers firm-year observations with non-missing values for all variables for the period 1981–2011. To economize on space, all the control variables (see Table 3) are suppressed. *t*-Statistics reported in parentheses are based on White standard errors corrected for firm clustering. Year and firm fixed effects are included. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. All variables are defined in the Appendix.

Taken together, the results in Panel B of Table 5 imply that short sellers are more likely to be well informed of managerial bad news hoarding behavior especially for firms with excessive risk-taking behavior. These results are consistent with *H2* that the influence of short interest on future crash risk is more concentrated (positive) in firms with high agency costs.

4.5.3. Information asymmetry

Agency problems arise when manager's interests are not aligned with shareholders' interests and there exists information asymmetry between the two sides so that shareholders cannot directly ensure that a manager always acts in their (shareholders) best interest. Firms with high information asymmetry between managers and shareholders are more likely to have severe agency conflicts than those with low information asymmetry. Following prior literature, we measure information asymmetry by reference to analysts' earnings forecasts errors and forecast dispersion. We obtain analyst forecast information from *I/B/E/S*. We measure analysts' forecast errors as the absolute difference between actual annual earnings per share and the median earnings per share forecast, standardized by the absolute value of the median earnings per share forecast. We measure analysts' forecast dispersion as the standard deviation of analysts' earnings per share forecast, standardized by the absolute value of the median earnings per share forecast.

Table 5, Panel C estimates regression Eq. (4) separately for subsamples with above- and below-median value of forecast errors and dispersions. We find that the coefficients on SIR_T are significant and positive only for firms with high forecast error and high forecast dispersion (*t*-statistics = 3.47 and 2.42). Further, the coefficients on SIR_T are much larger for the subsample with high forecast error and dispersion than for the subsample with low forecast error and dispersion. We also conduct *F*-tests comparing the coefficients for *SIR* across the subsamples. The results show that the differences between the coefficient estimates for the groups with high and low forecast errors and dispersions are significant and positive (*p* values = 0.0126 and 0.0214, respectively).

Again, the results in Panel C of Table 5 are in line with *H2*, namely, that the impact of short interest on future crash risk is more pronounced for firms with severe agency conflicts.

4.6. Verification of bad news hoarding in stock price crash

The literature on crash risk is based on the maintained hypothesis that idiosyncratic crashes are caused by bad news hoarding. By and large, the extant literature tests the *implications* of this maintained hypothesis but refrains from testing the maintained hypothesis per se. How is the researcher to know if bad news is being hoarded *ex ante* if the market does not know? But, even *ex post* after the crash, it is impossible to determine in all but the most egregious cases that bad news hoarding was the cause of the crash based on public information such as firm press releases or from the press itself.

Table 6
Bad news hoarding, restatements and crash risk.

	# of observations	Mean Firm-specific daily returns	Mean *SIR*	Median *SIR*
Treatment group				
Restatements with crash	393	−18.01%	4.36%	2.40%
Matched Control group (matched by industry and size)				
Restatements without crash	393	−4.28%	3.60%	1.61%
t-Statistic for difference between groups		*17.72****	*2.00***	*2.20***

This table describes the mean firm-specific daily returns for the three days before and after the restatement announcement, and the mean and median *SIR* for the group of restatements with crashes versus a matched control group of restatements without crashes (matched by industry and size). *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

To try to ensure that the subsequent crash is a consequence of bad news hoarding, we focus on the firms that restated accounting data and suffered a stock price crash as a result. The restatement firms in our sample are those involved in accounting irregularities that resulted in material misstatements of financial results. Generally, these irregularities are discovered at least one year, and often many years, after the event and typically involve hiding poor revenues or increased expenses (or both) by management.[27] In other words, these are firms that we are fairly certain suffered a crash because management hid negative information.

We initially collect data for a sample of firms identified as restatement firms by *Audit Analytics* and that are available from January 2000.[28] We further impose the restriction that restating firms have the necessary financial and equity data on *Compustat* and *CRSP*. We restrict the restatement sample to the period that overlaps our primary results, yielding a total of 3819 distinct restatements from 2000 to 2011.

Based on Eq. (1), we calculate firm-specific daily returns for the restatement sample on the three days before and after the restatement announcement. Following Hutton et al. (2009), we define a stock price crash if the firm-specific daily return on any day during the announcement window is 3.09 standard deviations below the annual mean. Table 6 shows that, out of the 3819 sample restatements, 393 restatements resulted in stock price crashes over the restatement announcement window. The mean firm-specific daily return for the 393 crash events is −18.01% (t-statistic = −23.95, p-value <0.0001). Thus, restatements followed by crashes are consistent with bad news hoarding. Specifically, managers withhold firm-specific income-decreasing news from investors by exaggerating financial statements, and accumulate the adverse information until the restatement announcement period when the revelation of bad news results in a corresponding crash.

For each of 393 firms in the sample, we further identify firms in the same industry from the group of restatements firms that did not suffer a crash. From the latter, we choose a control firm whose total assets are closest to those of the treatment firm (and in the same industry). We compare the mean of the firm-specific daily returns for both groups. As shown in Table 6, the mean firm-specific daily return for the control group is −4.28%, which is much less negative than for the treatment group. The difference in returns for the two groups is statistically significant (t-statistics = 17.72, p-value <0.0001). The comparison suggests that relative to the control group, the group of restatement firms that suffered a crash were much more likely to have hoarded material bad news from investors.

We further calculate mean and median values of *SIR* for both samples. The difference in mean and median values of *SIR* between the two samples are 21.11% (= (0.0436–0.036)/0.036) and 49.07% (= (0.024–0.0161)/0.0161), respectively. The restatement group with crashes demonstrates significantly higher levels of short interest as compared to the control group (t-statistic = 2.00 (2.20), p-value = 0.0463 (0.0281), for the difference in means (medians)). These results are broadly consistent with the idea that firms with higher levels of short interest are more likely to hoard bad news and, thus, are more prone to crashes.

5. Conclusion

We investigate whether short interest is associated with future stock price crash risk. Using a large sample of U.S. public firms from the years 1981 to 2011, we find robust evidence that short interest is positively related to one-year ahead stock price crash risk. This positive association is incrementally significant even after controlling for accrual manipulation (Hutton et al., 2009), trading volumes and past returns (Chen et al., 2001), and other factors known to affect stock price crash risk. Our empirical results are consistent with the view that, on average, short sellers are able to detect bad news hoarding activities by managers that gives rise to subsequent price crashes.

The additional evidence shows that the positive relation between short interest and future stock price crash is more salient for firms with weak governance monitoring mechanisms, excessive risk taking behavior, and high information asymmetry between managers and shareholders. These findings enhance our understanding of short selling in predicting future stock price crash risk and corroborate our explanation of the role of short sellers in detecting bad news hoarding behavior by managers. These findings also suggest that investors would be well served investing in corporations with low or no short interest and avoiding corporations with high agency conflicts. Hence, our study may provide investors with an effective strategy to help predict and eschew future stock price crash risk in their portfolio investment decisions.

A series of recent studies on crash risk suggest that managerial bad news hoarding activities are related to accrual manipulation, tax avoidance, and CFO's equity incentives. Our paper extends the growing body of work on the bad news hoarding theory of stock price crash risk by providing empirical evidence of a positive relation between short selling and future crash risk, implying that short sellers are able to detect *ex ante* bad news hoarding activities in the firms they short sell. Collectively, the results in this study provide a clear picture of how short interest is related to higher moments of the stock return distribution and, thus, should be of interest to academicians, investors, and policy makers. Future research might focus on understanding more about the information sources of short sellers in uncovering managerial bad news hoarding. For example, are short selling positions based on private information or a superior analysis of public information? This is a promising area for further exploration.

[27] Irregularities discovered within the year are corrected in that year and do not result in restatements.

[28] Restatements in the *Audit Analytics* database are defined in the following terms: "Previous and current financial statements can no longer be relied upon due to significant accounting errors, and they must be restated" (http://www.auditanalytics.com/blog/different-types-of-financial-statement-error-corrections/).

Appendix

Variable definitions

Crash risk measures:

NCSKEW is the negative coefficient of skewness of firm-specific daily returns over the fiscal year.

DUVOL is the log of the ratio of the standard deviation of firm-specific daily returns for the "down-day" sample to standard deviation of firm-specific daily returns for the "up-day" sample over the fiscal year.

COUNT is the number of firm-specific daily returns exceeding 3.09 standard deviations below the mean firm-specific daily return over the fiscal year, minus the number of firm-specific daily returns exceeding 3.09 standard deviations above the mean firm-specific daily return over the fiscal year, with 3.09 chosen to generate frequencies of 0.1% in the normal distribution.

We estimate firm-specific daily returns from an expanded market and industry index model regression for each firm and year (Hutton et al., 2009):

$$r_{j,t} = \alpha_j + \beta_{1,j} r_{m,t-1} + \beta_{2,j} r_{i,t-1} + \beta_{3,j} r_{m,t} + \beta_{4,j} r_{i,t} + \beta_{5,j} r_{m,t+1} + \beta_{6,j} r_{i,t+1} + \varepsilon_{j,t},$$

where $r_{j,t}$ is the return on stock j in day t, $r_{m,t}$ is the return on the CRSP value-weighted market index in day t, and $r_{i,t}$ is the return on the value-weighted industry index based on the two-digit SIC code. The firm-specific daily return is the natural log of one plus the residual return from the regression model.

Short interest measure

SIR is the number of shares sold short divided by total shares outstanding from the last month of fiscal year *T*, with a range from 0 to 1. *Compustat Supplemental Short Interest File* provides the available data to calculate short interest.

Other variables

KUR is the kurtosis of firm-specific daily returns over the fiscal year.

SIGMA is the standard deviation of firm-specific daily returns over the fiscal year.

RET is the mean of firm-specific daily returns over the fiscal year, times 100.

MB is the ratio of the market value of equity to the book value of equity measured at the end of the fiscal year.

LEV is the book value of all liabilities divided by total assets at the end of the fiscal year.

ROA is the income before extraordinary items divided by total assets at the end of the fiscal year.

LNSIZE is the log value of market capitalization at the end of the fiscal year.

DTURNOVER is the average monthly share turnover over the fiscal year *T* minus the average monthly share turnover over the previous year, where monthly share turnover is calculated as the monthly share trading volume divided by the number of shares outstanding over the month.

ACCRM is the three-year moving sum of the absolute value of annual performance-adjusted discretionary accruals developed by Kothari et al. (2005).

FERROR is the absolute difference between actual annual earnings per share and the median earnings forecast, standardized by the absolute value of the median earnings forecast.

ANA is the log value of one plus the number of analysts that issue earnings forecasts for a given firm during the fiscal year.

TRA is the percentage of a specific firm's equity held by transient institutional investors at the end of the fiscal year.

TENURE is the number of consecutive years in the fiscal year that the auditor has been employed by the firm (in the case of audit firm mergers, the incumbent auditor–client relationship is considered as a continuation of prior auditor).

REL is the number of religious adherents in the state to the total population in the state as reported by American Religion Data Archive.

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