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Accruals and price crashes

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Abstract I investigate the relation between accruals and firm-level price crashes, representing extreme price decreases in weekly returns. I find that high accruals predict a higher price crash probability than low accruals. This finding can be explained by managers' use of income-increasing accrual estimates to hoard bad news. Once accumulated bad news crosses a tipping point, it is released all at once and results in a price crash. Consistent with this explanation, I find the observed relation to be the strongest for operating assets (the least reliable accrual components). Cross-sectional analyses further support the bad news hoarding explanation.

Keywords Accruals · Crashes · Bad news hoarding · Default risk

JEL Classification G12 · M41

1 Introduction

The recent financial crisis has renewed interest in understanding tail risk. In particular, a growing stream of finance and accounting literature attempts to link firm characteristics to the probability of price crashes, representing extreme negative observations in the distribution of firm-level weekly returns (e.g., Hutton et al. 2009).[1] Motivation for examining price crashes includes equity valuation

[1] Consistent with prior price crash studies (Hutton et al. 2009), I define price crashes based on the distribution of firm-specific weekly *log* returns, to remove the well-known right skewness in raw returns.

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(Conrad et al. 2013) and option pricing (Cox and Ross 1976; Merton 1976). Firm characteristics indicative of future price crashes include proxies for (a) risk of operations (Chen et al. 2001), (b) properties of investor beliefs (Cao et al. 2002; Hong and Stein 2003), and (c) attributes of financial reporting (e.g., Hutton et al. 2009; Kim et al. 2011b).

Hutton et al. (2009) provide the first piece of evidence that establishes an association between the opacity of financial reporting and crash risk. Using earnings management as the proxy for reporting opacity, they show that the sum of absolute discretionary operating accruals over the past 3 years is positively associated with subsequent price crashes. They interpret this finding as suggesting that both positive *and* negative discretionary operating accruals are associated with hidden bad news. This interpretation, however, contradicts the conventional wisdom in the accruals literature that firms with negative discretionary accruals are associated with less hidden bad news than those with positive discretionary accruals (Dechow et al. 1995; Xie 2001).[2] To reconcile these two seemingly conflicting points of view, I conduct a comprehensive investigation of the relationship between accruals and future price crashes.

To reconcile the above contrasting predictions for the relation between negative accruals and hidden bad news, I consider two opposing mechanisms, suggested in the literature, that relate accruals to future price crashes. Under the first mechanism, managers seeking to suppress or hoard bad news tend to make aggressive income-increasing accrual estimates (Dechow et al. 1995, 2011; Richardson et al. 2006), which in turn leads to more hidden bad news among high accruals firms in comparison to low accruals firms.[3] Therefore, when accumulated bad news crosses a tipping point, it is released all at once and results in a price crash (Jin and Myers 2006; Benmelech et al. 2010). Under the second mechanism, extreme negative accruals reflect severe performance deterioration due to financial distress and consequently high default risk (Ng 2005; Khan 2008). Firms with higher default risk are more likely to fail, leading to more price crashes for low accruals firms relative to high accruals firms.

Following prior literature, I measure the probability of price crashes in two ways. The first measure is a continuous variable that equals the number of standard deviations by which the most extreme negative weekly return over the year falls below its mean (Bradshaw et al. 2010). The mean and standard deviation are based on firm-specific weekly return distributions for that year. The second measure is an indicator variable that equals one if the firm experiences one or more extreme negative weekly returns that are more than 3.09 standard deviations below the mean over the year and zero otherwise (Hutton et al. 2009). As the results for these two measures are similar, I refer to them collectively as price crashes for brevity. Following Richardson et al. (2006) and Dechow et al. (2008), I define accruals as

[2] Accruals literature finds that high (low) accruals are associated with future bad (good) returns and more (fewer) SEC enforcement actions for alleged earnings manipulation. This suggests that high (low) accruals firms hide more (less) bad news than investors expect and those expectations are corrected in future periods.

[3] Managers seeking to hoard bad news also may make excessive investments (Kedia and Philippon 2009; McNichols and Stubben 2008), leading to a positive association between accruals and hidden bad news.

growth in net operating assets, deflated by average total assets. This comprehensive measure reflects the notion that all operating assets and liabilities accounts are products of the accrual accounting system.

I find a strong positive association between *total* accruals and future price crashes. For example, the probability of observing price crashes (defined as weekly returns that are more than 3.09 standard deviations below the mean) over the next year increases from 12.88 % for the lowest decile of the current year's accruals to 17.27 % for the highest decile. The monotonic increase of crash risk across the increasing accruals portfolios is the highest for the current year's accruals but also holds for accruals of the past 2 years. This remains true after I control for variables considered in prior research to predict price crashes. In multivariate regression models forecasting price crashes, accruals in the most recent year are among the strongest predictors in both economic and statistical significance. These findings are consistent with the hidden bad news explanation.[4]

I continue to examine variation in the association between accruals and price crashes across components of accruals. Following Richardson et al. (2005), I decompose accruals into four components according to their relative reliability in accrual estimation, with current and non-current operating asset accruals being the least reliable, non-current operating liability accruals being more reliable, and current operating liability accruals being the most reliable.[5] Less reliable components of accruals provide managers with greater discretion when attempting to hoard bad news and therefore are expected to have a stronger positive association with future price crashes. Consistent with this prediction, I find that current operating asset accruals and non-current operating asset accruals are significantly positively associated with price crashes, while non-current operating liability accruals are not significantly related to crashes over the next year. Surprisingly, current operating liability accruals turn out to be negatively associated with price crashes. Finding that firms with increased current operating liabilities are more likely to experience future price crashes is consistent with the default risk explanation but inconsistent with the bad news hoarding explanation. The collective evidence from accrual decomposition suggests that the relation between different accrual components and subsequent price crashes depends on the relative reliability of that component.

To further validate the bad news hoarding explanation for the positive association between operating asset accruals and price crashes and the default risk explanation for the negative association between current operating liability accruals and price crashes, I examine the implications of bad news hoarding (default risk) for cross-

[4] Untabulated results show that *total* accruals are negatively associated with future price jumps, representing extreme positive observations in firm-specific returns distributions. This negative association rules out alternative risk-based explanations that predict both more price crashes and more price jumps for high accruals firms.

[5] Current and non-current operating asset accruals are defined as the change in non-cash current assets and non-current operating assets, respectively. Current and non-current operating liability accruals are defined as the *negative* of the change in non-debt current liabilities and non-current operating liabilities, respectively.

sectional variation in the positive (negative) association.[6] Consistent with the predictions of the bad news hoarding mechanism, the positive association between operating asset accruals and future price crashes is stronger in three instances: (1) when CFOs have a stronger incentive to hide bad news, as captured by a higher option incentive ratio (Core and Guay 2002; Coles et al. 2006); (2) when it is more difficult for investors to unravel hidden bad news, as captured by a high-tech firm or a higher sales growth rate; and (3) when external monitoring is weaker, as captured by a higher level of transient institutional holding or a shorter auditor tenure. In contrast, and inconsistent with the prediction of the default risk mechanism, I do not find the negative association between current operating liability accruals and future price crashes to be stronger among firms with higher default risk, as captured by a lower Altman (1968) Z score, a higher Shumway (2001) bankruptcy score, or a higher Vassalou and Xing (2004) default probability. This finding suggests that neither bad news hoarding nor default risk explains the negative association between current operating liability accruals and future price crashes.

Despite its puzzling nature, the negative relation between current operating liability accruals and price crashes helps to explain the U-shaped relation between discretionary operating accruals and price crashes documented by Hutton et al. (2009). This U-shaped relation results from nonlinearities in the relations between future price crashes and accruals derived from current operating assets and current operating liabilities. The likelihood of a price crash declines as current operating asset accruals decrease from high to medium levels but remains constant between medium and low levels. In contrast, the likelihood of a price crash declines as current operating liability accruals increase from low to medium levels but remains constant between medium and high levels.[7] As working capital accruals are simply current operating asset accruals *plus* current operating liability accruals, the above nonlinearities result in a U-shaped relation between the level of working capital accruals and future price crashes, which in turn leads to the U-shaped relation between discretionary operating accruals and price crashes.[8] My evidence suggests that, while the positive association observed when discretionary operating accruals are positive is consistent with the bad news hoarding explanation, the negative association when discretionary operating accruals are negative is inconsistent with both the bad news hoarding explanation and the default risk explanation.

[6] Operating asset accruals are defined as the sum of current and non-current operating asset accruals.

[7] Recall that I define current operating liability accruals as the *negative* of change in non-debt current operating liabilities. A low level of current operating liability accruals corresponds to a high level of increase in current operating liabilities.

[8] I first show that the cash-flows-based discretionary operating accruals examined by Hutton et al. (2009) are subsumed by balance-sheet-based discretionary operating accruals in predicting subsequent price crashes. I define balance-sheet-based discretionary operating accruals as the residual portion of operating accruals estimated from the Jones model (1991), where operating accruals equal change in non-cash current operating assets minus change in non-debt current operating liabilities minus depreciation and amortization. I then demonstrate that, when discretionary operating accruals are positive, the positive association between those accruals and price crashes is driven by discretionary current operating asset accruals. In contrast, when discretionary operating accruals are negative, the negative association is driven by discretionary current operating liability accruals.

My study contributes mainly to two literatures. It adds to the growing body of work on price crashes by comprehensively examining the link between accruals and price crashes. I find that high total accruals in the most recent year best predict future price crashes. The focus in Hutton et al. (2009) on reporting opacity, measured as the absolute value of discretionary operating accruals summed over the past 3 years, masks this dominant relation. I also show that the exact pattern of the association between accruals and future price crashes hinges critically on the definition of accruals. This is because different accrual components have different degrees of reliability in accrual estimation and consequently are associated with different levels of hidden bad news.

My study also contributes to the literature on the accruals anomaly by helping to differentiate two competing explanations for the lower mean returns observed for high accruals firms (Sloan 1996). One explanation argues that investors fail to recognize the lower persistence of accruals caused by hidden bad news (Xie 2001; Richardson et al. 2006) and consequently overprice firms with high accruals.[9] The other explanation maintains that high accruals firms have lower default risk and therefore are compensated with lower returns (Ng 2005; Khan 2008). While both explanations make the same prediction on the relation between accruals and the mean of returns distribution, they make opposing predictions on the association between accruals and the left tail of returns distribution. The fact that *total* accruals and all major accrual components, except for current operating liability accruals, are positively associated with price crashes implies that the accruals anomaly is mainly driven by investors' accrual mispricing due to a failure to recognize the hidden bad news reflected in the accruals.

2 Literature review on firm-level price crashes

2.1 Crash risk and asset pricing

There is growing interest in understanding the role of crash risk (i.e., the likelihood of sudden but infrequent large price decreases) in asset pricing. At the market level, crash risk explains a significant fraction of the equity premium (Barro 2006; Gabaix 2012). At the firm level, crash risk is an important determinant of expected returns in the cross-section (Yan 2011; Conrad et al. 2013). Crash risk also determines option prices, incrementally to stock return volatility (Cox and Ross 1976; Merton 1976; Pan 2002). These important economic consequences call for a deeper understanding of the causes of price crashes.

[9] The lower persistence of accruals may also be explained by firm growth (Fairfield et al. 2003). Differentiating these two explanations is beyond the scope of this study.

2.2 Explanations of price crashes

2.2.1 Bad news hoarding

Prior literature has proposed a number of explanations for the origin of firm-level price crashes. The two explanations most relevant to my study are bad news hoarding and default risk. The bad news hoarding explanation comes from theories of managers hoarding bad news (Jin and Myers 2006; Bleck and Liu 2007; Benmelech et al. 2010). In these models, managers attempt to hide bad news because they have a higher discount rate than shareholders and their personal wealth is tied to stock and accounting performance.[10] When accumulated bad news crosses a tipping point in the future, it will be released all at once and result in a price crash.

There is ample evidence consistent with bad news hoarding. Using earnings management as the proxy for financial reporting opacity, Hutton et al. (2009) show that more opaque firms experience more price crashes over the next year. To measure earnings management, they sum the absolute value of discretionary operating accruals from the modified Jones model (Dechow et al. 1995) over the past 3 years. They interpret this finding as suggesting that firms with consistently large values of discretionary accruals, both positive *and* negative, are more likely to be managing reported earnings to conceal bad news.

Hutton et al. (2009) inspires a handful of other proxies for bad news hoarding as price crash predictors. Kim et al. (2011a) show that the CFO's option incentive ratio is positively associated with future price crashes. This finding suggests that a higher sensitivity of the value of the options portfolio to stock price increase creates a stronger incentive for CFOs to hide bad news, consistent with the prediction by Benmelech et al. (2010). Other predictors of price crashes include tax avoidance (Kim et al. 2011b), internal control weakness (Kim et al. 2013a, b), accounting conservatism (Kim and Zhang 2013), management forecast frequency (Hamm et al. 2012), and CEO overconfidence (Kim et al. 2013a, b).

2.2.2 Default risk

Price crashes also could result from corporate failure (i.e., the failure to meet financial obligations). Firms with higher default risk are more likely to suddenly release extremely bad news (resulting in a price crash) or extremely good news (resulting in a price jump), because they have a more extreme bimodal outcome: failure or continuance as a going concern.

So far, prior literature has failed to provide evidence consistent with the above prediction using proxies like firm size and leverage. Hutton et al. (2009) and Kim et al. (2011a, b) find a positive relationship between firm size and future price crashes, which contradicts the observation that larger firms have a lower bankruptcy

[10] Managers have a higher discount rate than shareholders because managers are less diversified, have a shorter horizon due to possible early departure from the firm or death, or both (Benmelech et al. 2010). The value of managers' option and stock portfolios depends on stock price performance. A manager's bonus is often a function of accounting earnings.

probability than smaller firms (Campbell et al. 2008).[11] As explained by Hutton et al. (2009), this surprising result could stem from the definition of a price crash: a tail event of sufficient magnitude to fall in the lower 0.1 % of normal distribution. As larger firms have lower standard deviations of returns than smaller firms, the absolute magnitude of a return needed to qualify as a crash is thus lower for larger firms. This mechanical positive association between firm size and price crashes overwhelms the negative relation predicted by the default risk explanation.

The above studies also document a negative association between leverage and future price crashes, which is inconsistent with the observation that high leverage firms have a higher probability of failures than low leverage firms (Campbell et al. 2008). One potential explanation for this surprising result is that investors underprice high leverage firms, making it less likely to observe price crashes for these firms ex post. Consistent with this explanation, Campbell et al. (2008) show that high leverage firms generate higher future mean returns than low leverage firms.

2.2.3 Other explanations

Other price crash explanations in the literature include differences of opinion (Hong and Stein 2003) and information blockage (Cao et al. 2002).[12] Consistent with these explanations, Chen et al. (2001) document that share turnover (the proxy for differences of opinion) and past stock returns (the proxy for information blockage) positively predict the likelihood of future price crashes, measured as the negative returns skewness.

2.3 Predictability of price crashes and market inefficiency

It is worth noting that the predictability of price crashes does not require market inefficiency of price crash predictors. Consider the following example, where X is a noisy signal of hidden bad news. For simplicity, I assume that the amount of hidden bad news equals 20 % of market value, and 15 % (0 %) of firms with a high (low) value of X are hiding bad news.[13] Holding everything else constant, rational

[11] Campbell et al. (2008) define failures broadly to include bankruptcies, financially driven delistings, and D ("default") ratings issued by a leading credit rating agency.

[12] In the differences-of-opinion model (Hong and Stein 2003), a group of investors (e.g., mutual funds) cannot short-sell stocks. Because of short-sale constraints, bearish investors do not initially participate in the market, and their negative information is not revealed in the prices. However, if other previously bullish investors exit the market, these originally bearish investors may become the marginal buyers. Thus accumulated hidden bad news surfaces and results in a price crash. In the information blockage model (Cao et al. 2002), an upward price trend triggers trading on the part of favorably informed investors. In contrast, adversely informed traders become less confident that they have received correct signals and may delay trading until the price drops. Thus, if the true state of the economy is actually low, there is a large correction upon the eventual entry of the sidelined investors with adverse signals. This information blockage leads to negative returns skewness following price run-ups and positive skewness following price rundowns.

[13] Hutton et al. (2009) show that the mean returns for crash weeks are −22.74 %, that the average standard deviation of firm-specific weekly return is 5.8 %, and that 17 % of firms have price crash weeks in their sample.

investors would value firms with a high X 3 % less than those with a low X. When future news arrives, half of the high X firms will be hit with another piece of bad news, and a sudden price drop of at least 17 % (20–3 %) will occur when the hidden bad news is released all at once. This example illustrates the existence of price crash predictability, even if the market correctly prices the noisy signal X of bad news hoarding. In fact, all theoretical models of price crashes reviewed above assume market efficiency.

On the other hand, market inefficiency could reinforce the likelihood and magnitude of price crashes. Ak et al. (2015) show that mean stock returns over the next 6 months are significantly lower for high crash risk portfolio than low crash risk portfolio, which suggests market inefficiency of price crash predictors. Continuing the above example, I assume instead that investors fail to understand the signal X. Under this assumption, irrational investors value high X and low X firms at the same price. When future news arrives, half of the high X firms will be hit with another piece of bad news, and a sudden price drop of at least 20 % will occur when the hidden bad news is released all at once. This example suggests that we could find stronger evidence of price crash predictability when the market fails to adjust for bad news hoarding.

3 Hypothesis development

In my study, I conduct a comprehensive investigation of the link between accruals and price crashes. I first examine the association between total accruals and price crashes, and then explore the variation in this association across accrual components and across firms.

3.1 Accruals and price crashes

The price crash theories discussed earlier suggest two opposing mechanisms that relate accruals to future price crashes. Under the first, accruals predict price crashes because of the hidden bad news reflected in the accruals. The accruals literature has provided robust evidence that accruals are less reliable than the cash component of earnings because of the greater subjectivity involved in the identification and measurement of non-cash assets and liabilities (Dechow and Dichev 2002; Richardson et al. 2005). The subjectivity in accrual estimation provides managers with room to hide bad news by over-estimating accruals (Dechow et al. 1995; Richardson et al. 2006; Dechow et al. 2011). For example, managers could conceal negative product market shocks by delaying inventory write-offs. Firms also tend to over-invest when hiding bad news (Kedia and Philippon 2009; McNichols and Stubben 2008), which likewise results in a positive association between bad news hoarding and the level of accruals.[14] When accumulated bad news crosses a tipping

[14] I do not attempt to differentiate between the over-estimation of accruals and over-investment as the source of bad news reflected in accruals because both predict more price crashes for high accruals firms.

point, it will be released all at once and will result in more price crashes for high accruals firms compared to low accruals firms.

Under the second mechanism, accruals predict price crashes because of the default risk reflected in accruals. Ng (2005) and Khan (2008) analyze the characteristics of firms with different levels of accruals. They find that low accruals firms generate less income, lower sales growth, and lower Altman Z scores (Altman 1968) than do high accruals firms and that all three attributes are symptoms of higher default risk. As firms of higher default risk are more likely to fail, the default risk explanation predicts more price crashes for low accruals firms.

In light of the opposing predictions from the bad news hoarding and default risk explanations, my first research hypothesis is stated as follows:

(H1) The level of accruals is positively (negatively) related to the probability of weekly price crashes over the next year under the bad news hoarding (default risk) mechanism.

Even though hidden bad news and default risk predict opposing signs of the association between accruals and the left-tail of firm-specific returns distribution, both have been used to explain the negative relation between accruals and the *mean* of firm-specific returns distribution first documented by Sloan (1996). Xie (2001) shows that the accruals anomaly is driven by the discretionary portion of accruals. He interprets this finding as suggesting that the lower returns associated with high accruals are due to the market's failure to recognize hidden bad news reflected in accruals. In contrast, Ng (2005) and Khan (2008) show that hedge returns from buying low accruals firms and shorting high accruals firms significantly decrease after controlling for distress risk. They interpret this finding as suggesting that low accruals firms have higher default risk and therefore are compensated with higher expected returns. My examination of hypothesis *H1* could help to differentiate between these competing explanations of the accruals anomaly.

3.2 Accrual components and price crashes

Richardson et al. (2005) provide a comprehensive accrual categorization and detailed analysis of the degrees of subjectivity involved in estimating different components. Components that involve a higher degree of discretion are expected to have more intentional and unintentional estimation errors and hence be less reliable. Less reliable accruals offer more freedom for opportunistic managers to overstate accrual estimates; therefore these accruals are expected to be more associated with hidden bad news. Assuming a constant level of default risk across accrual components, the above variation in reliability leads to my second research hypothesis:

(H2) A less reliable accrual component is more positively associated with the probability of weekly price crashes over the next year under the bad news hoarding mechanism.

Empirical results consistent with hypothesis *H2* corroborate the bad news hoarding explanation for the association between accruals and future price crashes.

3.3 Cross-sectional variation in the association between accruals and price crashes

Under the bad news hoarding explanation, accruals positively predict future price crashes due to the use of positive accruals to conceal bad news. Such aggressive use of accruals is expected to be elevated in instances when the incentive to hide bad news is stronger, the constraint on hiding bad news is weaker, and it is more difficult for investors to unravel hidden bad news. Under the default risk explanation, accruals negatively predict future price crashes because of higher default risk reflected in low accruals. As corporate failure is a low probability event, the noise in the proxies for default risk is expected to be larger when the level of default risk is sufficiently low. Consequently, the association between accruals and default risk is expected to be stronger when default risk is higher.[15] This leads to a more negative, or less positive, association between accruals and future price crashes among firms with higher default risk. The above discussion leads to my third research hypothesis:

(H3a) Under the bad news hoarding mechanism, the association between the level of accruals and the probability of weekly price crashes over the next year is more positive when the incentive to hide bad news is stronger, when the constraint on hiding bad news is weaker, and when it is more difficult for investors to unravel hidden bad news.

(H3b) Under the default risk mechanism, the association between the level of accruals and the probability of weekly price crashes over the next year is more negative when the default risk is higher.

Cross-sectional variation consistent with hypothesis *H3a* (*H3b*) corroborates the bad news hoarding (default risk) explanation for the association between accruals and future price crashes.

4 Variable definition and research design

4.1 Variable definition

Following prior literature, I use one continuous variable $VCRASH_{t+1}$ (Bradshaw et al. 2010) and one indicator variable $CRASH_{t+1}$ (Hutton et al. 2009) to measure the probability of weekly price crashes over year $t + 1$, where year $t + 1$ is defined as the 12 months starting from the fifth month after the end of fiscal year t.[16] (Please refer to the "Appendix" for variable definitions.) To calculate these measures, I first estimate firm-specific weekly returns for year $t + 1$. The firm-specific weekly return

[15] Consistent with this prediction, Vassalou and Xing (2004) show that size and book-to-market, which are conjectured by Fama and French (1993) to reflect distress information, are associated with default risk only in the portfolio with the highest default risk.

[16] The four-month lag allows me to avoid the look-ahead bias by ensuring that the financial data are available to investors when forecasting the probability of future weekly price crashes.

is defined as the log of one plus the residual $\varepsilon_{i,w}$ from the following expanded market model regression[17]:

$$Ret_{i,w} = \alpha_{i,0} + \beta_{i,-1} * MRet_{w-1} + \beta_{i,0} * MRet_{w} + \beta_{i,1} * MRet_{w+1} + \gamma_{i,-1} * IRet_{w-1} + \gamma_{i,0} * IRet_{w} + \gamma_{i,1} * IRet_{w+1} + \varepsilon_{i,w}, \tag{1}$$

where $Ret_{i,w}$ represents the returns of firm i for week w of year $t + 1$, $MRet_w$ represents the market returns for week w of year $t + 1$, and $IRet_w$ represents the industry returns for week w of year $t + 1$.

I define $VCRASH_{t+1}$ as the absolute value of the difference between minimum firm-specific weekly return and its mean over year $t + 1$, divided by its standard deviation for year $t + 1$ (Bradshaw et al. 2010; Kim et al. 2013a, b). To define $CRASH_{t+1}$, I first define price crash weeks in year $t + 1$ for a given firm as those weeks during which firm-specific weekly return is at least 3.09 times the standard deviation below the mean, with 3.09 chosen to generate a frequency of 0.1 % in the normal distribution. Following Hutton et al. (2009), the indicator variable $CRASH_{t+1}$ equals one if the firm experiences one or more crash weeks over year $t + 1$ and zero otherwise. Compared with $CRASH_{t+1}$, $VCRASH_{t+1}$ captures both the frequency and the magnitude of extreme negative returns and does not depend on the choice of a distribution cut-off. Nevertheless, I report results for both measures.

Following Richardson et al. (2006) and Dechow et al. (2008), I define accruals (ΔNOA) as the growth in net operating assets deflated by average total assets. This definition of accruals is arguably the most comprehensive one because it includes changes in all operating assets and liabilities, all of which reflect the accounting accrual system's estimate of firm value.

4.2 Research design

4.2.1 Test of hypothesis H1

To test hypothesis *H1*, I estimate the following regression model that links the probability of price crashes in year $t + 1$, $VCRASH_{t+1}$ and $CRASH_{t+1}$, to accruals of the most recent 3 years and a set of control variables:

$$VCRASH_{t+1} \text{ or } CRASH_{t+1} = \alpha_0 + \sum_{k=0}^{2} \beta_k * \Delta NOA_{t-k} + \sum_{l=1}^{m} \theta_l * Control_{l,t} + \varepsilon_{t+1}, \tag{2}$$

I include accruals of the most recent 3 years (ΔNOA_t, ΔNOA_{t-1}, and ΔNOA_{t-2}) in regression model (2) to be consistent with Hutton et al. (2009), who use absolute discretionary operating accruals of the most recent 3 years to predict price crashes over the next year. This design choice also accounts for the predictability of price crashes that goes beyond 1 year. I assume a linear relation between accruals and

[17] At least 26 weeks are required to estimate the regression model (1) for each firm-year. This requirement may create a forward-looking bias.

price crashes, given the linear relationship between accruals and future mean returns documented in accruals anomaly literature.

The control variables are obtained from prior studies on predicting price crashes (Chen et al. 2001; Hutton et al. 2009; Kim et al. 2011a, b). I include book-to-market ratio (BTM_t) as a proxy for mispricing and past annual size-adjusted stock returns ($SARET_t$) as a proxy for information blockage.[18] In prior studies, BTM_t negatively predicts price crashes, while $SARET_t$ positively predicts price crashes. Share turnover ($TURN_t$) is included as a proxy for differences of opinion, which positively predicts price crashes in prior research. Controls for firm risk include firm size ($SIZE_t$) and book leverage (LEV_t). However, prior studies find $SIZE_t$ to be positively correlated with price crashes and LEV_t to be negatively correlated with price crashes. I also include idiosyncratic volatility ($IVOL_t$) to control for potential mechanical correlation between return volatility and price crashes. Finally, the lagged dependent variable, $VCRASH_t$ or $CRASH_t$, and return skewness ($SKEW_t$) are included to control for the persistence of the dependent variable.

In a few specifications of regression model (2), I also include variables that are important for documenting the incremental predictive power of accruals. I include free cash flows of the most recent 3 years (FCF_t, FCF_{t-1}, and FCF_{t-2}) to rule out the possibility that the ability of accruals to predict price crashes is due to the strong correlation between accruals and cash flows. I include other proxies for bad news hoarding from prior literature to isolate the incremental hidden bad news reflected in accruals: the long-run effective tax rate $LRETR_t$ (Kim et al. 2011b), CFO option incentive ratio $INCENTIVE_t$ (Kim et al. 2011a), transient institutional ownership TRA_t (Callen and Fang 2013), short interest SIR_t (Callen and Fang 2014), and sales growth $SALEGR_t$ (Bradshaw et al. 2010).[19]

4.2.2 Test of hypothesis H2

To test hypothesis *H2*, I decompose accruals into components with different levels of reliability and compare their associations with future price crashes. Richardson et al. (2005) provide a detailed categorization of accruals based on relative reliability. I follow their extended categorization to decompose accruals (ΔNOA) into four components: current operating asset accruals (ΔCOA), non-current operating asset accruals ($\Delta NCOA$), current operating liability accruals (Δ-COL), and non-current operating liability accruals (Δ-$NCOL$). Based on analysis of the nature of assets and liabilities underlying each accrual component, Richardson et al. (2005) predict that ΔCOA and $\Delta NCOA$ have low reliability, Δ-$NCOL$ has medium reliability, and Δ-COL has high reliability. The earnings persistence of these components is largely consistent this prediction. With this decomposition of accruals, I estimate the following regression model that links the probability of price

[18] Results remain quantitatively similar if I use returns of past three years instead of returns of the previous year in the regressions.

[19] Results remain quantitatively similar if I use the number of consecutive annual revenue increases over the previous three fiscal years (Bradshaw et al. 2010), instead of revenue growth over the previous year in the regressions.

crashes in year $t+1$, $VCRASH_{t+1}$ and $CRASH_{t+1}$, to accrual components of the most recent 3 years and a set of control variables:

$$\begin{aligned} VCRASH_{t+1} \text{ or } CRASH_{t+1} &= \alpha_0 + \sum_{k=0}^{2} \beta_{1,k} * \Delta COA_{t-k} + \sum_{k=0}^{2} \beta_{2,k} * \Delta\text{-}COL_{t-k} \\ &+ \sum_{k=0}^{2} \beta_{3,k} * \Delta NCOA_{t-k} + \sum_{k=0}^{2} \beta_{4,k} * \Delta\text{-}NCOL_{t-k} + \sum_{l=1}^{m} \theta_l * Control_{l,t} + \varepsilon_{t+1} \end{aligned} \tag{3}$$

Hypothesis *H2* predicts $\beta_{1,k}$ and $\beta_{3,k}$ to be the most positive (or the least negative) and $\beta_{2,k}$ to be the least positive (or the most negative) among coefficients on accrual components.

4.2.3 Test of hypotheses H3a and H3b

To test hypotheses *H3a* and *H3b*, I construct proxies for the hypothesized determinants of the cross-sectional variation in the association between accruals and price crashes, and then I examine the interactions between these proxies and accruals in forecasting future price crashes.

I use the CFO's option incentive ratio (*INCENTIVE*) to measure CFO's incentive to hide bad news. Jiang et al. (2010) and Chava and Purnanandam (2010) show that the incentive ratio for CFO stock and option holdings is positively associated with earnings management. Kim et al. (2011a) show that, when CFOs have a larger option incentive ratio, they are more likely to hide bad news; this finding is consistent with Benmelech et al.'s (2010) theoretical prediction.

Benmelech et al. (2010) also conjecture that it is more difficult for investors to distinguish between an increase in economic capital and the hoarding of bad news among firms in industries characterized by high R&D expenditures and intellectual property and firms that are rapidly growing. Following this logic, I use the dummy variable *HIGHTECH*, which equals one if a firm belongs to a high-tech industry, and sales growth (*SALEGR*) to proxy the difficulty of unravelling hidden bad news.

Stronger external monitoring should more effectively constrain managers' opportunistic use of accruals to conceal bad news. I consider three monitoring mechanisms: dedicated and transient institutional holding (*DED* and *TRA,* respectively), analyst following (*ANCOV*), and auditor tenure (*TENURE*). Callen and Fang (2013) show that dedicated institutional ownership is negatively associated with future price crashes, while transient institutional ownership is positively associated; this suggests that dedicated institutional investors reduce bad news hoarding, and transient institutional investors encourage it.[20] Using multiple measures of earnings management, Yu (2008) finds that firms with a higher analyst following manage their earnings less, suggesting that analyst following may constrain bad news hoarding. Geiger and Raghunandan (2002) and Carcello and Nagy (2004) document significantly more audit reporting failures and fraudulent financial reports in earlier

[20] Bushee (1998, 2001) classifies institutional investors into three groups—dedicated, quasi-indexer, and transient institutions—based on their past investment behavior.

years of an auditor/client relationship than when auditors have served the same clients for longer tenures. Their findings suggest that longer audit tenure facilitates better understanding of clients' business and critical issues by auditors, and consequently leaves fewer opportunities for managers to hide bad news.

Turning to default risk, I consider three alternative measures of default risk: Altman's (1968) Z score (*ALTMAN*), Shumway's (2001) bankruptcy score (*SHUMWAY*), and Vassalou and Xing's (2004) default probability (*DEFPROB*). These variables have been shown to predict bankruptcies. Specifically, firms with a lower *ALTMAN*, a higher *SHUMWAY*, or a higher *DEFPROB* are more likely to go bankrupt.

With the above proxies, I estimate the following regression model that links the probability of price crashes in year $t+1$, $VCRASH_{t+1}$ and $CRASH_{t+1}$, to the interactions between accruals and these proxies:

$$\begin{aligned} VCRASH_{t+1} \text{ or } CRASH_{t+1} &= \alpha_0 + \sum_{k=0}^{2} \beta_k * \Delta NOA_{t-k} \\ &+ \sum_{k=0}^{2} \gamma_k * X_{t-k} + \sum_{k=0}^{2} \delta_k * \Delta NOA_{t-k} * X_{t-k} + \sum_{l=1}^{m} \theta_l * Control_{l,t} + \varepsilon_{t+1} \end{aligned} \tag{4}$$

where X is defined as *INCENTIVE*, *HIGHTECH*, *SALEGR*, *DED*, *TRA*, *ANCOV*, *TENURE*, *ALTMAN, SHUMWAY*, or *DEFPROB*.

Hypothesis *H3a* predicts δ_k to be positive for $INCENTIVE_{t-k}$, positive for $HIGHTECH_{t-k}$, positive for $SALEGR_{t-k}$, negative for DED_{t-k}, positive for TRA_{t-k}, negative for $ANCOV_{t-k}$, and negative for $TENURE_{t-k}$. Hypothesis *H3b* predicts δ_k to positive for $ALTMAN_{t-k}$, negative for $SHUMWAY_{t-k}$, and negative for $DEFPROB_{t-k}$.

4.2.4 Other design choices

To facilitate interpretation of the coefficients' economic magnitudes, I rank all non-indicator independent variables in regression models (2)–(4) into deciles of 0–9 and then divide their decile ranking by 9. Unless otherwise stated, regression results reported below are based on ranked independent variables. I use pooled OLS regression to estimate models predicting $VCRASH_{t+1}$ and pooled logistic regression to estimate models predicting $CRASH_{t+1}$. The significance levels of coefficient estimates are assessed using standard errors clustered by both firm and year (Petersen 2009; Gow et al. 2010). When estimating pooled regression models (2)–(4), I also include fixed industry effects and fixed year effects, where industries are defined as Fama and French 48 industries (Fama and French 1997).

4.3 Sample selection

My main sample consists of non-financial (SIC codes 6000–6999), non-utility (SIC codes 4900–4999) firms with non-missing values for price crashes of both the current year and the next year, accruals of the most recent 3 years, firm size, book-to-market ratio, leverage, size-adjusted returns, idiosyncratic volatility, share turnover, and returns skewness. These variables are required to estimate regression model (2). I also require an average share price of at least $2.5 for the 12 months starting from the fifth month of fiscal year t (Hutton et al. 2009). The final sample includes 108,184 firm-year observations for fiscal years between 1965 and 2013.

Table 1 presents the descriptive statistics and correlations for my key variables. The sample mean of $VCRASH_{t+1}$ is 2.485, suggesting that the magnitude of the worst weekly return is 2.485 times the standard deviation below the mean for that firm-year. The sample mean of $CRASH_{t+1}$ is 15.9 %, which is significantly higher than the 5.1 % frequency of crashes generated by a normal distribution.[21] The mean value decreases from 8.2 % for ΔNOA_{t-2} to 6.5 % for ΔNOA_t, suggesting a slowing expansion in net operating assets for the average firm in my sample. The distributions of other variables are similar to those obtained in prior studies (Kim et al. 2011a, b). Panel B of Table 1 reports pair-wise correlations for the key variables. Consistent with the hoarding of bad news, ΔNOA_t is significantly positively correlated with both $VCRASH_{t+1}$ and $CRASH_{t+1}$, and ΔNOA_{t-1} is significantly positively correlated with $VCRASH_{t+1}$. The correlations between price crash measures and other control variables are generally consistent with the findings in prior studies. For example, both $SARET_t$ and $TURN_t$ are positively correlated with price crashes (Chen et al. 2001; Hutton et al. 2009).

5 Empirical results

5.1 Examination of H1

Figure 1(1) and (2) depict strong positive correlations between accruals and measures of price crashes over the next year, consistent with the bad news hoarding explanation. Figure 1(1) presents the portfolio mean of $VCRASH_{t+1}$ by deciles of accruals for the past 3 years. For the lowest decile of ΔNOA_t, the magnitude of worst weekly return is 2.41 times the firm-specific standard deviation below the mean. This magnitude increases monotonically as the level of ΔNOA_t increases and reaches 2.51 times the standard deviation for the highest decile. The increase of $VCRASH_{t+1}$ across increasing levels of accruals with a slower pace is also observed for ΔNOA_{t-1} and ΔNOA_{t-2}. Figure 1(2) presents similar monotonic increases in $CRASH_{t+1}$ across increasing accruals portfolios. For example, 12.88 % of firms in the lowest decile of ΔNOA_t experience price crashes over the next year, and this probability increases to 17.27 % for the highest decile. Such an increase in price crash likelihood is economically meaningful.

Table 2 reports results from the estimation of regression model (2). In Panel A, I estimate OLS regressions predicting $VCRASH_{t+1}$. In almost all regression specifications (models M1–M7), accruals of the past 3 years (ΔNOA_t, ΔNOA_{t-1}, and

[21] Given my definition of a price crash, if firm-specific weekly returns were normally distributed, one would expect to observe 0.1 % of the sample firms crashing in any week. The probability of observing at least a price crash over the course of a year would then be 5.1 % = $1-(1 - 0.001)^{52}$.

Table 1 Descriptive statistics and correlations

Panel A: Descriptive statistics

	$VCRASH_{t+1}$	$CRASH_{t+1}$	ΔNOA_t	ΔNOA_{t-1}	ΔNOA_{t-2}	BTM_t	$SARET_t$	$TURN_t$	$SIZE_t$	LEV_t	$IVOL_t$	$SKEW_t$
MEAN	2.485	0.159	0.065	0.076	0.082	0.736	0.010	0.729	5.149	0.475	0.055	0.174
MEDIAN	2.330	0.000	0.045	0.050	0.054	0.569	−0.061	0.429	5.015	0.475	0.049	0.189
STD	0.719	0.365	0.175	0.182	0.192	0.660	0.536	0.867	2.047	0.219	0.029	0.783

Panel B: Correlations*

	$VCRASH_{t+1}$	$CRASH_{t+1}$	ΔNOA_t	ΔNOA_{t-1}	ΔNOA_{t-2}	BTM_t	$SARET_t$	$TURN_t$	$SIZE_t$	LEV_t	$IVOL_t$	$SKEW_t$
$VCRASH_{t+1}$		0.63	0.03	0.01	0.01	−0.09	0.05	0.11	0.10	−0.01	0.02	−0.06
$CRASH_{t+1}$	0.78		0.03	0.01	*0.00*	−0.07	0.03	0.10	0.08	−0.01	0.02	−0.04
ΔNOA_t	0.03	0.02		0.17	0.08	−0.09	0.02	0.06	0.06	−0.06	−0.04	−0.04
ΔNOA_{t-1}	0.01	*0.00*	0.23		0.20	−0.02	−0.09	0.04	0.01	−0.02	0.06	−0.06
ΔNOA_{t-2}	*0.00*	*0.00*	0.11	0.25		−0.01	−0.04	0.02	−0.01	−0.01	0.09	−0.03
BTM_t	−0.10	−0.09	−0.11	−0.04	−0.01		−0.27	−0.20	−0.40	−0.05	0.03	0.01
$SARET_t$	0.05	0.03	0.01	−0.10	−0.05	−0.31		0.10	0.17	−0.01	−0.01	0.21
$TURN_t$	0.11	0.11	0.05	0.03	0.01	−0.34	0.05		0.39	0.03	0.18	−0.13
$SIZE_t$	0.12	0.09	0.07	0.01	−0.01	−0.42	0.23	0.47		0.05	−0.40	−0.17
LEV_t	−0.02	−0.02	−0.06	−0.03	−0.02	−0.02	−0.01	0.04	0.04		*0.00*	0.02
$IVOL_t$	*0.00*	0.02	−0.04	0.05	0.08	−0.02	−0.16	0.17	−0.45	−0.04		0.02
$SKEW_t$	−0.06	−0.04	−0.05	−0.06	−0.03	0.02	0.22	−0.14	−0.20	0.02	0.08	

* Correlation coefficient in *Italics* has a p value larger than 0.10

This table presents descriptive statistics and pair−wise correlations for measures of weekly price crash probability over the next year, accruals of the most recent 3 years, and other control variables of the current year. The sample contains 108,184 firm-year observations from 1965 to 2013. Mean (MEAN), median (MEDIAN), and standard deviation (STD) are reported in Panel A. Pearson correlation coefficients are reported above the diagonal in Panel B, and Spearman correlation coefficients are reported below the diagonal. All variables are defined in the "Appendix"

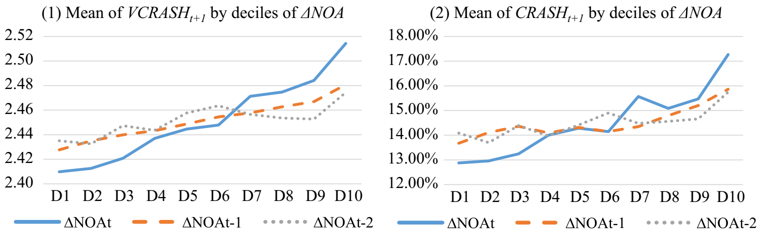


Fig. 1 Likelihood of weekly price crashes over the next year, by deciles of accruals. The following figures plot the time-series average of the annual mean value of $VCRASH_{t+1}$ and $CRASH_{t+1}$ by deciles of accruals of the most recent 3 years (ΔNOA_t, ΔNOA_{t-1}, and ΔNOA_{t-2}). $VCRASH_{t+1}$ represents the number of standard deviations by which the worst firm-specific weekly return over the next year falls below its mean, and $CRASH_{t+1}$ represents the incidence of weekly returns that are more than 3.09 times the standard deviation below its mean over the next year. The sample is ranked into 10 deciles of accruals each year, with decile D1 (D10) representing the lowest (highest) accruals decile. The annual mean value of $VCRASH_{t+1}$ ($CRASH_{t+1}$) is obtained by taking the average of $VCRASH_{t+1}$ ($CRASH_{t+1}$) for each decile of accruals. The sample includes 108,184 firm-year observations for fiscal years between 1965 and 2013. Variables are defined in the "Appendix"

ΔNOA_{t-2}) are significantly positively associated with $VCRASH_{t+1}$ after controlling for other price crash predictors used in prior studies. The sum of coefficients on ΔNOA_t, ΔNOA_{t-1}, and ΔNOA_{t-2} is approximately 0.12 in these regressions, suggesting that the magnitude of worst weekly return increases by 0.12 times the standard deviation when accruals of the past 3 years all increase from the lowest to the highest decile. Moreover, the coefficient and associated *t*-statistic on accruals are among the largest in magnitude in these regressions.[22] Model M1 of Panel A also indicates an attenuation of the association between accruals and $VCRASH_{t+1}$ as the temporal distance between the two increases. The coefficient on accruals decreases from 0.077 (with a *t*-statistic of 8.63) for ΔNOA_t to 0.017 (with a *t*-statistic of 2.00) for ΔNOA_{t-2}, suggesting that accruals in the most recent year best predict future price crashes. This finding also implies that the hidden bad news reflected in accruals is released at a decreasing speed over the next 3 years. In Panel B, I estimate logistic regressions predicting $CRASH_{t+1}$. In almost all regression specifications, accruals of the past 3 years are significantly positively associated with $CRASH_{t+1}$.

The coefficients on control variables in model M1 of Table 2 are, for the most part, consistent with those in prior literature. As $CRASH_{t+1}$ is a more widely used crash risk measure, I focus on the results in Panel B. BTM_t is negatively correlated with $CRASH_{t+1}$, and $SARET_t$ and $TURN_t$ are positively correlated with $CRASH_{t+1}$. These results resemble the findings of Hutton et al. (2009) and Kim et al. (2011a, b). Unlike them, however, I do not observe a significant coefficient on $SIZE_t$ or LEV_t in model M1. I also find $IVOL_t$ to be uncorrelated with $CRASH_{t+1}$, which is consistent with the finding by Callen and Fang (2013) but differs from the positive correlation documented by Kim et al. (2011a, b).

[22] The magnitude of the regression coefficient is comparable across independent variables because all non-indicator independent variables are ranked into deciles and then scaled between 0 and 1.

Table 2 The impact of accruals on price crashes over the next year

Panel A: OLS regression predicting $VCRASH_{t+1}$

Variable	STAT	M1	M2 X = *FCF*	M3 X = *LRETR*	M4 X = *INCENTIVE*	M5 X = *TRA*	M6 X = *SIR*	M7 X = *SALEGR*
Intercept	Est	2.270	2.290	2.220	2.524	2.203	2.243	2.261
	T	*78.96*	*53.43*	*61.43*	*35.59*	*69.52*	*68.58*	*78.40*
ΔNOA_t	Est	0.077	0.066	0.097	0.088	0.081	0.077	0.066
	T	*8.63*	*3.70*	*6.83*	*2.72*	*7.59*	*5.21*	*6.90*
ΔNOA_{t-1}	Est	0.025	0.029	0.037	0.036	0.030	0.021	0.022
	T	*3.12*	*1.84*	*3.49*	*1.93*	*3.30*	*1.51*	*2.59*
ΔNOA_{t-2}	Est	0.017	0.010	0.025	0.039	0.023	0.038	0.017
	T	*2.00*	*0.74*	*1.90*	*1.88*	*2.35*	*2.73*	*2.06*
BTM_t	Est	−0.074	−0.075	−0.091	−0.082	−0.090	−0.078	−0.068
	T	*−7.77*	*−7.51*	*−7.38*	*−3.09*	*−8.04*	*−4.53*	*−7.19*
$SARET_t$	Est	0.083	0.084	0.099	0.079	0.091	0.060	0.078
	T	*6.85*	*7.06*	*5.59*	*2.59*	*6.86*	*3.29*	*6.54*
$TURN_t$	Est	0.052	0.052	0.126	0.195	0.034	0.097	0.049
	T	*3.89*	*3.94*	*7.81*	*4.63*	*2.46*	*5.39*	*3.76*
$SIZE_t$	Est	0.050	0.051	0.029	−0.016	−0.025	0.022	0.052
	T	*2.28*	*2.35*	*1.11*	*−0.28*	*−1.10*	*0.83*	*2.35*
LEV_t	Est	−0.009	−0.012	−0.017	−0.067	−0.002	−0.031	−0.009
	T	*−0.98*	*−1.28*	*−1.13*	*−1.93*	*−0.21*	*−2.35*	*−1.00*
$IVOL_t$	Est	−0.022	−0.026	0.008	0.021	0.011	0.027	−0.025
	T	*−1.26*	*−1.40*	*0.33*	*0.58*	*0.57*	*1.69*	*−1.43*
$SKEW_t$	Est	−0.015	−0.015	−0.007	0.061	0.002	−0.014	−0.015
	T	*−1.51*	*−1.51*	*−0.45*	*2.50*	*0.19*	*−0.69*	*−1.53*

Table 2 continued

Panel A: OLS regression predicting $VCRASH_{t+1}$

Variable	STAT	M1	M2 $X = FCF$	M3 $X = LRETR$	M4 $X = INCENTIVE$	M5 $X = TRA$	M6 $X = SIR$	M7 $X = SALEGR$
$VCRASH_t$	Est	0.070	0.070	0.063	0.120	0.080	0.062	0.069
	T	*7.32*	*7.43*	*5.25*	*6.00*	*8.11*	*4.09*	*7.18*
X_t	Est		−0.015	0.007	−0.035	0.101	0.037	0.031
	T		*−0.87*	*0.65*	*−1.44*	*6.25*	*2.01*	*3.38*
X_{t-1}	Est		0.004					
	T		*0.23*					
X_{t-2}	Est		−0.009					
	T		*−0.69*					
DED_t	Est					0.015		
	T					*1.76*		
QIX_t	Est					0.039		
	T					*2.57*		
# Obs.		108,184	108,184	57,167	14,240	84,975	42,215	107,382
Adj. RSQ		5.05 %	5.05 %	3.41 %	3.05 %	3.75 %	4.62 %	5.06 %

Panel B: Logistic regression predicting $CRASH_{t+1}$

Variable	STAT	M1	M2 $X = FCF$	M3 $X = LRETR$	M4 $X = INCENTIVE$	M5 $X = TRA$	M6 $X = SIR$	M7 $X = SALEGR$
Intercept	Est	−2.257	−2.223	−2.020	−1.664	−2.146	−2.237	−2.289
	Z	*−26.25*	*−18.74*	*−20.41*	*−10.77*	*−22.23*	*−24.31*	*−26.62*
ΔNOA_t	Est	0.257	0.234	0.279	0.194	0.251	0.243	0.211
	Z	*7.63*	*4.35*	*5.71*	*1.81*	*6.69*	*4.73*	*6.10*

Table 2 continued

Panel B: Logistic regression predicting $CRASH_{t+1}$								
Variable	STAT	M1	M2 $X = FCF$	M3 $X = LRETR$	M4 $X = INCENTIVE$	M5 $X = TRA$	M6 $X = SIR$	M7 $X = SALEGR$
ΔNOA_{t-1}	Est	0.079	0.101	0.121	0.131	0.101	0.055	0.061
	Z	*2.30*	*1.75*	*2.79*	*2.03*	*2.77*	*0.95*	*1.73*
ΔNOA_{t-2}	Est	0.061	0.039	0.095	0.132	0.066	0.131	0.061
	Z	*2.27*	*0.90*	*2.83*	*2.03*	*2.38*	*3.29*	*2.26*
BTM_t	Est	−0.231	−0.233	−0.253	−0.210	−0.278	−0.226	−0.209
	Z	*−7.29*	*−7.05*	*−6.87*	*−3.02*	*−8.10*	*−4.05*	*−6.52*
$SARET_t$	Est	0.267	0.271	0.286	0.127	0.283	0.173	0.250
	Z	*6.20*	*6.12*	*4.59*	*1.61*	*6.26*	*2.71*	*5.76*
$TURN_t$	Est	0.278	0.278	0.433	0.548	0.182	0.390	0.271
	Z	*5.72*	*5.73*	*7.91*	*4.16*	*3.62*	*6.48*	*5.59*
$SIZE_t$	Est	0.022	0.024	0.035	−0.138	−0.167	−0.050	0.022
	Z	*0.29*	*0.32*	*0.49*	*−0.78*	*−2.33*	*−0.62*	*0.29*
LEV_t	Est	0.002	−0.003	0.029	−0.146	0.021	−0.029	0.009
	Z	*0.07*	*−0.08*	*0.63*	*−1.66*	*0.62*	*−0.67*	*0.28*
$IVOL_t$	Est	−0.085	−0.093	0.005	0.043	0.030	0.036	−0.103
	Z	*−1.55*	*−1.54*	*0.09*	*0.36*	*0.52*	*0.65*	*−1.89*
$SKEW_t$	Est	−0.065	−0.065	−0.049	−0.045	−0.040	−0.101	−0.060
	Z	*−1.77*	*−1.77*	*−1.05*	*−0.52*	*−1.04*	*−2.49*	*−1.64*
$CRASH_t$	Est	0.163	0.164	0.122	0.078	0.149	0.103	0.168
	Z	*5.69*	*5.75*	*3.92*	*1.38*	*5.32*	*3.16*	*5.86*
X_t	Est		−0.031	0.015	−0.053	0.270	0.080	0.134
	Z		*−0.54*	*0.42*	*−0.60*	*5.42*	*1.29*	*3.86*

Table 2 continued

Panel B: Logistic regression predicting $CRASH_{t+1}$

Variable	STAT	M1	M2 $X = FCF$	M3 $X = LRETR$	M4 $X = INCENTIVE$	M5 $X = TRA$	M6 $X = SIR$	M7 $X = SALEGR$
X_{t-1}	Est		0.026					
	Z		*0.45*					
X_{t-2}	Est		−0.032					
	Z		*−0.62*					
DED_t	Est					0.041		
	Z					*1.25*		
QIX_t	Est					0.179		
	Z					*3.15*		
# Obs.		108,184	108,184	57,167	14,240	84,975	42,215	107,382
Pseudo RSQ		3.68 %	3.68 %	2.72 %	2.77 %	2.87 %	3.98 %	3.70 %

This table reports the OLS (logistic) regression results of models linking accruals of the most recent 3 years to price crashes over the next year. The *T*-statistics in OLS regressions (*Z*-statistics in logistic regressions) are based on standard errors clustered by both firm and year. Fixed industry effects and fixed year effects are included in all regressions. The largest sample contains 108,184 firm-year observations for the fiscal years from 1965 to 2013. All variables are defined in the "Appendix"

Model M2 of Table 2 compares accruals and free cash flows (*FCF*) in predicting price crashes over the next year. Desai et al. (2004) show that the ability of accruals to predict the next year's size-adjusted buy-and-hold returns is subsumed by cash flows. Their finding implies that the positive association between accruals and price crashes may be a simple manifestation of a negative association between cash flows and price crashes. In contrast, I find free cash flows to be uncorrelated with price crashes after controlling for accruals. Models M3–M7 present the associations between other proxies for bad news hoarding used in prior studies and price crashes. I confirm previous findings that TRA_t, SIR_t, and $SALEGR_t$ are positively associated with price crashes; however, in my sample, I do not find $LRETR_t$ or $INCENTIVE_t$ to be significantly associated with crashes.

In summary, Fig. 1 and Table 2 document a robust positive association between *total* accruals and subsequent price crashes, which is consistent with the bad news hoarding explanation but inconsistent with the default risk explanation.

5.2 Examination of H2

Table 3 presents univariate statistics and pair-wise correlations for accrual components used to test hypothesis *H2*. Panel A of Table 3 shows that ΔCOA_t and $\Delta NCOA_t$ have positive means and $\Delta\text{-}COL_t$ and $\Delta\text{-}NCOL_t$ have negative means, suggesting that the average firm is growing in both operating assets and operating liabilities. Both the means and standard deviations of these accrual components in my sample are comparable to those reported by Richardson et al. (2005). Panel B reports the pair-wise correlations for the accrual decomposition. These correlations reveal several regularities. First, ΔCOA_t and $\Delta NCOA_t$ are strongly positively correlated with $\Delta\text{-}COL_t$ and $\Delta\text{-}NCOL_t$, implying that operating liabilities provide one source of funding for operating assets growth. This also highlights the importance of including all four components simultaneously in the regression when examining their abilities to predict price crashes. Second, ΔCOA_t and $\Delta NCOA_t$ have comparable correlations with ΔOA_t, suggesting that both current and non-current operating assets contribute to the variation in *total* operating asset accruals. In contrast, $\Delta\text{-}COL_t$ is more correlated with $\Delta\text{-}OL_t$ than $\Delta\text{-}NCOL_t$, suggesting that current operating liabilities explain more of the variation in *total* operating liability accruals. Third, ΔCOA_t is much more correlated with ΔWC_t than $\Delta\text{-}COL_t$, implying that most of the variation in ΔWC_t is attributable to ΔCOA_t. Similarly, most of the variation in ΔNCO_t is attributable to $\Delta NCOA_t$.

Figure 2 presents the portfolio mean of $VCRASH_{t+1}$ or $CRASH_{t+1}$ by deciles of each accrual component for the past 3 years. These figures reveal a wide range of variation across accrual components in their associations with price crashes. The likelihood of a price crash increases monotonically across increasing portfolios of ΔCOA and $\Delta NCOA$, does not change much with $\Delta\text{-}NCOL$, and decreases monotonically as the level of $\Delta\text{-}COL$ increases. The negative association between $\Delta\text{-}COL$ and price crashes is consistent with the default risk explanation but may also be driven by the positive association between ΔCOA and price crashes, given the strong negative correlation between ΔCOA and $\Delta\text{-}COL$.

Panel A of Table 4 presents results for the estimation of model (3), which includes all four accrual components simultaneously and assumes linear relations

Table 3 Descriptive statistics and correlations of accrual components

Panel A: Descriptive statistics

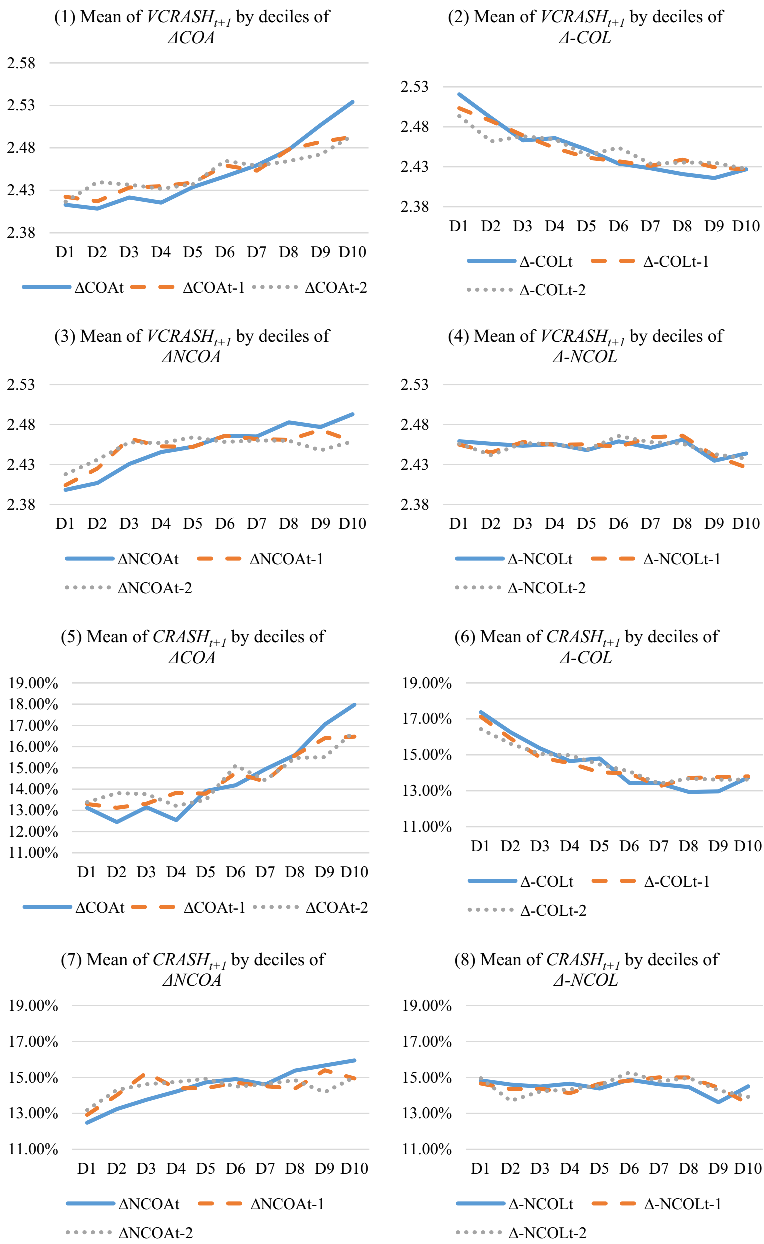
Variable	$VCRASH_{t+1}$	$CRASH_{t+1}$	ΔCOA_t	$\Delta\text{-}COL_t$	$\Delta NCOA_t$	$\Delta\text{-}NCOL_t$	ΔOA_t	$\Delta\text{-}OL_t$	ΔWC_t	ΔNCO_t	ΔNOA_t
MEAN	2.485	0.159	0.038	−0.022	0.052	−0.004	0.090	-0.026	0.016	0.049	0.065
MEDIAN	2.330	0.000	0.025	−0.015	0.025	0.000	0.064	−0.018	0.011	0.023	0.045
STD	0.719	0.365	0.102	0.063	0.141	0.023	0.201	0.072	0.083	0.142	0.175

Panel B: Correlations*

	$VCRASH_{t+1}$	$CRASH_{t+1}$	ΔCOA_t	$\Delta\text{-}COL_t$	$\Delta NCOA_t$	$\Delta\text{-}NCOL_t$	ΔOA_t	$\Delta\text{-}OL_t$	ΔWC_t	ΔNCO_t	ΔNOA_t
$VCRASH_{t+1}$		0.63	0.03	−0.04	0.04	−0.02	0.04	−0.04	0.01	0.03	0.03
$CRASH_{t+1}$	0.78		0.03	−0.03	0.03	−0.02	0.04	−0.03	0.01	0.03	0.03
ΔCOA_t	0.03	0.03		−0.59	0.29	-0.05	0.73	−0.54	0.77	0.28	0.61
$\Delta\text{-}COL_t$	−0.03	−0.03	−0.56		−0.32	0.09	−0.53	0.91	0.04	−0.30	-0.22
$\Delta NCOA_t$	0.03	0.02	0.35	−0.33		−0.16	0.86	−0.34	0.17	0.97	0.84
$\Delta\text{-}NCOL_t$	−0.02	−0.01	−0.07	0.09	−0.17		−0.14	0.45	−0.01	0.05	0.04
ΔOA_t	0.04	0.03	0.77	−0.53	0.82	−0.14		−0.52	0.50	0.79	0.92
$\Delta\text{-}OL_t$	−0.04	−0.03	−0.53	0.93	−0.34	0.31	−0.52		0.03	−0.26	−0.17
ΔWC_t	0.02	0.01	0.72	0.04	0.11	0.00	0.48	0.04		0.11	0.58
ΔNCO_t	0.03	0.02	0.34	−0.31	0.96	−0.01	0.83	−0.23	0.17		0.87
ΔNOA_t	0.03	0.02	0.64	−0.22	0.78	−0.02	0.90	−0.19	0.63	0.81	

* Correlation coefficient in *Italics* has a p value larger than 0.10

This table presents descriptive statistics and pair-wise correlations for measures of the weekly price crash probability over the next year and accrual components of the current year. The sample contains 108,184 firm-year observations from 1965 to 2013. Mean (MEAN), median (MEDIAN), and standard deviation (STD) are reported in Panel A. Pearson correlation coefficients are reported above the diagonal in Panel B, and Spearman correlation coefficients are reported below the diagonal. All variables are defined in the "Appendix"



between these components and price crashes. The coefficients on ΔCOA of the most recent 3 years (ΔCOA_t, ΔCOA_{t-1}, and ΔCOA_{t-2}) are significantly positive in models predicting $VCRASH_{t+1}$ and $CRASH_{t+1}$ and consistent with the prediction of bad news hoarding. These coefficients are higher than those on the other three accrual components of the same year. Also consistent with the bad news hoarding explanation is the significantly positive coefficient on the current year's $\Delta NCOA$

◀ **Fig. 2** Likelihood of weekly price crashes over the next year, by deciles of accrual components. The following figures plot the time-series average of annual mean value of $VCRASH_{t+1}$ and $CRASH_{t+1}$ by deciles of each accrual component of the most recent 3 years. $VCRASH_{t+1}$ represents the number of standard deviations by which the worst firm-specific weekly return over the next year falls below its mean, and $CRASH_{t+1}$ represents the incidence of weekly returns that are more than 3.09 times the standard deviation below its mean over the next year. The four accrual components are current operating asset accruals (ΔCOA), current operating liability accruals (Δ-COL), non-current operating asset accruals ($\Delta NCOA$), and non-current operating liability accruals (Δ-$NCOL$). The sample is ranked into 10 deciles of each accrual component each year, with decile D1 (D10) representing the lowest (highest) decile. The annual mean value of $VCRASH_{t+1}$ ($CRASH_{t+1}$) is obtained by taking the average of $VCRASH_{t+1}$ ($CRASH_{t+1}$) for each decile of accrual component. The sample includes 108,184 firm-year observations for fiscal years between 1965 and 2013. Variables are defined in the "Appendix"

($\Delta NCOA_t$). However, $\Delta NCOA$ of earlier years ($\Delta NCOA_{t-1}$ and ΔCOA_{t-2}) do not appear to predict future price crashes. Turning to liability accruals, none of Δ-$NCOL_t$, Δ-$NCOL_{t-1}$, and Δ-$NCOL_{t-2}$ is significantly related to price crashes. Interestingly, coefficients on Δ-COL of the most recent 3 years (Δ-COL_t, Δ-COL_{t-1}, and Δ-COL_{t-2}) are generally significantly negative. These negative associations are consistent with the default risk explanation that firms with large increases of current operating liabilities have higher default risk and subsequently experience more crashes.

Further inspection of Fig. 2 indicates potential nonlinearities in the associations between accrual components and price crashes. As a result, I modify regression model (3) by allowing the coefficients on accrual components to differ between the top and bottom five deciles. Panel B of Table 4 presents results for this modified regression model. Consistent with the observation from Fig. 2, ΔCOA and Δ-COL are associated with price crashes in a nonlinear fashion. More precisely, the positive association between ΔCOA and price crashes is only present in the top five deciles of ΔCOA (i.e., $HIGH\_\Delta COA = 1$). None of ΔCOA_t, ΔCOA_{t-1}, and ΔCOA_{t-2} is significantly associated with $VCRASH_{t+1}$ when below the cross-sectional median, while ΔCOA_t and ΔCOA_{t-2} are significantly positively associated with $VCRASH_{t+1}$ when above the median.[23] In contrast, the negative association between Δ-COL and price crashes is only present in the bottom five deciles of Δ-COL. For example, Δ-COL_t and Δ-COL_{t-1} are significantly negatively associated with $VCRASH_{t+1}$ when below the median, while none of Δ-COL_t, Δ-COL_{t-1}, and Δ-COL_{t-2} is significantly associated with $VCRASH_{t+1}$ when above the median.[24] These nonlinearities suggest that current operating asset (liability) accruals may be associated with hidden bad news (default risk) in nonlinear fashions. Unlike these two components, Panel B of Table 4 does not provide robust nonlinearities in the associations between non-current operating asset and liability accruals and future price crashes.

Overall, the results in Table 4 provide evidence consistent with hypothesis *H2* that a less reliable accrual component is more positively associated with price

[23] The t-statistic for the coefficient 0.137 (= 0.156 − 0.019) on ΔCOA_t when it is above the median is 6.08, t-statistic for the coefficient 0.016 (= 0.019 − 0.003) on ΔCOA_{t-1} when it is above the median is 0.64, and t-statistic for the coefficient 0.042 (= 0.058 − 0.016) on ΔCOA_{t-2} when it is above the median is 1.95.

[24] The t-statistic for the coefficient 0.019 (= 0.052 − 0.033) on Δ-COL_t when it is above the median is 0.80, t-statistic for the coefficient 0.025 (= 0.124 − 0.099) on Δ-COL_{t-1} when it is above the median is 1.32, and t-statistic for the coefficient −0.007 (= 0.019 − 0.026) on Δ-COL_{t-2} when it is above the median is −0.35.

Table 4 The impact of accrual components on price crashes over the next year

Panel A: Assume linear relations between accrual components and price crashes

Variable	$VCRASH_{t+1}$		$CRASH_{t+1}$	
	Est	T	Est	Z
ΔCOA_t	0.060	*5.71*	0.220	*4.95*
$\Delta\text{-}COL_t$	−0.019	*−2.29*	−0.066	*−2.21*
$\Delta NCOA_t$	0.039	*4.26*	0.097	*2.83*
$\Delta\text{-}NCOL_t$	0.012	*1.59*	0.021	*0.62*
ΔCOA_{t-1}	0.025	*2.65*	0.110	*3.02*
$\Delta\text{-}COL_{t-1}$	−0.027	*−2.81*	−0.079	*−2.66*
$\Delta NCOA_{t-1}$	0.002	*0.17*	−0.013	*−0.34*
$\Delta\text{-}NCOL_{t-1}$	0.004	*0.62*	0.024	*0.89*
ΔCOA_{t-2}	0.028	*3.15*	0.073	*2.22*
$\Delta\text{-}COL_{t-2}$	−0.013	*−1.43*	−0.079	*−2.01*
$\Delta NCOA_{t-2}$	−0.007	*−0.76*	−0.008	*−0.21*
$\Delta\text{-}NCOL_{t-2}$	0.003	*0.51*	0.035	*1.59*
# Obs.	108,184		108,184	
Adj. (Pseudo) RSQ	5.15 %		3.78 %	

Panel B: Assume nonlinear relations between accrual components and price crashes

Variable	$VCRASH_{t+1}$		$CRASH_{t+1}$	
	Est	T	Est	Z
ΔCOA_t	−0.019	*−0.79*	0.056	*0.59*
ΔCOA_t * $HIGH\_\Delta COA_t$	0.156	*5.01*	0.323	*2.91*
$\Delta\text{-}COL_t$	−0.033	*−1.67*	−0.017	*−0.21*
$\Delta\text{-}COL_t$ * $HIGH\_\Delta\text{-}COL_t$	0.052	*1.62*	0.088	*0.77*
$\Delta NCOA_t$	0.037	*1.75*	0.177	*2.13*
$\Delta NCOA_t$ * $HIGH\_\Delta NCOA_t$	0.021	*0.76*	−0.029	*−0.28*
$\Delta\text{-}NCOL_t$	−0.025	*−1.13*	−0.109	*−1.51*
$\Delta\text{-}NCOL_t$ * $HIGH\_\Delta\text{-}NCOL_t$	0.078	*1.99*	0.301	*2.37*
ΔCOA_{t-1}	−0.003	*−0.13*	0.089	*0.98*
ΔCOA_{t-1} * $HIGH\_\Delta COA_{t-1}$	0.019	*0.62*	−0.018	*−0.16*
$\Delta\text{-}COL_{t-1}$	−0.099	*−3.58*	−0.288	*−2.96*
$\Delta\text{-}COL_{t-1}$ * $HIGH\_\Delta\text{-}COL_{t-1}$	0.124	*3.76*	0.338	*2.81*
$\Delta NCOA_{t-1}$	0.006	*0.23*	−0.058	*−0.63*
$\Delta NCOA_{t-1}$ * $HIGH\_\Delta NCOA_{t-1}$	0.012	*0.34*	0.196	*1.44*
$\Delta\text{-}NCOL_{t-1}$	0.026	*1.10*	−0.004	*−0.03*
$\Delta\text{-}NCOL_{t-1}$ * $HIGH\_\Delta\text{-}NCOL_{t-1}$	−0.068	*−1.72*	−0.074	*−0.45*
ΔCOA_{t-2}	−0.016	*−0.74*	−0.077	*−0.89*
ΔCOA_{t-2} * $HIGH\_\Delta COA_{t-2}$	0.058	*1.70*	0.190	*1.60*
$\Delta\text{-}COL_{t-2}$	−0.026	*−0.98*	−0.042	*−0.50*
$\Delta\text{-}COL_{t-2}$ * $HIGH\_\Delta\text{-}COL_{t-2}$	0.019	*0.56*	0.016	*0.14*

Table 4 continued

Panel B: Assume nonlinear relations between accrual components and price crashes

Variable	$VCRASH_{t+1}$		$CRASH_{t+1}$	
	Est	T	Est	Z
$\Delta NCOA_{t-2}$	0.023	*1.02*	0.104	*1.27*
$\Delta NCOA_{t-2}$ * $HIGH\_\Delta NCOA_{t-2}$	−0.005	*−0.18*	−0.026	*−0.20*
$\Delta\text{-}NCOL_{t-2}$	−0.005	*−0.19*	0.004	*0.04*
$\Delta\text{-}NCOL_{t-2}$ * $HIGH\_\Delta\text{-}NCOL_{t-2}$	−0.017	*−0.42*	−0.088	*−0.59*
# Obs.	108,184		108,184	
Adj. (Pseudo) RSQ	5.22 %		3.82 %	

This table reports the OLS (logistic) regression results of models linking accrual components of the most recent 3 years to price crashes over the next year. The *T*-statistics in OLS regressions predicting $VCRASH_{t+1}$ (*Z*-statistics in logistic regressions predicting $CRASH_{t+1}$) are based on standard errors clustered by both firm and year. All regressions include the following control variables: BTM_t, $SARET_t$, $TURN_t$, $SIZE_t$, LEV_t, $IVOL_t$, lag dependent variable $VCRASH_t$ or $CRASH_t$, and $SKEW_t$. Regression models in Panel B also include the following main effects of interaction variables: $HIGH\_\Delta COA_t$, $HIGH\_\Delta\text{-}COL_t$, $HIGH\_\Delta NCOA_t$, $HIGH\_\Delta\text{-}NCOL_t$, $HIGH\_\Delta COA_{t-1}$, $HIGH\_\Delta\text{-}COL_{t-1}$, $HIGH\_\Delta NCOA_{t-1}$, $HIGH\_\Delta\text{-}NCOL_{t-1}$, $HIGH\_\Delta COA_{t-2}$, $HIGH\_\Delta\text{-}COL_{t-2}$, $HIGH\_\Delta NCOA_{t-2}$, and $HIGH\_\Delta\text{-}NCOL_{t-2}$. Interaction variable *HIGH_X* is a dummy variable that equals 1 if *X* is among the top five deciles and 0 otherwise. Fixed industry effects and fixed year effects are included in all regressions. The sample contains 108,184 firm-year observations for the fiscal years from 1965 to 2013. All variables are defined in the "Appendix"

crashes over the next year. This finding corroborates the bad news hoarding explanation for the positive association between *total* accruals and price crashes documented in Table 2.

5.3 Examination of H3a and H3b

Results in the previous section suggest that hidden bad news reflected in accruals is concentrated in the current and non-current operating asset components (*ΔCOA* and *ΔNCOA*), while default risk reflected in accruals, if any, is concentrated in the current operating liability component (*Δ-COL*). As a result, I test the prediction of the bad news hoarding explanation in hypothesis *H3a* with operating asset accruals ($\Delta OA = \Delta COA + \Delta NCOA$) and the prediction of the default risk explanation in hypothesis *H3b* with current operating liability accruals (*Δ-COL*).

5.3.1 Examination of H3a

Table 5 presents results from the estimation of regression model (4) modified by replacing *ΔNOA* with *ΔOA*.[25] In each regression specification, I also control for the interaction between operating asset accruals (*ΔOA*) and firm size (*SIZE*), as most of

[25] Results from the estimation of regression model (4), which is based on *ΔNOA*, lead to the same conclusions. These results are reported in Table A1 of the online appendix (https://business.illinois.edu/profile/wei-zhu/publications).

Table 5 Cross-sectional variations of the association between operating asset accruals and price crashes over the next year

Panel A: OLS regression predicting $VCRASH_{t+1}$

Variable	STAT	M1 X = *INCENTIVE*	M2 X = *HIGHTECH*	M3 X = *SALEGR*	M4 X = *TRA*	M5 X = *ANCOV*	M6 X = *TENURE*
$\Delta OA_t * X_t$	Est	0.238	0.045	0.098	0.096	0.079	−0.077
	T	*3.14*	*2.22*	*5.08*	*2.65*	*2.19*	*−2.77*
$\Delta OA_{t-1} * X_{t-1}$	Est	0.016	0.015	−0.008	0.059	0.004	−0.072
	T	*0.21*	*0.68*	*−0.34*	*1.72*	*0.12*	*−2.67*
$\Delta OA_{t-2} * X_{t-2}$	Est	−0.054	0.017	0.038	0.073	0.079	−0.039
	T	*−0.41*	*0.77*	*1.48*	*2.13*	*2.65*	*−1.77*
$\Delta OA_t * SIZE_t$	Est	−0.174	0.135	0.125	0.043	0.071	0.152
	T	*−1.59*	*4.62*	*4.17*	*0.98*	*1.81*	*4.81*
$\Delta OA_{t-1} * SIZE_{t-1}$	Est	−0.183	0.026	0.023	−0.001	0.016	0.043
	T	*−1.83*	*1.15*	*1.03*	*−0.04*	*0.58*	*1.81*
$\Delta OA_{t-2} * SIZE_{t-2}$	Est	−0.139	0.019	0.015	−0.009	−0.050	0.030
	T	*−0.92*	*0.86*	*0.64*	*−0.25*	*−1.41*	*1.26*
# Obs.		8653	102,859	101,747	76,953	86,242	102,643
Adj. RSQ		2.75 %	5.05 %	5.05 %	3.77 %	4.07 %	5.09 %

Panel B: Logistic regression predicting $CRASH_{t+1}$

Variable	STAT	M1 X = *INCENTIVE*	M2 X = *HIGHTECH*	M3 X = *SALEGR*	M4 X = *TRA*	M5 X = *ANCOV*	M6 X = *TENURE*
$\Delta OA_t * X_t$	Est	0.578	0.138	0.214	0.249	0.268	−0.268
	Z	*2.39*	*2.07*	*2.91*	*1.89*	*2.10*	*−2.86*
$\Delta OA_{t-1} * X_{t-1}$	Est	0.338	0.091	−0.055	0.184	0.043	−0.298
	Z	*1.28*	*1.06*	*−0.72*	*1.58*	*0.39*	*−2.96*
$\Delta OA_{t-2} * X_{t-2}$	Est	−0.368	0.000	0.096	0.061	0.248	−0.003

Table 5 continued

Panel B: Logistic regression predicting $CRASH_{t+1}$

Variable	STAT	M1 X = *INCENTIVE*	M2 X = *HIGHTECH*	M3 X = *SALEGR*	M4 X = *TRA*	M5 X = *ANCOV*	M6 X = *TENURE*
	Z	*−0.85*	*0.00*	*1.03*	*0.46*	*2.19*	*−0.03*
$\Delta OA_t * SIZE_t$	Est	−0.464	0.309	0.277	0.072	0.121	0.366
	Z	*−1.55*	*3.10*	*2.83*	*0.45*	*0.79*	*3.28*
$\Delta OA_{t-1} * SIZE_{t-1}$	Est	−0.761	0.126	0.117	0.046	0.065	0.189
	Z	*−2.26*	*1.40*	*1.27*	*0.32*	*0.58*	*1.95*
$\Delta OA_{t-2} * SIZE_{t-2}$	Est	−0.018	0.151	0.149	0.127	−0.072	0.151
	Z	*−0.04*	*1.40*	*1.33*	*0.79*	*−0.48*	*1.32*
# Obs.		8653	102,859	101,747	76,953	86,242	102,643
Adj. (Pseudo) RSQ		3.00 %	3.70 %	3.70 %	2.87 %	3.03 %	3.73 %

This table reports the OLS (logistic) regression results of models linking the interaction terms of operating asset accruals to price crashes over the next year. The *T*-statistics in OLS regressions predicting $VCRASH_{t+1}$ (*Z*-statistics in logistic regressions predicting $CRASH_{t+1}$) are based on standard errors clustered by both firm and year. All regression models include the following control variables: BTM_t, $SARET_t$, $TURN_t$, $SIZE_t$, LEV_t, $IVOL_t$, lag dependent variable $VCRASH_t$ or $CRASH_t$, $SKEW_t$, and the main effects of interaction terms. Model M4 also includes the control variables DED_t, DED_{t-1}, DED_{t-2}, $\Delta OA_t * DED_t$, $\Delta OA_{t-1} * DED_{t-1}$, $\Delta OA_{t-2} * DED_{t-2}$, QIX_t, QIX_{t-1}, QIX_{t-2}, $\Delta OA_t * QIX_t$, $\Delta OA_{t-1} * QIX_{t-1}$, $\Delta OA_{t-2} * QIX_{t-2}$. Fixed industry effects and fixed year effects are included in all regressions. The sample contains firm-year observations for the fiscal years from 1965 to 2013. All variables are defined in the "Appendix" the interaction variables are highly correlated with firm size (e.g., institutional holding and analyst following). Since results for the interaction terms in models predicting $CRASH_{t+1}$ are qualitatively similar to those in models predicting $VCRASH_{t+1}$, I focus on the results in Panel A.

Model M1 shows that the coefficient on $\Delta OA_t * INCENTIVE_t$ is positive and statistically significant (0.238 with a *t*-statistic of 3.14), consistent with the prediction of hypothesis *H3a* that managers are more likely to use aggressive accrual estimates when the incentive to hide bad news is stronger. The coefficient on $\Delta OA_t * HIGHTECH_t$ (0.045 with a *t*-statistic of 2.22) in model M2 and on $\Delta OA_t * SALEGR_t$ (0.098 with a *t*-statistic of 5.08) in model M3 are also significantly positive, suggesting that it is easier for managers to hide bad news using aggressive accrual estimates when it is more difficult for investors to distinguish between an increase in economic capital and bad news hoarding.

Models M4–M6 examine the impact of external monitoring on the association between ΔOA and $VCRASH_{t+1}$. Regarding institutional holdings, $\Delta OA * TRA$ of the past 3 years are all significantly positively associated with $VCRASH_{t+1}$. In contrast, neither $\Delta OA * DED$ nor $\Delta OA * QIX$ is significantly associated with $VCRASH_{t+1}$ in model M4.[26] These findings imply that transient institutional investors encourage the use of accruals in bad news hoarding and that dedicated institutional investors fail to constrain such opportunistic use of accruals. With regard to analyst following, model M5 shows that the positive association between ΔOA and $VCRASH_{t+1}$ is stronger instead of weaker when the firms are followed by more analysts, indicated by the positive coefficients on $\Delta OA_t * ANCOV_t$ and $\Delta OA_{t-2} * ANCOV_{t-2}$. One potential explanation is that, when analyst following is higher, managers are under greater pressure to meet or beat earnings targets and consequently more likely to hide bad news. Finally, consistent with my expectation, the positive association between ΔOA and $VCRASH_{t+1}$ is weaker when the auditor has a longer tenure with the firm, as indicated by the negative coefficients on $\Delta OA * TENURE$ of the past 3 years.

Overall, the findings in Table 5 are consistent with hypothesis *H3a*, supporting the bad news hoarding explanation with regard to the link between accruals and future price crashes.

5.3.2 Examination of H3b

Table 6 presents results from the estimation of regression model (4) modified by replacing ΔNOA with Δ-COL.[27] In each regression specification, I also control for the interaction between current operating liability accruals (Δ-COL) and firm size

[26] Coefficient estimates for $\Delta OA * DED$ and $\Delta OA * QIX$ are not tabulated in Table 5 for simplicity. These results are available upon request.

[27] Results from the estimation of regression model (4), which is based on ΔNOA, are reported in Table A2 of the online appendix (https://business.illinois.edu/profile/wei-zhu/publications). The coefficient before the interaction between ΔNOA and the proxy for default risk is largely insignificant. The only exceptions are the positive coefficient before $\Delta NOA_t * ALTMAN_t$ in predicting $VCRASH_{t+1}$ and the positive coefficient before $\Delta NOA_{t-2} * DEFPROB_{t-2}$ in predicting $CRASH_{t+1}$. While the former finding is consistent with *H3b*, the latter is not.

Table 6 Cross-sectional variations of the association between current operating liability accruals and price crashes over the next year

Panel A: OLS regression predicting $VCRASH_{t+1}$

Variable	M1 $X = ALTMAN$	M2 $X = SHUMWAY$	M3 $X = DEFPROB$	Variable	M4 $X = ALTMAN$	M5 $X = SHUMWAY$	M6 $X = DEFPROB$
$\Delta\text{-}COL_t * X_t$	−0.093	0.078	0.037	$D\Delta\text{-}COL_t * X_t$	−0.017	0.015	−0.010
	−4.16	*2.73*	*1.06*		*−0.73*	*0.52*	*−0.29*
				$ND\Delta\text{-}COL_t * X_t$	−0.146	0.099	0.038
					−5.69	*3.30*	*1.02*
$\Delta\text{-}COL_{t-1} * X_{t-1}$	−0.057	−0.001	0.007	$D\Delta\text{-}COL_{t-1} * X_{t-1}$	−0.003	−0.021	−0.024
	−1.95	*−0.03*	*0.13*		*−0.10*	*−0.66*	*−0.51*
				$ND\Delta\text{-}COL_{t-1} * X_{t-1}$	−0.058	0.065	0.042
					−1.80	*2.32*	*0.69*
$\Delta\text{-}COL_{t-2} * X_{t-2}$	0.025	0.046	−0.005	$D\Delta\text{-}COL_{t-2} * X_{t-2}$	0.061	0.006	−0.001
	0.87	*1.33*	*−0.13*		*2.23*	*0.17*	*−0.02*
				$ND\Delta\text{-}COL_{t-2} * X_{t-2}$	0.005	0.036	−0.070
					0.18	*1.11*	*−1.56*
$\Delta\text{-}COL_t * SIZE_t$	−0.051	−0.007	−0.085	$D\Delta\text{-}COL_t * SIZE_t$	0.003	0.014	0.005
	−1.94	*−0.25*	*−2.00*		*0.14*	*0.48*	*0.14*
				$ND\Delta\text{-}COL_t * SIZE_t$	−0.120	−0.059	−0.200
					−4.13	*−1.68*	*−4.14*
$\Delta\text{-}COL_{t-1} * SIZE_{t-1}$	−0.034	−0.041	−0.115	$D\Delta\text{-}COL_{t-1} * SIZE_{t-1}$	0.006	−0.013	−0.038
	−1.54	*−1.33*	*−3.43*		*0.29*	*−0.44*	*−0.94*
				$ND\Delta\text{-}COL_{t-1} * SIZE_{t-1}$	−0.009	0.024	−0.038
					−0.42	*0.96*	*−0.91*
$\Delta\text{-}COL_{t-2} * SIZE_{t-2}$	−0.024	0.006	−0.039	$D\Delta\text{-}COL_{t-2} * SIZE_{t-2}$	0.009	0.013	0.042
	−0.98	*0.15*	*−1.37*		*0.40*	*0.44*	*1.17*
				$ND\Delta\text{-}COL_{t-2} * SIZE_{t-2}$	−0.105	−0.072	−0.180

Table 6 continued

Panel A: OLS regression predicting $VCRASH_{t+1}$

Variable	M1 $X = ALTMAN$	M2 $X = SHUMWAY$	M3 $X = DEFPROB$	Variable	M4 $X = ALTMAN$	M5 $X = SHUMWAY$	M6 $X = DEFPROB$
					−3.89	*−2.18*	*−5.39*
# Obs.	93,552	93,538	35,397	# Obs.	92,571	92,559	35,093
Adj. RSQ	4.78 %	4.83 %	3.46 %	Adj. RSQ	4.87 %	4.87 %	3.62 %

Panel B: Logistic regression predicting $CRASH_{t+1}$

Variable	M1 $X = ALTMAN$	M2 $X = SHUMWAY$	M3 $X = DEFPROB$	Variable	M4 $X = ALTMAN$	M5 $X = SHUMWAY$	M6 $X = DEFPROB$
$\Delta\text{-}COL_t * X_t$	−0.203	0.183	0.096	$D\Delta\text{-}COL_t * X_t$	−0.003	0.004	−0.193
	−2.37	*1.54*	*0.60*		*−0.04*	*0.04*	*−1.12*
				$ND\Delta\text{-}COL_t * X_t$	−0.323	0.275	0.237
					−2.86	*2.19*	*1.31*
$\Delta\text{-}COL_{t-1} * X_{t-1}$	−0.207	−0.038	0.175	$D\Delta\text{-}COL_{t-1} * X_{t-1}$	−0.090	−0.125	0.155
	−2.23	*−0.32*	*0.83*		*−0.86*	*−0.96*	*0.76*
				$ND\Delta\text{-}COL_{t-1} * X_{t-1}$	−0.220	0.151	−0.083
					−1.93	*1.67*	*−0.31*
$\Delta\text{-}COL_{t-2} * X_{t-2}$	0.038	0.025	−0.055	$D\Delta\text{-}COL_{t-2} * X_{t-2}$	0.123	−0.110	0.012
	0.35	*0.20*	*−0.24*		*1.16*	*−0.85*	*0.06*
				$ND\Delta\text{-}COL_{t-2} * X_{t-2}$	0.119	0.074	−0.154
					1.45	*0.78*	*−0.73*
$\Delta\text{-}COL_t * SIZE_t$	−0.093	0.008	−0.323	$D\Delta\text{-}COL_t * SIZE_t$	0.043	0.050	−0.095
	−1.03	*0.07*	*−1.86*		*0.55*	*0.48*	*−0.76*
				$ND\Delta\text{-}COL_t * SIZE_t$	−0.271	−0.148	−0.543
					−2.62	*−1.08*	*−2.53*

Table 6 continued

Panel B: Logistic regression predicting $CRASH_{t+1}$

Variable	M1 X = *ALTMAN*	M2 X = *SHUMWAY*	M3 X = *DEFPROB*	Variable	M4 X = *ALTMAN*	M5 X = *SHUMWAY*	M6 X = *DEFPROB*
$\Delta\text{-}COL_{t-1} * SIZE_{t-1}$	−0.110	−0.190	−0.271	$D\Delta\text{-}COL_{t-1} * SIZE_{t-1}$	−0.039	−0.170	−0.113
	−1.17	*−1.58*	*−1.67*		*−0.43*	*−1.40*	*−0.58*
				$ND\Delta\text{-}COL_{t-1} * SIZE_{t-1}$	0.059	0.106	−0.041
					0.58	*1.04*	*−0.18*
$\Delta\text{-}COL_{t-2} * SIZE_{t-2}$	−0.102	−0.075	−0.132	$D\Delta\text{-}COL_{t-2} * SIZE_{t-2}$	−0.010	−0.075	0.136
	−1.03	*−0.58*	*−1.02*		*−0.10*	*−0.66*	*0.95*
				$ND\Delta\text{-}COL_{t-2} * SIZE_{t-2}$	−0.455	−0.342	−0.823
					−4.19	*−2.53*	*−4.98*
# Obs.	93,552	93,538	35,397	# Obs.	92,571	92,559	35,093
Pseudo RSQ	3.54 %	3.62 %	2.27 %	Pseudo RSQ	3.58 %	3.65 %	2.36 %

This table reports the OLS (logistic) regression results of models linking the interaction terms of current operating liability accruals to price crashes over the next year. The *T*-statistics in OLS regressions predicting $VCRASH_{t+1}$ (*Z*-statistics in logistic regressions predicting $CRASH_{t+1}$) are based on standard errors clustered by both firm and year. All regression models include the following control variables: BTM_t, $SARET_t$, $TURN_t$, $SIZE_t$, LEV_t, $IVOL_t$, lag dependent variable $VCRASH_t$ or $CRASH_t$, $SKEW_t$, and the main effects of interaction terms. Fixed industry effects and fixed year effects are included in all regressions. The sample contains firm-year observations for the fiscal years from 1965 to 2013. All variables are defined in the "Appendix"

(*SIZE*), because proxies for default risk are correlated with firm size and there may be a mechanical relationship between firm size and future price crashes. Since results for the interaction terms in models predicting $CRASH_{t+1}$ are qualitatively similar to those in models predicting $VCRASH_{t+1}$, I focus on the results in Panel A. The coefficient on Δ-COL_t * $ALTMAN_t$ (−0.093 with a *t*-statistic of −4.16) in model M1 is significantly negative and that on Δ-COL_t * $SHUMWAY_t$ (0.078 with a *t*-statistic of 2.73) in model M2 is significantly positive, suggesting that the negative association between Δ-COL_t and price crashes is weaker among firms of higher default risk. These findings are opposite to the prediction of hypothesis *H3b* that the association between accruals and price crashes is more negative for more distressed firms. Also inconsistent with *H3b*, none of the coefficients on *Δ-COL* * *DEFPROB* of the past 3 years is significant in model M3.

To explain the above puzzling results, I decompose *Δ-COL* into nondiscretionary and discretionary portions (*NDΔ-COL* and *DΔ-COL*, respectively). *NDΔ-COL* is proportional to sales growth, but *DΔ-COL* is independent of it. Model M4 (M5) shows that the negative (positive) coefficient on Δ-COL_t * $ALTMAN_t$ (Δ-COL_t * $SHUMWAY_t$) in model M1 (M2) is driven by $ND\Delta$-COL_t rather than $D\Delta$-COL_t. The negative coefficients on *NDΔ-COL* * *ALTMAN* in model M4 and the positive coefficients on *NDΔ-COL* * *SHUMWAY* in model M5 of the past 2 years essentially reflect a weaker positive association between sales growth and $VCRASH_{t+1}$ among firms with higher default risk.[28] This finding is consistent with the explanation that high sales growth is less associated with hidden bad news for more financially distressed firms but difficult to reconcile with the default risk explanation. Models M4 and M5 also show that the association between *DΔ-COL* and $VCRASH_{t+1}$ does not vary cross-sectionally with *ALTMAN* or *SHUMWAY*.

Overall, the results in Table 6 are inconsistent with the default risk explanation for the negative association between current operating liability accruals and future price crashes. As a result, neither bad news hoarding nor default risk seems to explain the link between current operating liability accruals and price crashes.[29]

[28] Recall from Table 2 that $SALEGR_t$ is positively associated with $VCRASH_{t+1}$. Untabulated results show that $SALEGR_t$ ($ND\Delta$-COL_t) is weakly positively (negatively) associated with $VCRASH_{t+1}$ even among firms with the highest level of default risk (i.e., the lowest decile of $ALTMAN_t$ or the highest decile of $SHUMWAY_t$).

[29] To better understand the causes of price crashes following low current operating liability accruals, I randomly sample 40 firm-years that have low total accruals (ΔNOA_{t-1} in the lowest quintile) due to large increases of current operating liabilities (Δ-COL_{t-1} in the lowest quintile) and subsequent price crashes ($CRASH_{t+1} = 1$) for the 1996–2013 sample period. I sample observations with low *Δ-COL* in year t − 1 because Δ-COL_{t-1} is slightly more negatively associated with price crashes than Δ-COL_t, as shown in Table 4. I identify the events that cause these price crashes by searching company-related news on Bloomberg over the price crash weeks. As reported in Table A3 of the online appendix (https://business.illinois.edu/profile/wei-zhu/publications), only three price crashes in my sample were caused by news about company financial distress, suggesting that default risk is unlikely to explain the negative association between *Δ-COL* and future price crashes. The two most common reasons for crashes in my sample are a disappointing earnings announcement (17 cases) and the announcement of R&D failure like a disappointing clinical trial for a new drug (8 cases). This finding suggests that firms with lower *Δ-COL* may experience more extreme negative shocks to future earnings or have higher failure rates in R&D projects, leading to the negative association between *Δ-COL* and price crashes. I leave the examination of these alternative explanations to future research. I thank Richard Sloan for suggesting this analysis.

5.4 Reexamination of the association between financial reporting opacity and price crashes

5.4.1 Accrual components from initial decomposition of accruals and price crashes

The results in previous sections show that the association between accruals and future price crashes hinges critically on the definition of accruals because accrual components differ in reliability in accrual estimation and consequently the association with hidden bad news. In this section, I examine two common definitions of accruals in literature: working capital and non-current operating accruals (ΔWC and ΔNCO) from the initial decomposition of accruals (Richardson et al. 2005). As ΔWC equals ΔCOA plus Δ-COL, I expect the nonlinear positive association between ΔCOA and price crashes and the nonlinear negative association between Δ-COL and price crashes documented in Table 4 to result in a U-shaped relation between ΔWC and price crashes. By the same logic, as ΔNCO equals $\Delta NCOA$ plus Δ-$NCOL$, I expect the close linear positive association between $\Delta NCOA$ and price crashes and the lack of correlation between Δ-$NCOL$ and price crashes to result in a close linear positive association between ΔNCO and price crashes.

Panel A of Table 7 presents results consistent with the above predictions. In the multivariate model predicting $VCRASH_{t+1}$, the coefficients on ΔWC_t and ΔWC_{t-1} are significantly negative and the coefficient on ΔWC_{t-2} is insignificantly negative when they are below their cross-sectional medians (i.e., $HIGH\_\Delta WC = 0$). In contrast, coefficients on ΔWC_t, ΔWC_{t-1}, and ΔWC_{t-2} are all significantly positive when above their cross-sectional medians.[30] Based on the results in Table 4, it is straightforward to conclude that the negative association for below-median ΔWC is caused by the negative association between Δ-COL and $VCRASH_{t+1}$, while the positive association for above-median ΔWC is driven by the positive association between ΔCOA and $VCRASH_{t+1}$. This U-shaped relation remains in the model predicting $CRASH_{t+1}$, but the significance level for the negative association is weaker.[31] Turning to ΔNCO of the past 3 years, they are all positively associated with price crashes over the next year without detectable nonlinearities. This is consistent with the finding in Table 4 that $\Delta NCOA$ is positively associated with future price crashes in a close-to-linear fashion.

The U-shaped relation between ΔWC and price crashes and the close linear relation between ΔNCO and price crashes imply nonlinearity in the positive association between ΔNOA and price crashes documented in Table 2. To test this prediction, I modify regression model (2) by allowing the coefficient on ΔNOA to differ between the bottom and top five deciles. Panel B of Table 7 presents results

[30] The t-statistic for the coefficient 0.137 (= 0.190 − 0.053) on ΔWC_t when it is above the median is 8.31, t-statistic for the coefficient 0.049 (= 0.101 − 0.052) on ΔWC_{t-1} when it is above the median is 2.84, and t-statistic for the coefficient 0.067 (= 0.100 − 0.033) on ΔWC_{t-2} when it is above the median is 2.94.

[31] The weaker significance level for the negative association in the model predicting $CRASH_{t+1}$ relative to that in the model predicting $VCRASH_{t+1}$ is likely due to the definition of $CRASH_{t+1}$ as an indicator variable.

Table 7 The impact of accrual components on price crashes over the next year—initial decomposition of accruals

Panel A: Assume non-linear relations between accrual components and price crashes

Variable	$VCRASH_{t+1}$		$CRASH_{t+1}$	
	Est	*T*	Est	*Z*
ΔWC_t	−0.053	*−3.07*	−0.110	*−1.36*
ΔWC_t * $HIGH\_\Delta WC_t$	0.190	*7.93*	0.506	*4.83*
ΔNCO_t	0.054	*2.35*	0.267	*3.06*
ΔNCO_t * $HIGH\_\Delta NCO_t$	0.036	*1.21*	0.004	*0.03*
ΔWC_{t-1}	−0.052	*−2.80*	−0.117	*−1.63*
ΔWC_{t-1} * $HIGH\_\Delta WC_{t-1}$	0.101	*3.59*	0.245	*2.23*
ΔNCO_{t-1}	0.036	*1.79*	0.088	*1.03*
ΔNCO_{t-1} * $HIGH\_\Delta NCO_{t-1}$	0.002	*0.08*	0.093	*0.76*
ΔWC_{t-2}	−0.033	*−1.62*	−0.147	*−1.68*
ΔWC_{t-2} * $HIGH\_\Delta WC_{t-2}$	0.100	*2.93*	0.325	*2.49*
ΔNCO_{t-2}	0.021	*1.00*	0.124	*1.55*
ΔNCO_{t-2} * $HIGH\_\Delta NCO_{t-2}$	0.012	*0.42*	0.020	*0.16*
Main effects	*Yes*		*Yes*	
# Obs.	108,184		108,184	
Adj. (Pseudo) RSQ	5.14 %		3.74 %	

Panel B: Assume non-linear relations between accruals and price crashes

Variable	$VCRASH_{t+1}$		$CRASH_{t+1}$	
	Est	*T*	Est	*Z*
ΔNOA_t	0.029	*1.45*	0.233	*3.19*
ΔNOA_t * $HIGH\_\Delta NOA_t$	0.114	*3.81*	0.174	*1.40*
ΔNOA_{t-1}	−0.002	*−0.13*	0.029	*0.36*
ΔNOA_{t-1} * $HIGH\_\Delta NOA_{t-1}$	0.068	*2.35*	0.292	*2.77*
ΔNOA_{t-2}	0.011	*0.48*	0.045	*0.52*
ΔNOA_{t-2} * $HIGH\_\Delta NOA_{t-2}$	0.021	*0.71*	0.051	*0.39*
Main effects	*Yes*		*Yes*	
# Obs.	108,184		108,184	
Adj. (Pseudo) RSQ	5.07 %		3.70 %	

This table reports the OLS (logistic) regression results of models linking working capital accruals and non-current operating accruals of the most recent 3 years to price crashes over the next year. The *T*-statistics in OLS regressions predicting $VCRASH_{t+1}$ (*Z*-statistics in logistic regressions predicting $CRASH_{t+1}$) are based on standard errors clustered by both firm and year. All regressions include the following control variables: BTM_t, $SARET_t$, $TURN_t$, $SIZE_t$, LEV_t, $IVOL_t$, lag dependent variable $VCRASH_t$ or $CRASH_t$, and $SKEW_t$. Main effects of interaction variables (*Main effects*) include $HIGH\_\Delta WC_t$, $HIGH\_\Delta NCO_t$, $HIGH\_\Delta WC_{t-1}$, $HIGH\_\Delta NCO_{t-1}$, $HIGH\_\Delta WC_{t-2}$, and $HIGH\_\Delta NCO_{t-2}$ in Panel A and $HIGH\_\Delta NOA_t$, $HIGH\_\Delta NOA_{t-1}$, and $HIGH\_\Delta NOA_{t-2}$ in Panel B. Interaction variable $HIGH\_X$ is a dummy variable that equals 1 if *X* is among the top five deciles and 0 otherwise. Fixed industry effects and fixed year effects are included in all regressions. The sample contains 108,184 firm-year observations for the fiscal years from 1965 to 2013. All variables are defined in the "Appendix" for this modified regression. In the case of predicting $VCRASH_{t+1}$, the positive associations between ΔNOA of the past 2 years and $VCRASH_{t+1}$ are concentrated in their top five deciles. In the case of predicting $CRASH_{t+1}$, the positive association between ΔNOA_{t-1} and $CRASH_{t+1}$ is present only when ΔNOA_{t-1} is above the median. Overall, Panel B shows that the likelihood of price crashes does not differ much between low and medium ΔNOA, due to the offsetting roles of ΔWC and ΔNCO in predicting price crashes when ΔNOA is below the median.

5.4.2 Financial reporting opacity and price crashes

The U-shaped relation between ΔWC and price crashes in Table 7 resembles the U-shaped relation between discretionary operating accruals and price crashes implied by the positive association between reporting opacity and crash risk first documented by Hutton et al. (2009).[32] This observation suggests that accrual decomposition could help to better understand the mechanisms underlying the U-shaped relation between discretionary operating accruals and price crashes.

I first replicate the strong positive association between reporting opacity ($SUM|DACC2_t|$) defined by Hutton et al. (2009) and price crashes over the next year for the sample period from 1989 to 2013, as shown in model M1 of Panel A in Table 8. In model M2, I further include the balance-sheet-based measure of opacity ($SUM|DACC_t|$).[33] When both measures of opacity are included, the balance-sheet-based measure subsumes the cash-flows-based measure. This finding allows me to focus on the balance-sheet-based measure in the following analysis, which can be easily linked to accrual components constructed from the balance sheet. Model M3 confirms that the positive association between balance-sheet-based opacity and subsequent price crashes holds in my full sample period of 1965–2013. As a result, I conduct the rest of the analysis in this section over the full sample period.

The positive association between $SUM|DACC_t|$ and price crashes implies a U-shaped relation between the level of discretionary operating accruals (*DACC*) and price crashes, as shown in model M1 of Panel B. *DACC* is negatively associated with price crashes when it is negative but positively associated with crashes when it is positive.[34] Similar to ΔWC, the significance level for the negative associations of *DACC* is stronger when predicting $VCRASH_{t+1}$ than when predicting $CRASH_{t+1}$. To understand the mechanism underlying this U-shaped relation, I decompose *DACC* into three components: discretionary current operating asset accruals ($D\Delta COA$), discretionary current operating liability accruals ($D\Delta\text{-}COL$), and discretionary

[32] Hutton et al. (2009) define operating accruals as net income minus operating cash flows, and they use the modified Jones model (Dechow et al., 1995) to estimate the discretionary portion of accruals. Reporting opacity is defined as the sum of absolute discretionary operating accruals over the past three years.

[33] For the balance-sheet-based measure, I define operating accruals as change of net current operating assets minus depreciation and amortization, and I use the Jones model (Jones, 1991) to estimate the discretionary portion of accruals. I use the Jones model instead of the modified Jones model because the former makes it easier to decompose discretionary operating accruals into discretionary portions of accrual components.

[34] Because the mean value of *DACC* is zero, the bottom five deciles of *DACC* ($HIGH\_DACC = 0$) mainly include negative *DACC*.

Table 8 The impact of discretionary portions of accrual components on price crashes over the next year

Panel A: Absolute discretionary operating accruals

Variable	$VCRASH_{t+1}$						$CRASH_{t+1}$					
	M1		M2		M3		M1		M2		M3	
	Est	*T*	Est	*T*	Est	*T*	Est	*Z*	Est	*Z*	Est	*Z*
$SUM\|DACC2_t\|$	0.046	*4.04*	0.016	*1.10*			0.082	*1.92*	−0.005	*−0.09*		
$SUM\|DACC_t\|$			0.053	*3.95*	0.064	*7.94*			0.148	*3.62*	0.194	*6.62*
# Obs.	63,603		63,490		106,724		63,603		63,490		106,724	
Adj. (Pseudo) RSQ	3.20 %		3.22 %		4.97 %		2.51 %		2.53 %		3.61 %	

Panel B: Decomposition of balance-sheet-based discretionary operating accruals

Variable	$VCRASH_{t+1}$				$CRASH_{t+1}$			
	M1		M2		M1		M2	
	Est	*T*	Est	*T*	Est	*Z*	Est	*Z*
$DACC_t$	−0.039	*−2.29*			−0.099	*−1.32*		
$DACC_t$ * $HIGH\_DACC_t$	0.112	*3.91*			0.352	*3.70*		
$D\Delta COA_t$			0.005	*0.37*			0.052	*0.96*
$D\Delta COA_t$ * $HIGH\_DACC_t$			0.075	*3.79*			0.204	*3.04*
$D\Delta\text{-}COL_t$			−0.036	*−2.76*			−0.071	*−1.38*
$D\Delta\text{-}COL_t$ * $HIGH\_DACC_t$			0.034	*2.11*			0.044	*0.74*
DDP_t			0.017	*1.04*			0.039	*0.57*
DDP_t * $HIGH\_DACC_t$			−0.010	*−0.65*			−0.015	*−0.22*
$DACC_{t-1}$	−0.059	*−3.06*			−0.120	*−1.48*		
$DACC_{t-1}$ * $HIGH\_DACC_{t-1}$	0.134	*4.64*			0.361	*3.11*		
$D\Delta COA_{t-1}$			0.012	*0.90*			0.072	*1.21*

Table 8 continued

Panel B: Decomposition of balance-sheet-based discretionary operating accruals

Variable	$VCRASH_{t+1}$				$CRASH_{t+1}$			
	M1		M2		M1		M2	
	Est	*T*	Est	*T*	Est	*Z*	Est	*Z*
$D\Delta COA_{t-1}$ * $HIGH\_DACC_{t-1}$			0.031	*1.46*			0.047	*0.54*
$D\Delta\text{-}COL_{t-1}$			−0.043	*−3.51*			−0.069	*−1.17*
$D\Delta\text{-}COL_{t-1}$ * $HIGH\_DACC_{t-1}$			0.047	*3.09*			0.027	*0.31*
DDP_{t-1}			0.015	*0.79*			0.100	*1.36*
DDP_{t-1} * $HIGH\_DACC_{t-1}$			−0.004	*−0.26*			−0.079	*−1.52*
$DACC_{t-2}$	−0.022	*−1.04*			−0.099	*−1.21*		
$DACC_{t-2}$ * $HIGH\_DACC_{t-2}$	0.081	*2.83*			0.306	*2.29*		
$D\Delta COA_{t-2}$			0.001	*0.06*			−0.048	*−0.86*
$D\Delta COA_{t-2}$ * $HIGH\_DACC_{t-2}$			0.047	*2.53*			0.250	*3.08*
$D\Delta\text{-}COL_{t-2}$			−0.030	*−2.43*			−0.122	*−2.03*
$D\Delta\text{-}COL_{t-2}$ * $HIGH\_DACC_{t-2}$			0.033	*1.89*			0.123	*1.48*
DDP_{t-2}			−0.031	*−2.25*			−0.114	*−2.36*
DDP_{t-2} * $HIGH\_DACC_{t-2}$			0.006	*0.39*			0.012	*0.21*
# Obs.	106,724		106,724		106,724		106,724	
Adj. (Pseudo) RSQ	4.98 %		5.04 %		3.63 %		3.69 %	

This table reports the OLS (logistic) regression results of models linking the discretionary portions of accruals components to price crashes over the next year. The *T*-statistics in OLS regressions predicting $VCRASH_{t+1}$ (*Z*-statistics in logistic regressions predicting $CRASH_{t+1}$) are based on standard errors clustered by both firm and year. All regression models include the following control variables: BTM_t, $SARET_t$, $TURN_t$, $SIZE_t$, LEV_t, $IVOL_t$, lag dependent variable $VCRASH_t$ or $CRASH_t$, and $SKEW_t$. Models in Panel B also include the main effects of interaction variables: $HIGH\_DACC_t$, $HIGH\_DACC_{t-1}$, and $HIGH\_DACC_{t-2}$. Interaction variable $HIGH\_X$ is a dummy variable that equals 1 if *X* is among the top five deciles and 0 otherwise. Fixed industry effects and fixed year effects are included in all regressions. The sample contains firm-year observations for the fiscal years from 1965 to 2013. All variables are defined in the "Appendix" depreciation and amortization (*DDP*). Model M2 of Panel B modifies model M1 by allowing these three components of *DACC* to have different associations with future price crashes.

The results show that the negative association between *DACC* and price crashes for negative *DACC* is driven by the negative association between *DΔ-COL* and crashes. For example, in the model predicting $VCRASH_{t+1}$, coefficients on *DΔ-COL* of the past 3 years are all significantly negative among the bottom five deciles of *DACC*, while neither *DΔCOA* nor *DDP* has a stable relation with $VCRASH_{t+1}$. This finding, combined with the analysis in Sect. 5.3.2, suggests that neither default risk nor bad news hoarding (the explanation provided by Hutton et al. 2009) explains the negative association between *DACC* and price crashes when *DACC* is negative. For bad news hoarding to explain said negative association, we would need to observe *DΔCOA* to drive this negative relation, and we also would need an argument for more hidden bad news among firms with low *DΔCOA*. With regard to the positive association between *DACC* and price crashes for positive *DACC*, model M2 shows that this positive association is driven by the positive association between *DΔCOA* and price crashes, which is consistent with the explanation of more hidden bad news among firms with high *DΔCOA* (Hutton et al. 2009).[35]

Overall, the results of Table 8 show that the negative (positive) association between *DACC* and price crashes when *DACC* is negative (positive) is driven by the most (least) reliable accrual component *DΔ-COL* (*DΔCOA*).

6 Additional analysis

6.1 Accruals and price crashes in the pre-/post-SOX periods

Cohen et al. (2008) show that the passage of the Sarbanes–Oxley Act, which substantially increased the penalties for earnings manipulation, materially reduced the incidence of accounting-based earnings management. Presumably, the act also would have reduced the use of accruals in bad news hoarding. Therefore it follows that the positive association between *ΔNOA* and future price crashes would become weaker or even dissipate after SOX.

I first compare the associations between accrual components and price crashes over the next year in the pre-SOX period with those in the post-SOX period. The results reported in Table 9 Panel A show that *ΔCOA* and *ΔNCOA* of the past 3 years in general become less positively associated with $VCRASH_{t+1}$ and $CRASH_{t+1}$. In addition, *Δ-COL* of the past 2 years become more negatively associated with $VCRASH_{t+1}$. Overall, the weaker positive associations between these accrual components and price crashes over the next year are consistent with the prediction that SOX reduces hidden bad news reflected in accruals. The results for *ΔNOA* reported in Panel B lead to the same conclusion. However, the positive association

[35] In model M2, $D\Delta COA_t$, $D\Delta COA_{t-1}$, and $D\Delta COA_{t-2}$ are all significantly positively associated with $VCRASH_{t+1}$ and $CRASH_{t+1}$, while none of $D\Delta\text{-}COL_t$, $D\Delta\text{-}COL_{t-1}$, $D\Delta\text{-}COL_{t-2}$, DDP_t, DDP_{t-1}, and DDP_{t-2} is significantly positively associated with $VCRASH_{t+1}$ or $CRASH_{t+1}$ when *DACC* is positive (*HIGH_DACC = 1*).

Table 9 The impact of accrual components on price crashes over the next year—Pre/Post-SOX comparison

Panel A: Assume linear relations between accrual components and price crashes

Variable	$VCRASH_{t+1}$				$CRASH_{t+1}$			
	Pre-SOX		Post-SOX		Pre-SOX		Post-SOX	
	Est	T	Est	T	Est	Z	Est	Z
ΔCOA_t	0.070	*6.58*	0.041	*1.86*	0.274	*4.71*	0.136	*2.38*
$\Delta\text{-}COL_t$	−0.007	*−0.98*	−0.046	*−2.43*	−0.042	*−1.27*	−0.106	*−1.85*
$\Delta NCOA_t$	0.041	*4.15*	0.026	*1.21*	0.105	*2.93*	0.063	*0.85*
$\Delta\text{-}NCOL_t$	0.014	*1.63*	0.008	*0.49*	0.021	*0.51*	0.017	*0.29*
ΔCOA_{t-1}	0.029	*2.94*	0.028	*1.27*	0.135	*3.22*	0.100	*1.36*
$\Delta\text{-}COL_{t-1}$	−0.021	*−1.76*	−0.033	*−2.24*	−0.088	*−2.22*	−0.053	*−1.11*
$\Delta NCOA_{t-1}$	0.005	*0.40*	−0.009	*−0.62*	−0.005	*−0.09*	−0.033	*−0.68*
$\Delta\text{-}NCOL_{t-1}$	−0.001	*−0.11*	0.014	*1.09*	−0.003	*−0.08*	0.066	*1.55*
ΔCOA_{t-2}	0.034	*3.42*	0.032	*1.54*	0.052	*1.23*	0.143	*2.70*
$\Delta\text{-}COL_{t-2}$	−0.012	*−1.20*	−0.007	*−0.35*	−0.111	*−2.09*	−0.015	*−0.24*
$\Delta NCOA_{t-2}$	−0.013	*−1.25*	0.007	*0.39*	−0.027	*−0.54*	0.020	*0.34*
$\Delta\text{-}NCOL_{t-2}$	−0.002	*−0.25*	0.016	*1.40*	0.032	*1.11*	0.039	*1.19*
# Obs.	78,490		29,694		78,490		29,694	
Adj. (Pseudo) RSQ	4.52 %		3.04 %		2.92 %		2.51 %	

Panel B: Assume linear relations between total accrual and price crashes

Variable	$VCRASH_{t+1}$				$CRASH_{t+1}$			
	Pre-SOX		Post-SOX		Pre-SOX		Post-SOX	
	Est	T	Est	T	Est	Z	Est	Z
ΔNOA_t	0.083	*8.72*	0.064	*3.84*	0.303	*7.82*	0.175	*3.68*

Table 9 continued

Panel B: Assume linear relations between total accrual and price crashes

Variable	$VCRASH_{t+1}$				$CRASH_{t+1}$			
	Pre-SOX		Post-SOX		Pre-SOX		Post-SOX	
	Est	*T*	Est	*T*	Est	*Z*	Est	*Z*
ΔNOA_{t-1}	0.030	*3.30*	0.019	*1.34*	0.105	*2.72*	0.044	*0.71*
ΔNOA_{t-2}	0.016	*1.84*	0.031	*1.50*	0.050	*1.38*	0.093	*2.48*
# Obs.	78,490		29,694		78,490		29,694	
Adj. (Pseudo) RSQ	4.41 %		2.96 %		2.82 %		2.40 %	

This table reports the OLS (logistic) regression results of models linking accrual components of the most recent 3 years to price crashes over the next year separately for Pre-SOX and Post-SOX periods. The *T*-statistics in OLS regressions predicting $VCRASH_{t+1}$ (*Z*-statistics in logistic regressions predicting $CRASH_{t+1}$) are based on standard errors clustered by both firm and year. All regressions include the following control variables: BTM_t, $SARET_t$, $TURN_t$, $SIZE_t$, LEV_t, $IVOL_t$, lag dependent variable $VCRASH_t$ or $CRASH_t$, and $SKEW_t$. Fixed industry effects and fixed year effects are included in all regressions. The sample contains 78,490 firm-year observations for the fiscal years from 1965 to 2001 (pre-SOX period) and 29,694 firm-year observations for the fiscal years from 2002 to 2013 (post-SOX period). All variables are defined in the "Appendix" between ΔNOA_t and price crashes remains statistically and economically significant in the post-SOX period, suggesting that SOX does not eliminate bad news hoarding through accruals.[36]

6.2 Accruals and price crashes over earnings announcement versus non-announcement weeks

This section examines the implication of the bad news hoarding explanation on the timing of price crashes. Under the bad news hoarding explanation, a price crash results from a sudden release of accumulated bad news when managers cannot continue concealing it. Ak et al. (2015) show that a sudden release of accumulated bad news is more likely to occur over an earnings announcement week than a non-announcement week. Specifically, they show that the percentage of price crashes caused by earnings announcements increases from 20 % in 2001 to 70 % in 2013. Given the concentration of price crashes over earnings announcements, I expect a stronger positive association between accruals and price crashes over earnings announcement weeks than non-announcement weeks.[37]

Figure 3 presents results consistent with this prediction. In Fig. 3, I separately plot the probability of observing a weekly price crash ($WCRASH_{t+1,w} = 1$) over the next year's earnings announcement weeks (the solid line) and non-announcement weeks (the dashed line) by deciles of accruals (ΔNOA_t, ΔNOA_{t-1}, or ΔNOA_{t-2}).[38,39] Fig. 3(1) shows that the spread of this probability between the low and high deciles of ΔNOA_t is 0.630 % over earnings announcement weeks, which is statistically and economically larger than the spread of 0.060 % over non-announcement weeks. Figure 3(2) and (3) present similar but weaker differences between earnings announcement and non-announcement weeks for ΔNOA_{t-1} and ΔNOA_{t-2}.

Table 10 examines the relation between ΔNOA and the probability of weekly price crashes ($WCRASH_{t+1,w} = 1$) after controlling for other price crash predictors used in prior literature. I allow the coefficient on ΔNOA to differ between earnings announcement weeks ($EAW_{t+1,w} = 1$) and non-announcement weeks ($EAW_{t+1,w} = 0$) in order to examine the timing of price crashes. Consistent with the observation from Fig. 3, the positive association between ΔNOA_t and $WCRASH_{t+1,w}$ is significantly stronger over earnings announcements, as indicated by the

[36] Hutton et al. (2009) and Bradshaw et al. (2010) find that reporting opacity is uncorrelated with price crashes in the post-SOX period. I confirm their finding in my sample.

[37] Ak et al. (2015) also find earnings preannouncement/updated guidance and other firm announcements as two additional important events leading to price crashes. Therefore I expect the positive association between accruals and price crashes to also exist over the non-announcement weeks.

[38] The probability of a weekly price crash over an earnings announcement week is calculated as follows: for each year, I collect earnings announcement weeks over the next year for all firms within the same accrual decile. I then calculate the probability of observing a weekly price crash among these firm-weeks. The probability of a weekly price crash over a non-announcement week is calculated similarly.

[39] As each week has only one weekly return observation, it is not feasible to define a variable that mimics $VCRASH_{t+1}$ on a weekly frequency.

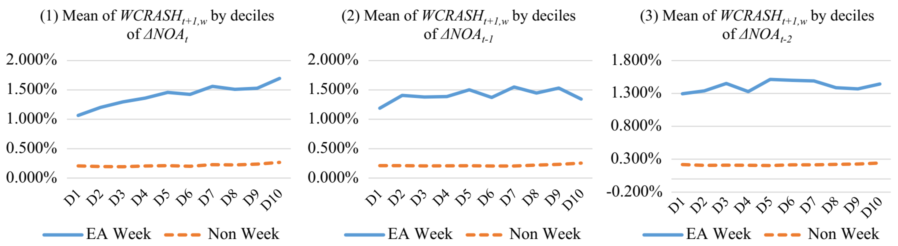


Fig. 3 Likelihood of a price crash during earnings announcement weeks versus non-announcement weeks. The following figures present the time-series mean for the annual probability of observing a weekly price crash ($WCRASH_{t+1,w} = 1$), defined as a firm-specific weekly return more than 3.09 times the standard deviation below its mean, by deciles of accruals of the most recent 3 years (ΔNOA_t, ΔNOA_{t-1}, and ΔNOA_{t-2}). The *solid* (*dashed*) *line* plots the series calculated over earnings announcement (non-announcement) weeks, with D1 (D10) in the figures representing the lowest (highest) accruals decile. The sample includes 5204,134 firm-weeks for fiscal years between 1970 and 2013. Variables are defined in the "Appendix"

Table 10 The impact of accruals on price crashes over the next year—earnings announcement weeks versus non-announcement weeks

Variable	STAT	$WCRASH_{t+1,w}$
ΔNOA_t	Est	0.193
	Z	*6.29*
$\Delta NOA_t * EAW_{t+1,w}$	Est	0.114
	Z	*2.11*
ΔNOA_{t-1}	Est	0.094
	Z	*3.06*
$\Delta NOA_{t-1} * EAW_{t+1,w}$	Est	−0.049
	Z	*−0.92*
ΔNOA_{t-2}	Est	0.063
	Z	*2.15*
$\Delta NOA_{t-2} * EAW_{t+1,w}$	Est	−0.046
	Z	*−0.89*
# Obs.		5,204,134
Pseudo RSQ		0.26 %

This table reports the logistic regression results of models linking accruals of the most recent 3 years to the probability of a weekly price crash ($WCRASH_{t+1,w} = 1$) over the next year. The *Z*-statistics in logistic regressions are based on standard errors clustered by both firm and week. The regression model includes the following control variables: BTM_t, $SARET_t$, $TURN_t$, $SIZE_t$, LEV_t, $IVOL_t$, $CRASH_t$, $SKEW_t$, and $EAW_{t+1,w}$. Fixed industry effects and fixed year effects are included in the regressions. The sample contains 5204,134 firm-week observations for the fiscal years from 1970 to 2013. All variables are defined in the "Appendix" significantly positive coefficient on $\Delta NOA_t * EAW_{t+1,w}$. However, the coefficient on $\Delta NOA_{t-1} * EAW_{t+1,w}$ and that on $\Delta NOA_{t-2} * EAW_{t+1,w}$ are insignificant. Overall, I find a stronger positive association between accruals of the current year and weekly price crashes over the next year during earnings announcement weeks than non-announcement weeks.

7 Conclusion

This study investigates the relationship between accruals and future price crashes. I find that high accruals predict a higher probability of future price crashes than low accruals. Moreover, in multivariate regression models of future price crashes, accruals in the most recent year are among the strongest predictors in both economic and statistical significance. This finding can be explained by managers' use of income-increasing accrual estimates to hoard bad news. Once accumulated bad news crosses a tipping point, it is released all at once and results in a price crash. Consistent with this explanation, I find the observed relation to be strongest for current and non-current operating assets, which are the least reliable accrual components. I also find the observed relation to be stronger among firms (1) with a higher option incentive ratio for CFOs, (2) in high-tech industries, (3) with higher sales growth, (4) with a higher level of transient institutional holding, and (5) with shorter auditor tenure. Surprisingly, I find a negative association between current operating liability accruals, a relatively reliable accrual component, and price crashes over the next year. This negative association is opposite to the prediction of the bad news hoarding explanation and cannot be explained by potential default risk reflected in large increases of current operating liabilities. I leave the explanation of this puzzling result for future research.

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Appendix

See Table 11.

Table 11 Variable definition

Variable*	Definition**
Dependent variables	
$CRASH_{t+1}$	An indicator measure of the probability of weekly price crashes over fiscal year $t+1$. It equals 1 if a firm experiences one or more price crash weeks over the 12-month period starting from the fifth month after the end of fiscal year t and 0 otherwise. A price crash week is a week during which the firm-specific weekly return is 3.09 or more times the standard deviation below its mean. 3.09 is chosen to generate frequencies of 0.1 % in the normal distribution. Firm-specific weekly return is defined as $\log(1+\varepsilon_{i,w})$, where $\varepsilon_{i,w}$ is the residual from the expanded market model $Ret_{i,w} = \alpha_{i,0} + \beta_{i,-1} * MRet_{w-1} + \beta_{i,0} * MRet_w + \beta_{i,1} * MRet_{w+1} + \gamma_{i,-1} * IRet_{w-1} + \gamma_{i,0} * IRet_w + \gamma_{i,1} * IRet_{w+1} + \varepsilon_{i,w}$. In this model, $Ret_{i,w}$ represents the returns of week w for firm i, $MRet_w$ represents the market returns of week w, and $IRet_w$ represents the industry returns of week w. The market returns are value-weighted returns on the NYSE/AMEX/NASDAQ composite index. The industry classification follows Fama and French's 48 industry definitions, and industry returns are collected from Ken French's data library. The expanded market model is estimated with the weekly returns of firm i for the 12-month period starting from the fifth month after the end of fiscal year t, with a minimum requirement of 26 weeks
$VCRASH_{t+1}$	A continuous measure of the probability of weekly price crashes over fiscal year $t+1$. It equals $\left\lvert \mathrm{Min}\left(\log\left(1+\varepsilon_{i,w}\right)\right) - \mathrm{Mean}\left(\log\left(1+\varepsilon_{i,w}\right)\right)\right\rvert / STD\left(\log\left(1+\varepsilon_{i,w}\right)\right)$, where $\varepsilon_{i,w}$ is obtained from the expanded market model. *Min*(.)., *Mean*(.), and *STD*(.) are calculated over the 12-month period starting from the fifth month after the end of fiscal year t
Accruals and accrual components	
ΔNOA_t	Accruals; defined as the change in net operating assets (COMPUSTAT "AT"–"CHE"–"LT" + "DLC" + "DLTT") over fiscal year t, scaled by the average total assets of fiscal year t
ΔCOA_t	Current operating asset accruals; defined as the change in current operating assets (Compustat "ACT"–"CHE") over fiscal year t, scaled by the average total assets of fiscal year t
$\Delta\text{-}COL_t$	Current operating liability accruals; defined as the *negative* of change in current operating liabilities (Compustat "LCT"–"DLC") over fiscal year t, scaled by the average total assets of fiscal year t
$\Delta NCOA_t$	Non-current operating asset accruals; defined as the change in non-current operating assets (Compustat "AT"–"ACT"–"TXDB") over fiscal year t, scaled by the average total assets of fiscal year t[a]
$\Delta\text{-}NCOL_t$	Non-current operating liability accruals; defined as the *negative* of change in non-current operating liabilities (Compustat "LT"–"LCT"–"DLTT"–"TXDB") over fcal year t, scaled by the average total assets of fiscal year t
ΔOA_t	Operating asset accruals; defined as $\Delta COA_t + \Delta NCOA_t$.
$\Delta\text{-}OL_t$	Operating liability accruals; defined as $\Delta\text{-}COL_t + \Delta\text{-}NCOL_t$
ΔWC_t	Working capital accruals; defined as $\Delta COA_t + \Delta\text{-}COL_t$
ΔNCO_t	Non-current operating accruals; defined as $\Delta NCOA_t + \Delta\text{-}NCOL_t$

Table 11 continued

Variable*	Definition**
$SUM\|DACC2_t\|$	The sum of absolute cash-flow-based discretionary operating accruals over fiscal years $t-2$ to t, or financial reporting opacity; defined in the same way as by Hutton et al. (2009). Operating accruals in this measure ($ACC2_t$) are defined as net income minus cash flows from operating activities (Compustat "IBC" + "XIDOC"–"OANCF"). The discretionary portion of this accruals is estimated using the modified Jones model (Dechow et al. 1995)
$SUM\|DACC_t\|$	The sum of absolute balance-sheet-based discretionary operating accruals over fiscal year $t-2$ to t. Balance-sheet-based operating accruals ACC_t are defined as $\Delta WC_t - DP_t$, where DP_t is depreciation and amortization (COMPUSTAT "DP") scaled by average total assets. Discretionary operating accruals $DACC_t$ are the residual from the following cross-sectional regression equation using firms in each Fama and French 48 industry for each fiscal year $ACC_t = \alpha_0 \frac{1}{(AT_t+AT_{t-1})/2} + \beta_1 \frac{SALE_t-SALE_{t-1}}{(AT_t+AT_{t-1})/2} + \beta_2 \frac{PPENT_t}{(AT_t+AT_{t-1})/2} + \varepsilon_t$. A minimum of 10 firms is required for each industry-year. "AT," "SALE," and "PPENT" in the regression are items from Compustat
$D\Delta COA_t$	The discretionary portion of ΔCOA_t is the residual from the following cross-sectional regression equation using firms in each Fama and French 48 industry for each fiscal year $\Delta COA_t = \alpha_0 \frac{1}{(AT_t+AT_{t-1})/2} + \beta_1 \frac{SALE_t-SALE_{t-1}}{(AT_t+AT_{t-1})/2} + \beta_2 \frac{PPENT_t}{(AT_t+AT_{t-1})/2} + \varepsilon_t$. A minimum of 10 firms is required for each industry-year
$D\Delta\text{-}COL_t$	The discretionary portion of $\Delta\text{-}COL_t$ is the residual from the following cross-sectional regression equation using firms in each Fama and French 48 industry for each fiscal year $\Delta - COL_t = \alpha_0 \frac{1}{(AT_t+AT_{t-1})/2} + \beta_1 \frac{SALE_t-SALE_{t-1}}{(AT_t+AT_{t-1})/2} + \beta_2 \frac{PPENT_t}{(AT_t+AT_{t-1})/2} + \varepsilon_t$. A minimum of 10 firms is required for each industry-year
DDP_t	The discretionary portion of DP_t is the residual from the following cross-sectional regression equation using firms in each Fama and French 48 industry for each fiscal year $DP_t = \alpha_0 \frac{1}{(AT_t+AT_{t-1})/2} + \beta_1 \frac{SALE_t-SALE_{t-1}}{(AT_t+AT_{t-1})/2} + \beta_2 \frac{PPENT_t}{(AT_t+AT_{t-1})/2} + \varepsilon_t$. DP_t is depreciation and amortization (Compustat "DP") scaled by average total assets. A minimum of 10 firms is required for each industry-year
$ND\Delta\text{-}COL_t$	The nondiscretionary portion of $\Delta\text{-}COL_t$ is defined as $\Delta\text{-}COL_t - D\Delta\text{-}COL_t$.
Control variables in the main analysis	
Proxies for mispricing	
BTM_t	The book-to-market ratio; defined as the ratio of book value of equity (Compustat "CEQ") at the end of fiscal year t to the market value 4 months after fiscal year t
Proxies for information blockage	
$SARET_t$	Past returns; defined as size-adjusted stock returns for the 12-month period starting from the fifth month after the end of fiscal year $t-1$. The size-adjusted returns are the difference between the buy-and-hold raw returns of a firm and the buy-and-hold raw returns of the corresponding size portfolio. The size portfolio assignment for each firm is taken from the CRSP DPORT1 file. When a firm's portfolio assignment is missing from the CRSP DPORT1 file, I use the NYSE/AMEX/NASDAQ value-weighted returns to adjust firm returns

Table 11 continued

Variable*	Definition**
Proxies for difference of opinion	
$TURN_t$	The measure of difference of opinion; defined as the average monthly share turnover over the 12-month period starting from the fifth month after the end of fiscal year $t-1$. The monthly share turnover is calculated as the monthly trading volume divided by the total number of shares outstanding. For NASDAQ firms, the trading volume from CRSP is divided by 2 before calculating this variable
Proxies for bad news hoarding	
$INCENTIVE_t$	The incentive ratio for CFO option holdings; defined as ONEPCT_OPT/(ONEPCT_OPT + SALARY + BONUS). The variable ONEPCT_OPT (or option delta) measures the dollar change in CFO option holdings resulting from a 1 % increase in the firm's stock price (Core and Guay 2002; Coles et al. 2006) and it is obtained from Naveen Daniel's data library on http://astro.temple.edu/~lnaveen/data.html.[b] SALARY and BONUS are obtained from the EXECCOMP database. Following Jiang et al. (2010) and Kim et al. (2011a), I classify managers as CFOs if their title includes any of the following terms: CFO, chief financial officer, treasurer, controller, finance, and vp-finance. If there is more than one manager classified as CFO for a firm-year, the CFO option incentive ratio for this firm-year equals the average of option incentive ratios for these managers
$LRETR_t$	Long-run effective tax rate is computed as the sum of income tax paid (Compustat "TXPD") over the previous 5 years, with a minimum requirement of 3 years, divided by the sum of a firm's pre-tax income minus special items (Compustat "PI"–"SPI") (Dyreng et al. 2008). When the special item is missing, it is coded as zero. This variable is Winsorized at zero and one
$SALEGR_t$	Growth rate of sales (Compustat "SALE") over fiscal year t
SIR_t	Short interest; defined as the number of shares sold short divided by total shares outstanding for the fourth month after the end of fiscal year t. Short interest is collected from the COMPUSTAT Supplemental Short Interest file
TRA_t	The average percentage of shares outstanding held by transient institutions for the 12-month period ending in the fourth month after the end of fiscal year t. Institutional holdings are collected from the Thompson-Reuters Institutional Holdings database and the transient institution identities are collected from Brian Bushee's website http://acct.wharton.upenn.edu/faculty/bushee/IIclass.html
Proxies for default risk	
$ALTMAN_t$	Altman (1968) Z score; defined as 1.2*WCAP/AT + 1.4*RE/AT + 3.3*(IB + TXT + XINT)/AT + 0.6*PRCC_F*CSHO/LT + SALE/AT using Compustat items
$SHUMWAY_t$	Shumway (2001) bankruptcy score; defined as $e^{\alpha}/(1+e^{\alpha})$, where $\alpha = -3.303 - 1.982$*NI/AT + 3.593*LT/AT − 0.467*RSIZE − 1.089*MARET + 5.791*SIGMA. NI (= IB + XIDO), LT, and AT are Compustat items. RSIZE is the natural logarithm of the firm's market capitalization (Compustat PRCC_F*CSHO) relative to the total size of the NYSE and AMEX market. MARET is the firm's market-adjusted returns over fiscal year t. SIGMA is the standard deviation of monthly market-adjusted returns over fiscal year t
$DEFPROB_t$	Vassalou and Xing (2004) default probability, collected from http://maria-vassalou.com/research/data/

Table 11 continued

Variable*	Definition**
Other controls (t)	
$ANCOV_t$	Log of one plus the number of analysts that issue earnings forecasts for the firm over fiscal year t
DED_t	The average percentage of shares outstanding held by dedicated institutions for the 12-month period ending in the fourth month after the end of fiscal year t
FCF_t	Free cash flows; defined as returns on assets minus ΔNOA_t, where returns on assets equal Compustat "IB" scaled by average "AT"
$HIGHTECH_t$	A dummy variable equals 1 if the SIC code belongs to any of the following ranges—2833–2836, 3570–3577, 3600–3674, 7371–7379, or 8731–8734—and 0 otherwise
$IVOL_t$	The idiosyncratic volatility; defined as the standard deviation of firm-specific weekly returns over the 12-month period ending in the fourth month after the end of fiscal year t
LEV_t	Book leverage; defined as the ratio of total debt to total assets at the end of fiscal year t
QIX_t	The average percentage of shares outstanding held by quasi-indexer institutions for the 12-month period ending in the fourth month after the end of fiscal year t
$SIZE_t$	Firm size; defined as the log of market cap at the end of fourth month after fiscal year t
$SKEW_t$	Return skewness; defined as skewness of firm-specific weekly returns for the 12-month period ending in the fourth month after the end of fiscal year t
$TENURE_t$	Auditor tenure; defined as the number of consecutive years for which auditor has been employed by the firm at the end of fiscal year t
Variables in the additional analysis	
$EAW_{t+1,w}$	A dummy variable that equals 1 if the quarterly earnings was announced during week w of year $t+1$ and 0 otherwise
$WCRASH_{t+1,w}$	A dummy variable that equals 1 if week w of year $t+1$ is a price crash week and 0 otherwise

[a] Compustat does not separately disclose deferred tax assets but rather bundles it with other items in assets (other "AOX"). Since deferred tax liabilities ("TXDB") and deferred tax assets are simply the credit and debit balances of the same account and therefore should have the same level of accrual reliability, I treat "TXDB" as one component of non-current operating assets

[b] Option delta is not directly provided in the data library. Instead, overall delta for the option and equity portfolio is provided. To obtain option delta, I subtract the delta of equity portfolio from the overall delta. Delta of equity portfolio is computed as *SHROWN_EXCL_OPTS***PRCC_F**0.01, where *SHROWN_EXCL_OPTS* is from the EXECCOMP ANNCOMP file and *PRCC_F* is from the COMPUSTAT FUNDA file

*Firm subscript i is omitted in the variable name

**When CRSP and Compustat datasets or data items are referred to, I maintain the same notations as defined on WRDS

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