Bad News Holding and Banks' Stock Price Crash Risk

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Abstract

Using U.S. bank quarterly data from 1995 through 2014, this study examines the channel through which delayed expected loss recognition (DELR) affects the stock price crash risk of banks. We first show that DELR is positively associated with a subsequent crash in stock price (Jin and Myers 2006). We then find that this association is only present when bank managers have more discretion in concealing bad news, as proxied by the proportion of heterogeneous loans (e.g., commercial and industrial loans). Default risk does not explain our findings; the association between DELR and stock price crash does not increase with banks' default risk. We also find that DELR leads to a greater stock price crash during a financial crisis. These findings provide policy implications to bank regulators regarding the importance of specific loan types and time horizons when monitoring banks' accounting treatment.

1. Introduction

Large declines in bank stock prices (i.e., crash risk) are of great concern to investors, regulators, and the financial market. Banks represent over 20 percent of the total public equity market capitalization in the United States (Fields, Fraser, and Wilkins 2004), and troubled banks aggravate systematic crises in the financial market (Beatty and Liao 2011). Prior research shows that the accounting decisions of banks have real implications on their downside risks. For example, banks' crash risk (or similar extreme tail risks) is associated with their credit cycles, earnings management (Cohen, Cornett, Marcus, and Tehranian 2014), opacity (Bushman and Williams 2015), and conservativism in accounting treatments (Andreou, Cooper, Louca, and Philip 2017).

However, empirical evidence on the exact channel through which banks' accounting decisions affect their downside risk is, at best, weak and mixed (Beatty and Liao 2014). For example, banks' accounting treatments on loan loss can result in tail risk for two reasons. On one hand, the delayed expected loan loss recognition (DELR) of banks could occur because managers withhold bad news (e.g., Jin and Myers 2006; Bushman and Williams 2015; Zhu 2016). Managers at banks with DELR could hoard bad news until a tipping point where the accumulated bad news is released all at once and leads to a sudden stock price crash. On the other hand, DELR may represent severe performance deterioration and may be associated with high default risk (Beatty and Liao, 2011). As firms with greater default risk are more likely to fail than those with low default risk (Hutton, Marcus and Tehranian 2009), banks with greater DELR are more likely to experience a stock price crash or a price jump. An important difference between the two channels is that DELR does not necessarily trigger stock price crash in the latter channel. Although high (low) default risk is commonly associated with high (low) DELR, high default risk confounds the link between managers' hoarding of bad news and banks' stock price crash. We perform various falsification tests to verify the inherent relationship between bad news hoarding and stock price crash.

In this study, we use loan type categorization to identify the mechanism through which banks' DELR affects their stock price crash risk. First, we examine the bad news holding channel by exploiting variations in the ability of bank managers to conceal bad news. If DELR leads to a price crash primarily because managers withhold bad news, we would observe a stronger association between DELR and crash risk when managers have more discretion in concealing bad news. On the other hand, if default risk confounds the inherent relationship between DELR and crash risk, then a stronger association between DELR and crash risk will be observed when banks' default risk is higher. Therefore, we attempt to falsify this channel by examining bank default risk measured by Z-score and bond credit ratings. We also analyze (a)symmetric responses between stock crash or jump and DELR.

We proxy managers' *ability* to conceal bad news by exploiting the differences in banks' loan types. We follow prior research (Liu and Ryan 1995; Ryan and Keeley 2013) and categorize loans into homogeneous loans vis-à-vis heterogeneous loans based on the Bank Regulatory Database (BRD) data. For example, Ryan and Keeley (2013) argue that homogeneous loans (e.g., consumer loans and residential mortgages) are small, similar, and rarely renegotiated and their loss reserves are primarily determined through a statistical analysis of historical loss rates. By contrast, heterogeneous loans (e.g., commercial and industrial loans) are large, dissimilar, and frequently renegotiated. Loss reserves for heterogeneous loans involve more judgment on the current circumstances and loan status of the borrower. Therefore, bank managers have more discretion in determining expected loan losses for heterogeneous loans than for homogenous loans.

We proxy for default risk with a simplified z-score, defined as the ratio of an individual bank's return on assets and its capital ratio divided by the standard deviation of return on assets (Boyd, De Nicoló, and Al Jalal 2006; Fiordelisi and Marques-Ibanez 2013). A low Z-score is a proxy for a high likelihood of becoming insolvent. The S&P credit ratings of banks are also used as a proxy for default risk. A high credit rating implies a low default risk. We then investigate the association between DELR and a price jump, defined as a bank-quarter with one or more *bank-specific daily returns* (*W*) exceeding 3.09 standard deviations of the mean *bank-specific daily returns* over the fiscal quarter. We examine whether the association between DELR and a price *jump* show symmetric patterns with the association between DELR and price *crash*.

Our results indicate that banks' DELR is positively associated with bank stock price crash. We use bank-quarter observations from COMPUSTAT bank data between calendar quarter 1995:Q1 and 2014:Q4. Specifically, banks with a higher proportion of DELR are more likely to experience stock price crash in a subsequent period after controlling for prior-period stock price crash and various other variables. We find evidence consistent with the bad news holding channel but fail to find evidence supporting the default risk channel. We find a statistically significant and positive association between DELR and subsequent period stock price crash only when managers have greater discretion in concealing bad news, as proxied by the proportion of heterogeneous (i.e., commercial and industrial) loans. We fail to find a positive association between DELR and subsequent period stock price crash when the bank's default risk is higher. Additional analyses and robustness tests that use alternative specifications confirm our findings. We also find that the association between DELR and stock price crash is more pronounced during a financial crisis.

Our research contributes to extant literature in the following ways. First, we contribute to a specific research stream that examines the association between the DELR and stock price crash risk of banks. Although Jin and Myers (2006) show that countries with more opaque financial information are more likely to experience sudden stock price crash, bank-level empirical evidence is mixed. For example, Cohen et al. (2014) find that banks' opportunistic management of loan loss provision is positively associated with negative tail risk during a financial crisis. On the other hand, Andreou et al. (2017), using annual U.S. bank data between 1995 and 2010, do not find a significant association between DELR and crash risk. We use detailed quarterly observations for extended time-periods to support the positive association between the DELR and stock price crash of banks.

Second, we distinguish between the two competing channels through which delays in loan loss recognition result in price crash risk. In this sense, this study is closely in line with Zhu (2016), who supports the bad news holding channel but not the default risk channel. Zhu (2016) uses discretionary accruals as a measure for earnings management in a sample of industrial firms. To the best of our knowledge, no such findings exist using bank-level data, although results from industrial firms do not necessarily extend to banks because of their different information environment and regulatory conditions. The primary reason for this void is the difficulty in identifying the bad news hoarding of bank managers. In this study, we provide new evidence that withholding bad news is the mechanism through which delays in loan loss recognition result in stock price crash risk by exploiting a novel measure of manager discretion in hoarding bad news. Specifically, we find that the association between DELR and crash risk is stronger when managers have great discretion in concealing bad news, but not when banks are financially constrained.

Third, our study provides regulators with policy implications on banks' accounting treatments. Banks are characterized by a high degree of information uncertainty (Autore, Billingsley, and Schneller 2009) and regulation (Beatty and Liao 2014). Our study shows that DELR is more strongly associated with stock price crash during a financial crisis, which increases pro-cyclicality and exacerbates a credit crunch (Beatty and Liao 2011). Our study urges bank regulators to closely monitor banks' accounting treatment on loan provisions to prevent the worsening of a credit crunch during financial crises. We likewise show that managers use discretion on heterogeneous loans as a means of withholding bad news from investors. We help regulators focus their limited resources on monitoring bank's accounting treatments for loan loss provisioning.

The rest of this paper is organized as follows. Section 2 reviews prior literature and develops empirical hypotheses. Section 3 describes the sample selection process and our research design. Section 4 presents our empirical results, and Section 5 discusses the additional analyses and robustness checks. Section 6 provides a conclusion to the study.

2. Literature Review and Hypothesis Development

Jin and Myers (2006) show that large, negative return outliers (i.e., stock price crash) are more common for firms in countries with an opaque information environment. In their model, opaque firms have a large amount of hidden, firm-specific bad news. Insiders hide bad news until a tipping point where all the bad news are revealed at once, causing investors to incur great losses. Following Jin and Myers (2006), numerous finance and accounting studies have examined how opaqueness affects stock price crash. For example, Hutton et al. (2009) argue that firms with greater amounts of discretionary accruals are more prone to stock price crashes. Kim and Zhang (2013) show that less conservative accounting practice is associated with a higher likelihood of a firm's future stock price crash risk. Zhu (2016) reports that firms with high unreliable accruals tend to experience more crash in stock prices. Similarly, Chen, Kim and Yao (2017) find that a high degree of earnings smoothing is associated with increased stock price crash risk. Taken together, prior literature generally concludes that industrial firm managers hoard bad news in an opaque information environment, which leads to stock price crashes.

However, it is unclear whether empirical evidence based on industrial firms extend to banks. No prior studies have directly examined whether and how the bad news holding of banks is associated with their stock price crash[1]. Results from industrial firms may not hold for banks because banks are characterized by a high level of information uncertainty and have relatively more opaque asset values that are difficult for investors to verify (Flannery, Kwan, and Nimalendran 2004; Cheng, Dhaliwal, and Neamtiu 2011). Moreover, in the aftermath of the 2008 global financial crisis, regulators and investors are increasingly concerned about the opacity of banks' information and accounting treatments. For example, FASB (2012) expresses concern regarding the overstatement of bank assets caused by the accounting treatment of credit loss recognition. If bank managers delay the recognition of credit losses to hide bad news from investors, then bad news will likely accumulate to a point where no such hoarding is feasible and thus result in a large stock price crash. On the other hand, it is also possible that bad news withholding may not necessarily have the first-order impact on the bank's stock price crash. For example, a bank's failure to meet obligations to depositors may cause a stock price crash. The primary role of a bank is to facilitate efficient allocation of capital by borrowing from depositors and lending to borrowers. Hence, banks tend to operate on high leverage ratios and thin net interest margins. If a bank fails and faces default risk, its stock returns will likely crash suddenly. In such cases, a researcher would not be able to distinguish *ex-post* whether the observed association between DELR and stock price crash is due to (i) the managers hoarding of bad news or (ii) the inherent business risk of the bank. That is, banks facing greater default risk are more likely to delay the recognition of losses (Beatty and Liao, 2011)[2], potentially confounding the relationship between bad news withholding and stock price crash.

Therefore, we first examine whether banks' DELR has a direct impact on their stock

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[1] Cohen et al. (2014) and Andreou et al. (2017) examine how the stock price crash risk of banks is affected by the earnings management and conditional conservatism of the banks, respectively.

[2] Credit rating agencies such as Fitch (2009) argue that the ratio of the allowance to nonperforming loans is a useful measure. For example, they state that "its usefulness will relate to how effective a bank is in identifying specific impaired loans. It is also important to recognize that the performing portfolio needs to be reserved against for expected risk as well, although accounting standards may not allow for this."

price crash (H1) and then distinguish the exact channel through which DELR affects sudden crash in stock returns (H2). Specifically, our first hypothesis is that, to an extent that managers delay expected credit losses to conceal bad news from investors, DELR will likely result in stock price crash at a later period when the accumulated bad news is revealed all at once. Therefore, we provide our first hypothesis as follows:

H1. Delayed Expected Loss Recognition is positively associated with stock price crash at banks.

Next, we examine whether DELR is associated with stock price crash because managers concealed bad news or because a high DELR is associated with higher default risk. On the one hand, DELR may indicate that managers are withholding bad news, which in turn precipitates stock price crash. On the other hand, it is possible that DELR is associated with the default risk of banks (Beatty and Liao, 2011), and the default risk could trigger a sudden crash in bank stock prices. Therefore, we provide our second hypothesis as follows:

H2. The positive association between Delayed Expected Loss Recognition and stock price crash is stronger for banks that are more likely to withhold bad news.

3. Sample Selection and Research Design

3.1. Sample Selection

Our initial sample selection begins with COMPUSTAT banks that have the necessary data during the calendar period 1995:Q1 to 2014:Q4[3]. The crash risk measures are constructed using daily stock return data of the Center for Research in Security Prices. Initial sample banks have common shares listed in NYSE, AMEX, or NASDAQ. We exclude bank-quarter observations with non-positive book values and total assets and those that do not have enough

[3] Our sample begins in 1995 because COMPUSTAT banks provide nonperforming loan data from 1994.

data to calculate financial and crash-risk-related variables. We also require banks to have daily returns for at least half of the quarterly trading days.

[Insert Table 1 Here]

Panel A of Table 1 summarizes our sample selection process. Beginning with 66,002 bank-quarter observations from 1995 to 2014, we first delete bank-quarter observations with negative assets or equity. Then, we limit our samples to bank-quarters that have complete data necessary for calculating DELR, stock price crash, and other control variables. Our final sample contains 37,788 bank-quarter observations, representing 1,334 banks during the period 1995:Q1 to 2014:Q4.

3.2. Variable Definition

Stock Price Crash

Consistent with prior literature (Jin and Myers 2006; Hutton et al. 2009; Kim, Li, and Zhang 2011; Chen et al. 2017), we measure quarterly realized stock price crash using three variables based on the negative *bank-specific* conditional skewness of stock return distribution. Bank-specific daily returns are calculated based on a market- and industry-adjusted returns model in Equation (1):

$$r_{i,d} = \alpha + (\beta_1 r_{m,d-1} + \beta_2 r_{m,d} + \beta_3 r_{m,d+1}) + (\beta_4 r_{j,d-1} + \beta_5 r_{j,d} + \beta_6 r_{j,d+1}) + \varepsilon_{i,d}, \quad (1)$$

where $r_{i,d}$ is the raw stock returns of bank *i* on day *d*, $r_{j,d}$ is the return for the banking industry on day *d*, and $r_{m,d}$ is the value-weighted market return on day *d*. To exclude synchronous trading, we include lead and lag industry and market returns. We require each bank to have more than 30 days of trading returns during each fiscal quarter. From Equation (1), we calculate the *bank-specific* daily return for bank *i* on day *d* as the natural log of 1 plus the residual return (i.e., $W_{i,t} = log(1+\varepsilon_{i,d})$).

Then, we define our three variables representing stock price crash: $NCSKEW_{i,t}$,

$DUVOL_{i,t}$, and $COUNT_{i,t}$. First, $NCSKEW_{i,t}$ is defined as the negative coefficient of skewness of bank-specific daily return during the fiscal quarter *t*, such that

$$NCSKEW_{i,t} = -\left[n(n-1)^{3/2} \sum W_{j,d}^{3}\right] / \left[(n-1)(n-2)\left\{\sum W_{j,d}^{2}\right\}^{3/2}\right], \tag{2}$$

where *n* is the number of observations $W_{i,d}$ during fiscal quarter *t*. Therefore, higher negative skewness of bank-specific daily returns implies that the bank's returns are more likely to be in the negative extreme area, namely, stock price crash. Second, we define our second measure of stock price crash, $DUVOL_{i,t}$, as the down-to-up volatility of $W_{i,d}$ during the fiscal quarter *t*, such that

$$DUVOL_{i,t} = \log\left\{(n_u - 1) \sum_{Down} W_{j,d}^{2} / (n_d - 1) \sum_{Up} W_{j,d}^{2}\right\}, \tag{3}$$

where n_u and n_d are the number of days the stock returns are above ("up-days") and below ("down-days") the mean $W_{i,d}$, respectively, during the fiscal quarter *t*. Therefore, $DUVOL_{i,t}$ is the log of the ratio of standard deviations of the two subsample days: down-days and up-days. Similarly, our third measure of stock price crash risk, $COUNT_{i,t}$, is defined as the difference between the number of days $W_{i,d}$ exceeding 3.09 standard deviation below the mean of $W_{i,d}$ in the quarter *t* (i.e., $CRASH_{i,t}$) and the number of days $W_{i,d}$ exceeding 3.09 standard deviation above the mean of $W_{i,d}$ in the quarter *t* (i.e., $JUMP_{i,t}$).

Delayed Expected Loss Recognition (DELR)

To measure the degree of delayed expected loss recognition (DELR), $DELR_{i,t}$ is defined as the ratio of allowance of loan loss provision (COMPUSTAT "rclq") divided by nonperforming loans (COMPUSTAT "npatq"). This measure captures the extent to which banks effectively identify impaired loans related to expected risk. $DELR_{i,t}$ is a useful measure if banks can recognize expected risk in their performing loans and the incurred losses in their nonperforming loans (Beatty and Liao, 2011). Following prior studies, we use an indicator variable for whether banks recognize higher expected loss recognition. When $DELR_{i,t}$ is lower than its respective sample median during the quarter t, $HIGH\_DELR_{i,t}$ is defined as 1, and 0 otherwise (Beatty and Liao 2011; Bushman and Williams 2015). Other relevant variables are defined in Appendix A.

3.3. Research Design

To examine whether banks' DELR is associated with stock price crash (H1), we empirically test whether the three measures of stock price crash risk (i.e., $NCSKEW_{i,t}$, $DUVOL_{i,t}$, and $COUNT_{i,t}$) are explained by $DELR_{i,t}$. Specifically, we estimate the following equation:

$$\begin{aligned} Crash\,risk_{i,t} = {} & \alpha_0 + \beta_1 HIGH\_DELR_{i,t-1} + \beta_2 SIZE_{i,t-1} + \beta_3 NCSKEW_{i,t-1} \\ & + \beta_4 MTB_{i,t-1} + \beta_5 Leverage_{i,t-1} + \beta_6 ROA_{i,t-1} \\ & + \beta_7 TURNOVER_{i,t-1} + \beta_8 SIGMA_{i,t-1} + RET_{i,t-1} + \beta_9 Q4_{i,t} \end{aligned} \tag{4}$$

where the dependent variable $Crash\ Risk_{i,t}$ represents one of the three stock price crash risk variables (i.e., $NCSKEW_{i,t}$, $DUVOL_{i,t}$, and $COUNT_{i,t}$) for each bank i in fiscal quarter t. Following prior literature (Hutton et al. 2009; Kim et al. 2011; Kim and Zhang 2016; Chen et al. 2017), we also control for a set of variables that affect the *bank-specific* stock price crash risk. We include log of total assets (*SIZE*), market-to-book ratio (*MTB*), total long-term debt scaled by total assets (*LEVERAGE*), income before extraordinary items divided by lagged total assets (*ROA*), de-trended average daily stock turnover (*TURNOVER*), standard deviation of bank-specific daily returns during the quarter $t-1$ (*SIGMA*), and arithmetic average of bank-specific daily returns in quarter $t-1$ (*RET*). We also include an additional indicator variable representing the fourth fiscal quarter (*Q4*) because fourth-quarter financial reporting is different from that of other quarters (Jacob and Jorgensen 2007; Das, Shroff, and Zhang 2009). Lastly, we impose year and quarter fixed effects and cluster standard errors from the regression by each bank. Consistent with Hypothesis 1, we expect to find a significant and positive coefficient estimate for β_1.

Our second hypothesis examines the effect of two channels (i.e., bad news holding vis-à-vis default risk) on the association between DELR and stock price crash. Identifying the circumstances under which banks are more likely to delay loss recognition with the purpose of withholding bad news is an empirical challenge, but not because of default risk. We attempt to solve this issue by exploiting data on loan type categorization from the Bank Regulatory Database (BRD) (Beck and Narayanamoorthy 2013). Consistent with Liu and Ryan (1995) and Ryan and Keeley (2013), we classify banks' loan types into two categories: (1) homogenous loans that are small, similar, and rarely renegotiated (e.g., consumer loans and residential mortgages) and (2) heterogeneous loans that are large, dissimilar, and frequently renegotiated (e.g., commercial and industrial loans and industrial real estate loans). These two loan types could reflect the degree of managers' *discretion* in concealing bad news. For example, Ryan and Keeley (2013) argue that loss reserves for homogeneous loans are primarily determined through a statistical analysis of historical loss rates, including the examination of underwriting criteria, loan performance statuses, migration rates between loan statuses, and loan severities. Thus, there is little room for managers to exercise discretion in determining expected loan losses for homogeneous loans. On the other hand, loss reserves for heterogeneous loans are more likely to be determined based on the judgment of managers on the current circumstances and loan status of borrowers. Moreover, these loans tend to originate from soft information and personal connections (Berger and Udell 2002). In short, managers have greater discretion in determining expected loan losses for heterogeneous loans than for homogenous loans.

On the basis of our hypothesis that withholding bad news is the primary reason through which DELR affect stock price crash, we expect the association between DELR and stock price crash risk to be more prominent when banks have larger heterogeneous loans than homogenous loans (H2). We distinguish between homogenous and heterogeneous loans following Beck and Narayanamoorthy (2013). We define $HET_{i,t}$ as a fraction of commercial loans over total loans

(BRD "BHCK1766" divided by BRD "BHCK2122") to represent the proportion of heterogeneous loans at bank i in fiscal quarter t. Similarly, the proportion of homogenous loans at bank i in fiscal quarter t, $HOM_{i,t}$, is defined as the fraction of individual non-mortgage loans over total loans (BRD "BHCK1975/BHCK2122"). Empirically, we re-run Eq. (4) in a subsample of banks where (i) $HOM_{i,t}$ is higher than the highest quartile of its quarterly population (high homogenous loans) and where (ii) $HET_{i,t}$ is higher than the highest quartile of its quarterly population (high heterogeneous loans). We expect to find a positive and significant β_1 coefficient for the subsample of high heterogeneous loans but not from the subsample of high homogenous loans if DELR causes a stock price crash because managers intentionally hid bad news.

The default risk of banks could confound the relationship between DELR and stock price crash. High default risk may cause an increase in DELR and in the likelihood of a sudden stock price crash. Under this mechanism, a stronger association between DELR and stock price crash risk is observed when banks have increased default risk. We use two variables to proxy for banks' default risk. First, we use simplified z-score ($ZSCORE_{i,t}$), defined as the ratio of an individual bank's return on assets and its capital ratio divided by the standard deviation of return on assets (Boyd et al. 2006; Fiordelisi and Marques-Ibanez 2013). A lower $ZSCORE_{i,t}$ would proxy for a higher likelihood of insolvency. Second, we use default risk implied by the S&P long-term credit ratings of banks ($SPSCORE_{i,t}$). Credit rating agencies examine relevant public information and private information based on meetings with issuers to assess the overall credit-worthiness of firms (Bonsall, Koharki, and Neamtiu 2017). Therefore, a high credit rating implies a low default risk. Once again, we divide banks into subsamples based on our measure of default risk (i.e., $ZSCORE_{i,t}$ and $SPSCORE_{i,t}$). Then we compare the estimated coefficient β_1 from regressing equation (4) using high and low default risk subsamples. Banks are classified into a high (low) default risk subsample if the $ZSCORE_{i,t}$ or $SPSCORE_{i,t}$ of bank

i on fiscal quarter t is greater (smaller) than the highest quartile of its respective population in quarter t. If default risk is the underlying mechanism through which DELR affects stock price crash risk, we will find a greater β_1 coefficient estimate for the subsample of banks with higher default risk.

4. Empirical Results

4.1. Summary Statistics and Univariate Analysis

Panel A of Table 2 reports the descriptive statistics for our final sample of COMPUSTAT banks from 1995:Q1 to 2014:Q4. With respect to variables representing stock price crash risk, Panel A shows that the mean (median) values of $NCSKEW_{i,t}$ and $DUVOL_{i,t}$ are -0.106 (-0.062) and -0.056 (-0.045), respectively, indicating that bank-specific daily stock returns are negatively skewed. Similarly, the mean (median) value of $COUNT_{i,t}$ is -0.091 (0). Our main independent variable, $DELR_{i,t}$, has a mean (median) value of -2.94 (-1.27). This means that the amount of allowance for loan loss provisions is around 2.94 percent of nonperforming loans.

[Insert Table 2 Here]

Panel B of Table 2 provides a correlation matrix for the variables. First, we find that measures of stock price crash risk are highly correlated among one another. For example, $NCSKEW_{i,t}$ is positively correlated with $DUVOL_{i,t}$ and $COUNT_{i,t}$ with correlation coefficients of 0.873 and 0.724, respectively. Similarly, the correlation coefficient between $DUVOL_{i,t}$ and $COUNT_{i,t}$ is 0.607. These large positive correlations suggest that our measures of stock price crash capture at least some common components. All correlation coefficients are significant at a p-value smaller than 0.001. We also find positive correlations between $DELR_{i,t}$ and our measures of stock price crash risk. $DELR_{i,t}$ is positively correlated with $NCSKEW_{i,t}$, $DUVOL_{i,t}$, and $COUNT_{i,t}$ with correlation coefficients (p-value) of 0.009 (0.091), 0.011 (0.030), and 0.010

(0.044), respectively.[4] These positive correlations provide preliminary evidence that DELR is positively associated with stock price crash risk. With respect to control variables, $DELR_{i,t}$ positively correlates with the size (*SIZE*) and volatility of returns (*SIGMA*) of banks, suggesting that large banks and banks with a risky business environment tend to have greater *DELR*. In addition, $DELR_{i,t}$ is negatively correlated with market-to-book ratio (*MTB*), profitability (*ROA*), and stock returns (RET), suggesting that banks with poor operating performance and low growth potentials tend to have greater *DELR*.

Next, Panel C of Table 2 examines the difference in means of our main and control variables between *High_DELR* group and *Low_DELR* group of banks. Similar to the correlation coefficients reported in Panel B, we find that two out of three measures of stock price crash risk (*NCSKEW* and *DUVOL*) are significantly higher in the *High_DELR* group of banks. For example, mean (median) *NCSKEW* is -0.094 (-0.058) and -0.118 (-0.066) in the *High_DELR* and *Low_DELR* groups, respectively, suggesting that banks that delay the expected loss recognition are more likely to experience stock price crash.

[Insert Figure 1 Here]

We further examine the simple univariate association between DELR and our three measures of stock price crash risk on a portfolio basis. Figure 2 plots the mean value of *NCSKEW*, *DUVOL*, and *COUNT* by decile portfolio based on DELR. Similar to Panel B and C of Table 2, we find that two of three measures of stock price crash (i.e., *NCSKEW* and *DUVOL*) increase monotonically with DELR.

4.2. Main Results (H1)

[4] We also test the correlation between *HIGH_DELR* and crash risk variables and find that *NCSKEW* and *DUVOL* are highly correlated with *HIGH_DELR* variables, whereas *COUNT* is not significantly correlated.

Table 3 provides the OLS regression results for Equation (4). Consistent with Hypothesis 1, we find that DELR is positively associated with all three measures of stock price crash risk. Specifically, the estimated coefficients on $HIGH\_DELR_{i,t-1}$ are 0.033, 0.022 and 0.018 for *NCSKEW*, *DUVOL*, and *COUNT,* respectively. All coefficient estimates are statistically significant with p-values less than 0.05.

[Insert Table 3 Here]

Consistent with prior literature, our proxies for bank risk, *SIZE* and *LEVERAGE* are positively and negatively associated, respectively, with crash risk (Zhu 2016). Market-to-book ratio (*MTB*) is positively associated with crash risk, indicating that high information uncertainty inherent in growth firms is more prone to sudden stock price crash. Profitability (*ROA*) is negatively associated with stock price crash (Andreou et al. 2017), and banks with high past returns are more likely to experience stock price crash than those with low past returns.

4.3. Main Results (H2)

Bad News Withholding Explanation

Our second hypothesis concerns identifying the channel through which *DELR* relates to stock price crash (i.e., bad news withholding vis-à-vis default risk). Therefore, we investigate whether the association between $DELR_{i,t}$ and our measures of stock price crash risk (i.e., $NCSKEW_{i,t}$, $DUVOL_{i,t}$, and $COUNT_{i,t}$) is more pronounced in a subset of banks with a high likelihood of withholding bad news or have a higher risk of default. Panel A of Table 4 compares the coefficient estimates from regressing equation (4) for high and low homogeneous loan subsamples.

[Insert Table 4 Here]

Odd-numbered columns (Columns 1, 3, and 5) in Panel A pertain to a subsample of banks with high homogenous loans, while even-numbered columns (Columns 2, 4, and 6) pertain to a subsample of banks with high heterogeneous loans. We find that the associations between $HIGH\_DELR_{i,t-1}$ and all three measures of stock price crash risk are significantly positive only for banks in the high heterogeneous loan subsample. Specifically, the estimated β_1 coefficients (t-statistics) are 0.095 (4.00), 0.054 (3.73), and 0.075 (3.17) for *NCSKEW*, *DUVOL*, and *COUNT*, respectively, in even-numbered columns for the high heterogeneous loan subsample. However, the estimated β_1 coefficients (t-statistics) are 0.014 (0.59), 0.011 (0.73), and 0.004 (0.20) for *NCSKEW*, *DUVOL*, and *COUNT*, respectively, in odd-numbered columns for the high homogeneous loans subsample. A comparison of the two reveals that the estimated β_1 coefficient is considerably smaller, although the t-statistics is not statistically significant for the high homogenous loan subsample. Collectively, these results indicate that the hypothesized positive association between DELR and stock price crash exists only in a subsample of banks where managers have greater discretion in estimating expected loan losses.

Panel B of Table 4 further examines the joint effect of heterogeneous loans and homogenous loans. Specifically, we examine a subsample crossing over subsamples of (i) high homogenous loans and low heterogeneous loans and (ii) low homogenous loans and high heterogeneous loans. In this way, Panel B can be considered as a falsification test over Panel A. Consistent with Panel A, the estimated β_1 coefficient is positive and t-statistics is significant only for firms with low homogenous loans and high heterogeneous loans. Specifically, the estimated β_1 coefficients (t-statistics) are 0.194 (3.41), 0.091 (2.59), and 0.166 (3.31) for even-numbered columns only. Conversely, estimated β_1 coefficients and t-statistics are neither positive nor statistically significant for the subsample of high homogenous loans and low heterogeneous loans in odd-numbered columns. Taken together, we suggest that bad news withholding is the channel through which DELR associates with bank stock price crash.

Default Risk Explanation

We also examine whether the default risk channel explains the association between DELR and stock price crash risk at banks. Panel A of Table 5 reports the OLS regression results of Equation (4) on high and low default risk (as measured by Z-Score) subsamples. Odd-numbered columns (Columns 1, 3, and 5) pertain to the subsample of banks with high default risk, while even-numbered columns (Columns 2, 4, and 6) pertain to the subsample of banks with low default risk. Surprisingly, we find statistically significant and positive associations between $HIGH\_DELR_{i,t-1}$ and three measures of stock price crash risk (i.e., $NCSKEW_{i,t}$, $DUVOL_{i,t}$, and $COUNT_{i,t}$) only for a subsample of banks with low default risk. For example, the estimated β_1 coefficients (t-statistics) are 0.037 (3.91), 0.023 (3.72), and 0.018 (1.95) in even-numbered columns, representing banks with low default risk. By contrast, we do not find statistically significant associations between $HIGH\_DELR_{i,t-1}$ and the three measures of stock price crash risk in odd-numbered columns representing a subsample of banks with high default risk. This outcome is contrary to the default risk explanation that the association between DELR and stock price crash risk should be more pronounced in banks with high default risk.

[Insert Table 5 Here]

We also use a different measure of default risk to confirm our findings. Panel B of Table 5 reports the OLS regression results of Equation (4) on high and low default risk (as measured by S&P credit rating score) subsamples. The potential advantage of using S&P credit rating is that it is arguably more exogenous than a simple z-score based on a quantitative calculation of the components of banks' financial statement information. For example, although credit rating agencies use financial statement information to evaluate the credit-worthiness of a firm, it also relies on publicly available outside information and soft information based on qualitative evaluations. Similar to Panel A, the association between $HIGH\_DELR_{i,t-1}$ and three measures of stock price crash risk is positive and significant only in a subsample of banks that have high credit rating score. These findings contradict the default risk explanation and reaffirm that bad news holding is the primary channel through which DELR affects stock price crash risk at banks.

5. Additional Analyses and Robustness Checks

5.1. Financial Crisis

Beatty and Liao (2011) argue that the extent to which banks delay the expected loss recognition affects the ability of loan loss reserves to protect banks from credit losses during economic downturns. Regulators are also concerned that pro-cyclicality may worsen during a financial crisis if banks cannot absorb recessionary credit losses because greater provisioning is required (Financial Stability Forum Report 2009). In addition, we note that the association between DELR and banks' stock price crash risk may be greater during a financial crisis (Ryan, 2007). We define crisis as an indicator variable equal to 1 for periods between 2008 Q1 and 2009 Q2 and 0 otherwise, which is consistent with Beatty and Liao (2011).[5]

[Insert Table 6 Here]

In Panel A of Table 6, we report the yearly distribution of stock price crash risk (*NCSKEW*, *DUVOL*, and *COUNT*). Consistent with prior literature, stock price is more likely to crash in 2008. The mean values of *NCSKEW*, *DUVOL*, and *COUNT* for 2008 are 0.116, 0.112, and 0.013, respectively. These values are extremely high compared to other years. In Panel B of Table 6, we perform subsample analysis based on crisis versus non-crisis period. Consistent with our findings above, the associations between *HIGH_DELR* and all three proxies of stock price crash risks are significantly greater during the period of financial crises. A comparison of columns 1 and 2 in Table 6 indicates that the estimated β_1 coefficient (t-statistic) on *HIGH_DELR* is 0.107 (3.61) during the period of financial crisis (Column 1) while

[5] To examine the relation between DELR and stock price crash risk during a financial crisis, we only focus on the recent financial crisis. Results remain similar when we include 2001:Q2–2001:Q4 (dot-com bubble) as a crisis period.

that of the non-financial crisis period is only 0.026 (2.70) in Column 2. We also find similar results for *DUVOL* (Columns 3 and 4) and *COUNT* (Columns 5 and 6) variables, showing that the association between DELR and stock price crash risk is more pronounced (e.g., *DUVOL*) or only significant (e.g., *COUNT*) during a financial crisis.

5.2. Robustness Tests

Table 7 shows the results of various robustness tests performed to confirm our findings. With respect to our independent variable of interest, we repeat our analysis using the raw value of *DELR* instead of the categorical variable (*HIGH_DELR*). Panel A shows that the associations between $DELR_{i,t-1}$ and the three proxies of stock price crash risk are significant and positive throughout Columns 1 to 3. All coefficient estimates are statistically significant at a p-value less than 0.05.

[Insert Table 7 Here]

We also change our dependent variable of interest to reaffirm our results in Panel B. Specifically, in column 1, we use *CRASH* as a dependent variable. Note that *CRASH* is previously defined as an indicator variable that takes the value of 1 for a bank-quarter that experiences one or more bank-specific daily returns (W) falling 3.09 standard deviation below the mean bank-specific daily returns over the fiscal quarter *t*, and 0 otherwise. Essentially, it is an indicator variable for a bank's stock price crash. The β_1 coefficient estimate and t-statistics are 0.007 and 3.38, respectively, confirming that our findings persist when *CRASH* is used as the dependent variable.

In Column 2, we repeat our analysis by using *JUMP* as an alternative dependent variable. In direct contrast to *CRASH*, *JUMP* is defined as an indicator variable that takes the value of 1 when a bank-quarter experiences one or more bank-specific daily returns (W) that *exceeds* 3.09 standard deviations above the mean bank-specific daily returns over the fiscal quarter *t; JUMP* represents a stock price *jump* as opposed to a stock price *crash*. There are two potential advantages in using *JUMP*. First, it serves as a falsification test for Hypothesis 2 that DELR is associated with stock price crash risk for banks' bad news withholding. Although we control for *SIGMA* throughout our empirical tests, bank stock volatility may cause the association between DELR and stock price crash. Highly volatile stock is likely to have both high DELR from its inherent uncertainty and, simultaneously, large standard deviations in stock returns that mechanically inflate our stock price crash measures. If the documented association between DELR and stock price crash is indeed mechanical, we will find a positive and significant association between *HIGH_DELR* and *JUMP*. Second, using *JUMP* serves as an alternative robustness test for the hypothesized default risk channel. Prior literature suggests that firms with great default risk may experience either extremely negative or extremely positive outcomes (Hutton et al. 2009; Zhu 2016). Therefore, if default risk is the underlying mechanism, we will find a stock price jump for banks with high DELR. However, in Column 2, we do not find either a positive or a statistically significant association between *HIGH_DELR* and *JUMP*. The coefficient estimate is -0.002 and t-statistics is -1.20, showing that high DELR is associated with stock price jump and that no mechanical relationship exists between DELR and extreme outcomes. In Panel C, we include bank-fixed effect in the main results. Throughout the columns, the coefficient estimates and t-statistics between *HIGH_DELR* and the three proxies of stock price crash remain positive and significant. Collectively, these results reaffirm our earlier findings that managers delay the recognition of expected losses to withhold bad news, and the sudden release of accumulated bad news triggers a crash in stock price.

6. Conclusion

In this study, we examine whether and how banks' DELR affects their stock price crash risk by using loan type categorization as a proxy for the bank manager's degree of *discretion* in concealing bad news. Our results indicate that banks with greater delays in the recognition of expected losses experience a greater risk of stock price crash in a subsequent period, and this effect is more pronounced when managers have more discretion in concealing bad news. Moreover, our results reject the alternative channel through which DELR could affect stock price crash (i.e., default risk). We do not find evidence that DELR is associated with stock price crash for banks with high default risk, proxied by z-score and the S&P credit rating score. These findings suggest that bank managers' withholding of bad news manifests in their accounting treatments and has a real impact on the banks' stock price crash. We also find that the association between DELR and stock price crash is higher during a financial crisis, implying that hidden bad news may aggravate pro-cyclicality if the price crash at an individual bank spreads to systematic risk.

Banks, unlike industrial firms, are characterized by more opaque information environment (Autore et al. 2009) and high regulation intensity (Beatty and Liao 2014). Our study provides important policy implications to standard setters and regulators concerning loan accounting decisions at banks and their potential implications on banks' stock prices. For example, regulators may find it helpful to encourage more timely and transparent release of bad news of banks to prevent extreme negative outcomes in the stock market. Regulators may likewise find that the marginal benefit of monitoring is greater for banks with more commercial and industrial loans than for banks with more consumer loans and mortgages.

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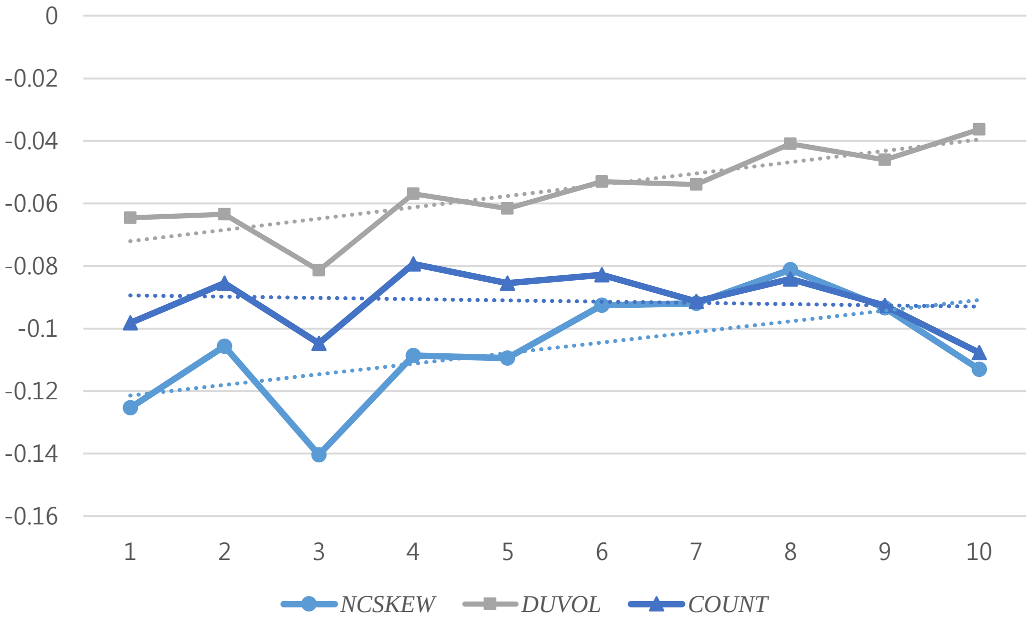
Appendix A. Variable Definitions

Variables	Definition
W	*W* is the log of 1 plus the residual from estimating the following expanded market and industry-adjusted model regression: $r_{i,d} = \alpha + \beta_1 r_{m,d-1} + \beta_2 r_{m,d} + \beta_3 r_{m,d+1} + \beta_4 r_{j,d-1} + \beta_5 r_{j,d} + \beta_6 r_{j,d+1} + \varepsilon_{i,d}$, where $r_{i,d}$ is the return of bank *i*, $r_{j,d}$ is the banking industry (to which bank *i* belongs) return, and $r_{m,d}$ is the value-weighted market return on day *d*.
NCSKEW	The negative coefficient of skewness of *bank-specific daily returns* (*W*). *NCSKEW* is calculated as $-\left[n(n-1)^{3/2}\sum W_{j,\tau}^{3}\right] / \left[(n-1)(n-2)\left\{\sum W_{j,\tau}^{2}\right\}^{3/2}\right]$.
DUVOL	The down-to-up volatility of *W*. *DUVOL* is calculated as $\log\left\{(n_u - 1)\sum_{Down} W_{j,\tau}^{2} / (n_d - 1)\sum_{Up} W_{j,\tau}^{2}\right\}$,where n_u and n_d are the number of up and down days (i.e., above or below the mean *W*), respectively, during the quarter.
CRASH	An indicator variable that takes the value of 1 for a bank-quarter that experiences one or more *bank-specific daily returns* (*W*) falling 3.09 standard deviation below the mean bank-specific daily returns over the fiscal quarter; 0 otherwise. W is the log of 1 plus the residual from estimating the following expanded market and industry-adjusted model regression.
JUMP	An indicator variable that takes the value of 1 for a bank-quarter that experiences one or more *bank-specific daily returns* (*W*) exceeding 3.09 standard deviation of the mean *bank-specific daily returns* over the fiscal quarter; 0 otherwise.
COUNT	Difference between (a) the number of days that bank-specific daily returns (*W*) fall 3.09 standard deviation below the mean bank-specific daily returns over the fiscal quarter and (b) the number of days that *W* falls 3.09 standard deviation below the mean bank-specific daily returns over the fiscal quarter.
DELR	The ratio of the allowance of loan loss provisions (COMPUSTAT "rclq") divided by nonperforming loans (COMPUSTAT "npatq") multiplied by (-1).
HIGH_DELR	An indicator variable equal to 1 if the *DELR* of the bank-quarter is above the median value of DELR for the full sample; 0 otherwise.
SIZE	The natural log of total assets (COMPUSTAT "atq") at the beginning of the quarter.
MTB	The market-to-book ratio, measured as the market value of equity (COMPUSTAT "prccq" x "cshoq"), scaled by book value of equity (COMPUSTAT "ceqq") in quarter (t-1).
LEVERAGE	The leverage ratio, defined as total long-term debts (COMPUSTAT "dlttq") divided by total assets (COMPUSTAT "atq") at the beginning of the quarter.
ROA	Return on assets, measured as income before extraordinary items (COMPUSTAT "ibq") divided by the beginning-of-the-quarter total

	assets.
TURNOVER	Average daily share turnover, measured as the average daily share turnover in quarter t-1 minus the average daily share turnover in the previous quarter (quarter t-2), where the daily share turnover is calculated as the number of shares traded in a day divided by the total number of shares outstanding in the day.
SIGMA	The standard deviation of bank-specific daily returns in quarter t-1.
RET	The average bank-specific daily returns in quarter t-1, multiplied by 100.
Q4	An indicator variable that takes the value of 1 if Qt is the fourth fiscal year, and 0 otherwise
HOM	Homogeneous loans, calculated as a fraction of individual non-mortgage loans over total loans (BRD "BHCK1975/BHCK212").
HET	Heterogeneous loans, calculated as a fraction of commercial loans over total loans (BRD "BHCK1766/BHCK2122").
ZSCORE	The ratio of an individual bank's return on assets (COMPUSTAT "roaq") and its capital ratio (COMPUSTAT "capr1q"/100) divided by the standard deviation of return on assets (Boyd et al. 2006; Fiordelisi and Marques-Ibanez 2013).
SPSCORE	S&P long-term issuer credit rating for the fiscal year-quarter end (COMPUSTAT "spltic rm").

Figure 1. Mean of stock price crash risk variables by deciles of DELR



Note: This figure shows the mean value of stock price crash variables by deciles of DELR. See Appendix A for the variable definitions.

Table 1. Sample Selection

Bank-Quarter observations from 1995 to 2014		66,002
Less	(28,214)	
Bank-Quarter observations with negative assets or equity		(5,349)
Bank-Quarter observations do not have enough financial variables		(11,736)
Bank-Quarter observations missing crash risk related variables		(11,129)
Final sample		37,788

Note: This table shows the sample selection procedure.

Table 2. Descriptive Statistics and Univariate Analysis

Panel A. Summary Statistics

Variable	N	Mean	Std.Dev.	Q1	Median	Q3
NCSKEW	37,788	-0.106	0.751	-0.426	-0.062	0.266
DUVOL	37,788	-0.056	0.444	-0.320	-0.045	0.222
COUNT	37,788	-0.091	0.689	0	0	0
DELR	37,788	-2.944	8.633	-2.525	-1.265	-0.648
SIZE	37,788	7.394	1.603	6.283	7.069	8.162
MTB	37,788	1.497	0.724	0.991	1.368	1.877
LEVERAGE	37,788	0.100	0.090	0.027	0.077	0.149
ROA	37,788	0.002	0.003	0.001	0.002	0.003
DTURN	37,788	-0.002	1.790	-0.408	-0.006	0.400
SIGMA	37,788	0.024	0.016	0.014	0.019	0.028
RET	37,788	0.001	0.003	-0.001	0.001	0.002
Q4	37,788	0.270	0.444	0	0	1

Panel B. Correlation Matrix

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
(1) *NCSKEW*											
(2) *DUVOL*	0.873 <0.001										
(3) *COUNT*	0.724 <0.001	0.607 <0.001									
(4) *DELR*	0.009 0.091	0.011 0.030	0.010 0.044								
(5) *SIZE*	0.033 <0.001	0.019 0.000	0.033 <0.001	0.058 <0.001							
(6) *MTB*	0.019 0.000	0.014 0.007	0.030 <0.001	-0.146 <0.001	0.258 <0.001						
(7) *LEVERAGE*	-0.007 0.163	-0.007 0.156	-0.006 0.235	0.000 0.979	0.060 <0.001	-0.084 <0.001					
(8) ROA	-0.028 <0.001	-0.040 <0.001	-0.001 0.772	-0.076 <0.001	0.077 <0.001	0.382 <0.001	-0.063 <0.001				
(9) DTURN	0.014 0.006	0.012 0.015	0.014 0.006	0.000 0.993	0.025 <0.001	0.019 0.000	0.008 0.133	0.001 0.881			
(10) *SIGMA*	0.035 <0.001	0.058 <0.001	-0.001 0.859	0.083 <0.001	-0.111 <0.001	-0.301 <0.001	0.009 0.068	-0.431 <0.001	0.087 <0.001		
(11) *RET*	-0.007 0.167	-0.013 0.014	0.005 0.341	-0.013 0.009	-0.029 <0.001	0.147 <0.001	-0.021 <0.001	0.145 <0.001	-0.001 0.835	0.041 <0.001	
(12) *Q4*	-0.021 <0.001	-0.019 0.000	-0.002 0.637	-0.008 0.136	-0.014 0.006	0.010 0.054	0.035 <0.001	-0.048 <0.001	-0.036 <0.001	0.021 <0.001	0.024 <0.001

Panel C. Descriptive Statistics by DELR partitions

	Low_DELR			***High_DELR***			
Variables	Mean	Median	Std	Mean	Median	Std	Diff in mean
NCSKEW	-0.118	-0.066	0.738	-0.094	-0.058	0.764	**0.002**
DUVOL	-0.066	-0.055	0.440	-0.046	-0.038	0.449	**<0.001**
COUNT	-0.092	0	0.703	-0.091	0	0.675	**0.881**
SIZE	7.534	7.176	1.665	7.253	6.978	1.525	**<0.001**
MTB	1.799	1.682	0.731	1.195	1.106	0.576	**<0.001**
LEVERAGE	0.095	0.072	0.088	0.104	0.083	0.090	**<0.001**
ROA	0.003	0.003	0.002	0.001	0.002	0.004	**<0.001**
DTURN	0.019	0.001	1.246	-0.023	-0.013	2.203	**0.024**
SIGMA	0.020	0.018	0.010	0.028	0.022	0.020	**<0.001**
RET	0.001	0.001	0.002	0.001	0.001	0.003	**<0.001**
Q4	0.269	0	0.443	0.271	0	0.444	**0.635**

Note: This table shows the descriptive statistics for the sample and univariate analysis. Panel A provides descriptive statistics for the full sample from 1995:Q1–2014:Q4. Panel B reports Pearson correlation matrix among the variables used in the main analysis. In Panel C. we divide the sample into two different groups based on the median value of DELR and reports the univariate comparison between two groups. See Appendix A for the variable definitions.

Table 3. Delayed Expected Loss Recognition and Stock Price Crash Risk

Dep.Variable =	**(1) *NCSKEW***	**(2) *DUVOL***	**(3) *COUNT***
Intercept	-0.278***	-0.182***	-0.233***
	(-7.77)	(-7.41)	(-6.34)
HIGH_DELR $_{t-1}$	0.033***	0.022***	0.018**
	(3.59)	(3.92)	(2.17)
SIZE $_{t-1}$	0.010***	0.002	0.009***
	(2.92)	(0.99)	(3.02)
MTB $_{t-1}$	0.056***	0.036***	0.040***
	(7.01)	(7.35)	(5.56)
LEVERAGE $_{t-1}$	-0.095*	-0.065**	-0.066
	(-1.77)	(-2.07)	(-1.37)
NCSKEW $_{t-1}$	0.020***	0.013***	0.015***
	(3.17)	(3.51)	(2.69)
ROA $_{t-1}$	-5.743***	-3.406***	-2.041
	(-2.94)	(-3.09)	(-1.27)
TURNOVER $_{t-1}$	0.002	0.000	0.003
	(0.81)	(0.16)	(1.57)
SIGMA $_{t-1}$	0.528	0.776***	-0.363
	(1.48)	(3.84)	(-1.11)
RET $_{t-1}$	5.605***	3.139***	6.066***
	(3.03)	(2.82)	(3.48)
Q4 $_{t}$	-0.032	0.016	0.043
	(-0.66)	(0.52)	(0.96)
Year-Quarter Fixed	Included	Included	Included
Clustering	Bank	Bank	Bank
Obs.	37,788	37,788	37,788
Adjusted R^2	0.018	0.028	0.010

Notes: Table 3 reports the results of estimating the effect of delayed loss recognition (DELR) on the extent of crash risk. We winsorize all the continuous variables at the 1st and 99th percentiles. *t*-statistics based on standard errors clustered by bank are shown in parentheses. All variables are defined in the Appendix A. ***, **, and * denote significance at the 1 percent, 5 percent, and 10 percent levels, respectively (two-tailed tests).

Table 4. Bad News Holding Explanation

Panel A. Each Loan Type Analysis

Dep.Variable =	***NCSKEW***		***DUVOL***		***COUNT***	
	(1) High *HOM*	**(2) High *HET***	**(3) High *HOM***	**(4) High *HET***	**(5) High *HOM***	**(6) High *HET***
Intercept	-0.287***	-0.340***	-0.171***	-0.221***	-0.215***	-0.358***
	(-3.79)	(-4.07)	(-3.48)	(-4.28)	(-2.94)	(-3.91)
$HIGH\_DELR_{t-1}$	0.014	0.095***	0.011	0.054***	0.004	0.075***
	(0.59)	(4.00)	(0.73)	(3.73)	(0.20)	(3.17)
$SIZE_{t-1}$	0.009	0.017***	-0.000	0.009**	0.006	0.017***
	(1.16)	(2.64)	(-0.02)	(2.24)	(0.94)	(3.05)
MTB_{t-1}	0.060***	0.057***	0.032**	0.021*	0.054***	0.047***
	(2.97)	(3.12)	(2.27)	(1.82)	(2.90)	(2.67)
$LEVERAGE_{t-1}$	-0.146	-0.118	-0.038	-0.006	-0.167	-0.201
	(-0.94)	(-0.64)	(-0.41)	(-0.06)	(-1.15)	(-1.09)
$NCSKEW_{t-1}$	0.040**	0.032**	0.025***	0.024***	0.031**	0.025**
	(2.45)	(2.10)	(2.69)	(2.77)	(2.13)	(1.98)
ROA_{t-1}	-6.391	-19.614***	-1.890	-8.393***	-4.850	-12.542**
	(-0.83)	(-3.30)	(-0.39)	(-2.66)	(-0.77)	(-2.41)
$TURNOVER_{t-1}$	0.004	-0.000	0.004	0.000	0.005	-0.003
	(0.81)	(-0.01)	(1.00)	(0.03)	(0.83)	(-0.48)
$SIGMA_{t-1}$	1.519	1.567	0.982	1.504**	0.608	1.425
	(1.04)	(1.45)	(1.17)	(2.17)	(0.48)	(1.38)
RET_{t-1}	11.400**	6.300	7.583**	3.628	10.254**	7.078
	(1.99)	(1.21)	(2.23)	(1.15)	(1.99)	(1.39)
$Q4_t$	-0.141	-0.109	0.051	-0.041	-0.081	-0.065
	(-1.10)	(-0.97)	(0.66)	(-0.64)	(-0.74)	(-0.62)
Year-Quarter Fixed	Included	Included	Included	Included	Included	Included
Clustering	Bank	Bank	Bank	Bank	Bank	Bank
Obs.	6,430	6,430	6,430	6,430	6,430	6,430
Adjusted R^2	0.023	0.025	0.028	0.032	0.013	0.011

Panel B. Joint Analysis

Dep.Variable =	*NCSKEW*		*DUVOL*		*COUNT*	
	(1) High *HOM* & Low *HET*	**(2) Low *HOM* & High *HET***	**(3) High *HOM* & Low *HET***	**(4) Low *HOM* & High *HET***	**(5) High *HOM* & Low *HET***	**(6) Low *HOM* & High *HET***
Intercept	-0.035	-0.801***	-0.118	-0.442**	-0.043	-0.983***
	(-0.20)	(-3.45)	(-1.17)	(-2.41)	(-0.36)	(-3.67)
$HIGH\_DELR_{t-1}$	-0.045	0.194***	-0.023	0.091**	-0.089*	0.166***
	(-0.90)	(3.41)	(-0.67)	(2.59)	(-1.91)	(3.31)
$SIZE_{t-1}$	-0.026	0.028*	-0.010	0.014	-0.009	0.030*
	(-0.98)	(1.72)	(-0.72)	(1.44)	(-0.53)	(1.81)
MTB_{t-1}	0.146***	0.025	0.096***	0.017	0.062	0.022
	(2.90)	(0.39)	(2.94)	(0.49)	(1.42)	(0.48)
$LEVERAGE_{t-1}$	0.364	-0.117	0.156	-0.064	0.260	-0.239
	(1.35)	(-0.28)	(1.01)	(-0.24)	(1.00)	(-0.64)
$NCSKEW_{t-1}$	0.008	0.083***	0.002	0.056***	0.028	0.055**
	(0.18)	(2.99)	(0.07)	(3.46)	(0.81)	(2.08)
ROA_{t-1}	6.615	-21.826**	-4.812	-9.918**	9.284	-12.726*
	(0.56)	(-2.44)	(-0.61)	(-2.11)	(0.82)	(-1.78)
$TURNOVER_{t-1}$	0.018	-0.006	0.008	-0.002	-0.002	-0.004
	(0.58)	(-0.40)	(0.66)	(-0.31)	(-0.09)	(-0.28)
$SIGMA_{t-1}$	-2.722	0.729	-1.486	-0.503	-1.082	0.266
	(-1.05)	(0.40)	(-1.02)	(-0.47)	(-0.50)	(0.14)
RET_{t-1}	9.120	11.194	6.322	5.506	16.160**	13.464
	(0.93)	(1.30)	(0.89)	(1.04)	(2.05)	(1.63)
$Q4_t$	0.023	0.251	0.115	0.058	0.092	0.292
	(0.11)	(0.91)	(0.78)	(0.28)	(0.47)	(0.81)
Year-Quarter Fixed	Included	Included	Included	Included	Included	Included
Clustering	Bank	Bank	Bank	Bank	Bank	Bank
Obs.	1,042	1,345	1,042	1,345	1,042	1,345
Adjusted R^2	0.028	0.022	0.033	0.032	0.036	0.017

Notes: Table 4 present the results of equation (4) conditioned on the loan type subsamples. In Panel A, we report the results of Bank-Quarter of high individual loans (*HOM*) and high commercial loans (*HET*) separately. In Panel B, we analyze joint analysis based on the quartile of *HOM* and *HET*. We winsorize all the continuous variables at the 1st and 99th percentiles. *t*-statistics based on standard errors clustered by bank are shown in parentheses. All variables are defined in the Appendix A. ***, **, and * denote significance at the 1 percent, 5 percent, and 10 percent levels, respectively (two-tailed tests).

Table 5. Default Risk Explanation

Panel A. Altman's Z-Score (*ZSCORE*)

Dep.Variable =	***NCSKEW***		***DUVOL***		***COUNT***	
	(1) Lowest Quartile (=High default risk)	**(2) Others**	**(3) Lowest Quartile (=High default risk)**	**(4) Others**	**(5) Lowest Quartile (=High default risk)**	**(6) Others**
Intercept	-0.314***	-0.275***	-0.196***	-0.179***	-0.266***	-0.224***
	(-3.78)	(-7.11)	(-3.47)	(-6.54)	(-3.01)	(-5.67)
$HIGH\_DELR_{t-1}$	0.007	0.039***	0.016	0.023***	0.009	0.018*
	(0.32)	(3.91)	(1.20)	(3.72)	(0.45)	(1.95)
$SIZE_{t-1}$	0.018***	0.007*	0.006	0.001	0.015***	0.006**
	(3.05)	(1.81)	(1.64)	(0.34)	(2.91)	(1.97)
MTB_{t-1}	0.073***	0.050***	0.048***	0.034***	0.048***	0.040***
	(4.30)	(5.28)	(4.75)	(5.84)	(3.22)	(4.54)
$LEVERAGE_{t-1}$	-0.121	-0.094	-0.045	-0.076**	-0.162*	-0.048
	(-1.10)	(-1.58)	(-0.73)	(-2.22)	(-1.68)	(-0.88)
$NCSKEW_{t-1}$	0.018	0.019***	0.011	0.013***	0.016	0.013**
	(1.47)	(2.67)	(1.56)	(3.02)	(1.47)	(2.09)
ROA_{t-1}	-8.727***	-5.618	-4.701***	-6.036**	-3.879*	-4.001
	(-3.56)	(-1.40)	(-3.40)	(-2.56)	(-1.83)	(-1.09)
$TURNOVER_{t-1}$	-0.001	0.004	-0.002	0.002	0.000	0.005*
	(-0.10)	(1.45)	(-0.79)	(0.95)	(0.04)	(1.81)
$SIGMA_{t-1}$	0.414	1.183***	0.698*	1.143***	-0.408	0.147
	(0.62)	(2.80)	(1.84)	(4.65)	(-0.71)	(0.36)
RET_{t-1}	3.122	7.298***	0.208	4.897***	6.081**	6.127***
	(1.01)	(3.10)	(0.11)	(3.58)	(2.03)	(2.80)
$Q4_{t}$	-0.075	-0.015	-0.005	0.022	-0.014	0.065
	(-0.67)	(-0.29)	(-0.07)	(0.65)	(-0.14)	(1.31)
Year-Quarter Fixed	Included	Included	Included	Included	Included	Included
Clustering	Bank	Bank	Bank	Bank	Bank	Bank
Obs.	8,229	29,559	8,229	29,559	8,229	29,559
Adjusted R^2	0.022	0.018	0.033	0.027	0.011	0.009

Panel B. Credit Rating(*SPSCORE*)

Dep.Variable =	*NCSKEW*		*DUVOL*		*COUNT*	
	(1) Lowest Quantile	**(2) Others**	**(3) Lowest Quantile**	**(4) Others**	**(5) Lowest Quantile**	**(6) Others**
Intercept	-0.377	-0.244	-0.179	-0.141	-0.606**	-0.232
	(-1.21)	(-1.53)	(-0.75)	(-1.50)	(-2.07)	(-1.47)
HIGH_DELR $_{t-1}$	-0.018	0.132***	-0.000	0.077***	-0.007	0.071**
	(-0.30)	(3.55)	(-0.00)	(3.73)	(-0.13)	(2.03)
SIZE $_{t-1}$	-0.007	0.017	-0.019	0.006	0.033	0.013
	(-0.27)	(1.32)	(-1.02)	(0.86)	(1.37)	(1.03)
MTB $_{t-1}$	0.134**	0.031	0.089***	0.012	0.080**	0.028
	(2.49)	(1.42)	(2.72)	(0.96)	(2.09)	(1.35)
LEVERAGE $_{t-1}$	-0.076	-0.440**	0.023	-0.219**	-0.135	-0.389**
	(-0.30)	(-2.27)	(0.14)	(-2.17)	(-0.56)	(-2.10)
NCSKEW $_{t-1}$	-0.036	0.026	-0.010	0.018*	0.012	0.013
	(-1.17)	(1.28)	(-0.62)	(1.70)	(0.49)	(0.75)
ROA $_{t-1}$	-30.866*	-4.640	-12.564	0.149	-8.970	8.055
	(-1.74)	(-0.43)	(-1.64)	(0.03)	(-0.99)	(0.76)
TURNOVER $_{t-1}$	0.006	-0.004	0.001	-0.002	0.006	-0.001
	(0.68)	(-0.61)	(0.26)	(-0.60)	(0.88)	(-0.11)
SIGMA $_{t-1}$	-1.326	-0.913	-1.934	1.059	-1.291	-1.794
	(-0.31)	(-0.42)	(-0.99)	(0.81)	(-0.51)	(-0.95)
RET $_{t-1}$	9.779	9.793	3.722	8.800	9.669	7.356
	(1.09)	(1.11)	(0.67)	(1.60)	(0.92)	(0.98)
Q4 $_{t}$	-0.057	0.163	0.155	0.043	-0.146	0.282*
	(-0.22)	(0.68)	(0.82)	(0.31)	(-0.56)	(1.72)
Year-Quarter Fixed	Included	Included	Included	Included	Included	Included
Clustering	Bank	Bank	Bank	Bank	Bank	Bank
Obs.	1,198	3,627	1,198	3,627	1,198	3,627
Adjusted R^2	0.044	0.031	0.074	0.037	0.023	0.020

Notes: Table 5 present the results of equation (4) conditioned on the default risk subsamples. In Panel A, we divide the sample into high default risk group (=lowest *ZSCORE* quartiles) and others. We re-estimate the equation (4) by each subsample separately. In Panel B, we divide the sample into lowest quantile credit rating group and others based on S&P long-term credit ratings (*SPSCORE*) and report the results of each group separately. We winsorize all the continuous variables at the 1st and 99th percentiles. *t*-statistics based on standard errors clustered by bank are shown in parentheses. All variables are defined in the Appendix A. ***, **, and * denote significance at the 1 percent, 5 percent, and 10 percent levels, respectively (two-tailed tests).

Table 6. Financial Crisis

Panel A. Distribution of crash risk measures by fiscal year

Year	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004
NCSKEW	-0.178	-0.197	-0.283	-0.116	-0.081	-0.111	-0.125	-0.092	-0.183	-0.119
DUVOL	-0.116	-0.134	-0.184	-0.048	-0.017	-0.061	-0.091	-0.064	-0.102	-0.062
COUNT	-0.147	-0.143	-0.220	-0.084	-0.081	-0.133	-0.089	-0.069	-0.125	-0.094
Year	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014
NCSKEW	-0.124	-0.079	-0.001	0.116	-0.107	-0.024	-0.113	-0.105	-0.154	-0.102
DUVOL	-0.064	-0.035	0.025	0.112	-0.032	-0.018	-0.064	-0.056	-0.087	-0.063
COUNT	-0.103	-0.053	-0.009	0.013	-0.107	-0.063	-0.125	-0.085	-0.102	-0.073

Panel B: Multivariate Analysis

Dep.Variable =	***NCSKEW***		***DUVOL***		***COUNT***	
	(1) Crisis	**(2) Non-crisis**	**(3) Crisis**	**(4) Non-crisis**	**(5) Crisis**	**(6) Non-crisis**
Intercept	-0.104	-0.284***	0.045	-0.190***	-0.189**	-0.234***
	(-1.36)	(-7.56)	(0.96)	(-7.45)	(-2.28)	(-6.17)
$HIGH\_DELR_{t-1}$	0.107***	0.026***	0.089***	0.016***	0.066**	0.014
	(3.61)	(2.70)	(4.82)	(2.77)	(2.21)	(1.61)
Other Controls	Included	Included	Included	Included	Included	Included
Year-Quarter Fixed	Included	Included	Included	Included	Included	Included
Clustering	Bank	Bank	Bank	Bank	Bank	Bank
Obs.	2,987	34,801	2,987	34,801	2,987	34,801
Adjusted R^2	0.029	0.014	0.033	0.020	0.019	0.007

Notes: Table 6 present the distribution of crash risk measures by each year and the results of equation (4) for the crisis and non-crisis period, respectively. In Panel A, we report the mean value of three different crash risk measure by each year. In Panel B, we divide the sample into crisis period (2008:Q1‒2009:Q2) and non-crisis period and re-estimate the equation (4). Other control variables are included but we only report the interest of variables for brevity. We winsorize all the continuous variables at the 1st and 99th percentiles. *t*-statistics based on standard errors clustered by bank are shown in parentheses. All variables are defined in the Appendix A. ***, **, and * denote significance at the 1 percent, 5 percent, and 10 percent levels, respectively (two-tailed tests).

Table 7. Robustness Tests

Panel A. Raw value of DELR

Dep.Variable =	**(1) *NCSKEW***	**(2) *DUVOL***	**(3) *COUNT***
Intercept	-0.248***	-0.162***	-0.214***
	(-7.04)	(-6.69)	(-5.92)
$DELR_{t-1}$	0.001**	0.001**	0.001***
	(2.16)	(2.56)	(3.07)
$SIZE_{t-1}$	0.008**	0.001	0.008***
	(2.56)	(0.57)	(2.67)
MTB_{t-1}	0.053***	0.034***	0.039***
	(6.65)	(7.04)	(5.47)
$LEVERAGE_{t-1}$	-0.079	-0.054*	-0.057
	(-1.47)	(-1.72)	(-1.19)
$NCSKEW_{t-1}$	0.020***	0.013***	0.015***
	(3.17)	(3.51)	(2.69)
ROA_{t-1}	-6.068***	-3.621***	-2.193
	(-3.11)	(-3.29)	(-1.37)
$TURNOVER_{t-1}$	0.002	0.000	0.003
	(0.78)	(0.12)	(1.55)
$SIGMA_{t-1}$	0.585	0.813***	-0.335
	(1.64)	(4.02)	(-1.02)
RET_{t-1}	5.581***	3.124***	6.060***
	(3.01)	(2.81)	(3.48)
$Q4_{t}$	-0.026	0.020	0.047
	(-0.53)	(0.66)	(1.04)
Year-Quarter Fixed	Included	Included	Included
Clustering	Bank	Bank	Bank
Obs.	37,788	37,788	37,788
Adjusted R^2	0.018	0.028	0.009

Panel B. Alternative measure of stock price crash risk and asymmetric response

Dep.Variable =	**(1) *CRASH***	**(2) *JUMP***
Intercept	-1.993***	-0.758***
	(-9.98)	(-5.05)
HIGH_DELR $_{t-1}$	0.007***	-0.002
	(3.38)	(-1.20)
SIZE $_{t-1}$	-0.021*	-0.047***
	(-1.84)	(-4.68)
MTB $_{t-1}$	0.031	-0.150***
	(1.20)	(-5.15)
LEVERAGE $_{t-1}$	-0.141	0.106
	(-0.83)	(0.68)
NCSKEW $_{t-1}$	0.021	-0.055***
	(1.11)	(-3.36)
ROA $_{t-1}$	-24.662***	-8.939*
	(-5.08)	(-1.92)
TURNOVER $_{t-1}$	0.005	-0.013*
	(0.75)	(-1.81)
SIGMA $_{t-1}$	-2.762**	-0.795
	(-2.38)	(-0.73)
RET $_{t-1}$	11.166*	-15.307***
	(1.88)	(-2.84)
Q4 $_{t}$	0.730***	0.192
	(3.15)	(1.03)
Year-Quarter Fixed	Included	Included
Clustering	Bank	Bank
Obs.	37,788	37,788
Pseudo R^2	0.023	0.012

Panel C. Bank-fixed Effects

Dep.Variable =	**(1) *NCSKEW***	**(2) *DUVOL***	**(3) *COUNT***
Intercept	-0.766***	-0.467***	-0.593***
	(-6.13)	(-6.29)	(-5.49)
$HIGH\_DELR_{t-1}$	0.041***	0.026***	0.019*
	(3.55)	(3.67)	(1.75)
$SIZE_{t-1}$	0.092***	0.049***	0.065***
	(4.82)	(4.48)	(3.99)
MTB_{t-1}	0.095***	0.061***	0.074***
	(7.35)	(8.17)	(6.69)
$LEVERAGE_{t-1}$	-0.133	-0.086*	-0.117
	(-1.51)	(-1.77)	(-1.44)
$NCSKEW_{t-1}$	-0.018***	-0.008**	-0.012**
	(-2.87)	(-2.15)	(-2.16)
ROA_{t-1}	-8.215***	-4.556***	-4.202**
	(-3.86)	(-3.84)	(-2.45)
$TURNOVER_{t-1}$	0.002	0.000	0.003
	(0.85)	(0.24)	(1.54)
$SIGMA_{t-1}$	-0.045	0.143	-0.682*
	(-0.11)	(0.60)	(-1.84)
RET_{t-1}	4.164**	2.448**	4.809***
	(2.19)	(2.14)	(2.70)
$Q4_{t}$	-0.308***	-0.169***	-0.202***
	(-6.54)	(-5.43)	(-4.32)
Year-Quarter Fixed	Included	Included	Included
Bank Fixed	Included	Included	Included
Clustering	Bank	Bank	Bank
Obs.	37,788	37,788	37,788
Adjusted R^2	0.017	0.024	0.009

Notes: Table 7 present the various robustness tests. In Panel A, we report the results of equation (4) after replacing the independent variable to the raw value of *DELR*, not indicator variable for the highly delayed expected loss recognition. In Panel B, we estimate the results with alternative stock price crash risk variable (*CRASH*) and positive jump in stock price (*JUMP*). In Panel C, we include bank fixed effects to capture various time-invariant each bank characteristics. We winsorize all the continuous variables at the 1st and 99th percentiles. *t*-statistics based on standard errors clustered by bank are shown in parentheses. All variables are defined in the Appendix A. ***, **, and * denote significance at the 1 percent, 5 percent, and 10 percent levels, respectively (two-tailed tests).