Does Accounting Conservatism Mitigate Banks' Crash Risk?

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Abstract

We show that banks that follow conservative accounting on average benefit from a reduction in the likelihood of stock price crashes and the key discretionary channel is conservatism arising within the banks' loan loss provisions. The marginal benefit of conservatism in reducing crash risk is greatest among small banks and at the low part of the bank lending cycle. While large banks exhibit crash risk, particularly during the boom periods of the bank lending cycle, the risk for stock price crashes is not reduced by more conservative accounting, even for large banks with more asymmetric information. The implication for bank regulation is that further regulation for conservative bank loan loss accounting does not present a significant opportunity to limit any systemic crash risks of the banking sector.

Keywords: Accounting conservatism, loan loss accounting, bank lending, crash risk

JEL classification: G21, G28.

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1. Introduction

The global financial crisis highlights the importance of banks' reporting transparency for regulatory discussions. One important aspect emphasized by the Financial Accounting Standards Board (FASB) and the International Accounting Standards Board (IASB) is "the overstatement of assets caused by a delayed recognition of credit losses associated with loans (and other financial instruments)" (FASB 2012). In fact, previous studies documents evidence of bad news hoarding, particularly through the use of discretionary loan loss accounting (see Collins et al., 1995; Beatty and Harris, 1999; Beatty et al., 2002; Fonseca and Gonzalez, 2008). Because of agency risk (Jensen and Meckling, 1976), factors such as performance targets, remuneration contracts, and future career prospects can incentivize bank managers to distort loan loss accounting by altering the timely recognition of positive and negative information, with the ultimate aim of manipulating reported earnings (see Watts, 2003).

The agency problem in banks' loan loss accounting is a mechanism that affects firm-level risk and inherently could affect banking system risk. Jin and Myers (2006) and Hutton et al. (2009) observe that accounting opacity increases the probability of large negative stock returns, known as crash risk. They develop an imperfect information model where outside investors observe only partially firm-specific information, enabling inside managers to benefit by hiding firm-specific negative news. Managers are willing to hide firm-specific negative news when the cost of hiding, for instance loss of reputation or private benefits, outweighs the benefit such as future earnings smoothing or job retention. Hiding bad news for an extended period of time, however, is unsustainable (Bleck and Liu, 2007, Kothari et al., 2009). Hence, after a time, the accumulated negative information suddenly becomes publicly available, causing an unexpected large negative return outlier in the distribution of the firm's stock returns. Since banks are innately opaque institutions, the effect of discretionary accounting on equity risk could be large.

However, banks that follow conditional conservatism in their accounting policy would have an asymmetric disposition to recognizing gains and losses in current-period accounting income (Basu, 1997; Beaver and Ryan, 2005).[1] More conditional conservatism implies that accounting earnings will reflect bad news in a timely manner. In fact, since banks are highly leveraged institutions, we would expect banks to exhibit higher levels of conditional conservatism due to contracting demands, litigation costs and regulators' preference (Watts 2003; Armstrong et al., 2010). Hence, under conservative accounting, banks that recognize losses in a timely manner constrain shareholders' optimism and limit manager's tendency to hide bad news. Therefore banks that follow conservative accounting will have a lower probability of a price crash.

In this paper we examine whether the relationship between bank conservatism in earnings and crash risk exists and if so, attempts to identify the mechanism and the defining bank characteristics for which this relationship persists. Our study is motivated by the fact that, on the one hand, banks' assets are inherently opaque and difficult to value by outside investors (Cheng et al., 2011; Gordon, 2013). Banks have an incentive to innovate using loans where default probabilities are hard to assess (Thakor, 2011) and the potential damage from marking-to-market is greatest for many loan assets which are long-lived, illiquid, and senior (Plantin et al., 2008). Within such environment managers can easily overstate financial performance by withholding bad news. Accordingly, conservatism with its lower degree of verification to recognize bad news than to good news should offset manager's tendency to hide bad news, and thus conservatism should reduce crash risk. On the other hand, banks are highly regulated in terms of capital adequacy, limits on accounting discretion, and risk

[1] In this paper we use the term *conservatism* to mean *conditional conservatism* as in Basu (1997).

control. Regulation could reduce information opacity, and if so, may attenuate the link between accounting conservatism and crash risk for banks (Bushman and Williams, 2012).

For our empirical investigation, we use a large sample of US bank-level information during the period 1995-2010. We measure the crash risk of individual banks by employing four different measures of firm-specific stock price crashes following Chen et al. (2001), Hutton et al. (2009), Bradshaw et al. (2010) and Kim et al. (2011). To capture the degree of conservatism of a bank, we use conservatism measures that utilize information from the bank's income statement as well as its balance sheet (Khan and Watts, 2009; Beatty and Liao, 2011).

Our empirical results show that conservatisms in earnings, operating through loan loss provisions, significantly limit future crash risk of banks. In contrast, conservatism operating through earnings before loan loss provisions does not affect crash risk, suggesting either that the discretion over other income items is more limited or investors find it easier to see through accounting manipulation of non-loan items.[2] Since conservatism in loan loss provisions reduces reported net income in the income statement and also increases loan loss allowances in the balance sheet, accounting conservatism can also be reflected in the balance sheet item of loan loss allowances. As loan loss allowances represent an aggregation of past years' loan loss provisions as well as the accounting treatments of net loan charge offs and loan recoveries, as a further investigation, we test whether conservatism operating through these various components of loan loss accounting are good predictors of crash risk. Our results show that accounting conservatism reflected in the loan loss allowances significantly reduces future stock price crash risk. However, this relation is not driven by the discretionary treatment of net loan charge offs and loan recoveries. Hence, we confirm that loan loss

[2] The result holds even when we consider only banks with large non-loan portfolios, confirming that earnings before provisions measure of conservatism does not have signalling effect on crash risk.

provisions from the income statement is the primary accounting channel through which conservatism impacts crash risk for banking sector firms.[3]

To further examine this, we test whether the impact of banks' conservatism on future stock price crash risk varies at different states of the banking business cycle. During high lending cycles, banks engage in excessive risk taking through lending (Berger and Udell, 2004; Foos et al., 2010). Hence, where agency problems are high, bank managers have the incentives to hide bad news to enhance firm performance. Despite managers being capable of hiding bad news, they can only do so for a limited time period, and hence the abrupt release of accumulated bad news will lead to stock price crashes. Similar agency problems arise and are heightened during the low banking business cycles. Negative economic outcomes and dwindling bank performance create incentives for bank managers to delay bad news, which then cumulates and when released in the market will cause stock price crashes. If conditional conservatism indeed restricts managers opportunistic behavior and reduces agency problems (Watts, 2003; LaFond and Watts, 2008; among others), banks adopting conservative accounting practices are expected to exhibit less crash risk especially during the high and low states of the banking business cycle. As far as the moderate stage of the banking business cycle is concerned, since the agency problem is less severe, we do not expect a significant relation between conservatism and crash risk. Consistent with this conjecture, we observe that the incentive to hide bad news is greatest at the height of the lending cycle, with the general level of crash risk seen to be significant during the high state of the lending cycle, but not at the low state. However, our empirical results indicate that during both the high and low lending periods, banks following conservative accounting practices significantly reduce their

[3] It is plausible that the conservatism results could be driven by earnings management, although while conservatism concerns a bank's fundamental accounting policy, earnings management is a transitory phenomenon. In fact, Cohen et al. (2014) find that bank earnings management increase tail risk during the financial crisis. Hence, we control for earnings management in our analyses using the bank earnings management variable of Cohen et al. (2014). (We thank the authors for sharing this data with us.) We observe that even after controlling for earnings management, bank conservatism in loan loss provisions remains significant for crash risk.

stock price crash risk, with the highest impact observed during the low lending periods. This may be driven by stakeholders increased demand for conservatism during economic downturns, along with increased risk of litigation. In the moderate bank lending cycles, we do not see a significant relationship between conservatism and crash risk, as expected.

It is possible that the cyclical variation in crash risk and the effect of conservatism on crash risk is caused more by the general business cycle than the bank lending cycle. Therefore, in the additional analysis, we also carry out tests using alternative and broader proxies of the banking business cycle including the monetary base (M1) and aggregate financial sector risk measure (CATFIN) developed by Allen et al., (2012). These results suggest that the cyclical variation in the effect of conservatism on crash risk is, indeed, related to the bank lending cycle rather than only to broader measures of monetary activity or general economic cycles. In other words, since conservatism in loan loss accounting relates to the quality of loan portfolios, the association between conservatism and crash risk is significantly influenced by bank lending cycles rather than broader business cycles.

Finally, we examine the asymmetric effect of conservatism on crash risk for small and large banks. Smaller banks tend to disclose less information and attract less analyst coverage. So there is a greater informational asymmetry between managers and outside investors. In addition, the nature of informational flow is generally clustered among small banks, with discrete news arrivals much more surrounding key events such as earnings announcements. Thus, small banks have greater opportunities to delay negative information in an attempt to show better firm performance, especially during economic downturns. In contrast, the demand for conservatism is greater when the separation of ownership and control is greater (Ahmed and Duellman, 2007; LaFond and Roychowdhury, 2008) and when there is greater ownership by institutions (Ramalingegowda and Yu, 2012). These tend to be characteristics of large banks. Large banks tend to release information on a regular basis and hence should experience less aggregation of hidden information. Hence, we would expect the relation between accounting conservatism and crash risk to matter much more for small banks and be less pronounced for large banks. Since the most important regulatory concern is the risk of the banking system, it is the crash risk of large banks that is of interest for regulators. Therefore any difference in the effect of conservatism on crash risk between large and small banks is important in assessing the regulatory implications of accounting conservatism. Our results show that there is no effect of conservatism on crash risk among large banks, regardless of the level of information asymmetry. This is consistent with models of equilibrium where the managers of large banks with publicly traded equity have a stronger incentive to be conservative (see Watts, 2003; LaFond and Watts, 2008; Nichols et al., 2009). In contrast, as expected, we find that conservatism matters for smaller banks that are inherently less transparent. Such banks are more prone to crash in low business cycle periods but the presence of higher levels of accounting conservatism significantly reduces the probability of a future price crash during such periods.

Our findings contribute to the literature that investigates determinants of stock price crash risk in the banking industry (Cohen et al., 2011). Our results imply that conservatism of bank loan loss accounting reduces crash risk only for small banks. Conservatism in loan loss accounting does not reduce the crash risk of the large too-big to fail class of banks, which are the main contributors to systemic risk. As a result, conservatism does not present a significant policy tool for regulators to limit systemic risk of the banking sector. Our findings are distinct from and complement those of Cohen et al. (2011), who find that banks manage earnings using loan loss provisions and hide relevant information for some time, but when a crisis strikes, negative information comes out at greater quantity, resulting in increased crash risk. They focus on the use of earnings management as a possible early warning sign of impending problems.

Our results using conditional conservatism show that banks following conservative accounting benefit *on average* from a reduction in the likelihood of stock price crashes, and that the key discretionary channel is loan loss provisions. We show that the relationship is present during both high and low periods of the banking cycle. However, since the effect is predominant only for small banks, it limits the importance of policies that enhance accounting conservatism in potentially controlling the systemic risk of the banking sector.

The remainder of this paper is organised as follows. Section 2 develops the hypotheses. Section 3 presents the data and measurement of variables. Section 4 reports the empirical results and Section 5 presents the conclusions and implications for bank regulation.

2. Hypothesis development

Bank regulators expect managers to maintain accurate financial statements so that investors can effectively determine a bank's earnings and risk. Under the agency theory, however, excessive or deficient treatment of discretionary key accounting policies such as loan loss accounting may be used by bank managers to manage earnings. Jin and Myers (2006), Hutton et al. (2009), Cohen et al. (2011), among others, show that bad news hoarding is associated with an increased future crash risk. Under certain circumstances, bank managers may exhibit a propensity to hide negative news from outside investors. When the cost of hiding negative information outweighs its benefits, the accumulated negative news is abruptly released in the market, causing a firm-specific price crash in the market. Cohen et al. (2011) document evidence of this agency problem among banking sector firms, which is heightened during periods of severe distress.

However, accounting conservatism is widely shown to reduce managers' incentives to manipulate earnings and reduce the agency problems between managers and outside investors

(Watts, 2003; LaFond and Watts, 2008; among others). Under conservatism, the asymmetric treatment of gains and losses impacts the likelihood of future price crashes in the market. The higher recognition of losses over gains offsets the managers' tendency to hide negative information and thus earnings reflect more timely information. Kim and Zhang (2013) show that firms practicing earnings conservatism effectively monitor the timely release of bad news, thereby reducing future crash risk. Hence conservatism among banking sector firms can act as a governance mechanism that prevents accumulation of hidden negative news and hence reduces future crash risk, although this relationship is unclear due to heavy regulation of the banking industry.

Since a bank's earnings are aggregated from various elements of the income statement, insight into the mechanism through which conservatism operates can be gained by decomposing earnings conservatism into conservatism in the discretionary treatment of loan loss provisions and conservatism in the reporting of non-loan items reflected in the earnings before provisions. Bank managers are required to exercise considerable discretion in maintaining sound and accurate estimates of loan loss provisions. Loan loss provisions intend to safeguard the bank against future loan failures by quantifying changes in expected future losses from credit risk in the loan portfolio. Loan loss provisions are reported in income statement as expenses and thus reduce net income. At the same time, loan loss provisions reduce net loans outstanding by increasing the loan loss allowance on the balance sheet. Hence, conservative behavior in the recognition of loan loss provisions should be reflected in the balance sheet item of loan loss allowance. However, conservatism in loan loss allowances would also require an accurate reflection of expected future losses in a bank's loan portfolio, after timely recognition of charge-offs and recoveries. More specifically, greater recognition of loan loss allowances and net loan charge-offs, and a slower recognition of loan recoveries by bank managers can be associated with accounting conservatism behavior. Hence, conservatism may also operate through the alternative components of loan loss accounting, namely, loan loss allowances, net loan charge offs and loan recoveries.

Since conservative accounting practices reduce the amount of hidden negative news and hence reduce the agency problem between managers and outside investors, we would expect that banks with a high degree of conservatism in loan loss accounting treatments should experience lower stock price crashes. These assertions lead us to the following hypothesis:

***H_1*:** *Conservatism in loan loss accounting reduces bank's future crash risk.*

The relationship between conservatism and crash risk can vary during the different banking business cycle environments. During periods of expansion and periods of high demand for banking activities, the potential agency problem is high, as bank managers have the incentive to cater to these high cycles through excessive lending (Berger and Udell, 2004; Foos et al., 2010). Excessive lending behavior, however, will reduce the quality of loan portfolio, leading to the need for hiding bad news. However, the ability to hide bad news diminishes as bad news accumulates, thereby increasing the risk of abrupt release and stock prices crashes. Beatty and Liao (2011) provide evidence that the lending behavior of (non-) conservative banks (does not) remain(s) conservative during periods of high cycle periods. As a result, we expect banks that follow conservative accounting practices to exhibit less future stock price crash risk. During the moderate banking cycles, when business is as usual, the agency problem is less severe, as the incentives to cater to the market are low. Hence the relation between conservatism and crash risk should be less pronounced. As far as periods of low banking cycle are concerned, the agency problem can be severe since bad performance will exaggerate the incentives to hide bad news, which when released in the market will cause stock price crashes. However, during periods of economic downturns, since regulatory scrutiny as well as the risk of litigation is high, accounting conservatism increases the contracting efficiency by discouraging bad news hoarding (Watts, 2003; Armstrong et al., 2010). Additionally, during low banking business cycles, when information frictions are high, debt holders will demand conservative financial reporting (Balakrishnan, Watts and Zuo, 2014). Hence we expect conservative banks to reduce crash risk during periods of low banking cycle. Overall, the above predicts that the relationship between conservatism and crash risk will persist during extreme (high and low) business cycles. Hence, our second hypothesis is as follows:

H_2: *The relationship between conservatism and future stock price crashes is pronounced during extreme (high and low) banking business cycles.*

The potential for information opacity between managers and outside investors among small banks is generally considered to be higher than in large banks. Small banks disclose less information and have limited analyst coverage. Information tends to be clustered around key events such as earnings announcements. Furthermore, small banks, with high growth options and thus high information asymmetry between managers and outside investors, have greater opportunities to hide negative information in an attempt to show better firm performance. Hence we expect the impact of conservative accounting on crash risk to be pronounced among smaller banks. In contrast, large banks naturally exhibit less growth options and attract more analyst coverage, thus reducing the information asymmetry between managers and shareholders. Further, large banks, due to certain characteristics, exhibit an incentive to engage in a level of accounting conservatism and transparency that is roughly optimal (Watts, 2003; and LaFond and Watts, 2008). Since the demand for conservatism is greater when the separation of ownership and control is greater (Ahmed and Duellman, 2007; LaFond and Roychowdhury, 2008) and when there is greater ownership by institutions (Ramalingegowda and Yu, 2012), we expect to find no strong relationship between conservatism and crash risk for large banks. This is due to the fact that large banks' accounting policy choices may result in a level of transparency that limits the scope for large negative accounting surprises. This gives our final hypothesis:

H_3: *The relationship between conservatism and future stock price crashes is more pronounced for small banks, while such relationship is insignificant for large banks.*

3. Variable Measurement

3.1 Measurement of firm-specific crash risk

In this study we investigate the impact of firm-specific conservatism on firm-specific crash risk. Therefore, we estimate firm-specific weekly returns using the following expanded index model regression:

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

where $r_{j,t}$ is the return on stock *j* in week *t* and $r_{m,t}$ is the CRSP value-weighted market index in week *t*. To allow for non-synchronous trading we include lead and lag variables for the market index (Dimson, 1979). This regression removes market-wide return movements from firm returns, and thus residuals capture weekly firm-specific returns. Since residuals from Equation (1) are skewed, we define the firm-specific weekly return for firm *j* in week *t* ($w_{j,t}$) as the natural logarithm of one plus the residual. Then following Chen et al., (2001), Hutton et al. (2009), Bradshaw et al. (2010) and Kim et al. (2011) we estimate four primary measures of crash risk.

First, we define an indicator variable *CRASH* that is equal to one when a firm experiences at least one crash week during the fiscal year, and zero otherwise. A crash week occurs when a firm experiences firm-specific weekly returns 3.09 standard deviations below the mean firm-specific weekly returns for the entire fiscal year (3.09 is chosen to generate a frequency of 0.1% in the normal distribution).

The second measure is the negative conditional skewness (*NCSKEW*). *NCSKEW* is the negative of the third moment of firm-specific weekly returns for each firm and year divided by the standard deviation of firm-specific weekly returns raised to the third power. Specifically, for a given firm in a fiscal year we calculate *NCSKEW* as follows:

$$NCSKEW_{j,t} = -[n(n-1)^{\frac{3}{2}} \sum W_{j,t}^{3} / [(n-1)(n-2)(\sum W_{j,t}^{2})^{\frac{3}{2}} \tag{2}$$

The third measure is the extreme sigma (*EXTR_SIGMA*). *EXTR_SIGMA* is the negative of the worst deviation of firm-specific weekly returns from the average firm-specific weekly return divided by the standard deviation of firm-specific weekly returns. Particularly, for a given firm in a fiscal year we compute *EXTR_SIGMA* as follows:

$$EXTR\_SIGMA = -Min[\frac{W - \overline{W}}{\sigma_W}] \tag{3}$$

Finally, following Chen et al. (2001), we compute the fourth measure of crash risk, the down-to-up volatility (*DUVOL*). *DUVOL* is calculated as follows: for each firm *j* over a fiscal year *t*, we separate all the weeks with firm-specific returns below the annual mean from those firm-specific weekly returns which are above the annual mean and categorize them as "down weeks" and "up weeks" respectively. We then compute the standard deviation for the two predefined subsamples. *DUVOL* is the log of the ratio of the standard deviations of the two subsamples, the one for the "down weeks" over the standard deviation of the "up weeks". Larger values of *NCSKEW*, *EXTR_SIGMA* and *DUVOL* signify greater crash risk. *CRASH* and *EXTR_SIGMA* focus on capturing negative firm-specific returns at the lowest tail of the return distribution and thus may be viewed as measures of extreme crash risk. In contrast, *NCSKEW* and *DUVOL* focus on capturing a standardized skewness of negative firm-specific returns or the asymmetry in standard deviation between "down" and "up" weeks, respectively, which implies that they also measure medium crash risk.

3.2 Measurement of accounting conservatism

We utilize information from banks' income statements as well as their balance sheets in order to construct various income statement and balance sheet based measures of accounting conservatism.

3.2.1 Income statement measures of conservatism

Based on Khan and Watts (2009) and Beatty and Liao (2011) we use bank quarter analysis and cross-sectional regressions to estimate Basu (1997) earnings conservatism measure. In accordance with previous literature, we remove bank-quarters with a price per share of less than \$1 and bank-quarters with negative book value of equity. Furthermore, we require twenty observations per quarter to run each regression. Particularly, we estimate the following model:

$$NI = \beta_0 + \beta_1 \times D + Returns \times (\mu_1 + \mu_2 MV + \mu_3 MTB + \mu_4 LEV) + \\ D \times Returns \times (\lambda_1 + \lambda_2 MV + \lambda_3 MTB + \lambda_4 LEV) + \varepsilon \tag{4}$$

where *NI* is net income (Compustat "niq") divided by lagged market value of equity (Compustat "cshoq" x share price at the end of the fiscal quarter), *Returns* are quarterly returns compounded from monthly returns beginning at the second month after fiscal quarter end, *D* is an indicator variable which takes the value of one for negative *Returns* and zero otherwise, *MV* is market value of equity defined as the natural log of market value (Compustat "cshoq" x share price at the end of the fiscal quarter), *MTB* is the market-to-book value calculated as the ratio of market value of equity (Compustat "cshoq" x share price at the end of the fiscal quarter) over book value of equity (Compustat "ceqq"), and *LEV* is the long term debt (Compustat "dlttq") divided by market value of equity (Compustat "cshoq" x share price at the end of the fiscal quarter).

Using the coefficient estimates from Equation (4) we calculate the earnings conservatism measure, *NI_CSCORE* by cumulating *CS* over the previous three-year period to eliminate bias arising from less persistent conservatism. *CS* is calculated as follows:

$$CS = \hat{\lambda}_1 + \hat{\lambda}_2 MV + \hat{\lambda}_3 MTB + \hat{\lambda}_4 LEV \tag{5}$$

By construction, banks with higher *NI_CSCORE* values are considered more conservative and as a result they exhibit a smaller delay in expected loss recognition. Hence *NI_CSCORE* is a measure of asymmetric timeliness of net income in recognizing bad news versus good news. Net income, however, aggregates several line items of the income statement. Thus, to understand better the sources of conservatism, we decompose the net income conservatism into two components: (i) loan loss provision conservatism and (ii) earnings before provision conservatism. In doing so, we re-run the equation using as dependent variables either loan loss provision, *LLP*, or earnings before provision, *EBP*. Following the approach outlined above, we estimate *LLP_CSCORE* and *EBP_CSCORE*. Our primary prediction is that conservatism operates through loan loss provisions, which are the discretionary accruals of banks, rather than earnings before provisions.

3.2.2 Balance sheet measures of conservatism

In constructing our loan loss allowance measure of conservatism, we follow Beatty and Liao (2011) and use the ratio of the allowance of loan loss provisions (Compustat “rclq”) divided by the non-performing loans (Compustat “npatq”). Banks which are more conservative are expected to have recognized more allowance of loan loss provisions relative to non-performing loans. Following this reasoning, our balance sheet conservatism measure, *R_LLA_NPAT*, is the decile rank of the difference between lagged ratio and the median during the quarter. We also decompose loan loss allowances into "initial" loan loss allowances (i.e. before adjustments in loan loss charged-offs and loan recoveries), loan loss charge offs and loan loss recoveries (Nichols et al., 2009). Using these components, we create a measure of conservatism for each component of loan loss allowances following the rationale of Beatty and Liao (2011). Particularly, we calculate "initial" loan loss allowance as the loan loss allowances plus loan charge offs minus loan loss recoveries (Compustat "rclq" plus "llwocr" minus "llrcr") divided by the non-performing loans (Compustat "npatq"). Banks which are more conservative are expected to have recognized more initial loan loss provisions relative to non-performing loans. Following this reasoning, our conservatism measure of “initial” loan loss allowances (R_INITIAL_LLA_NPAT) is the decile rank of the difference between the lagged ratio and the median during the quarter.

We use the ratio of loan charge offs (Compustat "llwocr") divided by the non-performing loans (Compustat "npatq") to construct the measure of conservatism in loan loss charged-offs. Nichols et al (2009) suggest that loan charge offs likely reflect realizations of manager's expectations of loan losses that became delinquent during the previous and the current period. At the same time, managers may be concerned with the size of loan loss allowance (preferring to avoid appearing over-reserved and receiving negative scrutiny from regulators and analysts), thus conservative banks should charge off more loans to avoid the appearance of overly large loan loss allowance. If they do so, however, during periods where the quality of the loan portfolio deteriorates then greater charge offs may simply signal the quality of the loan portfolio rather than conservatism. No such signal is revealed in the market in periods where the loan portfolio quality improves. Assuming that positive changes in non-performing loans proxies indicate an improvement in a bank's loan portfolio (Nichols et al., 2009), our measure of conservatism in loan loss charged-offs (*R_NCO_NPAT*) is the decile rank of the difference between the lagged ratio and the median during the quarter, when the lagged loan loss allowance plus charge offs deflated by the non-performing loans is greater than the median of the previous quarter and the lagged change in non-performing loans is negative.

Finally, we use the ratio of loan loss recoveries (Compustat "llrcr") divided by lagged loan charge offs (Compustat "llwocr") to construct the measure of conservatism in loan loss recoveries. Loan recoveries likely relate to loan charge offs during the previous periods and according to Nichols et al. (2009) more conservative banks should exhibit smaller recoveries. This ratio, however, during periods where the loan loss portfolio quality deteriorates may reflect an earnings management practice aiming to increase temporarily loan loss allowance enabling in this respect the recognition of lower loan loss provisions. In contrast, in periods where loan loss portfolio quality improves there is less such need for earnings management, rendering this ratio more appropriate in capturing conservatism. Following this reasoning, our measure of conservatism in loan recoveries (*R_REC_NCO*) is the decile rank of the difference between the lagged ratio and the median during the quarter, when the lagged change in non-performing loans is negative. Note that we multiply the ratio with minus one, so greater values of (*R_REC_NCO*) indicate more conservatism in loan recoveries.

3.3 Control variables

In accordance with previous literature, we include several control variables. First, Hong and Stein's (2003) model predicts that investor heterogeneity causes greater crash risk. Therefore, we control for investor heterogeneity using the detrended average weekly stock trading volume in year *t-1* ($DTURN_{t-1}$). We also include lagged average firm-specific weekly returns (RET_{t-1}) and lagged volatility of firm-specific weekly returns ($SIGMA_{t-1}$) over the fiscal year period *t-1* since Chen et al. (2001) provide evidence that firms with high past returns and more volatile firms are more prone to crash risk. Following Hutton et al. (2009) we include lagged firm-size defined as the natural logarithm of market value of equity in year *t-1* ($SIZE_{t-1}$), lagged market-to-book value of equity in year *t-1* (MB_{t-1}), lagged financial leverage defined as the total liabilities to total assets in year *t-1* (LEV_{t-1}), and lagged return-on-assets defined as income before extraordinary items to total assets at year *t-1* (ROA_{t-1}). Finally, we also include the capital ratio in year *t-1* ($CAPITAL_{t-1}$) as the tier one risk-adjusted capital ratio and the bank's deposits over total assets in year *t-1* ($DEPOSITS_{t-1}$). To address concerns for endogeneity between past crash risk experiences and conservatism – i.e. firms which have experienced stock price crashes in the past improve their earnings conservatism to prevent such events from reoccurring – we use lagged values for the dependent variable in our regressions (see for example Harford, Mansi and Maxwell, 2008).

4. Dataset

Our analysis consists of Compustat banks with available information to perform the analysis during the period 1995 to 2010.[4] We focus on Bank Compustat since our crash risk measures require publicly traded banks. Crash risk measures are estimated using weekly stock returns from CRSP. Similar to prior literature we exclude firm-year observations with (i) a stock price at the fiscal year-end of less than $2.5, and (ii) less than 26 weeks of stock returns during a fiscal year. Conservatism measures and control variables are calculated using information from Bank Compustat. The final sample includes 1108 banks with 6687 firm-year observations.

Table 1 reports the yearly distribution of our sample during the period 1995 to 2010, with firm-year observations and stock price crashes estimated each year. Based on our definition of crashes, and assuming that firm-specific returns are normally distributed, we would expect to observe 0.1% of the firms crashing in any week. Accordingly, the likelihood of a crash would be $1 - (1 - 0.001)^{52} = 5.07\%$. From our analysis, and consistent with Hutton et al. (2009), it seems that crashes are more prevalent (about 15%) than what would have been expected. Interestingly, the frequency of crashes is independent of the market cycles, which is not surprising because we employ an index model to define crashes. Finally, the average weekly return of crashes throughout the period of investigation is substantial, and equals -14.6%. Both the prevalence and the magnitude of the crashes indicate that stock price crashes is an event with substantial consequences for market participants, especially for the shareholders of the affected firm, and therefore understanding the determinants of crashes is of paramount importance.

Table 2 presents the descriptive statistics for the major variables along with additional variables that are used as controls in our multivariate analysis. The mean (median) value of

[4] Note that a main control variable, capital ratio, is available since 1993, the first year of adoption of the Federal Depository Insurance Corporation Improvement Act of 1991.

CRASH is 0.150 (0.0000), suggesting that, on average, about 15% of firm-years demonstrate one or more firm-specific weekly returns that fall within 3.09 standard deviations below the annual mean. Regarding the remaining crash risk measures, the mean (median) value of *NCSKEW* is -0.146 (-0.114), of *EXTR_SIGMA* is 2.483 (2.360) and of *DUVOL* is -0.104 (-0.096). Despite the fact that we employ a dataset that includes bank related firm-year observations, all the aforementioned crash risk statistics are qualitatively similar to those reported in Kim et al. (2011) and Bradshaw et al. (2011).

Within the income statement conservatism variables, the mean (median) value of *NI_CSCORE* is -0.012 (-0.002), of *LLP_CSCORE* is -0.001 (0.000), and of *EBP_CSCORE* is -0.011 (-0.001). Regarding the balance sheet conservatism variables, the mean (median) value of *LLA_NPAT* is 0.979 (0.193), of *INITIAL_LLA_NPAT* is 4.986 (0.224), of *NCO_NPAT* is 0.091 (0.000), and of REC_NPAT is 0.058 (0.000). Differences in mean and median figures of balance sheet conservatism variables indicate a skewed distribution. To avoid the influence of skewness we use the decile rank of each of these variables in our main analysis.

As far as the control variables are concerned, our sample consists of relatively large firms with mean (median) *SIZE* values of 7.405 (7.037), with moderate growth as indicated by *MB* ratio of 1.670 (1.548). As expected, due to the nature of their operations, banks rely heavily on leverage with *LEV* that equals to 0.908 (0.912) and they are marginally profitable as captured by *ROA* values of 0.009 (0.009). Finally, banks hold *CAPITAL* that equals to 0.111 (0.106) and maintain *DEPOSITS* that equal to 0.738 (0.752); notably, all these statistics are comparable to the average bank figure reported in Beatty and Liao (2011). More generally, our sample is fairly representative of studies that utilize data from the same sources.

Table 3 presents Pearson (Spearman) correlation coefficients above (below) the diagonal among crash risk variables, accounting conservative variables, and control variables. The crash measures NCSKEW and DUVOL are highly correlated, since both are essentially measures of skewness and captures smaller and medium-sized crashes. On the other hand, CRASH and EXTR_SIGMA are highly correlated with each other, but appear to pick up a different dimension of crash risk to the other two measures, since these two measures are more sensitive to large share price falls.

Overall, we observe that the crash risk measures are negatively correlated to the income statement accounting conservatism measures of *NI_CSCORE*, *LLP_CSCORE* and *EBP_CSCORE*. Largely, negative but less significant relations exists also between crash risk measures and balance sheet accounting conservatism measures of *R_LLA_NPAT*, *R_INITIAL_LLA_NPAT* and *R_NCO_NPAT*. In contrast, R_REC_NCO does not exhibit a negative relation with crash risk measures. Overall, the evidence of inverse relation between the crash risk and the different conservatism measures is consistent with the predictions of our first hypothesis (H_1) according to which banks displaying higher loan loss accounting conservatism should experience a reduction in future crash risk.

As far as the control variable is concerned, the correlation between *RET* and *SIGMA* is -0.96 suggesting that they largely pose similar but opposite information content. To avoid multicollinearity issues in the multivariate analysis we include only the *RET*. The remaining correlations are not high to raise other concerns for multicollinearity.

5. Empirical results

5.1 Test results for accounting conservatism and crash risk

In this section we test whether accounting conservatism helps reduce crash risk among banking sector firms. Using the two dimensions of earnings conservatism – loan loss provisions and earnings before provisions (developed in Section 3) – we examine the channels through which accounting conservatism impacts future crash risk. We estimate the model:

$$CR\_RISK_t = \alpha_1 + \alpha_2 CSCORE_{t-1} + \sum_i \lambda_i CONTROLS_{i,t-1} + \varepsilon_t \qquad (6)$$

where CR_RISK_t denotes the four different crash risk measures (*CRASH*, *NCSKEW*, *EXTRA_SIGMA* and *DUVOL*) calculated in year *t* and *CSCORE* denotes the conservatism measures *NI_CSCORE*, *LLP_CSCORE* and *EBP_CSCORE* defined in Section 3.2. We would expect the slope coefficients associated to *CSCORE* to be negative, reflecting the prediction in Hypothesis H_1 that firms displaying accounting conservatism should experience a reduction in future crash risk. We include in the regressions all the control variables outlined in Section 3.3 and also control for year fixed effects in the regressions. The standard errors are adjusted for clustering at the firm level.

Table 4 presents the results from the regressions. Columns 1 and 2 display the logistic regression estimates for the crash risk variable *CRASH* and Columns 3 to 8 report results from piece-wise linear regressions for crash risk variables *NCSKEW*, *EXTR_SIGMA* and *DUVOL*. We find that the coefficients associated with the aggregate net income measure of conservatism are significant for the crash measures *NCSKEW* and *DUVOL* that capture smaller and medium-sized crashes. Hence, firms that exhibit a higher degree of earnings conservatism at the aggregate profit level are less prone to this type of crash risk. When we consider conservatism operating through the different components of net income, we find that the loan loss provision based measure of conservatism, *LLP_CSCORE,* is statistically significant (at a minimum level of 5 percent) and negative for all the crash risk variables. The earnings before provisions measure of conservatism, *EBP_CSCORE*, which is unaffected by loan provisions is insignificant in all regressions. Hence, decomposing earnings into the two components reveals that timely recognition of loan loss provisions is the key discretionary component through which accounting conservatism operates in reducing future crash risk. Discretion in non-loan components of the income statement does not have an effect. Overall, the results indicate that, in line with Hypothesis H_1, accounting conservatism has a significant impact in reducing future crash risks among banking sector firms. As a robustness check, we rerun the analysis separately for banks with large and small non-loan portfolios. The untabulated results show that conservatism operating through loan loss provisions remains significant for banks, independent of the size of loans on their balance sheet. In addition, the results confirm that the earnings before provisions measure of conservatism does not have a signaling effect on crash risk even for banks holding large non-loan portfolios.

Next, we explore the relationship between accounting conservatism and crash risk using balance sheet measures of conservatism. We first examine whether conservatism in the balance sheet recognition of loan losses, reflecting the cumulative accounting treatment of loan loss allowances, predicts future crash risk. Loan loss allowances in the balance sheet reflect a series of loan loss provisions over past periods. Hence being more or less conservative in the current period is linked in the balance sheet measure with the level of conservatism in previous periods. Further, this balance sheet measure is an aggregated measure of conservatism which reflects the various discretionary components of banks' loan loss accounting, namely loan loss provisions, net loan charge-offs, and loan recoveries. We also test whether conservatism operating through the disaggregated components of net loan charge offs and loan recoveries are good predictors of crash risk. Greater recognition of loan loss allowances and net loan charge-offs, and a slower recognition of loan recoveries could be associated with accounting conservatism behavior.

The test results are reported in Table 5. We find that the coefficients of the aggregated loan loss balance sheet variable *R_LLA_NPAT* are statistically significant (at a minimum level of 5 percent) for crash measures, except for *CRASH*. For *NCSKEW*, the significance is less than when *LLP_CSCORE* is used. Thus, although the results are broadly consistent with *LLP_CSCORE*, this measure of conservatism seems to do a worse job at predicting crash risk for the measures that reflect large share price falls. The income statement and balance sheet measures of conservatism appear to be picking up different information, having a Pearson correlation of only 2%. As a further untabulated analysis, we test whether the weak relations of *R_LLA_NPAT* and crash risk persist during high, moderate and low bank lending cycles. We find that using this measure reduces the predictive power of conservative accounting for crash risk over the cycle. During periods of high and moderate lending cycles there is some significance, but we do not find this causal link significant during periods of low lending cycles. Hence the overall results using loan loss allowances in the balance sheet as a measure of conservatism confirm the link between conservative accounting and crash risk but demonstrate that this is inferior to an income statement measure of conservatism for that purpose.

When we consider conservatism measure of loan loss allowance before the treatment of net loan charge offs and loan recoveries (*R_INITIAL_LLA_NPAT*) simultaneously with the measures of net loan charge offs (*R_NCO_NPAT*) and loan recoveries (*R_REC_NCO*), we find weaker significance than for loan loss allowance and limited evidence for the case of conservatism operating through net loan charge offs and loan recoveries (with only *CRASH* measure significant at 10% level). So disaggregating the balance sheet measure does not improve the information about future crashes contained in the treatment of loan loss allowances. In summary, the results confirm that the main dimension through which accounting conservatism operates in reducing future crash risk is the discretionary channel of loan loss provisions.

5.2 Accounting conservatism, banking business cycle and crash risk

In this section, we test whether the effect of conservatism on future stock price crash risk varies at different states of the banking business cycle. Since loan loss provisions is the main channel through which accounting conservatism operates in reducing crash risk, we use the *LLP_CSCORE* measure of conservatism for the rest of our analyses. We proxy banking business cycles using the macroeconomic variable "Commercial and industrial loans outstanding plus non-fin commercial paper (*FCLNBW*)" compiled by The Conference Board, which measures the volume of business loans held by banks and commercial papers issued by nonfinancial companies. Commercial and industrial loans represent a major line of business for the banking industry and also act as an important source of funding for the business sector. *FCLNBW* provides an indication of the lending activity of the banking sector to the business sector. We use the Hodrick-Prescott (1997) filter to obtain an estimate of a flexible trend of the *FCLNBW*. The parameter λ takes the value of 100. We then classify the period of investigation into terciles, reflecting the three states of the business cycle (high, moderate, and low), based on the difference between the growth rates in *FCLNBW* and the growth rates of the *FCLNBW* according to the flexible trend.

To investigate the relationship between accounting conservatism and crash risk under the different states of the banking business cycle, we employ the following model:

$$\begin{aligned}
&CR_RISK_t = \alpha_1 + \alpha_2 LLP_CSCORE_{t-1} * HIGH_CYCLE_{t-1} \\
&+\alpha_3 LLP_CSCORE_{t-1} * MODERATE_CYCLE_{t-1} + \alpha_4 LLP_CSCORE_{t-1} * LOW_CYCLE_{t-1} \\
&+\alpha_5 HIGH_CYCLE_{t-1} + \alpha_6 LOW_CYCLE_{t-1} + \sum_i \lambda_i CONTROLS_{i,t-1} + \varepsilon_t
\end{aligned} \tag{7}$$

where the *High_Cycle* variable is equal to one for years 2001 and 2006-2009, with zero otherwise; the *Moderate_Cycle* variable is equal to one for years 1995-2000, with zero otherwise; and the *Low_Cycle* variable is equal to one for years 2002-2005 and 2010, with zero otherwise. The test results are reported in Table 6. In line with Hypothesis H_2, we find that the coefficients associated with *LLP_CSCORE* during high and low states of the business cycle are all negative and significant in almost all cases (except once for the *CRASH* measure during the high cycle period). This shows that accounting conservatism among banks helps reduce future crash risks at the extremes of the banking business cycle. At the high stage of the cycle more conservative banks seem to benefit from a reduction in future stock price crashes, perhaps because conservative banks do not over-lend at such times (Beatty and Liao, 2011). However the impact of conservatism on future crash risk is even more pronounced during low business cycle periods, as seen by the higher magnitudes and the stronger significance (at one percent level) of the slope coefficients for *LLP_CSCORE* during the low states of the business cycle. Thus, although non-conservative banks are more prudent in their lending behavior during periods of capital crunch (as noted by Beatty and Liao, 2011) the extra prudence of the more conservative banks has a greater incremental effect on crash risk at these times. During moderate times, the effect of accounting conservatism is insignificant. On average, we find that banks are more prone to crash after high period of the banking business cycle than after low periods. However, banks with more conservative loan loss accounting experience a significant reduction in future crash risk after periods of high lending and an even greater reduction in crash risk after the low part of the banking cycle.

5.3 Accounting conservatism and crash risk for small and large banks

In this section, we study the asymmetric effect of conservatism on crash risk for small and large banks. Bank size is important for two reasons. First, it is closely related to information asymmetry. Larger banks are much more followed by press, analysts, and institutional investors, and therefore compared to smaller banks it is more difficult for managers to withhold negative information from the market. Therefore, under Hypothesis H3, we predict that the relationship between accounting conservatism and the reduction in future crash risks will be more pronounced for smaller banks. Second, large banks are the primary focus of attempts to control systemic risks of the banking sector. If conservatism affects the crash risk of large banks differently to its effect for small banks, that has important implications for banking regulation.

We test these predictions by considering the specification Equation (7) for banks classified according the size of their total assets. A bank is considered small (large) when the size of their total assets is below (above) the median size of the sample considered. We report the results in Table 7. We observe that large banks show no relationship between crash risk and accounting conservatism. For large banks the coefficients of *LLP_CSCORE* are insignificant for all measures of crash risk and all stages of the credit cycle. Although the coefficients are negative, as predicted, they are insignificant and much smaller than the corresponding coefficients for small banks. This is consistent with Jin and Myers (2006) who argue that less opaque stocks are less likely to crash, and with Watts (2003), and LaFond and Watts (2008) who suggest that large banks with publicly traded equity will have incentives to engage in more conservative accounting. For the case of small banks, consistent with Hypothesis H_3, we observe that accounting conservatism in loan loss provisions is significantly associated with a decrease in large stock prices crashes, with *LLP_CSCORE* coefficients being significant for the *CRASH* and *EXTR_SIGMA* measures, and the interaction term at the low stage of the banking cycle being significant for all measures. Conservatism in accounting significantly reduces the probability of future price crashes mainly during the low states of the banking business cycle for small banks.

In addition, we find different exposure of large and small banks to crash risk at different stages of the banking cycle. Regardless of their conservatism, large banks generally have significantly higher crash risk at the high part of the banking cycle. In contrast, small banks show much less unconditional link between crash risk and the banking cycle. However, conditional on the low part of the banking cycle they show a strong link between conservatism and crash risk. Conservatism does not seem to matter during moderate cycles.

Due to the importance of the finding that large banks show no link between conservatism and crash risk, Table 8 further investigates the relationship between accounting conservatism and crash risk using the subsample of large banks that have high analyst forecast dispersion.[5] We test whether conservatism matters for large banks regardless of high levels of opacity. The results indicate no systematic relationship between crash risk and conservatism, confirming that the general result of no link between conservatism and crash risk for large banks holds even within the subset of large banks that have high information opacity.

6. Additional analysis - which cycle matters for crash risk?

The results so far suggest that the cyclical variation in crash risk and the effect of conservatism on crash risk is influenced by the banking business cycles that measure bank lending activity. However, it is possible that the effect of conservatism on crash risk varies according to the cycle in general economic conditions or other measures of monetary activity. Therefore, we also carry out tests using alternative and broader proxies of the banking business cycle such as the monetary base (M1), the aggregate financial sector risk measure (CATFIN) developed by Allen, Bali, and Tang (2012), as well as the growth in GDP.

[5] Some firms in our sample have missing values for analyst forecasts or have a single analyst forecast. In such cases, we are unable to calculate the dispersion measure and we classify such firms as high dispersion firms in our regressions. The results remain unchanged if we remove such firms from our regressions.

The results for the monetary base and CATFIN are reported in Tables 9 and 10. We find that the results using the monetary base and CATFIN confirm the bank lending cycle results, but are slightly less significant. These results suggest that the cyclical variation in the effect of conservatism on crash risk is, indeed, related to the bank lending cycle rather than only to broader measures of bank or monetary activity. The results (unreported) using the GDP cycle are much weaker, confirming that the cyclical variation is more closely related to banking sector cycles than general economic cycles. Since conservatism in loan loss accounting relates to the quality of loan portfolios, we find the association between conservatism and crash risk is significantly influenced by bank lending cycles rather than broader business cycles.

7. Conclusion

This paper investigates whether there is a link between conditional conservatism and banks' crash risk. We find that conditional conservatism limits bank crash risk on average and the key channel of influence is the discretionary treatment of loan loss provisions. We observe that the impact of conservatism on crash risk is magnified during the low state of the banking cycle, with some increased effect also during the high lending stage of the banking cycle. Conservatism does not matter during moderate business cycles that correspond to "business-as-usual" periods.

The effect of conservatism on crash risk is limited to small banks and is absent from large banks. Small banks can significantly reduce future crash risk by maintaining conservative accounting, especially during low lending periods. However, consistent with theories which state that large banks have a private incentive to be conservative, we find no relationship between conservatism and crash risk for large banks, even those with high asymmetric information. The crash risk of large banks is highest in the boom periods of the credit cycle, but this effect is unrelated to conservatism. The policy implications of these results for regulators are that, since conservatism has a limited effect on the crash risk of large banks, further regulation of bank accounting conservatism does not present a significant opportunity to limit systemic banking risk.

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Appendix: Definition of Variables

Variables	Definitions
Dependent Variables:	
NCSKEW	Negative of the third moment of firm-specific weekly returns for each firm and year divided by the standard deviation of firm-specific weekly returns raised to the third power.
EXTR_SIGMA	Negative of the worst deviation of firm-specific weekly returns from the average firm-specific weekly return divided by the standard deviation of firm-specific weekly returns.
CRASH	An indicator variable that equals one when a firm experiences at least one crash week during the fiscal year, and zero otherwise.
DUVOL	Log of the ratio of the standard deviation of the "down weeks" over the standard deviation of the "up weeks".
Independent Variables:	
NI_CSCORE	Conservatism measure computed by cumulating Basu (1997) net income conservatism measure over the previous three-year period.
LLP_CSCORE	Conservatism measure computed by cumulating Basu (1997) loan loss provisions conservatism measure over the previous three-year period.
EBP_CSCORE	Conservatism measure computed by cumulating Basu (1997) earnings before provisions conservatism measure over the previous three-year period.
R_LLA_NPAT	Balance sheet conservatism measure computed as the decile rank of the difference between lagged ratio and the median during the quarter ratio of the allowance of loan loss provisions divided by the non-performing loans.
R_INITIAL_LLA_NPAT	Balance sheet conservatism measure computed as the decile rank of the difference between the lagged ratio and the median during the quarter ratio of the initial loan loss allowance which is computed as the loan loss allowances plus loan charge offs minus loan loss recoveries divided by the non-performing loans.

R_NCO_NPAT	Conservatism in loan loss charged-offs computed as the decile rank of the difference between the lagged ratio and the median during the quarter, when the lagged loan loss allowance plus charge offs deflated by the non-performing loans is greater than the median of the previous quarter and the lagged change in non-performing loans is negative. Loan loss charged-offs is the ratio of loan charge offs divided by the non-performing loans.
R_REC_NCO	Conservatism in loan recoveries is the decile rank of the difference between the lagged ratio of loan loss recoveries and the median during the quarter, when the lagged change in non-performing loans is negative. The ratio is computed as loan loss recoveries divided by lagged loan charge offs.
DTURN	Detrended average weekly stock trading volume.
RET	Average firm-specific weekly returns.
SIGMA	Volatility of firm-specific weekly returns.
SIZE	Firm-size defined as the natural logarithm of market value of equity.
MB	Market-to-book value of equity.
LEV	Financial leverage defined as the total liabilities to total assets.
ROA	Return-on-assets defined as income before extraordinary items to total assets.
CAPITAL	Capital ratio computed as the tier one risk-adjusted capital ratio.
DEPOSITS	Deposits over total assets.

Table 1: Distribution of firm-year observations and stock price crashes

This table presents information regarding the distribution of firm-year observations and stock price crashes. The sample consists of 6687 bank firm-year observations during the period 1995-2010. Banks are defined using the following SIC codes: 6020, 6022, 6035 and 6036.

Year	Number of Observations	Number of no Crashes	No of Stock Price Crashes	Percentage of Crashes	Average Returns during Crashes
1995	114	99	15	0.132	-0.108
1996	287	263	24	0.084	-0.096
1997	488	462	26	0.053	-0.106
1998	473	410	63	0.133	-0.149
1999	460	370	90	0.196	-0.140
2000	444	376	68	0.153	-0.166
2001	464	392	72	0.155	-0.133
2002	518	428	90	0.174	-0.126
2003	502	430	72	0.143	-0.098
2004	442	375	67	0.152	-0.100
2005	413	354	59	0.143	-0.116
2006	425	364	61	0.144	-0.083
2007	458	371	87	0.190	-0.149
2008	421	353	68	0.162	-0.234
2009	390	313	77	0.197	-0.247
2010	388	327	61	0.157	-0.184
Total	6687	5687	1000	0.150	-0.146

Table 2: Descriptive Statistics

This table presents descriptive statistics of the main variables. The sample consists of 6687 bank firm-year observations during the period 1995-2010. Banks are defined using the following SIC codes: 6020, 6022, 6035 and 6036. All variables are described in Appendix.

Variables	Mean	Median	Std Dev.	25^{th} Percentile	75^{th} Percentile
Dependent Variables					
$CRASH_t$	0.150	0.000	0.357	0.000	0.000
$NCSKEW_t$	-0.146	-0.114	0.753	-0.529	0.260
$EXTR\_SIGMA_t$	2.483	2.360	0.630	2.043	2.803
$DUVOL_t$	-0.104	-0.096	0.344	-0.319	0.113
Conservatism Variables					
NI_CSCORE_{t-1}	-0.012	-0.002	0.185	-0.079	0.059
LLP_CSCORE_{t-1}	-0.001	0.000	0.009	-0.004	0.004
EBP_CSCORE_{t-1}	-0.011	-0.001	0.077	-0.039	0.028
LLA_NPAT_{t-1}	0.979	0.193	2.418	-0.560	1.399
$INITIAL\_LLA\_NPAT_{t-1}$	4.986	0.224	92.434	-0.584	1.571
NCO_NPAT_{t-1}	0.091	0.000	1.453	0.000	0.000
REC_NPAT_{t-1}	0.058	0.000	0.181	0.000	0.000
Control Variables					
$DTURN_{t-1}$	0.902	0.193	6.182	-1.266	2.069
RET_{t-1}	-0.076	-0.049	0.084	-0.088	-0.029
$SIGMA_{t-1}$	0.036	0.031	0.017	0.024	0.042
$SIZE_{t-1}$	7.405	7.037	1.700	6.212	8.229
MB_{t-1}	1.670	1.548	0.748	1.140	2.073
LEV_{t-1}	0.908	0.912	0.028	0.897	0.925
ROA_{t-1}	0.009	0.009	0.007	0.006	0.012
$CAPITAL_{t-1}$	0.111	0.106	0.033	0.088	0.128
$DEPOSITS_{t-1}$	0.738	0.752	0.104	0.673	0.819

Table 3: Pearson (Spearman) correlation above (below) the diagonal among crash risk and conservatism variables

This table presents Pearson/Spearman correlation coefficients among the main variables. The sample consists of 6687 bank firm year-observations during the period 1995-2010. Banks are defined using the following SIC codes: 6020, 6022, 6035 and 6036. All variables are described in Appendix. The significance is designated by 'a' at 1%, 'b' at 5% and 'c' at 10%.

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
Dependent Variables																				
1. $CRASH_t$	1.00	0.51 [a]	0.76 [a]	0.48 [a]	0.00	-0.03[b]	0.02 [c]	-0.02	-0.02	-0.03 [a]	-0.01	0.01	-0.01	0.01	-0.02	0.00	-0.02	-0.02	-0.01	-0.02
2. $NCSKEW_t$	0.50 [a]	1.00	0.74[a]	0.95[a]	-0.08 [a]	-0.06[a]	-0.08 [a]	0.00	0.01	0.02	0.05 [a]	0.06[a]	-0.04[a]	0.05[a]	0.13[a]	0.09[a]	0.02	-0.01	-0.04 [a]	-0.08 [a]
3. $EXTR\_SIGMA_t$	0.62 [a]	0.72 [a]	1.00	0.72 [a]	-0.03 [b]	-0.04 [a]	-0.01	-0.02	-0.01	-0.02	0.01	0.03 [b]	-0.02 [b]	0.02 [c]	0.03 [b]	0.02	-0.02 [c]	-0.03 [b]	-0.02 [c]	-0.05 [a]
4. $DUVOL_t$	0.46 [a]	0.98 [a]	0.71 [a]	1.00	-0.09 [a]	-0.06 [b]	-0.09 [a]	0.00	0.01	0.02 [b]	0.06 [a]	0.04 [a]	-0.03 [b]	0.03 [b]	0.13 [a]	0.11 [a]	0.01	0.01	-0.04 [a]	-0.09 [a]
Conservatism Variables																				
5. NI_CSCORE	0.01	-0.09 [a]	-0.03 [b]	-0.09 [a]	1.00	-0.21 [a]	0.38 [a]	-0.13 [a]	-0.17 [a]	-0.25 [a]	-0.37 [a]	-0.11 [a]	-0.19 [a]	0.18 [a]	-0.48 [a]	-0.25 [a]	0.01	-0.20 [a]	0.13 [a]	0.22 [a]
6. LLP_CSCORE_{t-1}	-0.02	-0.05 [a]	-0.02 [c]	-0.05 [a]	-0.23 [a]	1.00	0.02	0.02 [c]	-0.01	-0.04 [a]	-0.17 [a]	-0.08 [a]	0.04 [a]	-0.02 [b]	-0.24 [a]	-0.08 [a]	-0.06 [a]	0.06 [a]	0.02 [c]	0.13 [a]
7. EBP_CSCORE_{t-1}	0.02	-0.10 [a]	-0.01	-0.09 [a]	0.61 [a]	-0.02 [c]	1.00	-0.19 [a]	-0.24 [a]	-0.33 [a]	-0.47 [a]	-0.09 [a]	-0.11 [a]	0.13 [a]	-0.64 [a]	-0.55 [a]	-0.08 [a]	-0.27 [a]	0.13 [a]	0.14 [a]
8. $R\_LLA\_NPAT_{t-1}$	-0,02	0,00	-0,02	0,00	-0,13 [a]	0,04 [a]	-0,20 [a]	1.00	0.93 [a]	0.18 [a]	0.16 [a]	0.04 [a]	0.08 [a]	-0.08 [a]	0.14 [a]	0.24 [a]	-0.03 [b]	0.16 [a]	0.08 [a]	0.05 [a]
9. $R\_INITIAL\_LLA\_NPAT_{t-1}$	-0,02	0,00	-0,01	0,01	-0,16 [a]	0,02	-0,24 [a]	0,93 [a]	1.00	0.23 [a]	0.24 [a]	0.05 [a]	0.08 [a]	-0.09 [a]	0.20 [a]	0.27 [a]	-0.01	0.17 [a]	0.06 [a]	0.03 [b]
10. $R\_NCO\_NPAT_{t-1}$	-0,03	0,02	-0,02	0,02 [b]	-0,26 [a]	-0,01	-0,30 [a]	0,18 [a]	0,23 [a]	1.00	0.60 [a]	0.02	0.12 [a]	-0.15 [a]	0.40 [a]	0.22 [a]	0.08 [a]	0.14 [a]	-0.05 [a]	-0.06 [a]
11. $R\_REC\_NCO_{t-1}$	-0,01	0,05 [a]	0,01	0,06 [a]	-0,38 [a]	-0,14 [a]	-0,45 [a]	0,16 [a]	0,24	0,60	1.00	0.12 [a]	0.09 [a]	-0.12 [a]	0.64 [a]	0.31 [a]	0.10 [a]	0.15 [a]	-0.08 [a]	-0.13 [a]
Control Variables																				
12. $DTURN_{t-1}$	0.01	0.06 [a]	0.03 [b]	0.05 [a]	-0.10 [a]	-0.07 [a]	-0.16 [a]	0,06 [a]	0,07 [a]	0,03 [a]	0,11	1.00	-0.21 [a]	0.21 [a]	0.24 [a]	0.03 [b]	-0.03 [b]	-0.09 [a]	0.01	-0.09 [a]
13. RET_{t-1}	-0.01	-0.05 [a]	-0.02 [c]	-0.03 [a]	-0.14 [a]	0.01	-0.10 [a]	0,07 [a]	0,08 [a]	0,19 [a]	0,16	-0.15 [a]	1.00	-0.96 [a]	0.03 [b]	0.29 [a]	-0.05 [a]	0.44 [a]	0.02 [c]	-0.02
14. $SIGMA_{t-1}$	0.01	0.06 [a]	0.02	0.04 [a]	-0.13 [a]	-0.01	0.10 [a]	-0,07 [a]	-0,08 [a]	-0,18 [a]	-0,16	0.15 [a]	-0.99 [a]	1.00	-0.06 [a]	-0.28 [a]	0.07 [a]	-0.41 [a]	-0.03 [a]	0.03 [b]
15. $SIZE_{t-1}$	-0.02	0.12 [a]	0.01	0.12 [a]	-0.55 [a]	-0.20 [a]	-0.68 [a]	0,14 [a]	0,19 [a]	0,35 [a]	0,54	0.21 [a]	0.07 [a]	-0.07 [a]	1.00	0.35 [a]	0.21 [a]	0.10 [a]	-0.21 [a]	-0.35 [a]
16. MB_{t-1}	0.00	0.09 [a]	0.01	0.10 [a]	-0.29 [a]	-0.05 [a]	-0.55 [a]	0,24 [a]	0,27 [a]	0,21 [a]	0,29	0.11 [a]	0.24 [a]	-0.24 [a]	0.38 [a]	1.00	0.19 [a]	0.44 [a]	0.00	0.05 [a]
17. LEV_{t-1}	-0.02	0.02	-0.01	0.02	0.01	-0.06 [a]	-0.06 [a]	-0,03 [a]	-0,03 [b]	0,07 [a]	0,08	-0.01	-0.08 [a]	0.08 [a]	0.19 [a]	0.18 [a]	1.00	-0.12 [a]	-0.55 [a]	0.02
18. ROA_{t-1}	-0.03 [b]	0.01	-0.04 [a]	0.02	-0.21 [a]	0.03 [b]	-0.41 [a]	0,23 [a]	0,24 [a]	0,20 [a]	0,24	0.03 [a]	0.27 [a]	-0.27 [a]	0.20 [a]	0.60 [a]	-0.20 [a]	1.00	0.16 [a]	0.03 [b]
19. $CAPITAL_{t-1}$	-0.01	-0.04 [a]	-0.03 [a]	-0.04 [a]	0.18 [a]	-0.02 [c]	0.10 [a]	0,09 [a]	0,07 [a]	-0,05 [a]	-0,07	0.02 [c]	0.03 [a]	-0.03 [a]	-0.16 [a]	0.04 [a]	-0.49 [a]	0.22 [a]	1.00	0.16 [a]
20. $DEPOSITS_{t-1}$	-0.02 [c]	-0.09 [a]	-0.06 [a]	-0.09 [a]	0.24 [a]	0.07 [a]	0.15 [a]	0,04 [a]	0,01	-0,07 [a]	-0,15	-0.03 [b]	-0.05 [a]	0.05 [a]	-0.30 [a]	0.07 [a]	-0.05 [a]	0.10 [a]	0.23 [a]	1.00

Table 4: Income statement measures of accounting conservatism and crash risk

This table report estimates of the relation between income statement measures of conservatism on crash risk. Models (1) and (2) display logistic regression coefficient estimates while the models (3) - (8) report linear regression coefficient estimates. All standard errors are adjusted for clustering at the firm level. The sample consists of 6687 bank firm year-observations (*N*) during the period 1995-2010. Banks are defined using the following SIC codes: 6020, 6022, 6035 and 6036. All regressions include intercepts, control variables and year fixed effects. All variables are described in Appendix. z- / t-statistic is in parenthesis below the coefficient estimates. The significance is designated by '***' at 1%, '**' at 5% and '*' at 10%.

	Predicted sign	$CRASH_t$		$NCSKEW_t$		$EXTR\_SIGMA_t$		$DUVOL_t$	
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
NI_CSCORE_{t-1}	-	0.148		-0.123*		-0.074		-0.087***	
		(0.56)		(-1.72)		(-1.21)		(-2.65)	
LLP_CSCORE_{t-1}	-		-8.821***		-2.206**		-2.001***		-1.061**
			(-2.79)		(-2.48)		(-2.59)		(-2.54)
EBP_CSCORE_{t-1}	-		0.714		0.322		0.166		0.105
			(0.78)		(1.34)		(0.81)		(0.95)
Control variables									
$DTURN_{t-1}$	+	0.001	0.000	-0.000	-0.000	0.000	0.000	-0.001	-0.000
		(0.19)	(0.08)	(-0.00)	(-0.06)	(0.41)	(0.37)	(-0.73)	(-0.71)
RET_{t-1}	+	0.495	0.525	-0.283*	-0.212	0.080	0.133	-0.127*	-0.082
		(0.90)	(0.97)	(-1.88)	(-1.42)	(0.69)	(1.15)	(-1.95)	(-1.26)
$SIZE_{t-1}$	-	-0.066**	-0.074**	0.024***	0.032***	-0.007	-0.005	0.009***	0.014***
		(-2.22)	(-2.22)	3.02	(3.52)	(-1.15)	(-0.59)	(2.78)	(3.35)
MB_{t-1}	+	0.139**	0.163**	0.107***	0.123***	0.049***	0.058***	0.049***	0.055***
		(2.34)	(2.41)	(6.33)	(6.29)	(3.43)	(3.49)	(6.17)	(6.04)
LEV_{t-1}	-	-3.086**	-3.225**	-0.725*	-0.987**	-1.043***	-1.192***	-0.346*	-0.479***
		(-2.04)	(-2.18)	(-1.80)	(-2.40)	(-2.91)	(-3.26)	(-1.92)	(-2.60)
ROA_{t-1}	-	-4.183	-2.813	-2.321	-1.646	-2.927**	-2.444*	-0.781	-0.445
		(-0.81)	(-0.53)	(-1.61)	(-1.15)	(-2.30)	(-1.93)	(-1.16)	(-0.66)
$CAPITAL_{t-1}$	-	-3.018**	-3.271**	-0.640*	-0.858**	-0.720**	-0.859***	-0.273*	-0.385**
		(-2.27)	(-2.48)	(-1.85)	(-2.42)	(-2.45)	(-2.86)	(-1.80)	(-2.48)
$DEPOSITS_{t-1}$	-	-0.438	-0.363	-0.269***	0.257***	-0.167*	-0.157*	-0.126***	-0.123***
		(-1.16)	(-0.97)	(-2.82)	(2.69)	(-1.90)	(-1.77)	(-2.98)	(-2.92)
$DEPENDENT_{t-1}$	?	0.046	0.046	0.026*	0.026**	0.027**	0.027**	0.034***	0.034***
		(0.86)	(0.85)	(1.95)	(1.99)	(2.07)	(2.10)	(2.63)	(2.67)
N		6687	6687	6687	6687	6687	6687	6687	6687
QIC / Adj. R^2		5599.19	5592.64	0.055	0.055	0.031	0.032	0.063	0.063

Table 5: Balance sheet measures of accounting conservatism and crash risk

This table report estimates of the relation between the balance sheet measures of conservatism on crash risk. Models (1) and (2) display logistic regression coefficient estimates while the models (3) - (8) report linear regression coefficient estimates. All standard errors are adjusted for clustering at the firm level. The sample consists of 6687 bank firm year-observations (*N*) during the period 1995-2010. Banks are defined using the following SIC codes: 6020, 6022, 6035 and 6036. All regressions include intercepts, control variables and year fixed effects. All variables are described in Appendix. z- / t-statistic is in parenthesis below the coefficient estimates. The significance is designated by '***' at 1%, '**' at 5% and '*' at 10%.

	Predicted sign	$CRASH_t$		$NCSKEW_t$		$EXTR\_SIGMA_t$		$DUVOL_t$	
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$R\_LLA\_NPAT_{t-1}$	-	-0.115 (-1.54)		-0.047^{**} (-2.53)		-0.035^{**} (-2.20)		-0.023^{***} (-2.71)	
$R\_INITIAL\_LLA\_NPAT_{t-1}$	-		-0.092 (-1.19)		-0.044** (-2.31)		-0.030* (-1.87)		-0.020** (-2.35)
$R\_NCO\_NPAT_{t-1}$	-		-0.320* (-1.71)		-0.034 (-0.79)		-0.035 (-0.92)		-0.004 (-0.23)
$R\_REC\_NCO_{t-1}$	-		0.241* (1.71)		-0.025 (-0.67)		0.053 (1.58)		-0.07 (-0.41)
Control variables									
$DTURN_{t-1}$	+	0.001 (0.18)	0.001 (0.11)	0.000 (0.11)	0.000 (0.06)	0.000 (0.49)	0.000 (0.45)	-0.000 (-0.58)	-0.000 (-0.60)
RET_{t-1}	+	0.485 (0.90)	0.462 (0.86)	-0.212 (-1.43)	-0.207 (-1.40)	0.126 (1.08)	0.116 (1.00)	-0.083 (-1.29)	-0.083 (-1.29)
$SIZE_{t-1}$	-	-0.069** (-2.45)	-0.085*** (-2.57)	0.030*** (4.21)	0.036*** (4.42)	-0.003 (-0.64)	-0.008 (-1.18)	0.014*** (4.29)	0.015*** (4.23)
MB_{t-1}	+	0.155*** (2.62)	0.151** (2.54)	0.118*** (6.89)	0.119*** (6.92)	0.057*** (3.91)	0.055*** (3.78)	0.055*** (6.87)	0.054*** (6.81)
LEV_{t-1}	-	-3.033** (-2.05)	-2.984** (-2.01)	-0.882** (-2.23)	-0.916** (-2.32)	-1.141*** (-3.25)	-1.117*** (-3.16)	-0.448** (-2.53)	-0.455** (-2.57)
ROA_{t-1}	-	-4.019 (-0.78)	-4.065 (-0.78)	-1.965 (-1.37)	-1.958 (-1.37)	-2.689** (-2.13)	-2.696*** (-2.13)	-0.570 (-0.84)	-0.576 (-0.85)
$CAPITAL_{t-1}$	-	-2.851** (-2.18)	-2.939** (-2.23)	-0.693** (-2.01)	-0.695** (-2.02)	-0.747** (-2.58)	-0.763*** (-2.63)	-0.318** (-2.09)	-0.319** (-2.11)
$DEPOSITS_{t-1}$	-	-0.386 (-1.03)	-0.419 (-1.10)	-0.263*** (-2.77)	-0.252*** (-2.65)	-0.162* (-1.83)	-0.173* (-1.94)	-0.124*** (-2.96)	-0.122*** (-2.90)
$DEPENDENT_{t-1}$	?	0.046 (0.85)	-0.045 (0.84)	0.026* (1.94)	0.026** (1.97)	0.027** (2.10)	0.027** (2.08)	0.033*** (2.64)	0.034*** (2.67)
N		6687	6687	6687	6687	6687	6687	6687	6687
QIC / Adj. R^2		5597.16	5597.90	0.055	0.055	0.032	0.032	0.063	0.063

Table 6: Accounting conservatism, banking cycle and crash risk

This table report estimates of the relation between conservatism on crash risk conditional on banking cycle. As a proxy for the banking cycle we use the macroeconomic variable "Commercial and industrial loans outstanding plus non-fin commercial paper (*FCLNBW*)" compiled by The Conference Board which measures the volume of business loans held by banks and commercial papers issued by nonfinancial companies. Then, we use the Hodrick-Prescott (1997) filter to obtain an estimate of a flexible trend of the *FCLNBW*. The parameter λ takes the value of 100. Finally, we classify the period of investigation into three sub-periods (High, Moderate, Low) depending on the difference between the growth rates in *FCLNBW* and the growth rates of the *FCLNBW* according to the flexible trend. High Cycle_{t-1} is a dummy variable that equals 1 for years 2001, 2006-2009, and zero otherwise. Moderate Cycle_{t-1} is a dummy variable that equals 1 for years 1995-2000, and zero otherwise. Low Cycle_{t-1} is a dummy variable that equals 1 for years 2002-2005, 2010, and zero otherwise. Models (1)-(2) display logistic regression coefficient estimates while the rest models report linear regression coefficient estimates. All standard errors are adjusted for clustering at the firm level. The sample consists of 6687 bank firm year-observations (*N*) during the period 1995-2010. Banks are defined using the following SIC codes: 6020, 6022, 6035 and 6036. All regressions include intercepts, control variables and year fixed effects. All the rest variables are described in Appendix. z- / t-statistic is in parenthesis below the coefficient estimates. The significance is designated by '***' at 1%, '**' at 5% and '*' at 10%.

	Predicted sign	$CRASH_t$ (1)	$NCSKEW_t$ (2)	$EXTR\_SIGMA_t$ (3)	$DUVOL_t$ (4)
LLP_CSCORE_{t-1} * $HIGH\ CYCLE_{t-1}$	-	-7.42	-3.687**	-3.682**	-1.977**
		(-1.14)	(-2.11)	(-2.27)	(-2.49)
LLP_CSCORE_{t-1} * $MODERATE\ CYCLE_{t-1}$	-	-2.378	0.891	0.602	0.911
		(-0.33)	(0.56)	(0.43)	(1.11)
LLP_CSCORE_{t-1} * $LOW\ CYCLE_{t-1}$	-	-17.22***	-5.368***	-4.164***	-2.880***
		(-2.58)	(-3.26)	(-2.62)	(-4.03)
$HIGH\ CYCLE_{t-1}$	+	0.466**	0.143***	0.088*	0.055**
		(2.29)	(2.76)	(1.76)	(2.27)
$LOW\ CYCLE_{t-1}$	+	0.242	-0.000	0.046	0.000
		(1.15)	(-0.01)	(0.92)	(0.02)
N		6687	6687	6687	6687
QIC / Adj. R^2		5594.11	0.056	0.033	0.065

Table 7: Accounting conservatism, banking cycle and crash risk: The impact for small and large banks

This table report estimates of the relation between conservatism on crash risk conditional on banking cycle for large and small banks (classified according to their size of total assets). As a proxy for the banking cycle we use the macroeconomic variable "Commercial and industrial loans outstanding plus non-fin commercial paper (FCLNBW)" compiled by The Conference Board which measures the volume of business loans held by banks and commercial papers issued by nonfinancial companies. Then, we use the Hodrick-Prescott (1997) filter to obtain an estimate of a flexible trend of the FCLNBW. The parameter λ takes the value of 100. Finally, we classify the period of investigation into three sub-periods (High, Moderate, Low) depending on the difference between the growth rates in FCLNBW and the growth rates of the FCLNBW according to the flexible trend. High Cycle_{t-1} is a dummy variable that equals 1 for years 2001, 2006-2009, and zero otherwise. Moderate Cycle $_{t-1}$ is a dummy variable that equals 1 for years 1995-2000, and zero otherwise. Low Cycle $_{t-1}$ is a dummy variable that equals 1 for years 2002-2005, 2010, and zero otherwise. Models (1)-(2) display logistic regression coefficient estimates while the rest models report linear regression coefficient estimates. All standard errors are adjusted for clustering at the firm level. The sample consists of 6687 bank firm year-observations (N) during the period 1995-2010. Banks are defined using the following SIC codes: 6020, 6022, 6035 and 6036. All regressions include intercepts, control variables and year fixed effects. All the rest variables are described in Appendix. z- / t-statistic is in parenthesis below the coefficient estimates. The significance is designated by '***' at 1%, '**' at 5% and '*' at 10%.

	Predicted sign	$CRASH_t$ (1)	$CRASH_t$ (2)	$NCSKEW_t$ (3)	$NCSKEW_t$ (4)	$EXTR\_SIGMA_t$ (5)	$EXTR\_SIGMA_t$ (6)	$DUVOL_t$ (7)	$DUVOL_t$ (8)
Panel A: Results for small banks									
LLP_CSCORE_{t-1}	-	-12.732**		-2.520		-2.503*		-0.807	
		(-2.20)		(-1.45)		(-1.82)		(-0.99)	
LLP_CSCORE_{t-1} * $HIGH\ CYCLE_{t-1}$	-		-21.041**		-2.799		-4.602		-1.086
			(-2.04)		(-0.76)		(-1.42)		(-0.69)
LLP_CSCORE_{t-1} * $MODERATE\ CYCLE_{t-1}$	-		0.435		0.269		0.286		0.534
			(0.04)		(0.09)		(0.12)		(0.34)
LLP_CSCORE_{t-1} * $LOW\ CYCLE_{t-1}$	-		-19.976*		-5.989*		-4.696*		-2.372*
			(-1.90)		(-1.91)		(-1.88)		(-1.75)
$HIGH\ CYCLE_{t-1}$	+	0.391	0.473*	0.046	0.063	0.023	0.041	-0.011	-0.003
		(1.47)	(1.74)	(0.63)	(0.83)	(0.32)	(0.58)	(-0.33)	(-0.08)
$LOW\ CYCLE_{t-1}$	+	0.179	0.248	-0.154*	-0.138*	-0.011	0.005	-0.076**	-0.068**
		(0.61)	(0.84)	(-1.88)	(-1.66)	(-0.15)	(0.08)	(-2.11)	(-1.85)
N		3341	3341	3341	3341	3341	3341	3341	3341
QIC / Adj. R^2		2942.80	2944.56	0.069	0.070	0.046	0.046	0.088	0.088
Panel B: Results for large banks									
LLP_CSCORE_{t-1}	-	-1.709		-0.849		-0.621		-0.539	
		(-0.50)		(-0.99)		(-0.72)		(-1.29)	
LLP_CSCORE_{t-1} * $HIGH\ CYCLE_{t-1}$	-		12.384		-1.553		-1.333		-1.090
			(1.16)		(-0.15)		(-0.81)		(-1.33)
LLP_CSCORE_{t-1} * $MODERATE\ CYCLE_{t-1}$	-		-4.432		-0.239		0.105		0.138
			(-0.50)		(-0.15)		(0.06)		(0.17)
LLP_CSCORE_{t-1} * $LOW\ CYCLE_{t-1}$	-		-6.563		-1.059		-0.949		-0.913
			(-1.00)		(-0.65)		(-0.50)		(-1.30)
$HIGH\ CYCLE_{t-1}$	+	0.566*	0.543*	0.206***	0.207***	0.146**	0.146**	0.101***	0.101***
		(1.75)	(1.68)	(2.71)	(2.72)	(1.99)	(2.00)	(2.78)	(2.80)
$LOW\ CYCLE_{t-1}$	+	0.249	0.245	0.114	0.114	0.097	0.098	0.054	0.055
		(0.82)	(0.80)	(1.50)	(1.52)	(1.38)	(1.40)	(1.56)	(1.59)
N		3346	3346	3346	3346	3346	3346	3346	3346
QIC / Adj. R^2		2641.78	2644.47	0.059	0.059	0.038	0.037	0.075	0.075

Table 8: Accounting conservatism, banking cycle and crash risk: Large banks with asymmetric information

This table report estimates of the relation between conservatism on crash risk conditional on banking cycle for large banks with high information asymmetry. Banks with total asset greater the medium-level in our sample are classified as large banks, while banks with high analyst forecast dispersion per year are classified as the ones with high information asymmetry. As a proxy for the banking cycle we use the macroeconomic variable "Commercial and industrial loans outstanding plus non-fin commercial paper (*FCLNBW*)" compiled by The Conference Board which measures the volume of business loans held by banks and commercial papers issued by nonfinancial companies. Then, we use the Hodrick-Prescott (1997) filter to obtain an estimate of a flexible trend of the *FCLNBW*. The parameter λ takes the value of 100. Finally, we classify the period of investigation into three sub-periods (High, Moderate, Low) depending on the difference between the growth rates in *FCLNBW* and the growth rates of the *FCLNBW* according to the flexible trend. High Cycle_{t-1} is a dummy variable that equals 1 for years 2001, 2006-2009, and zero otherwise. Moderate Cycle_{t-1} is a dummy variable that equals 1 for years 1995-2000, and zero otherwise. Low Cycle_{t-1} is a dummy variable that equals 1 for years 2002-2005, 2010, and zero otherwise. Models (1)-(2) display logistic regression coefficient estimates while the rest models report linear regression coefficient estimates. All standard errors are adjusted for clustering at the firm level. The sample consists of 6687 bank firm year-observations (*N*) during the period 1995-2010. Banks are defined using the following SIC codes: 6020, 6022, 6035 and 6036. All regressions include intercepts, control variables and year fixed effects. All the rest variables are described in Appendix. z- / t-statistic is in parenthesis below the coefficient estimates. The significance is designated by '***' at 1%, '**' at 5% and '*' at 10%.

	Predicted sign	$CRASH_t$ (1)	(2)	$NCSKEW_t$ (3)	(4)	$EXTR\_SIGMA_t$ (5)	(6)	$DUVOL_t$ (7)	(8)
LLP_CSCORE_{t-1}	-	-9.005 (-1.08)		-2.347 (-1.00)		-3.099 (-1.41)		-1.282 (-1.12)	
LLP_CSCORE_{t-1} * $HIGH\ CYCLE_{t-1}$	-		31.025 (1.57)		1.788 (0.51)		-0.765 (-0.23)		0.979 (0.54)
LLP_CSCORE_{t-1} * $MODERATE\ CYCLE_{t-1}$	-		-31.001** (-2.23)		1.087 (0.25)		-1.958 (-0.54)		0.310 (0.14)
LLP_CSCORE_{t-1} * $LOW\ CYCLE_{t-1}$	-		-12.164 (-1.17)		-7.420* (-1.88)		-5.373 (-1.42)		-3.841** (-2.06)
$HIGH\ CYCLE_{t-1}$	+	0.746 (1.30)	0.736 (1.30)	0.247* (1.71)	0.257* (1.88)	0.274* (1.93)	0.279** (1.97)	0.129* (1.85)	0.134* (1.93)
$LOW\ CYCLE_{t-1}$	+	0.232 (0.37)	0.130 (0.20)	0.132 (0.80)	0.129 (0.79)	0.248* (1.70)	0.246* (1.69)	0.045 (0.60)	0.044 (0.58)
N		896	896	896	896	896	896	896	896
QIC / Adj. R^2		916.23	924.02	0.069	0.071	0.039	0.037	0.094	0.096

Table 9: Accounting conservatism, banking cycle and crash risk: Alternative proxy for banking cycle (Monetary base)

This table report estimates of the relation between conservatism on crash risk conditional on banking cycle. As a proxy for the banking cycle we use the macroeconomic variable "FM1 (FM1)" which is the monetary base as defined by M1. Then, we use the Hodrick-Prescott (1997) filter to obtain an estimate of a flexible trend of the FM1. The parameter λ takes the value of 100. Finally, we classify the period of investigation into three sub-periods (High, Moderate, Low) depending on the difference between the growth rates in FM1 and the growth rates of the FM1 according to the flexible trend. High $Cycle_{t-1}$ is a dummy variable that equals 1 for years 1996-1999, 2001, 2008, and zero otherwise. Moderate Cycle $_{t-1}$ is a dummy variable that equals 1 for years 1999, 2000, 2002, 2006, 2007, and zero otherwise. Low Cycle $_{t-1}$ is a dummy variable that equals 1 for years 1995, 2003-2005, 2010, and zero otherwise. Models (1)-(2) display logistic regression coefficient estimates while the rest models report linear regression coefficient estimates. All standard errors are adjusted for clustering at the firm level. The sample consists of 6687 bank firm year-observations (*N*) during the period 1995-2010. Banks are defined using the following SIC codes: 6020, 6022, 6035 and 6036. All regressions include intercepts, control variables and year fixed effects. All the rest variables are described in Appendix. z- / t-statistic is in parenthesis below the coefficient estimates. The significance is designated by '***' at 1%, '**' at 5% and '*' at 10%.

	Predicted sign	$CRASH_t$ (1)	$NCSKEW_t$ (2)	$EXTR\_SIGMA_t$ (3)	$DUVOL_t$ (4)
LLP_CSCORE_{t-1} * $HIGH\ CYCLE_{t-1}$	-	-13.643**	-1.444	-2.747*	-0.807
		(-1.98)	(-0.78)	(-1.81)	(-1.00)
LLP_CSCORE_{t-1} * $MODERATE\ CYCLE_{t-1}$	-	-10.060**	-1.653	-1.506	-0.703
		(-2.30)	(-1.31)	(-1.30)	(-1.18)
LLP_CSCORE_{t-1} * $LOW\ CYCLE_{t-1}$	-	-4.728	-4.181***	-2.419**	-1.922***
		(-0.78)	(-2.90)	(-1.96)	(-2.83)
$HIGH\ CYCLE_{t-1}$	+	-0.226	-0.145***	-0.042	-0.055**
		(-1.19)	(-2.85)	(-0.91)	(-2.32)
$LOW\ CYCLE_{t-1}$	+	-0.372*	-0.049	-0.042	-0.020
		(-1.89)	(-0.98)	(-0.87)	(-0.84)
N		6687	6687	6687	6687
QIC / Adj. R^2		5594.421	0.055	0.032	0.063

Table 10: Accounting conservatism, banking cycle and crash risk: Alternative proxy for banking cycle (CATFIN)

This table report estimates of the relation between conservatism on crash risk conditional on banking cycle. As a proxy for the banking cycle we use "*CATFIN*" a measure of aggregate systemic risk developed by Allen, Bali and Tang (2012). We classify the period of investigation into three sub-periods (High, Moderate, Low) depending on the *CATFIN* measured at the 1st of February of each year as follows: High $SRISK_{t-1}$ is a dummy variable that equals 1 for years 2000-2002, 2009-2010, and zero otherwise. Moderate $SRISK_{t-1}$ is a dummy variable that equals 1 for years 1995, 1996, 1998, 1999, 2003-2004, and zero otherwise. Low $SRISK_{t-1}$ is a dummy variable that equals 1 for years 1997, 2005-2008, and zero otherwise. Models (1)-(2) display logistic regression coefficient estimates while the rest models report linear regression coefficient estimates. All standard errors are adjusted for clustering at the firm level. The sample consists of 6687 bank firm year-observations (*N*) during the period 1995-2010. Banks are defined using the following SIC codes: 6020, 6022, 6035 and 6036. All regressions include intercepts, control variables and year fixed effects. All the rest variables are described in Appendix. z- / t-statistic is in parenthesis below the coefficient estimates. The significance is designated by 'a' at 1%, '**' at 5% and '*' at 10%.

	Predicted sign	$CRASH_t$ (1)	$NCSKEW_t$ (2)	$EXTR\_SIGMA_t$ (3)	$DUVOL_t$ (4)
LLP_CSCORE_{t-1} * $LOW\ SRISK_{t-1}$	-	-6.039	-4.076^{**}	-3.671^{**}	-1.923^{**}
		(-0.80)	(-2.25)	(-2.38)	(-2.25)
LLP_CSCORE_{t-1} * $MODERATE\ SRISK_{t-1}$	-	-8.759	-0.951	-1.092	-0.182
		(-1.58)	(0.62)	(-0.89)	(-0.25)
LLP_CSCORE_{t-1} * $HIGH\ SRISK_{t-1}$	-	-11.546^{**}	-3.055^{**}	-2.229^{*}	-1.707^{***}
		(-2.43)	(-2.40)	(-1.89)	(-3.01)
$HIGH\ SRISK_{t-1}$	+	0.270	0.074	0.084^{*}	0.022
		(1.21)	(1.27)	(1.65)	(0.83)
$LOW\ SRISK_{t-1}$	+	0.125	0.166^{***}	0.083^{**}	0.054^{**}
		(0.66)	(3.44)	(1.99)	(2.38)
N		6687	6687	6687	6687
QIC / Adj. R^2		5595.45	0.055	0.032	0.064