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# Bank loan loss accounting treatments, credit cycles and crash risk

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**Abstract**

Banks that follow conditional conservatism in their loan loss accounting treatments benefit from a reduction in crash risk. The key discretionary loan loss accounting channels are provisions and allowances. We show that conditional conservatism reduces crash risk of small banks during periods of credit contraction and boom. Interestingly, for large banks, crash risk is not reduced by more conservative accounting even for those with higher levels of opacity. Hence regulation prompting for more conservative bank loan loss accounting does not present a significant opportunity to limit systemic effects arising from abrupt price declines in the stocks of large banks.

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## 1. Introduction

Investors in banks and bank regulators are concerned with large declines in bank stock prices, also referred to as crash risk. Banks' crash risk has been shown to be associated with measures of their loan loss accounting treatments (Cohen et al., 2014). The source of the relationship is the inherent opacity of banks, which makes the risks they take on hard to verify and exposes them to crash risk resulting from the accumulation of undisclosed bad news (Jin and Myers, 2006, Hutton et al., 2009). Along these lines, the regulatory bodies, Financial Accounting Standards Board (FASB) and the International Accounting Standards Board (IASB), have raised concerns about bank accounting behavior, particularly the potential overstatement of assets caused by a delayed recognition of credit losses associated with loans (and other financial instruments), particularly during the financial crisis (FASB, 2012).

Cohen et al. (2014) examine the relationship between one specific aspect of bank accounting behavior in the context of earnings management and stock price crashes. In a broader context, another aspect of accounting behavior, conditional conservatism, has been shown to predict crash risk for firms (Kim and Zhang, 2015, Andreou et al., 2016a), although not tested explicitly for banks. Following the ideas in Basu (1997), conditional conservatism refers to accounting treatments that require a higher degree of verification to recognize good news as gains than to recognize bad news as losses. In this respect, although earnings management and conditional conservatism are related, they are not the same (Watts, 2003). Conditional conservatism is a more persistent behavior than earnings management; and banks have been shown to have a strong persistent component that exposes them to crash risk (Fahlenbrach et al., 2012). Therefore, it remains an important unresolved empirical question whether the effect of conditional conservatism, to offset managers' opportunistic behaviour as reported by previous studies (e.g., Watts, 2003, Kothari et al., 2009), can contribute further to the understanding and possibly control of banks' crash risk. Therefore, this study examines the relationship between conditional conservatism and bank-specific crash risk. Further, we examine how the relationship varies over the banking lending cycle, between large and small banks, and between opaque and transparent banks. We also differentiate the effect of conservatism from the effect of earnings management.[1]

For our empirical investigation, we use a large sample of US bank-level information during the period 1995-2010. Following Chen et al. (2001), Hutton et al. (2009) and Kim et al. (2011), we measure the crash risk of individual banks by employing three different measures of firm-specific stock price crashes. These measures of crash risk capture different aspects of the relative size and magnitude of share price crashes. To capture the degree of conservatism of a bank, we use Basu's (1997) cross-sectional measure of conservatism using information from the bank's income statement and balance sheet (Khan and Watts, 2009; Beatty and Liao, 2011).

Since conditional conservatism restricts managers' opportunistic behavior to strategically withhold bad news and accelerate the release of good news and hence reduces agency problems (Watts, 2003; LaFond and Watts, 2008; Kim and Zhang, 2015, Andreou et al., 2016a), we expect that banks adopting conservative accounting practices to exhibit

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

less crash risk. However, the unique nature of banks and the extensive regulatory scrutiny that characterizes the industry suggest that the general relationship between conservatism and crash risk, found by Kim and Zhang (2015), need not necessarily hold for banks. Therefore, we first examine whether the relationship between conservatism and crash risk exists, and if so, attempt to identify the specific bank loan loss accounting channels and the defining bank characteristics for which this relationship persists.

The empirical results indicate banks that follow conservatism in loan loss accounting on average significantly benefit from a reduction in future stock price crash risk. The main income statement channel between this accounting behavior and crash risk is via the loan loss provision treatment and not through the non-loan income statement item of earnings before provisions, suggesting either that the discretion over other income items is more limited or that investors find it easier to see through accounting treatment of non-loan items. Further, banks' motivation to manage changes in earnings and maintain their loan portfolio risk to avoid regulatory scrutiny can lead to banks inflating their loan loss allowances in the balance sheet. Loan loss allowances represent an aggregation of past years' loan loss provisions and the accounting treatment of net loan charge offs and loan recoveries. Prior studies indicate that banks attempt to manage these loan loss accounting treatments, for instance, to overstate their loan loss allowances to establish reserve buffers and maintain their capital ratios (e.g., Liu and Ryan, 2006; and Beck and Narayanamoorthy, 2013). 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 should also be reflected in the aggregate balance sheet item of loan loss allowances. Moreover, greater recognition of net loan charge offs and a slower recognition of loan recoveries by bank managers can reflect accounting conservatism behavior. Hence, as a further investigation, we test whether conservatism operating through these various components of loan loss accounting – loan loss allowances, net loan charge offs and loan recoveries – can mitigate stock price crashes. The results indicate that conservatism behavior captured in the balance sheet item of loan loss allowances jointly predicts future crash risks, along with the conservatism operating through loan loss provisions. Additionally, we find that conservatism in the loan items of charge offs and recoveries contains no additional information related to crash risk. This results indicate the fact that loan charge offs and recoveries generally involve limited managerial discretion.

Overall, the results show that loan loss provisions from the income statement and the balance sheet of loan loss allowances operate as the primary accounting channels through which conservatism in banks' accounting behavior impacts crash risk. Our results are also economically significant, since an increase in conservatism in loan loss provisions from $10^{th}$ to the $90^{th}$ percentile reduces the probability of a crash by 14.2%. Similarly, for the continuous measures of crash risk, a one standard deviation increase in conservatism in loan loss provisions or loan loss allowances significantly decreases crash risk by 2.9% to 3.2% standard deviations.

Since prior research has demonstrated that earnings management predicts banks' crash risk during the financial crisis (Cohen et al, 2014), we investigate the robustness of our findings and established that earnings management and lack of conservatism are associated with crash risk at different times. More specifically, consistent with Cohen et al.

(2014), earnings management tends to predict crash risk during crisis periods only, whereas lack of conservatism predicts crash risk more generally. This result is in line with the idea that conservatism has a more pervasive effect, whereas earnings management tends to be transitory and peaks during specific times.

Next, we test whether the impact of banks' conservatism on future stock price crash risk varies at different states of the banking cycle. Because conservatism seems to operate through loan loss accounting treatment, the quality of loan portfolios becomes an influential factor that may moderate the relation between conservatism and crash risk. As a result, the lending growth cycle represents an ideal setting to explore the impact of credit expansion/contraction that affects lending portfolio quality, on the relation between conservatism and crash risk. During high lending growth periods or the credit boom periods, banks take excessive risk through over-lending (Berger and Udell, 2004; Foos et al., 2010). Hence, in the high part of the cycle, agency problems are higher, suggesting a greater potential for bad news hoarding to generate future crash risk. Similar agency problems are heightened during the low part of the lending growth cycle or the credit crunch periods. 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. Consistent with this conjecture, our empirical results indicate that during both credit boom and credit crunch periods, banks following conservative accounting practices significantly reduce their stock price crash risk, with the highest impact observed during the credit crunch periods. In the moderate phase of the lending growth cycle we do not see a significant relationship between conservatism and crash risk.

As an additional analysis, we test for the relationship using alternative banking business cycles that affect the lending portfolio quality. In particular, we test whether the relationship between conservatism and crash risk is pronounced during extreme market liquidity growth cycles (proxied by the monetary base variable, M1) as well as enhanced growth in the aggregate financial sector risk (measured by the systemic risk variable, *CATFIN*, developed by Allen et al., 2012). The results suggest that there is cyclical variation in the effect of conservatism on crash risk, and the relationship is indeed heightened during the extreme periods of monetary cycles and systemic risk.

Our final tests concern the impact of banks' information opacity (measured by the dispersion of analysts' forecasts) and bank size on the relationship between conservatism and crash risk. The ability to hide bad news is related to the degree of information opacity between managers and outside investors, which is also related to the size of the bank. Therefore, we expect a stronger effect of conservatism on crash risk for banks with greater information opacity and for smaller banks. Consistent with the information hypothesis, the results show that more bank opaqueness leads to a stronger relationship between conservatism and crash risk. However, this effect is present only for small banks. For large banks there is no relationship between conservatism and crash risk, even for those with higher levels of opacity.

Our findings complement other studies that have found a relationship between banks' accounting behavior and crash risk. The result that conservatism affects crash risk differs from that of Cohen et al. (2014) who find that the relationship between earnings management and crash risk is only prominent during the crisis period. We also extend the analysis of the general relationship between accounting conservatism and crash risk of Kim and Zhang (2015) for banking institutions, by investigating the specific bank loan loss accounting channels through which conservatism is related to crash risk for banks, as well as the effect of the lending growth cycle on this relationship. They also complement studies which find, for firms in general, a relationship between crash risk and governance variables (Andreou et al, 2016a, Andreou et al, 2017). Using analysts' forecast dispersion we also demonstrate how the relationship depends on banks' opacity and bank size. Finally, we also show an important negative result which has significant policy implications: that there is no relationship between conservatism and crash risk for large banks, even among those with greater information opacity.

The study makes several contributions to the debate on bank regulation and bank-specific risk. It shows that the main channel whereby accounting conservatism influences crash risk is through loan loss accounting, and that this operates only at the high and low parts of the credit cycle (not the general economic cycle). It does not operate for large banks, suggesting that the existing level of transparency and accounting regulation already limits this effect for large banks. The results imply that it is important for smaller banks and their investors to be wary of non-conservative accounting practices on loans at the extremes of the credit cycle (but not necessarily at extremes of the economic cycle). For regulators, it implies that there may be scope to limit the crash risk of smaller banks through regulating accounting conservatism but there appears to be limited scope for controlling the systemic crash risk of the banking sector by further use of that mechanism.

The remainder of this paper is organized as follows. Section 2 gives a literature review and 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.

## 2. Hypothesis Development

The agency problem in accounting has been recognized as a mechanism that affects firm-level 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 managers are willing to hide firm-specific negative news when the cost of hiding outweighs the benefit. 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.

In this context, banks' assets are inherently opaque and difficult to value by outside investors (Cheng et al., 2011; Gordon, 2014). Within such an environment managers might be able to overstate financial performance by withholding bad news when they have incentives to do so. Such accounting manipulation, however, may result in crash risk. Kim and Zhang (2015) and Andreou et al. (2016a) show that firms practicing earnings conservatism effectively monitor the timely release of bad news, thereby reducing future crash risk. In a similar vein, conservatism among banking sector firms can act as a governance mechanism that prevents accumulation of hidden negative news resulting in less crash risk. This relationship, however, may be weaker within banks due to high regulatory scrutiny and supervision. In addition, since banks are highly leveraged instituti0ons, we would also expect banks to exhibit higher levels of conditional conservatism due to contracting demands, litigation costs and regulators' preference (Watts 2003; Armstrong et al., 2010). As a result, the relation between conservatism and crash risk for banks is still unclear.

Banks have an incentive to innovate using loans where default probabilities are hard to assess (Thakor, 2011), and the potential for distortion is greatest for many loan assets which are long-lived, illiquid, and senior (Plantin et al., 2008). This implies that the most important channel from a potential relation between conservatism and crash risk is through the treatments of loans which directly affect banks' earnings. Banks' earnings are aggregated from various elements of the income statement, and thus to gain more insight into the mechanism through which conservatism may affect crash risk, it is important to decompose earnings conservatism into conservatism in the discretionary treatment of loan loss provisions and conservatism in the reporting of non-loan items, earnings before provisions. Bank managers are required to exercise considerable discretion in maintaining sound and accurate estimates of the future 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. Provisions are reported in the income statement as expenses and thus reduce net income. At the same time, provisions reduce net loans outstanding by increasing the loan loss allowance on the balance sheet. Bank managers who practice conservative accounting recognize appropriate loan loss provisions each period in a timely manner depending on their forecasts of the expected losses and the balance of their loan loss allowance. Therefore, conservatism can also operate through the alternative components of loan loss accounting – loan loss allowances, net loan charge offs and loan recoveries. Loan loss allowances should accurately reflect expected future losses in a bank's loan portfolio, after timely accounting recognition of charge offs and recoveries. 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. 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 information (both in the income statement and the balance sheet) should experience less crash risk. These assertions lead us to the following hypothesis:

***$H_1$*:** *Conservatism in loan loss accounting, operating through the income statement as well as the balance sheet treatments, reduces a bank's future crash risk.*

Since we expect the primary channel linking conservatism and crash risk to be through loans, we expect the relationship between conservatism and crash risk to vary over the bank lending growth cycle. During periods of expansion and high demand for loans (credit boom), the potential agency problem is high, as bank managers have the incentive to cater to this high demand through excessive lending (Berger and Udell, 2004; Foos et al., 2010). Excessive lending will reduce the quality of the loan portfolio, however, leading to the temptation to hide bad news. The ability to hide bad news diminishes as bad news accumulates, thereby increasing the risk of abrupt release and stock prices crashes. Hence, there will be demand for conservative behavior by shareholders during the credit boom or the high cycle periods. Beatty and Liao (2011) provide evidence that the lending behavior of conservative banks remain conservative during periods of high lending growth. As a result, we expect the effect of conservatism on crash risk to be strong at the high part of the lending growth cycle. During the moderate part of the lending growth cycle, 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. At the low part of the lending growth cycle or credit crunch periods, the agency problem could also be severe since bad performance will exaggerate managerial career concerns and 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 contracting efficiency by discouraging bad news hoarding (Watts, 2003; Armstrong et al., 2010). Additionally, during the low part of the lending growth cycle, debt holders will demand conservative financial reporting (Balakrishnan, et al., 2015). Hence we expect conservative banks to reduce crash risk during the low period of the lending growth cycle. Overall, we expect a stronger relationship between conservatism and crash risk during the extremes (high and low) of the lending growth cycle. Hence, our second hypothesis is as follows:

***$H_2$:*** *The relationship between conservatism and future crash risk is more pronounced during the credit boom (high bank lending growth) periods and the credit crunch (low bank lending growth) periods.*

Finally, we examine how the effect of conservatism on crash risk is related to information opacity and bank size. We capture information opacity through dispersion in analysts' earnings forecasts. Higher information opaqueness may aid bank managers in withholding valuable negative information from investors. For example, 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 performance, especially during uncertain environments. In such environments, however, litigation risk will be high and, under accounting conservatism, bank managers would report conservatively in order to reduce the risk of litigation (Watts 2003). Hence the relationship between conservatism and crash risk will be more pronounced for banks with a high level of information asymmetry between inside managers and investors.

In terms of bank size, smaller banks tend to disclose less information and attract less analyst coverage. So there is generally greater informational asymmetry among small banks. In addition, the nature of informational flow is largely 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, large banks naturally exhibit proportionately less growth options and attract more analyst coverage, thus reducing the information asymmetry between managers and shareholders. Further, large banks have an incentive to engage in a higher level of accounting conservatism and transparency (Watts, 2003; and LaFond and Watts, 2008). Additionally, 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), all of which characterize larger than smaller 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 more for small banks and be less pronounced for large banks. Furthermore, since conservatism is a persistent behavior, it will be easier to monitor and control by outside agents, including regulators, shareholders, and other stakeholders. Therefore, we expect that large banks' accounting policy choices may result in a level of transparency that limits the scope for large negative accounting surprises arising from persistent lack of conservatism.

Based on the above arguments, we expect the impact of conservative accounting on crash risk to be related to the degree of information opacity and be more pronounced among banks with higher dispersion in banks' earnings forecasts and for smaller banks. Hence, our third and fourth hypotheses are as follows:

***$H_3$:** The relationship between conservatism and future crash risk is greater for banks with higher dispersion in analysts' earnings forecasts.*

***$H_4$:** The relationship between conservatism and future crash risk is more pronounced for smaller banks.*

## 3. Variable Measurement

### 3.1 Measurement of banks' crash risk

To investigate the impact of conservatism on bank-specific crash risk, we use three different measures of crash risk that reflect different aspects of the distribution of returns. We estimate bank-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 bank-specific returns. Since residuals from Equation (1) are skewed, we define the bank-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), and Kim et al. (2011), we estimate three primary measures of crash risk.

First, we define an indicator variable *CRASH* that is equal to one when a bank experiences at least one crash week during the fiscal year, and zero otherwise. A crash week occurs when a bank 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 bank-specific weekly returns for each firm and year divided by the standard deviation of bank-specific weekly returns raised to the third power. Specifically, for a given firm in a fiscal year we calculate *NCSKEW* as follows:

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

Finally, following Chen et al. (2001), we compute the third measure of crash risk, the down-to-up volatility (*DUVOL*). *DUVOL* is calculated as follows: for each bank *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 that are above the annual mean and categorize them as “down weeks” and “up weeks” respectively. We then compute the standard deviation for the two pre-defined subsamples. *DUVOL* is the log of the ratio of the standard deviations of the two subsamples, that for the “down weeks” over the standard deviation of the “up weeks”. Larger values of *NCSKEW* and *DUVOL* signify greater crash risk. *CRASH* focus on capturing negative firm-specific returns at the lowest tail of the return distribution and thus may be viewed as a measure 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 capture smaller crashes.

### 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’s (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 a negative book value of equity. Furthermore, we require twenty observations per quarter to run each regression. In particular, we estimate the following model:

$$\begin{aligned} NI = \beta_0 + \beta_1 \times D + Returns \times (\mu_1 + \mu_2 MV + \mu_3 MTB + \mu_4 LEV) + \\ D \times Returns \times (\lambda_1 + \lambda_2 MV + \lambda_3 MTB + \lambda_4 LEV) + \varepsilon \end{aligned} \tag{3}$$

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 the 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 (3) we calculate the earnings conservatism measure, *NI_CONS*, by cumulating *CS* over the previous three-year period to eliminate bias arising from less persistent conservatism. *CS* is calculated as follows:

$$CS = \hat{\lambda}_1 + \hat{\lambda}_2 MV + \hat{\lambda}_3 MTB + \hat{\lambda}_4 LEV \tag{4}$$

By construction, banks with higher *NI_CONS* values are considered more conservative and as a result they exhibit a smaller delay in expected loss recognition. Hence *NI_CONS* 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_CONS* and *EBP_CONS*. Our primary prediction is that conservatism operates through loan loss provisions, which largely involve discretionary treatment rather than earnings before provisions whose treatment is non-discretionary.

### 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 that 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, *LLA_CONS*, is the decile rank of the difference between lagged ratio and the median during the quarter. We also decompose loan loss allowances into "unadjusted" loan loss allowances (i.e. before adjustments in loan loss charge 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 "unadjusted" 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 that are more conservative are expected to have recognized more unadjusted loan loss provisions relative to non-performing loans. Following this reasoning, our conservatism measure of "unadjusted" loan loss allowances (*LLA_CONS_UNADJ*) 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 charge offs. Nichols et al (2009) suggest that loan charge offs likely reflect realizations of managers' expectations of loan losses that became delinquent during the previous and the current periods. At the same time, managers may be concerned about 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, 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 indicate an improvement in a bank's loan portfolio (Nichols et al., 2009), our measure of conservatism in loan loss charge offs (*NCO_CONS*) is a binary variable used to code 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 need for such earnings management behavior, rendering this ratio more appropriate in capturing conservatism. Following this reasoning, our measure of conservatism in loan recoveries

(*REC_CONS*) is a binary variable used to code 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 by minus one, so greater values of (*REC_CONS*) 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 average firm-specific weekly returns ($RET_{t-1}$) and 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 firm-size defined as the natural logarithm of market value of equity in year *t-1* ($SIZE_{t-1}$), market-to-book value of equity in year *t-1* ($MB_{t-1}$), financial leverage defined as the total liabilities to total assets in year *t-1* ($LEV_{t-1}$), and 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 the lagged values for the dependent variable in our regressions (Harford et al., 2008).

## 4. Dataset

Our analysis consists of Compustat banks with available information to perform the analysis during the period 1995 to 2010. 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 bank-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 bank-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 prior literature (e.g., Hutton et al., 2009, Kim and Zhang, 2015, Andreou et al., 2016a), 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 to -14.6%. Both the prevalence and the magnitude of the stock price crashes indicate that they constitute events 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.

[Insert Table 1 about here]

Table 2 presents the descriptive statistics for the key variables along with additional variables used as controls in our multivariate analysis. The mean (median) value of *CRASH* is 0.150 (0.000), 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) and of *DUVOL* is -0.104 (-0.096). Despite these figures refer to bank-year observations, all the aforementioned crash risk statistics are qualitatively similar to those reported in prior studies (e.g., Kim et al., 2011, Bradshaw et al. 2010, Andreou et al., 2017).

[Insert Table 2 about here]

Within the income statement conservatism variables, the mean (median) value of *NI_CONS* is -0.012 (-0.002), of *LLP_CONS* is -0.001 (0.000), and of *EBP_CONS* is -0.011 (-0.001). Regarding the balance sheet conservatism variables, the mean (median) value of *LLA_CONS* is 0.979 (0.193), of *LLA_CONS_UNADJ* is 1.299 (0.211), of *NCO_CONS* is 0.091 (0.000), and of *REC_CONS* 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. Our main findings, however, are qualitatively similar to using the initial variables.

As far as the control variables are concerned, our sample consists of relatively large banks 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 mean *LEV* equal to 0.908 (median 0.912) and they are marginally profitable as captured by *ROA* mean and median values of 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 figures 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 capture smaller and medium-sized crashes. On the other hand, *CRASH* is less correlated with the other two measures and appears to pick up a different dimension of crash risk as it is more sensitive to large share price falls.

[Insert Table 3 about here]

Overall, we observe that the crash risk measures are negatively correlated to the income statement accounting conservatism measures of *NI_CONS*, *LLP_CONS* and *EBP_CONS*. Largely, negative but less significant relations also exist between crash risk measures and balance sheet accounting conservatism measures of *LLA_CONS*, *LLA_CONS_UNADJ* and *NCO_CONS*. In contrast, *REC_CONS* 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 conservatism in their loan loss accounting treatments 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 sufficiently high to raise other concerns for multicollinearity.

## 5. Empirical results

### 5.1 Accounting conservatism channels and crash risk

In this section we test whether accounting conservatism helps to reduce banks' crash risk. Using the various net income and loan loss accounting dimensions, we examine the channels through which accounting conservatism impacts a bank's future crash risk. We estimate the model:

$$CR\_RISK_t = \alpha_1 + \sum_i \alpha_i CONS_{t-1} + \sum_j \lambda_j CONTROLS_{t-1} + \varepsilon_t \qquad (5)$$

where $CR\_RISK_t$ denotes the three different crash risk measures (*CRASH*, *NCSKEW* and *DUVOL*) calculated in year *t* and *CONS* denotes the various net income and balance sheet measures of conservatism, namely *NI_CONS*, *LLP_CONS, EBP_CONS, LLA_CONS*, *LLA_CONS_UNADJ*, *NCO_CONS*, and *REC_CONS* calculated in year *t-1*. We would expect the slope coefficients associated with CONS 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. The standard errors are adjusted for clustering at the firm level.

Table 4 presents the results from the regressions. Columns 1-5 display the logistic regression marginal estimates for the crash risk variable *CRASH* and Columns 6 to 15 report results from linear regressions for the crash risk variables *NCSKEW* and *DUVOL*. The results show that the coefficients associated with the aggregate net income measure of conservatism are significant for the crash measures *NCSKEW* and *DUVOL*, which 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_CONS,* is statistically significant (at a minimum level of 5%) and negative for all the crash risk variables. The earnings before provisions measure of conservatism, *EBP_CONS*, which is unaffected by loan provisions, is insignificant in all regressions. Hence, the decomposition of 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 any effect.[2]

[2] 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.

[Insert Table 4 about here]

With regard to the balance sheet measures of conservatism, we first examine whether conservatism in the balance sheet recognition of loan losses, as reflected in loan loss allowances, predicts future crash risk. Loan loss allowances capture a series of loan loss provisions over past periods. Hence being more or less conservative in the current period is directly linked in the balance sheet measure with the level of loan loss provisions conservatism in previous periods. In addition, 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. Hence, 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 results in Table 4 show that the coefficients of the aggregated loan loss balance sheet variable *LLA_CONS* are statistically significant (at a minimum level of 5%) for crash risk measures, except for *CRASH*. When we consider the conservatism measure of loan loss allowances before the treatment of net loan charge offs and loan recoveries (*LLA_CONS_UNADJ*) simultaneously with the measures of net loan charge offs (*NCO_CONS*) and loan recoveries (*REC_CONS*), we find that conservatism in loan loss allowances remains significant jointly with *LLP_CONS*, while there is little evidence for conservatism operating through net loan charge offs and loan recoveries (with only the *CRASH* measure significant at 10% level). So disaggregating the income statement and balance sheet measures of conservatism reveals that the main dimensions through which accounting conservatism operates in reducing future crash risk is the discretionary channel of loan loss provisions as well as the aggregate treatment of loan loss allowances.

To assess the impact of conservatism for crash risk, we estimate the realized economic significance in terms of likelihood reduction in crash risk. Specifically, we calculate the *CRASH* logit function for *LLP_CONS* at its $90^{th}$ and the $10^{th}$ percentile values and find that banks increasing their conservatism in loan loss provisions from the $10^{th}$ to the 90th percentile decrease their probability of crash risk by 14.2%. Additionally, for *NSKEW* and *DUVOL*, we measure the percentage standard deviations of the crash variable that is explained with a one-standard deviation change in the conservatism variables. Considering the full model in Table 4 (Columns 10 and 15), we find that a one standard deviation increase in *LLP_CONS* decreases *NCSKEW* (*DUVOL*) by 0.030 (0.032) standard deviations, while a standard deviation increase in *LLA_CONS* decreases *NCSKEW* (*DUVOL*) by 0.029 (0.029).

In summary, the results confirm $H_1$ that accounting conservatism has a significant impact in reducing future crash risks among banks and the main channels through which accounting conservatism operates in reducing future crash risk are the discretionary channels of loan loss provisions in the income statement and the aggregate treatment of loan loss allowances.

While our interpretation of the findings is more plausible (Watts, 2003), earnings management could also produce some evidence consistent with conservatism. Along this line, Cohen et al (2014) show that banks engaging in earnings management practices increase their exposure to crash risk, especially during the recent financial crisis. Hence, to preclude earnings management as an explanation of our findings, we test further whether the relations remain robust after controlling for earnings management. We expect that, while effects of earnings management on crash risk will be pronounced during crisis periods, conservatism predicts crash risk more generally and not only during crises periods. This is due to the nature of conservatism that relates more to persistent conservative reporting culture that a bank adopts, rather than a transient earnings smoothing mechanism (Watts, 2003). To test this, we use the earnings management variable *LLP_MGT* of Cohen et al (2014), which is available for most part of our wider sample.[3] Table 5 shows the results of a regression analysis of the measures of crash risk on lagged *LLP_CONS*, lagged *LLA_CONS_UNADJ,* lagged *LLP_MGT*, and the interaction of these with a dummy variable for the recent crisis.[4] Consistent with Cohen et al (2014), the relationship between *LLP_MGT* and crash risk is seen only in the crisis period and with highest (but marginal) significance for the *CRASH* variable. In contrast, the relationship between conditional conservatism and crash risk is seen for the other two crash variables with high significance and does not depend on the crisis periods. This confirms the conjecture that earnings management is picking up different information, particularly more transitory exposure to large crashes, whereas conservatism reflects more persistent accounting behavior that affects crash risk more generally.

[Insert Table 5 about here]

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[3] We thank the authors for kindly providing us with their *LLP_MGT* measure of earnings management.

[4] When using a logit regression, the interpretation of interaction term coefficients could be misleading. Thus, we follow Fiordelisi and Ricci (2013) and use the methodology developed by Ai and Norton (2003) and Norton et al., (2004) to compute correct marginal estimates and their standard errors.

### 5.2 Conservatism, banking lending growth 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 bank lending growth cycle. Since loan loss provisions and loan loss allowances constitute the main channels through which accounting conservatism operates in reducing crash risk, we use the *LLP_CONS* and *LLA_CONS_UNADJ* measures of conservatism for the rest of our analyses. We proxy banking lending growth 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 growth in *FCLNBW*. We then classify the period of investigation into terciles, reflecting the three states of the lending growth 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 lending growth cycle, we employ the following model:

$$\begin{aligned} CR\_RISK_t &= \alpha_1 + \sum_i \alpha_i CONS_{t-1} \times HIGH\_CYCLE_{t-1} \\ &+ \sum_j \alpha_j CONS_{t-1} \times MODERATE\_CYCLE_{t-1} + \sum_K \alpha_K CONS_{t-1} \times LOW\_CYCLE_{t-1} \\ &+ \alpha_8 HIGH\_CYCLE_{t-1} + \alpha_9 LOW\_CYCLE_{t-1} + \sum_i \lambda_i CONTROLS_{t-1} + \varepsilon_t \end{aligned} \tag{6}$$

where *CONS* corresponds to the conservatism measures, *LLP_CONS* and *LLA_CONS_UNADJ*, and *HIGH_CYCLE*, *MODERATE_CYCLE* and *LOW_CYCLE* corresponds to binary variables that capture the high, moderate and low lending growth cycles, respectively. The high lending cycle variable is equal to one for years 2000, 2005-2008, and zero otherwise; the moderate lending cycle variable is equal to one for years 1994-1999, and zero otherwise; and the low lending cycle variable is equal to one for years 2001-2004 and 2009, and zero otherwise. High, moderate and low lending cycles exhibit on average 13.5%, 7.4% and -11.8% growths in lending, respectively. The test results are reported in Table 6. In line with Hypothesis $H_2$, we find that the coefficients associated with *LLP_CONS* during the high and low states of the lending growth cycles are all negative and significant in almost all cases (except once for the *CRASH* measure during the high cycle period). *LLA_CONS_UNADJ* that reflects conservatism in the loan loss allowance items shows significant relations to crash risk during the high lending growth cycle. The results indicate that accounting conservatism among banks helps significantly reduce future crash risks at the extremes of the lending growth cycle, that is, during credit crunch and credit boom times. 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 and avoid making bad quality loans (Beatty and Liao, 2011). Similarly, at the low stage of the cycle, more conservative banks benefit from a more prudent representation of the quality of their loan portfolios that are particularly sensitive during credit crunch periods. Generally, the impact of conservatism on future crash risk is more pronounced during low business cycle periods, as seen by the stronger significance (at 1% level) of the slope coefficients for *LLP_CONS* during the low states of the business cycle. Thus, although non-conservative banks are more prudent in their lending behavior during periods of credit 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.

[Insert Table 6 about here]

### 5.3 Conservatism, information opacity, bank size and crash risk

In this section, we study the impact of conservatism on crash risk for banks with different levels of information opacity (proxied by dispersion among analyst forecasts) and for small and large banks. Under Hypotheses $H_3$ and $H_4$ we predict that the relationship between conservatism and the reduction in future crash risks will be more pronounced for banks with higher dispersion in analyst forecasts, and for smaller banks.

We test these predictions by considering Equation (6) for banks classified according to forecast dispersion and size.[5] Specifically, a bank is considered to have high (low) opaqueness when the analysts' forecast dispersion is above (below) the median of the year.[6] Similarly, we classify large (small) banks as those with above (below) \$1 billion in total assets, consistent with previous studies (e.g., Andreou et al., 2016b). We report the results in Tables 7 and 8, respectively. Consistent with $H_3$, Table 7 shows that the relationship

[5] We also measure information opacity by classifying banks with and without analyst forecasts, and the (unreported) empirical results are similar to the reported results for the forecast dispersion measure.

[6] 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.

between conservatism and crash risk is only significant for banks with high forecast dispersion and much more prevalent in the extreme cycles (Panel A). Similarly, Table 8 shows that the relationship is stronger for smaller banks, although the difference between large and small banks is not as pronounced as the difference between banks with high and low forecast dispersion. For the case of small banks, consistent with Hypothesis $H_4$, we observe that accounting conservatism in loan loss accounting items, both provisions and allowances, are significantly associated with a decrease in large stock prices crashes, with *LLP_CONS* and *LLA_CONS_UNADJ* coefficients being significant for various crash risk measures. Further, for small banks, we find that conservatism also helps reduce the occurrence of future price crashes during the extreme periods, with the effect of *LLP_CONS* pronounced during the credit crunch state of the lending growth cycle, while *LLA_CONS_UNADJ* effect is significantly observed during the credit boom state of the lending growth cycle.

[Insert Table 7 about here]

Interestingly, Table 8 Panel B shows that for large banks there is no relationship between crash risk and accounting conservatism. In particular, the conservatism coefficients, although negative, are mostly insignificant for all measures of crash risk and at all states of the credit cycle. In addition, the results show different exposure of large and small banks to crash risk at different states of the bank lending growth cycle. For example, regardless of their conservatism, large banks generally have significantly higher crash risk at the high part of the lending growth cycle, while small banks show enhanced unconditional link between crash risk and the low lending growth cycle. However, conservatism does not seem to matter during moderate cycles.

[Insert Table 8 about here]

Due to the importance of the finding that large banks show no link between conservatism and crash risk, we further investigate the relationship between accounting conservatism and crash risk using the subsample of large banks that have high analyst forecast dispersion. Untabulated results indicate no systematic relationship between crash risk and conservatism, confirming that the general result of no relation between conservatism and crash risk for large banks holds, even within the subset of large banks that have high information opacity.

To summarize, since the most important regulatory concern is the risk of the banking system, it is the crash risk of large banks that is of main 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 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).

### 5.4 Additional Analysis – growth in liquidity cycles, growth in aggregate financial sector risk and 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 cycle as measured by the growth in bank lending activity. As an additional analysis, we test for the relationship using alternative banking business cycles that affects the lending portfolio quality. In particular, we test whether the effect of conservatism on crash risk varies according to the market liquidity growth cycles, proxied by monetary base (*M1*) activity, and the growth in the aggregate financial sector risk using the *CATFIN* measure developed by Allen et al. (2012). Similar to the banking lending growth cycles, we construct high, moderate and low periods based on growth in market liquidity and growth in the aggregate financial sector risk.

The test results are reported in Tables 9 and 10, respectively. We see that the overall crash risk is significantly increased during the high liquidity growth cycle and periods of high aggregate growth in financial sector risk. Interestingly, we observe that the relations between conservatism and crash risk are pronounced during the periods of extremes, that is, mainly during the low liquidity growth cycle and periods of heightened aggregate growth in financial sector risk. This can be explained by the fact that conservatism in loan loss accounting relates to the quality of loan portfolios, which is in turn driven by the broader market conditions. Further, the results using growth in market liquidity and growth in the aggregate financial sector systemic risk measures confirm our previous findings that during moderate periods, the effect of conservatism on crash risk is non-existent.

[Insert Table 9 and 10 about here]

## 6. Conclusion

This paper documents a significant link between conditional conservatism and banks' future crash risk. The key channels of influence from conservatism to crash risk are the discretionary treatments of loan loss provisions in the income statement and loan loss allowances in the balance sheet. This effect is persistent and different from the transient relationship between earnings management and crash risk that holds mainly during crisis periods.

The impact of conservatism on crash risk is magnified during the low state of the lending growth cycle (credit crunch periods), with some increased effect also during the high state of the lending growth cycle (credit boom periods). Conservatism does not matter during moderate business cycles that correspond to "business-as-usual" periods. Further, for small banks the effect of conservatism on crash risk is closely related to bank opaqueness, measured by the dispersion of analysts' forecasts. More opaque small banks show a stronger relationship. 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 with publicly traded equity have a private incentive to be conservative, we find no relationship between conservatism and crash risk for large banks, even opaque ones. Although we observe that the crash risk of large banks is highest in the boom periods of the lending growth cycle, this effect is unrelated to conservatism.

These results contribute to the policy debate on bank accounting and bank regulation. They are consistent with the view that the private incentives of large banks to adopt conservative accounting practices result in very little possibility for using the regulation of accounting conservatism to control the crash risk of large banks. Since large banks are the main source of systemic risk, these results indicate that there is limited scope for controlling systemic risk by regulating the behavior that is captured by the conditional conservatism measure of accounting behavior.

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## Appendix: Definition of Variables

| Variables | Definitions |
|---|---|
| **Dependent Variables:** | |
| *CRASH* | An indicator variable that is equal to one when a firm experiences at least one crash week during the fiscal year, and zero otherwise. |
| *NCSKEW* | Negative of the third moment of firm-specific weekly returns for each firm and year divided by the standard deviation of bank-specific weekly returns raised to the third power. |
| *DUVOL* | Log of the ratio of the standard deviation of the "down weeks" over the standard deviation of the "up weeks". |
| **Independent Variables:** | |
| *NI_CONS* | Conservatism measure computed by cumulating Basu's (1997) net income conservatism measure over the previous three-year period. |
| *LLP_CONS* | Conservatism measure computed by cumulating Basu's (1997) loan loss provisions conservatism measure over the previous three-year period. |
| *EBP_CONS* | Conservatism measure computed by cumulating Basu's (1997) earnings before provisions conservatism measure over the previous three-year period. |
| *LLA_CONS* | 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 allowance of loan loss provisions divided by the non-performing loans. |
| *LLA_CONS_UNADJ* | 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 unadjusted 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. |

| | |
|---|---|
| *NCO_CONS* | Conservatism in loan loss charge offs coded with a binary variable to capture 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 charge offs is the ratio of loan charge offs divided by the non-performing loans. |
| *REC_CONS* | Conservatism in loan recoveries coded with a binary variable to capture 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 during the fiscal year. |
| *SIGMA* | Volatility of firm-specific weekly returns during the fiscal year. |
| *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 bank-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 Banks With No Crashes | Number of Banks Experiencing 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 the 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 |
| $DUVOL_t$ | -0.104 | -0.096 | 0.344 | -0.319 | 0.113 |
| Conservatism Variables | | | | | |
| $NI\_CONS_{t-1}$ | -0.012 | -0.002 | 0.185 | -0.079 | 0.059 |
| $LLP\_CONS_{t-1}$ | -0.001 | 0.000 | 0.009 | -0.004 | 0.004 |
| $EBP\_CONS_{t-1}$ | -0.011 | -0.001 | 0.077 | -0.039 | 0.028 |
| $LLA\_CONS_{t-1}$ | 0.979 | 0.193 | 2.418 | -0.560 | 1.399 |
| $LLA\_CONS\_UNADJ_{t-1}$ | 1.299 | 0.211 | 4.174 | -0.591 | 1.493 |
| $NCO\_CONS_{t-1}$ | 0.091 | 0.000 | 1.453 | 0.000 | 0.000 |
| $REC\_CONS_{t-1}$ | 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 the Appendix. The significance is designated by *** at 1%, ** at 5% and * at 10%.

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 | 16 | 17 | 18 | 19 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Dependent Variables** | | | | | | | | | | | | | | | | | | | |
| 1. $CRASH_t$ | 1.00 | 0.51*** | 0.48*** | 0.00 | -0.03** | 0.02* | -0.02 | -0.02 | -0.03*** | -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*** | 1.00 | 0.95*** | -0.08*** | -0.06*** | -0.08*** | 0.00 | 0.01 | 0.02 | 0.05*** | 0.06*** | -0.04*** | 0.05*** | 0.13*** | 0.09*** | 0.02 | -0.01 | -0.04*** | -0.08*** |
| 3. $DUVOL_t$ | 0.46*** | 0.98*** | 1.00 | -0.09*** | -0.06** | -0.09*** | 0.00 | 0.01 | 0.02** | 0.06*** | 0.04*** | -0.03** | 0.03** | 0.13*** | 0.11*** | 0.01 | 0.01 | -0.04*** | -0.09*** |
| **Conservatism Variables** | | | | | | | | | | | | | | | | | | | |
| 4. $NI\_CONS_{t-1}$ | 0.01 | -0.09*** | -0.09*** | 1.00 | -0.21*** | 0.38*** | -0.13*** | -0.17*** | -0.25*** | -0.37*** | -0.11*** | -0.19*** | 0.18*** | -0.48*** | -0.25*** | 0.01 | -0.20*** | 0.13*** | 0.22*** |
| 5. $LLP\_CONS_{t-1}$ | -0.02 | -0.05*** | -0.05*** | -0.23*** | 1.00 | 0.02 | 0.02* | -0.01 | -0.04*** | -0.17*** | -0.08*** | 0.04*** | -0.02** | -0.24*** | -0.08*** | -0.06*** | 0.06*** | 0.02* | 0.13*** |
| 6. $EBP\_CONS_{t-1}$ | 0.02 | -0.10*** | -0.09*** | 0.61*** | -0.02* | 1.00 | -0.19*** | -0.24*** | -0.33*** | -0.47*** | -0.09*** | -0.11*** | 0.13*** | -0.64*** | -0.55*** | -0.08*** | -0.27*** | 0.13*** | 0.14*** |
| 7. $LLA\_CONS_{t-1}$ | -0,02 | 0,00 | 0,00 | -0,13*** | 0,04*** | -0,20*** | 1.00 | 0.93*** | 0.18*** | 0.16*** | 0.04*** | 0.08*** | -0.08*** | 0.14*** | 0.24*** | -0.03** | 0.16*** | 0.08*** | 0.05*** |
| 8. $LLA\_CONS\_UNADJ_{t-1}$ | -0,02 | 0,00 | 0,01 | -0,16*** | 0,02 | -0,24*** | 0,93*** | 1.00 | 0.23*** | 0.24*** | 0.05*** | 0.08*** | -0.09*** | 0.20*** | 0.27*** | -0.01 | 0.17*** | 0.06*** | 0.03** |
| 9. $NCO\_CONS_{t-1}$ | -0,03 | 0,02 | 0,02** | -0,26*** | -0,01 | -0,30*** | 0,18*** | 0,23*** | 1.00 | 0.60*** | 0.02 | 0.12*** | -0.15*** | 0.40*** | 0.22*** | 0.08*** | 0.14*** | -0.05*** | -0.06*** |
| 10. $REC\_CONS_{t-1}$ | -0,01 | 0,05*** | 0,06*** | -0,38*** | -0,14*** | -0,45*** | 0,16*** | 0,24 | 0,60 | 1.00 | 0.12*** | 0.09*** | -0.12*** | 0.64*** | 0.31*** | 0.10*** | 0.15*** | -0.08*** | -0.13*** |
| **Control Variables** | | | | | | | | | | | | | | | | | | | |
| 11. $DTURN_{t-1}$ | 0.01 | 0.06*** | 0.05*** | -0.10*** | -0.07*** | -0.16*** | 0,06*** | 0,07*** | 0,03*** | 0,11 | 1.00 | -0.21*** | 0.21*** | 0.24*** | 0.03** | -0.03** | -0.09*** | 0.01 | -0.09*** |
| 12. $RET_{t-1}$ | -0.01 | -0.05*** | -0.03*** | -0.14*** | 0.01 | -0.10*** | 0,07*** | 0,08*** | 0,19*** | 0,16 | -0.15*** | 1.00 | -0.96*** | 0.03** | 0.29*** | -0.05*** | 0.44*** | 0.02* | -0.02 |
| 13. $SIGMA_{t-1}$ | 0.01 | 0.06*** | 0.04*** | -0.13*** | -0.01 | 0.10*** | -0,07*** | -0,08*** | -0,18*** | -0,16 | 0.15*** | -0.99*** | 1.00 | -0.06*** | -0.28*** | 0.07*** | -0.41*** | -0.03*** | 0.03** |
| 14. $SIZE_{t-1}$ | -0.02 | 0.12*** | 0.12*** | -0.55*** | -0.20*** | -0.68*** | 0,14*** | 0,19*** | 0,35*** | 0,54 | 0.21*** | 0.07*** | -0.07*** | 1.00 | 0.35*** | 0.21*** | 0.10*** | -0.21*** | -0.35*** |
| 15. $MB_{t-1}$ | 0.00 | 0.09*** | 0.10*** | -0.29*** | -0.05*** | -0.55*** | 0,24*** | 0,27*** | 0,21*** | 0,29 | 0.11*** | 0.24*** | -0.24*** | 0.38*** | 1.00 | 0.19*** | 0.44*** | 0.00 | 0.05*** |
| 16. $LEV_{t-1}$ | -0.02 | 0.02 | 0.02 | 0.01 | -0.06*** | -0.06*** | -0,03*** | -0,03** | 0,07*** | 0,08 | -0.01 | -0.08*** | 0.08*** | 0.19*** | 0.18*** | 1.00 | -0.12*** | -0.55*** | 0.02 |
| 17. $ROA_{t-1}$ | -0.03** | 0.01 | 0.02 | -0.21*** | 0.03** | -0.41*** | 0,23*** | 0,24*** | 0,20*** | 0,24 | 0.03*** | 0.27*** | -0.27*** | 0.20*** | 0.60*** | -0.20*** | 1.00 | 0.16*** | 0.03** |
| 18. $CAPITAL_{t-1}$ | -0.01 | -0.04*** | -0.04*** | 0.18*** | -0.02* | 0.10*** | 0,09*** | 0,07*** | -0,05*** | -0,07 | 0.02* | 0.03*** | -0.03*** | -0.16*** | 0.04*** | -0.49*** | 0.22*** | 1.00 | 0.16*** |
| 19. $DEPOSITS_{t-1}$ | -0.02* | -0.09*** | -0.09*** | 0.24*** | 0.07*** | 0.15*** | 0,04*** | 0,01 | -0,07*** | -0,15 | -0.03** | -0.05*** | 0.05*** | -0.30*** | 0.07*** | -0.05*** | 0.10*** | 0.23*** | 1.00 |

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

This table reports estimates of the relation between income statement and balance sheet measures of conservatism on crash risk. Models (1)-(5) display logistic regression marginal estimates while models (6)-(15) 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 and year fixed effects. All variables are described in the Appendix. z- / t-statistic is in parentheses below the coefficient estimates. The significance is designated by *** at 1%, ** at 5% and * at 10%.

| | Predicted sign | $CRASH_t$ | | | | | $NCSKEW_t$ | | | | | $DUVOL_t$ | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) | (13) | (14) | (15) |
| $NI\_CONS_{t-1}$ | - | 0.018 | | | | | -0.123* | | | | | -0.087*** | | | | |
| | | (0.55) | | | | | (-1.72) | | | | | (-2.65) | | | | |
| $LLP\_CONS_{t-1}$ | - | | -1.110*** | | | -1.067*** | | -2.206** | | | -2.174** | | -1.061** | | | -1.050** |
| | | | (-2.80) | | | (-2.74) | | (-2.48) | | | (-2.45) | | (-2.54) | | | (-2.51) |
| $EBP\_CONS_{t-1}$ | - | | 0.089 | | | 0.082 | | 0.322 | | | 0.313 | | 0.105 | | | 0.104 |
| | | | (0.78) | | | (0.72) | | (1.34) | | | (1.31) | | (0.95) | | | (0.95) |
| $LLA\_CONS_{t-1}$ | - | | | -0.015 | | | | | -0.047** | | | | | -0.023*** | | |
| | | | | (-1.55) | | | | | (-2.53) | | | | | (-2.71) | | |
| $LLA\_CONS\_UNADJ_{t-1}$ | - | | | | -0.012 | -0.012 | | | | -0.044** | -0.044** | | | | -0.020** | -0.020** |
| | | | | | (-1.22) | (-1.19) | | | | (-2.31) | (-2.28) | | | | (-2.35) | (-2.30) |
| $NCO\_CONS_{t-1}$ | - | | | | -0.039* | -0.036 | | | | -0.034 | -0.023 | | | | -0.004 | 0.000 |
| | | | | | (-1.67) | (-1.52) | | | | (-0.79) | (-0.54) | | | | (-0.23) | (0.01) |
| $REC\_CONS_{t-1}$ | - | | | | 0.030* | 0.026 | | | | -0.025 | -0.031 | | | | -0.07 | -0.010 |
| | | | | | (1.71) | (1.49) | | | | (-0.67) | (-0.86) | | | | (-0.41) | (-0.61) |
| *Control variables* | | | | | | | | | | | | | | | | |
| $DTURN_{t-1}$ | + | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | -0.000 | -0.000 | 0.000 | 0.000 | -0.000 | -0.001 | -0.000 | -0.000 | -0.000 | -0.000 |
| | | (0.18) | (0.08) | (0.18) | (0.11) | (0.04) | (-0.00) | (-0.06) | (0.11) | (0.06) | (-0.06) | (-0.73) | (-0.71) | (-0.58) | (-0.60) | (-0.69) |
| $RET_{t-1}$ | + | 0.061 | 0.065 | 0.060 | 0.056 | 0.068 | -0.283* | -0.212 | -0.212 | -0.207 | -0.185 | -0.127* | -0.082 | -0.083 | -0.083 | -0.072 |
| | | (0.88) | (0.96) | (0.88) | (0.83) | (1.01) | (-1.88) | (-1.42) | (-1.43) | (-1.40) | (-1.24) | (-1.95) | (-1.26) | (-1.29) | (-1.29) | (-1.10) |
| $SIZE_{t-1}$ | - | -0.008** | -0.009** | -0.009** | -0.011*** | -0.011** | 0.024*** | 0.032*** | 0.030*** | 0.036*** | 0.039*** | 0.009*** | 0.014*** | 0.014*** | 0.015*** | 0.016*** |
| | | (-2.22) | (-2.21) | (-2.45) | (-2.58) | (-2.31) | (3.02) | (3.52) | (4.21) | (4.42) | (3.93) | (2.78) | (3.35) | (4.29) | (4.23) | (3.57) |
| $MB_{t-1}$ | + | 0.017** | 0.020** | 0.019*** | 0.019** | 0.022*** | 0.107*** | 0.123*** | 0.118*** | 0.119*** | 0.132*** | 0.049*** | 0.055*** | 0.055*** | 0.054*** | 0.059*** |
| | | (2.31) | (2.39) | (2.59) | (2.50) | (2.57) | (6.33) | (6.29) | (6.89) | (6.92) | (6.59) | (6.17) | (6.04) | (6.87) | (6.81) | (6.34) |
| $LEV_{t-1}$ | - | -0.387** | -0.404** | -0.381** | -0.374** | -0.407** | -0.725* | -0.987** | -0.882** | -0.916** | -1.053** | -0.346* | -0.479*** | -0.448** | -0.455** | -0.503*** |
| | | (-2.05) | (-2.18) | (-2.05) | (-2.01) | (-2.19) | (-1.80) | (-2.40) | (-2.23) | (-2.32) | (-2.57) | (-1.92) | (-2.60) | (-2.53) | (-2.57) | (-2.73) |
| $ROA_{t-1}$ | - | -0.523 | -0.351 | -0.502 | -0.506 | -0.319 | -2.321 | -1.646 | -1.965 | -1.958 | -1.478 | -0.781 | -0.445 | -0.570 | -0.576 | -0.371 |
| | | (-0.81) | (-0.53) | (-0.77) | (-0.78) | (-0.48) | (-1.61) | (-1.15) | (-1.37) | (-1.37) | (-1.03) | (-1.16) | (-0.66) | (-0.84) | (-0.85) | (-0.55) |
| $CAPITAL_{t-1}$ | - | -0.380** | -0.411** | -0.358** | -0.370** | -0.410** | -0.640* | -0.858** | -0.693** | -0.695** | -0.821** | -0.273* | -0.385** | -0.318** | -0.319** | -0.369** |
| | | (-2.27) | (-2.48) | (-2.18) | (-2.23) | (-2.47) | (-1.85) | (-2.42) | (-2.01) | (-2.02) | (-2.33) | (-1.80) | (-2.48) | (-2.09) | (-2.11) | (-2.38) |
| $DEPOSITS_{t-1}$ | - | -0.055 | -0.046 | -0.049 | -0.053 | -0.045 | -0.269*** | 0.257*** | -0.263*** | -0.252*** | -0.232** | -0.126*** | -0.123*** | -0.124*** | -0.122*** | -0.114*** |
| | | (-1.17) | (-0.97) | (-1.03) | (-1.11) | (-0.95) | (-2.82) | (2.69) | (-2.77) | (-2.65) | (-2.43) | (-2.98) | (-2.92) | (-2.96) | (-2.90) | (-2.69) |
| $DEPENDENT_{t-1}$ | ? | 0.006 | 0.006 | 0.006 | 0.006 | 0.006 | 0.026* | 0.026** | 0.026* | 0.026** | 0.026** | 0.034*** | 0.034*** | 0.033*** | 0.034*** | 0.034*** |
| | | (0.93) | (0.90) | (0.91) | (0.93) | (0.90) | (1.95) | (1.99) | (1.94) | (1.97) | (1.99) | (2.63) | (2.67) | (2.64) | (2.67) | (2.67) |
| *N* | | 6687 | 6687 | 6687 | 6687 | 6687 | 6687 | 6687 | 6687 | 6687 | 6687 | 6687 | 6687 | 6687 | 6687 | 6687 |
| *Pseudo/ Adj.* $R^2$ | | 0.017 | 0.018 | 0.017 | 0.018 | 0.019 | 0.055 | 0.055 | 0.055 | 0.055 | 0.056 | 0.063 | 0.063 | 0.063 | 0.063 | 0.064 |

**Table 5: Income statement and balance sheet measures of accounting conservatism and crash risk: The impact of earnings management**

This table reports estimates of the relation between income statement and balance sheet measures of conservatism, and earnings management on crash risk. Models (1)-(3) display logistic regression marginal estimates, with margins for interaction terms calculated as shown in Ai and Norton (2003) and Norton, Wang and Ai (2004). Models (4)-(12) report linear regression coefficient estimates. The earnings management variable (*LLP_MGT*) is defined as in Cohen et al (2014). All standard errors are adjusted for clustering at the firm level. The sample consists of 3471 bank firm year-observations (*N*) during the period 1997-2009. Banks are defined using the following SIC codes: 6020, 6022, 6035 and 6036. All regressions include intercepts and year fixed effects. All variables are described in the Appendix. z- / t-*statistic* is in parentheses below the coefficient estimate. The significance is designated by *** at 1%, ** at 5% and * at 10%.

| | Predicted sign | $CRASH_t$ | | | $NCSKEW_t$ | | | $DUVOL_t$ | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| $LLP\_CONS_{t-1}$ | - | -0.937 | | -0.881 | -5.967*** | | -5.785*** | -3.034*** | | -2.967*** |
| | | (1.20) | | (1.09) | (-3.31) | | (-3.22) | (-3.74) | | (-3.67) |
| $LLP\_CONS_{t-1}$ * $CRISIS$ | ? | 3.413 | | 3.544 | -0.602 | | -1.094 | 0.748 | | 0.518 |
| | | (0.78) | | (0.79) | (-0.10) | | (-0.17) | (0.29) | | (0.20) |
| $LLA\_CONS\_UNADJ_{t-1}$ | - | | -0.021 | -0.020 | | -0.073** | -0.071** | | -0.028** | -0.027** |
| | | | (1.48) | (1.41) | | (-.255) | (-2.48) | | (-2.24) | (-2.14) |
| $LLA\_CONS\_UNADJ_{t-1}$ * $CRISIS$ | - | | -0.023 | -0.027 | | 0.0156 | 0.027 | | 0.011 | 0.014 |
| | | | (-0.38) | (-.045) | | (0.22) | (0.37) | | (0.31) | (0.41) |
| $LLP\_MGT_{t-1}$ | + | 0.553 | 0.564 | 0.338 | -0.111 | 0.204 | -0.872 | -0.295 | -0.015 | -0.585 |
| | | (0.40) | (0.41) | (0.24) | (-0.04) | (0.07) | (-0.31) | (-0.23) | (-0.01) | (-0.45) |
| $LLP\_MGT_{t-1}$ * $CRISIS$ | + | 15.497* | 13.928* | 14.776* | 16.859* | 16.476* | 16.671* | 7.422 | 7.099 | 7.450* |
| | | (2.11) | (1.84) | (1.94) | (1.78) | (1.78) | (1.76) | (1.63) | (1.61) | (1.66) |
| Control variables | | | | | | | | | | |
| *CRISIS* | + | 0.136** | 0.152** | 0.144** | 0.179* | 0.160 | 0.183* | 0.056 | 0.047 | 0.055 |
| | | (2.29) | (2.41) | (2.17) | (1.91) | (1.61) | (1.75) | (1.27) | (0.98) | (1.11) |
| $DTURN_{t-1}$ | + | 0.000 | -0.000 | 0.000 | -0.003 | -0.003 | -0.003 | -0.001 | -0.002 | -0.001 |
| | | (0.12) | (0.01) | (0.13) | (-0.88) | (-1.02) | (-0.89) | (-1.13) | (-1.33) | (-1.15) |
| $RET_{t-1}$ | + | 0.254* | 0.268* | 0.261* | -0.491* | -0.511** | -0.469* | -0.208* | -0.218* | -0.200 |
| | | (1.70) | (1.82) | (1.75) | (-1.87) | (-1.99) | (-1.78) | (-1.66) | (-1.75) | (-1.58) |
| $SIZE_{t-1}$ | - | -0.002 | 0.000 | -0.001 | 0.036*** | 0.048*** | 0.038*** | 0.0186*** | 0.024*** | 0.0193*** |
| | | (0.38) | (0.03) | (0.27) | (3.13) | (4.42) | (3.32) | (3.52) | (4.89) | (3.66) |
| $MB_{t-1}$ | + | 0.020* | 0.025** | 0.023** | 0.106*** | 0.119*** | 0.119*** | 0.046*** | 0.051*** | 0.050*** |
| | | (1.76) | (2.29) | (2.09) | (4.59) | (5.17) | (5.02) | (4.25) | (4.83) | (4.62) |
| $LEV_{t-1}$ | - | -0.688* | -0.729* | -0.740* | -1.300* | -1.599** | -1.438* | -0.549 | -0.668* | -0.599* |
| | | (1.81) | (1.93) | (1.94) | (-1.72) | (-2.13) | (-1.92) | (-1.56) | (-1.91) | (-1.70) |
| $ROA_{t-1}$ | - | -1.152 | -1.113 | -1.137 | 1.287 | 0.579 | 1.388 | 1.263 | 0.937 | 1.306 |
| | | (0.80) | (0.76) | (0.79) | (0.46) | (0.20) | (0.50) | (0.96) | (0.71) | (1.00) |
| $CAPITAL_{t-1}$ | - | -0.278 | -0.259 | -0.281 | -0.414 | -0.426 | -0.418 | -0.021 | -0.019 | -0.022 |
| | | (1.06) | (1.01) | (1.08) | (-0.84) | (-0.88) | (-0.86) | (-0.09) | (-0.09) | (-0.10) |
| $DEPOSITS_{t-1}$ | - | 0.028 | 0.034 | 0.035 | -0.119 | -0.147 | -0.094 | -0.057 | -0.074 | -0.049 |
| | | (0.39) | (0.48) | (0.49) | (-0.83) | (-1.02) | (-0.66) | (-0.92) | (-1.16) | (-0.77) |
| $DEPENDENT_{t-1}$ | ? | 0.007 | 0.007 | 0.006 | 0.018 | 0.022 | 0.018 | 0.030* | 0.034** | 0.030* |
| | | (0.70) | (0.76) | (0.67) | (1.08) | (1.22) | (1.04) | (1.80) | (1.98) | (1.77) |
| *N* | | 3471 | 3471 | 3471 | 3471 | 3471 | 3471 | 3471 | 3471 | 3471 |
| *Pseudo/Adj.* $R^2$ | | 0.0194 | 0.0199 | 0.0204 | 0.055 | 0.054 | 0.056 | 0.065 | 0.062 | 0.066 |

**Table 6: Accounting conservatism, lending growth cycles and crash risk**

This table reports estimates of the relation between conservatism on crash risk conditional on banking cycle. As a proxy for the banking cycle we use growth in lending as captured by the change in 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 change in *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 is equal to 1 for years 2000, 2005-2008, and zero otherwise. $MODERATE\_CYCLE_{t-1}$ is a dummy variable that is equal to 1 for years 1994-1999, and zero otherwise. $LOW\_CYCLE_{t-1}$ is a dummy variable that is equal to 1 for years 2001-2004, 2009, and zero otherwise. Model (1) display logistic regression marginal estimates while models (2) and (3) 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 remaining variables are described in the Appendix. z- / t-statistic is in parentheses below the coefficient estimates. The significance is designated by *** at 1%, ** at 5% and * at 10%.

| | Predicted sign | $CRASH_t$ (1) | $NCSKEW_t$ (2) | $DUVOL_t$ (3) |
|---|---|---|---|---|
| $LLP\_CONS_{t-1} * HIGH\_CYCLE_{t-1}$ | - | -0.940 | -3.653** | -1.968** |
| | | (-1.16) | (-2.13) | (-2.51) |
| $LLP\_CONS_{t-1} * MODERATE\_CYCLE_{t-1}$ | - | -0.384 | 0.885 | 0.904 |
| | | (-0.44) | (0.56) | (1.10) |
| $LLP\_CONS_{t-1} * LOW\_CYCLE_{t-1}$ | - | -2.152*** | -5.344*** | -2.848*** |
| | | (-2.57) | (-3.24) | (-3.99) |
| $LLA\_CONS\_UNADJ_{t-1} * HIGH\_CYCLE_{t-1}$ | - | -0.014 | -0.071** | -0.028** |
| | | (-0.94) | (-2.20) | (-1.96) |
| $LLA\_CONS\_UNADJ_{t-1} * MODERATE\_CYCLE_{t-1}$ | - | -0.025 | -0.048 | -0.024* |
| | | (-1.52) | (-1.59) | (-1.77) |
| $LLA\_CONS\_UNADJ_{t-1} * LOW\_CYCLE_{t-1}$ | - | -0.003 | -0.013 | -0.009 |
| | | (-0.22) | (-0.42) | (-0.70) |
| $HIGH\_CYCLE_{t-1}$ | + | 0.055* | 0.057*** | 0.058** |
| | | (1.95) | (2.77) | (2.23) |
| $LOW\_CYCLE_{t-1}$ | + | 0.022 | -0.012 | -0.004 |
| | | (0.73) | (-0.20) | (-0.15) |
| *N* | | 6687 | 6687 | 6687 |
| *Pseudo/ Adj.* $R^2$ | | 0.019 | 0.057 | 0.066 |

**Table 7: Accounting conservatism, lending growth cycles and crash risk: The impact of information opacity**

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 growth in lending as captured by the change in 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 change in *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 is equal to 1 for years 2000, 2005-2008, and zero otherwise. $MODERATE\_CYCLE_{t-1}$ is a dummy variable that is equal to 1 for years 1994-1999, and zero otherwise. $LOW\_CYCLE_{t-1}$ is a dummy variable that is equal to 1 for years 2001-2004, 2009, and zero otherwise. Panel A (B) reports results for banks with above (below) median analysts' forecast dispersion for the year. Models (1)-(2) display logistic regression marginal estimates while models (3) – (6) 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 | $CRASH_t$ | | $NCSKEW_t$ | | $DUVOL_t$ | |
|---|---|---|---|---|---|---|---|
| | | (1) | (2) | (3) | (4) | (5) | (6) |
| **Panel A: Results for high dispersion at t-1** | | | | | | | |
| $LLP\_CONS_{t-1}$ | - | -1.091***<br>(-2.61) | | -2.225**<br>(-2.38) | | -1.016**<br>(-2.29) | |
| $LLA\_CONS\_UNADJ_{t-1}$ | | -0.010<br>(-1.01) | | -0.048**<br>(-2.29) | | -0.024***<br>(-2.61) | |
| $LLP\_CONS_{t-1}$ * $HIGH\_CYCLE_{t-1}$ | - | | -0.885<br>(-1.02) | | -2.525<br>(-1.37) | | -1.428*<br>(-1.67) |
| $LLP\_CONS_{t-1}$ * $MODERATE\_CYCLE_{t-1}$ | - | | -0.334<br>(-0.33) | | 0.892<br>(0.53) | | 0.859<br>(0.97) |
| $LLP\_CONS_{t-1}$ * $LOW\_CYCLE_{t-1}$ | - | | -2.072***<br>(-2.19) | | -5.860***<br>(-3.09) | | -3.000***<br>(-3.66) |
| $LLA\_CONS\_UNADJ_{t-1}$ * $HIGH\_CYCLE_{t-1}$ | - | | -0.010<br>(-0.60) | | -0.075**<br>(-2.14) | | -0.034**<br>(-2.14) |
| $LLA\_CONS\_UNADJ_{t-1}$ * $MODERATE\_CYCLE_{t-1}$ | - | | -0.019<br>(-1.08) | | -0.044<br>(-1.34) | | -0.021<br>(-1.41) |
| $LLA\_CONS\_UNADJ_{t-1}$ * $LOW\_CYCLE_{t-1}$ | - | | -0.001<br>(-0.07) | | -0.017<br>(-0.50) | | -0.014<br>(-0.96) |
| $HIGH\_CYCLE_{t-1}$ | + | 0.047*<br>(1.68) | 0.045<br>(1.48) | 0.111**<br>(1.98) | 0.137**<br>(2.24) | 0.034<br>(1.32) | 0.047*<br>(1.69) |
| $LOW\_CYCLE_{t-1}$ | + | 0.027<br>(0.91) | 0.021<br>(0.63) | -0.044<br>(-0.71) | -0.045<br>(-0.67) | -0.025<br>(-0.87) | -0.021<br>(-0.66) |
| *N* | | 5652 | 5652 | 5652 | 5652 | 5652 | 5652 |
| *Pseudo/ Adj.* $R^2$ | | 0.020 | 0.021 | 0.057 | 0.058 | 0.067 | 0.069 |
| **Panel A: Results for low dispersion at t-1** | | | | | | | |
| $LLP\_CONS_{t-1}$ | - | -0.162<br>(-0.15) | | -0.890<br>(-0.34) | | -0.441<br>(-0.44) | |
| $LLA\_CONS\_UNADJ_{t-1}$ | | -0.034<br>(-1.44) | | -0.038<br>(-0.75) | | -0.011<br>(-0.47) | |
| $LLP\_CONS_{t-1}$ * $HIGH\_CYCLE_{t-1}$ | - | | 1.380<br>(0.55) | | -4.493<br>(-0.85) | | -1.756<br>(-0.73) |
| $LLP\_CONS_{t-1}$ * $MODERATE\_CYCLE_{t-1}$ | - | | 0.135<br>(0.08) | | -1.344<br>(-0.29) | | -0.243<br>(-0.12) |
| $LLP\_CONS_{t-1}$ * $LOW\_CYCLE_{t-1}$ | - | | -0.898<br>(-0.61) | | 0.748<br>(0.20) | | -0.048<br>(-0.03) |
| $LLA\_CONS\_UNADJ_{t-1}$ * $HIGH\_CYCLE_{t-1}$ | - | | -0.038<br>(-1.07) | | -0.033<br>(-0.37) | | -0.000<br>(-0.00) |
| $LLA\_CONS\_UNADJ_{t-1}$ * $MODERATE\_CYCLE_{t-1}$ | - | | -0.071<br>(-1.38) | | -0.046<br>(-0.50) | | -0.029<br>(-0.68) |
| $LLA\_CONS\_UNADJ_{t-1}$ * $LOW\_CYCLE_{t-1}$ | - | | -0.010<br>(-0.26) | | -0.041<br>(-0.55) | | -0.013<br>(-0.35) |
| $HIGH\_CYCLE_{t-1}$ | + | 0.136**<br>(-2.20) | 0.105<br>(1.33) | 0.235*<br>(1.69) | 0.247<br>(1.45) | 0.125*<br>(1.93) | 0.113<br>(1.50) |
| $LOW\_CYCLE_{t-1}$ | + | 0.044<br>(0.74) | 0.003<br>(0.04) | 0.106<br>(0.81) | 0.105<br>(0.63) | 0.074<br>(1.20) | 0.063<br>(0.83) |
| *N* | | 1035 | 1035 | 1035 | 1035 | 1035 | 1035 |
| *Pseudo/ Adj.* $R^2$ | | 0.048 | 0.050 | 0.077 | 0.074 | 0.092 | 0.089 |

**Table 8: Accounting conservatism, lending growth cycles and crash risk: The impact bank size**

This table reports estimates of the relation between conservatism on crash risk conditional on banking cycle. As a proxy for the banking cycle we use growth in lending as captured by the change in 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 change in *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 is equal to 1 for years 2000, 2005-2008, and zero otherwise. $MODERATE\_CYCLE_{t-1}$ is a dummy variable that is equal to 1 for years 1994-1999, and zero otherwise. $LOW\_CYCLE_{t-1}$ is a dummy variable that is equal to 1 for years 2001-2004, 2009, and zero otherwise. Panel A (B) reports results for banks with total assets below (above) $1 billion. Models (1)-(2) display logistic regression marginal estimates while models (3) – (6) 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 remaining variables are described in the Appendix. z- / t-statistic is in parentheses below the coefficient estimates. The significance is designated by *** at 1%, ** at 5% and * at 10%.

| | Predicted sign | $CRASH_t$ | | $NCSKEW_t$ | | $DUVOL_t$ | |
|---|---|---|---|---|---|---|---|
| | | (1) | (2) | (3) | (4) | (5) | (6) |
| **Panel A: Results for small banks at t-1** | | | | | | | |
| $LLP\_CONS_{t-1}$ | - | -1.627** | | -2.827* | | -0.937 | |
| | | (-2.11) | | (-1.65) | | (-1.13) | |
| $LLA\_CONS\_UNADJ_{t-1}$ | | -0.003 | | -0.052* | | -0.029** | |
| | | (-0.21) | | (-1.72) | | (-2.20) | |
| $LLP\_CONS_{t-1}$ * $HIGH\_CYCLE_{t-1}$ | - | | -2.358* | | -1.342 | | -0.224 |
| | | | (-1.77) | | (-0.37) | | (-0.14) |
| $LLP\_CONS_{t-1}$ * $MODERATE\_CYCLE_{t-1}$ | - | | -0.367 | | -0.917 | | -0.211 |
| | | | (-0.27) | | (-0.31) | | (0.14) |
| $LLP\_CONS_{t-1}$ * $LOW\_CYCLE_{t-1}$ | - | | -3.128** | | -6.490** | | -2.354* |
| | | | (-2.06) | | (-1.96) | | (-1.66) |
| $LLA\_CONS\_UNADJ_{t-1}$ * $HIGH\_CYCLE_{t-1}$ | - | | -0.007 | | -0.128** | | -0.048** |
| | | | (-0.33) | | (-2.50) | | (-2.22) |
| $LLA\_CONS\_UNADJ_{t-1}$ * $MODERATE\_CYCLE_{t-1}$ | - | | -0.031 | | -0.014 | | -0.014 |
| | | | (-1.23) | | (-0.29) | | (-0.70) |
| $LLA\_CONS\_UNADJ_{t-1}$ * $LOW\_CYCLE_{t-1}$ | - | | 0.029 | | -0.016 | | -0.022 |
| | | | (1.19) | | (-0.32) | | (-1.04) |
| $HIGH\_CYCLE_{t-1}$ | + | 0.082** | 0.081** | 0.097 | 0.153* | 0.015 | 0.032 |
| | | (2.24) | (2.06) | (1.30) | (1.87) | (0.45) | (0.87) |
| $LOW\_CYCLE_{t-1}$ | + | 0.058 | 0.039 | -0.178** | -0.171* | -0.076** | -0.070* |
| | | (1.40) | (0.86) | (-1.98) | (-1.79) | (-1.96) | (-1.67) |
| *N* | | 3101 | 3101 | 3101 | 3101 | 3101 | 3101 |
| *Pseudo/ Adj.* $R^2$ | | 0.035 | 0.037 | 0.080 | 0.080 | 0.101 | 0.102 |
| **Panel B: Results for large banks at t-1** | | | | | | | |
| $LLP\_CONS_{t-1}$ | - | -0.281 | | -0.584 | | -0.446 | |
| | | (-0.66) | | (-0.63) | | (-1.01) | |
| $LLA\_CONS\_UNADJ_{t-1}$ | | -0.023* | | -0.036 | | -0.01 | |
| | | (-1.92) | | (-1.57) | | (-1.34) | |
| $LLP\_CONS_{t-1}$ * $HIGH\_CYCLE_{t-1}$ | - | | 0.977 | | -1.579 | | -1.151 |
| | | | (0.76) | | (-0.83) | | (-1.34) |
| $LLP\_CONS_{t-1}$ * $MODERATE\_CYCLE_{t-1}$ | - | | --0.627 | | -0.023 | | 0.277 |
| | | | (-0.62) | | (-0.01) | | (0.33) |
| $LLP\_CONS_{t-1}$ * $LOW\_CYCLE_{t-1}$ | - | | -0.674 | | -0.551 | | -0.738 |
| | | | (-0.93) | | (-0.35) | | (-1.08) |
| $LLA\_CONS\_UNADJ_{t-1}$ * $HIGH\_CYCLE_{t-1}$ | - | | -0.018 | | -0.023 | | -0.010 |
| | | | (-0.96) | | (-0.57) | | (-0.59) |
| $LLA\_CONS\_UNADJ_{t-1}$ * $MODERATE\_CYCLE_{t-1}$ | - | | -0.023 | | -0.065 | | -0.025 |
| | | | (1.08) | | (-1.60) | | (-1.35) |
| $LLA\_CONS\_UNADJ_{t-1}$ * $LOW\_CYCLE_{t-1}$ | - | | -0.027 | | -0.023 | | -0.007 |
| | | | (-1.40) | | (-0.61) | | (-0.41) |
| $HIGH\_CYCLE_{t-1}$ | + | 0.051 | 0.047 | 0.187*** | 0.163* | 0.087** | 0.079** |
| | | (1.46) | (1.16) | (2.59) | (1.94) | (2.57) | (2.04) |
| $LOW\_CYCLE_{t-1}$ | + | 0.020 | 0.022 | 0.127* | 0.102 | 0.059* | 0.049 |
| | | (0.60) | (0.57) | (1.82) | (1.21) | (1.83) | (1.27) |
| *N* | | 3586 | 3586 | 3586 | 3586 | 3586 | 3586 |
| *Pseudo/ Adj.* $R^2$ | | 0.021 | 0.022 | 0.051 | 0.050 | 0.065 | 0.065 |

**Table 9: Accounting conservatism, liquidity growth cycles and crash risk**

This table reports estimates of the relation between conservatism on crash risk conditional on banking cycle. As a proxy for the banking cycle we use growth in liquidity as captured by the change in 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 is equal to 1 for years 1995-1998, 2000, 2007, and zero otherwise. $MODERATE\_CYCLE_{t-1}$ is a dummy variable that is equal to 1 for years 1998, 1999, 2001, 2005, 2006 and zero otherwise. $LOW\_CYCLE_{t-1}$ is a dummy variable that is equal to 1 for years 1994, 2002-2004, 2009, and zero otherwise. Model (1) display logistic regression marginal estimates while models (2) and (3) 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 remaining variables are described in the Appendix. z- / t-statistic is in parentheses below the coefficient estimates. The significance is designated by *** at 1%, ** at 5% and * at 10%.

| | Predicted sign | $CRASH_t$ | $NCSKEW_t$ | $DUVOL_t$ |
|---|---|---|---|---|
| | | (1) | (2) | (3) |
| $LLP\_CONS_{t-1}$ * $HIGH\_CYCLE_{t-1}$ | - | -1.650* | -1.161 | -0.687 |
| | | (-1.86) | (-0.62) | (-0.85) |
| $LLP\_CONS_{t-1}$ * $MODERATE\_CYCLE_{t-1}$ | - | -1.138** | -2.017 | -0.916 |
| | | (-2.12) | (-1.55) | (-1.44) |
| $LLP\_CONS_{t-1}$ * $LOW\_CYCLE_{t-1}$ | - | -0.805 | -3.574** | -1.582** |
| | | (-1.04) | (-2.51) | (-2.35) |
| $LLA\_CONS\_UNADJ_{t-1}$ * $HIGH\_CYCLE_{t-1}$ | - | -0.011 | -0.049 | -0.022 |
| | | (-0.62) | (-1.42) | (-1.42) |
| $LLA\_CONS\_UNADJ_{t-1}$ * $MODERATE\_CYCLE_{t-1}$ | - | -0.011 | -0.007 | -0.004 |
| | | (-0.82) | (-0.25) | (-0.29) |
| $LLA\_CONS\_UNADJ_{t-1}$ * $LOW\_CYCLE_{t-1}$ | - | -0.019 | -0.088*** | -0.043*** |
| | | (-1.16) | (-2.91) | (-3.08) |
| $HIGH\_CYCLE_{t-1}$ | + | -0.028 | -0.123** | -0.045* |
| | | (-1.06) | (-2.21) | (-1.76) |
| $LOW\_CYCLE_{t-1}$ | + | -0.044* | -0.012 | -0.002 |
| | | (-1.66) | (-0.21) | (-0.08) |
| *N* | | 6687 | 6687 | 6687 |
| *Pseudo/ Adj.* $R^2$ | | 0.019 | 0.056 | 0.064 |

**Table 10: Accounting conservatism, growth in systemic risk and crash risk**

This table reports estimates of the relation between conservatism on crash risk conditional on banking cycle. As a proxy for the banking cycle we use the change in "*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 change in *CATFIN* measured on February 01 of each year as follows: *HIGH* $SRISK_{t-1}$ is a dummy variable that is equal to 1 for years 1999-2001, 2008, 2009, and zero otherwise. *MODERATE* $SRISK_{t-1}$ is a dummy variable that is equal to 1 for years 1994, 1995, 1997, 1998, 2002, 2003, and zero otherwise. *LOW* $RISK_{t-1}$ is a dummy variable that is equal to 1 for years 1996, 2004-2007, and zero otherwise. Model (1) display logistic regression marginal estimates while models (2) and (3) 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 remaining variables are described in the Appendix. z- / t-statistic is in parentheses below the coefficient estimates. The significance is designated by *** at 1%, ** at 5% and * at 10%.

| | Predicted sign | $CRASH_t$ | $NCSKEW_t$ | $DUVOL_t$ |
|---|---|---|---|---|
| | | (1) | (2) | (3) |
| $LLP\_CONS_{t-1}$ * *HIGH* $SRISK_{t-1}$ | - | -1.410* | -4.611*** | -2.521*** |
| | | (-1.88) | (-2.73) | (-3.27) |
| $LLP\_CONS_{t-1}$ * *MODERATE* $SRISK_{t-1}$ | - | -1.730** | -1.425 | -0.596 |
| | | (-2.58) | (0.99) | (-0.90) |
| $LLP\_CONS_{t-1}$ * *LOW* $SRISK_{t-1}$ | - | -0.415 | -1.344 | -0.317 |
| | | (-0.62) | (-0.96) | (-0.47) |
| $LLA\_CONS\_UNADJ_{t-1}$ * *HIGH* $SRISK_{t-1}$ | - | -0.022 | -0.060* | -0.028** |
| | | (-1.54) | (-1.94) | (-2.06) |
| $LLA\_CONS\_UNADJ_{t-1}$ * *MODERATE* $SRISK_{t-1}$ | - | -0.014 | -0.019 | -0.009 |
| | | (-0.83) | (-0.63) | (-0.71) |
| $LLA\_CONS\_UNADJ_{t-1}$ * *LOW* $SRISK_{t-1}$ | - | -0.004 | -0.058* | -0.026* |
| | | (-0.25) | (-1.79) | (-1.80) |
| *HIGH* $SRISK_{t-1}$ | + | 0.077*** | 0.248*** | 0.078*** |
| | | (2.82) | (4.49) | (3.02) |
| *LOW* $SRISK_{t-1}$ | + | 0.041 | 0.060* | 0.024 |
| | | (1.35) | (1.76) | (0.88) |
| *N* | | 6687 | 6687 | 6687 |
| *Pseudo/ Adj.* $R^2$ | | 0.019 | 0.056 | 0.064 |