Delayed Expected Loss Recognition and the Risk Profile of Banks

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Abstract

Policy makers and regulators argue that loan loss accounting can potentially reinforce pro-cyclical effects of bank capital regulation. Banks that delay recognition of expected loan losses (*DELR*) create an overhang of unrecognized expected losses that carry forward to future periods. Further, we hypothesize that *DELR* can reduce bank transparency, increasing investors' uncertainty about a bank's intrinsic value and impeding the bank's ability to raise equity capital in downturns. Expected loss overhangs together with heightened equity financing frictions exacerbate capital inadequacy concerns during economic downturns, thereby increasing the probability that a bank must significantly reduce assets via deleveraging and reductions in lending. We empirically investigate how *DELR* affects three distinct aspects of bank risk: 1) stock market liquidity risks that can increase equity-financing frictions during downturns; 2) the tail risk of individual banks with respect to balance sheet contraction and the sensitivity of tail risk to systemic financial events; and 3) the contribution of individual banks to systemic risk (Adrian and Brunnermeier, 2011). We document that liquidity of high *DELR* banks decreases significantly more in recessions relative to banks that delay less, and that the liquidity of high *DELR* banks co-moves significantly more with market-level liquidity. We find that higher *DELR* is associated with significantly more tail risk during recessions as reflected in a bank's value-at-risk, where the increase in tail risk is driven by increased skewness in the left tail of the distribution. We also find *DELR* increases the sensitivity of a bank's tail risk to systemic financial events. Finally, we show that banks with higher *DELR* contribute more to systemic risk during downturns.

1. Introduction

It has long been recognized that the imposition of minimum capital requirements for banks may have pro-cyclical effects in which the deterioration of the quality of loan portfolios during economic downturns necessitates increases in bank capital precisely when capital becomes more expensive or even unavailable to some institutions. Concerns about capital adequacy could in turn lead to reduced credit supply in periods of economic slowdown, sometimes referred to as a capital crunch (e.g., Bernanke and Lown (1991), Peek and Rosengren (1995), Kishan and Opiela (2006)).

Policy makers and regulators argue that current loan loss accounting rules reinforce pro-cyclical effects of bank capital regulation.[1] The idea is that when banks delay recognition of expected loan losses in current loss provisions, they create an overhang of unrecognized expected losses that carry forward to future periods. Such loss overhangs imply that unrecognized expected losses are included in Tier 1 Capital and mingled together with economic capital available to cover unexpected losses. Such expected loss overhangs compromise the ability of loan loss reserves to cover credit losses during economic downturns and exacerbate capital inadequacy concerns. Further, if banks that more extensively delay expected loss recognition also face more severe financing frictions that impede their ability to raise equity capital in a downturn, capital inadequacy concerns may push such banks to significantly reduce assets via deleveraging and reductions in lending.

[1] U.S. GAAP and IFRS utilize an incurred loss model where loan losses are recognized only after loss events have occurred prior to the reporting date that are likely to result in future non-payment of loans. The Financial Stability Forum (2009) identifies loan loss provisioning as one of three policy priorities for addressing pro-cyclicality. See also Comptroller of the Currency John C. Dugan's remarks on March 2, 2009 to the Institute of International Bankers entitled ''Loan Loss Provisioning and Pro-cyclicality'' similarly reflect these concerns.

In this paper, we exploit differences in the application of loan loss accounting rules across U.S. commercial banks to estimate the relative delay in recognizing expected loan losses. We utilize the incremental R^2 in explaining variation in current loan loss provisions from adding current and future changes in non-performing loans over and above lagged changes in non-performing loans to capture the timeliness of expected loss recognition (Beatty and Liao (2011) and Nicholas et al. (2009)). Higher incremental R^2 implies less delayed loss recognition. Using this measure, we investigate how delayed expected loss recognition (*DELR*) impacts three important aspects of a bank's risk profile in economic downturns. First, we show that banks with higher *DELR* exhibit greater increases in stock market liquidity risk relative to more timely banks, increasing the relative costs of raising new equity capital. Second, we find that higher *DELR* is associated with significantly higher increases in tail risk during recessions as reflected in the value-at-risk of individual banks. Third, we find that the tail risk of individual banks is significantly more sensitive to systemic financial events when *DELR* is higher. Finally, we show that banks that delay loss recognition more contribute more to systemic risk as reflected in a significant marginal contribution to the tail risk of the banking system during downturns.

Our first analysis builds on Beatty and Liao (2011) who document that, consistent with capital crunch theory, banks that delay loss recognition more reduce lending more during recessions relative to banks that delay less, and their lending decisions during recessions are more sensitive to capital levels than more timely banks. We extend Beatty and Liao (2011) by showing that, in addition to direct effects that operate through unrecognized loss overhangs, *DELR* can impact pro-cyclicality indirectly via a transparency channel that manifests in higher costs of raising new equity. Bushman and Williams (2011) show that in countries with less timely loss provisioning regimes, market discipline over bank risk-taking is weaker than in countries with more timely recognition, consistent with *DELR* reducing bank transparency and inhibiting monitoring by outsiders. We hypothesize that banks with more *DELR* are less transparent to outside investors than banks delaying less, where less transparency induces greater uncertainty about the banks' intrinsic value, particularly during economic downturns.

Illiquidity and liquidity risk impose costs on investors that are reflected in equity pricing (e.g., Amihud, et al. (2005)). Brunnermeier and Pedersen (2009) suggest that stock liquidity for firms with more uncertainty about intrinsic value tends to be less predictable and more sensitive to economy-wide shocks and funding availability. Brunnermeier and Pedersen (2009) further argue that systematic shocks to the funding of liquidity providers can generate co-movement in liquidity across assets, particularly for stocks with greater uncertainty about intrinsic value.[2] Focusing on crisis periods in an international setting, Lang and Maffett (2011) document that firms with greater transparency experience less liquidity volatility, fewer extreme illiquidity events and lower correlations between firm-level liquidity and both market liquidity and market returns. Consistent with *DELR* reducing transparency and increasing uncertainty over bank fundamentals, we document that the stock liquidity of high *DELR* banks decreases significantly more in a recession relative to banks that delay less. Further, we find that as *DELR* increases, bank-level liquidity exhibits significantly higher co-movement with aggregate market-level liquidity, especially during economic downturns.

Next, we investigate the role played by delayed loss recognition in creating tail risk at the individual bank level. As discussed earlier, capital inadequacy concerns and equity financing

[2] Acharya and Petersen (2005) decompose the CAPM beta to show that cost of capital is a function of the covariance between firm liquidity and both market returns and market liquidity. Hameed, et al. (2010) finds that liquidity decreases and co-movement increases during market downturns, consistent with a reduction in liquidity supply when the market drops. Brunermeier and Pedersen (2009) and Vayanos (2004) show that liquidity can dry up in a flight to quality where liquidity providers flee assets with high levels of uncertainty about fundamental value.

frictions can push banks to significantly reduce assets via deleveraging and reductions in lending, potentially exacerbating economic downturns (e.g., Adrian and Shin (2011, 2010), Shin (2010) and Achraya et al. (2010)). We adopt the approach of Adrian and Brunnermeier (2011) and focus our tail risk analysis on the value at risk (*VaR*) with respect to the distribution over changes in market-valued total bank assets. We use quantile regressions to estimate time varying *VaR* measures that capture the percentage change in a bank's assets that will occur with a specific probability (1%, 50% or 99%). Holding the probability of loss constant across banks, estimated *VaRs* allow us to compare the potential for severe balance sheet contraction across banks in order to assess relative tail risk.[3] We find that higher *DELR* is associated with significantly more tail risk during recessions as reflected in a bank's value-at-risk, where this increase in tail risk is driven by increased skewness in the left tail of the asset change distribution.

Next, we investigate whether more *DELR* makes the tail risk of individual banks more sensitive to systemic financial events. To the extent that unrecognized expected loss overhangs must be recognized during an economic downturn, bank capital comes under pressure as it must cover the overhang and stand ready to absorb potentially significant unexpected losses caused by the downturn. High *DELR* banks are thus more vulnerable in that a systemic shock is more likely to push the bank to a tipping point where it must quickly and significantly contract its balance sheet. To examine this issue, we use the Adrian and Brunnermeier (2011) *CoVaR* measure to investigate how the *VaR* of individual banks are affected by systemic financial events. We define $CoVaR_q^{i|system}$ as VaR_q^i of bank *i conditional* on the state of the banking system. Then, the

[3] Let VaR_q^i represents the q% quantile of the distribution, meaning that bank i will lose VaR_q^i or more with a q% probability. For example, if $VaR_{1\%}$ of Bank 1 is -12% at a one-week horizon, there is a 1% chance that the bank's assets will drop by 12% or more in the upcoming week. If $VaR_{1\%}$ of Bank 2 is -15%, Bank 2 has more tail risk than Bank 1. With the same 1% probability, Bank 2 will suffer more extreme balance sheet contraction than Bank 1.

difference between $CoVaR_q^{i|system}$ conditional on the banking system being in distress (e.g., system outcome $= VaR_{q=1\%}^{system}$) and $CoVaR_q^{i|system}$ conditional on the median state of the banking system (system outcome $= VaR_{q=50\%}^{system}$), $\Delta CoVaR_q^{i|system}$, captures the marginal contribution of the banking system to the tail risk of bank *i*. We find that during recessions, banks with more *DELR* become relatively more sensitive to the distress of the system in that their $\Delta CoVaR_q^{i|system}$ increases significantly more relative to banks that delay less.

Finally, the above analyses focus on the tail risk of individual banks. However, an individual bank's risk measure does not necessarily reflect systemic risk.. As discussed earlier, we show that co-movement in stock liquidity across banks is higher in downturns for banks with more delayed loss recognition. Now, if a group of banks all significantly delay loss recognition in good times, they will likely all face large loss overhangs and equity financing frictions in an economic downtown. As a result, the asset contraction and loan curtailment decisions of such banks will be highly correlated which can potentially create systemic effects due to herd behavior (Brunnermeier et al. (2009)).

To investigate the contribution of an individual bank to systemic risk, we now define $CoVaR_q^{system|i}$ as VaR_q^{system} of the banking system *conditional* on the state of bank *i*. In this case, the difference between $CoVaR_q^{system|i}$ conditional on bank *i* being in distress (e.g., bank *i* outcome $= VaR_{q=1\%}^{i}$) and $CoVaR_q^{system|i}$ conditional on the median state of bank *i* (bank *i* outcome = $VaR_{q=50\%}^{i}$), $\Delta CoVaR_q^{system|i}$, captures the marginal contribution of a particular institution to overall systemic risk. We show that banks with more *DELR* contribute more to systemic risk.

The rest of the paper is organized as follows. In section 2 we develop the conceptual framework underlying our empirical analysis. Section 3 contains the empirical analysis of the relation between *DELR* and stock market liquidity risk. Section 4 discuss our empirical analysis of how *DELR* influences the tail risk of individual banks, the sensitivity of a bank's tail risk to systemic financial events, and the contribution of individual banks to systemic risk. Section 5 concludes.

2. Conceptual Framework

In section 2.1 we develop the nature of delayed expected loss recognition (*DELR*) and our approach to empirically estimating *DELR* at the individual bank level. Section 2.2 describes how *DELR* can accentuate the pro-cyclical effects of capital adequacy concerns. Section 2.3 discusses the potential for *DELR* to impact equity financing frictions via the influence of bank transparency about a bank's intrinsic value on stock market liquidity risk. Finally, section 2.4 develops the conceptual framework underpinning our empirical analysis of the relation between *DELR* and bank-specific tail risk, and between *DELR* and an individual bank's contribution to systemic risk.

2.1 Delayed Recognition of Expected Loan Losses

U.S. GAAP and IFRS currently utilize an incurred loss model where loan losses are recognized in the income statement when a loss is probable based on past events and conditions existing at the financial statement date. While the incurred loss model does not generally allow for consideration of future expected losses based on trends suggestive of additional future losses, it does allow scope for discretion in determining loss provisions. In fact, the report by the Financial Stability Forum (2009) recommends that accounting standard setters publicly reiterate that existing standards require the use of judgment to determine an incurred loss for provisioning of loan losses. We exploit the extent to which variation across banks in the application of discretion applied within the confines of the incurred loss model leads to differences in *DELR*.

Considering bank capital and loan provisioning jointly from a risk management perspective, the banking literature generally posits that the role of loan loss provisioning is to provide a cushion against *expected* losses, while bank capital is designed to provide a buffer against *unexpected* losses (e.g., Laeven and Majnoni (2003)). This perspective underpins calls for loan loss provisioning to be more forward looking by considering the full extent of future expected losses (e.g., Wall and Koch (2000), Borio et al. (2001), Financial Stability Forum (2009)).

There is a direct link between a bank's common equity that underlies Tier 1 capital and loan loss provisions. Loan provisions are current period expenses which reduce common equity via retained earnings. If banks delay recognition of expected losses, a current expense is not recorded for any unrecognized expected losses and common equity is not reduced. This implies that common equity, and thus Tier 1 capital, will mingle unrecognized expected losses together with economic capital available to cover unexpected losses. Because unrecognized expected losses will on average have to be recognized in the future, this creates an expected loss overhang that looms over future profits and Tier 1 capital. The focus of our interest in this study is the implications of expected loss overhang for the risk profile of commercial banks. We therefore need a measure to capture cross-sectional differences in the extent to which banks delay the recognition of expected loan losses.

We estimate bank-quarter measures of *DELR* following Beatty and Liao (2011) and Nicholas et al. (2009). For a given bank, we capture *DELR* with the incremental R^2 of current and future changes in non-performing loans over and above past changes in explaining current loan loss provisions.[4] Higher incremental R^2 implies less *DELR*. The idea is that *more timely* banks use their discretion to recognize loss provisions concurrently with or in advance of loans becoming nonperforming, where less timely banks use their discretion to delay loss recognition until after loans become nonperforming.[5] That is, banks with less *DELR* more comprehensively reflect expected losses based on current economic conditions.

For each bank quarter, we estimate the following two equations using quarterly data on a three-year rolling window, requiring the firm to have data for all twelve quarters.

$$LLP_t = \beta_0 + \beta_1 \Delta NPL_{t-1} + \beta_2 \Delta NPL_{t-2} + \beta_3 Capital_{t-1} + \beta_4 EBLLP_t + \beta_5 Size_{t-1} + \varepsilon_t \tag{1}$$

$$\begin{aligned} LLP_t = {} & \beta_0 + \beta_1 \Delta NPL_{t-1} + \beta_2 \Delta NPL_{t-2} + \beta_3 \Delta NPL_t + \beta_4 \Delta NPL_{t+1} + \beta_5 Capital_{t-1} \\ & + \beta_6 EBLLP_t + \beta_7 Size_{t-1} + \varepsilon_t \end{aligned} \tag{2}$$

LLP is defined as loan loss provisions scaled by lagged total loans; *ΔNPL* is the change in non-performing loans scaled by lagged total loans; *Capital* is the beginning of the periods tier 1 capital ratio; *Ebllp* is defined as earnings before loan loss provision scaled by lagged total loans; *Size* is the natural log of beginning period total assets (all variables and their construction are detailed in the appendix). We include *Capital* to control for banks incentives to manage capital through loan loss provisions (Beatty et al., 1995; Chamberlin et al., 1995). *Ebllp* is included to control for banks incentives to smooth earnings (Ahmed et al., 1999; Bushman and Williams, 2011). We then take the difference in the adjusted R^2 of (2) - (1), and then rank banks based on

[4] Supporting arguments made by Gambera (2000), Beatty and Liao (2011) show that both current and next period's changes in nonperforming loans are positively correlated with current and lagged unemployment and negatively correlated with current and lagged industrial production. That is, current economic conditions can be used to predict future and concurrent nonperforming loans.

[5] In addition to being correlated with macro variables, the classification of loans as non-performing involves relatively little discretionary judgment and therefore management's ability to alter the classification of a loan as non-performing is limited.

their incremental R^2 in every quarter. For each bank-quarter observation, the variable *Less DELR* is set equal to 1 if the bank is above the median on this measure, and 0 otherwise.

2.2 DELR, Pro-cyclicality and Balance Sheet Responses to Economic Downturns

Banks that delay recognition of expected losses create an overhang of unrecognized expected losses that may compromise the ability of loan loss reserves to cover credit losses during economic downturns and exacerbate capital inadequacy concerns. Further, if banks that more extensively delay expected loss recognition also face more severe external-financing frictions that impede their ability to raise equity capital in a downturn, capital inadequacy concerns may push such banks to significantly reduce assets via deleveraging and curtailed lending.

Van den Heuvel (2009) provides a model of reduced bank lending driven by recessionary decreases in bank capital. His model demonstrates that given high costs of raising new equity, banks with sufficiently low equity will reduce lending due to capital requirements[6]; further, banks may reduce lending even when capital requirements are not currently binding as vulnerable banks may forgo lending opportunities to mitigate risks of future capital inadequacy. Van den Heuvel (2009) also shows that lending by capital constrained banks declines may remain suppressed for several periods in response to shocks to bank profits such as increased recognition of loan losses.

Beatty and Liao (2011) empirically examine implications of the Van den Heuvel (2009) model by extending the empirical capital crunch model of Bernanke and Lown (1991) to incorporate *DELR* considerations. Beatty and Liao (2011) find that loan growth is lower during

[6] Kashyap and Stein (1995) and Stein (1998), among others, also argue that financing frictions can the lending channel of financial intermediaries.

recessions for banks with greater *DELR* compared to banks with smaller delays. These results are consistent with loss overhangs accentuating banks concerns over capital adequacy during recessions, driving them to reduce their lending more. Beatty and Liao (2011) also find that during recessions, the lending decisions of banks with greater *DELR* are more sensitive to capital levels compared to banks with smaller delays.

Key to the capital crunch story is that banks face external-financing frictions that impede their ability to raise equity capital in an economic downturn. Beatty and Liao (2011) attempt to address this aspect of the story by examining how changes in common equity differ for banks with greater versus smaller *DELR* during recessions versus expansions They find that banks with less *DELR* increase their pre-provision common equity more during expansions, and that for banks with higher *DELR* pre-provision equity is reduced more during recessions.

We extend Beatty and Liao (2011) by showing that *DELR* can impact pro-cyclicality via a transparency channel that manifests in higher costs of raising new equity.

2.3 DELR and Stock Market Liquidity Risk

In general, investors prefer stocks that are liquid as illiquidity is costly (e.g., Amihud, et al. (2005)). Beyond the average level of liquidity, investors also care about the extent to which a stock's liquidity is variable, as such variability increases the uncertainty attached to a position and makes it difficult for investors to predict trading costs associated with transacting. Another important factor is the extent to which the illiquidity of a stock is highly correlated with the state of the economy or with illiquidity of other stocks. Acharya and Petersen (2005) decompose the CAPM beta to show that cost of capital is a function of the covariance between firm liquidity and both market returns and market liquidity. Hameed, et al. (2010) finds that liquidity decreases and co-movement increases during market downturns, consistent with a reduction in liquidity supply when the market drops.

As suggested by Brunnermeier and Pedersen (2009), stock liquidity for firms with more uncertainty about intrinsic value tends to be less predictable and more sensitive to economy-wide shocks and funding availability.[7] Brunnermeier and Pedersen (2009) further argue that systematic shocks to the funding of liquidity providers generates co-movement in liquidity across assets, particularly for stocks with greater uncertainty about intrinsic value that are more sensitive to liquidity shocks. It is well established that in the U.S., stock liquidity significantly decreases during economic recessions (Naes et al. (2011)). Focusing on crisis periods and utilizing an international setting, Lang and Maffett (2011) document that firms with greater transparency experience less liquidity volatility, fewer extreme illiquidity events and lower correlations between firm-level liquidity and both market liquidity and market returns.

The banking literature posits that informational transparency of banks plays a fundamental role in promoting market discipline by outside investors as a lever of prudential bank regulation.[8] Bushman and Williams (2011) show that in countries with less timely loss provisioning regimes, market discipline over bank risk-taking is weaker than in countries with more timely recognition, consistent with less timely provisioning reducing bank transparency and inhibiting monitoring by outsiders.

Building on this idea, we conjecture that banks with more *DELR* are less transparent to outside investors than banks delaying less, and this lower transparency induces greater

[7] Brunermeier and Pedersen (2009) and Vayanos (2004) show that liquidity can dry up in a flight to quality where liquidity providers flee assets with high levels of uncertainty about fundamental value.

[8] The regulatory emphasis on market discipline is exemplified by its codification in recent international prudential standards, such as Pillar 3 in the Basel II Framework (See Basel Committee on Banking Supervision (2006) for details).

uncertainty about the banks' intrinsic value, particularly during economic downturns. Further, following Brunnermeier and Pedersen (2009) we hypothesize that greater uncertainty about fundamentals associated with high *DELR* banks will exacerbate pro-cyclicality effects by negatively impacting the stock liquidity of these banks during recessions, and thus increasing equity financing frictions relative to low *DELR* banks. Specifically, we hypothesize that: (1) the greater uncertainty about fundamentals associated with high *DELR* banks will result in the stock liquidity of these banks decreasing significantly more during recessions than the liquidity of low *DELR* banks; and (2) greater uncertainty over intrinsic value will result in the co-movement between the liquidity of high *DELR* banks and the liquidity of banking system increasing significantly more during recessions than will the co-movement between the liquidity of lower *DELR* banks and the system's liquidity. We empirically investigate these hypotheses in section 3 of the paper.

2.4 DELR, Bank-specific Tail Risk, and Individual Banks' Contribution to Systemic Risk

Capital inadequacy concerns and equity financing frictions can push banks to significantly reduce assets via deleveraging and curtailed lending, potentially exacerbating economic downturns (e.g., Adrian and Shin (2011, 2010, Shin (2010) and Achraya et al. (2010)). As discussed earlier, Beatty and Liao (2011) show that banks with high *DELR* on average reduce lending during recessions more than do low *DELR* banks. But it is important to note that the Beatty and Liao (2011) analysis focuses solely on the impact of *DELR* on the average lending behavior of banks. But in terms of the prudential regulation of banks and issues of systemic risk, it is important to consider not only mean changes, but to also consider the entire distribution over banks' balance sheet changes and more importantly the potential for extreme negative outcomes.

Value at risk or VaR, has long been used as a measure of the risk of extreme negative outcomes or tail risk for banks, because VaR measures the expected loss for a given probability.

In this spirit, we first examine the impact of *DELR* on the tail risk of individual banks. To capture tail risk we adopt the approach developed in Adrian and Brunnermeier (2011) and estimate the *VaR* with the respect to the distribution over growth rates of market-valued total bank assets. The value at risk of the distribution over the random variable representing changes in market-valued total assets, X^i, for bank *i* at a probability of loss *q*, is defined implicitly as

$$probability(X^i \leq VaR_q^i) = q.$$

Note that VaR_q^i is typically a negative number, and indicates that there is a probability of *q* that the realization of random variable X^i will be VaR_q^i or less over a given time horizon. For each bank we compute quarterly values of VaR_q^i (at *q*= 1% or 50% or 99%). The larger VaR_q^i (i.e., more negative), the larger is the potential drop in asset value at a fixed probability. Holding the probability of loss constant across banks, estimated *VaRs* allow us to compare the potential for severe balance sheet contraction across banks in order to assess relative tail risk.[9] We hypothesize that relative to low *DELR* banks, high *DELR* banks will exhibit significantly higher increases in the tail risk of severe balance sheet contraction during recessions (i.e., more negative $VaR_{q=1\%}^i$).

VaR is a key measure used by regulators and risk managers of banks to capture risk exposure of a bank. However, it is now well recognized that an individual bank's VaR_q^i does not

[9] Let VaR_q^i represents the *q*% quantile of the distribution, meaning that bank *i* will lose VaR_q^i or more with a q% probability. For example, if $VaR_{1\%}$ of Bank 1 is -12% at a one-week horizon, there is a 1% chance that the bank's assets will drop by 12% or more in the upcoming week. If $VaR_{1\%}$ of Bank 2 is -15%, Bank 2 has more tail risk than Bank 1. With the same 1% probability, Bank 2 will suffer more extreme balance sheet contraction than Bank 1.

capture a bank's vulnerability to significant negative shocks to the entire banking system, nor reflect the potential contribution of the individual bank to systemic risk. To examine these two important questions, we adopt the *CoVaR* approach developed in Adrian and Brunnermeier (2011), where *CoVaR* is defined as the *VaR* of one random variable, conditional on the *VaR* of a second random variable. A particular *CoVaR* is then defined by the specific choice of the two random variables, one the variable of interest, the other the conditioning variable.

To examine how vulnerable a bank's tail risk is to significant negative shocks to the entire banking system, we first define $CoVaR_q^{i|system}$ as VaR_q^i of bank *i conditional* on the state of the banking system. Then, the difference between $CoVaR_q^{i|system}$ conditional on the banking system being in distress (e.g., system outcome $= VaR_{q=1\%}^{system}$) and $CoVaR_q^{i|system}$ conditional on the median state of the banking system (system outcome $= VaR_{q=50\%}^{system}$), $\Delta CoVaR_q^{i|system}$, captures the marginal contribution of the banking system to the tail risk of bank *i*.

To the extent that an overhang of unrecognized expected losses is forced to be recognized during an economic downturn, bank capital becomes constrained as it must cover the overhang as well as stand ready to absorb potentially significant unexpected losses driven by the downturn. This makes more *DELR* banks more vulnerable in that a systemic shock is more likely to push the bank to a tipping point where they must quickly and significantly contract their balance sheet. Therefore for a given probability the asset shrinkage will be higher for the high *DELR* banks. More formally, we hypothesize that the tail risk of banks with high *DELR* will be more vulnerable banking system than will banks with lower *DELR*. Moreover, the effect will be the most pronounced during economic downturns.

Finally, to investigate the contribution of an individual bank to systemic risk, we now define $CoVaR_q^{system|i}$ as VaR_q^{system} of the banking system *conditional* on the state of bank *i*. In this case, the difference between $CoVaR_q^{system|i}$ conditional on bank *i* being in distress (e.g., bank *i* outcome $= VaR_{q=1\%}^{i}$) and $CoVaR_q^{system|i}$ conditional on the median state of bank *i* (bank *i* outcome $= VaR_{q=50\%}^{i}$), $\Delta CoVaR_q^{system|i}$, captures the marginal contribution of a particular institution to overall systemic risk.

As stressed by Adrian and Brunnermeier (2011), the $\Delta CoVaR_q^{system|i}$ measure captures both causal contributions of an individual bank to systemic risk (e.g., a bank is so interconnected and large that it can cause negative risk spillover effects on others) and contributions driven by a common factor. In our analysis, we posit that unrecognized loss overhangs created by *DELR* are a source of common co-movement across banks. As discussed earlier, we show in this paper that co-movement in stock liquidity across banks is higher in downturns for banks with more delayed loss recognition. Now, consider the possibility that a group of banks simultaneously delay loss recognition in good times. As a result, they will all face large loss overhangs and equity financing frictions in an economic downtown. As a result, the asset contraction and loan curtailment decisions of such banks will be highly correlated potentially creating systemic effects due to herd behavior. We therefore hypothesize that banks with high *DELR* will contribute more to systemic risk, particularly in recessions, than will banks with low *DELR*.

3. Data, DELR and Liquidity – Methodology and Results

3.1 Data

Our quarterly data comes primarily from Compustat and CRSP. We require all observations to have the necessary data. Our sample starts in 1996 and goes until the end of 2009. We chose this sample because 1993 was the first full year of the use of risk bask capital as well as the FDICIA. To ensure that our results are not impacted by mergers and acquisitions, we eliminate observations that had any M&A activity over the quarter. We measure economic cycles using NBER dates to define recessionary periods ('Bust') and non-recessionary ('Boom') periods. Our final sample has a total of 9,737 bank-quarter observations, 1,997 of which are during 'Bust' periods.

3.2 Liquidity

To examine the effects of *DELR* on a bank's stock illiquidity we follow Amihud (2002) and define illiquidity of a stock as the absolute value of the daily return divided by daily volume in dollars. Our measure, *Illiquidity,* is the natural logarithm of average daily illiquidity over the quarter. To estimate co-movement in illiquidity we regress daily percent changes in illiquidity of the bank on daily percent changes in illiquidity for a value weighted portfolio of the rest of the banking sector over the quarter.[10] The bank-quarter coefficient on the changes in the portfolio illiquidity is as our proxy for illiquidity co-movement termed β_{Liquid}.

To examine the effects of *DELR* on *Illiquidity* and β_{Liquid} we estimate the following OLS pooled regressions with year fixed effects, clustering the standard errors by both time and bank to correct for possible time-series and cross-sectional correlation.

[10] For the bank specific time series estimation over the quarter, we require an individual bank to have a minimum of fifty valid trading days during the quarter.

$$Illiquidity_t\ (\beta_{Liquid,t}) = \delta_0 + \delta_1 DELR_{t-1} + \delta_2 \beta_{Mrkt,t-1} + \delta_3 Mismatch_{t-1} + \delta_4 Deposits_{t-1} + \delta_5 Trading_{t-1}$$
$$+\delta_6 Size_{t-1} + \delta_7 MTB_{t-1} + \delta_8 Capital_{t-1} + \delta_9 \sigma_{e,t-1} + \varepsilon_t. \quad (3)$$

The variables *Illiquidity,* β_{Liquid}, *DELR, Deposits, Size, Capital* and σ_e were defined previously (see the appendix for detailed descriptions of all variables). β_{Mrkt}, the bank's market beta from a traditional CAPM model estimated on daily returns over the prior quarter, is included to control for differences in systematic market risks.[11] *Mismatch*, defined as short-term liabilities net of cash all divided by total liabilities, controls for differences in financing risk of the bank. *Trading* is defined as the ratio of trading assets to total assets of the bank and is included to control for the banks own assets exposure to external market fluctuations. We also include market-to-book (*MTB*) as a control for expected growth differences. We estimate (1) for four samples: 1) pooled regression, 2) 'Boom' subsample, 3) 'Bust' subsample (i.e., time periods designated by NBER as recessions) and 4) 'Boom to Bust' subsample. The 'Boom to Bust' subsample estimates regressions using only the first quarter following the transition from a boom to bust period. We use this period to isolate how decisions made during 'Boom' periods affect outcomes in 'Bust' periods. A quarter is classified as 'Boom to Bust' if quarter t-1 is in a 'Boom' period and quarter t is in a 'Bust' period.

Table 2, panel A reports the *Illiquidity* results. In the pooled analysis we find no relation between *LowDELR* and *Illiquidity.* Moving to the subsamples however, we find that there is a negative a significant relationship between *LowDELR* and *Illiquidity* in the 'Bust' subsample. The reported coefficient for *LowDELR* is −0.0865 (p-value < 0.05). Further, the negative

[11] In unreported results we also control for contemporaneous market risk and results are robust.

coefficient in the ‘Bust’ period is significantly different from the coefficient in the ‘Boom’ period at the 0.05 level. Lastly we examine the transition period, ‘Boom to Bust’ and find a significant negative coefficient of −0.0966 (p value < 0.05) on the *LowDELR*. Overall the results in Table 2, panel A are consistent with our predictions that increasing *DELR* will increase the a bank’s stock illiquidity during recessionary periods.

Turning to the illiquidity co-movement results in panel B, we find negative coefficients on *LowDELR* in all four samples. Panel B also provides evidence that impact of *DELR* on illiquidity is more pronounced in Bust relative to Boom periods. In ‘Boom’ periods the reported coefficient is −0.0211 (p value < 0.10) suggesting that even in good times, banks with less *DELR* face somewhat lower illiquidity co-movement than banks with higher *DELR*. However, the impact on illiquidity co-movement is even more pronounced during ‘Bust’ periods (−0.1054, p value<0.05) where the difference between ‘Boom’ and ‘Bust’ periods (−0.0843) is statistically different at the 0.05 level. We also find in the ‘Boom to Bust’ sub sample, banks with lower *DELR* have lower illiquidity co-movement.

In summary, we find that the stock liquidity of higher *DELR* banks decreases significantly more in a recession relative to banks that delay less. Further, we find that as *DELR* increases, bank-level liquidity exhibits significantly higher co-movement with aggregate market-level liquidity, especially during economic downturns. These results support our conjecture that *DELR*, by reducing transparency and increasing uncertainty over bank fundamentals, impacts stock liquidity risk of the bank especially in economic downturns. These results provide insight into the Beatty and Liao (2011) finding that banks with higher *DELR* raise relatively less equity capital during recessions, by showing that the increased uncertainty over fundamentals driven by *DELR* saddles the bank with a less liquid market in which to raise capital.

4. *DELR* and VaR, ΔCoVaR$^{s|i}$, ΔCoVaR$^{i|s}$ – Methodology and Results

4.1 Tail Risk – VaR and other distributional characteristics

While there are many methods that can be used to compute VaR, we follow Adrian and Brunnermeier (2011) (AB hereafter) and use quantile regression to estimate time varying $VaRs$. Under the quantile regression, the predicted value for a given quantile (q%) can be interpreted as the expected outcome at the given quantile, making it straight forward to estimate conditional time-varying VaR.

Following AB, we first compute each bank's weekly assets growth rate (X) by taking the percentage change in the bank's market-valued total assets (MVA), where growth rates and MVA are defined as:

$$X_t = \frac{MVA_t - MVA_{t-1}}{MVA_{t-1}} = \frac{(MTB_t * BVA_t) - (MTB_{t-1} * BVA_{t-1})}{MTB_{t-1} * BVA_{t-1}}. \qquad (4)$$

MTB is the weekly market to book ratio and BVA is the weekly book value of assets. Because book value of equity and book value of assets are only reported on a quarterly basis, we follow AB and linearly interpolate the book value over the quarter on a weekly basis.

To compute conditional time-varying VaR at the q-percentile, we estimate the following quantile regression over the full time series of the bank, requiring the bank to have a minimum of 260 observations.

$$X_t^i = \alpha^i + \beta^i M_{t-1} + \varepsilon_t^i \qquad (5)$$

M in (5) is a vector of macro state variables including: 1) *VIX,* which captures the implied volatility of the S&P 500 reported by the CBOE. 2) *Liquidity Spread*, defined as the difference between the 3-month general collateral repo rate and the 3-month bill rate. *Liquidity Spread* is a proxy for short-term liquidity risk in market. We obtain the repo rates from Bloomberg and the bill rates from the Federal Bank of New York. 3) Following AB we include the change in the 3-month T-Bill rate (*Δ3T-Bill*), as it seems to predict the tails of the distribution better in the financial sector than the level. 4) Δ*Yield Curve Slope*, measured as the yield spread between the 10-year Treasury rate and the 3-month rate. 5) *ΔCredit Spread*, defined as change in the spread between BAA-rated bonds and the Treasury rate with the same 10-year maturity. 6) The weekly value weighted equity market return (Ret_{Mrkt}) and 7) the weekly real estate (SIC code 65-66) sector return in excess of the market return (Ret_{Estate}). The 3-month T-Bill, 10-year Treasury, and spread between BAA-rated bonds and Treasuries are obtained from the Federal Reserve. The market returns are from CRSP. Our conditional weekly time-varying VaR at the *q*-percentile is compute as follows:

$$VaR^{i}_{q\%,t} = \hat{\alpha}^{i} + \hat{\beta}^{i} M_{t-1} \ . \tag{6}$$

Following AB, we compute a quarterly *VaR* by summing up the weekly $VaR_{q\%}$.

Our first measure of tail risk is the 1% quantile *VaR* or $VaR_{1\%}$. More negative values of $VaR_{1\%}$ indicate the bank has a higher value at risk. Our second measure of tail risk is the distance from $VaR_{50\%}$ *to* $VaR_{1\%}$, which we term ΔVaR_{Left}. ΔVaR_{Left} captures the expected change in the asset growth rate when a bank moves from the median state to a distressed state. Larger values of ΔVaR_{Left} indicate that the bank's distribution over expected asset growth rates has a longer left tail. Our third measure of tail risk is the skewness in expected asset growth rate distribution, Skew, which is computed as:

$$Skew = \frac{\left(\left(VaR_{50\%} - VaR_{1\%}\right) - \left(VaR_{99\%} - VaR_{50\%}\right)\right)}{\left(VaR_{99\%} - VaR_{1\%}\right)} \tag{7}$$

Skew captures the relative differences in the length of the left and right tail of the asset growth distribution. Positive (negative) values of *Skew* indicate that the left tail or downside of the distribution is longer (shorter) than the right tail of the expected asset growth rate distribution. We also report ΔVaR_{Right}, the distance between $VaR_{50\%}$ and $VaR_{99\%}$. For our multivariate analysis of tail risk we estimate the following:

$$\begin{aligned} TailRiskMeaures_t = {} & \beta_1 + \beta_2 LowDELR_{t-1} + \beta_3 \beta_{Mrkt,t-1} + \beta_4 Mismatch_{t-1} + \beta_5 Deposits_{t-1} + \beta_6 Trading_{t-1} \\ & + \beta_7 Size_{t-1} + \beta_8 MTB_{t-1} + \beta_9 Capital_{t-1} + \beta_{10} \sigma_{e,t-1} + \beta_{11} Illiquid_{t-1} + \varepsilon_t \end{aligned} \tag{8}$$

Table 1 reports descriptive statistics. Univariate tests show that *LowDELR* banks have lower $VaR_{1\%}$, smaller ΔVaR_{Left} and more negative *Skew*, consistent with our prediction that higher *DELR* increases tail risk of the bank. Table 1 also shows that there is no difference in $VaR_{50\%}$, ΔVaR_{Right}, and $VaR_{99\%}$ between the *DELR* partitions. This indicates that all differences in ΔVaR_{Left} and *Skew* between the two groups are coming from differences in the left tail and not differences in the median or right tail of the distribution, providing preliminary evidence that effects of *DELR* are primarily in the tail risk or downside risk of the distribution.

In Table 3 we further examine the effects of *DELR* on tail risk in a multivariate framework. Table 3, panel A reports results for each of our tail risk measures from a pooled OLS regression. The multivariate results found in the panel A are consistent with the univariate results. Specifically, *LowDELR* banks have relatively less extreme $VaR_{1\%}$, shorter left tails. and shorter left tails relative to the right tails. We test the robustness of this result by examining the within firm variation by including firm fixed effects. The results are reported in panel B confirms the results reported in panel A.

Next we examine the effect of *LowDELR* on the tail risk during economic 'Boom' and 'Bust' states, as capital inadequacy concern are at their highest in Bust states. Table 4, panels A, B and C report results for 'Boom', 'Bust' and transitional periods ('Boom to Bust').[12] Panel A shows that *LowDELR* reduces the expected tail risk of banks as indicated by the lower $VaR_{1\%}$ (0.0351, p value < 0.05), shorter ΔVaR_{Left} (−0.0348, p value< 0.05) and a more negative *Skew* (−0.0079, p value<0.10). Importantly, the effects are much stronger in 'Bust' periods as reported in panel B. For example, $VaR_{1\%}$ has a significant increase from 0.0351 to 0.0646 (p value<0.01) when comparing 'Boom' and 'Bust' subsamples, a significant increase (pvalue< 0.01) of 84%. Panel C also shows that in a transitional period *LowDELR* reduces the expected tail risk of the bank. Taken together Table 3 and 4 suggests that *LowDELR* banks have relatively lower tail risk or downside risk in asset growth rates while maintaining the same upside of the distribution. Also *LowDELR* banks face relatively less expected tail risk during economic downturns precisely when capital crunch concerns are greatest.

4.2 Sensitivity of Tail Risk to Systemic Events – $\Delta CoVaR_q^{i|system}$

To estimate the sensitivity of the banks tail risk to systemic events we estimate the following two equations using quantile regerssions.

$$X_t^{system} = \gamma_1^s + \gamma_2^s M_{t-1} + \varepsilon_t^{system} \tag{9a}$$

[12] For a parsimonious presentation we only report the coefficients on *LowDELR* however the full results are available from the authors upon request.

$$X_t^i = \alpha^{i|system} + \delta^{i|system} X_t^{system} + \beta^{i|system} M_{t-1} + \varepsilon_t^i \tag{10a}$$

Where X^i is bank i's weekly asset growth rate, X^{system} is the value-weighted asset growth rate from the index of banks in the economy (excluding bank i), and M is the vector of macro state variable defined above. Equation (9a) is analogues to equation (2) in that we are computing a conditional time-varying expected *VaR* for a portfolio of banks'using weekly value-weighted asset growth rates for the index. Equation (10a) is an extension of (2) because we further condition the asset growth rate of a bank on a value-weighted index of other banks in the system.

We estimate (9a) and (10a) using a quantile regression with the $q\%$ = 1%. Using the predicted values from both (9a) and (10a) we specify

$$VaR_{1\%,t}^{system} = \hat{\gamma}_1^s + \hat{\gamma}_2^s M_{t-1} \tag{9b}$$

$$CoVaR_{1\%,t}^{i|system} = \hat{\alpha}^{i|system} + \hat{\delta}^{i|system} VaR_{1\%,t}^{system} + \hat{\beta}^{i|system} M_{t-1} \tag{10b}$$

$CoVaR_{1\%,t}^{i|system}$ captures the bank's conditional time t *VaR* at $q\%$ = 1% given the conditional *VaR* of the system. To capture the sensitivity of the bank's conditional $VaR_{1\%}$ to systemic financial events, we re-estimate (10b) setting $q\%$ = 50% and then compute

$$\Delta CoVaR_t^{i|system} = \hat{\alpha}^{i|system} + \hat{\delta}^{i|system}(VaR_{1\%,t}^{system} - VaR_{50\%,t}^{system}) + \hat{\beta}^{i|system} M_{t-1} \tag{11}$$

$\Delta CoVaR_q^{i|system}$, captures the marginal contribution of the banking system to the tail risk of bank *i*. Following AB we sum the weekly $\Delta CoVaR^{i|system}$ to create a quarterly measure. In interpreting $\Delta CoVaR^{i|system}$, more negative values indicate that the bank's tail risk is more effected by the system moving from a 'normal' to 'distressed' states and therefore is indicative of the bank being more vulnerable to to systemic events.

Table 1 reports the univariate results of $\Delta CoVaR^{i|\mathrm{system}}$ across *DELR* groups. The univariate results report a mean $\Delta CoVaR^{i|system}$ for *HighDELR* banks of −0.534 and a mean $\Delta CoVaR^{i|system}$ for *LowDELR* banks of −0.509 both significantly different from zero at the 0.01 level. The difference across groups of 0.025 is significantly different at the 0.01 level. This provides preliminary evidence that the tail risk for *LowDELR* banks is less sensitive to movements in systemic events.

Table 5 reports the results of the multivariate tests. Results in the first column are estimated from a pooled OLS regression and reports a positive coefficient (0.0168, p value < 0.10) on *LowDELR*, consistent with the univariate results that the expected tail risk of *LowDELR* banks is less sensitive to systemic movements. Moreover, consistent with our predictions we find that the effect is most pronounced during 'Bust' periods, where higher *DELR* makes banks more vulnerable to systemic events.

4.3 Contribution to Systemic Risk – $\Delta CoVaR_q^{system|i}$

$\Delta CoVaR_q^{system|i}$ captures how the *VaR* of the banking system is affected by distress of an individual bank. To compute $\Delta CoVaR_q^{system|i}$ we estimate the following quantile regressions equations again using weekly data with $q\% = 1\%$.

$$X_t^i = \alpha^i + \beta^i M_{t-1} + \varepsilon_t^i \tag{2}$$

$$X_t^{system} = \gamma_1^{system|i} + \gamma_2^{system|i} M_{t-1} + \gamma_3^{system|i} X_t^i + \varepsilon_t^{system} \tag{10a}$$

Similarly to $\Delta CoVaR_q^{system|i}$ we then compute the predicted values

$$VaR_{1\%,t}^i = \hat{\alpha}^i + \hat{\beta}^i M_{t-1} \tag{2'}$$

$$CoVaR_{1\%,t}^{system|i} = \hat{\gamma}_1^{system|i} + \hat{\gamma}_2^{system|i} M_{t-1} + \hat{\gamma}_3^{system|i} VaR_{1\%,t}^i \tag{10b}$$

We then obtain $\Delta CoVaR_q^{system|i}$ by

$$\Delta CoVaR_t^{system|i} = \hat{\gamma}_1^{system|i} + \hat{\gamma}_2^{system|i} M_{t-1} + \hat{\gamma}_3^{system|i} (VaR_{1\%,t}^i - VaR_{50\%,t}^i) \tag{11}$$

Finally to calculate a quarterly measure of the bank's expected contribution to systemic risk we sum the wwekly $\Delta CoVaR_q^{system|i}$ to obtain a quarterly measure. Again, more negative values of $\Delta CoVaR_q^{system|i}$ indicates that a move of bank *i* from a median state of asset growth rates to a 'distressed' state produces a larger marginal contribution to overall systemic risk.

Table 1 reports univariate results. The univariate results provide initial evidence that is consistent with *LowDELR* reduces a bank's contribution to systemic risk. The mean $\Delta CoVaR^{system|i}$ for *LowDELR* (*HighDELR*) is −0.231 (−0.249) with mean for *LowDELR* being significantly (p value, 0.01) less negative than the mean for *HighDELR*. In Table 6 we again further investigate the univariate results in a multivariate setting. All five of the specifications in Table 6 provide evidence that *DELR* effects the contribution of a bank to systemic risk. The results also provide evidence that the effects are most pronounced during ‘Bust’ periods, specifically the coefficient for *LowDELR* during ‘Boom’ periods 0.0109 (p value < 0.05), whereas there is a 143% increase to 0.0265 (pvalue < 0.01) during ‘Bust’ periods.

4.4 Robustness

In addition to controlling for firm fixed effects in the VaR and CoVaR regressions we also control for lagged values of VaR and CoVaR both with and without firm fixed effects. Table 9, panel A and B report the results from the estimation controlling for the lags of both system and bank VaR. In the tables we only report the coefficients of interest however all controls used above are included but coefficient are not reported for parsimony. The VaR and CoVaR results reported above are robust to the inclusion of these lagged variables.

5. Summary

Policy makers and regulators argue that loan loss accounting reinforces pro-cyclical effects of bank capital regulation. By delaying recognition of expected loan losses, banks’ create an overhang of unrecognized expected losses that carry forward to future periods. Further, banks that delay expected loss recognition more may face more severe external-financing frictions that impede their ability to raise equity capital in a downturn. Expected loss overhangs together with heightened equity financing frictions can exacerbate capital inadequacy concerns during economic downturns and push banks to significantly reduce assets via deleveraging and reductions in lending.

In this paper, we first investigate whether more delayed expected loss recognition (*DELR*) increases the cost of raising equity during downturns by negatively impacting the market liquidity of a bank’s stock. Consistent with *DELR* reducing transparency and increasing investor uncertainty over bank fundamentals, we document that liquidity of high *DELR* banks decreases significantly more in a recession relative to banks that delay less. Further, as *DELR* increases, bank-level liquidity exhibits significantly higher co-movement with aggregate market-level liquidity during downturns.

Using the *CoVaR* methodology of Adrian and Brunnermeier (2011) we next investigate how *DELR* influences the tail risk of individual banks, the sensitivity of a bank's tail risk to systemic financial events, and the contribution of individual banks to systemic risk. We find that higher *DELR* is associated with significantly more tail risk during recessions as reflected in a bank's value-at-risk, where this increase in tail risk is driven by increased skewness in the left tail of the distribution. Second, we show that the tail risk of individual banks with more *DELR* is more sensitive to systemic financial events. Finally, we show that banks that delay loss recognition more contribute more to systemic risk during downturns.

Appendix A

Variable	Description	Source(s)
LowDELR	An indicator variable equal to 1 (0) if the incremental R^2 from (2) over (1) is above (below) the quarter median. Where equations (1) and (2) are defined as: (1) $LLP_t = \Delta NPL_{t-1} + \Delta NPL_{t-2} + Ebllp_t + Capital_{t-1} + Size_{t-1} + \varepsilon_t$ (2) $LLP_t = \Delta NPL_{t+1} + \Delta NPL_{t+} \Delta NPL_{t-1} + \Delta NPL_{t-2} + Ebllp_t + Capital_{t-1} + Size_{t-1} + \varepsilon_t$	Compustat
Timing Partitioning Variables:		
Bust (Boom)	Using NBER dates we classify 'Bust' periods as those periods classified as recessions. All other periods are classified as 'Boom' periods.	NBER
Boom to Bust	Periods in which the quarter t-1 is classified as a 'Boom' period and quarter t is classified as a 'Bust' periods.	NBER
Dependent Variables:		
Illiquidity	The natural logarithm of the average Amihud (2002) daily illiquidity ratio over the quarter.	CRSP
β_{Liquid}	The coefficient from a regression of daily changes in the bank's Amihud (2002) measure of illiquidity over the quarter on daily changes in a value weighted index of banks' Amihud (2002) measure of illiquidity.	CRSP
$VaR_{1\%}$ ($VaR_{99\%}$) ($VaR_{50\%}$)	The quarterly estimated conditional 1% (99%) (50%) value at risk of the market value of assets. This is computed using quantile regressions using weekly market value of asset returns regressed on macro state variable and taking the predict value. We then sum the weekly-predicted values over the quarter.	Compustat, CRSP, Federal Reserve, CBOE
ΔVaR_{Left} (ΔVaR_{Right})	Is the distance between the $VaR_{50\%}$ and $VaR_{1\%}$ ($VaR_{99\%}$), where the VaR is defined above.	Compustat, CRSP, Federal Reserve, CBOE
Skew	Is defined as : $\frac{\left((VaR_{50\%} - VaR_{1\%}) - (VaR_{99\%} - VaR_{50\%})\right)}{(VaR_{99\%} - VaR_{1\%})}$ where the VaR is defined above.	Compustat, CRSP, Federal Reserve, CBOE
$\Delta CoVaR^{system\|i}$	The measure of a individual bank's contribution to systemic risk, estimated as the difference in the systems predicted 1% conditional VaR using both a banks $VaR_{1\%}$ and $VaR_{50\%}$. Where the VaR is defined above.	Compustat, CRSP, Federal Reserve, CBOE
$\Delta CoVaR^{i\|system}$	The sensitivity of a individual bank's tail risk or $VaR_{1\%}$ to changes in systemic risk.	Compustat, CRSP, Federal Reserve, CBOE

Control Variables:		
β_{Mrkt}	The firms market beta from a single factor CAPM estimated on daily return over the quarter.	CRSP
Mismatch	(Current liabilities – Cash) / Total liabilities	Compustat
Trading	The ratio of trading assets to total assets.	Compustat
MTB	The market to book ratio.	CRSP, Compustat
σ_e	The standard deviation of daily equity returns over the quarter.	CRSP
Deposits	Total deposit scaled by lagged total loans.	Compustat
LLP	Loan loss provisions scaled by lagged total loans.	Compustat
ΔNPL	Change in non-performing loans scaled by lagged total loans.	Compustat
Ebllp	Earnings before loan loss provisions and taxes scaled by lagged total loans.	Compustat
Capital	Tier 1 Capital Ratio.	Compustat
Size	Natural Logarithm of total assets.	Compustat
Macro State Variables:		
VIX	Expect volatility from options on the S&P 500 index	CBOE
Liquidity Spread	Difference between the 3-month general collateral repo and the 3-month bill rate.	Bloomberg, Federal Reserve bank of New York.
Δ3T-Bill	Change in the 3-month T-Bill rate	Federal Reserve Board's H.15
ΔYield Curve Slope	Yield spread between the 10-year Treasury rate and the 3-month rate.	Federal Reserve Board's H.15
ΔCredit Spread	Change in the spread between the BAA-rated bonds and the Treasury rate with the same 10-year maturity.	Federal Reserve Board's H.15
Ret_{Mrkt}	The weekly value weight market return.	CRSP
Ret_{Estate}	The weekly real estate (SIC 65-66) sector return in excess of the market return.	CRSP

Table 1 – Descriptive Statistics

The table below contains the descriptive statistics for the sample period 1996-2009. The *DELR* measure is the incremental explanatory power of current and future changes in non-performing loans on current loan loss provisions. $VaR^i_{1\%}$ $(VaR^i_{50\%}; VaR^i_{99\%})$ is defined as the sum of the firms weekly 1% (50%; 99%) value at risk over the quarter. ΔVaR^i_{Left} (ΔVaR^i_{Right}) is defined as the difference between $VaR^i_{1\%}$ $(VaR^i_{99\%})$ and $VaR^i_{50\%}$. The variable *Skew* is defined as $\left((VaR^i_{50\%} - VaR^i_{1\%}) - (VaR^i_{99\%} - VaR^i_{50\%})\right)/(VaR^i_{99\%} - VaR^i_{1\%})$. $\Delta CoVaR^{s|i}_t$ $(\Delta CoVaR^{i|s}_t)$ is defined as the sum of the firm's weekly $\Delta CoVaR^{s|i}_t$ $(\Delta CoVaR^{i|s}_t)$ over the quarter. β_{Mrkt} is the firms market beta from a traditional CAPM. *Mismatch* is the maturity mismatch defined as current liabilities minus cash all divided by total liabilities. *Deposits* is the banks total deposits scaled by beginning period loans. *Trading* is the ratio of trading account assets to total assets. *Size* is the natural logarithm of total assets. *MTB* is the market-to-book ratio of the firm. *Capital* is the firms tier 1 capital ratio. σ_e is the standard deviation of equity returns over the quarter market adjusted. *Illiquid* is Amihud (2002) measure of illiquidity.

Panel A. DELR – Descriptive Statistics

	Mean	Median	Q1	Q3	Std Dev
DELR	0.1669	0.1144	0.0449	0.2371	0.1621

Panel B. Descriptive Statistics by DELR Partitions

	HighDELR			***LowDELR***		
Variables	**Mean**	**Median**	**StdDev**	**Mean**	**Median**	**StdDev**
VaR^i_1	-1.522	-1.327	0.716	-1.482***	-1.131*	0.673
ΔVaR^i_{Left}	1.602	1.355	0.976	1.552***	1.337*	0.925
Skew	-0.145	-0.141	0.166	-0.156***	-0.149***	0.167
VaR^i_{50}	0.006	0.007	0.041	0.006	0.007	0.041
ΔVaR^i_{Right}	1.596	1.353	0.975	1.540	1.330	0.907
VaR^i_{99}	2.346	1.815	2.813	2.357	1.837	3.042
$\Delta CoVaR^{s\|i}$	-0.249	-0.218	0.208	-0.231***	-0.199***	0.200
$\Delta CoVaR^{i\|s}$	-0.534	-0.451	0.510	-0.509***	-0.428***	0.489
β_{MRKT}	0.655	0.565	0.617	0.646	0.555	0.609
Mismatch	0.852	0.869	0.087	0.856**	0.874**	0.084
Deposit	1.192	1.137	0.287	1.208**	1.153***	0.285
Trading	0.003	0.000	0.012	0.003	0.000	0.012
Size	7.809	7.532	1.584	7.727**	7.493	1.536
MTB	1.802	1.746	0.749	1.807	1.743	0.731
Capital	0.107	0.105	0.025	0.108**	0.106	0.026
σ_e	0.020	0.016	0.015	0.020	0.016	0.014
Illiquid	1.077	0.048	3.446	1.065**	0.048	3.323

***, **, * indicates the difference across columns is significant at the 0.01, 0.05 and 0.10 level respectively.

Table 2 – *DELR* and Liquidity Risk

OLS pooled regressions over the time period 1996-2009. The dependent variable is *Illiquidity*. *Illiquidity* is defined as log of illiquidity (Amihud, 2002). *Timely* measures the incremental explanatory power of current and future changes in non-performing loans on current loan loss provisions. *Size* is the natural logarithm of total assets. *Capital* is the firms tier 1 capital ratio. *Trading* is the ratio of trading account assets to total assets. *Deposits* is the banks total deposits scaled by beginning period loans. *MTB* is the market-to-book ratio of the firm. β_{Mrkt} is the firms market beta from a traditional CAPM. *Mismatch* is the maturity mismatch. σ_e is the idiosyncratic volatility in equity returns. Bust years are defined using the NBER dates for recessionary periods. Year-fixed effects are included in all regressions and standard errors are reported in parentheses are clustered on both firm and time dimensions.

Panel A. – Illiquidity Level

		Dependent Variable: Illiquidity			
Variables	**Prediction**		**Boom**	**Bust**	**Boom To Bust**
$LowDELR_{t-1}$	–	0.0055	0.0266	-0.0865**	-0.0966**
		(0.028)	(0.030)	(0.047) ††	(0.048)
$\beta_{Mrkt,t-1}$		-0.8154***	-0.7181***	-1.3200***	-1.3043***
		(0.075)	(0.069)	(0.120)	(0.287)
$Mismatch_{t-1}$		-0.4230	-0.4945	-0.3200	0.3424
		(0.341)	(0.369)	(0.435)	(0.631)
$Deposits_{t-1}$		-0.1928	-0.2080	-0.2718	-0.5714***
		(0.132)	(0.136)	(0.179)	(0.144)
$Trading_{t-1}$		14.6747***	14.4170***	14.8586***	17.4575***
		(3.662)	(4.010)	(3.931)	(3.926)
$Size_{t-1}$		-1.4845***	-1.5029***	-1.3964***	-1.3617***
		(0.035)	(0.038)	(0.050)	(0.068)
MTB_{t-1}		-0.4623***	-0.4788***	-0.4065***	-0.3606***
		(0.051)	(0.053)	(0.097)	(0.075)
$Capital_{t-1}$		0.3972	0.3481	0.6934	1.3201***
		(1.212)	(1.396)	(1.414)	(0.508)
$\sigma_{e,t-1}$		35.7072***	35.7750***	28.4904***	26.9882***
		(3.033)	(3.183)	(3.465)	(1.009)
Fixed Effects		Year	Year	Year	Year
N		9,737	7,657	1,997	560
R^2		0.8818	0.8846	0.8731	0.8778

***, **, * indicates significance at the 0.01, 0.05 and 0.10 respectively.
†††, ††, † indicates that the difference between boom and bust coefficients are significant at the 0.01, 0.05 and 0.10 respectively.

Panel B. - Liquidity Covariance

OLS pooled regressions over the time period 1996-2009. The dependent variable is β_{Liquid}, which is the coefficient from a regression of changes in firm illiquidity on changes in the index illiquidity estimated over the quarter. *LowDELR* measures the incremental explanatory power of current and future changes in non-performing loans on current loan loss provisions. *Size* is the natural logarithm of total assets. *Capital* is the firms tier 1 capital ratio. *Trading* is the ratio of trading account assets to total assets. *Deposits* is the banks total deposits scaled by beginning period loans. *MTB* is the market-to-book ratio of the firm. β_{Mrkt} is the firms market beta from a traditional CAPM. *Mismatch* is the maturity mismatch. σ_e is the idiosyncratic volatility in equity returns. Bust years are defined using the NBER dates for recessionary periods. Year-fixed effects are included in all regressions and standard errors are reported in parentheses are clustered on both firm and time dimensions.

		Dependent Variable: β_{Liquid}			
Variables	**Predictions**		**Boom**	**Bust**	**Boom to Bust**
LowDELR$_{t-1}$	−	-0.0402**	-0.0211*	-0.1054**	-0.2308**
		(0.020)	(0.016)	(0.053) ††	(0.140)
β_{Mrkt}		0.0133	0.0074	0.0217	-0.0517
		(0.015)	(0.019)	(0.026)	(0.047)
Mismatch$_{t-1}$		0.0030	0.0897	-0.3603	-0.7043
		(0.100)	(0.100)	(0.247)	(0.806)
Deposits$_{t-1}$		-0.0161	-0.0650***	0.1763*	0.3782***
		(0.032)	(0.023)	(0.091)	(0.141)
Trading$_{t-1}$		1.5198*	2.0560**	-0.6453	-2.3624
		(0.843)	(0.809)	(3.086)	(2.433)
Size$_{t-1}$		0.0312**	0.0220	0.0692	0.0879
		(0.015)	(0.016)	(0.043)	(0.057)
MTB$_{t-1}$		0.0071	0.0066	-0.0065	0.0811
		(0.013)	(0.018)	(0.018)	(0.077)
Capital$_{t-1}$		0.1075	0.1915	0.0187	0.6084
		(0.471)	(0.408)	(0.757)	(1.905)
$\sigma_{e,t-1}$		-0.0128	0.2754	-0.9263	-0.3101
		(1.076)	(1.071)	(2.244)	(2.407)
Fixed Effect		Year	Year	Year	Year
N		9,737	7,657	1,997	560
R^2		0.0202	0.0194	0.0228	0.0361

***, **, * indicates significance at the 0.01, 0.05 and 0.10 respectively.
†††, ††, † indicates that the difference between boom and bust coefficients are significant at the 0.01, 0.05 and 0.10 respectively.

Table 3 – *DELR* and Tail Risk

OLS pooled regressions of the time period 1996-2009, where the dependent variables are: 1) $VaR_{1\%}^{i}$ $\left(VaR_{99\%}^{i}\right)$ is defined as the sum of the firms weekly 1% (99%) value at risk over the quarter. 2) $\Delta VaR_{Left}(\Delta VaR_{Right})$ is the variable and is defined as the difference between the sum of the firm's weekly 1% (99%) value-at-risk over the quarter, $VaR_{1\%}^{i}(VaR_{99\%}^{i})$, and the sum of the firms' weekly 50% value-at-risk over the quarter, $VaR_{50\%}^{i}$. 3) The dependent variable *Skew* is defined in the following manner $\left((VaR_{50\%}^{i}-VaR_{1\%}^{i})-(VaR_{99\%}^{i}-VaR_{50\%}^{i})\right)/(VaR_{99\%}^{i}-VaR_{1\%}^{i})$. $LowDELR$ measure the incremental explanatory power of current and future changes in non-performing loans on current loan loss provisions. See Appendix A for detailed descriptions of all variables. Year-fixed effects are included in all regressions and standard errors are reported in parentheses are clustered on both firm and time dimensions.

Panel A: Distributional Properties of Asset Returns (Across Firm)

	Dependent Variable				
Variables	$VaR_{1\%,t}^{i}$	$\Delta VaR_{left,t}^{i}$	$Skew_{t}^{i}$	$\Delta VaR_{right,t}^{i}$	$VaR_{99\%,t}^{i}$
LowDELR$_{t-1}$	0.0403***	-0.0418***	-0.0093**	-0.0111	-0.0120
	(0.017)	(0.019)	(0.005)	(0.047)	(0.047)
$\beta_{Mrkt,t-1}$	-0.0558	0.0386	0.0254***	-0.1840	-0.1833
	(0.041)	(0.055)	(0.009)	(0.215)	(0.215)
Mismatch$_{t-1}$	0.1981	-0.2834	-0.0414	-0.8108	-0.7985
	(0.217)	(0.267)	(0.049)	(0.954)	(0.953)
Deposits$_{t-1}$	0.0584	-0.0510	-0.0112	-0.0331	-0.0292
	(0.089)	(0.091)	(0.016)	(0.177)	(0.177)
Trading$_{t-1}$	-0.7139	-0.5584	1.1884**	-13.8062	-13.7482
	(2.375)	(3.408)	(0.498)	(14.258)	(14.236)
Size$_{t-1}$	-0.0784*	0.1047*	-0.0144***	0.3870	0.3871
	(0.040)	(0.058)	(0.005)	(0.249)	(0.248)
MTB$_{t-1}$	0.0904**	-0.0782*	0.0109	-0.1270	-0.1222
	(0.038)	(0.043)	(0.007)	(0.127)	(0.127)
Capital$_{t-1}$	1.3473	-1.3839	-0.1997	-0.5350	-0.5556
	(0.862)	(0.862)	(0.210)	(1.866)	(1.850)
$\sigma_{e,t-1}$	-18.0783***	18.1193***	-0.6861***	31.5862***	31.0744***
	(2.213)	(2.273)	(0.230)	(3.834)	(3.792)
Illiquid$_{t-1}$	0.0011	0.0009	0.0019**	0.0013	0.0018
	(0.005)	(0.006)	(0.000)	(0.020)	(0.020)
Fixed Effects	Year	Year	Year	Year	Year
N	9,737	9,737	9,737	9,737	9,737
R^2	0.3331	0.2696	0.0266	0.0854	0.0842

***, **, * indicates significance at the 0.01, 0.05 and 0.10 respectively.

Panel B: Distributional Properties of Asset Returns (Within Firm)

Variables	**Dependent Variable**				
	$VaR^{i}_{1\%,t}$	$\Delta VaR^{i}_{left,t}$	$Skew^{i}_{t}$	$\Delta VaR^{i}_{right,t}$	$VaR^{i}_{99\%,t}$
LowDELR$_{t-1}$	0.0294***	-0.0309***	-0.0062***	-0.0072	-0.0070
	(0.007)	(0.008)	(0.001)	(0.020)	(0.020)
$\beta_{Mrkt,t-1}$	-0.0273	0.0292	0.0200***	-0.0183	-0.0181
	(0.023)	(0.023)	(0.002)	(0.037)	(0.037)
Mismatch$_{t-1}$	-0.1452	0.1441	-0.0053	0.1108	0.1137
	(0.097)	(0.099)	(0.022)	(0.259)	(0.258)
Deposits$_{t-1}$	0.0123	-0.0114	-0.0172**	0.0953	0.0913
	(0.045)	(0.047)	(0.008)	(0.068)	(0.067)
Trading$_{t-1}$	-2.0348***	2.0000***	0.6621***	1.7374	1.7968
	(0.668)	(0.675)	(0.202)	(2.236)	(2.206)
Size$_{t-1}$	-0.0685*	0.0556	0.0073	-0.0109	0.0014
	(0.037)	(0.037)	(0.007)	(0.100)	(0.100)
MTB$_{t-1}$	0.0787	-0.0818	0.0020	-0.1771	-0.1779
	(0.052)	(0.055)	(0.004)	(0.107)	(0.107)
Capital$_{t-1}$	1.5448***	-1.6759***	-0.0538	-2.2478***	-2.2117***
	(0.389)	(0.432)	(0.080)	(0.734)	(0.738)
$\sigma_{e,t-1}$	-11.9813***	11.8959***	-0.2090	17.5402***	17.8563***
	(2.564)	(2.596)	(0.135)	(3.470)	(3.506)
Illiquid$_{t-1}$	0.0007	-0.0003	0.0014**	-0.0076	-0.0080
	(0.004)	(0.004)	(0.000)	(0.006)	(0.006)
Fixed Effects	Year, Firm	Year, Firm	Year, Firm	Year, Firm	Year, Firm
N	9,737	9,737	9,737	9,737	9,737
R^2	0.7142	0.7594	0.5275	0.8664	0.8663

***, **, * indicates significance at the 0.01, 0.05 and 0.10 respectively.

Table 4 – The Impact of *DELR* on Tail Risk across Boom and Bust Periods

OLS pooled regressions of the time period 1996-2009, where the dependent variables are: 1) $VaR^i_{1\%}$ $(VaR^i_{99\%})$ is defined as the sum of the firms weekly 1% (99%) value at risk over the quarter. 2) $\Delta VaR_{Left}(\Delta VaR_{Right})$ is the variable and is defined as the difference between the sum of the firm's weekly 1% (99%) value-at-risk over the quarter, $VaR^i_{1\%}(VaR^i_{99\%})$, and the sum of the firms' weekly 50% value-at-risk over the quarter, $VaR^i_{50\%}$. 3) The dependent variable *Skew* is defined in the following manner $\left((VaR^i_{50\%} - VaR^i_{1\%}) - (VaR^i_{99\%} - VaR^i_{50\%})\right)/(VaR^i_{99\%} - VaR^i_{1\%})$.*LowDELR* measure the incremental explanatory power of current and future changes in non-performing loans on current loan loss provisions. See Appendix A for detailed descriptions of all variables. Year-fixed effects are included in all regressions and standard errors are reported in parentheses and are clustered on both firm and time dimensions.

Panel A: Distributional Properties of Asset Returns – During Boom Periods

	Dependent Variable				
Variables	$VaR^i_{1\%,t}$	$\Delta VaR^i_{left,t}$	$Skew^i_t$	$\Delta VaR^i_{right,t}$	$VaR^i_{99\%,t}$
LowDELR$_{t-1}$	0.0351**	-0.0348**	-0.0079*	-0.0029	-0.0038
	(0.018)	(0.020)	(0.005)	(0.048)	(0.048)
Controls	Included	Included	Included	Included	Included
Fixed Effects	Year	Year	Year	Year	Year
N	7,657	7,657	7,657	7,657	7,657
R^2	0.3356	0.2655	0.0261	0.0811	0.0804

Panel B: Distributional Properties of Asset Returns – During Bust Periods

	Dependent Variable				
Variables	$VaR^i_{1\%,t}$	$\Delta VaR^i_{left,t}$	$Skew^i_t$	$\Delta VaR^i_{right,t}$	$VaR^i_{99\%,t}$
LowDELR$_{t-1}$	0.0646***	-0.0732***	-0.0163**	-0.0441	-0.0451
	(0.021) †††	(0.031) †††	(0.009) ††	(0.105)	(0.106)
Controls	Included	Included	Included	Included	Included
Fixed Effects	Year	Year	Year	Year	Year
N	1,997	1,997	1,997	1,997	1,997
R^2	0.2686	0.2252	0.0485	0.0769	0.0751

Panel C: Distributional Properties of Asset Returns – Transition From Boom Period To Bust Period

	Dependent Variable				
Variables	$VaR^i_{1\%,t}$	$\Delta VaR^i_{left,t}$	$Skew^i_t$	$\Delta VaR^i_{right,t}$	$VaR^i_{99\%,t}$
LowDELR$_{t-1}$	0.0958***	-0.0972***	-0.0107**	-0.1215	-0.1222
	(0.025)	(0.026)	(0.004)	(0.083)	(0.083)
Controls	Included	Included	Included	Included	Included
Fixed Effects	Year	Year	Year	Year	Year
N	560	560	560	560	560
R^2	0.2304	0.2199	0.0507	0.0996	0.0990

***, **, * indicates significance at the 0.01, 0.05 and 0.10 respectively.
†††, ††, † indicates that the difference between boom and bust coefficients are significant at the 0.01, 0.05 and 0.10 respectively.

Table 5 – Sensitivity of Tail Risk to Systemic Events ($\Delta CoVaR_t^{i|system}$)

OLS pooled regressions of the time period 1996-2009, where $\Delta CoVaR_t^{i|system}$ is the dependent variable and is defined as the sum of the system weekly contribution to the bank's VaR over the quarter. $LowDELR$ measure the incremental explanatory power of current and future changes in non-performing loans on current loan loss provisions. See Appendix A for detailed descriptions of all variables. Year-fixed effects are included in all regressions and standard errors are reported in parentheses clustered on both firm and time dimensions.

	Dependent Variable: $\Delta CoVaR_t^{i\|system}$				
Variables			**Boom**	**Bust**	**Boom to Bust**
$LowDELR_{t-1}$	0.0168*	0.0079*	0.0053	0.0586**	0.0578**
	(0.013)	(0.004)	(0.010)	(0.033) ††	(0.023)
$\beta_{Mrkt,t-1}$	-0.0514*	0.0070	-0.0238	-0.1405*	-0.0281
	(0.026)	(0.017)	(0.018)	(0.080)	(0.062)
$Mismatch_{t-1}$	-0.1568	-0.0812	-0.1039	-0.3579	0.0053
	(0.157)	(0.054)	(0.139)	(0.251)	(0.270)
$Deposits_{t-1}$	0.1106**	0.0172	0.1132***	0.0900	0.0767
	(0.044)	(0.018)	(0.042)	(0.069)	(0.050)
$Trading_{t-1}$	-1.5555	0.2749	-2.2677**	0.1103	0.8145
	(1.170)	(0.544)	(1.094)	(1.588)	(0.878)
$Size_{t-1}$	-0.1027***	-0.0107	-0.0955***	-0.1208***	-0.1202***
	(0.012)	(0.019)	(0.012)	(0.018)	(0.013)
MTB_{t-1}	-0.0162	0.0289	-0.0314*	0.0353	-0.0116
	(0.023)	(0.038)	(0.016)	(0.065)	(0.028)
$Capital_{t-1}$	-0.0345	0.2484	-0.2101	0.1750	-0.1262
	(0.513)	(0.270)	(0.470)	(0.749)	(0.672)
$\sigma_{e,t-1}$	-5.7267***	-4.3481***	-4.4148***	-6.0570**	-0.3347
	(1.275)	(1.385)	(1.037)	(2.719)	(0.549)
$Illiquid_{t-1}$	0.0116***	0.0044	0.0102***	0.0159	0.0002
	(0.004)	(0.002)	(0.003)	(0.011)	(0.001)
Fixed Effects	Year	Year, Firm	Year	Year	Year
N	9,737	9,737	7,657	1,997	560
R^2	0.3478	0.7829	0.3999	0.2356	0.2559

***, **, * indicates significance at the 0.01, 0.05 and 0.10 respectively.
†††, ††, † indicates that the difference between boom and bust coefficients are significant at the 0.01, 0.05 and 0.10 respectively.

Table 6 – Impact of Individual Bank on Systemic Risk ($\Delta \boldsymbol{CoVaR}_t^{system|i}$)

OLS pooled regressions of the time period 1996-2009, where $\Delta CoVaR_t^{system|i}$ is the dependent variable and is defined as the sum of the firm's weekly contribution to systemic risk over the quarter. *LowDELR* measure the incremental explanatory power of current and future changes in non-performing loans on current loan loss provisions. See Appendix A for detailed descriptions of all variables. Year-fixed effects are included in all regressions and standard errors are reported in parentheses and are clustered on both firm and time dimensions.

	Dependent Variable: $\Delta CoVaR_t^{system\|i}$				
Variables			**Boom**	**Bust**	**Boom to Bust**
$LowDELR_{t-1}$	0.0137**	0.0029**	0.0109**	0.0265***	0.0159**
	(0.005)	(0.001)	(0.005)	(0.009) †††	(0.010)
$\beta_{Mrkt,t-1}$	-0.0233***	-0.0034	-0.0149*	-0.0481***	-0.0185
	(0.008)	(0.004)	(0.007)	(0.014)	(0.037)
$Mismatch_{t-1}$	-0.1106	0.0122	-0.1046	-0.1552	-0.0969
	(0.078)	(0.018)	(0.078)	(0.103)	(0.100)
$Deposits_{t-1}$	0.0242	0.0195***	0.0179	0.0475	0.0433
	(0.025)	(0.006)	(0.025)	(0.033)	(0.040)
$Trading_{t-1}$	0.0969	-0.0068	0.0687	-0.0957	-0.8817
	(0.676)	(0.156)	(0.657)	(0.803)	(0.906)
$Size_{t-1}$	-0.0125**	-0.0083	-0.0125**	-0.0105	-0.0113
	(0.006)	(0.005)	(0.006)	(0.008)	(0.010)
MTB_{t-1}	-0.0268***	0.0069	-0.0295***	-0.0199	-0.0398***
	(0.009)	(0.005)	(0.009)	(0.014)	(0.011)
$Capital_{t-1}$	-0.3378	0.0595	-0.4133	-0.1667	-0.2563
	(0.280)	(0.066)	(0.281)	(0.326)	(0.252)
$\sigma_{e,t-1}$	-1.0199**	-1.4437***	-0.8871*	-0.5282	-0.2900
	(0.403)	(0.324)	(0.461)	(0.584)	(0.480)
$Illiquid_{t-1}$	0.0025**	0.0007	0.0028**	0.0021	0.0008
	(0.001)	(0.001)	(0.001)	(0.002)	(0.003)
Fixed Effects	Year	Year, Firm	Year	Year	Year
N	9,737	9,737	7,657	1,997	560
R^2	0.1699	0.8385	0.1860	0.1251	0.1312

***, **, * indicates significance at the 0.01, 0.05 and 0.10 respectively.
†††, ††, † indicates that the difference between boom and bust coefficients are significant at the 0.01, 0.05 and 0.10 respectively.

Table 7 – Robustness

The table below contains OLS regression over the sample period 1996-2009. *LowDELR* measure the incremental explanatory power of current and future changes in non-performing loans on current loan loss provisions. $VaR^i_{1\%}$ $(VaR^i_{99\%})$ is defined as the sum of the firms weekly 1% (99%) value at risk over the quarter. $\Delta VaR_{Left}(\Delta VaR_{Right})$ is the variable and is defined as the difference between the sum of the firm's weekly 1% (99%) value-at-risk over the quarter, $VaR^i_{1\%}(VaR^i_{99\%})$, and the sum of the firms' weekly 50% value-at-risk over the quarter, $VaR^i_{50\%}$. The dependent variable *Skew* is defined in the following manner $\left((VaR^i_{50\%} - VaR^i_{1\%}) - (VaR^i_{99\%} - VaR^i_{50\%})\right)/(VaR^i_{99\%} - VaR^i_{1\%})$. $\Delta CoVaR^{s|i}_t$ $(\Delta CoVaR^{i|s}_t)$ is defined as the sum of the firm's weekly $\Delta CoVaR^{s|i}_t$ $(\Delta CoVaR^{i|s}_t)$ over the quarter. See Appendix A for detailed descriptions of all variables.

Panel A: Controlling for lagged VaR's & CoVaR's

	Dependent Variable						
Variables	$VaR^i_{1,t}$	$\Delta VaR^i_{left,t}$	$Skew^i_t$	$\Delta VaR^i_{right,t}$	$VaR^i_{99,t}$	$\Delta CoVaR^{system\|i}_t$	$\Delta CoVaR^{i\|system}_t$
LowDELR$_{t-1}$	0.0131**	-0.0166**	-0.0078*	0.0134	0.0121	0.0030**	0.0073*
	(0.005)	(0.007)	(0.005)	(0.029)	(0.029)	(0.001)	(0.004)
VaR^i_{t-1}	0.8710***	-0.8346***	-0.0433***	-1.0945***	-1.0866***	-0.0234***	-0.0243**
	(0.042)	(0.048)	(0.013)	(0.171)	(0.171)	(0.004)	(0.011)
VaR^s_{t-1}	-0.3256**	0.3289**	0.0133	0.5057**	0.5096**	-0.0391**	-0.2464**
	(0.150)	(0.141)	(0.012)	(0.216)	(0.215)	(0.016)	(0.104)
$\Delta CoVaR^{s\|i}_{t-1}$						0.9280***	
						(0.031)	
$\Delta CoVaR^{i\|s}_{t-1}$							0.9537***
							(0.078)
Controls	Included	Included	Included	Included	Included	Included	Included
Fixed Effects	Year	Year	Year	Year	Year	Year	Year
N	9,737	9,737	9,737	9,737	9,737	9,737	9,737
R^2	0.6932	0.6895	0.0429	0.4013	0.3969	0.8719	0.8012

***, **, * Indicates significance at the 0.01, 0.05 and 0.10 respectively.

Panel B: Controlling for lagged Firm Fixed Effects, VaR's & CoVaR's

Variables	**Dependent Variable**						
	$VaR^i_{1,t}$	$\Delta VaR^i_{left,t}$	$Skew^i_t$	$\Delta VaR^i_{right,t}$	$VaR^i_{99,t}$	$\Delta CoVaR^{system\|i}_t$	$\Delta CoVaR^{i\|system}_t$
$LowDELR_{t-1}$	0.0159**	-0.0187**	-0.0040**	-0.0061	-0.0068	0.0022**	0.0066*
	(0.006)	(0.008)	(0.001)	(0.015)	(0.016)	(0.001)	(0.004)
VaR^i_{t-1}	0.5728***	-0.5705***	-0.0693***	-0.5439***	-0.5339***	-0.0126**	-0.0234**
	(0.045)	(0.045)	(0.009)	(0.052)	(0.052)	(0.006)	(0.011)
VaR^s_{t-1}	-0.1833	0.1933	0.0509***	0.0929	0.0920	-0.0185	-0.1406
	(0.153)	(0.159)	(0.010)	(0.202)	(0.200)	(0.018)	(0.105)
$\Delta CoVaR^{s\|i}_{t-1}$						0.6197***	
						(0.048)	
$\Delta CoVaR^{i\|s}_{t-1}$							0.6278***
							(0.071)
Controls	Included	Included	Included	Included	Included	Included	Included
Fixed Effects	Year, Firm	Year, Firm	Year, Firm	Year, Firm	Year, Firm	Year, Firm	Year, Firm
N	9,737	9,737	9,737	9,737	9,737	9,737	9,737
R^2	0.7457	0.7318	0.5274	0.6761	0.6740	0.8962	0.8274

***, **, * Indicates significance at the 0.01, 0.05 and 0.10 respectively.

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