Delayed Expected Loss Recognition and the Risk Profile of Banks

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Abstract

Capital inadequacy concerns combined with financing frictions may pressure banks to contract their balance sheets during economic downturns. Focusing on loan loss accounting, we investigate the extent to which delayed expected loss recognition (*DELR*) impacts the drivers of balance sheet contraction by increasing both capital inadequacy concerns and financing frictions of raising new equity during downturns. *DELR* creates an overhang of unrecognized expected losses that carry forward to future periods, potentially increasing capital inadequacy concerns by compromising the ability of loan loss reserves to cover both unexpected recessionary loan losses and the overhang. We document that *DELR* is associated with the existence of loss overhangs, and that the impact of overhangs on recognized loan losses is magnified during downturns. We also document that *DELR* is associated with stock market illiquidity risks that increase financing frictions associated with raising new equity. We then investigate how *DELR* impacts three dimensions of a bank's risk profile: (1) balance sheet contraction risk of individual banks; (2) the sensitivity of contraction risk of individual banks to systemic financial events; and (3) the contribution of individual banks to the contraction risk of the banking system as a whole. We find that higher *DELR* is associated with significantly higher risk of severe balance sheet contraction during recessions. We also find *DELR* increases the sensitivity of a bank's contraction risk to distress of the banking system, and that banks with higher *DELR* contribute more to systemic risk during downturns.

1. Introduction

An important literature in economics posits that due to external financing frictions, negative shocks to the right hand side of the balance sheet (e.g., contraction in monetary policy, recession) causes banks to contract the left hand side by selling off assets and reducing lending (e.g., Kashyap and Stein (1994)). An important stream of this literature focuses specifically on the role played by bank capital in exacerbating economic downturns (e.g., Bernanke and Lown (1991), Van den Heuvel (2009)), arguing that deterioration in the quality of loan portfolios and increased loan losses during downturns necessitates increases in bank capital precisely when capital becomes more expensive or even unavailable to some institutions (i.e., a "capital crunch"). Thus, concerns about capital inadequacy combined with financing frictions may pressure banks to contract their balance sheets during economic downturns.

In this paper, we extend this literature by investigating the extent to which loan loss provisioning practices of banks impact the drivers of balance sheet contractions by increasing both capital inadequacy concerns and financing frictions of raising new equity during economic downturns. We also examine how cross-sectional differences in loan loss accounting impact three dimensions of a bank's risk profile: (1) balance sheet contraction risk of an individual bank; (2) the sensitivity of contraction risk of an individual bank to systemic financial events; and (3) the contribution of an individual bank to the contraction risk of the banking system as a whole. Our analyses complements and extends Beatty and Liao (2011) who document that banks that delay loss recognition more reduce lending more during recessions relative to banks that delay less, and that their lending decisions during recessions are more sensitive to capital levels than more timely banks.

We exploit differences in the application of loan loss accounting rules across U.S. commercial banks to estimate the extent to which individual banks delay the recognition of expected loan losses (*DELR*).[1] 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 expected loss overhangs can increase capital inadequacy concerns during economic downturns by compromising the ability of loan loss reserves to cover both unexpected recessionary loan losses and the overhang of expected losses from previous periods. *DELR* has long been recognized as a crucial aspect of loan loss accounting. Policy makers argue that *DELR* reinforces pro-cyclical effects of bank capital regulation, and should therefore be changed to allow bank managers more discretion to incorporate forward-looking judgments into loan loss provisions.[2] We document that *DELR* is associated with the existence of loss overhangs, and that the impact of overhangs on recognized loan losses is magnified during economic downturns.

Further, we explore the possibility that *DELR* increases financing frictions via a transparency channel that manifests in higher costs of raising new equity. Beatty and Liao (2011) show that banks with more *DELR* exhibit smaller increases in book equity during economic downturns than banks with less *DELR*. 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. Bushman and Williams (2012) 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,

[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.

[2] Pro-cyclicality refers to the exaggeration of cyclical tendencies in aggregate economic activity that amplifies business cycle fluctuations. Important policy proposals include Dugan (2009), Financial Stability Forum (2009), and U.S. Treasury (2009).

consistent with *DELR* reducing transparency and inhibiting monitoring by outsiders. We find that banks with higher *DELR* exhibit greater increases in stock market liquidity risk during downturns relative to more timely banks.

A key premise of our analysis is that *DELR* generates expected loss overhangs that increase capital inadequacy concerns during economic downturns. To establish the credibility of this premise, we develop an expectation model to isolate surprise increases in non-performing loans (NPL), and examine how high and low *DELR* banks differentially exploit available accounting discretion in determining *when* to recognize in provisions increased expected losses associated with shocks to NPL. We predict that in good times, loan loss provisions of untimely, high *DELR* banks will be less sensitive to contemporaneous unexpected NPL (delayed recognition) and more sensitive to lagged unexpected NPL (recognizing overhang from past surprises), relative to provisions of low *DELR* banks. Further, we predict that for high *DELR* banks, the sensitivity of provisions to lagged unexpected NPL will be higher in downturns relative to good times as economic stress pressures banks to more quickly recognize built up overhang rather than smoothing recognition over future periods. We provide evidence consistent with these predictions.

Next, we investigate whether *DELR* increases financing frictions during downturns. Illiquidity levels and liquidity risk impose costs on investors that are reflected in equity pricing (e.g., Amihud, et al. (2005) and Acharya and Petersen (2005)). Brunnermeier and Pedersen (2009) suggest that 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. Focusing on crisis periods, Lang and Maffett (2011) document that firms with greater transparency experience 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 bank-level liquidity of high *DELR* banks exhibits relatively higher co-movement with aggregate market-level liquidity, especially during economic downturns. Further the stock liquidity of high *DELR* banks decreases significantly more in a recession relative to banks that delay less.

Having established a connection between *DELR* and both capital inadequacy concerns and financing frictions, we next directly investigate how cross-sectional differences in *DELR* impacts the risk of balance sheet contraction. First, we investigate associations between *DELR* and balance sheet contraction risk at the individual bank level. Following Adrian and Brunnermeier (2011; hereafter AB) we focus our risk analysis on a bank's value-at-risk (*VaR*) with respect to the distribution over changes in market-valued total bank assets. Estimated *VaRs* allow us to compare the potential for severe balance sheet contraction across banks.[3] We find that higher *DELR* is associated with significantly higher risk of severe balance sheet contraction during recessions.

Our final two analyses investigate how *DELR* influences the risk of individual banks *in relation* to the banking system as a whole. The first analysis examines how *DELR* impacts the sensitivity of an individual bank's asset contraction risk to distress of the banking system, while

[3] Let VaR_q^i represents the *q*% quantile of the distribution, meaning that bank *i's* balance sheet will contract by 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 contract 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.

the second examines how *DELR* impacts the contribution of individual banks to the asset contraction risk of the entire system. To capture sensitivity of an individual bank to distress of the banking system, we use the exposure *CoVaR* construct from AB, defined as the *VaR* of an individual bank *conditional* on the state of the banking system.[4] Exposure Δ*CoVaR* is the difference between exposure *CoVaR* conditional on the banking system being in distress and *CoVaR* conditional on the system at its median state. Exposure Δ*CoVaR* captures the marginal contribution of the banking system to the contraction risk of a given bank. We find that during recessions, high *DELR* banks become relatively more sensitive to the distress of the system.

To investigate contributions of individual banks to systemic risk we use AB's *CoVaR* measure, which just reverses the order of conditioning relative to exposure *CoVaR*. *CoVaR* is the *VaR* of the banking system conditional on the state of an individual bank, and Δ*CoVaR* captures the marginal contribution of a specific bank to systemic risk. We show that banks with more *DELR* contribute more to systemic risk. Why? A group of banks that all significantly delay loss recognition in good times will all face loss overhang and financing frictions in a downturn. As a result, the asset contraction decisions of such banks will be highly correlated, creating systemic effects due to herd behavior (Brunnermeier et al. (2009)). The notion that *DELR* creates a herd of banks with similar vulnerabilities is consistent with our earlier result that co-movement in stock liquidity across banks is higher in downturns for banks with higher *DELR*.

We provide evidence that *DELR* is associated with expected loss overhang that can increase capital inadequacy concerns during downturns, with illiquidity risk that increases equity financing frictions, and with three dimensions of a bank's risk of severe balance sheet

[4] The exposure *CoVaR* construct is conceptually related to the systemic expected shortfall (*SES*) measure from Acharya, Pedersen, Philippon and Richardson (2010). *SES* is defined as the expected amount that a bank is undercapitalized in a future systemic event in which the overall financial system is undercapitalized. See the discussion in Brunnermeier et al. (2012).

contraction, including a bank's contribution to systemic risk. However, we recognize that association is not the same as causality. Is it plausible that *DELR* directly influences banks' risk of balance sheet contraction by impacting capital inadequacy concerns via loss overhangs and equity financing frictions via liquidity? In this regard, an extensive academic literature and stream of public policy proposals argue that loan loss accounting directly exacerbates pro-cyclical forces in the economy, and that accounting should therefore be changed to allow bank managers more discretion to incorporate *forward-looking* judgments into loan loss provisions.[5] While we believe that our *DELR* theory is plausible, we also take extensive efforts to mitigate correlated omitted variables concern by including a large set of important control variables.

First, differences in *DELR* may be a consequence of differences in the composition of banks' balance sheets. To rule this out, we control for detailed differences in the composition of banks' securities portfolios, loan portfolios, and liability structures. We also control for differences in revenue mix by including the proportion of non-interest income in revenue (Brunnermier et al. (2012)). Another possibility is that variation in *DELR* results from variation in regulator-imposed loss recognition on weaker versus stronger banks (e.g., Skinner (2008)). Here we include proxies for regulator's CAMELS ratings[6]: **C** (tier 1 capital), **A** (non-performing loans/total loans), **M&E** (ROA), **L** (cash/deposits), **S** ([short-term assets-short-term liabilities]/total assets). Banks may also be less likely to end up in the low *DELR* category when uncertainty is high. We thus control for a range of fundamental risk measures including equity

[5] The Financial Stability Forum (2009) identifies loan loss provisioning as one of three policy priorities, along with capital, and valuation and leverage, for addressing pro-cyclicality. See also Dugan (2009) and U.S. Treasury (2009) for related policy proposals. Discussions of alternative loan loss accounting models include Borio et al. (2001), Fernández de Lis et al. (2001), Laeven and Majnoni (2003), and Benston and Wall (2005)).

[6] CAMELS: **C**apital adequacy, **A**sset quality, **M**anagement, Earnings, **L**iquidity, **S**ensitivity to market risk. CAMELS is a United States supervisory rating of a bank's overall condition. This rating is based on financial statements of the bank and on-site examination by regulators. These ratings are not released to the public, and so we create proxies from publicly available data following Duchin and Sosyura (2012).

volatility, market beta, prior illiquidity, and lagged values of *VaR,* exposure *CoVar*, and *CoVAR*. Finally, we include individual bank fixed-effects to control for unobservable bank characteristics that do not vary over time. Results are robust to inclusion of these control variables.

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 develops the connection between *DELR* and loss overhang. Section 2.4 discusses the potential for *DELR* to impact equity financing frictions via the influence of bank transparency. Finally, section 2.5 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 income when a loss is probable based on past events and conditions existing at the financial statement date. However, the incurred loss model does allow scope for discretion in determining loss provisions. The report by the Financial Stability Forum (2009) actually

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 (see also Dugan (2009) on this point). We exploit variation across banks in the application of the incurred loss model to isolate cross-sectional differences in *DELR*.

Viewing bank capital and loan provisioning jointly from a risk management perspective, the banking literature generally posits that loan loss provisioning should provide a cushion against *expected* losses, while bank capital is designed to buffer *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 tier 1 capital and loan loss provisions. Loan provisions are current period expenses that reduce common equity via retained earnings. If banks delay recognition of expected losses, a current expense is not recorded for some portion of the expected losses, and so common equity is not reduced by the delayed amount. This implies that tier 1 capital will mingle unrecognized expected losses together with economic capital available to cover unexpected losses. Because unrecognized expected losses will be recognized on average in the future, an expected loss overhang looms over future profits and tier 1 capital.

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.[7] Higher incremental R^2 implies less *DELR*. The idea is that *more timely*

[7] 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

banks recognize loss provisions concurrently with or in advance of loans becoming nonperforming, where less timely banks delay loss recognition related to contemporaneous non-performing loans and do not anticipate loans become nonperforming.[8]

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.

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

$$LLP_t = \beta_0 + \beta_1 \Delta NPL_{t-1} + \beta_2 \Delta NPL_{t-2} + \beta_3 \Delta NPL_t + \beta_4 \Delta NPL_{t+1} + \beta_5 Capital_{t-1} + \beta_6 EBLLP_t + \beta_7 Size_{t-1} + \varepsilon_t \quad (2)$$

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, 2012). We take the difference in the adjusted R^2 of (2) - (1), and rank banks based on their incremental R^2 in every quarter. For each bank-quarter observation, the variable *LowDELR* is set

correlated with current and lagged industrial production. That is, current economic conditions can be used to predict future and concurrent nonperforming loans.

[8] 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.

equal to 1 if the bank is above the median on this measure, and 0 otherwise. Descriptive statistics for *DELR* are included in table 1, which is discussed further in section 3.1.

2.2 DELR and Balance Sheet Responses to Economic Downturns

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[9]; 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 may remain suppressed for several periods in response to shocks to bank profits such as recognition of unexpected loan losses.[10]

Beatty and Liao (2011; BL hereafter) 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. BL find that loan growth is lower during 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. BL 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. Further, BL find that, consistent with financing frictions, banks with less

[9] Van den Heuvel (2009) focuses on the relation between balance sheet contraction and capital requirements. Another stream of literature focuses on how shocks to banks' reservable liabilities impact bank lending and securities holdings. The idea is that information asymmetries deriving from the opaqueness of banks creates financing frictions that impede banks' ability to offset drops in reservable liabilities with nonreservable liabilities, leading to balance sheet contraction. See Kashyap and Stein (1995) and Stein (1998), among others.

[10] See also Adrian and Shin (2010; 2011) for a different perspective on the role of bank capital in driving balance sheet contraction.

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 BL in several fundamental ways. First, while BL appeal to expected loss overhang as the driver of their results, we explicitly document that *DELR* is associated with the existence of loss overhang, and that the impact of overhangs on recognized loan losses is magnified during downturns. A novel contribution of our paper is that we establish precise channels through which *DELR* influence equity financing frictions, showing that the bank-level liquidity of high *DELR* banks exhibits relatively higher co-movement with aggregate market-level liquidity, and that the liquidity of high *DELR* banks decreases significantly more in a recession relative to banks that delay less.

Finally, while BL establish the important result that *DELR* impacts recessionary bank lending, we extend the analysis to consider the impact of *DELR* on the distribution over the severity of balance sheet contraction. Notably, we find that banks with more *DELR* contribute more to systemic risk and offer a novel theory of why this is the case. Specifically, when a large group of banks all significantly delay loss recognition, they will simultaneously face large loss overhangs and financing frictions in a downturn. As a result, the asset contraction decisions of these banks will be highly correlated, creating systemic effects due to herd behavior (Brunnermeier et al. (2009)).

2.3 DELR and Loss Overhangs

We are aware of no unified theory of why banks differ on the extent of *DELR*. While we provide evidence consistent with *DELR* being a consequence of opportunistic earnings management by bank executives, it could also result from differences in sophistication of credit risk modeling (Bhat, Ryan and Vyas (2012)), or something else. We econometrically deal with

omitted variables concerns by taking extensive efforts to rule out alternative explanations by including a large set of important control variables. Another key to the credibility of our study is the plausibility of the theory that expected loss overhang is a direct driver of bank risk.

With respect to plausibility, we first note that an extensive body of both academic literature and public policy proposals argues forcefully that current loan loss accounting rules exacerbate pro-cyclical forces in the economy, and the accounting should therefore be changed to allow bank managers more discretion to incorporate forward-looking judgments into loan loss provisions. That is, forward-looking provisioning is basically proposed to counter *DELR* in provisioning practices by fully incorporating all expected loan losses into current provisions (see footnote 5).

Further, we examine how provisioning decisions of high and low *DELR* banks differentially respond to contemporaneous and lagged unexpected increases in non-performing loans (see section 3.2 for tests of these predictions).This analysis establishes the credibility of our premise that *DELR* itself directly exacerbates capital inadequacy concerns during downturns. Our focus on *surprise* increases in non-performing loans provides evidence consistent with some bank managers choosing to opportunistically delay recognition of losses. While this analysis does not provide sufficient evidence to definitively conclude that *DELR* via loss overhang is a causal force impacting the risk of balance sheet contraction, it does establish a necessary condition for this to be the case by showing that *DELR* is actually associated with the existence of loss overhangs, and that the impact of overhangs on recognized loan losses is magnified during downturns.

2.4 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 liquidity level, an important factor is the extent to which the illiquidity of a stock is correlated with the state of the economy or with illiquidity of other stocks. Acharya and Petersen (2005) 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.

Brunnermeier and Pedersen (2009) argue that the liquidity of firms with more uncertainty about intrinsic value tends to be less predictable and more sensitive to economy-wide shocks, and 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. It is well established that stock liquidity significantly decreases during economic recessions (Naes et al. (2011)). Focusing on crisis periods, 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 bank transparency plays a fundamental role in promoting market discipline by outside investors as a lever of prudential bank regulation.[11] Bushman and Williams (2012) 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,

[11] 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).

consistent with less timely provisioning reducing bank transparency and inhibiting monitoring by outsiders.

We conjecture that banks with more *DELR* are less transparent to outside investors than banks delaying less, with lower transparency inducing greater uncertainty about the banks' intrinsic value, particularly during economic downturns. Further, we hypothesize that: (1) 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) the co-movement between the liquidity of high *DELR* banks and the liquidity of banking system will increase more during recessions than co-movement of low *DELR* banks. We empirically investigate these hypotheses in section 3.3 of the paper.

2.5 DELR and Three Dimensions of a Bank's Risk of Severe Balance Sheet Contraction

Beatty and Liao (2011) show that banks with high *DELR* on *average* reduce lending during recessions more than do low *DELR* banks. But in addition to the average lending behavior of banks, it is also important to consider the distribution over changes in banks' entire balance sheet, and in particular the potential for extreme negative balance sheet contraction.

In this spirit, we first examine the impact of *DELR* on the asset contraction risk of individual banks. We follow Adrian and Brunnermeier (2011) and estimate value at risk (*VaR*) with respect to the distribution over percentage changes in market-valued total bank assets. Let X^i represent the percentage change in a bank i's total assets, and q represent a given probability threshold. VaR_q^i is then defined implicitly as

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

Note that VaR_q^i is typically a negative number, and indicates that with probability q the realization of random variable X^i will be VaR_q^i or less over a given time horizon. Using quantile regression, we compute VaR_q^i quarterly for each bank. The more negative is VaR_q^i, the larger is the potential balance sheet contraction at a fixed probability. Holding the probability of loss constant across banks, estimated *VaRs* allow us to assess relative tail risk across banks (see footnote 3). We hypothesize that relative to low *DELR* banks, high *DELR* banks will exhibit significantly higher increases in risk of severe balance sheet contraction during recessions (i.e., more negative $VaR_{q=1\%}^i$).

We also investigate how *DELR* influences the risk of individual banks *in relation* to the banking system. We examine both how *DELR* impacts the sensitivity of an individual bank's asset contraction risk to distress of the banking system, and how *DELR* impacts the contribution of individual banks to asset contraction risk of the entire system. We adopt the *CoVaR* approach developed in Adrian and Brunnermeier (2011; AB), where *CoVaR* is defined as the *VaR* of one random variable, conditional on the *VaR* of a second random variable. Here the two random variables are the asset contraction of an individual bank and contraction for the banking system as a whole. A particular *CoVaR* is then defined by the specific ordering of the two asset contraction variables, where one serves as the variable of interest and the other as the conditioning variable.

First, we examine how *DELR* impacts the vulnerability of an individual bank's asset contraction risk to distress of the banking system. We hypothesize that banks with high *DELR* will be more vulnerable to banking system distress than will banks with lower *DELR*. Moreover, the effect will be the most pronounced during economic downturns. To the extent that loss

overhangs are forced to be recognized during a downturn, bank capital becomes constrained as it must cover the overhang as well as unexpected losses driven by the downturn. Thus, high *DELR* banks are more vulnerable in that a systemic shock is more likely to push these banks to a tipping point where they must quickly and significantly contract their balance sheet. To examine this hypothesis we use the exposure *CoVaR* construct from AB, defined as the *VaR* of an individual bank *conditional* on the state of the banking system. Specifically, we 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*. We then empirically examine how $\Delta CoVaR_q^{i|system}$ varies across high and low *DELR* banks in recessions relative to boom periods.

Finally, we hypothesize that high *DELR* banks contribute relatively more 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 AB, the $\Delta CoVaR_q^{system|i}$ measure captures both causal contributions of an individual bank to systemic risk (e.g., distress at large, interconnected banks directly cause negative spillover effects on others) and contributions driven by herd

reactions to a common factor. We posit that unrecognized loss overhangs created by *DELR* are a source of common co-movement across banks. When a large group of banks delay loss recognition, they will simultaneously face large loss overhangs and heightened financing frictions in a downturn. As a result, the asset contraction decisions of these banks will be highly correlated, creating systemic effects due to herd behavior (Brunnermeier et al. (2009)).

3. *DELR*, Loss Overhang and Equity Financing Frictions – Data, Methodology and Results

3.1 Data and Descriptive Statistics

Our quarterly data comes primarily from Compustat, Bank Call reports and CRSP. We require all observations to have the necessary data for the respectively analysis. Similar to Beatty and Liao (2011), our sample starts in 1993 and goes until the end of 2009.[12] To ensure that mergers and acquisitions do not impact our results, 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. There are two recessionary periods in our sample, March 2001 – November 2002, and December 2007 – June 2009.

In section 2.1, we developed our bank-quarter measure of *DELR*, estimated from equations (1) and (2), as 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 (Beatty and Liao (2011) and Nicholas et al. (2009)). Table 1 panel A provides descriptive statistics on estimated *DELR.* First, we illustrate the *DELR* estimation by reporting equations (1) and (2) estimated for the pooled sample of all bank-quarter observations.

[12] Bank Compustat does not report quarterly non-performing levels prior to 1993. Due to the data demands for estimating *DELR* using 12 quarter rolling windows, our cross-sectional analysis spans the period 1996 – 2009.

We see that the difference in R^2 between (2) and (1) for this pooled sample equals 0.103 (0.230 - 0.127). Also noteworthy in the pooled regression is that the coefficients on all *ΔNPL* variables are positive and significant, and that the coefficient on ΔNPL_t is much larger than the coefficient on ΔNPL_{t+1}. When we estimate *DELR* for individual bank quarters, we see that *DELR* has mean (median) value of 0.167 (0.114) and exhibits significant cross-sectional variation with a standard deviation of 0.162, value at the 25th percentile of 0.045 and 0.237 at the 75th percentile.

Table 1 panel B splits the sample into high and low *DELR* groups and examines how the fundamental control variables differ across groups.[13] Our fundamental control variable set consists of the following (all variables are described in detail in Appendix A). *Trading,* defined as the ratio of trading securities to total assets, controls for differences in the composition of banks' securities portfolios. Securities classified as trading are accounted for using fair value accounting, with gains or losses from value changes included in net income. We control for the composition of the loan portfolio with *Commercial*, *Consumer* and *Real Estate*, which represent commercial, consumer and real estate loans, respectively, all scaled by total loans. *Mismatch*, defined as short-term liabilities net of cash, all divided by total liabilities, controls for differences in financing roll over risk. To complete our balance sheet controls we include *Deposits*, defined as total deposits scaled by lagged total loans, and *Capital,* the tier 1 capital ratio. To control for differences in revenue mix, we include *Revenue Mix,* the ratio of non-interest revenue to total revenue. We include two risk measures, σ_e, the standard deviation of daily equity returns over the quarter, and β_{Mrkt}, the bank's market beta from a traditional CAPM model estimated on

[13] As discussed earlier, in our reported analyses we utilize an indicator variable, *LowDELR,* which is set equal to 1 if the *DELR* of the bank is above the median *DELR* (i.e., timely recognition of expected losses), and zero otherwise.

daily returns over the prior quarter. Finally, we control for *Size* with the log of total assets, and market-to-book (*MTB*) as a control for expected growth differences.[14]

Table 1 panel B reveals that many of the control variables differ significantly across the low and high *DELR* groups, justifying their inclusion in the analysis.

3.2 Is DELR Associated with Expected Loss Overhang?

We posit that an important channel through which *DELR* influences the risk of balance sheet contraction is by expected loss overhangs exacerbating capital adequacy concerns. A necessary condition for this to be the case is that *DELR* is actually associated with loss overhangs, and that the impact of overhangs on recognized loan losses is magnified during downturns. We investigate this issue by comparing how loss provisioning decisions of high and low *DELR* banks respond to contemporaneous and lagged *unexpected* increases in non-performing loans.

To isolate surprise increases in non-performing loans, we build on the expectation model of Wahlen (1994). Wahlen (1994) models ΔNPL_t (change in non-performing loans over quarter t scaled by total loans at t-1) as a linear function of ΔNPL_{t-1} and the composition of the loan portfolio, $Commercial_{t-1}$, $Real\ Estate_{t-1}$, $Consumer_{t-1}$ and $OtherLoans_{t-1}$. We extend Wahlen by including the percentage change in U.S. unemployment over the month at the beginning of each quarter, *%ΔUnEm* (e.g., Gambria (2001)). Table 2, Panel A illustrates the model using a pooled sample of all bank quarter observation. Columns I, II and III show that *%ΔUnEm* adds significant, incremental explanatory power over and above the Wahlen model (column II).

[14] To further address the issue of correlated omitted, we later include a range of additional control variables including proxies for CAMELS ratings and additional risk measures. See section 4.4 for robustness analyses.

Column IV represents the full model that we use to model changes non-performing loans in which we interact all the Wahlen variables with *%ΔUnEm*.

We estimate the model in column IV in quarterly time series for each bank, and use the residual from the model in a given period to represent unexpected NPL. We then set *UNPL* equal to 1 if the residual is positive and 0 otherwise. This proxy captures surprises *increases* in ΔNPL for the bank. We then estimate the following panel regression using OLS:

$$\begin{aligned} LLP_t = {} & \delta_0 + \delta_1 LowDELR_{t-1}*UNPL_t + \delta_2 LowDELR_{t-1}*UNPL_{t-1} + \delta_3 LowDELR_{t-1} + \\ & \delta_4 UNPL_t + \delta_5 UNPL_{t-1} + \delta_6 Trading_{t-1} + \delta_7 Commercial_{t-1} + \delta_8 Consumer_{t-1} + \\ & \delta_9 Real\ Estate_{t-1} + \delta_{10} Mismatch_{t-1} + \delta_{11} Deposits_{t-1} + \delta_{12} Revenue\ Mix_{t-1} + \\ & \delta_{13} Capital_{t-1} + \delta_{14}\beta_{Mrkt,t-1} + \delta_{15}\sigma_{e,t-1} + \delta_{16} Size_{t-1} + \delta_{17} MTB_{t-1} + FE + \varepsilon_t. \end{aligned} \quad (3)$$

We predict that in *boom periods*, provisions of high *DELR* banks will be relatively less sensitive to contemporaneous unexpected NPL due to delayed recognition ($\delta_1 > 0$), and relatively more sensitive to lagged unexpected NPL as they recognize overhang from past surprises ($\delta_2 < 0$). Further, we predict that for high *DELR* banks, the sensitivity of provisions to lagged unexpected NPL will be higher in *bust periods* relative to booms as economic stress pressures banks to more quickly recognize built up overhang rather than smoothing recognition over future periods. That is, $\delta_2^{Bust} < \delta_2^{Boom}$.

In table 2, Panel B we report the results of estimating equation (3) separately in boom and bust periods (NBER recessions). In boom periods, we see that $\delta_1 > 0$ and $\delta_2 < 0$, consistent with high *DELR* banks delaying expected loss recognition associated with surprise increases NPL. Further, comparing boom with busts, we see that $\delta_2^{Bust} < \delta_2^{Boom}$ (-0.0004 versus -0.0002), consistent with high *DELR* banks being pressured to quickly recognize built up overhang during

busts. It is this recognition of built up overhang during busts that we argue exacerbates capital inadequacy concerns.

3.2 DELR, Liquidity and Liquidity Co-Movement

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.[15] 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 calendar quarter and bank to correct for possible time-series and cross-sectional correlation.

$$\begin{aligned}\beta_{Liquid,t}\,(Illiquidity_t) = {} & \delta_0 + \delta_1 LowDELR_{t-1} + \delta_2 Trading_{t-1} + \delta_3 Commercial_{t-1} + \\ & \delta_4\, Consumer_{t-1} + \delta_5 Real\ Estate_{\,t-1} + \delta_6 Mismatch_{t-1} + \delta_7 Deposits_{t-1} + \\ & \delta_8 Revenue\ Mix_{t-1} + \delta_9 Capital_{t-1} + \delta_{10}\beta_{Mrkt,t-1} + \delta_{11}\sigma_{e,t-1} + \delta_{12} Size_{t-1} + \\ & \delta_{13} MTB_{t-1} + FE + \varepsilon_t.\end{aligned} \tag{4}$$

We estimate (4) for three samples: 1) pooled, 2) 'Boom' subsample, and 3) 'Bust' subsample (i.e., time periods designated by NBER as recessions).

Table 3, panel A reports the illiquidity co-movement results. In the pooled analysis, we find a negative relation between *LowDELR* and β_{Liquid} (-0.04, significant at the 5% level). Moving to the boom and bust subsamples, we find a negative and significant relation between

[15] 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.

LowDELR and β_{Liquid} in the 'Bust' subsample, but not the 'Boom" sample. The reported coefficient for *LowDELR* in busts is −0.14 (p-value < 0.01). Further, the negative coefficient in the 'Bust' period is significantly different from the coefficient in the 'Boom' period at the 0.01 level. Overall, we see that liquidity co-movement is significantly higher for high *DELR* banks relative to low *DELR* banks, and this effect is concentrated in recessionary periods.

Table 3, panel B reports the *Illiquidity* results. In the pooled analysis, contrary to our prediction, we find a positive relation between *LowDELR* and *Illiquidity* (-0.03, significant at the 10% level). However, when we turn to the subsamples, there is a negative and significant relationship between *LowDELR* and *Illiquidity* in the 'Bust' subsample, but not the 'Boom" sample. The reported coefficient for *LowDELR* in busts is −0.044 (p-value < 0.010). Further, the negative coefficient in the 'Bust' period is significantly different from the coefficient in the 'Boom' period at the 0.05 level, consistent with illiquidity being relatively higher for high *DELR* banks during recessions.

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.

4. *DELR* and 3 Dimensions of Balance Sheet Contraction Risk

In this section, we examine how differences in *DELR* impact three dimensions of a bank's risk profile. Section 4.1 examines balance sheet contraction risk of an individual bank, (*VaR*), section 4.2 the sensitivity of contraction risk of an individual bank to systemic financial

events (exposure $CoVaR$), and section 4.3 examines the contribution of an individual bank to the contraction risk of the banking system as a whole ($CoVaR$).

4.1 Unconditional Contraction Risk of Individual Banks – VaR

We use quantile regression to estimate time varying $VaRs$. With 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 time-varying VaR.

Following AB, we first compute each bank's weekly percentage change in market-valued total assets (MVA), defined as:

$$X_t = \frac{MVA_t - MVA_{t-1}}{MVA_{t-1}} = \frac{(MTB_t * BVA_t) - (MTB_{t-1} * BVA_{t-1})}{MTB_{t-1} * BVA_{t-1}}. \quad (5)$$

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 time-varying VaR at the q-percentile, we estimate the following quantile regression over the bank's full weekly time series, requiring a minimum of 260 observations.

$$X_t^i = \alpha^i + \beta^i M_{t-1} + \varepsilon_t^i . \quad (6)$$

M in (6) 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) The change in the 3-month T-Bill rate (*Δ3T-*

Bill), as it predicts 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 computed as follows, where the coefficients are the estimates from equation (6):

$$VaR^{i}_{q\%,t} = \hat{\alpha}^{i} + \hat{\beta}^{i} M_{t-1} \ . \tag{7}$$

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

Our first measure of balance sheet contraction risk is the 1% quantile *VaR*. More negative values of $VaR_{1\%}$ indicate the bank has a higher value at risk. Our second measure is the distance from $VaR_{50\%}$ *to* $VaR_{1\%}$, which we term ΔVaR_{Left}. ΔVaR_{Left} captures the expected change in asset change rates when a bank moves from the median state to a distressed state. Larger values of ΔVaR_{Left} indicate that the bank's distribution 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:

$$Skew = \frac{\left(\left(VaR_{50\%} - VaR_{1\%}\right) - \left(VaR_{99\%} - VaR_{50\%}\right)\right)}{\left(VaR_{99\%} - VaR_{1\%}\right)} \tag{8}$$

Skew captures the relative differences in the length of the left and right tail of the 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:

$$ContractionRiskMeasure_t = \delta_0 + \delta_1 LowDELR_{t-1} + \delta_2 Trading_{t-1} + \delta_3 Commercial_{t-1} + \delta_4 Consumer_{t-1} + \delta_5 Real\ Estate_{t-1} + \delta_6 Mismatch_{t-1} + \delta_7 Deposits_{t-1} + \delta_8 Revenue\ Mix_{t-1} + \delta_9 Capital_{t-1} + \delta_{10}\beta_{Mrkt,t-1} + \delta_{11}\sigma_{e,t-1} + \delta_{12} Size_{t-1} + \delta_{13} MTB_{t-1} + FE + \varepsilon_t. \quad (9)$$

Table 1, panel B reports descriptive statistics. Univariate tests show that *LowDELR* banks have less severe $VaR_{1\%}$, smaller ΔVaR_{Left} and more negative *Skew*, consistent with higher *DELR* increasing asset contraction 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 downside risk of the distribution.

In Table 4 we the effects of *DELR* on *VaR* in a multivariate framework. Table 4, 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 in Table 1. 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 5 reports

results for 'Boom' and 'Bust' and periods.[16] Panel A shows that *LowDELR* reduces expected tail risk as indicated by a less negative $VaR_{1\%}$ (0.0426, p value < 0.10 and *shorter* ΔVaR_{Left} (−0.044, 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 0.0426 to 0.0602 (p value<0.01) when comparing 'Boom' and 'Bust' subsamples, a significant increase (pvalue< 0.01) of 84%. Taken together Table 4 and 5 show that *LowDELR* banks have relatively less downside risk of asset contraction, while maintaining the same upside of the distribution. Also *LowDELR* banks face relatively less tail risk during economic downturns when capital crunch concerns are greatest.

4.2 Sensitivity of Contraction Risk to Systemic Events – Exposure *CoVar* ($CoVaR_q^{i|system}$)

We use the exposure *CoVaR* construct from AB, defined as the *VaR* of an individual bank *conditional* on the state of the banking system. Specifically, we define $CoVaR_q^{i|system}$ as VaR_q^i of bank *i conditional* on the state of the banking system. Specifically, we estimate the following two equations using quantile regressions.

$$X_t^{system} = \gamma_1^s + \gamma_2^s M_{t-1} + \varepsilon_t^{system} \tag{10}$$

$$X_t^i = \alpha^{i|system} + \delta^{i|system} X_t^{system} + \beta^{i|system} M_{t-1} + \varepsilon_t^i \ . \tag{11}$$

Where X^i is bank *i*'s weekly percent asset change rate, X^{system} is the value-weighted asset change rate from the index of banks in the economy (excluding bank *i*), and *M* is the vector of macro state variable defined above. Equation (10) is analogous to equation (6), except now in we are

[16] For parsimony, we only report the coefficients on *LowDELR*.

computing a conditional time-varying *VaR* for a portfolio of banks. Equation (11) extends equation (7) by *conditioning* the asset change rate of bank i on a value-weighted index of other banks in the system (X^{system}).

We estimate (10) and (11), where (10) is estimated at both *q*% = 1% and 50%, and (11) at *q%* = 1%. Using the predicted values from (10) and (11) we specify

$$VaR_{q,t}^{system} = \hat{\gamma}_1^s + \hat{\gamma}_2^s M_{t-1} \tag{12}$$

$$CoVaR_{1\%,t}^{i|system} = \hat{\alpha}^{i|system} + \hat{\delta}^{i|system} VaR_{1\% or 50\%,t}^{system} + \hat{\beta}^{i|system} M_{t-1} \quad . \tag{13}$$

$CoVaR_{1\%,t}^{i|system}$, equation (13), is the bank's time t *VaR* at *q*% = 1%, *conditional* on the *VaR* of the system being at either the 1% or 50% quantile. To capture the sensitivity of the bank's conditional $VaR_{1\%}$ to systemic financial events, we compute

$$\begin{aligned} \Delta CoVaR_t^{i|system} &= CoVaR_t^{i|system=VaR_{1\%}} - CoVaR_t^{i|system=VaR_{50\%}} \\ &= \hat{\alpha}^{i|system} + \hat{\delta}^{i|system}(VaR_{1\%,t}^{system} - VaR_{50\%,t}^{system}) + \hat{\beta}^{i|system} M_{t-1} \end{aligned} \tag{14}$$

$\Delta CoVaR^{i|system}$ captures the marginal contribution of distress in the banking system to the risk of bank *i*. Following AB we sum the weekly $\Delta CoVaR^{i|system}$ to create a quarterly measure. More negative values indicate that the bank's asset contraction risk is more affected by the system moving from '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 $\Delta CoVaR^{i|\text{system}}$ across *DELR* groups. The univariate results report a mean $\Delta CoVaR^{i|system}$ for *HighDELR* banks of −0.541 and a mean $\Delta CoVaR^{i|system}$ for *LowDELR* banks of −0.518 both significantly different from zero at the 0.01 level, where this difference across groups is significantly 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 6 reports the results of multivariate tests. Results in the first two column are estimated from pooled OLS regression, where the second regression also includes bank fixed effects. Both columns report positive coefficients on *LowDELR* (0.0136 and 0.008, respectively, p values < 0.10), consistent with the univariate results that the tail risk of *LowDELR* banks is less sensitive to systemic movements. Splitting the sample into boom and bust periods, we find that the positive coefficient on *LowDELR* is isolated to recessionary periods. That is, higher *DELR* banks are more vulnerable to systemic events than are low *DELR* banks in economic downturns.

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

To investigate contributions of individual banks to systemic risk we use AB's *CoVaR* measure, which just reverses the order of conditioning relative to exposure *CoVaR*. *CoVaR* is the *VaR* of the banking system conditional on the state of an individual bank, and $\Delta CoVaR$ captures the marginal contribution of a specific bank to systemic risk. To compute $\Delta CoVaR_q^{system|i}$ we estimate the following quantile regressions equations again using weekly data with $q\% = 1\%$.

$$X_t^i = \alpha^i + \beta^i M_{t-1} + \varepsilon_t^i \tag{15}$$

$$X_t^{system} = \gamma_1^{system|i} + \gamma_2^{system|i} M_{t-1} + \gamma_3^{system|i} X_t^i + \varepsilon_t^{system} \tag{16}$$

We then compute the predicted values

$$VaR^{i}_{q\%,t} = \hat{\alpha}^{i} + \hat{\beta}^{i} M_{t-1} \tag{17}$$

$$CoVaR^{system|i}_{1\%,t} = \hat{\gamma}^{system|i}_{1} + \hat{\gamma}^{system|i}_{2} M_{t-1} + \hat{\gamma}^{system|i}_{3} VaR^{i}_{1\% or 50\%,t} \ , \tag{18}$$

and further

$$\begin{aligned} \Delta CoVaR^{system|i}_{t} &= CoVaR^{system|i=VaR_{1\%}}_{t} - CoVaR^{system|i-VaR_{50\%}}_{t} \\ &= \hat{\gamma}^{system|i}_{1} + \hat{\gamma}^{system|i}_{2} M_{t-1} + \hat{\gamma}^{system|i}_{3} (VaR^{i}_{1\%,t} - VaR^{i}_{50\%,t}) \end{aligned} \ . \tag{19}$$

We again sum weekly $\Delta CoVaR^{system|i}_{q}$ to obtain a quarterly measure, where *more negative* values of $\Delta CoVaR^{system|i}_{q}$ 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, panel B provides initial evidence consistent with *LowDELR* banks contributing less to systemic risk. The mean $\Delta CoVaR^{system|i}$ for *LowDELR* (*HighDELR*) is −0.236 (−0.252), where this difference significant at the 1% level. Table 7 reports the results of the multivariate tests. Results in the first two columns are estimated from pooled OLS regression, where the second regression also includes bank fixed effects. Both columns report positive coefficients on *LowDELR* (0.0119 and 0.0026, respectively, p values < 0.10). Splitting the sample into boom and bust periods, we find that the positive coefficient on *LowDELR* is isolated to recessionary periods. That is, higher *DELR* banks contribute more to balance sheet contraction risk of the banking system during downturns than do low *DELR* banks.

4.4 Robustness

An alternative explanation for our reported results is that the variation in *DELR* arises from variation in regulator-imposed loss recognition (e.g., for weaker vs. stronger banks). To control for such differences, we include the CAMELS ratios for the banks. Such ratios are used by regulators to evaluate the banks current position. As these ratings are not released to the public, we follow Duchin and Sosyura (2012) and include proxies for regulator's CAMELS rating[17]: **C** (tier 1 capital), **A** (non-performing loans/total loans), **M&E** (ROA)[18], **L** (cash/deposits), **S** ([short-term assets-short-term liabilities]/total assets). We re-run the *VaR* and *CoVaR* analyses after including of these variables. Results are reported in Table 8. For brevity we only report the coefficients on *DELR* and CAMELS proxies. All previously reported results on the three dimensions of contraction risk are robust to inclusion of CAMELS.

Next, we control for lagged values of *VaR* and *CoVaR*. We do this in an effort to control for the possibility that banks may be less likely to end up in the low *DELR* category when uncertainty is high. Table 9 reports the results. While we only report the coefficients of interest, all controls, including CAMELS and our other risk measures (equity volatility, market beta and prior illiquidity), are included. The *VaR* and *CoVaR* results reported above are robust to inclusion of these lagged variables.

Third, we examine whether the results are a general recessionary effect or specific to only one of the two recessionary periods in our sample. To examine this, we re-run our analyses

[17] CAMELS: **C**apital adequacy, **A**sset quality, **M**anagement, **E**arnings, **L**iquidity, **S**ensitivity to market risk.
[18] Our use of ROA to proxy for management quality follows Beatty and Liao (2011) and DeYoung (1998). Using confidential information on CAMELS ratings, DeYoung (1998) finds regulators' management quality assessments correlate with multiple bank characteristics, among which ROA is most highly correlated with management quality with a simple correlation of 45%.

including only one of the recessionary periods at a time, while excluding the other. We perform this for both periods and find our results hold in both recessionary periods.

Finally, we confront the possibility that the risk measures of high and low *DELR* banks trend differently before the two recessions in our sample. If so, we may inappropriately attribute higher differences in risk between high and low *DELR* banks during recessions to capital inadequacy concerns and financing frictions, when such differences really reflects trends in the data that began during boom times.[19] First, we note that this concern is somewhat mitigated by the fact that in all but one of our analysis during boom periods, there is no difference between high and low *DELR* firms. Given this fact, differential trends in the data for high and low *DELR* firms would have to be small or focused tightly around transitional period in the economy.

To explore this further, consider first the $VaR_{1\%}$ metric, the only risk metric exhibiting a marginal difference between high and low *DELR* banks during boom periods. We focus on the final boom quarter just before the economy turns to bust. For each bank, we trace $VaR_{1\%}$ back in time 3 quarters and forward one quarter into the bust periods. Thus for each bank, we have the last four quarterly risk measures leading up to the bust and the first quarter of the bust. In Figure 1 we plot in event time the average $VaR_{1\%}$ metrics separately for high and low *DELR* banks. Figure 1 shows that prior to the bust, $VaR_{1\%}$ metrics for high and low *DELR* banks are not statistically different from each other for periods, t-3, t-2, t-1, and t. However, in t+1, the first quarter in the bust period, the mean $VaR_{1\%}$ metrics for high and low *DELR* banks are statistically different from each other at the 0.05 level (similar results are found at t+2). We perform similar tests on both *CoVaR* risk measures, finding no evidence of trends prior to downturns.

[19] Our empirical design is not a pure difference in difference design, although we do compare differences between high and low *DELR* banks in boom periods versus bust periods. The issue is that we do not have a constant treatment group as banks are not exclusively either high or low *DELR*. We estimate *DELR* quarterly for each bank using a 12 quarter rolling window, and some banks shift categories over the sample period.

5. Summary and Conclusions

An important issue for policy makers concerns potentially severe pro-cyclical effects driven by the response of banks' balance sheets to recessionary shocks to bank capital. Such shocks to bank capital increase concerns about capital inadequacy that, when combined with equity financing frictions, may pressure banks to significantly contract their balance sheets during economic downturns (e.g., Bernanke and Lown (1991), Van den Heuvel (2009), Beatty and Liao (2011)). Further, an extensive body of academic literature and public policy proposals argues forcefully that current loan loss accounting rules exacerbate pro-cyclical forces in the economy, and that accounting should be changed to allow bank managers more discretion to incorporate forward-looking judgments into loan loss provisions.[20] While specific details vary across this literature, a common refrain is that pro-cyclicality is impacted by the fact that current loan loss accounting prevents loss provisions fully incorporating all expected losses. The idea behind the forward-lookingness construct is to require banks to fully incorporate all *expected* loan losses in current loan loss provisions.

Focusing on loan loss accounting, this paper first investigates the extent to which delayed expected loss recognition (*DELR*) impacts the drivers of balance sheet contraction by increasing both capital inadequacy concerns and financing frictions of raising new equity during downturns. We exploit differences in the application of loan loss accounting rules across U.S. commercial banks to estimate the extent to which individual banks delay the recognition of expected loan losses (*DELR*). We posit that *DELR* creates an overhang of unrecognized expected losses that carry forward to future periods, potentially increasing capital inadequacy concerns by

[20] Important policy proposals include Dugan (2009), Financial Stability Forum (2009), and U.S. Treasury (2009). Discussions of alternative loan loss accounting models include Borio et al. (2001), Fernández de Lis et al. (2001), Laeven and Majnoni (2003), and Benston and Wall (2005)).

compromising the ability of loan loss reserves to cover both unexpected recessionary loan losses and the overhang. To establish the credibility of this premise, we develop an expectation model to isolate surprise increases in non-performing loans (NPL), and examine how high and low *DELR* banks differentially exploit available accounting discretion in determining *when* to recognize in provisions increased expected losses associated with shocks to NPL. We document that *DELR* is associated with the existence of loss overhangs, and that the impact of overhangs on recognized loan losses is magnified during downturns.

We also hypothesize that banks with more *DELR* are less transparent than banks delaying less, where less transparency induces greater uncertainty about intrinsic value, particularly during economic downturns. We document that *DELR* is associated with stock market illiquidity risks that increase financing frictions associated with raising new equity. Specifically, the bank-level liquidity of high *DELR* banks exhibits relatively higher co-movement with aggregate market-level liquidity during economic downturns, and the liquidity levels of high *DELR* banks decreases more in recessions relative to banks that delay less.

Having established a connection between *DELR* and both capital inadequacy concerns and financing frictions, we next investigate how cross-sectional differences in *DELR* impacts the risk of balance sheet contraction. We investigate three dimensions of a bank's risk profile: (1) balance sheet contraction risk of individual banks; (2) the sensitivity of contraction risk of individual banks to systemic financial events; and (3) the contribution of individual banks to the contraction risk of the banking system as a whole. We find that higher *DELR* is associated with significantly higher risk of severe balance sheet contraction during recessions. We also find *DELR* increases the sensitivity of a bank's contraction risk to distress of the banking system, and that banks with higher *DELR* contribute more to systemic risk during downturns.

We provide evidence that *DELR* is associated with expected loss overhang that increases capital inadequacy concerns, with illiquidity risk that increases equity financing frictions, and with three dimensions of banks' risk of severe balance sheet contraction. This evidence is consistent with proposals to dampen pro-cyclicality by changing accounting rules to require banks to more fully incorporate *expected* loan losses in current provisions. However, it is crucial to note that our results are derived in an environment where all banks are subject to the FASB's/IASB's incurred loss model for loan provisioning. Thus, there is substantial variation across banks in the way the incurred loss is applied. Some banks are timely in their recognition, while other banks delay recognition of expected losses. If, as we conjecture, *DELR* results from opportunistic earnings management, then the real problem is with bank governance, not the accounting rules. Without addressing the governance problem, changing the rules for loan loss accounting may simply impose costs on banks and financial statement users, without really changing the pro-cyclical effects of loan loss accounting.

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:		
Commercial	Total commercial loans outstanding divided by total loans outstanding.	Call Reports
Consumer	Total consumer loans outstanding divided by total loans outstanding.	Call Reports
Real Estate	Total real estates loans outstanding divided by total loans outstanding.	Call Reports
Revenue Mix	Non-interest Revenue divided by total Revenue.	Compustata
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 pooled regression for the sample period 1996-2009. The dependent variable is loan loss provisions scaled by beginning period loans. *ΔNPL* is the quarter change in non-performing loans scaled by beginning total loans. *Capital* is the tier 1 capital ratio. *EBLLP* is earnings before provisions and taxes scaled by beginning period total loans. *Size* is the natural log of beginning period total assets. Standards errors are reported in the parentheses and are clustered by bank and quarter. *DELR* measures the incremental explanatory power of current and future changes in non-performing loans on current loan loss provisions.

Panel A. DELR – Pooled Regression and Descriptive Statistics

Dependent Variable: LLP_t

Model	**ΔNPL_{t+1}**	**ΔNPL_t**	**ΔNPL_{t-1}**	**ΔNPL_{t-1}**	**$Capital_{t-2}$**	**$EBLLP_t$**	**$Size_{t-1}$**
(1)			0.0754**	0.0686**	0.0010	-0.0681***	0.0003***
			(0.030)	(0.028)	(0.002)	(0.025)	(0.000)
N	11,008						
R^2	0.1268						
(2)	0.0660***	0.1679***	0.0702***	0.0492***	-0.0001	-0.0254	0.0002***
	(0.012)	(0.022)	(0.016)	(0.016)	(0.002)	(0.016)	(0.000)
N	11,008						
R^2	0.2303						

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

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

Table 1 – Descriptive Statistics (continued)

The table below contains the descriptive statistics for the sample period 1996-2009. *DELR* is the incremental explanatory power of current and future changes in non-performing loans on current loan loss provisions. *LowDELR* contains banks with *DELR* measures above the median *DELR*, and *HighDELR* reflects banks with below median measures. $VaR^i_{1\%}$ ($VaR^i_{50\%}$; $VaR^i_{99\%}$) 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. *Trading* is the ratio of trading account assets to total assets. *Commercial* is total commercial loans scaled by total loans outstanding. *Consumer* is total consumer loans outstanding scaled by total loans outstanding. *Real Estate* is total real estate loans outstanding scaled by total loans. *Mismatch* is the maturity mismatch. *Deposits* is the banks total deposits scaled by beginning period loans. *Revenue Mix* is defined as the ratio of non-interest revenue to total revenue. *Capital* is the firms tier 1 capital ratio. β_{Mrkt} is the firms market beta from a traditional CAPM. $\sigma_e$is the idiosyncratic volatility in equity returns. *Size* is the natural logarithm of total assets. *MTB* is the market-to-book ratio of the firm. *Illiquid* is Amihud (2002) measure of illiquidity.

Panel B. Descriptive Statistics by DELR Partitions

	HighDELR			***LowDELR***		
Variables	**Mean**	**Median**	**StdDev**	**Mean**	**Median**	**StdDev**
VaR^i_1	-1.506	-1.324	0.684	-1.477***	-1.311*	0.653
ΔVaR^i_{Left}	1.584	1.349	0.949	1.517***	1.332**	0.799
Skew	-0.143	-0.139	0.166	-0.154***	-0.148***	0.165
VaR^i_{50}	0.006	0.007	0.041	0.006	0.007	0.041
ΔVaR^i_{Right}	2.292	1.789	2.639	2.208	1.817	2.077
VaR^i_{99}	2.298	1.805	.,631	2.213	1.831	2.070
$\Delta CoVaR^{s\|i}$	-0.252	-0.220	0.213	-0.236***	-0.202***	0.204
$\Delta CoVaR^{i\|s}$	-0.541	-0.457	0.516	-0.518***	-0.434***	0.501
Trading	0.003	0.001	0.012	0.002**	0.000**	0.012
Commercial	0.147	0.131	0.135	0.146	0.128	0.130
Consumer	0.016	0.000	0.048	0.015	0.000	0.045
Real Estate	0.548	0.664	0.329	0.559*	0.669	0.323
Mismatch	0.850	0.867	0.088	0.854**	0.872**	0.084
Deposit	1.190	1.136	0.288	1.206***	1.150***	0.287
Revenue Mix	0.837	0.852	0.098	0.839*	0.856**	0.097
Capital	0.107	0.104	0.025	0.108**	0.105	0.027
β_{MRKT}	0.662	0.573	0.618	0.652	0.558	0.611
σ_e	0.020	0.016	0.015	0.020	0.015*	0.014
Size	7.817	7.553	1.560	7.720***	7.500*	1.512
MTB	1.795	1.734	0.754	1.798	1.732	0.733
Illiquid	1.063	0.044	3.427	1.007*	0.048	3.156

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

Table 2 – *DELR* and Expected Loss Overhang

Pooled OLS regressions over the time period 1996-2009. Following Wahlen (1994) the dependent variable *ΔNPL* is defined as the change in non-performing loans over the quarter scaled by total loans outstanding at the beginning of the quarter. *%ΔUnEm* is the percentage change in unemployment over the month at the beginning of each quarter. *Commercial* is total commercial loans scaled by total loans outstanding. *Real Estate* is total real estate loans outstanding scaled by total loans. *Consumer* is total consumer loans outstanding scaled by total loans outstanding. *OtherLoans* is the total loans outstanding not classified as *Commercial, Real Estate, or Consumer* scaled by total loans outstanding. Standard errors are reported in parentheses and are clustered by both bank and calendar quarter.

Panel A. Estimating Unexpected Non-Performing Loans

	Dependent Variable: ΔNPL_t			
Variables	I	II	III	IV
*%ΔUnEm*Commercial*$_{t-1}$				-0.0319**
				(0.0133)
*%ΔUnEm*Real Estate*$_{t-1}$				0.0110**
				(0.0050)
*%ΔUnEm*Consumer*$_{t-1}$				0.0572
				(0.0491)
*%ΔUnEm*OtherLoans*$_{t-1}$				-0.0350*
				(0.0182)
%ΔUnEm ΔNPL*$_{t-1}$				0.3866
				(0.6842)
%ΔUnEm	0.0268***		0.0243***	0.0224***
	(0.0081)		(0.0071)	(0.0070)
Commercial$_{t-1}$		-0.0013***	-0.0010**	-0.0008*
		(0.0004)	(0.0004)	(0.0004)
Real Estate$_{t-1}$		0.0003*	0.0003*	0.0002*
		(0.0002)	(0.0002)	(0.0001)
Consumer$_{t-1}$		0.0091***	0.0070***	0.0057**
		(0.0025)	(0.0022)	(0.0027)
OtherLoans$_{t-1}$		-0.0029***	-0.0027***	-0.0021***
		(0.0007)	(0.0006)	(0.0007)
ΔNPL$_{t-1}$		0.0515**	0.0437**	0.0303
		(0.0248)	(0.0203)	(0.0239)
N	11,452	11,452	11,452	11,452
Adj R^2	0.040	0.027	0.059	0.062

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

Table 2 – *DELR* and Expected Loss Overhang

OLS pooled regressions over the time period 1996-2009. The dependent variable *LLP* is defined as loan loss provisions scaled by beginning total loans. *UNPL* is an indicator variable set equal to 1 if unexpected non-performing loans estimated from firm-specific time series regressions is positive, and set to zero otherwise. *LowDELR* (i.e., more timely banks) is an indicator variable set equal to 1 if a bank's *DELR* is above the median *DELR*, and zero otherwise. See Appendix A for detailed descriptions of all variables. Year-fixed effects are included in all regressions; standard errors are reported in parentheses and are clustered by both bank and calendar quarter.

Panel B. DELR and Expected Loss Overhang

		Dependent Variable: LLP_t	
Variables	Prediction	Boom	Bust
$LowDELR*UNPL_t$	+ (Boom)	0.0002**	-0.0002
		(0.0001)	(0.0002) ††
$LowDELR*UNPL_{t-1}$	− (Boom)	-0.0002**	-0.0004***
	− (Bust)	(0.0001)	(0.0001) ††
LowDELR		-0.0000	0.0000
		(0.0000)	(0.0001)
$UNPL_t$		0.0003***	0.0008***
		(0.0001)	(0.0002)
$UNPL_{t-1}$		0.0005***	0.0006***
		(0.0001)	(0.0001)
$Ebllp_t$		0.0014	-0.0045
		(0.0024)	(0.0035)
$Trading_{t-1}$		0.0074	0.0157**
		(0.0055)	(0.0076)
$Commercial_{t-1}$		0.0019***	0.0004
		(0.0005)	(0.0004)
$Consumer_{t-1}$		0.0022	0.0010
		(0.0021)	(0.0007)
$Real\ Estate_{t-1}$		0.0006***	0.0007**
		(0.0002)	(0.0003)
$Mismatch_{t-1}$		0.0000	0.0008
		(0.0004)	(0.0006)
$Deposits_{t-1}$		-0.0001	-0.0001
		(0.0002)	(0.0003)
$Revenue\ Mix_{t-1}$		-0.0006	-0.0004
		(0.0005)	(0.0010)
$Capital_{t-1}$		-0.0037***	-0.0061***
		(0.0014)	(0.0018)
β_{Mrkt}		0.0001	0.0004***
		(0.0001)	(0.0001)
$\sigma_{e,t-1}$		0.0314***	0.0306***
		(0.0079)	(0.0069)
$Size_{t-1}$		0.0001***	0.0002**
		(0.0000)	(0.0001)
MTB_{t-1}		-0.0003**	-0.0003***
		(0.0001)	(0.0001)
$Illiquid_{t-1}$		-0.0000*	-0.0000*
		(0.0000)	(0.0000)
Fixed Effects		Year	Year
N		6,952	1,862
Adj R^2		0.335	0.290

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

†††, ††, † indicates that the difference between boom and bust coefficient are significant at the 0.01, 0.05 and 0.10 level respectively.

Table 3 – *DELR* and Financing Frictions

OLS pooled regressions over the time period 1996-2009. The dependent variable is β_{Liquid}, defined as the coefficient from a regression of changes in firm illiquidity on changes in bank sector illiquidity estimated over the quarter. *LowDELR* (i.e., more timely banks) is an indicator variable set equal to 1 if a bank's *DELR* is above the median *DELR*, and zero otherwise. *Trading* is the ratio of trading account assets to total assets. *Commercial* is total commercial loans scaled by total loans outstanding. *Consumer* is total consumer loans outstanding scaled by total loans outstanding. *Real Estate* is total real estate loans outstanding scaled by total loans. *Mismatch* is the maturity mismatch. *Deposits* is the banks total deposits scaled by beginning period loans. *Revenue Mix* is defined as the ratio of non-interest revenue to total revenue. *Capital* is the firms tier 1 capital ratio. β_{Mrkt} is the firms market beta from a traditional CAPM. σ_e is the idiosyncratic volatility in equity returns. *Size* is the natural logarithm of total assets. *MTB* is the market-to-book ratio of the firm. 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 and are clustered by both bank and calendar quarter.

Panel A. - Liquidity Covariance

		Dependent Variable: β_{Liquid}		
Variables	**Predictions**	**Pooled**	**Boom**	**Bust**
LowDELR$_{t-1}$	–	-0.0396**	-0.0129	-0.1401***
		(0.02)	(0.01)	(0.05) †††
Trading$_{t-1}$		0.7069	1.5830**	-3.1565
		(0.75)	(0.77)	(3.05)
Commercial$_{t-1}$		0.0328	-0.1199*	0.4863*
		(0.10)	(0.06)	(0.27)
Consumer$_{t-1}$		-0.6620***	-0.2515	-1.4341***
		(0.20)	(0.20)	(0.26)
Real Estate $_{t-1}$		0.0824	0.0773*	0.0727
		(0.06)	(0.04)	(0.20)
Mismatch$_{t-1}$		-0.1250	0.0239	-0.6906
		(0.13)	(0.09)	(0.44)
Deposits$_{t-1}$		0.0264	-0.0136	0.2034***
		(0.03)	(0.04)	(0.06)
Revenue Mix$_{t-1}$		-0.0794**	0.0342	-0.7597**
		(0.03)	(0.09)	(0.34)
Capital$_{t-1}$		-0.1350	-0.0213	0.0903
		(0.61)	(0.52)	(1.18)
β_{Mrkt}		0.0072	0.0024	0.0011
		(0.01)	(0.01)	(0.02)
$\sigma_{e,t-1}$		0.2247	-0.0991	-0.1524
		(0.99)	(1.17)	(2.07)
Size$_{t-1}$		0.0258*	0.0208	0.0577
		(0.01)	(0.01)	(0.03)
MTB$_{t-1}$		0.0013	0.0058	-0.0544
		(0.01)	(0.01)	(0.05)
Fixed Effect		Year	Year	Year
N		7,883	6,168	1,715
Adj R^2		0.0172	0.0193	0.0306

*****, **, *** 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. – Illiquidity Level

OLS pooled regressions over the time period 1996-2009. The dependent variable is *Illiquidity*. *Illiquidity* is defined as log of illiquidity (Amihud, 2002). *LowDELR* (i.e., more timely banks) is an indicator variable set equal to 1 if a bank's *DELR* is above the median *DELR*, and zero otherwise. *Trading* is the ratio of trading account assets to total assets. *Commercial* is total commercial loans scaled by total loans outstanding. *Consumer* is total consumer loans outstanding scaled by total loans outstanding. *Real Estate* is total real estate loans outstanding scaled by total loans. *Mismatch* is the maturity mismatch. *Deposits* is the banks total deposits scaled by beginning period loans. *Revenue Mix* is defined as the ratio of non-interest revenue to total revenue. *Capital* is the firms tier 1 capital ratio. β_{Mrkt} is the firms market beta from a traditional CAPM. σ_e is the idiosyncratic volatility in equity returns. *Size* is the natural logarithm of total assets. *MTB* is the market-to-book ratio of the firm. 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 and are clustered by both bank and calendar quarter.

		Dependent Variable: Illiquidity		
Variables	**Prediction**	**Pooled**	**Boom**	**Bust**
$LowDELR_{t-1}$	−	0.0292*	0.0400	-0.0441*
		(0.03)	(0.03)	(0.04) ††
$Trading_{t-1}$		15.2192***	14.8563***	13.3424***
		(4.55)	(5.12)	(3.79)
$Commercial_{t-1}$		-0.2897	-0.3462	-0.1588
		(0.35)	(0.37)	(0.38)
$Consumer_{t-1}$		-0.8732	-0.9135	-1.5465**
		(0.64)	(0.85)	(0.78)
$Real\ Estate_{t-1}$		0.2406*	0.2268*	0.3837**
		(0.12)	(0.13)	(0.16)
$Mismatch_{t-1}$		-0.6189*	-0.7825**	-0.2906
		(0.35)	(0.38)	(0.48)
$Deposits_{t-1}$		-0.1446	-0.1464	-0.2465
		(0.14)	(0.15)	(0.17)
$Revenue\ Mix_{t-1}$		-0.3404	-0.3650	-0.8091
		(0.42)	(0.48)	(0.56)
$Capital_{t-1}$		0.0849	0.4558	-0.8779
		(1.29)	(1.43)	(1.56)
β_{Mrkt}		-0.8124***	-0.7162***	-1.2763***
		(0.07)	(0.07)	(0.11)
$\sigma_{e,t-1}$		35.1775***	36.8154***	26.8536***
		(2.80)	(3.32)	(2.78)
$Size_{t-1}$		-1.5144***	-1.5270***	-1.4549***
		(0.03)	(0.04)	(0.06)
MTB_{t-1}		-0.4650***	-0.4806***	-0.4632***
		(0.05)	(0.05)	(0.09)
Fixed Effects		Year	Year	Year
N		9,232	6,936	1,932
Adj R^2		0.8766	0.8787	0.8704

***, **, * 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 4 – *DELR* and Tail Risk of Individual Banks' Balance Sheet Contraction

OLS pooled regressions of the time period 1996-2009. Dependent variables are: 1) $VaR^i_{1\%}$ ($VaR^i_{99\%}$), defined as the sum of the firms weekly 1% (99%) value at risk over the quarter. 2) $\Delta VaR_{Left}(\Delta VaR_{Right})$, 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) *Skew,* defined as $\left((VaR^i_{50\%} - VaR^i_{1\%}) - (VaR^i_{99\%} - VaR^i_{50\%})\right)/(VaR^i_{99\%} - VaR^i_{1\%})$. *LowDELR* (i.e., more timely banks) is an indicator variable set equal to 1 if a bank's *DELR* is above the median *DELR*, and zero otherwise. 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 by both bank and calendar quarter.

Panel A:	Dependent Variables					
Variables	$VaR^i_{1\%,t}$	$\Delta VaR^i_{left,t}$	$VaR^i_{50\%}$	$\Delta VaR^i_{right,t}$	$VaR^i_{99\%,t}$	$Skew^i_t$
LowDELR$_{t-1}$	0.0459***	-0.0469**	-0.0011	-0.0806	-0.0817	-0.0090**
	(0.021)	(0.021)	(0.001)	(0.079)	(0.079)	(0.005)
Trading$_{t-1}$	-0.4331	0.4964	0.0633	-9.7873	-9.7240	1.1077*
	(3.099)	(3.108)	(0.120)	(11.693)	(11.670)	(0.633)
Commercial$_{t-1}$	-0.3364*	0.3342*	-0.0021	0.5244	0.5222	0.0034
	(0.185)	(0.187)	(0.012)	(0.359)	(0.359)	(0.043)
Consumer$_{t-1}$	0.0891	-0.0305	0.0587	0.8621	0.9207	0.0114
	(0.599)	(0.593)	(0.054)	(1.645)	(1.642)	(0.075)
Real Estate $_{t-1}$	-0.0361	0.0364	0.0003	0.2883*	0.2886*	-0.0656***
	(0.067)	(0.067)	(0.005)	(0.160)	(0.160)	(0.017)
Mismatch$_{t-1}$	0.2808	-0.2815	-0.0007	-0.7030	-0.7036	-0.0028
	(0.232)	(0.230)	(0.013)	(0.701)	(0.700)	(0.049)
Deposits$_{t-1}$	0.0686	-0.0616	0.0070	-0.0125	-0.0055	-0.0223
	(0.084)	(0.083)	(0.005)	(0.163)	(0.163)	(0.017)
Revenue Mix$_{t-1}$	-0.2835	0.2837	0.0002	0.7125	0.7127	-0.1284**
	(0.233)	(0.231)	(0.014)	(0.687)	(0.688)	(0.060)
Capital$_{t-1}$	1.1342	-1.1669	-0.0327	-1.0339	-1.0666	0.0171
	(0.866)	(0.854)	(0.050)	(1.841)	(1.830)	(0.212)
β_{Mrkt}	-0.0617	0.0628	0.0010	-0.1006	-0.0996	0.0239**
	(0.045)	(0.045)	(0.002)	(0.160)	(0.160)	(0.009)
$\sigma_{e,t-1}$	-16.1012***	15.6433***	-0.4578***	26.0729***	25.6151***	-0.5193**
	(2.198)	(2.131)	(0.110)	(3.769)	(3.704)	(0.249)
Size$_{t-1}$	-0.0679	0.0678	-0.0001	0.2771*	0.2770*	-0.0175***
	(0.042)	(0.042)	(0.001)	(0.158)	(0.158)	(0.005)
MTB$_{t-1}$	0.0006	-0.0004	0.0048***	-0.0022	-0.0019	0.0013
	(0.004)	(0.003)	(0.002)	(0.012)	(0.012)	(0.001)
Illiquid$_{t-1}$	0.0006	-0.0004	0.0002	-0.0022	-0.0019	0.0013
	(0.004)	(0.003)	(0.000)	(0.0123)	(0.012)	(0.001)
Fixed Effects	Year	Year	Year	Year	Year	Year
N	8,811	8,811	8,811	8,811	8,811	8,811
R^2	0.3013	0.2942	0.1007	0.0997	0.0977	0.0421

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

Table 4 – *DELR* and Tail Risk of Individual Banks' Balance Sheet Contraction (continued)

OLS pooled regressions of the time period 1996-2009. Dependent variables are: 1) $VaR^i_{1\%}$ ($VaR^i_{99\%}$), defined as the sum of the firms weekly 1% (99%) value at risk over the quarter. 2) $\Delta VaR_{Left}(\Delta VaR_{Right})$, 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) *Skew,* defined as $\left((VaR^i_{50\%} - VaR^i_{1\%}) - (VaR^i_{99\%} - VaR^i_{50\%})\right)/(VaR^i_{99\%} - VaR^i_{1\%})$. *LowDELR* (i.e., more timely banks) is an indicator variable set equal to 1 if a bank's *DELR* is above the median *DELR*, and zero otherwise. See Appendix A for detailed descriptions of all variables. Year- and Firm-fixed effects are included in all regressions and standard errors are reported in parentheses and are clustered by both bank and calendar quarter.

Panel B:	Dependent Variables					
Variables	$VaR^i_{1\%,t}$	$\Delta VaR^i_{left,t}$	$VaR^i_{50\%}$	$\Delta VaR^i_{right,t}$	$VaR^i_{99\%,t}$	$Skew^i_t$
LowDELR$_{t-1}$	0.0273***	-0.0280***	-0.0007	-0.0099	-0.0092	-0.0066***
	(0.008)	(0.008)	(0.001)	(0.017)	(0.017)	(0.002)
Trading$_{t-1}$	-0.4831	0.3931	-0.0900	1.1632	1.2532	0.4062**
	(0.761)	(0.726)	(0.093)	(2.124)	(2.143)	(0.201)
Commercial$_{t-1}$	-0.3729**	0.3704***	-0.0025	0.3909**	0.3934**	0.0187
	(0.139)	(0.135)	(0.011)	(0.182)	(0.185)	(0.041)
Consumer$_{t-1}$	0.8336***	-0.7963***	0.0374	-2.6309***	-2.6683***	-0.0059
	(0.241)	(0.239)	(0.038)	(0.660)	(0.652)	(0.045)
Real Estate $_{t-1}$	-0.2117***	0.2213***	0.0096**	0.2207**	0.2111**	0.0275*
	(0.042)	(0.041)	(0.004)	(0.099)	(0.101)	(0.016)
Mismatch$_{t-1}$	-0.0816	0.0720	-0.0096	-0.2298	-0.2202	0.0159
	(0.103)	(0.106)	(0.011)	(0.272)	(0.269)	(0.026)
Deposits$_{t-1}$	-0.0098	0.0151	0.0052	0.1633**	0.1580**	-0.0183*
	(0.050)	(0.051)	(0.003)	(0.075)	(0.074)	(0.009)
Revenue Mix$_{t-1}$	-0.3847	0.3970	0.0123	0.6177*	0.6054*	0.0168
	(0.262)	(0.260)	(0.011)	(0.337)	(0.338)	(0.028)
Capital$_{t-1}$	1.4404***	-1.4618***	-0.0214	-1.7461***	-1.7247***	-0.1084
	(0.394)	(0.386)	(0.035)	(0.623)	(0.628)	(0.093)
β_{Mrkt}	-0.0291	0.0291	0.0000	-0.0210	-0.0210	0.0201***
	(0.026)	(0.025)	(0.002)	(0.038)	(0.039)	(0.002)
$\sigma_{e,t-1}$	-10.3801***	10.0977***	-0.2824***	13.0055***	13.2879***	-0.0375
	(2.434)	(2.386)	(0.080)	(3.280)	(3.324)	(0.138)
Size$_{t-1}$	-0.0828**	0.0697*	-0.0131***	0.0157	0.0288	0.0092
	(0.037)	(0.036)	(0.004)	(0.084)	(0.083)	(0.008)
MTB$_{t-1}$	0.0803	-0.0787	0.0017	-0.1899*	-0.1915*	0.0034
	(0.049)	(0.048)	(0.002)	(0.097)	(0.098)	(0.004)
Illiquid$_{t-1}$	0.0033	-0.0032	0.0001	-0.0066	-0.0067	0.0004
	(0.002)	(0.002)	(0.000)	(0.004)	(0.004)	(0.001)
Fixed Effects	Year, Firm	Year, Firm	Year, Firm	Year, Firm	Year, Firm	Year, Firm
N	8,371	8,371	8,371	8,371	8,371	8,371
R^2	0.7137	0.7122	0.3633	0.8037	0.8038	0.5179

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

Table 5 – The Impact of *DELR* on Tail Risk of Individual Banks' Balance Sheet Contraction across Boom and Bust Periods

OLS pooled regressions of the time period 1996-2009. Dependent variables are: 1) $VaR^i_{1\%}$ ($VaR^i_{99\%}$), defined as the sum of the firms weekly 1% (99%) value at risk over the quarter. 2) $\Delta VaR_{Left}(\Delta VaR_{Right})$, 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) *Skew,* defined as $\left((VaR^i_{50\%} - VaR^i_{1\%}) - (VaR^i_{99\%} - VaR^i_{50\%})\right)/(VaR^i_{99\%} - VaR^i_{1\%})$. *LowDELR* (i.e., more timely banks) is an indicator variable set equal to 1 if a bank's *DELR* is above the median *DELR*, and zero otherwise. Control variables included in the regression but not reported (see Appendix A for detailed descriptions) include: *Trading, Commercial, Consumer, Real Estate*, *Mismatch, Deposits, Revenue Mix, Capital,* β_{Mrkt}, σ_e, *Size, MTB* and *Illiquidity.* Year-fixed effects are included in all regressions and standard errors are reported in parentheses and are clustered by both bank and calendar quarter.

Panel A: Boom Period	**Dependent Variables**					
Variables	$\boldsymbol{VaR^i_{1\%,t}}$	$\boldsymbol{\Delta VaR^i_{left,t}}$	$\boldsymbol{VaR^i_{50\%}}$	$\boldsymbol{\Delta VaR^i_{right,t}}$	$\boldsymbol{VaR^i_{99\%,t}}$	$\boldsymbol{Skew^i_t}$
LowDELR$_{t-1}$	0.0426*	-0.0440*	-0.0014	-0.0989	-0.1003	-0.0064
	(0.025)	(0.025)	(0.001)	(0.097)	(0.097)	(0.005)
Controls	Included	Included	Included	Included	Included	Included
Fixed Effects	Year	Year	Year	Year	Year	Year
N	6,950	6,950	6,950	6,950	6,950	6,950
R^2	0.2987	0.2956	0.0869	0.0868	0.0858	0.0394

Panel B: Bust Period	**Dependent Variables**					
Variables	$\boldsymbol{VaR^i_{1\%,t}}$	$\boldsymbol{\Delta VaR^i_{left,t}}$	$\boldsymbol{VaR^i_{50\%}}$	$\boldsymbol{\Delta VaR^i_{right,t}}$	$\boldsymbol{VaR^i_{99\%,t}}$	$\boldsymbol{Skew^i_t}$
LowDELR$_{t-1}$	0.0602***	-0.0607***	-0.0005	-0.0057	-0.0062	-0.0202**
	(0.020) †††	(0.021) †††	(0.003)	(0.08)	(0.08)	(0.008) ††
Controls	Included	Included	Included	Included	Included	Included
Fixed Effects	Year	Year	Year	Year	Year	Year
N	1,861	1,861	1,861	1,861	1,861	1,861
R^2	0.2511	0.2397	0.1323	0.1123	0.1096	0.0780

***, **, * 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 – Sensitivity of Individual Banks' Contraction 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's weekly contribution to the bank's *VaR* over the quarter. *LowDELR* (i.e., more timely banks) is an indicator variable set equal to 1 if a bank's *DELR* is above the median *DELR*, and zero otherwise. *Trading* is the ratio of trading account assets to total assets. *Commercial* is total commercial loans scaled by total loans outstanding. *Consumer* is total consumer loans outstanding scaled by total loans outstanding. *Real Estate* is total real estate loans outstanding scaled by total loans. *Mismatch* is the maturity mismatch. *Deposits* is the banks total deposits scaled by beginning period loans. *Revenue Mix* is defined as the ratio of non-interest revenue to total revenue. *Capital* is the firms tier 1 capital ratio. β_{Mrkt} is the firms market beta from a traditional CAPM. $\sigma_e$is the idiosyncratic volatility in equity returns. *Size* is the natural logarithm of total assets. *MTB* is the market-to-book ratio of the firm. *Illiquid* is Amihud (2002) measure of illiquidity. Bust years are defined using the NBER dates for recessionary periods. 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 by both bank and calendar quarter.

	Dependent Variable: $\Delta CoVaR_t^{i|system}$			
Variables	**Pooled**	**Pooled**	**Boom**	**Bust**
LowDELR$_{t-1}$	0.0136*	0.0081**	0.0022	0.0518**
	(0.012)	(0.004)	(0.011)	(0.027) ††
Trading$_{t-1}$	-2.2349*	0.5222	-2.6796**	-1.5582
	(1.354)	(0.748)	(1.300)	(1.841)
Commercial$_{t-1}$	0.0143	-0.0205	-0.0063	0.0639
	(0.131)	(0.047)	(0.121)	(0.182)
Consumer$_{t-1}$	-0.2159	-0.0263	-0.4326	0.0461
	(0.320)	(0.238)	(0.357)	(0.280)
Real Estate $_{t-1}$	-0.0773	-0.1253***	-0.0503	-0.1558**
	(0.051)	(0.034)	(0.050)	(0.065)
Mismatch$_{t-1}$	-0.0964	-0.1087	-0.0506	-0.2882
	(0.160)	(0.068)	(0.145)	(0.264)
Deposits$_{t-1}$	0.1029**	-0.0020	0.1118**	0.0870
	(0.047)	(0.019)	(0.043)	(0.078)
Revenue Mix$_{t-1}$	-0.1447	-0.1600	-0.0519	-0.3215
	(0.161)	(0.123)	(0.151)	(0.216)
Capital$_{t-1}$	0.1888	0.1867	-0.0480	0.5510
	(0.548)	(0.231)	(0.496)	(0.835)
β_{Mrkt}	-0.0480*	0.0060	-0.0219	-0.1375*
	(0.025)	(0.018)	(0.018)	(0.075)
$\sigma_{e,t-1}$	-4.8580***	-3.9352***	-3.4317***	-5.6512**
	(1.111)	(1.274)	(0.960)	(2.257)
Size$_{t-1}$	-0.1081***	-0.0193	-0.0980***	-0.1283***
	(0.014)	(0.016)	(0.013)	(0.018)
MTB$_{t-1}$	-0.0073	0.0260	-0.0207	0.0322
	(0.023)	(0.032)	(0.016)	(0.062)
Illiquid$_{t-1}$	0.0091**	0.0045**	0.0084**	0.0092
	(0.004)	(0.002)	(0.003)	(0.006)
Fixed Effects	Year	Year, Firm	Year	Year
N	8,811	8,371	6,950	1,861
Adj R^2	0.3516	0.7889	0.3953	0.2460

*****, **, *** 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 – Contribution of Individual Banks to Systemic Risk ($\Delta CoVaR_t^{system|i}$)

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* (i.e., more timely banks) is an indicator variable set equal to 1 if a bank's *DELR* is above the median *DELR*, and zero otherwise. *Trading* is the ratio of trading account assets to total assets. *Commercial* is total commercial loans scaled by total loans outstanding. *Consumer* is total consumer loans outstanding scaled by total loans outstanding. *Real Estate* is total real estate loans outstanding scaled by total loans. *Mismatch* is the maturity mismatch. *Deposits* is the banks total deposits scaled by beginning period loans. *Revenue Mix* is defined as the ratio of non-interest revenue to total revenue. *Capital* is the firms tier 1 capital ratio. β_{Mrkt} is the firms market beta from a traditional CAPM. $\sigma_e$is the idiosyncratic volatility in equity returns. *Size* is the natural logarithm of total assets. *MTB* is the market-to-book ratio of the firm. *Illiquid* is Amihud (2002) measure of illiquidity. Bust years are defined using the NBER dates for recessionary periods. 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 by both bank and calendar quarter.

	Dependent Variable: $\Delta CoVaR_t^{system|i}$			
Variables	**Pooled**	**Pooled**	**Boom**	**Bust**
LowDELR$_{t-1}$	0.0119**	0.0026*	0.0078	0.0284***
	(0.005)	(0.001)	(0.005)	(0.008) †††
Trading$_{t-1}$	-0.0275	0.1265	-0.0639	-0.2183
	(0.750)	(0.185)	(0.738)	(0.878)
Commercial$_{t-1}$	-0.0674	-0.0604***	-0.0586	-0.0927
	(0.060)	(0.018)	(0.061)	(0.067)
Consumer$_{t-1}$	0.1323	0.1131*	0.1201	0.1445*
	(0.101)	(0.058)	(0.126)	(0.084)
Real Estate $_{t-1}$	0.0290	-0.0415***	0.0320	0.0210
	(0.023)	(0.006)	(0.023)	(0.029)
Mismatch$_{t-1}$	-0.0903	0.0223	-0.0960	-0.1046
	(0.080)	(0.017)	(0.082)	(0.090)
Deposits$_{t-1}$	0.0390	0.0156**	0.0348	0.0600*
	(0.024)	(0.006)	(0.024)	(0.032)
Revenue Mix$_{t-1}$	0.0555	-0.0582	0.0644	0.0546
	(0.075)	(0.035)	(0.075)	(0.089)
Capital$_{t-1}$	-0.4751*	0.0519	-0.5492*	-0.3195
	(0.281)	(0.073)	(0.283)	(0.332)
β_{Mrkt}	-0.0242***	-0.0039	-0.0162**	-0.0492***
	(0.008)	(0.004)	(0.008)	(0.015)
$\sigma_{e,t-1}$	-0.7557**	-1.2614***	-0.5177	-0.5187
	(0.373)	(0.289)	(0.411)	(0.484)
Size$_{t-1}$	-0.0110	-0.0097	-0.0105	-0.0093
	(0.007)	(0.005)	(0.006)	(0.009)
MTB$_{t-1}$	-0.0259**	0.0080	-0.0284***	-0.0196
	(0.010)	(0.005)	(0.010)	(0.015)
Illiquid$_{t-1}$	0.0029**	0.0012**	0.0027**	0.0034***
	(0.001)	(0.001)	(0.001)	(0.001)
Fixed Effects	Year	Year, Firm	Year	Year
N	8,664	8,371	6,860	1,804
Adj R^2	0.1785	0.8405	0.1877	0.1481

*****, **, *** 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 8 – Robustness – *DELR* and Risk Profile, Controlling for CAMELS

The table below contains OLS regression over the sample period 1996-2009. *LowDELR* (i.e., more timely banks) is an indicator variable set equal to 1 if a bank's *DELR* is above the median *DELR*, and zero otherwise.. $VaR^{i}_{1\%}$ is defined as the sum of the firms weekly 1% value at risk over the quarter. $\Delta CoVaR^{s|i}_{t}$ ($\Delta CoVaR^{i|s}_{t}$) 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. Year-fixed effects are included in all regressions and standard errors are reported in parentheses and are clustered by both bank and calendar quarter.

	Pooled			Boom			Bust		
Variables	$VaR^{i}_{1,t}$	$\Delta CoVaR^{system\|i}_{t}$	$\Delta CoVaR^{i\|system}_{t}$	$VaR^{i}_{1,t}$	$\Delta CoVaR^{system\|i}_{t}$	$\Delta CoVaR^{i\|system}_{t}$	$VaR^{i}_{1,t}$	$\Delta CoVaR^{system\|i}_{t}$	$\Delta CoVaR^{i\|system}_{t}$
LowDELR$_{t-1}$	0.0426**	0.0120**	0.0133*	0.0407	0.0080	0.0021	0.0506**	0.0289***	0.0499**
	(0.021)	(0.005)	(0.012)	(0.025)	(0.005)	(0.011)	(0.019) ††	(0.0087) ††	(0.0270) ††
C – Capital$_{t-1}$	0.6713	-0.5072*	0.0386	0.5152	-0.5767**	-0.1935	1.1638	-0.3639	0.5521
	(0.839)	(0.274)	(0.552)	(0.815)	(0.279)	(0.500)	(1.182)	(0.311)	(0.888)
A – NPL$_{t-1}$	-10.1882***	0.3371	-1.4985	-9.4874***	0.4642	-1.4443	-11.6392***	0.1286	-1.2613
	(2.992)	(0.734)	(1.141)	(3.020)	(0.737)	(1.132)	(3.479)	(0.929)	(1.346)
M, E – ROA$_{t-1}$	28.8930*	2.0852	10.5631	24.4714	2.7127	10.1227	34.7912	-1.4846	8.0109
	(14.786)	(3.096)	(6.542)	(17.160)	(3.434)	(6.167)	(22.583)	(4.333)	(15.867)
L – B/S Liq$_{t-1}$	0.0212	0.1303	-0.0744	-0.0180	0.0664	0.0862	-0.3720	0.4395	-1.0535
	(0.619)	(0.253)	(0.472)	(0.625)	(0.238)	(0.441)	(1.023)	(0.388)	(0.931)
S – GAP$_{t-1}$	0.3024**	0.0169	0.1842***	0.1875	0.0058	0.1246*	0.5408***	0.0359	0.3357**
	(0.145)	(0.034)	(0.070)	(0.151)	(0.036)	(0.069)	(0.151)	(0.044)	(0.161)
Controls	Included	Included	Included	Included	Included	Included	Included	Included	Included
Fixed Effects	Year	Year	Year	Year	Year	Year	Year	Year	Year
N	8,811	8,811	8,811	6,950	6,950	6,950	1,861	1,861	1,861
Adj R^2	0.3207	0.1792	0.3546	0.3160	0.1887	0.3980	0.2754	0.1502	0.2503

***, **, * 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 9 – Robustness – *DELR* and Risk Profile, Controlling for Lagged VaR, ΔCoVaR and CAMELS

The table below contains OLS regression over the sample period 1996-2009. *LowDELR* (i.e., more timely banks) is an indicator variable set equal to 1 if a bank's *DELR* is above the median *DELR*, and zero otherwise. $VaR^{i}_{1\%}$ is defined as the sum of the firms weekly 1% value at risk over the quarter. $\Delta CoVaR^{s|i}_{t}$ ($\Delta CoVaR^{i|s}_{t}$) 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. Year-fixed effects are included in all regressions and standard errors are reported in parentheses and are clustered by both bank and calendar quarter.

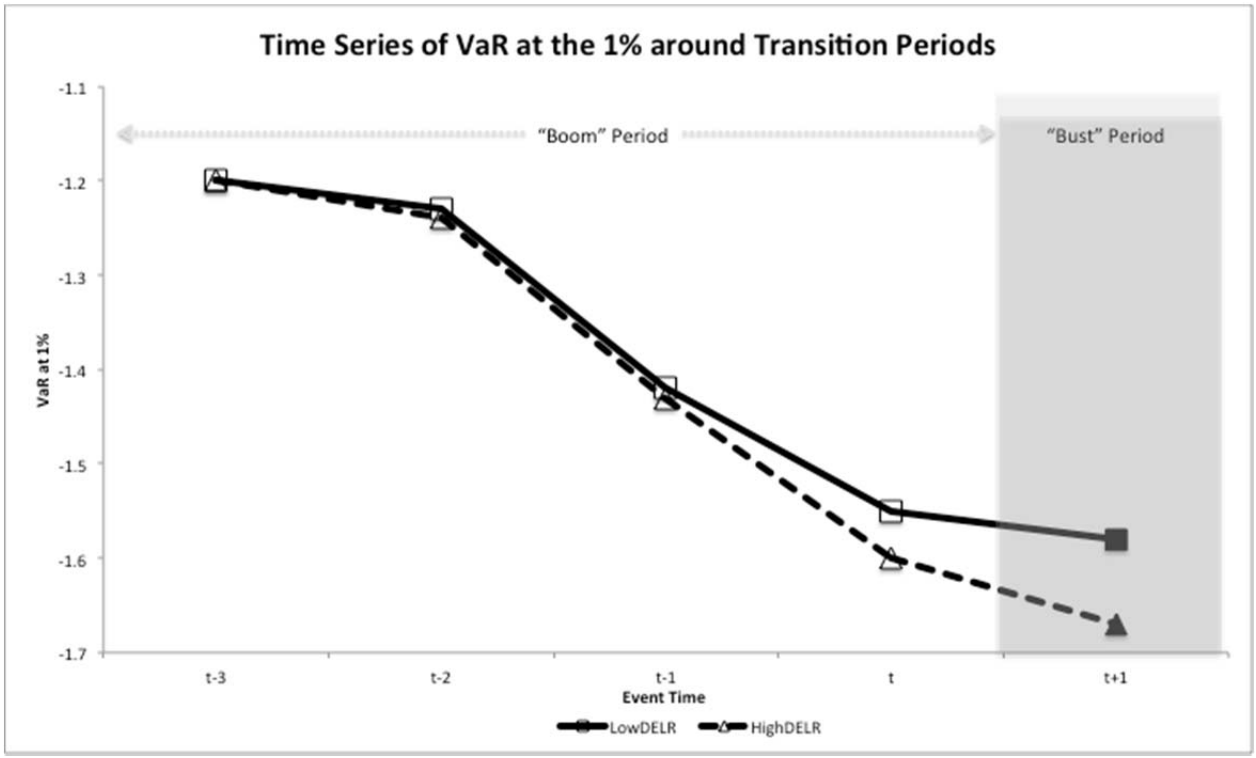
	Pooled			Boom			Bust		
Variables	$VaR^{i}_{1,t}$	$\Delta CoVaR^{system\|i}_{t}$	$\Delta CoVaR^{i\|system}_{t}$	$VaR^{i}_{1,t}$	$\Delta CoVaR^{system\|i}_{t}$	$\Delta CoVaR^{i\|system}_{t}$	$VaR^{i}_{1,t}$	$\Delta CoVaR^{system\|i}_{t}$	$\Delta CoVaR^{i\|system}_{t}$
LowDELR$_{t-1}$	0.0111*	0.0032**	0.0056*	0.0023	0.0024*	-0.0002	0.0239***	0.0043**	0.0125***
	(0.006)	(0.001)	(0.004)	(0.005)	(0.001)	(0.002)	(0.009) ††	(0.002) ††	(0.004) ††
VaR^{i}_{t-1}	0.7820***	-0.0269***	-0.0311***	0.7778***	-0.0234***	-0.0207***	0.7950***	-0.0392***	-0.0772**
	(0.0360)	(0.0044)	(0.0115)	(0.037)	(0.003)	(0.007)	(0.066)	(0.015)	(0.038)
VaR^{s}_{t-1}	-0.2702**	-0.0360**	-0.2279**	-0.1832***	-0.0287**	-0.1236***	-0.2527	-0.0350	-0.3739
	(0.1279)	(0.0159)	(0.0933)	(0.063)	(0.012)	(0.040)	(0.318)	(0.040)	(0.272)
$\Delta CoVaR^{s\|i}_{t-1}$		0.9339***			0.9099***			1.0091***	
		(0.0295)			(0.033)			(0.038)	
$\Delta CoVaR^{i\|s}_{t-1}$			0.9591***			0.8863***			1.1430***
			(0.0667)			(0.052)			(0.159)
Controls + CAMELS	Included	Included	Included	Included	Included	Included	Included	Included	Included
Fixed Effects	Year	Year	Year	Year	Year	Year	Year	Year	Year
N	8,666	8,666	8,666	6,816	6,816	6,816	1,850	1,850	1,850
Adj R^2	0.6795	0.8730	0.8089	0.7812	0.9059	0.9164	0.4853	0.7895	0.6609

***, **, * 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.

Figure 1 – Plotting $VaR_{1\%}$ through Event Time around Transition Periods

The figure below plots the times series behavior of $VaR_{1\%}$ in event time around transitions in the economy from boom periods to bust periods for both high and low *DELR* firms. *DELR* for each time series is computed as of time t and then held constant going back to t-3 and forward to t+1. Solid point markers in a given period indicate that there is a statistically significant difference at the 0.05 levels between high and low *DELR* portfolios.



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