Delayed Expected Loss Recognition and the Risk Profile of Banks

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Abstract

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

1. Introduction

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

2. Conceptual Framework

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

2.1 Delayed Recognition of Expected Loan Losses

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

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

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

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

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

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

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

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, 2011). We then take the difference in the adjusted R^2 of (2) - (1), and then rank banks based on

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

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

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

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

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

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

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

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

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

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

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

2.3 DELR and Stock Market Liquidity Risk

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

3. Data, DELR and Liquidity – Methodology and Results

3.1 Data

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

3.2 Liquidity

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

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

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

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

The variables *Illiquidity,* β_{Liquid}, *DELR, Deposits, Size, Capital* and σ_e were defined previously (see the appendix for detailed descriptions of all variables). β_{Mrkt}, the bank‟s market beta from a traditional CAPM model estimated on daily returns over the prior quarter, is included to control for differences in systematic market risks.[11] *Mismatch*, defined as short-term liabilities net of cash all divided by total liabilities, controls for differences in financing risk of the bank. *Trading* is defined as the ratio of trading assets to total assets of the bank and is included to control for the banks own assets exposure to external market fluctuations. We also include market-to-book (*MTB*) as a control for expected growth differences. We estimate (1) for four samples: 1) pooled regression, 2) „Boom‟ subsample, 3) „Bust‟ subsample (i.e., time periods designated by NBER as recessions) and 4) „Boom to Bust‟ subsample. The „Boom to Bust‟ subsample estimates regressions using only the first quarter following the transition from a boom to bust period. We use this period to isolate how decisions made during „Boom‟ periods affect outcomes in „Bust‟ periods. A quarter is classified as „Boom to Bust‟ if quarter t-1 is in a „Boom‟ period and quarter t is in a „Bust‟ period.

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

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

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

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

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

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

4.1 Tail Risk – VaR and other distributional characteristics

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

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

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

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

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

$$X_t^i = \alpha^i + \beta^i M_{t-1} + \varepsilon_t^i . \tag{5}$$

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

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

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

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

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

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

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

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

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

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

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

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

$$X_i^{system} = \gamma_1^s + \gamma_2^s M_{t-1} + \varepsilon_t^s \qquad (9a)$$

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

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

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

asset growth rates for the index. Equation (10a) is an extension of (2) because we further condition the asset growth rate of a bank on a value-weighted index of other banks in the system.

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

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

$$CoVaR_{1\%,t}^{i|system} = \hat{\alpha}_1^s + \hat{\delta}^{i|system} Var_{1\%,t}^{system} + \hat{\beta}^{i|system} M_{t-1} \tag{10b}$$

$CoVaR_{1\%,t}^{i|system}$ captures the bank"s conditional time t *VaR* at $q\%$ = 1% given the conditional *VaR* of the system. To capture the sensitivity of the bank"s conditional $VaR_{1\%}$ to systemic financial events, we re-estimate (10b) setting $q\%$ = 50% and then compute

$$\Delta CoVaR_{1\%,t}^{i|system} = \hat{\alpha}_1^s + \hat{\delta}^{i|system} (Var_{1\%,t}^{system} - Var_{50\%,t}^{system}) + \hat{\beta}^{i|system} M_{t-1} \tag{11}$$

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

Table 1 reports the univariate results of $\Delta CoVaR^{i|system}$ across *DELR* groups. The univariate results report a mean $\Delta CoVaR^{i|system}$ for *HighDELR* banks of −0.534 and a mean $\Delta CoVaR^{i|system}$ for *LowDELR* banks of −0.509 both significantly different from zero at the 0.01

level. The difference across groups of 0.025 is significantly different at the 0.01 level. This provides preliminary evidence that the tail risk for *LowDELR* banks is less sensitive to movements in systemic events.

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

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

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

$$X_t^i = \alpha^i + \beta^i M_{t-1} + \varepsilon_t^i \tag{12a}$$

$$X_t^{system} = \gamma_1^{system|i} + \gamma_2^{system|i} M_{t-1} + +\gamma_3^{system|i} X_t^i + \varepsilon_t^s \tag{13a}$$

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

$$VaR_{1\%,t}^i = \hat{\alpha}^i + \hat{\beta}^i M_{t-1} \tag{12b}$$

$$CoVaR_{1\%,t}^{system|i} = \hat{\gamma}_1^{system|i} + \hat{\gamma}_2^{system|i} M_{t-1} + \hat{\gamma}_3^{system|i} Var_{1\%,t}^{system|i} \tag{13b}$$

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

$$\Delta CoVaR_{1\%,t}^{system|i} = \hat{\gamma}_1^{system|i} + \hat{\gamma}_2^{system|i} M_{t-1} + \hat{\gamma}_3^{system|i} (Var_{1\%,t}^{system|i} - Var_{50\%,t}^{system|i}) \quad (14)$$

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

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

4.4 Robustness

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

5. Summary

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

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

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

Appendix A

Variable	Description	Source(s)
LowDELR	An indicator variable equal to 1 (0) if the incremental R^2 from (2) over (1) is above (below) the quarter median. Where equations (1) and (2) are defined as: (1) $LLP_t = \Delta NPL_{t-1}+\Delta NPL_{t-2}+Ebllp_t+Capital_{t-1}+Size_{t-1}+\varepsilon_t$ (2) $LLP_t = \Delta NPL_{t+1}+\Delta NPL_{t+}\Delta NPL_{t-1}+\Delta NPL_{t-2}+Ebllp_t+Capital_{t-1}+Size_{t-1}+\varepsilon_t$	Compustat
Timing Partitioning Variables:		
Bust (Boom)	Using NBER dates we classify „Bust‟ periods as those periods classified as recessions. All other periods are classified as „Boom‟ periods.	NBER
Boom to Bust	Periods in which the quarter t-1 is classified as a „Boom‟ period and quarter t is classified as a „Bust‟ periods.	NBER
Dependent Variables:		
Illiquidity	The natural logarithm of the average Amihud (2002) daily illiquidity ratio over the quarter.	CRSP
β_{Liquid}	The coefficient from a regression of daily changes in the bank‟s Amihud (2002) measure of illiquidity over the quarter on daily changes in a value weighted index of banks‟ Amihud (2002) measure of illiquidity.	CRSP
$VaR_{1\%}$ ($VaR_{99\%}$) ($VaR_{50\%}$)	The quarterly estimated conditional 1% (99%) (50%) value at risk of the market value of assets. This is computed using quantile regressions using weekly market value of asset returns regressed on macro state variable and taking the predict value. We then sum the weekly-predicted values over the quarter.	Compustat, CRSP, Federal Reserve, CBOE
ΔVaR_{Left} (ΔVaR_{Right})	Is the distance between the $VaR_{50\%}$ and $VaR_{1\%}$ ($VaR_{99\%}$), where the VaR is defined above.	Compustat, CRSP, Federal Reserve, CBOE
Skew	Is defined as : $\frac{((VaR_{50\%} - VaR_{1\%}) - (VaR_{99\%} - VaR_{50\%}))}{(VaR_{99\%} - VaR_{1\%})}$ where the VaR is defined above.	Compustat, CRSP, Federal Reserve, CBOE
$\Delta CoVaR^{system\|i}$	The measure of a individual bank‟s contribution to systemic risk, estimated as the difference in the systems predicted 1% conditional VaR using both a banks $VaR_{1\%}$ and $VaR_{50\%}$. Where the VaR is defined above.	Compustat, CRSP, Federal Reserve, CBOE
$\Delta CoVaR^{i\|system}$	The sensitivity of a individual bank‟s tail risk or $VaR_{1\%}$ to changes in systemic risk.	Compustat, CRSP, Federal Reserve, CBOE

Control Variables:		
β_{Mrkt}	The firms market beta from a single factor CAPM estimated on daily return over the quarter.	CRSP
Mismatch	(Current liabilities – Cash) / Total liabilities	Compustat
Trading	The ratio of trading assets to total assets.	Compustat
MTB	The market to book ratio.	CRSP, Compustat
σ_e	The standard deviation of daily equity returns over the quarter.	CRSP
Deposits	Total deposit scaled by lagged total loans.	Compustat
LLP	Loan loss provisions scaled by lagged total loans.	Compustat
ΔNPL	Change in non-performing loans scaled by lagged total loans.	Compustat
Ebllp	Earnings before loan loss provisions and taxes scaled by lagged total loans.	Compustat
Capital	Tier 1 Capital Ratio.	Compustat
Size	Natural Logarithm of total assets.	Compustat
Macro State Variables:		
VIX	Expect volatility from options on the S&P 500 index	CBOE
Liquidity Spread	Difference between the 3-month general collateral repo and the 3-month bill rate.	Bloomberg, Federal Reserve bank of New York.
Δ3T-Bill	Change in the 3-month T-Bill rate	Federal Reserve Board‟s H.15
ΔYield Curve Slope	Yield spread between the 10-year Treasury rate and the 3-month rate.	Federal Reserve Board‟s H.15
ΔCredit Spread	Change in the spread between the BAA-rated bonds and the Treasury rate with the same 10-year maturity.	Federal Reserve Board‟s H.15
Ret_{Mrkt}	The weekly value weight market return.	CRSP
Ret_{Estate}	The weekly real estate (SIC 65-66) sector return in excess of the market return.	CRSP

Table 1 – Descriptive Statistics

The table below contains the descriptive statistics for the sample period 1996-2009. The *DELR* measure is the incremental explanatory power of current and future changes in non-performing loans on current loan loss provisions. $VaR_{1\%}^{i}$ $(VaR_{50\%}^{i}; VaR_{99\%}^{i})$ is defined as the sum of the firms weekly 1% (50%; 99%) value at risk over the quarter. ΔVaR_{Left}^{i} (ΔVaR_{Right}^{i}) is defined as the difference between $VaR_{1\%}^{i}$ $(VaR_{99\%}^{i})$ and $VaR_{50\%}^{i}$. The variable *Skew* is defined as $\left((VaR_{50\%}^{i} - VaR_{1\%}^{i}) - (VaR_{99\%}^{i} - VaR_{50\%}^{i})\right)/(VaR_{99\%}^{i} - VaR_{1\%}^{i})$. $\Delta CoVaR_{t}^{s|i}$ $(\Delta CoVaR_{t}^{i|s})$ is defined as the sum of the firm's weekly $\Delta CoVaR_{t}^{s|i}$ $(\Delta CoVaR_{t}^{i|s})$ over the quarter. β_{Mrkt} is the firms market beta from a traditional CAPM. *Mismatch* is the maturity mismatch defined as current liabilities minus cash all divided by total liabilities. *Deposits* is the banks total deposits scaled by beginning period loans. *Trading* is the ratio of trading account assets to total assets. *Size* is the natural logarithm of total assets. *MTB* is the market-to-book ratio of the firm. *Capital* is the firms tier 1 capital ratio. σ_e is the standard deviation of equity returns over the quarter market adjusted. *Illiquid* is Amihud (2002) measure of illiquidity.

Panel A. DELR – Descriptive Statistics

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

Panel B. Descriptive Statistics by DELR Partitions

	HighDELR			***LowDELR***		
Variables	**Mean**	**Median**	**StdDev**	**Mean**	**Median**	**StdDev**
VaR_{1}^{i}	-1.522	-1.327	0.716	-1.482***	-1.131*	0.673
ΔVaR_{Left}^{i}	1.602	1.355	0.976	1.552***	1.337*	0.925
Skew	-0.145	-0.141	0.166	-0.156***	-0.149***	0.167
VaR_{50}^{i}	0.006	0.007	0.041	0.006	0.007	0.041
ΔVaR_{Right}^{i}	1.596	1.353	0.975	1.540	1.330	0.907
VaR_{99}^{i}	2.346	1.815	2.813	2.357	1.837	3.042
$\Delta CoVaR^{s\|i}$	-0.249	-0.218	0.208	-0.231***	-0.199***	0.200
$\Delta CoVaR^{i\|s}$	-0.534	-0.451	0.510	-0.509***	-0.428***	0.489
β_{MRKT}	0.655	0.565	0.617	0.646	0.555	0.609
Mismatch	0.852	0.869	0.087	0.856**	0.874**	0.084
Deposit	1.192	1.137	0.287	1.208**	1.153***	0.285
Trading	0.003	0.000	0.012	0.003	0.000	0.012
Size	7.809	7.532	1.584	7.727**	7.493	1.536
MTB	1.802	1.746	0.749	1.807	1.743	0.731
Capital	0.107	0.105	0.025	0.108**	0.106	0.026
σ_e	0.020	0.016	0.015	0.020	0.016	0.014
Illiquid	1.077	0.048	3.446	1.065**	0.048	3.323

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

Table 2 – *DELR* and Liquidity Risk

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

Panel A. – Illiquidity Level

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

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

Panel B. - Liquidity Covariance

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

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

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

Table 3 – *DELR* and Tail Risk

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

Table 7 – Robustness

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

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

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

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

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

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

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

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Bushman, R. and C. Williams, 2011. Accounting Discretion, Loan Loss Provisioning, and Discipline of Banks‟ Risk-Taking, *Working Paper University of North Carolina.*

Dugan, J. 2009. "Loan Loss Provisioning and Pro-cyclicality." Remarks by John C. Dugan, Comptroller of the Currency, before the Institute of International Bankers, March 2, 2009.

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Ivashina, V. and D. Scharfstein, 2010. Bank lending during the financial crises of 2008. *Journal of Financial Economics* 97, 319-338.

Kashap, A. and J. Stein, 2000. What do a million observations on banks say about the transmission of monetary policy? *The American Economic Review* 90, 407-428.

Kishan, R., Opiela, T., 2006. Bank capital and loan asymmetry in the transmission of monetary policy. Journal of Banking and Finance 30, 259–285.

Lang, M., Maffett, M., 2011. Transparency and Liquidity Uncertainty in Crisis Periods. Forthcoming *Journal of Accounting and Economics.*

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Wall, L. and T. Koch. 2000. “Bank loan-loss accounting: a review of theoretical and empirical evidence” *Economic Review*: 1-19.

Robert M. Bushman, Ph.D., C.P.A.
The Forensic Accounting Distinguished Professor
Chair of the Accounting Area
Curriculum Vitae

Kenan-Flagler Business School
University of North Carolina- Chapel Hill
Chapel Hill, North Carolina 27599-3490
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October, 2011

EDUCATION

Ph.D. in Accounting	University of Minnesota	1989
BBA - Accounting (summa cum laude)	Ohio University	1975

REFEREED RESEARCH PUBLICATIONS & ACCEPTANCES

"Capital Allocation and Timely Accounting Recognition of Economic Losses," with Abbie Smith and Joe Piotroski, *Journal of Business, Finance and Accounting*, 2011, Vol. 38, Issue 1/2.

"Price Discovery and Dissemination of Private Information by Loan Syndicate Participants." With Abbie Smith and Regina Wittenberg-Moerman, *Journal of Accounting Research* Vol. 48 No. 5 December 2010.

"Risk and CEO Turnover." with Zhonglan Dai and Xue Wang. *Journal of Financial Economics* Volume 96, Issue 3, June 2010, Pages 381-398

"The Pros and Cons of Regulating Corporate Reporting: A Critical Review of the Arguments," with Wayne Landsman. *Accounting and Business Research* Vol. 40 Number 3, 2010.

"A Discussion of Creditors' and Shareholders' Reporting Demands in Public versus Private Firms: Evidence from Europe," *Contemporary Accounting Research*, Vol. 27 No. 1 (Spring 2010) pp. 93–99.

"When "Weak" Governance is the Best Governance: A Discussion of Corporate Governance and Backdating of Executive Stock Options," *Contemporary Accounting Research* Volume 26, Number 2 / Summer 2009:447–451.

"The Debt-Contracting Value of Accounting Information and Loan Syndicate Structure," with Ryan Ball and Florin Vasvari, 2008. *Journal of Accounting Research* Vol. 46 No. 2 May 2008: 247-287.

"Financial reporting incentives for conservative accounting: The influence of legal and political institutions," with Joe Piotroski. *Journal of Accounting and Economics* Vol. 42 (October 2006), pp. 107-48.

“An Analysis of the Relation Between the Stewardship and Valuation Roles of Earnings,” with Ellen Engel, and Abbie Smith. *Journal of Accounting Research* Volume 44 Number 1 March 2006, pp. 53-83.

“Does Analyst Following Increase Upon the Restriction of Insider Trading?” with Joe Piotroski and Abbie Smith. *Journal of Finance* Volume 60 February 2005. (Nominated for the 2005 Smith Breeden Prize)

“Financial Accounting Information, Organizational Complexity and Corporate Governance Systems,” with Qi Chen, Ellen Engel, and Abbie Smith, *Journal of Accounting and Economics* 37 (2004), 167-201.

“What Determines Corporate Transparency?” with Joe Piotroski and Abbie Smith. *Journal of Accounting Research* 2004 , 42 (2).

“Transparency, Financial Accounting Information and Corporate Governance,” with Abbie Smith. Federal Reserve Bank of New York’s *Economic Policy Review*, April 2003 Volume 9, Number 1 : 65-87.

“Financial Accounting Information and Corporate Governance,” with Abbie Smith. *Journal of Accounting & Economics,* Vol. 32, Nos. 1-3, August/October/December 2001.

“Private Pre-Decision Information, Performance Measure Congruity and the Value of Delegation,” with Raffi Indjejikian and Mark Penno, *Contemporary Accounting Research* , Vol. 17 Winter 2000 pp. 561-587.

“Earnings Announcements and Market Depth,” Robert Bushman, Sunil Dutta, John Hughes and Raffi Indjejikian, *Contemporary Accounting Research*, Vol. 14 No. 1 (Spring 1997) pp. 43-68.

"CEO Compensation: The Role of Individual Performance Evaluation," Robert Bushman, Raffi Indjejikian and Abbie Smith. *Journal of Accounting and Economics*, Vol. 21 April 1996 pp. 161-193.

“A Model of Two-Tiered Financial Reporting,” Robert Bushman, Frank Gigler and Raffi Indjejikian. *Journal of Accounting Research*, Supplement 1996 pp. 51-74.

"A Note on Strategic Sampling in Agencies,” Robert Bushman and Chandra Kanodia. *Management Science*, Vol 43 January 1996 pp. 151-156.

“Aggregate Performance Measures in Business Unit Manager Compensation: The Role of Intrafirm Interdependencies,” Robert Bushman, R. Indjejikian and Abbie Smith. *Journal of Accounting Research*, Vol. 33 Supplement 1995 pp. 101-128.

"Voluntary Disclosures and the Trading Behavior of Corporate Insiders,” Robert Bushman and Raffi Indjejikian. *Journal of Accounting Research*, Vol. 33 No. 2 Autumn 1995 pp. 293-316.

"Stewardship Value of "Distorted" Accounting Disclosures," Robert Bushman and R. Indjejikian. *The Accounting Review*, October 1993 pp. 765-782.

"Accounting Income, Stock Price and Managerial Compensation," Robert Bushman and Raffi Indjejikian. *Journal of Accounting and Economics* , Jan./Feb./March 1993 pp. 3-23.

"Public Disclosure and the Structure of Private Information Markets", Robert Bushman *Journal of Accounting Research*, Autumn 1991 pp. 261-276.

"Escalation Errors and the Sunk Cost Effect: An Explanation Based on Reputation and Information Asymmetries," Robert Bushman, Chandra Kanodia and John Dickhaut. *Journal of Accounting Research*, Spring 1989 pp. 59-77.

WORKING PAPERS

"Delayed Expected Loss Recognition and the Risk Profile of Banks" with Christopher Williams, October 2011.

"The Role of Bank Reputation in "Certifying" Future Performance Implications of Borrowers' Accounting Numbers", with Regina Wittenberg-Moerman, October 2011.

"Accounting Discretion, Loan Loss Provisioning, and Discipline of Banks' Risk-Taking" with Christopher Williams, October 2011.

"Investment Cash Flow Sensitivities Really Reflect Related Investment Decisions," with Abbie Smith and Frank Zhang, September 2011

"Implied Bond Liquidity", with Ahn Le and Florin Vasvari, January 2010.

"Does secondary loan market trading destroy lenders' incentives?" with Regina Wittenberg-Moerman, November 2009.

"An Empirical Investigation of Trends in the Absolute and Relative Use of Earnings in Determining Cash Compensation of CEOs," with Ellen Engel, Jennifer Milliron and Abbie Smith. Working Paper, June 1998.

NON -REFEREED ARTICLES

"Degrees of Transparency," 2003 Robert Bushman, Joe Piotroski and Abbie Smith. *Investor Relations Quarterly* Volume 6, Number 1. This is a publication of the National Investor Relations Institute. This issue of the journal was entitled: Toward Transparency.

"Executive Compensation and Value Creation," Robert Bushman, Raffi Indjejikian and Abbie Smith. Mastering Management Series, *Financial Times*, June 7, 1996.

ACADEMIC AWARDS, HONORS & SERVICE

Member of the Program Committee:
Disclosure, Transparency, and Financial Reporting in the Financial Services Industry: A conference sponsored by Federal Reserve Bank of New York and the *Journal of Accounting Research.* To be held September 20-21, 2012.

Weatherspoon Award for Distinguished Research Contributions University of North Carolina at Chapel Hill	2008
American Accounting Association Member of the Planning Committee for the 2007 Annual Meeting Chicago, August 2007	2006-2007
UNC Academy of Distinguished Teaching Scholars	2006
The Distinguished Teaching Award for Post-Baccalaureate Instruction University-wide teaching award University of North Carolina at Chapel Hill	2006
Listed as one of "Recent Grad's Favorite Profs" <u>Business Week's Guide To The Best MBA Programs,</u> 9th Edition	2005
Named to The Forensic Accounting Distinguished Professorship University of North Carolina at Chapel Hill	2004
Sarah Graham Kenan Distinguished Scholar University of North Carolina at Chapel Hill	2003-2004
Listed as one of "Recent Grad's Favorite Profs" <u>Business Week's Guide To The Best Business Schools,</u> 8th Edition	2003
Weatherspoon Award for Teaching Excellence in the MBA Program University of North Carolina at Chapel Hill	2003
Weatherspoon Award for Teaching Excellence in the PhD Program University of North Carolina at Chapel Hill	2002
AAA Doctoral Consortium Resident Faculty Member	June 1999
AAA Research Advisory Council Member	1997-1998
AAA Doctoral Consortium, Distinguished Visiting Faculty	1996 &1997
AAA-FASB Financial Reporting Conference: Planning Committee	1996 &1998
AAA Doctoral Consortium Fellow	1985
Listed as an Outstanding Faculty Member <u>Business Week's Guide To The Best Business Schools,</u> 4th Edition	1995

"McKinsey Award for Excellence in Teaching", Graduate School of Business, University of Chicago	1992
Ernst & Whinney Doctoral Dissertation Fellowship	1987

PROFESSIONAL EXPERIENCE

UNC-Chapel Hill	Professor	7/99 - Present
University of Chicago	Associate Professor	7/92 - 6/99
University of Chicago	Assistant Professor	7/88 - 6/92
University of Minnesota	Accounting Instructor	9/79 - 6/88
Trans Union Corporation	Senior Internal Auditor	6/78 - 8/79
Arthur Andersen & Co	Senior Auditor	3/75 - 1/78
Marmac Corporation	Hotel Manager County Clare, Ireland	6/74 - 10/74

EDITORIAL RELATED ACTIVITIES

Associate Editor, *Management Science*	1/11- Present
Associate Editor, *Journal of Accounting Research*	1/93 - Present
Associate Editor, *Journal of Accounting and Economics*	4/06 - 4/09
Associate Editor, *Review of Accounting Studies*	1/07 - Present
Editorial Advisory and Review Board, *The Accounting Review*	7/93 - 7/96
Editorial Advisory and Review Board, *The Accounting Review*	7/99 - 7/06
Associate Editor, *Journal of Accounting and Public Policy*	1/02 - Present

Ad Hoc Reviewer for:
Abacus
American Economic Review
Contemporary Accounting Research
European Accounting Review
Journal of Accounting and Economics
Journal of Banking and Finance
Journal of Business
Journal of Business Finance and Accounting
Journal of Finance
Journal of Financial Economics
Journal of Financial Intermediation
Journal of International Financial Management and Accounting
Journal of Monetary Economics
Journal of Political Economy

PROFESSIONAL AFFILIATIONS

CPA, State of Ohio 1975
Member, American Institute of Certified Public Accountants
Member, American Accounting Association

KEYNOTE SPEECHES

Keynote Speaker: Baruch and SWUFE Conference
Topic: Accounting and Prudential Regulation of Financial Institutions
June 27, 2011, NY, NY

Keynote Speaker: UTS Australian Summer Accounting Conference
Topic: Price Discovery in Loan and Equity Markets
February 5-6, 2009, Sydney, Australia

Keynote Speaker: Taiwan Accounting Association Annual Meeting.
Topic: The Disciplining Role of Financial Accounting in International Banking and Debt Markets". December 4, 2008, Taipei, Taiwan.

Keynote Speaker: "Three-School Research Camp" bringing together faculties from Peking University, Tsinghua University and Cheungkong Graduate School of Business
Title of Talk: "The disciplining role of financial accounting information: Corporate governance, debt governance and regulatory governance"
Held at Peking University, Beijing, China, April 2008

Keynote Speaker: International Conference on Corporate Governance in China and Asia
Title of Talk: "Financial Reporting Incentives: Law, Politics and Corporate Discipline"
Conference co-organized by Chinese University of Hong Kong and Shanghai University of Finance and Economics. March 2005 in Shanghai, China

Featured Speaker , 11th Annual HKUST Summer Symposium on Accounting Research
Hong Kong University of Science and Technology
Theme: Global Capital Markets: Accounting Challenges and Opportunities
June 2004 in Hong Kong

University of Technology, Sydney: School of Accounting Summer PhD School
Featured Presenter. January 2004. Sydney, Australia
This program draws PhD students from across Australia

University of Technology, Sydney: School of Accounting Summer Research School
Keynote Speaker. January 2004. Sydney, Australia

INVITED SPEAKING ENGAGEMENTS

World View Symposium on East Asia and the Global Economy
Title of Talk: The State of Markets in China
Chapel Hill, NC March 2010

Speaker at the Weinberg Center for Corporate Governance conference on "Corporate Governance and Managing Firm Risk" held at the University of Delaware, October 1 & 2, 2009.

Discussant at 23rd *Contemporary Accounting Research* Conference
November 7 and 8, 2008 in Québec City, Québec Canada

Discussant at the London Business School Conference
June 20 and 21st , 2008 in London, U.K.

Speaker at a Research Symposium entitled: "Who Controls and Disciplines the Firm: Politicians, Regulators, Pyramids, Markets?"at the European Accounting Association's 31st Annual Congress
Venue: Erasmus University, Rotterdam, The Netherlands, April 2008

London Business School/PwC CFO Forum
Title of Talk: Shouldering the Weight of Integrity in Finance
Audience: CFOs of FTSE 100 corporations
London, England January 29, 2008

Discussant at 22nd *Contemporary Accounting Research* Conference
November 9 and 10, 2007 in Montréal, Québec, Canada

Panel member: Covering Activist Investors
Society of American Business Editors and Writers Fall Workshop
October 2007, Chapel Hill, NC

Panel member: Accounting and Economic Growth
American Accounting Association Annual Meeting
Chicago, Illinois August 2007

Commerce and Culture in China, UNC Program in the Humanities
Title of Talk: The State of Capital Markets in China
Chapel Hill, NC July 2007

Governance Roundtable: A Dialogue Between Academics and Board Members
January 2007, San Diego State University

World View Community College Symposium on The Global Economy
Title of Talk: The State of Capital Markets in China
Chapel Hill, NC November 2006

Discussant at 16th Annual Conference on Financial Economics and Accounting
November 2005, Chapel Hill, NC

Panel member: Panel on Corporate Governance in China and Asia. Held in San Francisco, CA, July 2005 at the American Accounting Association Annual Meeting. The panel also included Joseph Fan and TJ Wong from Chinese University of Hong Kong, and Wei-Guo Zhang, Chief Accountant at the Chinese Securities Regulatory Commission

Discussant at the 2003 UNC Tax Symposium

WorldatWork Summer Research Camp
One of four presenters. Conference concept: to foster in-depth discussion of leading edge research in economics, accounting,finance, organizational behavior, sociology, and psychology.
July 16-19, 2001, Deer Valley, Utah

1997 AAA Convention
CPE Session on Corporate Governance Research in Accounting
Dallas, Texas, August 1997

1997 AAA Doctoral Consortium
Plenary Session: Corporate Governance Research in Accounting
Tahoe City, California, June 1997

1996 AAA Doctoral Consortium
Plenary Session: Economic Models of Disclosure in Capital Markets
Tahoe City, California, June 1996

The Council of Strategic Planning Executives of the Conference Board
Presentation on Executive Compensation and Firm Growth
The Carleton Hotel, Washington DC, June 1996

The Conference Board: 1996 Executive Compensation Seminar
Presentation on Economic Value Measures and Executive Compensation
Hotel Nikko Chicago, May 1996

Tools for Executive Survival: Panel on Derivative Financial Instruments
Stanford University Law School,   June 1995

1995 Big Ten Doctoral Consortium
Plenary Session: Corporate Governance, University of Chicago, April 1995

DISSERTATION COMMITTEES

Dan Amiram (co-Chair)
University of North Carolina
Placed at Columbia University (2011)

Derrald Stice
University of North Carolina
Placed at Hong Kong University of Science and Technology (2011)

Ed Owens (Co-Chair)
University of North Carolina
Placed at University of Rochester (2010)

Hyungshin Park
University of North Carolina
Placed at Southern Methodist University (2010)

Paul Brown (Thesis Examiner)
University of Technology Sydney
Sydney, Australia (2010)

Christopher Williams (Chairman)
University of North Carolina at Chapel Hill
Placed at University of Michigan (2009)

Ryan Ball (Chairman)
University of North Carolina at Chapel Hill
Placed at University of Chicago, Booth School of Business (2008)

Scott Dyreng
University of North Carolina at Chapel Hill
Placed at Duke University (2008)

Sudarshan Jayaraman
University of North Carolina at Chapel Hill
Placed at Washington University, St. Louis (2007)

Jim Irving
University of North Carolina at Chapel Hill
Placed at College of William and Mary (2006)

Courtney Edwards
University of North Carolina at Chapel Hill
Placed at University of North Carolina at Chapel Hill (2005)

Zhonglan Dai (Chairman)
University of North Carolina at Chapel Hill
Placed at University of Texas at Dallas (2005)

Chris Petrovitz
University of North Carolina at Chapel Hill
Placed at New York University (2005)

Maria Nondorf (Co-Chairman)
University of North Carolina at Chapel Hill
Placed at University of California Berkeley (2003)

Jennifer Blouin
University of North Carolina at Chapel Hill
Placed at Wharton (2003)

Brian Rountree
University of North Carolina at Chapel Hill
Placed at Rice University (2003)

COMMITTEE SERVICE AT KENAN-FLAGLER BUSINESS SCHOOL

Area Chair of the Accounting Group	2006 – present
Promotion and Tenure Committee	2005 – 2009
Faculty Advisory Committee	2003-2004
Dean's Strategy Steering Committee	2003-2004
Entrepreneurial Concentration Committee	2003-2004
Kenan-Flagler Business School Branding Committee	2003-2004
Served on committees to chose the Weatherspoon Award winners for PhD Teaching , MBA Teaching and Distinguished Research	2003-2006

EXECUTIVE TEACHING

Adtran, Inc. Board of Directors Training	2011
Gearson Lehrman Group Education Master Class, New York City	2006
Philip Morris USA	2006 & 2007
Fidelity Investments, Boston	2005
Senior Executive's Institute	2003 & 2005
UNC Journalism Workshop	2004, 2005 & 2007
Glaxo Wellcome	2001
Andersen Consulting	1997-1999

INVITED RESEARCH PAPER PRESENTATIONS

1. Tsinghua University, Beijing, China	July	2011
2. Baruch CUNY	June	2011
3. Indiana University	April	2011
4. Rice University	March	2011
5. University of Arizona	February	2011
6. Carnegie Mellon University	January	2011
7. Penn State University	December	2010
8. Stanford University	August	2010
9. University of Chicago	April	2010
10. Wharton	February	2010
11. Tilburg University	January	2010
12. ICAEW Information for Better Markets Conference London, U.K.	December	2009
13. MIT	November	2009
14. University of Toronto	November	2009
15. University of Michigan	October	2009
16. Boston University	May	2009
17. Southern Methodist University	April	2009
18. University of Houston	February	2009
19. University of Technology Sydney	January	2009
20. University of Missouri	November	2008
21. Columbia University	November	2008
22. Danish Center for Accounting and Finance Conference Copenhagen, Denmark	June	2008
23. Shanghai University of Finance and Economics	April	2008
24. Peking University, Beijing, China	April	2008
25. Central University of Finance and Economics, Beijing	April	2008
26. Yale University, Finance Seminar	March	2008
27. London Business School	January	2008
28. Chinese University of Hong Kong	December	2007
29. Washington University in St. Louis	November	2007
30. Harvard Business School	June	2007
31. Tel Aviv University	May	2007
32. University of Chicago (*JAR* Conference)	May	2007
33. Wharton	April	2007
34. Rotterdam School of Management	March	2007
35. Harvard Business School	January	2007
36. University of Southern California	January	2007
37. UCLA	November	2006
38. University of Maryland	May	2006
39. Chinese University of Hong Kong	April	2006
40. Emory University	December	2005
41. University of Toronto	October	2005
42. London Business School	July	2005

43. International Conference on Corporate Governance In China and Asia, Shanghai, China	March	2005
44. Chinese University of Hong Kong	March	2005
45. Erasmus University, Rotterdam, The Netherlands	October	2004
46. University of Michigan	October	2004
47. Hong Kong University of Science and Technology	June	2004
48. University of Texas at Austin Interdisciplinary Corporate Governance Conference	April	2004
49. University of California Davis Interdisciplinary Corporate Governance Conference	April	2004
50. University of Virginia Law School John M. Olin Conference: Empirical Research in Corporate Bankruptcy and Securities Law	February	2004
51. University of Technology Sydney, Australia	January	2004
52. George Washington University	January	2004
53. University of Oregon	May	2003
54. University of Chicago (*JAR* Conference)	May	2003
55. University of Minnesota	May	2003
56. University of Wisconsin, Madison	February	2003
57. University of Iowa	January	2003
58. University of California Berkeley	January	2003
59. Duke/UNC Fall Research Camp	September	2002
60. Stanford Summer Camp	July	2002
61. Yale University	April	2002
62. University of Rochester	January	2002
63. Minnesota Accounting Theory Conference	October	2001
64. Duke	September	2001
65. Columbia University	February	2001
66. University of Rochester	May	2000
67. Carnegie Mellon University	April	2000
68. University of Minnesota	February	2000
69. *CAR* Conference, Vancouver British Columbia	October	1999
70. University of North Carolina, Chapel Hill	December	1997
71. UCLA	December	1997
72. University of British Columbia	November	1997
73. New York University	November	1997
74. University of Texas at Austin	October	1997
75. Ohio State University	October	1997
76. University of Iowa	February	1997
77. Cornell University	October	1996
78. Stanford Summer Camp	August	1996
79. Harvard University	October	1995
80. Wharton	December	1994
81. University of Michigan	November	1994
82. Columbia University	October	1994
83. University of Texas at Austin	October	1994
84. University of Maryland	November	1993

85. Northwestern University	October	1993
86. University of Illinois, Champaign	September	1993
87. University of Rochester	January	1993
88. University of Iowa	October	1992
89. University of California Berkeley	September	1992
90. College of William and Mary	March	1992
91. University of Minnesota	October	1990
92. Stanford University	May	1989
93. University of Chicago	May	1988
94. University of Florida	May	1988
95. Wharton	April	1988
96. Washington University in St. Louis	April	1988
97. University of Pittsburgh	April	1988