The Expected Rate of Credit Losses on Banks' Loan Portfolios

Trevor S. Harris
Arthur J. Samberg Professor of Professional Practice
Columbia Business School
Email: tsh1@columbia.edu

Urooj Khan
Assistant Professor
Columbia Business School
Email: uk2117@columbia.edu

Doron Nissim
Ernst & Young Professor of Accounting and Finance
Columbia Business School
Email: dn75@columbia.edu

September 2014

The authors gratefully acknowledge the helpful comments made by Mary Barth, Gauri Bhat, Leslie Hodder, Scott Liao, Dushyant Vyas, Chris Williams, two reviewers and seminar participants at the 2013 AAA Annual Meeting, the 24th Annual Conference on Financial Economics and Accounting, the Burton seminar at Columbia Business School, Emory University, London Business School, Singapore Management University and Washington University at St. Louis.

The Expected Rate of Credit Losses on Banks' Loan Portfolios

Abstract

Estimating expected credit losses on loan portfolios of banks has always been a difficult issue for investors and analysts when assessing the profitability of banks. The issue has become of increasing interest to academics and regulators as the FASB and IASB debate new regulations on how to adjust their impairment regulations for loans, and as banking regulators increase their utilization of top down stress tests. This study develops a measure of next year's expected rate of credit losses (*ExpectedRCL*) that is a linear combination of various credit risk-related measures disclosed by banks. *ExpectedRCL* performs substantially better than net charge-offs, realized credit losses, and fair value of loans in predicting realized credit losses, and reflects all the credit loss-related information in these variables. *ExpectedRCL* also contains incremental information about future credit losses relative to the allowance and provision for loan losses.

Keywords: Banks, credit loss, loans, loan loss provisions, standard setting

I. Introduction

This paper develops a measure of an expected rate of credit losses on a bank's loan portfolios using publicly available disclosures. For most banks, lending is a primary source of value creation and risk with economic profitability determined by the yield charged relative to the cost of funds and credit risk *realized*. There is a long history in the accounting literature of studying the information contained in the various measures of loans and the related credit risk disclosures (e.g., Wahlen 1994; Barth et al. 1996). Much of the academic research considers the discretionary nature of various disclosures and also whether fair-value measures of loans provide incremental information relative to amortized cost measures. We have seen renewed interest in the analysis of credit risk in banks (Blankespoor et al. 2013; Cantrell et al. 2014) as the potential inadequacy of current practices is debated after the recent financial crisis. This interest goes beyond the academic literature, for example, we see the Financial Accounting Standards Board [FASB] and the International Accounting Standards Board [IASB] discussing various changes in how expected credit losses might be reflected at the initiation of the loan. Their ideas differ somewhat but the IASB concluded their deliberations in July 2014 and will require recognition of credit losses up to one-year ahead at the initiation of a loan.[1]

Bank regulators are also interested in assessing the credit risk in loan portfolios with a renewed focus since the crisis as the Federal Reserve and other non-US Central Banks have deployed regular stress-tests to monitor the capital adequacy and capital distribution policies of banks. In these tests they have developed methodologies to assess the one-year ahead expected credit losses to include in their stress analysis. While the current stress tests for the largest banks

[1] The IASB issued IFRS 9 *Financial Instruments* on July 24, 2014 which requires recognition of expected credit losses. The new standard requires that "[A]t each reporting date, an entity would recognise a credit loss allowance or provision equal to 12-month expected credit losses (i.e., based on the probability of a default occurring in the next 12 months)." (Ernst and Young 2014, pg. 6). IFRS 9 is effective for annual periods beginning on or after January 1, 2018.

use highly detailed data there has been a growing interest in using top-down stress tests based on publicly available data suggesting a need for a model of expected credit losses (e.g. Kapinos and Mitnik 2014 and Hirtle et al 2014).

A measure of expected credit losses can also be useful to others. In order to assess a bank's profitability and value, it is important for analysts, investors and other users to find a good measure of expected credit losses that will be conditional on the accounting system.[2] It is also plausible that auditors and others concerned with the quality of accounting measures would seek to independently estimate a measure of expected credit losses benchmark for assessing the quality of a company's Allowance for Loan and Lease Losses (ALLL) (and by association the Provision for Loan and Lease Losses (PLLL)).

Managers and bank examiners have highly disaggregated data to set their expectations and come up with more precise estimates of expected credit losses. But all others have to rely on public disclosures to assess expected credit losses. The question we address is whether current, publicly available disclosures can be used to derive a measure of expected credit losses that improves on the currently reported measures such as ALLL. Cantrell et al (2014) suggest that net historical measures of loans do a better job than fair value measures of loans in predicting future credit losses (measured as charge offs and non-performing loans). We extend this analysis by asking the more direct question of whether we can derive an expected (one year ahead) realized credit loss measure. This paper develops (using current accounting disclosures) and then tests a measure of expected credit losses that can be estimated for a bank. We call this measure the Expected Rate of Credit Losses (*ExpectedRCL)* and compare it to various alternative

[2] One of the authors conducted an informal private survey of the analysts at a large sell side firm in 1997 asking for key drivers of profitability in their sectors. All the bank analysts included provisions for loan losses as one of the top 5 drivers. They also varied significantly in how they forecasted these provisions. A review of several sell side analysts models published in 2013 reveal that the provisions are loosely estimated as a function of expected charge-offs.

measures of credit risk. We focus on the one-year-ahead credit losses as this is the period used in the stress tests, in current definitions of ALLL used by other regulatory requirements (e.g. Federal Deposit Insurance Corporation (FDIC)) and is the focus of immediate impairment recognition currently favored by the IASB. In addition, moving beyond a year's credit introduces significant measurement problems because of the turnover of loans and changing macro conditions, making the control for other factors much more difficult using public disclosures.

Currently, banks disclose average loan yield, loan duration, and the composition of the loan portfolio, including the amount of nonperforming loans (NPLs). Each of these measures provides some indication of credit quality. On an ongoing basis banks write-off loans that are deemed to be uncollectible (charge-offs) and then periodically, when balance sheets are prepared, they report an allowance for loan and lease losses that reflects a reserve for future write-offs against period end loans. The ALLL is based on outstanding loan balances and presumably NPLs, but by regulation banks can only use current patterns of probable and estimable losses (usually referred to as incurred losses) rather than an ex ante notion of credit risk, when estimating the ALLL. The charge to income is termed a provision for loan and lease losses (PLLL), and reflects both net loan charge-offs (NCOs) and the change in ALLLs over the relevant period.

Past research has shown that each of these measures is problematic in measuring expected credit losses. We investigate whether the existing credit-related measures and disclosures provided by banks can be used together to better assess the next year's rate of credit losses. We estimate this measure, *ExpectedRCL*, by obtaining estimated annual coefficients from cross-sectional regressions and then apply these to each bank's periodic measures of the relevant variables, to evaluate its out-of-sample predictive accuracy relative to the next year's credit losses and manager's expectations of future credit losses embedded in the disclosed fair value of loans. We also compare the overall and incremental information in *ExpectedRCL* with that in the fair value of loans, ALLL and PLLL in explaining realized credit losses.

We use accounting data from regulatory consolidated financial statements (FR Y-9C reports) for the period Q1:1996 through Q3:2012. To mitigate the impact of discretionary managerial choices in recognizing loan losses (Beaver et al. 1989; Elliott et al. 1991; Bushman and Williams 2011), we make adjustments to the reported measures based on theoretical considerations and prior empirical findings. In our estimation of the structural model, the coefficients on the various credit-risk related variables have the expected signs and are highly significant. The most significant explanatory variables include current period NCOs, a measure of unexpected change in NPLs, and the level of NPLs. We also estimate the model separately for the period preceding the subprime financial crisis (Q4:1996-Q2:2007) and for the period since the financial crisis (Q3:2007-Q3:2012). The coefficients generally have the same signs in both sub-periods but, as expected, they almost all change significantly between the two sub-periods consistent with greater credit loss implications since the beginning of the financial crisis. An important fact that we document is that the proportion of the unexpected change in non-performing loans that turns into credit loss in the subsequent year has doubled since the start of the financial crisis

In our out-of-sample analyses, we find that *ExpectedRCL* performs well in predicting credit losses. More specifically, *ExpectedRCL* performs substantially better than NCOs or the realized rate of credit losses in predicting credit losses.[3] Further, *ExpectedRCL* reflects all the information in either of these two variables for predicting credit losses.

[3] We estimate the realized rate of credit losses by undoing the discretion embedded in loan charge-offs. See section 3 for more details on the estimation of the realized rate of credit losses.

Banks have been disclosing the fair value of their loan portfolios since 1992 and the fair value of a loan should reflect all of its *expected* credit and interest rate risk. Cantrell et al. (2014), compares the historical cost (net of ALLL) and fair value of loans to see which better reflects forward credit losses. We extend this analysis by first examining if *ExpectedRCL* reflects management's expectations of credit losses as incorporated in the disclosed fair value of loans. Consistent with the high significance of *ExpectedRCL* in explaining realized credit losses, the disclosed fair value of loans is negatively correlated with *ExpectedRCL*. Then we test if the disclosed fair value of loans adds to the information contained in *ExpectedRCL* in explaining realized credit losses, and find it does not. In contrast, *ExpectedRCL* contains substantial incremental information relative to the fair values of loans in explaining realized credit losses. Further, *ExpectedRCL* also contains incremental information about future credit losses relative to the ALLL and PLLL, , the explanatory power of *ExpectedRCL* for future credit losses is greater than that of the ALLL or PLLL, and unlike these measures it is a less biased predictor of credit losses.[4]

our measure has several potential applications. First, the recently issued IFRS 9 *Financial Instruments* requires entities to recognize 12-month's expected credit losses on its loan portfolio at initiation of a loan. Our metric, *ExpectedRCL*, serves as an objective benchmark to assess the adequacy of the new disclosure of 12-month expected credit losses under IFRS 9. Second, the Federal Reserve employs the Capital and Loss Assessment under Stress Scenarios (CLASS) model to assess the capital and performance of the US banking system under varying macroeconomic scenarios (Hirtle et al 2014). The CLASS model is intended to complement other detailed supervisory stress tests such as those used in Dodd Frank Act Stress Tests

[4]*ExpectedRCL* does not subsume all the information in ALLL and PLLL, as these are based on the more detailed information that managers have and while discretionary should contain private information.

(DFAST) or Comprehensive Capital Analysis and Review (CCAR). However, unlike these detailed supervisory stress tests which are based on very detailed proprietary information, the CLASS model uses public financial disclosures of banks to produce quarterly income and capital projections. An important input in the CLASS model and other top-down stress tests (e.g. Kapnos and Mitnik 2014) is the credit loss ratio on a bank's loan portfolio which is currently based on NCO rates. Our metric, *ExpectedRCL*, is substantially better in predicting credit losses than NCOs and potential exists for it to be used in CLASS models to improve quarterly income and capital projections. Finally, we find that *ExpectedRCL* is a less biased and more timely predictor of expected credit losses than ALLL. Thus, analysts and investors may consider using *ExpectedRCL* instead of ALLL (or the change in *ExpectedRCL* as a substitute for PLLL) to better assess the profitability and credit risk of banks.

In addition, by providing an improved measure of expected credit losses, this study is related to other research issues in accounting, banking and finance. Prior studies examine the cross-sectional and time-series determinants of banks' PLLL timeliness, such as loan portfolio composition and market, contractual, and regulatory incentives for bank managers to exercise discretion over LLPs (e.g., Liu and Ryan 1995; 2006). Laeven and Majnoni (2003) provide empirical evidence of banks delaying provisioning for bad loans until cyclical downturns have set in, thereby magnifying the impact of economic cycles on banks' income and capital. Some recent studies examine the impact of timeliness of loan loss provisioning on pro-cyclicality of bank lending (Beatty and Liao 2011), discipline and monitoring of bank risk-taking (Bushman and Williams 2012), stock liquidity risk, bank tail-risk, and the contribution to systemic risk (Bushman and Williams 2011). Bhat et al. (2012) document that the different types of credit risk modeling impacts the timeliness of loan loss provisioning and pro-cyclicality of loan origination.

Several studies have also used the timeliness and estimation errors of banks' loan loss provisioning as a proxy for their transparency or disclosure quality (Bushman and Williams 2011; Ng and Rusticus 2011).

ExpectedRCL is one particular linear combination of publicly available credit risk disclosures of banks that outperforms all other disclosed credit risk metrics in predicting one-year ahead credit losses. However, due to the richness of the detailed bank disclosures infinite summary statistics can be constructed using linear and nonlinear combinations. Since some of these possible summary statistics may predict credit losses better than *ExpectedRCL* we do not make any claims about *ExpectedRCL* being the optimal measure of expected credit losses constructed using public disclosures.

The rest of the study proceeds as follows. Section 2 describes existing credit risk related measures disclosed by banks and their limitations. Section 3 develops the methodology for estimating the expected rate of credit losses. Section 4 discusses the sample selection procedures and sample data. The empirical findings are presented in section 5 and section 6 concludes the paper.

II. Publicly Disclosed Metrics Relevant to a Structural Model ofCredit Risk

Lending is the primary, asset-based, income generating activity of most commercial banks. The income is derived from the yield that economically includes at least three components - the time-value of money, interest rate risk and credit risk. The first two components are impacted primarily by macroeconomic factors and the funding mix of the bank. It is widely accepted that the portion of the yield reflecting the time value of money and the interest rate risk should be recognized over time using an effective yield calculation. Currently, the credit loss or credit risk component at issuance is not separated for US GAAP accounting purposes. For loans that are measured at amortized cost, once a loss due to a borrower's inability to pay the full cash flow obligation is probable ("incurred") and reasonably estimable, an expected (impairment) loss is measured and recognized as a reserve or write-off.[5]

Currently credit risk is reflected in the balance sheet through an ALLL and in the income statement through the charge to income via the PLLL (i.e., the sum of net charge-offs (LCOs) and the change in the ALLL. Either of these might seem to be a good measure of expected credit losses. However, as discussed in Ryan (2007) there are other disclosures that reflect credit – related information, including details of the type and composition of loans, the yield on and duration of the loans, the extent to which loans are currently classified as non-performing and the loan charge offs (LCOs) themselves. We first discuss ALLL and PLLL and the related research that suggests why they may not be a good measure of *ExpectedRCL.* Then we discuss the other measures for evaluating the credit risk of banks' loan portfolios, and explain the logic for their incorporation in our structural model used to measure *ExpectedRCL*.

The allowance and provision for loan and lease losses

Under current GAAP, the reported ALLL represents management's estimate of the amount of loans and leases held for investment that the bank will be unable to collect, based on information and events as of the date of the financial statements, using an "incurred" loss perspective partly intended to minimize aggressive earnings management.[6] The allowance is

[5] Current U.S. GAAP is based primarily on SFAS 5 Accounting for Contingencies and SFAS 114 *Accounting by Creditors for Impairment of a Loan*, and international accounting standards is based on IAS 39 *Financial Instruments: Recognition and Measurement*, subject to the changes in IFRS 9 *Financial Instruments*, issued July 2014 and effective in 2018.

[6] In the late 1990s the SEC Chairman and Chief Accountant expressed concerns about excess loan loss provisioning and this led to SunTrust restating its earnings upwards from 1994 through 1996 (Wall and Koch 2000). Then in 2001 the SEC issued Staff Accounting Bulletin (SAB) 102 which "expresses certain of the staff's views on the

currently netted against loans on the balance sheet. Notably, no allowance is recognized for loans and leases held for sale because they are reported at the lower of cost or fair value. Thereby, already being a number net of an expected loss. ALLL relates only to period-end reported loans so provides a snapshot at a point in time and does not reflect activity during the entire accounting period. The ALLL will vary as a portion of loans as a result of the composition of the loan portfolio itself as well as due to the relative conservativeness of any charge-off policy, which impacts the loan balances themselves.

A common misconception is that the ALLL reflects all expected credit losses for the portfolio of loans. Under current GAAP this is not the case; as the ALLL generally reflects probable losses based on events that have incurred to that point rather than expected future losses. It is also plausible that once expected loss recognition is made, ALLL includes expected credit losses that go beyond the next twelve months. Currently, no disclosures exist for outsiders to be able to assess this.

While ALLL reflects the "stock" of expected credit losses, the PLLL is the charge for the period that is netted against the recognized interest to calculate bank profitability. It is calculated as the total of NCOs and the change in the ALLL during the period due to operating activities (i.e., excluding changes due to non-operating activities such as business combinations, divestitures, and foreign currency translation affects). As a result, PLLL includes both a measure of current credit risk and any measurement errors in either the beginning or ending ALLL. The PLLL is usually a major expense in banks' income statements reflecting a mix of realized and expected losses using the current incurred loss approach.

---

development, documentation, and application of a systematic methodology … for determining allowances for loan and lease losses in accordance with generally accepted accounting principles." SAB 102 reaffirms the need for clear documentation on why the losses are deemed to be probable and the methodology for estimation, thus reinforcing an "incurred" loss notion.

Although users of banks' financial information often utilize the ALLL and PLLL as indicators of credit risk or expected credit losses[7], these metrics have several important limitations. First, both measures are discretionary and any increment or decrement in ALLL has an equivalent impact on earnings before taxes, via the PLLL. Research shows that they have been used by banks to manage book value and earnings (e.g., Beaver et al. 1989; Elliott et al. 1991; Griffin and Wallach 1991; Beaver and Engel 1996; Wall and Koch 2000; Bushman and Williams 2011). Banks can exercise discretion over ALLL and PLLL to smooth earnings across business cycles, to adjust regulatory capital, or to manage taxes (e.g., Moyer 1990; Scholes et al 1990; Beatty et al 1995; Collins et al 1995; Ahmed et al 1999; Liu and Ryan 2006). Second, even in the absence of intentional bias, the ALLL and PLLL contain measurement error as they are based on subjective estimates. The relative magnitude of the error is likely to be especially large for the provision, which is calculated indirectly based on the change in the allowance and so reflects any measurement error in either the beginning or ending balance of the allowance.[8] Third, the ALLL and PLLL are supposed to reflect only incurred (probable) losses, not expected ones. "Under GAAP, the purpose of the ALLL is not to absorb all of the risk in the loan portfolio, but to cover probable credit losses that have already been incurred."[9]

Consistent with the above limitations, research shows that the ALLL and PLLL provide little or no incremental information relative to other credit risk measures—primarily NPLs—in explaining bank share prices (e.g. Beaver et al. 1989; Calomiris and Nissim 2012). Moreover, due to its timing limitations and the discretionary nature of the PLLL, in many cases loan loss

---

[7] Typical ratios reported in analysts' reports include PLLL/Average Loans, ALLL/Loans and NCOs/Loans.

[8] For a similar argument with respect to the relative measurement error of balance sheet versus income statement securities' gains and losses, see Barth 1994.

[9] The Interagency Policy Statement on the Allowance for Loan and Lease Losses, issued by the federal financial institution regulatory agencies in December 2006 (http://www.fdic.gov/news/news/financial/2006/fil06105a.pdf).

provisions are positively rather than negatively associated with bank stock returns and future cash flows (e.g., Beaver et al. 1989; Elliott et al. 1991; Griffin and Wallach 1991; Wahlen 1994; Liu and Ryan 1995; and Beaver and Engel 1995).

In sum, ALLL and perhaps PLLL are plausible measure of expected credit losses, but current measurement criteria and the flexibility in measuring them, combined with existing research suggest that empirically these may not be the best measures we can use to estimate expected realized credit losses. Moreover, ALLL as measured under GAAP is created from a series of primary indicators some of which are available in public disclosures. In assessing how to estimate an expected rate of credit losses for potential use in top down stress tests, in considering the estimates to be used under IFRS 9 and the future FASB standard or for profitability analysis we look to the other primary measures in constructing an alternative.

Loan balances and loan composition

The primary source of credit loss is the underlying loans. The loss results from a default and is determined by the amount of expected cash that is non-recoverable. The two key factors that arise are the probability of default occurring and then the loss given the default. The borrower, the existence of any collateral, the location, the timing and duration (relative to economic cycles) are among the factors that would influence the loss. Banks clearly have detailed information on all these components, but public disclosures are more limited, with the level of detail varying depending on the source of the data.

Moving one level below aggregate loans, we note that banks' loan portfolios consist primarily of real estate (the largest group), commercial and industrial (C&I), and consumer loans. Other loans include loans to: depository institutions, farmers, non-depository financial institutions, foreign governments and official institutions, and lease financing receivables. The actual and expected rate of credit losses vary substantially across and within these categories (Nissim and Penman 2007). The predictability of credit losses on loan portfolios also varies across loan categories. Credit losses on portfolios of individually small and homogenous loans (e.g., credit card receivables and other consumer loans) are usually estimated using statistical models based on historical data and past experiences. Thus, the ALLL recorded for such loans should be reasonably close to the expected credit losses on these loans even if an incurred loss model is used, subject to there being more variability at different stages of a credit cycle. On the other hand, credit losses on individually large and heterogeneous loans (e.g., C&I loans and commercial real estate loans) are typically evaluated on a loan-by-loan basis by loan officers and are often renegotiated. SFAS No. 5's criteria for recognizing credit losses for such loans often are not met until shortly before these types of loans default (Ryan 2007). Additionally, more discretion exists in estimating credit losses for large and heterogeneous loans and empirical research finds that loan officers' incentives are to hide loan default on the loans they originated (Udell 1989; Berger and Udell 2002).

Historically, the rate of credit losses was lowest for real estate loans and highest for consumer loans, especially credit card loans. However, this was largely as a result of the quality of the underlying collateral relative to the loans being made. During the 2005 through 2007 period when loans were being made on inflated real estate prices, the poor quality of the real estate collateral relative to the size of loans being made against it (including the second liens) realistically added to the credit risk, rather than mitigated against it. Yet ALLLs were low as the poor quality was not yet reflected in the underlying historical data. Then once the credit crisis set in, banks incurred large credit losses on real estate loans, especially closed-end loans secured by 1-4 family residential properties with junior liens.

In considering a model of expected credit losses it is therefore a natural starting point to consider the losses (as a rate) and key indicator measures relative to the loans. We also need to consider the composition of loans. As a result of the data set we use to begin with we limit the empirical analysis to consider real estate, consumer, and other loans including commercial and industrial (C&I). In time moving to incorporate call report data we expect to partition firms based on location and add additional sub categories of loan.

Loan Duration

Loan duration is likely to contain relevant information about expected credit losses for at least two reasons. In many cases, the longer the loan horizon, the more uncertainty there will be about the underlying business (e.g. potential for default). This makes banks more reluctant, in general, to extend long-term credit to high credit risk borrowers or for unsecured loans. Therefore, expected credit losses are likely to be negatively related to loan maturity. The second effect is related to uncertainty about the macro-economy and hence future interest rates, which can also lead to a liquidity premium. Holding credit risk constant, loan yield typically increases with loan duration leading to the norm of an upward sloping yield curve for US government bonds. Unlike the previous effect, however, this indirect effect reverses if the term-structure is inverted. Publicly available data does not allow for estimation of loan duration for the different loan categories.

Loan yield

IFRS 9 and the expected new FASB standard on Financial Instruments make it clear that a significant determinant of the interest rate that banks charge on loans is expected credit losses. So the (tax-equivalent[10]) average interest rate on the loan portfolio is likely to be an (imperfect) indicator of the expected rate of credit losses at loan origination. Measurement error in this credit quality proxy results from two sources. First, the loans' yield is affected by additional factors besides expected credit losses, including the macroeconomic and interest rate environment, loan duration, interest rate characteristics (e.g., fixed versus variable or hybrid rate), and embedded options (e.g., prepayment penalties, interest rate floors or ceiling).[11] Second, the expected credit losses on existing loans change over time, while the book yield remains unchanged or floats with market rates.[12] One issue with using loan yield in the empirical estimation is that the loan yield by loan type is not available in most of the time series.

Non-performing loans [NPLs]

Loans that are not paying interest or principal as a result of a borrower's credit problems are classified as non-performing loans [NPLs]. NPLs are usually defined as the total of nonaccrual loans and restructured (troubled) loans. Nonaccrual loans are loans on which interest accruals have been discontinued also due to borrowers' financial difficulties. Typically, an unsecured loan is placed on non-accrual status once interest payments are 90 days past due, but this is not a requirement. A loan is considered restructured when the bank grants a concession to the debtor that changes the terms of the loan to prevent it from being charged-off so long as the

[10] We gross up the interest rate on tax-exempt loans based on the disclosures provided. However, this is generally immaterial.
[11] Additionally, loan yield as well as credit risk is also impacted by the type of collateral and guarantees, if any.
[12] Market rates on loans can vary as a result of credit risk, market interest rate and potentially other factors e.g., tax rates and collateral.

debtor can fulfill the new terms. Given their nature NPLs are an obvious factor to use in a model of *ExpectedRCL.*

NPLs are considered relatively nondiscretionary (Beaver et al. 1989; Griffin and Wallach 1991) and accordingly have served as instruments in previous studies to partition other measures of credit quality into discretionary and nondiscretionary components (Wahlen 1994; Beaver and Engel 1996; Collins et al 1995). Beaver et al (1989) indicate that although nonaccrual and restructured loans are relatively nondiscretionary, their measurement does involve judgments that vary across banks.[13] For example, banks differ in the delinquency periods that trigger non-accrual classification, and some banks recast loan terms to avoid delinquency classification, a practice referred to as "evergreening." In addition, firms that employ relatively conservative charge-off policies have relatively lower NPL levels since they tend to remove large portions of problem loans from their books, and NPLs relate to reported loans only.

Even if all banks were using identical NPL classification and charge-off policies, empirical measures of NPL will vary across banks for various reasons including, loan composition and NPL classification criteria across loan categories. Relatedly, the likelihood of default and the expected loss given default vary substantially across categories of NPLs; for example, because of collateral such as guarantees by the U.S. government or its agencies versus other types of collateral (Araten et al. 2004). That said, as loans within a category change, we can expect some change in the rate of NPLs.

Loan charge-offs [LCOs]

When a loan is deemed uncollectible, the loan balance is charged-off effectively against the ALLL. LCOs minus recoveries of previously charged-off loans are known as Net Charge

[13] For example, in its 2007 Annual Report, CapitalSouth Bancorp states, "Anticipating an extended downturn in the real estate market, we took a more aggressive approach in determining which loans were put on nonaccrual status during 2007." page 42.

Offs [NCOs]. At each reporting period the ALLL is reevaluated and any additional charge occurs through income as the PLLL. So LCOs and NCOs are measures of realized credit loss in the period and have an indirect impact on the balance sheet and income statement. In principle, over relatively short periods (such as a quarter) an unbiased rate of NCOs (relative to the loans) should be an indicator of credit loss on a portfolio of loans, and it has been used as a measure of credit risk in prior research (e.g., Cantrell et al 2014) as well as in recent analyses of top-down stress tests (e.g., Kapinos and Mitnick 2014). So we consider a lagged measure of NCOs as a natural factor in a model of *ExpectedRCL*.

In assessing the degree of bias, research suggests that LCOs are often considered to be less discretionary than the PLLL or the ALLL (Moyer 1990; Wahlen 1994; Collins, Shackelford and Wahlen 1995; Beaver and Engel 1996). The likely reason is that banks are required to follow policies under which consumer loans are charged-off when they become a certain number of days delinquent (see Appendix A). However, banks still have some flexibility in implementing the guidance; for example, they are allowed to use more conservative charge-off policies. Moreover, for collateral-dependent loans (which includes mortgages) and for most commercial and industrial loans, banks have more discretion in measuring the amount of loss to be charged-off. Prior studies have demonstrated discretionary charge-off behavior by banks (e.g., Liu and Ryan 2006).

One approach to mitigate the impact of managerial discretion in LCOs is to measure charge-offs net of recoveries. NCOs may be less sensitive than gross charge-offs to variation in policies and implementation since firms that use conservative charge-off policies have large recoveries, which offset previously inflated charge-offs. However, NCOs can be relatively untimely; especially for large heterogeneous loans for which charge-off decisions are made loan by loan, as in the case of commercial loans. The lack of timeliness of NCOs is amplified when economic conditions are changing; for example, at the beginning of an economic downturn NCOs typically remain low for a while even though credit risk is rising. The opposite is true at the beginning of an economic upturn (Ryan 2007). This mismatch is especially likely during more extreme credit cycles. A bias in NCOs that can make it a poorer indicator of credit losses occurs when banks delay charging-off loans to avoid a decline in the ALLL which leads to an increase in the PLLL; as may have occurred in the recent financial crisis (Vyas 2011; Calomiris and Nissim 2012). Using a shorter horizon of the NCO may also reduce the impact of any bias.

III. Methodology

Given the currently disclosed measures we have discussed that are expected to reflect some dimension of expected credit losses, we specify the following model for the expected rate of credit losses for period t ($ExpectedRCL_t$) based on information available at time t-1:[14]

$$ExpectedRCL_t = \propto_0 + \propto_1 RealizedRCL_{t-1} + \propto_2 \frac{NPL_{t-1}}{Loans_{t-1}} + \propto_3 LoansYield_{t-1}$$

$$+ \propto_4 FloatLoanRatio_{t-1} + \propto_5 \frac{RELoans_{t-1}}{Loans_{t-1}} + \propto_6 \frac{ConsLoans_{t-1}}{Loans_{t-1}} + \varepsilon_{t-1} \qquad (1)$$

Where *RealizedRCL* is the realized rate of credit losses, measured relative to the average balance of loans, during the period. We will define this more precisely as we develop the model. *NPL* is non-performing loans, defined as the total of non-accruing loans, restructured loans, and delinquent loans accruing for more than 90 days. *LoansYield* is the ratio of tax-equivalent interest income on loans to the average balance of loans. *FloatLoanRatio* is an estimate of the

[14] We exclude the firm subscript from all specifications in the interest of parsimony.

proportion of loans that reprice or mature within one year, a proxy for loan duration.[15] The intercept ($\propto_0$) and the two loan composition variables capture the average effects of the three primary loan categories.[16,17] ε_{t-1} represents the net effect of all other relevant information at time *t*-1 for the prediction of the expected rate of credit losses in period *t* that is omitted from Equation (1).

Equation (1) is not directly estimable because the expected rate of credit losses (the measure we are aiming to estimate) is unobservable. However, with unbiased expectations, the difference between the realized and expected rates of credit losses should be unpredictable "white noise":

$$RealizedRCL_t = ExpectedRCL_t + \varepsilon_t^{RCL} \tag{2}$$

Thus, model (1) can be re-expressed by substituting Equation (2) into Equation (1):

$$\begin{aligned} RealizedRCL_t =& \propto_0 + \propto_1 RealizedRCL_{t-1} + \propto_2 \frac{NPL_{t-1}}{Loans_{t-1}} + \propto_3 LoansYield_{t-1} \\ &+ \propto_4 FloatLoanRatio_{t-1} + \propto_5 \frac{RELoans_{t-1}}{Loans_{t-1}} + \propto_6 \frac{ConsLoans_{t-1}}{Loans_{t-1}} + \varepsilon_t^{+} \end{aligned} \tag{3}$$

Where $\varepsilon_t^{+} = \varepsilon_{t-1} + \varepsilon_t^{RCL}$. Of course, $RealizedRCL_t$ can only be observed after the end of period *t* and is yet to be precisely defined.

[15] Specifically, we estimate the proportion of floating rate loans using the ratio of floating rate loans and securities to the total of loans and securities. We estimate floating rate loans and securities by subtracting the total of (1) "interest-bearing balances due from depository institutions," and (2) "federal funds sold and securities purchased under agreements to resell" from "earning assets that are repricable within one year or mature within one year."

[16] As discussed in Sections 2, loan portfolios also include additional smaller categories which are generally more comparable to C&I loans than to real estate or consumer loans.

[17] While using loan composition information in measuring expected credit loss rates is likely to improve the accuracy of prediction, it does have important limitations. First, there are many types of loan within each of the three major categories that we include in our estimation (real estate, consumer, and C&I), and considering the sub-categories would introduce too many parameters for our empirical analysis given we have limited sets of cross sections available for our analysis. Second, loans of the same type may still have different expected loss rates. For example, credit losses generally increase with bank size, with loan composition accounting for only a portion of that correlation (Nissim and Penman 2007). It appears that within each loan category, large banks have bigger losses presumably because they are willing to take on greater ex ante risk without fear of bankruptcy. In future analysis we will utilize call report data that impose some limitations on the variables we use but allows for more disaggregation of the loan composition.

To measure the realized rate of credit losses, we start with NCOs during the period. Ideally, we seek an unbiased measure of economically required charge-offs. As discussed in Section 2, banks exercise some discretion in recognizing charge-offs reported in their regulatory filings. Therefore, to derive a more unbiased estimate of credit losses we need to estimate and “undo” the discretionary component of NCOs. A biased NCO policy impacts the level of NPLs as discretionary acceleration or slowing down in the rate of charge-offs leads to unexpected changes in NPLs. Specifically, we estimate the unexpected change in nonperforming loans during a period and use a fraction of this to estimate the discretionary charge-offs (with a negative relation). Not all NPLs will become NCOs therefore we use a fraction of the unexpected change in NPLs to capture the discretionary portion of charge-offs. The fraction we use also captures the credit loss-equivalent of unexpected changes in NPLs that arises from changes in the credit quality of the loan portfolio.

To estimate the unexpected change in NPLs, we recognize that when the credit quality of loans is relatively stable, changes in NPLs should be due to changes in the size of the loan portfolios. Thus, any increase in NPLs that cannot be attributed to a change in the size of the loan portfolio suggests that either the credit quality of the loan portfolio has changed during the period or the bank has misstated NCOs. Either way, to derive a more representative measure of realized credit loss we need to adjust current NCOs for a portion of the unexplained change in NPLs. To do so, we start by estimating the unexpected change in NPLs during period *t* (ΔNPL_t^{unexp}) as:

$$\Delta NPL_t^{unexp} = NPL_t - Loans_t \times \frac{NPL_{t-1}}{Loans_{t-1}} \tag{4}$$

and specify the realized rate of credit losses as:

$$RealizedRCL_t = \frac{NCO_t + \gamma \Delta NPL_t^{unexp}}{AveLoans_t} = \frac{NCO_t}{AveLoans_t} + \gamma \frac{\Delta NPL_t^{unexp}}{AveLoans_t} \tag{5}$$

where *NCO* is Net Charge-Offs; γ is a parameter to be estimated, that represents the credit loss equivalent of a dollar of unexpected change in NPLs; $\gamma \Delta NPL_t^{unexp}$ is an estimate of either a changed credit quality or discretionary loan charge-offs; and *AveLoans* is the average balance of loans during the period.

Using Equation (5), Equation (3) can be re-expressed as follows:

$$\begin{aligned}\frac{NCO_t}{AveLoans_t} = &\propto_0 + \propto_1 \frac{NCO_{t-1}}{AveLoans_{t-1}} + \propto_1 \gamma \frac{\Delta NPL_{t-1}^{unexp}}{AveLoans_{t-1}} - \gamma \frac{\Delta NPL_t^{unexp}}{AveLoans_t} \\ &+ \propto_2 \frac{NPL_{t-1}}{Loans_{t-1}} + \propto_3 LoansYield_{t-1} + \propto_4 FloatLoanRatio_{t-1} \\ &+ \propto_5 \frac{RELoans_{t-1}}{Loans_{t-1}} + \propto_6 \frac{ConsLoans_{t-1}}{Loans_{t-1}} + \varepsilon_t^{+}\end{aligned} \tag{6}$$

Equation (6) is estimable because after period t all the variables are observable, including $\frac{\Delta NPL_t^{unexp}}{AveLoans_t}$. However, OLS estimation would result in biased and inconsistent estimates, because $\frac{\Delta NPL_t^{unexp}}{AveLoans_t}$ is likely to be strongly positively correlated with ε_t^{+}. This follows because unexpected shocks to credit quality are likely to affect both NPLs and realized credit losses. Fortunately, consistent estimates of the parameters can still be derived by redefining the intercept and disturbance of Equation (6) as follows:

$$\propto_0{}^{*} = \propto_0 - \gamma \overline{\frac{\Delta NPL_t^{unexp}}{AveLoans_t}} \tag{7}$$

$$\varepsilon_t^{*} = \varepsilon_t^{+} - \gamma \left(\frac{\Delta NPL_t^{unexp}}{AveLoans_t} - \overline{\frac{\Delta NPL_t^{unexp}}{AveLoans_t}} \right) \tag{8}$$

Where $\frac{\overline{\Delta NPL_t^{unexp}}}{AveLoans_t}$ is the cross-sectional average of $\frac{\Delta NPL_t^{unexp}}{AveLoans_t}$, and we estimate the following model:

$$\frac{NCO_t}{AveLoans_t} = \propto_0{}^* + \propto_1 \frac{NCO_{t-1}}{AveLoans_{t-1}} + \propto_1 \gamma \frac{\Delta NPL_{t-1}^{unexp}}{AveLoans_{t-1}}$$
$$+ \propto_2 \frac{NPL_{t-1}}{Loans_{t-1}} + \propto_3 LoansYield_{t-1} + \propto_4 FloatLoanRatio_{t-1}$$
$$+ \propto_5 \frac{RELoans_{t-1}}{Loans_{t-1}} + \propto_6 \frac{ConsLoans_{t-1}}{Loans_{t-1}} + \varepsilon_t^* \quad (9)$$

Equation (9) satisfies the OLS assumptions because, by definition, unexpected shocks to NPL are uncorrelated with time *t*-1 information, as measured by the explanatory variables. The adjustment to the intercept is required because in any given period the average credit loss shock across all banks is not likely to be zero. However, because this adjustment is assumed to be constant in the cross-section, it does not affect the cross-sectional differences in the estimated rate of credit losses across banks (on which we focus).[18]

Each quarter during the sample period, we estimate Equation (9) using all available observations and then use Equation (7) to estimate the intercept, $\propto_0$. We next use the estimated parameters and the current values of the explanatory variables for each firm to estimate the expected rate of credit losses for the next quarter ($\widehat{ExpectedRCL}_{t+1}$):

[18] It is counterintuitive that one can eliminate bias by excluding a variable and, indeed, in most cases omitting a variable would introduce or increase the bias of the remaining coefficients. However, our case is unique in that the regression coefficients are related to each other (through γ and $\propto_1$). To see a simpler example of the same effect, assume that both X1 and X2 affect Y, but X2 is correlated with the disturbance. Assume further that X1 is uncorrelated with either X2 or the disturbance, and that its effect on Y is the same as that of X2. The full model, i.e., Y = a0 + a1 X1 + a1 X2 + e, would result in a biased estimate of a1 because X2 is correlated with the disturbance. The reduced model, i.e., Y = a0 + a1 X1 + e, would result in an unbiased estimate of a1 because X1 is uncorrelated with the disturbance.

$$\widehat{ExpectedRCL}_{t+1} = \propto_0 + \propto_1 \frac{NCO_t}{AveLoans_t} + \propto_1 \gamma \frac{\Delta NPL_t^{unexp}}{AveLoans_t}$$

$$+ \propto_2 \frac{NPL_t}{Loans_t} + \propto_3 LoansYield_t + \propto_4 FloatLoanRatio_t$$

$$+ \propto_5 \frac{RELoans_t}{Loans_t} + \propto_6 \frac{ConsLoans_t}{Loans_t} \tag{10}$$

After estimating the expected rate of credit losses, we evaluate its ability to predict realized credit losses and compare it to alternative credit risk measures. For a sub-sample with available information, we also examine whether the estimated *ExpectedRCL* helps explain the disclosed fair value of loans, and whether it contains *all* the credit-related information contained in the disclosed fair value of loans as well as *incremental* information. Finally, we examine whether investors incorporate all the information in *ExpectedRCL* in pricing bank stocks.

IV. Sample and Data

We have chosen to focus on bank holding companies (BHCs) and so extract accounting data from regulatory consolidated financial statements (FR Y-9C reports) that BHCs submitted to the Federal Reserve System for the period Q1:1996-Q3:2012.[19] Under the Bank Holding Company Act, BHCs with total consolidated assets above a certain threshold amount, or that satisfy certain other conditions (e.g., have public debt), are required to file the FR Y-9C report on a quarterly basis. The asset-size threshold for filing the FR Y-9C report was $150 million through the fourth quarter of 2005, after which it was increased to $500 million. To make the sample comparable over time, we delete observations with total assets less than $500 million at March 2006 prices.

[19] In early versions of the paper we tested our results against market prices and were thus restricted to a sample of BHCs and the FR Y-9C data which has also been a source used for some top-down stress tests (Guerrieri and Welch 2012 and Hirtle et al 2014). We are in the process of redoing the analysis with Call Report data to increase the size of the sample and to facilitate further disaggregation by loan composition.

FR Y-9C reports contain a uniform and detailed calendar year-to-date income statement, an end-of-quarter balance sheet, and supplementary information. These data become available for all domestic BHCs approximately two months after the end of each calendar quarter, and are made available for download by the Federal Reserve.[20]

We start the sample period in 1996 because information required for measuring the FR Y-9C variables is unavailable for earlier periods. We measure all income statement quantities combining the trailing four quarters of data to eliminate the effects of seasonality and to smooth out short-term shocks.[21] Thus, the sample includes 64 quarters of data, Q4:1996 through Q3:2012. To mitigate the impact of outliers, we trim extreme values of each of the variables.[22] Summary statistics from the distributions of the variables are provided in Table 1. For our sample, the average (median) ALLL is 1.55% (1.37%) of gross loans held for investment. The ratio of PLLL to average gross loans has a mean (median) of 0.65% (0.37%). The average (median) NCOs as a percentage of average gross loans equals 0.52 (0.25). On average, 1.68% of gross loans are classified as NPLs and 0.23% of gross loans are estimated to be unexpected NPLs. The average (median) loan yield in our sample is 7.28% (7.08%).

Turning to loan composition, real estate loans constitute about 70% of loans on average, with commercial and industrial loans a distant second at 16%. Consumer loans on average account for less than 8% of loan portfolios, and all other loans are less than 5%. The variability

[20] FR Y-9C reports are available at http://chicagofed.org/applications/bhc_data/bhcdata_index.cfm.

[21] Seasonality affects quarterly data for accounting as well as economic reasons. For example, Liu et al. (1997) find that loan provisions are often delayed to the fourth fiscal quarter when the audit occurs.

[22] Extreme values of the variables were identified using the following procedure. For each variable, we calculated the 5th and 95th percentiles of the empirical distribution (P5 and P95, respectively) and trimmed observations outside the following range: P1 – 1 × (P95 – P5) to P95 + 1 × (P95 – P5). For normally distributed variables, this range covers approximately 4.95 standard deviations from the mean in each direction (= 1.65 + 1 × (1.65 - (-1.65)), which is more than 99.99% of the observations. For variables with relatively few outliers, the percentage of retained observations is also very high (often 100%). We repeated all the analyses using alternative outlier filters and estimation methodologies, and confirmed the robustness of the findings.

of the proportion of "other loans" across the observations is small relative to the other loan categories, suggesting that the sum of the three explicit loan composition ratios—real estate, commercial and industrial, and consumer—has very low variability. Therefore, to mitigate multicollinearity, only two of these ratios are included in the regressions.

Table 2 presents descriptive statistics from the distributions of the variables for two sub-periods – (1) the period preceding the subprime financial crisis (Q4:1996-Q2:2007), and (2) the period following the onset of the subprime financial crisis (Q3:2007-Q3:2012). The mean values of the explanatory variables have all changed significantly since the beginning of the financial crisis. In particular, each of the credit quality variables indicates considerably higher credit risk. The average of the ratio of ALLL to gross loans increased from 1.4% in the period preceding the financial crisis to 1.8% in the period starting with the onset of the financial crisis. The mean PLLL and NCOs as percentages of average gross loans nearly tripled from 0.41% and 0.31% in the pre-crisis period to 1.11% and 0.91% in the post-crisis period, respectively. Similarly, the average of the ratio of NPLs to gross loans increased from 0.84% to 3.16%.

V. Empirical Results

In the following sections we present the results of our empirical analyses. We begin with estimation of the expected rate of credit losses and then evaluate its out-of-sample predictive ability by comparing the significance of the expected rate of credit losses to that of other credit risk measures in explaining next-period's (annual) realized credit losses. Then, we examine the extent to which the expected rate of credit losses explains the variation in the fair value of loans and whether the fair value of loans contains all the information in the expected rate of credit losses. We also examine whether the information in the fair value of loans is incremental to that contained in the expected rate of credit losses. We then compare the overall and incremental explanatory power of the expected rate of credit losses with that of the ALLL and PLLL. Finally, we refine some of our analyses and perform robustness tests.

Estimating the expected rate of credit losses

To estimate the expected rate of credit losses, we perform quarterly cross-sectional regressions of Equation (9). The summary statistics from the cross-sectional regressions are presented in Table 3. Four sets of summary statistics are presented: (1) for all 64 cross-sectional regressions (Q4:1996-Q3:2012), (2) for the period preceding the financial crisis (Q4:1996-Q2:2007), (3) for the period since the financial crisis (Q3:2007-Q3:2012), and (4) for the difference between the two sub-periods. For each set of regressions and each coefficient, we report the time-series mean of the coefficient, the time series t-statistic (the ratio of the time-series mean to the time-series standard error), and the time-series median of the cross-sectional t-statistic. For the difference in the two sub-periods statistics (the last two rows in the table), we report the difference between the two mean coefficients and the corresponding t-statistic.

Focusing first on the estimates for the full sample period, we observe that most coefficients have the expected signs and are highly significant. As expected, the most significant explanatory variable for next period's net charge-offs rate is the current period's net charge-offs rate, with a persistence parameter greater than 0.5. Also highly significant are the unexpected change in NPL (γ) and the level of NPL (α_2). The γ coefficient is of particular interest – it represents the proportion of the unexpected change in NPL that turns into a credit loss in the following period. The estimated value of this parameter for the full sample period is approximately 0.17, implying that each dollar of unexpected NPL results in 17 cents of recognized loss in the following quarter. As we see in the later analysis this parameter differs across a credit cycle in the expected direction.

As expected, loans' yield and loan composition are also associated with future credit losses. High yield loans (α_3), floating rate loans (α_4), and consumer loans (α_6) are on average riskier than other loans, after controlling for other loan characteristics.

Turning to the sub-periods and related difference statistics, we observe that while the coefficients generally have the same signs in both sub-periods, the magnitudes of almost all changed significantly. Both, the persistence parameter (α_1) and the proportion of the unexpected change in NPL that turns into credit losses (γ) increased significantly in the period since the beginning of the financial crisis. The coefficient on NPL (α_2) also increased significantly. Thus, credit losses since the beginning of the financial crisis increased not only because of deteriorating credit profiles of borrowers as reflected in NPLs and NCOs (see Table 2), but also because of greater loss implications of each dollar of NPLs and NCOs. The only coefficient that changed sign between the two sub-periods is that on the proportion of real estate loans (α_5). Prior to the financial crisis real estate loans had much lower loss ratios than other loans because the real estate collateral was reflected at a high value, but this has changed since the beginning of the financial crisis as the pumped up prices deflated. In contrast, consumer loans have significantly larger loss ratios compared to other loans throughout the sample period.

Evaluating out-of-sample predictions

The results presented in Table 3 suggest that the variables used to model *ExpectedRCL* are useful in explaining subsequent credit losses. However, these results do not directly provide evidence on the out-of-sample predictive ability of *ExpectedRCL*, which aggregates the information in the explanatory variables. To evaluate the predictive ability of *ExpectedRCL* and to compare it to the predictive abilities of other credit risk measures, we estimate several models nested in the following specification:

$$RealizedRCL_{t+1} = \beta_0 + \beta_1 \widehat{ExpectedRCL}_{t+1} + \beta_2 RealizedRCL_t$$
$$+\beta_3 \frac{NCO_t}{AveLoans_t} + \beta_4 \frac{\Delta NPL_t^{unexp}}{AveLoans_t} + \beta_5 \frac{NPL_t}{Loans_t} + \beta_6 LoansYield_t$$
$$+\beta_7 FloatLoanRatio_t + \beta_8 \frac{RELoans_t}{Loans_t} + \beta_9 \frac{ConsLoans_t}{Loans_t} + \varepsilon_{t+1} \quad (11)$$

where $\widehat{ExpectedRCL}_{t+1}$ is estimated as described in Section 3 using the values of the explanatory variables in period *t* and the estimated coefficients from time *t* regression of Equation (9) (i.e., with period *t* NCOs as the dependent variable and time *t*-1 explanatory variables).

The results from the estimation of the various models nested in Equation (11) are presented in Table 4. Recall that part of our motivation is to identify a summary statistic that can be used as an indicator of credit risk for a bank. The results suggest that *ExpectedRCL* performs substantially better than either net charge-offs or the realized rate of credit losses in predicting next period's credit losses. Moreover, it reflects all the information that is captured by either one of these two variables. When *ExpectedRCL* is included in the model along with either the realized rate of credit losses or NCOs, it is the only significant variable. Further, the realized rate of credit losses performs substantially better than—and captures all the information in—NCOs, confirming the importance of adjusting NCOs for unexpected changes in NPLs due to the amount of loans extended. Given that NCO is being used as a basis input to top-down stress test analyses (e.g., Kapinos and Mitnick 2014), the results suggest that *ExpectedRCL* may be a better model of expected to losses to test future expected losses.[23]

The last regression demonstrates the out-of-sample predictive ability of the different components used to estimate *ExpectedRCL.* With the exception of real estate loans, all other credit-risk related measures disclosed by banks are significantly associated with next period's realized credit losses.

Loans' fair value and the expected rate of credit losses

Given that the fair value of all loans should capture all the information related to credit risk for these assets, we might expect them to be a good measure for assessing future credit losses. While Barth et al (1996) demonstrate that incremental information in fair value of loans is reflected in stock returns, it does not directly speak to the credit risk question. Cantrell et al (2014) ask the question more explicitly evaluating whether fair value or historical cost of loans are better predictors of expected credit losses. They conclude in favor of historical costs. We consider the relation between the fair value of loans and *ExpectedRCL* by testing if *ExpectedRCL* is associated with managements' estimate of the fair value of loans, and then if the fair value of loans captures incremental or all credit risk information relative to *ExpectedRCL.*

In an efficiently priced market with unbiased measures, the fair value of loans should aggregate forward-looking information about credit and interest rate and all other risk. Therefore, if *ExpectedRCL* reflects information relevant for the prediction of credit losses it should help explain management's estimate of the fair value of loans. To examine the extent to which *ExpectedRCL* explains variation in the disclosed fair value of loans, we estimate models nested in the following specification:

[23] We have not considered how the macro-scenario changes would impact *ExpectedRCL.* This is for future research.

$$\frac{FVLoans_t}{Loans_t} = \beta_0 + \beta_1 \widehat{ExpectedRCL}_{t+1} + \beta_2 RealizedRCL_t$$

$$+\beta_3 \frac{NCO_t}{AveLoans_t} + \beta_4 \frac{\Delta NPL_t^{unexp}}{AveLoans_t} + \beta_5 \frac{NPL_t}{Loans_t} + \beta_6 LoansYield_t$$

$$+\beta_7 FloatLoanRatio_t + \beta_8 \frac{RELoans_t}{Loans_t} + \beta_9 \frac{ConsLoans_t}{Loans_t} + \varepsilon_{t+1} \tag{12}$$

where $FVLoans_t$ is the disclosed fair value of all loans, including both loans held for investment and loans held for sale, and all other variables are as defined above.

We obtain fair value information from SNL Financial. US companies have been disclosing the fair value of most of their financial instruments—including loans—on an annual basis since 1992 and on a quarterly basis since the second quarter of 2009. SNL collects this information since 2005. Our sample for this analysis, therefore, includes 17 cross-sections (t): Q4:05, Q4:06, Q4:07, Q4:08, Q2:09-Q2:12. We merged the fair value data with the FR Y-9C data using various identifiers and verified that all matches are correct.

Before discussing the results, reported in Table 5, we note that given the small number of cross-sections, the time-series t-statistics should be interpreted with caution. However, the median cross-sectional t-statistics allow for meaningful inference given the reasonably large size of each cross-section. As shown, *ExpectedRCL* is highly significant in explaining the disclosed fair value of loans. However, unlike the results for predicting credit losses (presented in Table 4), NCOs are slightly more significant than the expected rate of credit losses and provide incremental information relative to *ExpectedRCL*. The final set of regressions indicates the source of this difference in results compared to Table 4. Loans' fair value increases rather than declines with the unexpected change in NPLs. This result suggests that banks "manage" NCOs and the disclosed fair value of loans in a consistent way. When banks understate NCOs, which causes an unexpected increase in NPLs, they also overstate the disclosed fair value of loans. This result is consistent with prior evidence regarding the quality and "management" of disclosed loans fair values (e.g., Barth et al. 1997; Eccher et al. 1997; Nissim 2003).

Having established that the disclosed fair value of loans reflects at least some of the information that is contained in *ExpectedRCL*, we next examine whether the disclosed fair value contains (1) *all* the information that is captured by *ExpectedRCL*, and (2) incremental information to that contained in *ExpectedRCL*. We conduct these tests by estimating models that are nested in the following specification:

$$RealizedRCL_{t+1} = \beta_0 + \beta_1 \frac{FVLoans_t}{Loans_t} + \beta_2 \widehat{ExpectedRCL}_{t+1} + \beta_3 \frac{NCO_t}{AveLoans_t} + \beta_4 \frac{\Delta NPL_t^{unexp}}{AveLoans_t} + \beta_5 \frac{NPL_t}{Loans_t} + \beta_6 LoansYield_t + \beta_7 FloatLoanRatio_t + \beta_8 \frac{RELoans_t}{Loans_t} + \beta_9 \frac{ConsLoans_t}{Loans_t} + \varepsilon_{t+1} \quad (13)$$

The results of estimating the various models nested in Equation (13) are presented in Table 6. As expected, loans' fair value is significantly related to subsequent credit losses. However, this relationship is substantially weaker than the correlation between the expected and realized rates of credit losses. Moreover, loans' fair value does not appear to add much to the *ExpectedRCL* when predicting credit losses. The association between *FVLoans* and *RealizedRCL* decreases substantially when *ExpectedRCL* are included in the model along with *FVLoans.* The coefficient on *FVLoans* reduces from -0.074 (t-stat -5.3) to -0.008 (t-stat -1.9) when *ExpectedRCL* are included. The final set of regressions indicates that the relatively low significance of loans' fair value in explaining credit losses is not due to loans' fair value reflecting variation in loan characteristics such as loan yield, as loans' fair value remains marginally significant after these variables are controlled for (the inclusion of other loan characteristics in the regression effectively orthogonalizes loans' fair value with respect to these variables, allowing its coefficient to capture credit-related information not reflected in the included loan characteristics or other non-credit related information in loans' fair value). In summary, we find that loan's fair value does not capture all the information in *ExpectedRCL*, and it does not seem to provide incremental information relative to *ExpectedRCL* in predicting credit losses. These results provide further support for the inferences from Table 5 regarding the low quality and potential "management" of loan fair value.[24] However, it could be the case that fair values of loans are more informative of credit losses beyond the one year horizon, but the results of Cantrell et al (2014) suggest this is unlikely.

ALLL, PLLL, and the expected rate of credit losses

Our objective is to provide an independent measure of expected credit losses so we do not included ALLL or PLLL in the model. Yet the question remains if we would be better just using ALLL or PLLL and whether these measures might still be useful as indicator variables of management's superior information. So we next compare the overall and incremental information in *ExpectedRCL* about future credit losses relative to that in the ALLL and PLLL. To this end, we estimate several models nested in the following specification:

$$
\begin{aligned}
RealizedRCL_{t+1} = \beta_0 + \beta_1 \widehat{ExpectedRCL}_{t+1} + \beta_2 \frac{ALLL_t}{Loans_t} + \beta_3 \frac{PLLL_t}{AveLoans_t} \\
+\beta_4 \frac{NCO_t}{AveLoans_t} + \beta_5 \frac{\Delta NPL_t^{unexp}}{AveLoans_t} + \beta_6 \frac{NPL_t}{Loans_t} + \beta_7\, LoansYield_t \\
+\beta_8\, FloatLoanRatio_t + \beta_9 \frac{RELoans_t}{Loans_t} + \beta_{10} \frac{ConsLoans_t}{Loans_t} + \varepsilon_{t+1} \qquad (14)
\end{aligned}
$$

[24] In finding that historical cost of loans are better predictors of NCOs (and NPLs) than the fair value of loans for both annual and aggregate multi-year NCOs, Cantrell et al (2014) conclude that this may be a result of the lack of scrutiny of the fair value measures.

The estimation results are reported in Table 7. The ALLL and, particularly, the PLLL are highly significant in explaining next period's credit losses, on a standalone basis as well as after controlling for other credit loss proxies. Yet, each of the credit loss proxies used to construct *ExpectedRCL*, except the proportion of real estate loans, contains incremental information about future credit losses relative to the ALLL and PLLL (see the results of the last regression). Accordingly, *ExpectedRCL* provides significant incremental explanatory power for future credit losses after controlling for the ALLL and PLLL. The coefficient on *ExpectedRCL* is 0.57 with a t-statistic of 17.8 even after ALLL and PLLL are included in the regression. And, importantly, because *ExpectedRCL* is measured using relatively non-discretionary credit metrics, unlike the ALLL and PLLL it is a less biased measure of expected credit losses.

Refinements and robustness tests

In this section, we examine the robustness of our findings by refining some of our analyses. Specifically, we consider alternative ways for measuring the coefficients and variables used in estimating *ExpectedRCL*.

In the main analysis we use only the most recent coefficients of Equation (9) to estimate *ExpectedRCL*, effectively assuming that there is no incremental information in prior coefficient estimates. Given the limited size of each cross section and the substantial variability of unexpected credit losses, we may be giving up some statistical power by excluding the longer time period of data in estimating the coefficients. On the other hand, as we show in Section 5, the coefficients change considerably over time, so the most recent estimates are likely to be less biased compared to prior estimates. To evaluate this bias/noise trade-off, we repeat the analysis extrapolating from the time-series of the coefficient estimates. Table 8 replicates the first regression of Table 4 using four alternative estimates of *ExpectedRCL*, derived using: (1) a moving average of the last four coefficient estimates, and (2) exponential smoothing of the coefficient estimates with a smoothing factor of 0.5, 0.25, 0.1, and 0.01.[25] As shown, extrapolating from past coefficient estimates rather than using the most recent coefficients improves the accuracy of credit loss forecasts, particularly when using low exponential smoothing factors (i.e., when giving higher weight to past estimates).

Since future (i.e., t+1) net charge-offs and the unexpected change in NPL used in estimating the parameters of Equations (7) and (9) are measured using trailing four quarter data, the explanatory variables of Equation (9) are at least a year old at the time the parameters are estimated. An alternative approach for measuring net charge-offs and the unexpected change in NPL, which allows for a substantially shorter delay, is to measure these variables using annualized quarterly data. This approach allows for more recent information to reflect itself in the estimated parameters, but at the cost of using seasonal and potentially noisy information. Table 8, Panel B replicates the first regression of Table 4 with *ExpectedRCL* estimated using annualized credit losses. As shown, using annualized instead of trailing four quarter information in estimating *ExpectedRCL* slightly improves the predictive-ability of this variable.

VI. Conclusion

Value creation in lending, the primary activity of most banks, can be estimated by netting expected credit losses against expected interest income. Estimating expected credit losses has been a vexing problem for analysts and investors, and has recently been of renewed interest to regulators with the IASB's passage of IFRS9 requiring initial recognition of twelve month

[25] The predicted value (s_{t+1}) for the series x_t under exponential smoothing with a smoothing factor f is $f*x_t + (1-f)*s_t$, where $s_1=x_0$.

expected credit losses in the calculation of income. We also find that regulators are interested in estimation of expected credit losses for top-down stress testing. This study develops a timely and less biased metric of expected credit losses using a linear combination of several credit-risk related measures currently disclosed by banks.

The proposed metric, the expected rate of credit losses (*ExpectedRCL*), performs substantially better than net charge-offs or the realized rate of credit losses in predicting credit losses and it appears to reflect all the credit loss-related information in either of these two variables. *ExpectedRCL* also contains incremental information about future credit losses relative to the ALLL and PLLL, although it does not subsume all the information in these discretionary measures of credit losses. Yet, the explanatory power of *ExpectedRCL* for future credit losses is greater than that of the ALLL or PLLL, and unlike these measures it is a less biased predictor of credit losses. These findings suggest that improvements can be made in banks estimating and providing for expected losses, and that the framework in this paper can be used to help predict future credit losses from current cross-sectional disclosures.

We also provide some insight on the question of whether the disclosed fair value of loans provides a good measure of expected credit losses as it should in principle. We find that the disclosed fair value of loans is correlated with *ExpectedRCL*. However, the loans' fair value does not capture all the information in *ExpectedRCL* and it does not provide much incremental information relative to *ExpectedRCL* in predicting credit losses.

We expect to add to the analysis by expanding the sample beyond bank holding companies so as to incorporate more disaggregated data that should enhance the power of our estimates. Future research can also consider how to incorporate calculations of *ExpectedRCL* in top down stress tests that require measures of expected credit losses.

Appendix A: UNIFORM RETAIL CREDIT CLASSIFICATION AND ACCOUNT MANAGEMENT POLICY

The following is the FDIC policy regarding retail credit classification. It has been in effect since 2000. See http://www.fdic.gov/news/news/financial/2000/fil0040a.pdf
The agencies' classifications used for retail credit are Substandard, Doubtful, and Loss. These are defined as follows:[26]

Substandard: An asset classified Substandard is protected inadequately by the current net worth and paying capacity of the obligor, or by the collateral pledged, if any. Assets so classified must have a well-defined weakness or weaknesses that jeopardize the liquidation of the debt. They are characterized by the distinct possibility that the institution will sustain some loss if the deficiencies are not corrected.

Doubtful: An asset classified Doubtful has all the weaknesses inherent in one classified Substandard with the added characteristic that the weaknesses make collection or liquidation in full, on the basis of currently existing facts, conditions, and values, highly questionable and improbable.

Loss: An asset, or portion thereof, classified Loss is considered uncollectible, and of such little value that its continuance on the books is not warranted. This classification does not mean that the asset has absolutely no recovery or salvage value; rather, it is not practical or desirable to defer writing off an essentially worthless asset (or portion thereof), even though partial recovery may occur in the future.

The Uniform Retail Credit Classification and Account Management Policy establishes standards for the classification and treatment of retail credit in financial institutions. Retail credit consists of open- and closed-end credit extended to individuals for household, family, and other personal expenditures, and includes consumer loans and credit cards. For purposes of this policy, retail credit also includes loans to individuals secured by their personal residence, including first mortgage, home equity, and home improvement loans. Because a retail credit portfolio generally consists of a large number of relatively small-balance loans, evaluating the quality of the retail credit portfolio on a loan-by-loan basis is inefficient and burdensome for the institution being examined and for examiners.

Actual credit losses on individual retail credits should be recorded when the institution becomes aware of the loss, but in no case should the charge-off exceed the time frames stated in this policy. This policy *does not preclude* an institution from adopting *a more conservative* internal policy. Based on collection experience, when a portfolio's history reflects high losses and low recoveries, more conservative standards are appropriate and necessary.

[26] Although the Board of Governors of the Federal Reserve System, Federal Deposit Insurance Corporation, Office of the Comptroller of the Currency, and Office of Thrift Supervision do not require institutions to adopt identical classification definitions, institutions should classify their assets using a system that can be easily reconciled with the regulatory classification system.

The quality of retail credit is best indicated by the repayment performance of individual borrowers. Therefore, in general, retail credit should be classified based on the following criteria:

- Open- and closed-end retail loans past due 90 cumulative days from the contractual due date should be classified Substandard.

- Closed-end retail loans that become past due 120 cumulative days and open-end retail loans that become past due 180 cumulative days from the contractual due date should be classified Loss and charged off. In lieu of charging off the entire loan balance, loans with non-real estate collateral may be written down to the value of the collateral, less cost to sell, if repossession of collateral is assured and in process.[27]

- One- to four-family residential real estate loans and home-equity loans that are past due 90 days or more with loan-to-value ratios greater than 60 percent should be classified Substandard. Properly secured residential real estate loans with loan-to-value ratios equal to or less than 60 percent are generally not classified based solely on delinquency status. Home-equity loans to the same borrower at the same institution as the senior mortgage loan with a combined loan-to-value ratio equal to or less than 60 percent need not be classified. However, home equity loans where the institution does not hold the senior mortgage, that are past due 90 days or more should be classified Substandard, even if the loan-to-value ratio is equal to, or less than, 60 percent.

  For open- and closed-end loans secured by residential real estate, a current assessment of value should be made no later than 180 days past due. Any outstanding loan balance in excess of the value of the property, less cost to sell, should be classified Loss and charged off.

- Loans in bankruptcy should be classified Loss and charged off within 60 days of receipt of notification of filing from the bankruptcy court or within the time frames specified in this classification policy, whichever is shorter, unless the institution can clearly demonstrate and document that repayment is likely to occur. Loans with collateral may be written down to the value of the collateral, less cost to sell. Any loan balance not charged off should be classified Substandard until the borrower re-establishes the ability and willingness to repay for a period of at least six months.

- Fraudulent loans should be classified Loss and charged off no later than 90 days of discovery or within the time frames adopted in this classification policy, whichever is shorter.

[27] For operational purposes, whenever a charge-off is necessary under this policy, it should be taken no later than the end of the month in which the applicable time period elapses. Any full payment received after the 120- or 180-day charge-off threshold, but before month-end charge-off, may be considered in determining whether the charge-off remains appropriate. OTS regulation 12 CFR 560.160(b) allows savings institutions to establish adequate (specific) valuation allowances for assets classified Loss in lieu of charge-offs. Open-end retail accounts that are placed on a fixed repayment schedule should follow the charge-off time frame for closed-end loans.

- Loans of deceased persons should be classified Loss and charged off when the loss is determined or within the time frames adopted in this classification policy, whichever is shorter.

Other Considerations for Classification

If an institution can clearly document that a *past due loan is well secured* and in the process of collection, such that *collection will occur* regardless of delinquency status, then the loan *need not be classified*. A well-secured loan is collateralized by a perfected security interest in, or pledges of, real or personal property, including securities with an estimable value, less cost to sell, sufficient to recover the recorded investment in the loan, as well as a reasonable return on that amount. In the process of collection means that either a collection effort or legal action is proceeding and is reasonably expected to result in recovery of the loan balance or its restoration to a current status, generally within the next 90 days.

Appendix B: Variable Definitions

ALLL	Allowance for loan and lease losses
ConsLoans	Loans categorized as consumer loans
ExpectedRCL	Expected rate of credit losses. See Section 3 for the details of estimating *ExpectedRCL.*
FloatLoanRatio	Proportion of loans that reprice or mature within one year
FVLoans	Fair value of loans held-for-investment and loans held-for-sale
Loans	Total loans held-for-investment
LoansYield	Ratio of tax-equivalent interest income on loans to the average balance of loans
LogBTM	Log of the book-to-market ratio; measured using book value at the end of the quarter and market value 75 days after the end of the fiscal quarter
NCO	Net charge-offs
NPL	Non-performing loans; estimated as the total of non-accruing loans, restructured loans and delinquent loans accruing for more than 90 days
Δ NPL^{unexp}	Unexpected change in non-performing loans. See Section 3 for the details of estimating Δ NPL^{unexp}.
PLLL	Provision for loan and lease losses
RealizedRCL	Realized rate of credit losses. See Section 3 for the details of estimating *RealizedRCL.*
RELoans	Loans categorized as real estate loans
Size	Log of the market value of equity measured 75 days after the end of the fiscal quarter

References

Ahmed, A., C. Takeda, and S. Thomas. 1999. Bank loan loss provisions: A reexamination of capital management, earnings management, and signaling effects. *Journal of Accounting and Economics* 28(1): 1 – 25.

Araten, M., M. Jacobs Jr., and P. Varshney. 2004. Measuring LGD on commercial loans: An 18-year internal study. The RMA Journal (May).

Bank for International Settlements. 2008. Note for the FSF Working Group on Market and Institutional Resilience Addressing Financial System Procyclicality: A Possible Framework.

Barber, B. M., and J. D. Lyon. 1997. Firm Size, Book-to-Market Ratio, and Security Returns: A Holdout Sample of Financial Firms. *Journal of Finance* 52(2): 875-883.

Barth, M. E. 1994. Fair value accounting: Evidence from investment securities and the market valuation of banks. *The Accounting Review* 69 (January): 1-25.

Barth, M., W. Beaver, and W. Landsman. 1996. Value-relevance of banks' fair value disclosures under SFAS No. 107. *The Accounting Review* (October): 513-537.

Barth, M. E., and W. R. Landsman. 2010. How did financial reporting contribute to the financial crisis? *European Accounting Review* 19 (3): 399 – 423.

Basel Committee on Banking Supervision. 2000. Financial stability and the Basel capital accord. March. Bank of Insternational Settlements.

Beatty, A., S. Chamberlain, and J. Magliolo. 1995. Managing financial reports of commercial banks: The influence of taxes, regulatory capital, and earnings. *Journal of Accounting Research* 33(2): 231 – 261.

Beatty, A. and S. Lido. 2001. Do delays in expected loss recognition affect banks' willingness to lend. *Journal of Accounting and Economics* 52, 1-20.

Beaver, W. H., C. Eger, S. Ryan, and M. Wolfson. 1989. Financial reporting, supplemental disclosures, and bank share prices. *Journal of Accounting Research* 27 (Autumn): 157-178.

Beaver, W. H. and E. E. Engel. 1996. Discretionary behavior with respect to allowance for loan losses and the behavior of security prices. *Journal of Accounting and Economics* 22, 177-206.

Berger, A., and G. Udell. 2002. Small business credit availability and relationship lending: The importance of bank organisational structure. *The Economic Journal* 122: 32 – 53.

Bikker, J.A., and P.A.J. Metzemakers. 2005. Bank provisioning behavior and procyclicality. *Journal of International Financial Markets, Institutions, and Money* 15(2): 141 – 157.

Bhat, G., S.G. Ryan, and D. Vyas. 2012. The Implications of Banks' Credit Risk Modeling Disclosures for their Loan Loss Provision Timeliness and Loan Origination Procyclicality. Working Paper New York University.

Blankespoor, E., T. Linsmeier, K. Petroni and C. Shakespeare. 2013. Fair value accounting for financial instruments: Does it improve the association between bank leverage and credit risk? *The Accounting Review* 88 (4): 1143-1177.

Bushman, R.M. and C.D. Williams. 2011. Delayed expected loss recognition and the risk profile of banks. Working Paper University of North Carolina at Chapel Hill.

Bushman, R.M., and C.D. Williams. 2012. Bank transparency and the discipline of risk-taking behavior. *Journal of Accounting and Economics* 54 1-18.

Calomiris, C., and D. Nissim. 2012. "Crisis-Related Shifts in the Market Valuation of Banking Activities", NBER Working Paper 17868.

Cantrell, B., J. McInnis, and C. Yust. 2014. Predicting credit losses: Loan fair values versus historical costs. *The Accounting Review* 89 (January): 147-176.

Collins, J. H., D. A. Shackelford and J. M. Wahlen. 1995. Bank Differences in the Coordination of Regulatory Capital, Earnings, and Taxes. *Journal of Accounting Research* 33, 263-291.

Dugan, J. 2009. Loan Loss Provisioning and Pro-Cyclicality. Available at http://www.occ.treas.gov/news-issuances/speeches/2009/pub-speech-2009-16.pdf

Eccher, E. A., K. Ramesh, and S. R. Thiagarajan. 1996. Fair value disclosures by bank holding companies. *Journal of Accounting and Economics* 22 (1-3): 79-117.

Elliott, J. A., J. D. Hanna, and W. H. Shaw. 1991. The evaluation by the financial markets of changes in bank loan loss reserve levels. *The Accounting Review* 66 (October): 847-861.

Ernst and Young 2014. *IASB Projects: A pocketbook guide: As at 31 March 2014*

Financial Accounting Standards Board. 1975. Statement of Financial Accounting Standards No.5 *Accounting by Contingencies.* FASB (March)

Financial Accounting Standards Board. 1993. Statement of Financial Accounting Standards No.114 *Accounting by Creditors for Impairment of a Loan.* FASB (May)

Financial Accounting Standards Board. 2010. *Exposure Draft: Accounting for Financial Instruments and Revisions to the Accounting for Derivative Instruments and Hedging Activities.*

Financial Accounting Standards Board. 2012. *Exposure Draft: Financial Instruments – Credit Losses* (Subtopic 825-15). December, 2012.

Financial Stability Forum. 2009a. Report of the FSF Working Group on Provisioning. March, 2009.

Financial Stability Forum. 2009b. Report of the FSF on Addressing Procyclicality in the Financial System. April, 2009.

Griffin, P. A., and S. J. R. Wallach. 1991. Latin American lending by major U.S. banks: The effects of disclosures about nonaccrual loans and loan loss provisions. *The Accounting Review* 66 (October): 830-846.

Guerrieri, L. and M. Welch. 2012. Can Macro Variables Used in Stress Testing Forecast the Performance of Banks? Working Paper Federal Reserve Bank Finance and Economics Discussion 49.

Hirtle, B., A. Kovner, J. Vickery and M. Bharat. 2014. The Capital and Loss Assessment under Stress Scenarios (CLASS) Model. Federal Reserve Bank of New York Staff Report 63, February.

International Accounting Standards Board. 2009. *International Accounting Standard 39, Financial Instruments: Recognition and Measurement*. IASB, London, UK.

International Accounting Standards Board. 2014. *International Financial Reporting Standard 9, Financial Instruments*. IASB, London, UK (July)

Kapinos, P. and O.A. Mitnick. 2014. A top Down Approach to the Stress-testing of Banks. Working paper Federal Deposit Insurance Corporation (July).

Laeven, L., and G. Majnoni. 2003. Loan loss provisioning and economic slowdowns: Too much, too late? *Journal of Financial Intermediation* 12: 178 – 197.

Liu, C., and S. Ryan. 1995. The effect of loan portfolio composition on the market reaction to and anticipation of loan loss provisions. *Journal of Accounting Research* 33 (Spring): 77-94.

Liu C. and S.G. Ryan. 2006. Income smoothing over the business cycle: Changes in banks' coordinated management of provisions for loan losses and loan charge-offs from the pre-1990 bust to the 1990s boom. *The Accounting Review* 81, (2): 421-441.

Liu C. and S.G. Ryan, and J. Wahlen. 1997. Differential valuation implications of loan loss provisions across banks and fiscal quarters. *The Accounting Review* 72, (1): 133–146.

Moyer, S. E. 1990. Capital Adequacy Ratio Regulations and Accounting Choices in Commercial Banks. *Journal of Accounting and Economics* (13): 123-154.

Nissim, D. 2003. Reliability of Banks' Fair Value Disclosure for Loans. *Review of Quantitative Finance and Accounting* (20): 355-384.

Nissim, D. and S. Penman. 2007. Fair Value Accounting in the Banking Industry, *Center for Excellence in Accounting and Security Analysis*, 1-75. Available at http://www.columbia.edu/~dn75/research.htm.

Ng, J., and T. O. Rusticus. 2011. Banks' Survival during the Financial Crisis: The Role of Financial Reporting Transparency. Working Paper Northwestern University.

Office of the Comptroller of the Currency. 2009. Comptroller Dugan urges less pro-cyclical approaches to reserves. OCC March 2.

Ryan, S. 2007. Financial instruments and institutions: Accounting and disclosure rules. Second edition. John Wiley & Sons.

Ryan, S. 2012. Financial Reporting for Financial Instruments. *Foundations and Trends in Accounting*: Vol. 6: No. 3-4, pp 187-354.

Scholes, M., G. Wilson, and M. Wolfson. 1990. Tax planning, capital planning, and financial reporting strategy for commercial banks. *Review of Financial Studies* 3 (4): 625 – 650.

Securities and Exchange Commission. 2001. Staff Accounting Bulletin No. 102 – Seleceted Loan Loss Allowance Methodology and Documentation Issues. SEC, Washington D.C. July.

Udell, G. 1999. Loan quality, commercial loan review and loan officer contracting. *Journal of Banking and Finance* 13(3): 367- 382.

Vyas, D. 2011. The timeliness of accounting write-downs by U.S. financial institutions during the financial crisis of 2007-2008. *Journal of Accounting Research* 49 (3): 823-860.

Wahlen, J. M. 1994. The Nature of Information in Commercial Bank Loan Loss Disclosures. *The Accounting Review* 69, 455-478.

Wall, L.D., and T.W. Kock. 2000. Bank Loan-Loss Accounting: A Theoretical Review and Empirical Evidence. *Economic Review* Federal Reserve Bank of Atlanta, Second Quarter, 1-19.

Table 1
Summary statistics for the full sample

	Obs.	Mean	SD	5%	25%	Med.	75%	95%
Charge-offs / average gross loans	47619	0.61%	0.80%	0.02%	0.15%	0.34%	0.71%	2.31%
Recoveries / average gross loans	47549	0.09%	0.10%	0.00%	0.03%	0.06%	0.12%	0.29%
Net charge-offs / average gross loans	47605	0.52%	0.74%	0.00%	0.10%	0.25%	0.58%	2.10%
Unexpected NPL / average gross loans	47267	0.23%	1.15%	-1.11%	-0.22%	0.03%	0.44%	2.41%
Nonaccruing loans / gross loans	49642	1.23%	1.63%	0.04%	0.28%	0.62%	1.46%	4.75%
Restructured loans / gross loans	49451	0.20%	0.50%	0.00%	0.00%	0.00%	0.09%	1.30%
Delinquent loans / gross loans	49453	0.15%	0.22%	0.00%	0.00%	0.06%	0.20%	0.61%
Nonperforming loans / gross loans	49689	1.68%	2.15%	0.10%	0.44%	0.87%	1.98%	6.29%
Real estate loans / gross loans	50256	69.95%	18.48%	35.32%	60.35%	72.98%	83.20%	94.44%
Consumer loans / gross loans	49731	7.56%	8.30%	0.25%	1.65%	4.47%	10.72%	24.74%
Commercial loans / gross loans	49974	16.07%	10.24%	2.63%	9.01%	14.45%	21.02%	35.12%
Other loans / gross loans	49535	4.54%	5.68%	0.01%	0.72%	2.52%	6.07%	16.53%
Average tax-equivalent loan yield	47964	7.28%	1.57%	5.17%	6.07%	7.08%	8.44%	9.85%
Estimated ratio of floating rate loans	50256	40.32%	17.13%	13.87%	28.20%	39.81%	51.50%	69.65%
Allowance / gross loans held for investment	49880	1.55%	0.72%	0.77%	1.12%	1.37%	1.76%	2.98%
Prov. for loan losses / average gross loans	47630	0.65%	0.84%	0.01%	0.19%	0.37%	0.73%	2.44%
Fair value of loans / gross loans	6793	0.982	0.034	0.913	0.972	0.986	0.999	1.026

The sample period is Q4:1996 through Q3:2012. Balance sheet items are generally measured at the end of the quarter. Income statement items are measured using trailing four quarters data. Details on variable definitions are provided in Section 3 and in Appendix B. The disclosed fair value of loans is available for a subset of firms in 18 quarters (Q4:05, Q4:06, Q4:07, Q4:08, and Q2:09-Q3:12).

Table 2
Summary statistics for sub-periods

	Q4:1996-Q3:2012			Q4:1996-Q2:2007			Q3:2007-Q3:2012			Difference	
	Mean	Med.	Q-Ran	Mean	Med.	Q-Ran	Mean	Med.	Q-Ran	Mean	t-stat
Charge-offs / average gross loans	0.61%	0.34%	0.55%	0.40%	0.26%	0.36%	1.01%	0.62%	1.13%	0.61%	69.3
Recoveries / average gross loans	0.09%	0.06%	0.09%	0.09%	0.06%	0.09%	0.09%	0.06%	0.09%	0.00%	-2.0
Net charge-offs / average gross loans	0.51%	0.25%	0.48%	0.31%	0.18%	0.30%	0.91%	0.54%	1.05%	0.60%	73.7
Unexpected NPL / average gross loans	0.24%	0.03%	0.65%	-0.03%	-0.03%	0.40%	0.75%	0.44%	1.58%	0.77%	57.2
Nonaccruing loans / gross loans	1.21%	0.61%	1.15%	0.60%	0.42%	0.55%	2.35%	1.70%	2.48%	1.75%	103.3
Restructured loans / gross loans	0.19%	0.00%	0.08%	0.05%	0.00%	0.02%	0.45%	0.07%	0.63%	0.40%	71.6
Delinquent loans / gross loans	0.15%	0.06%	0.20%	0.15%	0.08%	0.20%	0.14%	0.04%	0.18%	-0.01%	-4.9
Nonperforming loans / gross loans	1.65%	0.86%	1.49%	0.84%	0.62%	0.71%	3.16%	2.32%	3.26%	2.32%	104.8
Real estate loans / gross loans	69.86%	72.87%	22.85%	66.92%	69.68%	23.69%	74.82%	77.96%	18.43%	7.90%	48.0
Consumer loans / gross loans	7.63%	4.54%	9.16%	9.38%	6.81%	11.03%	4.67%	2.51%	4.45%	-4.70%	-67.5
Commercial loans / gross loans	16.10%	14.49%	12.00%	16.91%	15.29%	12.69%	14.72%	13.23%	10.60%	-2.19%	-23.5
Other loans / gross loans	4.54%	2.52%	5.34%	4.66%	2.66%	5.43%	4.33%	2.23%	5.02%	-0.33%	-6.2
Average tax-equivalent loans' yield	7.31%	7.11%	2.36%	7.86%	7.86%	2.17%	6.29%	6.08%	1.30%	-1.57%	-126.8
Estimated ratio of floating rate loans	40.49%	40.01%	23.22%	42.06%	41.94%	22.62%	37.54%	36.18%	23.05%	-4.52%	-28.3
Allowance / gross loans held for investment	1.54%	1.37%	0.63%	1.40%	1.31%	0.50%	1.80%	1.56%	0.97%	0.40%	53.9
Prov. for loan losses / average gross loans	0.65%	0.37%	0.53%	0.41%	0.29%	0.33%	1.11%	0.72%	1.16%	0.71%	75.9
Fair value of loans / gross loans	0.981	0.986	0.026	0.984	0.984	0.013	0.981	0.986	0.029	-0.003	-4.6

The sample period is Q4:1996 through Q3:2012. Balance sheet items are generally measured at the end of the quarter. Income statement items are measured using trailing four quarters data. Details on variable definitions are provided in Section 3 and in Appendix B. The disclosed fair value of loans is available for a subset of firms in 18 quarters (Q4:05, Q4:06, Q4:07, Q4:08, and Q2:09-Q3:12).

Table 3
Summary statistics from cross-sectional regressions for estimating expected credit losses

$$\frac{NCO_t}{AveLoans_t} = \propto_0^* + \propto_1 \frac{NCO_{t-1}}{AveLoans_{t-1}} + \propto_1 \gamma \frac{\Delta NPL_{t-1}^{unexp}}{AveLoans_{t-1}} + \propto_2 \frac{NPL_{t-1}}{Loans_{t-1}} + \propto_3 LoansYield_{t-1}$$
$$+ \propto_4 FloatLoanRatio_{t-1} + \propto_5 \frac{RELoans_{t-1}}{Loans_{t-1}} + \propto_6 \frac{ConsLoans_{t-1}}{Loans_{t-1}} + \varepsilon_t^* \quad (9)$$

	α_0^*	α_1	γ	α_2	α_3	α_4	α_5	α_6	Mean R^2	Mean Obs.
t=Q4:97-Q3:12										
mean(coef.)	-0.0019	0.5140	0.1659	0.0841	0.0313	0.0022	-0.0008	0.0042	0.4858	674
t(mean(coef.))	-3.4	27.8	12.1	19.6	5.6	5.6	-2.0	11.3		
median(t(coef.))	-1.5	13.0	3.8	5.0	2.3	1.0	-1.7	1.9		
t=Q4:97-Q2:07										
mean(coef.)	-0.0004	0.4869	0.1241	0.0786	0.0285	0.0006	-0.0023	0.0036	0.4826	643
t(mean(coef.))	-0.9	23.7	8.7	14.1	8.2	4.5	-8.0	7.7		
median(t(coef.))	-1.1	13.4	3.0	5.2	2.4	0.7	-2.5	2.3		
t=Q3:07-Q3:12										
mean(coef.)	-0.0047	0.5644	0.2435	0.0942	0.0365	0.0052	0.0021	0.0054	0.4919	731
t(mean(coef.))	-4.0	16.3	11.9	15.4	2.5	7.2	4.7	9.8		
median(t(coef.))	-2.3	12.5	4.6	4.4	1.6	3.0	1.1	1.0		
mean(diff)	-0.0043	0.0776	0.1194	0.0156	0.0080	0.0046	0.0044	0.0019	0.0094	89
t(diff)	-3.5	1.9	4.8	1.9	0.5	6.3	8.3	2.6	0.4	5.8

The sample period includes trailing four quarters observations ending in quarter t for t = Q4:1997 through Q3:2012. Balance sheet items are generally measured at the end of the quarter. Income statement items are measured using trailing four quarters data. Details on variable definitions are provided in Section 3 and in Appendix B. mean(coef.) is the time-series mean of the corresponding regression coefficient. t(mean(coef.)) is the t-statistic of the mean coefficient (the ratio of the time-series mean to its standard error). median(t(coef.)) is the time-series median of the regression t-statistic.

Table 4
Summary statistics from cross-sectional regressions for evaluating out-of-sample predictions of credit losses

$$RealizedRCL_{t+1} = \beta_0 + \beta_1 \widehat{ExpectedRCL}_{t+1} + \beta_2 RealizedRCL_t + \beta_3 \frac{NCO_t}{AveLoans_t} + \beta_4 \frac{\Delta NPL_t^{unexp}}{AveLoans_t}$$
$$+\beta_5 \frac{NPL_t}{Loans_t} + \beta_6 LoansYield_t + \beta_7 FloatLoanRatio_t + \beta_8 \frac{RELoans_t}{Loans_t} + \beta_9 \frac{ConsLoans_t}{Loans_t} + \varepsilon_{t+1} \qquad (11)$$

	β_0	β_1	β_2	β_3	β_4	β_5	β_6	β_7	β_8	β_9	Mean R^2	Mean Obs.
mean(coef.)	0.0018	0.9811									0.3891	670
t(mean(coef.))	4.2	23.1										
median(t(coef.))	2.7	21.5										
mean(coef.)	0.0023		0.6908								0.3616	670
t(mean(coef.))	7.8		22.1									
median(t(coef.))	7.3		20.9									
mean(coef.)	0.0027			0.7170							0.3340	670
t(mean(coef.))	6.8			22.6								
median(t(coef.))	7.7			19.0								
mean(coef.)	0.0018	0.9664	0.0000								0.3975	670
t(mean(coef.))	4.5	14.1	0.0									
median(t(coef.))	2.2	5.8	0.5									
mean(coef.)	0.0018	0.9036		0.0490							0.3996	670
t(mean(coef.))	4.5	14.4		1.3								
median(t(coef.))	2.5	8.0		0.8								
mean(coef.)	0.0022		1.5825	-0.9061							0.3758	670
t(mean(coef.))	7.7		2.1	-1.2								
median(t(coef.))	7.1		5.2	-1.3								
mean(coef.)	-0.0029			0.5448	0.0892	0.0645	0.0411	0.0031	0.0004	0.0036	0.4295	670
t(mean(coef.))	-3.7			24.8	8.4	9.1	5.7	5.1	0.7	7.3		
median(t(coef.))	-2.0			11.6	3.3	3.3	2.6	1.4	-1.5	1.5		

The sample period includes trailing four quarters observations ending in quarter t for t = Q4:1997 through Q3:2011. Balance sheet items are generally measured at the end of the quarter. Income statement items are measured using trailing four quarters data. Details on variable definitions are provided in Section 3 and in Appendix B. mean(coef.) is the time-series mean of the corresponding regression coefficient. t(mean(coef.)) is the t-statistic of the mean coefficient (the ratio of the time-series mean to its standard error). median(t(coef.)) is the time-series median of the regression t-statistic.

Table 5

Summary statistics from cross-sectional regressions for evaluating the extent to which the expected rate of credit losses explains variation in the disclosed fair value of loans

$$\frac{FVLoans_t}{Loans_t} = \beta_0 + \beta_1 \widehat{ExpectedRCL}_{t+1} + \beta_2 RealizedRCL_t + \beta_3 \frac{NCO_t}{AveLoans_t} + \beta_4 \frac{\Delta NPL_t^{unexp}}{AveLoans_t}$$

$$+\beta_5 \frac{NPL_t}{Loans_t} + \beta_6 LoansYield_t + \beta_7 FloatLoanRatio_t + \beta_8 \frac{RELoans_t}{Loans_t} + \beta_9 \frac{ConsLoans_t}{Loans_t} + \varepsilon_{t+1} \quad (12)$$

	β_0	β_1	β_2	β_3	β_4	β_5	β_6	β_7	β_8	β_9	Mean R^2	Mean Obs.
mean(coef.)	0.9990	-1.4575									0.1535	337
t(mean(coef.))	654.3	-6.9										
median(t(coef.))	342.6	-8.0										
mean(coef.)	0.9970		-1.0681								0.1475	337
t(mean(coef.))	695.5		-7.1									
median(t(coef.))	379.9		-7.6									
mean(coef.)	0.9970			-1.2639							0.1611	337
t(mean(coef.))	727.4			-7.4								
median(t(coef.))	405.8			-8.6								
mean(coef.)	0.9990	-1.5339	0.0628								0.1569	337
t(mean(coef.))	663.7	-5.9	0.3									
median(t(coef.))	321.4	-2.0	0.1									
mean(coef.)	0.9980	-0.5924		-0.7859							0.1676	337
t(mean(coef.))	680.3	-5.5		-5.7								
median(t(coef.))	342.0	-1.0		-2.1								
mean(coef.)	0.9980		0.2675	-1.4873							0.1661	337
t(mean(coef.))	685.5		1.4	-6.7								
median(t(coef.))	376.7		0.7	-2.4								
mean(coef.)	0.9860			-0.8221	0.1771	-0.2579	0.3791	-0.0141	-0.0018	-0.0304	0.2019	337
t(mean(coef.))	330.6			-5.6	3.7	-11.7	5.6	-5.9	-0.9	-5.2		
median(t(coef.))	57.2			-3.7	1.3	-2.5	1.3	-1.3	-0.4	-1.1		

The sample includes 18 cross-sections (t): Q4:05, Q4:06, Q4:07, Q4:08, Q2:09-Q3:12. Balance sheet items are generally measured at the end of the quarter. Income statement items are measured using trailing four quarters data. Details on variable definitions are provided in Section 3 and in Appendix B. mean(coef.) is the time-series mean of the corresponding regression coefficient. t(mean(coef.)) is the t-statistic of the mean coefficient (the ratio of the time-series mean to its standard error). median(t(coef.)) is the time-series median of the regression t-statistic.

Table 6

Summary statistics from cross-sectional regressions for comparing the predictive-ability of the estimated expected rate of credit losses and the disclosed fair value of loans

$$RealizedRCL_{t+1} = \beta_0 + \beta_1 \frac{FVLoans_t}{Loans_t} + \beta_2 \widehat{ExpectedRCL}_{t+1} + \beta_3 \frac{NCO_t}{AveLoans_t} + \beta_4 \frac{\Delta NPL_t^{unexp}}{AveLoans_t}$$
$$+\beta_5 \frac{NPL_t}{Loans_t} + \beta_6 LoansYield_t + \beta_7 FloatLoanRatio_t + \beta_8 \frac{RELoans_t}{Loans_t} + \beta_9 \frac{ConsLoans_t}{Loans_t} + \varepsilon_{t+1} \quad (13)$$

	β_0	β_1	β_2	β_3	β_4	β_5	β_6	β_7	β_8	β_9	Mean R^2	Mean Obs.
mean(coef.)	0.0837	-0.0741									0.0778	317
t(mean(coef.))	5.6	-5.3										
median(t(coef.))	5.9	-5.1										
mean(coef.)	0.0037		0.8741								0.4087	317
t(mean(coef.))	4.0		9.1									
median(t(coef.))	4.0		15.4									
mean(coef.)	0.0114	-0.0077	0.8620								0.4114	317
t(mean(coef.))	2.4	-1.9	8.9									
median(t(coef.))	0.5	-0.4	13.3									
mean(coef.)	-0.0015	-0.0071		0.4635	0.1064	0.0925	0.0770	0.0061	0.0054	0.0065	0.4496	317
t(mean(coef.))	-0.3	-2.1		6.7	4.9	5.2	3.8	6.0	4.1	2.4		
median(t(coef.))	-0.2	-0.6		6.2	1.9	3.4	1.1	2.0	1.6	1.3		

The sample includes 14 cross-sections (t): Q4:05, Q4:06, Q4:07, Q4:08, Q2:09-Q3:11. Balance sheet items are generally measured at the end of the quarter. Income statement items are measured using trailing four quarters data. Details on variable definitions are provided in Section 3 and in Appendix B. mean(coef.) is the time-series mean of the corresponding regression coefficient. t(mean(coef.)) is the t-statistic of the mean coefficient (the ratio of the time-series mean to its standard error). median(t(coef.)) is the time-series median of the regression t-statistic.

Table 7
Summary statistics from cross-sectional regressions for comparing the predictive-ability of the estimated expected rate of credit losses and ALLL and PLLL

$$RealizedRCL_{t+1} = \beta_0 + \beta_1 \widehat{ExpectedRCL}_{t+1} + \beta_2 \frac{ALLL_t}{Loans_t} + \beta_3 \frac{PLLL_t}{AveLoans_t} + \beta_4 \frac{NCO_t}{AveLoans_t} + \beta_5 \frac{\Delta NPL_t^{unexp}}{AveLoans_t}$$
$$+\beta_6 \frac{NPL_t}{Loans_t} + \beta_7\, LoansYield_t + \beta_8\, FloatLoanRatio_t + \beta_9 \frac{RELoans_t}{Loans_t} + \beta_{10} \frac{ConsLoans_t}{Loans_t} + \varepsilon_{t+1} \quad (14)$$

	β_0	β_1	β_2	β_3	β_4	β_5	β_6	β_7	β_8	β_9	β_{10}	Mean R^2	Mean Obs.
mean(coef.)	0.0018	0.9811										0.3891	670
t(mean(coef.))	4.2	23.1											
median(t(coef.))	2.7	21.5											
mean(coef.)	-0.0009		0.4431									0.1453	670
t(mean(coef.))	-4.5		8.6										
median(t(coef.))	-1.5		9.4										
mean(coef.)	0.0018			0.6945								0.3775	670
t(mean(coef.))	5.7			22.5									
median(t(coef.))	4.2			21.0									
mean(coef.)	0.0002	0.5708	0.1089	0.3171								0.4361	670
t(mean(coef.))	0.8	17.8	5.7	17.1									
median(t(coef.))	-0.8	7.1	2.1	5.5									
mean(coef.)	-0.0032		0.0791	0.4099	0.1411	0.0509	0.0610	0.0281	0.0026	0.0007	0.0030	0.4696	670
t(mean(coef.))	-4.2		5.9	11.2	4.0	7.8	9.0	5.5	4.8	1.1	6.8		
median(t(coef.))	-1.7		1.7	5.8	2.5	1.7	3.1	1.4	1.2	-1.2	1.5		

The sample period includes trailing four quarters observations ending in quarter t for t = Q4:1997 through Q3:2011. Balance sheet items are generally measured at the end of the quarter. Income statement items are measured using trailing four quarters data. Details on variable definitions are provided in Section 3 and in Appendix B. mean(coef.) is the time-series mean of the corresponding regression coefficient. t(mean(coef.)) is the t-statistic of the mean coefficient (the ratio of the time-series mean to its standard error). median(t(coef.)) is the time-series median of the regression t-statistic.

Table 8
Summary statistics from cross-sectional regressions for evaluating out-of-sample predictions of credit losses: Alternative Approaches

$$RealizedRCL_{t+1} = \beta_0 + \beta_1 \widehat{ExpectedRCL}_{t+1} + \varepsilon_{t+1}$$

Panel A: Alternative extrapolation methods for the coefficients of Equation (9)

		β_0	β_1	Mean R^2	Mean Obs.
Most recent	mean(coef.)	0.0018	0.9811	0.3891	670
	t(mean(coef.))	4.2	23.1		
	median(t(coef.))	2.7	21.5		
Moving average (4)	mean(coef.)	0.0017	1.0101	0.3905	670
	t(mean(coef.))	4.3	20.4		
	median(t(coef.))	2.4	21.6		
Exponential smoothing (0.5)	mean(coef.)	0.0017	1.0008	0.3921	670
	t(mean(coef.))	4.3	21.6		
	median(t(coef.))	2.1	21.5		
Exponential smoothing (0.1)	mean(coef.)	0.0014	1.0652	0.4027	670
	t(mean(coef.))	5.2	20.7		
	median(t(coef.))	2.8	21.8		
Exponential smoothing (0.01)	mean(coef.)	0.0011	1.1787	0.4416	670
	t(mean(coef.))	6.6	25.1		
	median(t(coef.))	3.8	23.9		

Panel B: Estimating the coefficient of Equation (9) with annualized instead of trailing-four-quarters dependent variable

		β_0	β_1	Mean R^2	Mean Obs.
Trailing four quarters	mean(coef.)	0.0018	0.9811	0.3891	670
	t(mean(coef.))	4.2	23.1		
	median(t(coef.))	2.7	21.5		
Annualized quarterly data	mean(coef.)	0.0017	1.0133	0.3978	670
	t(mean(coef.))	4.7	23.7		
	median(t(coef.))	3.5	21.5		

The sample period includes trailing four quarters observations ending in quarter t for t = Q4:1997 through Q3:2011. Balance sheet items are generally measured at the end of the quarter. Income statement items are measured using trailing four quarters data. Details on variable definitions are provided in Section 3 and in Appendix B. mean(coef.) is the time-series mean of the corresponding regression coefficient. t(mean(coef.)) is the t-statistic of the mean coefficient (the ratio of the time-series mean to its standard error). median(t(coef.)) is the time-series median of the regression t-statistic.