DO INVESTORS IMPOUND INFORMATION ABOUT UNRECOGNIZED EXPECTED CREDIT LOSSES INTO BANK STOCK PRICES?

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For Tyler, Caroline, and Ann Kempter.

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I examine the extent to which bank loan loss allowances under current accounting standards reflect expected credit losses required to be recognized under the FASB's new expected credit loss model. Further, I examine whether allowance understatements relative to expected losses are impounded into bank stock prices. Using a new measure of lifetime expected credit losses based on vintage analysis, I find that current standards are associated with understatements of bank allowances relative to expected losses and that banks are understated on average, consistent with bankers' assertions that adoption of the new standard will reduce reported regulatory capital for most banks. Conversely, I find that 31% of allowances are *greater* than expected losses, inconsistent with the recognition of only incurred losses. Importantly, I find that allowance understatements are negatively associated with bank stock prices, suggesting that investors impound information about expected losses into price despite a lack of explicit recognition in the financial statements. Taken together, my findings suggest that adoption of the new standard will reduce regulatory capital for most banks but should not result in negative stock market reactions to the extent that unrecognized expected losses are already impounded in stock prices.

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CHAPTER 1: INTRODUCTION

Forecasting expected future credit losses is a key concern for all bank stakeholders, including managers, regulators, and investors. Information about exposure to expected credit losses in the loan portfolio is necessary for managers to properly underwrite loans, for regulators to correctly assess bank health, and for investors to make informed capital allocation decisions. However, under current U.S. GAAP, banks should accrue for only the portion of total lifetime expected credit losses that are deemed "probable" at the balance sheet date.[1] Critics of this "incurred loss model" of accruing for loan losses contend that it masks the true level of credit risk in banks' loan portfolios and may have led investors to underestimate credit risk prior to the financial crisis of 2007-2008. However, little attempt has been made to empirically examine these concerns. In this paper, I develop a bank-specific measure of expected credit losses and provide evidence on the extent to which bank loan loss allowances understate (or overstate) expected losses.[2] I then examine two research questions. First, to what extent does the incurred loss model of loan loss accounting contribute to understatements of the allowance relative to lifetime expected losses? Second, to what extent do bank share prices impound information about understatements relative to lifetime expected losses?

In response to claims that investors lack decision-useful information about expected credit losses under the incurred loss model, the FASB recently issued a new accounting standard – the "current expected credit loss" or "CECL" model – that will require all firms to estimate and

[1] Current accounting is based on guidance found in ASC 450-20, previously SFAS 5, and ASC 310-10-35, previously SFAS 114. In SFAS 5, the FASB uses the term "probable" to mean "the future event or events are likely to occur."

[2] The terms "understatements," "understated," and "unrecognized expected credit losses" in this paper refer to the level of recorded allowances relative to estimates of expected losses. I do not attempt to measure understatements relative to what allowances should be under the incurred loss model, which is typically the focus of prior research.

report expected rather than incurred losses on financial instruments, including loans.[3] The new model is expected to have the most significant impact on banks, such that the American Bankers Association calls the new model "the biggest change in bank accounting over the past 40 years" (ABA 2016b).[4] Despite criticism of the incurred loss model, the CECL model has sparked considerable debate amongst bank stakeholders, including the FASB board members themselves.[5] Some express concerns about the cost of implementation (*e.g.*, Haslett 2016). Others are concerned that the new model will not accurately reflect bank performance by creating a mismatch between the recognition of credit losses and compensating interest income (*e.g.*, Cumming 2015; Haslett 2015) and that recognizing expected losses will adversely affect bank regulatory capital levels (Dobbs 2015).[6] While bank regulators appear to support the new standard (*e.g.*, Curry 2013), the response from the investor community has been mixed. Some investors support the proposed standard because they believe it will reduce earnings volatility by smoothing loan loss provisions over the credit cycle (*e.g.*, Keefe, Bruyette, and Woods 2015), while others argue that it will result in loan loss estimates that reflect financial risk rather than financial performance and increase the volatility of earnings (Cumming 2015). This paper helps inform this debate by providing empirical evidence on the extent to which allowances understate expected losses and the consequences of understatement.

To estimate allowance understatements, I develop a new measure of expected losses using vintage analysis. The FASB has suggested vintage analysis as one potential approach for estimating expected losses under the CECL model. Vintage analysis enables me to forecast loan

[3] The FASB issued an Accounting Standards Update (ASU) "Financial Instrument – Credit Losses" (Subtopic 825-15) in June 2016.
[4] In this paper, the term "expected credit losses" is synonymous with forecasted life-of-loan credit losses.
[5] In September 2015, FASB board member Lawrence Smith stated at a presentation at the AICPA's National Conference on Banks and Savings Institutions that, while he supports *disclosure* of expected losses, he would vote against the proposal because it would require banks to recognize a loss on the day it originates a loan.
[6] The Basel Committee on Banking Supervision has suggested delaying implementation of the IASB's expected loss model, IFRS 9, due to concerns that the impact of adoption will result in a material "capital shock." (Basel 2016)

losses over multiple years for multiple vintages of loan originations across different loan types for publicly-traded commercial banks and bank holding companies each quarter from 2006Q4-2014Q4.[7] While accounting research recognizes the limitations of bank loan loss allowances as measures of expected losses (*e.g.*, Beaver et al. 1989; Barth et al. 1991; Cantrell et al. 2012; Harris, Khan, and Nissim 2015), few studies forecast credit losses, and those that do typically forecast losses over only a one-year horizon. My measure is the first effort (of which I am aware) to forecast lifetime credit losses for a portfolio of loans in order to assess the relative adequacy of bank loan loss allowances.[8]

I find significant variation across banks and across time in the extent to which allowances understate expected credit losses, consistent with prior research that finds variation in the application of the incurred loss model. For the full sample, the mean (median) ratio of expected losses to loans is 3.1% (2.1%) compared to a mean (median) allowance to loans ratio of 1.8% (1.5%). Approximately 56% of bank-quarters have allowances that are less than expected losses, with 50% of bank-quarters being understated by 20% or more. Conversely, 31% of bank-quarters are overstated, with 29% of bank-quarters overstated by 20% or more.[9] Interestingly, in quarters leading up to the financial crisis (2006Q4-2007Q4), the average ratio of the allowance to loans was 1.20% compared to a ratio of expected losses to loans of 1.28%. This suggests that, contrary to critics' assertions, allowances estimated prior to the onset of the financial crisis largely reflected banks' historical life-of-loan losses on average.

To test the association between attributes of the incurred loss model and allowance

[7] Vintage analysis tracks the loss patterns of loans originated in a given period over their lives. Past loss patterns are then used as the basis for projecting remaining losses for outstanding vintages of loan originations.

[8] Validation tests show that my measure is positively associated with future charge-offs up to seven years ahead compared to only two years for loan loss allowances and has predictive power for future regulatory actions incremental to that in other credit-quality metrics.

[9] 13% of bank-quarters with an allowance to loans ratio within +/- 0.2% of estimated expected losses to loans are considered adequately reserved.

understatements, I exploit the fact that banks use two different loan loss estimation techniques under current GAAP. For most loans, banks estimate losses based on the familiar loss contingency principles of SFAS 5, recording losses when they are *probable* and *reasonably estimable*. For large, heterogeneous loans specifically identified as having a probable credit loss, however, loan loss accounting follows SFAS 114, which requires an estimate of lifetime expected credit losses. Thus, *all* loans accounted for under SFAS 114 have crossed the "probable" threshold and should have allowances equal to expected losses, while the pool of loans accounted for under SFAS 5 contains a mix of loans with expected losses that have and have not passed the "probable" threshold. If banks recognize only incurred losses in practice, then we should observe understatements increasing across banks with higher percentages of loans accounted for under SFAS 5. Further, if banks reserve for only a portion of lifetime expected credit losses (*e.g.*, losses expected over one year), then understatements should be increasing in length of the loss emergence period. In empirical tests, I find evidence consistent with these predictions, as allowance understatements are increasing in both the percentage of SFAS 5 loans and the length of the loss emergence period.

To test the extent to which bank stock prices reflect information about allowance understatements, I extend prior research on the relationship between loan loss allowances and firm value originating with Beaver et al. (1989). Placing firms into deciles based on the difference between expected loss estimates and bank loan loss allowances, I find that bank market values are decreasing across deciles of understatement in a pooled sample from 2006Q4-2014Q4 and in all sample years.[10] For example, among banks in deciles 1-3 (banks that are overstated, on average), average market-to-book ratios are greater than 1.25, whereas average market-to-book ratios among banks in deciles 8-10 (the most significantly understated banks) are

[10] This result is robust to scaling market value of equity by both shares outstanding and the book value of equity.

near or below 1.0. This suggests that bank stock prices reflect information about expected credit losses beyond the incurred losses explicitly recognized in the financial statements.

This paper should be of interest to accounting standard setters as well as various bank stakeholders, including managers, investors, standard setters, and regulators. First, while the FASB expects the new standard to enhance bank transparency by helping investors better understand the credit risk in banks' loan portfolios, my results suggest that information about lifetime expected losses is already incorporated into stock prices despite a lack of explicit recognition. Thus, adoption of the CECL model may not result in negative stock market reactions, a major concern of managers and shareholders. Second, descriptive evidence regarding the extent of understatement relative to expected losses should be of interest to stakeholders concerned with the potential regulatory capital consequences of the CECL model. Due to the cumulative-effect adjustment required at adoption, significant understatements at the time of adoption will have an adverse impact on regulatory capital ratios. While bank allowances approximated expected losses in the period prior to the crisis, my results suggest that bank allowances were significantly less than expected losses at the end of 2014, with average understatements equal to 1.1% of total assets and 11.5% of tangible common equity capital. To the extent that significant understatements exist at the time of adoption, banks will either need to raise new capital or address capital adequacy concerns with regulators.

This paper also makes several contributions to the academic literature on bank loan loss accounting. First, I contribute to the debate on the merits of an expected *vs.* incurred loss model for financial stability (Acharya and Ryan 2016). That unrecognized expected losses are already impounded into stock price suggests that increases in transparency under the CECL model are likely to depend on the extent to which managers incorporate private, forward-looking information into their expected loss estimates. Second, I contribute a new measure of expected credit losses that predicts cumulative net charge-offs up to seven years ahead. This measure may be useful to researchers interested in measuring expected lifetime credit losses. Third, because my measure of under- and over-statements is based on estimated loan origination data and historical charge-off patterns that are not explicitly disclosed, my results suggest that bank share prices incorporate information about expected credit losses well beyond those metrics currently disclosed to investors. Fourth, I extend the literature examining the relation between loan loss allowances and bank market values (*e.g.*, Beaver et al. 1989; Barth et al. 1991; Ahmed et al. 1999), which reports mixed results. I predict and find that both allowances and understatements of the allowance relative to expected losses are negatively associated with bank value.

The rest of this paper proceeds as follows. Chapter 2 provides background on loan loss accounting. Chapter 3 develops my hypotheses. Chapter 4 discusses my model for estimating expected credit losses and sample selection. Chapter 5 discusses hypothesis tests and results. Chapter 6 provides additional analysis. Chapter 7 concludes.

CHAPTER 2: BACKGROUND

Current Loan Loss Accounting: The Incurred Loss Model

At the time of origination, lenders have an expectation of future credit losses that they reflect in the interest rates charged for loans. Current accounting standards require that these expected losses be recognized in the financial statements over time in the period when they are incurred. This income-statement-focused method of accounting for credit losses is commonly referred to as the incurred loss model ("ILM"). Two standards govern loan loss accounting under current GAAP: Accounting Standards Codification (ASC) 450-20 (formerly SFAS 5) and ASC 310-10-35 (formerly SFAS 114). The particular standard used for a loan depends on whether it has been specifically identified as impaired.[11] Loans not individually identified as impaired are analyzed in aggregate following ASC 450-20, while impaired loans follow ASC 310-10-35.

An allowance for loan and lease losses ("ALLL") is recorded for loans analyzed in aggregate ("SFAS 5 loans") when (1) it is *probable* that a credit loss has been incurred at the balance sheet date and (2) the loss is reasonably estimable but not specifically identifiable.[12] SFAS 5 loans are a mixture of loans for which a loss *is* probable but not specifically identifiable and loans for which a loss *is not* probable. Loans that are specifically identified as impaired are removed from the pool of SFAS 5 loans, and an allowance is estimated for each specific loan. Thus the pool of loans specifically identified as impaired ("SFAS 114 loans") contains only loans for which a loss is deemed to be probable.[13] A key distinction between the allowances

[11] According to ASC 310-10-35-10, a loan should be considered impaired when "it is probable that the entity will be unable to collect all amounts due according to the contractual terms of the receivable."
[12] This portion of the ALLL is similar to the allowance for doubtful accounts for non-financial institutions.
[13] Various methods for estimating the allowance for these loans are permitted, including a comparison of discounted future cash flows to the carrying value of the loan as well as a comparison of the expected liquidation value of any underlying collateral, if applicable, to the loan's carrying value.

estimated for SFAS 5 and SFAS 114 loans is that the allowance for SFAS 114 more nearly represents an estimate of *expected* losses, while the allowance for SFAS 5 should theoretically recognize only *incurred* losses.[14]

Conceptually, then, an allowance estimated under the ILM should always be less than lifetime expected credit losses because it represents the portion of expected losses that are deemed probable but have not yet been charged off. This "understatement" of allowances relative to expected losses should be independent of the state of the economy.

The ILM and Allowance Understatement

Calls for a change to loan loss accounting standards typically discuss two key theoretical issues with the ILM. First is the ILM's reliance on the "probable" threshold for contingent loss recognition. In determining when this threshold has been crossed, critics argue that banks wait until an observed "loss event" before recognizing *any* allowance and thus record no allowance for many loans, even if past experience indicates that it is likely that a "loss event" will occur in the future. For example, the 2009 report of the Financial Crisis Advisory Group, formed in the wake of the financial crisis by the FASB and IASB, states that "The incurred loss model for loan loss provisioning and difficulties in applying the model – in particular, identifying the appropriate trigger points for loss recognition – in many instances has delayed the recognition of losses on loan portfolios."[15] The second concern often raised is that allowances estimated under the ILM are too reliant on historical charge-off rates and therefore too backward-looking. Over-

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[14] U.S. bank regulatory guidance significantly expands on the concepts in U.S. GAAP to provide guidance on methods banks should use to estimate an adequate allowance. The 2006 *Interagency Policy Statement on the Allowance for Loan and Lease Losses* (FDIC 2006) details factors banks should consider when adjusting historical loss rates in estimation of the loan loss allowance, including changes in underwriting standards, changes in economic conditions, changes in the volume and severity of delinquent loans, and changes in collateral values.

[15] Similarly, FASB board member Hal Schroeder noted in a 2015 FASB Outlook article that "some stakeholders have argued that investors were 'caught by surprise' by rising credit risk, and that accounting rules need to change accordingly." (Schroeder 2015) Further examples can be found in FSF (2009), White and Stovall (2013), and the feedback summary prepared by the FASB related to proposed standards update, *Financial Instruments – Credit Losses (Subtopic 825-15)*.

reliance on historical data could result in allowances that are not sensitive enough to changes in the credit environment.[16]

In addition to theoretical issues with the ILM, methods of applying the ILM could contribute to allowance understatement. For example, many banks use practical expedients to allowance estimation such as "loss emergence periods" (Grant Thornton 2012). Under this commonly-used technique, banks estimate an annual charge-off rate and forecast this rate to continue over some period beyond the balance sheet date, often only one year. For example, interagency guidance from bank regulators says (FDIC 2006):

> "Generally, institutions should use at least an "annualized" or 12-month average net charge-off rate that will be applied to the groups of loans when estimating credit losses."

Further, the Office of the Comptroller of the Currency states in its *Comptroller's Handbook*:

> "Many banks consider coverage of one year's losses an appropriate benchmark of an adequate reserve for most pools of loans. Except in the situations discussed below, OCC examiners should generally view this level of coverage as appropriate."

While loss emergence periods were not developed or promoted by the FASB and are not a theoretical part of the ILM, bank regulators have essentially authorized their use. The use of loss emergence periods for allowance estimation that are shorter than actual loss emergence periods can contribute to allowance understatement relative to expected losses.

Despite the theoretical and practical reasons that the ILM may lead to allowance understatements relative to expected losses, there are several reasons why banks may <u>not</u> wait until losses are "probable" before recognition. First, estimating the allowance for a pool of SFAS 5 loans requires estimating a percentage of loans within the pool for which a loss event

[16] Recent research on bank loan loss allowances finds that over-reliance on past charge-off data, while not an explicit feature of the ILM, may have been exacerbated by banking regulators in the early 2000's. Beck and Narayanmoorthy (2013) report evidence that the SEC's 2001 issuance of Staff Accounting Bulletin 102, *Selected Loan Loss Allowance Methodology and Documentation Issues*, caused bank loan loss provisions to become more highly associated with past charge-offs and less associated with non-accrual loans. This suggests that the lack of forward-looking information in bank allowances that standard setters seek to remedy with an expected loss model may be at least partially due to the implementation of the ILM rather than its concepts.

has occurred (the probability of default) and the average loss severity given default. In practice, banks estimate reserve rates based on historical charge-off rates, adjusting for qualitative factors that managers believe will cause future credit losses to differ from past credit losses. Banks commonly calculate reserve rates separately for disaggregated categories of loans (*e.g.*, loan types) and then apply one rate to <u>all</u> loans in that category, including newly-originated loans, inconsistent with waiting until it is probable that a "loss event" has occurred.

Second, the potential for allowance understatement will depend on whether the assumed loss emergence period is sufficiently less than or greater than the actual loss emergence period. If the assumed loss emergence period is less than the actual loss emergence period, then the allowance will be understated. On the other hand, if an annual charge-off rate is forecasted over a loss emergence period that is greater than or equal to the actual loss emergence period, the allowance may be *overstated* relative to expected losses. Appendix B provides an illustration.

Third, one could interpret the amount of allowance deemed "adequate" according to regulatory guidance to be life-of-loan losses. For instance, the OCC's *Comptroller's Handbook* states that the ALLL is "an estimate of uncollectible amounts that is used to reduce the book value of loans … to the amount that is expected to be collected." This implies an allowance equal to expected losses. Additionally, regulators often state that the allowance should be sufficient to cover losses "inherent" in the loan portfolio (OCC 2012, FRB 2014).[17] Further, in the Q&A to SAB 102, the SEC states that "The staff believes that a registrant's loan loss allowance methodology is considered valid when it accurately estimates the amount of loss **contained** in the portfolio." (emphasis added) The terms "inherent" and "contained" lend themselves to a life-of-loan interpretation.

[17] The dictionary definition of "inherent" is "existing in" while the glossary of the OCC Handbook clarifies the term "inherent loss" to mean losses that meet the conditions of SFAS 5.

CHAPTER 3: HYPOTHESIS DEVELOPMENT

ALLL Understatement vs. Overstatement

While current GAAP theoretically prohibits the recognition of loan losses until they are "probable," whether the application of the ILM in practice results in allowances that overstate or understate expected losses is an open question. If the ILM is applied in accordance with theory, then we should expect understatement to increase as the percentage of the loan portfolio for which loan losses are not deemed "probable" increases. Because the pool of SFAS 114 loans contains *only* loans for which losses are deemed "probable" while the pool of SFAS 5 loans contains a mix of loans for which losses are and are not probable, allowances for banks with a higher percentage of SFAS 5 loans to total loans should be more understated relative to expected losses. This leads to my first hypothesis, in alternate form:

H1a: *Allowance understatement is increasing in the ratio of SFAS 5 loans to total loans.*

Further, if banks assume loss emergence periods for incurred losses that are shorter than the emergence periods of total expected losses, then understatement should be associated with the total period of loss emergence. This leads to my next hypothesis, also in alternate form:

H1b: *Allowance understatement is increasing in the length of the loss emergence period.*

Allowance Understatements and Loan Market Values

To test the association between allowance understatements relative to expected losses and bank market values, I first develop a model predicting the relation between allowances, expected losses, and loan market values. At a given point in time, losses expected over the remaining life of a loan portfolio consist of both *compensated* losses – those credit losses expected at the time of loan origination and incorporated into a loan's interest rate – and *uncompensated* losses – those not anticipated at loan origination but arising due to unexpected changes in credit risk. At loan origination, the following relationships will hold assuming that the credit risk in a loan is correctly priced:

$$MVL = BVL \quad (1a)$$

$$ECL = CCL \quad (1b)$$

where *MVL* denotes the market value of loans, *BVL* the book value of loans, *ECL* total expected credit losses, and *CCL* compensated credit losses. The key point is that while expected losses are greater than zero, these losses are *compensated* and do not represent economic losses that cause market value and book value to differ (Beaver et al. 1989; Hodder et al. 2014).

Loan fair values are affected by both changes in market interest rates as well as changes in credit risk (*i.e.*, expected future cash flows). For modeling simplicity, I assume for the moment that loans reprice quickly enough that changes in interest rates do not result in material changes in market value. I will relax this assumption later when developing my empirical model. If credit risk increases, causing expected losses to exceed those anticipated at origination, the following will hold:

$$MVL = BVL - UCL \quad (1c)$$

$$ECL = CCL + UCL \quad (1d)$$

where *UCL* denotes uncompensated credit losses.

Because the allowance under the ILM captures only credit losses that are probable, it can be characterized as follows:[18]

$$ALLL = \varphi CCL + \lambda UCL \quad (1e)$$

where *ALLL* denotes the loan loss allowance and $\varphi \in [0,1]$ and $\lambda \in [0,1]$ represent the probable portions of *CCL* and *UCL*, respectively.

[18] This characterization assumes that bank managers include only estimates of future net charge-offs in their ALLL estimates and excludes potential signaling motivations discussed in prior literature on loan loss provisions and the ALLL (*e.g.* Grammatikos and Saunders 1990; Musumeci and Sinkey 1990; Wahlen 1994; Beaver and Engel 1996).

Similarly, *ECL*, consisting of probable credit losses and those not deemed probable, can be characterized as:

$$ECL = \varphi CCL + (1-\varphi)CCL + \lambda UCL + (1-\lambda)UCL \quad \text{(1f)}$$

The difference between total expected credit losses and the ALLL at the end of any given period, denoted *ECLDIFF*, is:

$$ECLDIFF = ECL - ALLL = (1-\varphi)CCL + (1-\lambda)UCL \quad \text{(1g)}$$

Understatements of the allowance relative to total expected losses, then, are made up of the portions of compensated and uncompensated credit losses that are not deemed "probable" at the balance sheet date.

To see how the allowance and understatements, *ECLDIFF*, relate to market value, Eq. (1e) and (1g) can be re-arranged and substituted into (1c) to yield:

$$MVL = BVL - \lambda UCL - (1-\lambda)UCL \quad \text{(1h)}$$

$$= BVL - ALLL + \varphi CCL - [ECLDIFF - (1-\varphi)CCL] \quad \text{(1i)}$$

$$= BVL - ALLL - ECLDIFF + CCL \quad \text{(1j)}$$

As Eq. (1j) shows, *ALLL* and *ECLDIFF* are negatively associated with loan market values after controlling for compensated credit losses because they contain information about uncompensated credit losses, including those that have been incurred (*ALLL*) and those that have not been incurred (*ECLDIFF*). This model of the relationship between the allowance and market value expands on prior research in accounting, which does not distinguish between compensated and uncompensated credit losses. It provides a clearer prediction for the sign of the coefficient for *ALLL* in a multivariate regression on the market value of loans by controlling for the portion of the allowance related to compensated credit losses, which should not create a difference between book value and market value.

Arguments in favor of replacing the ILM with an expected loss model suggest that the ILM results in systematically understated allowances and that investors are "fooled" by these understatements into believing that lifetime expected losses at any given balance sheet date are lower than they really are. In the context of the above model, this requires that investors overestimate φ, λ, or both. If this occurs, and investors are not aware that the allowance understates expected losses, then they will simultaneously underestimate credit risk and overestimate future bank profitability. This is a plausible scenario given a large body of prior research in accounting providing evidence that investors do not incorporate economic signals into stock price until they are realized in earnings (*e.g.*, Bernard and Thomas 1989, 1990; Abarbanell and Bushee 1998; Picconi 2006).

Exacerbating this problem for expected credit losses is that many credit quality signals disclosed by banks, including those examined in prior research, provide information about incurred rather than expected losses (*e.g.*, nonperforming or delinquent loans), while information about expected losses, such as historical loss emergence patterns and the amount of the allowance that represents compensated expected losses, is not calculated and disclosed. The incomplete revelation hypothesis (Bloomfield 2002) predicts that information that is more difficult to extract will be less fully revealed in price.[19] The lack of disclosure of information about expected losses relative to incurred losses could inhibit the incorporation of information about unrecognized expected losses into banks' stock prices.

On the other hand, given the significance of the allowance for banks, it is plausible that

[19] The FASB itself appears to be undecided regarding whether investors can detect ALLL understatements. For instance, in the same FASB Outlook piece where he claims that investors were "caught by surprise" by credit losses, FASB board member Hal Schroeder says: "[the] valuation gap, or discount, [between the market values and book values of banks relative to the gap for other industries] began to notably expand six quarters before the financial crisis and had doubled by its beginning in 2007. A reasonable explanation for the sharp devaluation is that investors had begun to question GAAP book values of banks. This was because they believed loan loss reserves were understated for the increasing credit risk."

investors have a sufficient understanding of the accounting for credit losses to expect the allowance to be less than lifetime expected losses and therefore estimate φ and λ. If this is the case, then unrecognized expected losses will be reflected in bank stock price. Information available to investors to estimate compensated and uncompensated life-of-loan credit losses include interest income (because compensated credit losses are incorporated into loan interest rates), historical charge-off patterns, discussions of loan portfolio composition such as loan types and average durations,[20] and loan performance data indicating unexpected increases or decreases in credit quality (*e.g.*, changes in nonperforming loans or delinquency rates).

Ultimately, whether investors detect and price expected losses not reflected in the allowance is an empirical question. Based on the relationship between understatements and loan market values in Eq. (1j), I predict the following:

> ***H2:*** *If bank share prices reflect allowance understatements, then the amount of understatement will be negatively associated with a bank's market value after controlling for the allowance and total compensated credit losses.*

[20] As discussed previously, the extent of understatement should be predictably related to portfolio duration and the period of loss emergence. For instance, a bank with only short-term loans (*e.g.*, credit card loans) for which losses emerge within one year may be adequately reserved under the ILM if they estimate the ALLL based on charge-offs anticipated over the next year. A bank with long-term loans (*e.g,*. residential mortgage or commercial real estate), on the other hand, could be significantly under-reserved relative to expected losses if the ALLL is intended to cover only charge-offs anticipated over the next year.

CHAPTER 4: ESTIMATING EXPECTED CREDIT LOSSES AND SAMPLE SELECTION

There is a large literature in banking and finance that addresses credit risk modeling. However, models of credit risk developed in this literature cannot be used to estimate expected credit losses in bank loan portfolios based on publicly-available data because they either require loan-level data (*e.g.*, Altman and Saunders 1998; Lopez and Saidenberg 2000; Dietsch and Petey 2002), focus on financial instruments other than those found in bank loan portfolios (*e.g.*, Lopez and Saidenberg 2000), or forecast losses over horizons shorter than the lifetime of portfolio loans. Little effort has been given to estimating the <u>lifetime</u> expected losses in a bank's loan portfolio based on publicly-available data.[21] In this paper, I develop a method to do so.

In the ASU on credit impairment, the FASB provides several examples of how firms can estimate expected losses on financial instruments. One suggested method is the use of "vintage" analysis.[22] Many in the industry expect that the use of vintage analysis will be the standard method of expected loss estimation required by auditors and regulators (McPhail and McPhail 2014; Sageworks 2016; ABA 2016a). Vintage analysis requires analysis of the performance of a static pool of financial instruments over time to determine marginal loss rates each period after the vintage is formed and cumulative loss rates over the life of the instruments. These loss rates are then applied to vintages of similar financial instruments outstanding at the balance sheet date to estimate remaining life-of-loan losses for a portfolio. According to the ASU, banks can use vintage analysis with historical data to develop a base estimate of expected losses. Bank managers can then adjust base estimates using "reasonable and supportable forecasts" of future economic conditions that will cause future loss rates to differ from historical rates.

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[21] In a recent paper, Harris et al. (2015) develop a new measure of expected credit losses, but their measure is not bank-specific and estimates only the rate of expected losses *one year ahead*.
[22] See "Example 3: Estimation of Expected Credit Losses Based on a By-Vintage Basis" in the ASU.

I develop a bank-specific model of expected lifetime credit losses at each balance sheet date based on the concept of vintage analysis as follows:

$$CO_{ijt} = \beta_{ij1} LO_{ijt-1} + \cdots + \beta_{ijN} LO_{ijt-N} + \varepsilon_{it} \quad (2)$$
$$\text{s.t. } \beta_{ijn} \geq 0$$

where *i*, *j*, and *t* are subscripts for firm, loan type, and quarter, respectively. *CO* denotes gross charge-offs and *LO* denotes loan originations.[23] By excluding an intercept, each regression coefficient β_{in} is an estimate of the average marginal loss rate *n* periods after origination while the sum of all coefficients ($\sum_{n=1}^{N} \beta_{iN}$) is an estimate of the lifetime cumulative loss rate for each loan origination vintage. Thus Eq. (2) estimates the historical loss emergence pattern for bank *i* and loan type *j* at the end of quarter *t*. Each coefficient β_{ijn} is constrained to be greater than or equal to 0 because an originated loan cannot result in negative charge-offs. Because this model estimates the historical relationship between loan originations and charge-offs, it represents the base expected loss estimate required under CECL. It is a useful benchmark for assessing the extent to which bank allowances reflect life-of-loan losses and whether investors detect and price differences between reported allowances and expected losses.

I estimate Eq. (2) by bank, loan type, and quarter, using rolling regressions that require 40 observations for each bank-quarter. Loans are disaggregated into four types: single-family residential real estate loans (including closed-end, revolving, and construction loans), non-single-family real estate loans (including multifamily and commercial real loans), consumer loans (*i.e.*

[23] Models with a series of lagged values of the independent variable are called distributed lag models. Judge et al. (1985) provide a good summary of econometric issues concerning distributed lag models as well as model selection. In cases where explanatory variables exhibit extreme multicollinearity, estimation of distributed lag models with OLS can be problematic due to difficulty determining how much weight to place on each lag. In such cases, alternative models such as Almon polynomial lag distribution models can be used. However, these models rely on assumptions regarding the functional form of the coefficients that are often not known *ex ante*, including in my setting. As Judge et al. (1985) note, incorrect assumptions about the functional form and the number of lags in such instances can lead to significant coefficient bias and misleading estimates. Further, they note that it is not clear that such models outperform OLS. Because I restrict all coefficients to be greater than or equal to zero, I employ a non-linear modeling technique using the SAS PROC NLIN procedure. For a short summary of non-linear modeling, see http://www.ats.ucla.edu/stat/sas/library/SASNLin_os.htm.

credit card and automobile loans), and other non-real estate loans (including commercial and industrial loans). Estimating Eq. (2) by loan type has several benefits. First, estimating by loan type helps to reduce noise in the relationship between loan originations and subsequent charge-offs, particularly for banks with highly diversified portfolios. Second, because Eq. (2) captures historic loss patterns, estimating by loan type allows projections of future expected credit losses to account for changes in loan portfolio mix.

Because each regression coefficient is constrained to be greater than or equal to 0, I estimate Eq. (2) using an iterative non-linear modeling technique. This process requires the researcher to supply initial estimates of each parameter, after which the program incrementally adjusts each coefficient to minimize the sum of the squared residuals. I estimate Eq. (2) for each bank using initial parameter values of 0.001, 0.0025, 0.005, and 0.0075. Further, because the appropriate number of explanatory lags N is likely to vary by bank, I estimate Eq. (2) for $N \in [1,24]$ for each bank. I then select the model for each bank with the highest pseudo-R^2 statistic.[24,25]

After estimating N lag coefficients for each bank-quarter, I apply these coefficients to the loan originations in quarters t to $t\text{-}N\text{+}1$ for each loan type j, summing together the remaining expected losses for each vintage of originations to obtain my estimate of expected life-of-loan

[24] Because different banks have different lending strategies, the duration of loans and the number of lags that explain net charge-offs in quarter t will vary by bank. Judge et al. (1985) note that the selection of N in a distributed lag model is critical, because if N is too low (*i.e.* N is less than the true number of lags), then regression coefficients will be biased, while if N is too high, then coefficient estimates are inefficient. Further, as N increases, sample size decreases and survivorship bias increases, decreasing the generalizability of the results. To determine the maximum N to use, I estimate Eq. (2) for my full pooled sample for N = 4, 8, 12, 16, 20, 24, 28, 32, and 36, thus allowing for charge-offs to occur anywhere up to 36 quarters after loan origination. I set the initial parameter estimate for each coefficient at 0.005. The pseudo R^2 is highest with 36 lagged quarters of loan originations (Pseudo R^2 = 76.8%). However, I set the maximum N at twenty-four quarters for two reasons. First, the bulk of lifetime credit losses are observed within the first 13 quarters for the full sample. Second, requiring 36 lags for each bank quarter limits the sample to observations from 2009-2014. While the use of 24 lags rather than 36 lags may inhibit my ability to estimate the true model for some banks, I believe the benefits of additional quarters of observation (including quarters in 2006-2008, which includes pre-crisis quarters) outweigh the costs.

[25] I calculate a pseudo-R^2 measure as 1-($SS_{residual}/SS_{corrected}$).

credit losses. Estimated expected credit losses for each loan type, *j*, are then summed to arrive at a total expected credit loss estimate, *ECL*, for the loans outstanding at the end of quarter *t*. Appendix C contains a simple example of the mechanics of this calculation. The resulting expected loss estimate is then compared to the allowance recorded on the balance sheet, with the variable *ECLDIFF* calculated as *ECL* minus the allowance for each bank-quarter. Positive values of *ECLDIFF* thus indicate understatements of the allowance relative to expected losses while negative values indicate overstatements.

Estimating Loan Originations

Estimation of Eq. (2) requires data on loan originations. Unfortunately, this information is not systematically disclosed by banks in aggregate. To address this, I develop an estimate of loan originations for each bank-quarter. For single- and multi-family loans, I gather loan origination data disclosed under the Home Mortgage Disclosure Act (HMDA) of 1975, which requires banks to disclose data on all residential and multifamily loan applications received and loan originations each calendar year. Obtaining direct loan origination data is particularly important for these loan types due to the sensitivity of their prepayment patterns to changes in market interest rates.

For loans that are less likely to prepay due to changes in market interest rates, I gather data on average loan durations from various sources, including static pool data from credit card and automobile loan securitization trusts and survey data on the average loan maturities of commercial and industrial loans and non-real-estate agriculture loans collected by the Federal Reserve. I assume that repayments occur ratably over time based on the average maturity period and then infer loan originations for each bank based on the change in the beginning and ending balances of each loan type and the estimated repayments. See Appendix D for further detail about how I estimate loan originations for each bank-quarter. To control for historical merger and acquisition activity in the time series of loan origination data for a given bank *i* at the end of quarter *t*, I sum together the loan originations in periods *t-n* of all banks acquired by bank *i* in quarters prior to quarter *t*.

Sample

I begin with regulatory data for all bank-quarters of publicly-traded commercial banks and bank holding companies (collectively "banks") available on SNL Financial from 1990-2014. To identify publicly-traded banks as well as to link to stock price information on CRSP, I utilize a table maintained by the Federal Reserve Bank of New York that matches regulatory identification numbers (RSSD ID) from the National Information Center to CRSP PERMCO.[26] I require that each bank-quarter in my final sample have at least 39 prior quarters of data, yielding 40 observations to estimate Eq. (2) for each bank quarter. To reduce the influence of outliers, I winsorize all continuous variables at the 1% level. After adding market data from CRSP and Compustat, my sample includes 8,107 bank-quarters for 364 individual banks.

Analysis of ECL Measure

Figure 1 illustrates the output of estimating Eq. (2) and shows the pattern of marginal loss rates, or "loss curves," generated by the model for select banks. A visual examination of these graphs suggests that (a) the model captures relatively consistent charge-off patterns across quarters for each bank and loan type and (b) banks' loss curves are noticeably different both in shape (*e.g.*, period of peak charge-offs) and number of explanatory lags.

To validate that my ECL estimates predict lifetime credit losses, I perform two tests. First, I test their predictive power for cumulative net charge-offs up to 7 years ahead and

[26] This table was most recently updated at March 31, 2014. To view the table as well as a description of process by which the Federal Reserve Bank of New York matches RSSD ID to PERMCO, see http://www.newyorkfed.org/research/banking_research/datasets.html.

compare this predictive ability to that of ALLLs. This test is similar to that employed by Cantrell et al. (2012), who perform a “horse race” between ALLLs and loan fair values in predicting year-ahead net charge-offs and changes in non-performing loans. If banks under-reserve relative to expected losses, then ECL estimates should predict net charge-offs further into the future than ALLLs. I then test whether ECLs help predict the likelihood that banks are subject to formal regulatory enforcement. If my measure of ECL captures useful information about credit risk, then it could help predict future regulatory actions.

The results for predicting cumulative net charge-offs for the full sample are presented in Appendix E in Table E1, Panel A. ECL estimates are positively associated with net charge-offs in each period when included as the sole explanatory variable. The dominance of the ALLL over ECL estimates over shorter horizons is not surprising, as the ALLL includes management’s private information about future charge-offs. However, ECL estimates add incremental explanatory power for cumulative charge-offs five, six, and seven years out, consistent with my measure capturing information about lifetime expected losses. Panel B and Panel C support this interpretation, as I find that the incremental predictive power is concentrated in bank-quarters with longer loss emergence periods.

I further examine the predictive power of ECLs and ALLLs for bank-quarters at various stages of the financial crisis: 2006-2007, 2008-2009, 2010-2011, and 2012-2013 (Panels D-G). A similar pattern emerges in these sub-samples, as ECLs are incrementally predictive of charge-offs one year ahead for each sub-period and the incremental predictive power of ECLs is stronger for charge-offs recognized further in the future.

As additional validation, I test the association between ECL estimates and future actions taken by bank safety and soundness regulators. This test should be viewed as exploratory and as a dual test of my measure and the enforcement process because, while evidence that my measure of expected credit losses is associated with future regulatory actions would provide support that I am capturing incremental information about credit risk, a lack of association does not invalidate the measure, as it is unclear *ex ante* whether bank regulators utilize information about expected credit losses in assessments of bank health.

I begin by placing bank-quarters that are subject to a regulatory enforcement action six quarter ahead into deciles based on ECL. Panel A of Table E2 shows that nearly 60% of bank-quarters under regulatory enforcement six quarters ahead fall into the top three deciles of ECL and nearly 70% in the top four deciles. Panel B of Table E2 shows the results of a multivariate regression to see if my measure of ECL has predictive power for future regulatory actions incremental to other credit quality metrics, including the allowance, nonperforming loans, and loan charge-offs. Specifically, I estimate the following model:

$$\Pr(ENF_{t+6}) = \alpha_0 + \alpha_1 HighECL_{it} + \alpha_2 \frac{ALLL_{it}}{Loans_{it}} + \alpha_3 \frac{NPL_{it}}{Loans_{it}} + \alpha_4 \frac{CO_{it}}{Loans_{it}} + \alpha_5 \frac{AvgInt_{it}}{Loans_{it}} + \alpha_6 Tier1Ratio_{it} + \alpha_7 \frac{NIBP_{it}}{TA_{it}} + \alpha_8 \frac{SGL_{it}}{TA_{it}} + \alpha_9 \frac{Cash_{it}}{TA_{it}} + \alpha_{10} \frac{BrokDep_{it}}{TA_{it}} + \alpha_{11} \frac{|GAP|_{it}}{TA_{it}} + \varepsilon_{it} \quad (3)$$

where *High ECL* is an indicator variable equal to 1 if a bank-quarter falls in the top four deciles of *ECL* and 0 otherwise. *ALLL* and *CO* are as defined previously. The remaining control variables, defined in Appendix A, are additional variables that are likely to be important to bank regulators when assessing a bank's safety and soundness.[27] The results of estimating Eq. (3) presented in Table E2 Panel B show that ECL estimates are incrementally predictive of enforcement actions six quarters ahead, suggesting that my measure of expected losses is

[27] As part of routine bank safety and soundness examinations, bank regulators assess each bank along a number of dimensions and then assign each bank a safety and soundness rating. Referred to as CAMELS ratings, these ratings range from 1-5 and entail an assessment of capital (C), asset quality (A), management (M), earnings (E), liquidity (L), and sensitivity to interest rate risk (S).

capturing information relevant to bank credit risk not captured by loan loss allowances or other disclosed credit quality indicators.

CHAPTER 5: EMPIRICAL DESIGN AND RESULTS

Descriptive Statistics

Table 1, Panel A provides descriptive statistics for the final sample and shows that the mean (median) ratio of *ECL/Loans* is 3.1% (2.1%) compared to a mean (median) ratio of *ALLL/Loans* of 1.8% (1.5%). This indicates that, on average, banks are understated relative to expected credit losses. The variation in *ECL* is greater than that observed in *ALLL*. The range of *ECL/Loans* is 15.9% compared to a range of 4.5% for *ALLL/Loans*.[28] The variation in understatements relative to expected losses is consistent with prior accounting research observing heterogeneity in the application of the incurred loss model (*e.g.*, Wahlen 1994; Beaver and Engel 1996; Liu and Ryan 2006; Nichols et al. 2009; Beatty and Liao 2011). Panel A also provides descriptive evidence about the extent of understatements relative to recorded loan loss allowances, which varies greatly across sample banks. Specifically, banks on average would need to increase loan loss reserves by 83% to achieve a reserve sufficient to account for expected credit losses. Examining the distribution of *ECLDIFF / ALLL*, the median bank would need to increase its allowance by 29%[29] while the interquartile range spans from a *decrease* in the allowance of 28% to an increase of 113% necessary for allowances to reflect expected losses. From a regulatory capital perspective, mean (median) understatements are equal to 0.9% (0.3%) of total assets and 14.7% (3.7%) of tangible common equity. The differences between mean and median reflect the skewness in understatements, with 25% of bank quarters understated by 1.3% or more of total assets and 17.4% or more of tangible common equity.

[28] To reduce the influence of extreme expected loss estimates on my sample tests, I trim the sample at the 1% level based on the ratio of *ECL* to loans.

[29] This is in line with remarks made by the Comptroller of the Currency, Thomas J. Curry, in a 2013 address at the AICPA banking conference that the OCC estimated the CECL model would require a roughly 30-50% increase in loan loss reserves, though he noted in the same address that some industry observers said the CECL model could result in increases of 200-300%.

In Table 1, Panel B, I classify banks as either under reserved, adequately reserved, or over reserved. Banks are considered "adequately" reserved if *ECLDIFF*/*Loans* is between +/- 0.2%. Panel B shows that 56% of bank-quarters are under-reserved, 13% are adequately reserved, and 31% are over-reserved. Comparing under-reserved bank-quarters to over-reserved bank-quarters, I find that while under-reserved banks have larger allowances relative to loans, these allowances are not large enough to account for substantially larger expected credit losses. I further find that under-reserved banks are larger, have negative "discretionary" allowances,[30] have a lower percentage of SFAS 5 loans (and therefore more impaired loans), and have longer loss emergence periods. Interestingly, while under-reserved bank-quarters have significantly higher cumulative loss rates and ECL estimates, the ratio of average interest over the prior eight quarters to loans is lower for under-reserved banks, raising questions about whether banks with higher credit losses are adequately compensated for these losses.

Panel C of Table 1 shows trends in *ALLL*, *ECL*, and *ECLDIFF* over the sample period. Panel C shows that between 48%-54% of banks were *over*-reserved relative to my measure of ECLs in 2006Q4-2008Q4 and that, on average, ECLs as a percent of loans were only 0.09% and 0.04% higher than ALLLs as a percent of loans in 2006 and 2007, respectively, before the onset of the financial crisis. Panel C also shows that cumulative loss rates for each vintage of loan originations were just under 1.4%, on average, from 1997-2007 but began to rise rapidly to a peak of 4.88% in 2012, which represents the average cumulative loss rate from 2003-2012. As credit losses rise, forecasted ECLs rise quickly relative to recorded ALLLs, resulting in the majority of banks being under-reserved from 2009-2014. The final two rows of Panel C show the percentage of bank-quarters each year that switch between under-reserved and over-reserved

[30] As discussed in Section VI, I estimate the "discretionary" portion of loan loss allowances following Beaver and Engel (1996).

categories. The results suggest that switching is relatively infrequent with the largest rate of switching occurring in 2008 and 2009 as expected credit losses rose faster than loan loss allowances, with 5.1% and 7.5% of firms that had been over-reserved becoming under-reserved.

Panel D of Table 1 provides statistics about loan loss allowances, expected losses, and charge-offs by decile of *ECL / Loans*. Confirming the previous observation about the wide range of ECL estimates relative to recorded allowances, Panel D shows that while loan loss allowances relative to loans increase nearly monotonically by decile of *ECL / Loans* from 1.21% to 2.53%, these increases are not sufficient to keep pace with increases in *ECL / Loans*, which climb from 0.40% in the bottom decile to 9.50% in the top decile. Panel D also shows that annualized charge-off rates and annualized loss rates, calculated by dividing the cumulative loss rate for a vintage by the number of prior quarters of loans that explain charge-offs and multiplying by four, also increase monotonically by decile of *ECL / Loans*, providing additional validation that my measure of expected credit losses captures meaningful variation in underlying credit risk.

Test of H1

H1 predicts that allowance understatements are increasing in the proportion of SFAS 5 loans to total loans and in the period of loss emergence. I test this with the following model:

$$\begin{aligned} ECLDIFF_{it} = \alpha_0 + \alpha_1 SFAS5_{it} + \alpha_2 WtdLags_{it} + \alpha_3 \ln(TA)_{it} + \alpha_4 Cumulative\ Loss_{it} \\ + \alpha_5 ConsLoans_{it} + \alpha_6 RE\ Loans_{it} + \alpha_7 Acquisition_{it} + \varepsilon_{it} \end{aligned} \tag{4}$$

where $SFAS5$ denotes the ratio of SFAS 5 loans to total loans; $WtdLags$ denotes the estimated loss emergence period, calculated by weighting the total potential loss emergence period of 24 quarters by the marginal loss rate observed in each quarter[31]; $ln(TA)$ is the natural log of total assets, as bank size could capture differences in bank sophistication, including its allowance

[31] For example, a bank with marginal loss rates of 0.01, 0.03, 0.02, and 0.01 in quarters *t*+1, *t*+2, *t*+3, and *t*+4, respectively would have *WtdLags* equal to 2.43, calculated as [(0.01*1) + (0.03*2) + (0.02*3) + (0.01*4)] / 0.07.

estimation methodology and its ability to predict future charge-offs; and $Cumulative\ Loss$ is the average cumulative loss rate for each loan origination vintage. I include $Cumulative\ Loss$ in the model to control for differences in *ECLDIFF* caused by differences in overall loan risk. H1a predicts a positive coefficient on $SFAS5$, and H1b predicts a positive coefficient on $NLags$.

In Eq. (4), I include controls for other factors that may influence over- and under-statements relative to expected losses. These include the levels of consumer loans and real estate loans, as differences in portfolio mix may affect loan loss estimation practices apart from their classification as SFAS 5 or SFAS 114 loans. I also control for whether a bank has made an acquisition during the prior eight quarters. Banks record acquired loans, including those obtained in acquisitions, on the balance sheet at fair value as of the date of acquisition. Therefore any allowance recorded by the acquired firm is not carried over to the purchaser's balance sheet. This will reduce the ratio of the allowance to total loans and could explain a portion of *ECLDIFF*. I expect a positive coefficient on *Acquisition*.

The results for H1 are presented in Table 3 and provide evidence of a positive association between attributes of the ILM and allowance understatements, supporting H1a and H1b. The results for the full sample are presented in column (1). As predicted, both the level of SFAS 5 loans and the loss emergence period (*WtdLags*) are significantly positively associated with understatements ($p<0.01$). Portfolio composition does not appear to be a significant driver of allowance understatements after controlling for cumulative loss rates, as neither the coefficients for the proportion of consumer loans nor real estate loans are significant.

I further examine the relationship between attributes of the ILM and allowance understatement in columns (2) and (3) of Table 3 by splitting my sample between under- and over-reserved bank quarters. The results for each subsample are consistent with the full sample, suggesting that understatements are increasing in the level of SFAS 5 loans and loss emergence periods, while overstatements are decreasing in SFAS 5 loans and loss emergence periods.[32] The latter result suggests that banks are less likely to over-reserve relative to expected losses when the proportion of SFAS 5 loans is high and loss emergence horizons are long.

Test of H2

To test the association between allowance understatements and bank market values predicted in H2, I substitute Eq. (1j) into Eq. (1a) from Beaver et al. (1989) equating the book and market values of equity. After scaling by shares outstanding, I obtain the following:[33]

$$\frac{MVE_{it}}{Shares_{it}} = \frac{BVE_{it}}{Shares_{it}} - \frac{ALLL_{it}}{Shares_{it}} - \frac{ECLDIFF_{it}}{Shares_{it}} + \frac{CCL_{it}}{Shares_{it}} + \frac{MVONA_{it} - BVONA_{it}}{Shares_{it}} \quad (4)$$

where *MVE* and *BVE* denote the market and book values of equity, respectively, and *MVONA* and *BVONA* denote the market and book values of other net assets, respectively. Following Beaver et al. (1989), I assume that $MVONA_{it} - BVONA_{it}$ is equal to $\mu BVE_{it} + \epsilon_{it}$ and is independent of $-ALLL_{it} - ECLDIFF_{it} + CCL_{it}$ and that ϵ_{it} is mean zero. Eq. (4) can be re-expressed as:

$$\frac{MVE_{it}}{Shares_{it}} = (1+\mu)\frac{BVE_{it}}{Shares_{it}} + \frac{ALLL_{it}}{Shares_{it}} + \frac{ECLDIFF_{it}}{Shares_{it}} + \frac{CCL_{it}}{Shares_{it}} + \frac{\epsilon_{it}}{Shares_{it}} \quad (5)$$

Because *CCL* is not observable, I include proxies for compensated credit losses to arrive at the following empirical specification:

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[32] Because *ECLDIFF* is measured as *ECL* minus *ALLL*, *ECLDIFF* becomes increasingly negative as overstatement increases. A positive association for this subsample means that *ECLDIFF* is less negative for banks with more SFAS 5 loans, and thus banks with more SFAS 5 loans are *less* overstated.

[33] In untabulated analysis, I find that my results are robust to scaling by book value of equity rather than shares outstanding.

$$\ln\left(\frac{MVE_{it}}{Shares_{it}}\right) = \beta_0 + \beta_1 \ln\left(\frac{BVE_{it}}{Shares_{it}}\right) + \beta_2 \ln\left(\frac{ALLL_{it}}{Shares_{it}}\right) + \beta_3 ECLDIFF\_RANK_{it} + \beta_4 \ln\left(\frac{AvgInt_{it}}{Shares_{it}}\right) + \beta_5 \ln\left(\frac{RELoans_{it}}{Shares_{it}}\right) + \beta_6 \ln\left(\frac{ConsLoans_{it}}{Shares_{it}}\right) + \beta_7 \ln\left(\frac{RSA_{it}}{Shares_{it}}\right) + \varepsilon_{it} \quad (6)$$

where the 1st decile of *ECLDIFF_RANK* represents the lowest *ECLDIFF* estimates and the 10th decile represents the highest (*i.e.*, the most under-reserved). I make two additional design choices in Eq. (6). First, I log-transform each variable to correct for skewness. Second, I place bank-quarters into deciles based on their rank of *ECLDIFF* because of the noise I anticipate in *ECL* due to the need to estimate loan originations.[34] H2 predicts a negative coefficient on *ECLDIFF_RANK* if ALLL understatements are impounded into stock price. *AvgInt* denotes average interest income on loans over the prior eight quarters; *RELoans* denotes total real estate loans; and *ConsLoans* denotes total consumer loans. Each of these could provide information about *CCL*, as compensated credit losses are embedded in loan interest rates, and the period over which they will be realized depends on loan duration. In this empirical specification, I relax the earlier assumption regarding loan repricing and include a variable, *RSA*, to capture the effect of changes in interest rates on loan fair values, where *RSA* denotes rate sensitive assets maturing within one year.

The results for H2 are presented in Table 4. Following prior research testing the association between the allowance and market values (*e.g.,* Beaver et al. 1989; Barth et al. 1991), I estimate Eq. (6) by year and pooled with year fixed effects. The coefficient on *ECLDIFF_RANK* is significantly negative in all nine years in my sample period and in the pooled regression, providing support for H2. The coefficient on *ALLL* is also significantly

[34] Because ECL estimates are necessarily backward-looking, decile ranking has the additional benefit of mitigating concerns that results are driven by underestimation of ECL's in pre-crisis periods and over-estimation in post-crisis periods. To the extent that changing macroeconomic conditions have similar effects on the expected losses of all banks, such factors would affect the dollar magnitudes of ECL estimates but not ordinal rankings.

negative in six out of nine years as well as in the pooled regression. Overall, the results in Table 4 show that investors detect and price understatements of the allowance relative to expected losses.

CHAPTER 6: ADDITIONAL ANALYSIS

Discretionary Allowances

Prior literature in accounting has attempted to distinguish between "discretionary" and "non-discretionary" allowances under the theory that bank investors may view discretionary allowances favorably (*e.g.*, Beaver and Engel 1996). I extend my main analysis in Table 4 by splitting the allowance into discretionary and non-discretionary components based on the following model from Beaver and Engel (1996). Because I use log-transformations in my main analysis, I log-transform their model as follows:

$$\ln(ALLL_{it}) = \alpha_0 \ln\left(\frac{1}{GBV}\right)_{it} + \alpha_1 \ln\left(\frac{CO}{GBV}\right)_{it} + \alpha_2 \ln\left(\frac{LOANS}{GBV}\right)_{it} + \alpha_3 \ln\left(\frac{NPA}{GBV}\right)_{it} + \alpha_4 \ln\left(1 + \frac{\Delta NPA}{GBV}\right)_{it+1} + \varepsilon_{it} \quad (7)$$

where 'gross book value' (*GBV*) is equal to the book value of equity plus the allowance for loan losses. Subscript *t* denotes years in Eq. (7), *CO* denotes gross loan charge-offs, and *NPA* denotes non-performing assets.[35]

In my setting, a discretionary allowance that results in an allowance greater than that required under the ILM would decrease any understatement relative to expected loss. Disaggregating the allowance into discretionary and non-discretionary components, Eq. (1j) can be re-expressed as follows:

$$MVL = BVL - NDALLL - DALLL - ECLDIFF + CCL \quad (8)$$

where *DALLL* denotes the discretionary portion of the allowance, the residual from estimating Eq. (7), and *NDALLL* denotes the non-discretionary portion of the allowance. Eq. (8) shows that, excluding signaling considerations, both *DALLL* and *NDALLL* should be negatively associated with market values, while a positive coefficient on *DALLL* would be consistent with signaling.

[35] Non-performing assets are equal to the sum of nonaccrual loans, loans 90 days or more past due but still accruing, and other real estate owned

Results for estimating the discretionary loan loss allowance model in Eq. (7) are presented in Panel A of Table 5. Consistent with the results in Beaver and Engel (1996), contemporaneous charge-offs, loans, and nonperforming assets are all positively associated with the level of the allowance for loan losses. On the other hand, I find a negative and significant coefficient for the quarter-ahead change in nonperforming loans, suggesting that nonperforming assets decrease (increase) after periods of high (low) loan loss allowances.

The results of estimating Eq. (8) after splitting the allowance into discretionary and non-discretionary portions are presented in Table 5, Panel B. These results show that the *DALLL* is significantly negatively associated with bank market values in three out of nine years and marginally significantly associated with bank market values in the pooled sample, though *less* negatively related than *NDALLL*, consistent with prior research (Beaver and Engel 1996, Ahmed et al. 1999). *NDALLL* is significantly negatively associated with market value in six out of nine years, and the rank of *ECLDIFF* is significantly negatively associated with market values in eight out of nine years. Splitting the ALLL into discretionary and non-discretionary portion causes the coefficient on *ECLDIFF_RANK* to become insignificant in 2014, though it remains significantly negatively associated at the 1% level in the pooled sample, consistent with the findings in Table 4.

CHAPTER 7: DISCUSSION AND CONCLUSION

Motivated by the hotly debated new current expected credit loss standard, this paper provides evidence on the extent to which bank allowances reflect lifetime expected credit losses, the association between attributes of the incurred loss model and understatements, and the association between understatements and bank market values. Consistent with the incurred loss model contributing to allowance understatements relative to expected losses, I find that understatements are increasing in both the proportion of loans accounted for under SFAS 5 and the period of loss emergence. However, I provide evidence that while approximately 57% of bank-quarters' allowances are understated relative to expected losses, understatements are negatively associated with bank market values, suggesting that investors are able to detect and impound into price information about expected losses above and beyond the incurred losses reflected in the financial statements.

These results should be of interest to accounting standard setters as well as various bank stakeholders, including managers, investors, standard setters, and regulators. First, while the FASB expects the new standard to enhance bank transparency by helping investors better understand the credit risk in banks' loan portfolios, my results suggest that information about lifetime expected losses is already incorporated into stock prices, and therefore the adoption of the CECL model may not result in negative stock market reactions, a major concern of managers and shareholders. Second, descriptive evidence regarding the extent of understatement relative to expected losses should be of interest to stakeholders concerned with the potential regulatory capital consequences of the CECL model. While bank allowances approximated expected losses in the period prior to the crisis, my results suggest that bank allowances were significantly less than expected losses at the end of 2014, with average understatements equal to 1.1% of total assets and 10.8% of tangible common equity capital. Because the new standard is not expected to be implemented until fiscal years beginning after December 31, 2019, early identification of allowance understatements relative to expected credit losses will allow managers and regulators to address capital adequacy concerns prior to implementation.

This paper also makes several contributions to the academic literature on bank loan loss accounting. First, I contribute to the debate over the merits of an expected *vs.* incurred loss model for financial stability (Acharya and Ryan 2016). The results suggest that, because investors already impound information about expected losses into price, any increase in bank transparency under the CECL model is likely to depend on the extent to which managers incorporate private, forward-looking information about macroeconomic conditions into their expected loss estimates that investors cannot obtain from other sources. Second, I contribute a new measure of expected credit losses that goes beyond the near-term horizon examined in most studies (*e.g.*, Cantrell et al. 2012; Harris et al. 2015) and predicts cumulative net charge-offs up to seven years ahead. This measure may be useful to researchers interested in measuring expected lifetime credit losses. Third, because my measure of under- and over-statements is based on estimated loan origination data and historical charge-off patterns that are not explicitly disclosed, my results suggest that bank share prices incorporate information about expected credit losses well beyond those metrics currently disclosed to investors. Fourth, I extend the literature examining the relation between loan loss allowances and bank market values (*e.g.*, Beaver et al. 1989; Barth et al. 1991; Ahmed et al. 1999) and find that both allowances and understatements of the allowance relative to expected losses are negatively associated with bank value in my sample period after controlling for compensated credit losses (*i.e.*, losses expected at origination).

The findings and implications in this paper are subject to limitations. First, while my results inform the debate surrounding the CECL model, they do not speak directly to the potential efficacy of the CECL model. For instance, the new model, like the current model, does not provide investors with disclosures about compensated and uncompensated credit losses that could aid in forecasting future bank profitability. Second, my estimate of expected losses is analogous to the base allowance estimates banks would develop using historical loss experience. While proponents of the CECL model claim that the new model will result in more forward-looking information being incorporated into bank allowances, my evidence cannot address whether or not bank managers will do so to a greater extent under CECL than they do currently under the incurred loss model. While there is a growing literature on whether banks incorporate forward-looking information into loan loss provisions under the ILM (*e.g.* Nichols et al., 2009; Beatty and Liao, 2011; Bushman and Williams 2012; Beck and Narayanamoorthy, 2013), future research could provide a better understanding of the types of forward-looking information banks incorporate into loan loss provisions and loan loss allowances.

References

Abarbanell, J. S., & Bushee, B. J. (1998). *Abnormal returns to a fundamental analysis strategy*. Accounting Review, 19-45.

Acharya, V. V., & Ryan, S. G. (2016). *Banks' financial reporting and financial system stability*. Journal of Accounting Research, 54(2), 277-340.

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

Altman, E. I., & Saunders, A. (1998). *Credit risk measurement: Developments over the last 20 years*. Journal of Banking and Finance, 21(11/12).

American Bankers Association (2016a). *CECL Implementation Challenges: The Life of Loan Concept.*

American Bankers Association (2016b). *RE: Current Expected Credit Loss Model of Impairment (CECL).*

Basel Committee on Banking Supervision (2016). *Regulatory Treatment of Accounting Provisions – Interim Approach and Transitional Arrangements.* Consultative document.

Barth, M. E., Beaver, W. H., & Stinson, C. H. (1991). *Supplemental data and the structure of thrift share prices*. Accounting Review, 56-66.

Beatty, A., & Liao, S. (2011). *Do delays in expected loss recognition affect banks' willingness to lend?* Journal of Accounting and Economics, 52(1), 1-20.

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

Beaver, W. H., & Engel, E. E. (1996). *Discretionary behavior with respect to allowances for loan losses and the behavior of security prices*. Journal of Accounting and Economics, 22(1), 177-206.

Beck, P. J., & Narayanamoorthy, G. S. (2013). *Did the SEC impact banks' loan loss reserve policies and their informativeness?* Journal of Accounting and Economics, 56(2), 42-65.

Bernard, V. L., & Thomas, J. K. (1989). *Post-earnings-announcement drift: delayed price response or risk premium?*. Journal of Accounting research, 1-36.

Bernard, V. L., & Thomas, J. K. (1990). *Evidence that stock prices do not fully reflect the implications of current earnings for future earnings*. Journal of Accounting and Economics, 13(4), 305-340.

Bloomfield, R. J. (2002). *The "incomplete revelation hypothesis" and financial reporting*. Accounting Horizons, 16(3), 233-243.

Bushman, R. M., & Williams, C. D. (2012). *Accounting discretion, loan loss provisioning, and discipline of banks' risk-taking*. Journal of Accounting and Economics, 54(1), 1-18.

Cantrell, B. W., McInnis, J. M., & Yust, C. G. (2013). *Predicting credit losses: Loan fair values versus historical costs*. The Accounting Review, 89(1), 147-176.

Cumming (2015). *Loan Loss Rule Change Nears, Despite Critics' Howls.* American Bankers Association.

Curry, T. *Remarks by Thomas J. Curry Before the AICPA Banking Conference*. September 16, 2013.

Dobbs, K. (2015). *As FASB's new loan-loss rule approaches, outcry intensifies*. SNL Financial. November 13, 2015.

Dietsch, M., & Petey, J. (2002). *The credit risk in SME loans portfolios: Modeling issues, pricing, and capital requirements*. Journal of Banking & Finance, 26(2), 303-322.

Federal Reserve System Board of Governors (2014). *Bank Holding Company Supervision Manual.*

Federal Deposit Insurance Corporation (2006). *Interagency Policy Statement on the Allowance for Loan and Lease Losses*.

Federal Reserve System Board of Governors (2014). *Bank Holding Company Supervision Manual.*

Financial Stability Forum (2009). *Report of the Financial Stability Forum on addressing procyclicality in the financial system.*

Grammatikos, T., & Saunders, A. (1990). *Additions to bank loan-loss reserves: Good news or bad news?* Journal of Monetary Economics, 25(2), 289-304.

Grant Thornton (2012). *Allowance for loan and lease losses (ALLL): Loss discovery periods*.

Harris, T. S., Khan, U., & Nissim, D. (2015). *The Expected Rate of Credit Losses on Banks' Loan Portfolios*. Working paper.

Haslett, K.L. (2015). *2 FASB board members will vote against CECL proposal*. SNL Financial. September 17, 2015.

Haslett, K.L. (2016). *FASB, vendors disagree on need for CECL software systems*. SNL Financial. March 8, 2016.

Hodder, L. D., Hopkins, P. E., & Schipper, K. (2014). *Fair Value Measurement in Financial Reporting*. Foundations and Trends in Accounting, 9.

Judge, G.G., Griffiths, W.E., Hill, R.C., Lutkepohl, H., and Lee, T.S. (1985). *The Theory and Practice of Econometrics*. Second Edition. John Wiley & Sons, Inc.

Keefe, Bruyette, and Woods (2015). *Industry Update: FASB Is About to Accelerate Loan Loss Recognition for the Financial Industry*.

Liu, C. C., & Ryan, S. G. (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.

Lopez, J. A., & Saidenberg, M. R. (2000). *Evaluating credit risk models*. Journal of Banking & Finance, 24(1), 151-165.

McPhail, J., & McPhail, L. (2014). *Forecasting lifetime credit losses: Modelling considerations for complying with the new FASB and IASB current expected credit loss models*. Journal of Risk Management in Financial Institutions, 7(4), 375-388.

Musumeci, J. J., & Sinkey, J. F. (1990). *The international debt crisis, investor contagion, and bank security returns in 1987: The Brazilian experience*. Journal of Money, Credit and Banking, 209-220.

Nichols, D. C., Wahlen, J. M., & Wieland, M. M. (2009). *Publicly traded versus privately held: implications for conditional conservatism in bank accounting*. Review of Accounting Studies, 14(1), 88-122.

Office of the Comptroller of the Currency (2012). *Allowance for Loan and Lease Losses*. Comptroller's Handbook.

Picconi, M. (2006). *The perils of pensions: Does pension accounting lead investors and analysts astray?* The Accounting Review, 81(4), 925-955.

Sageworks (2016). *The Basics Of Vintage Analysis.*

Schroeder, R. H., (2015). *For the Investor: The Benefits of the "CECL" Model and "Vintage" Disclosures*. FASB Outlook. April 29, 2015.

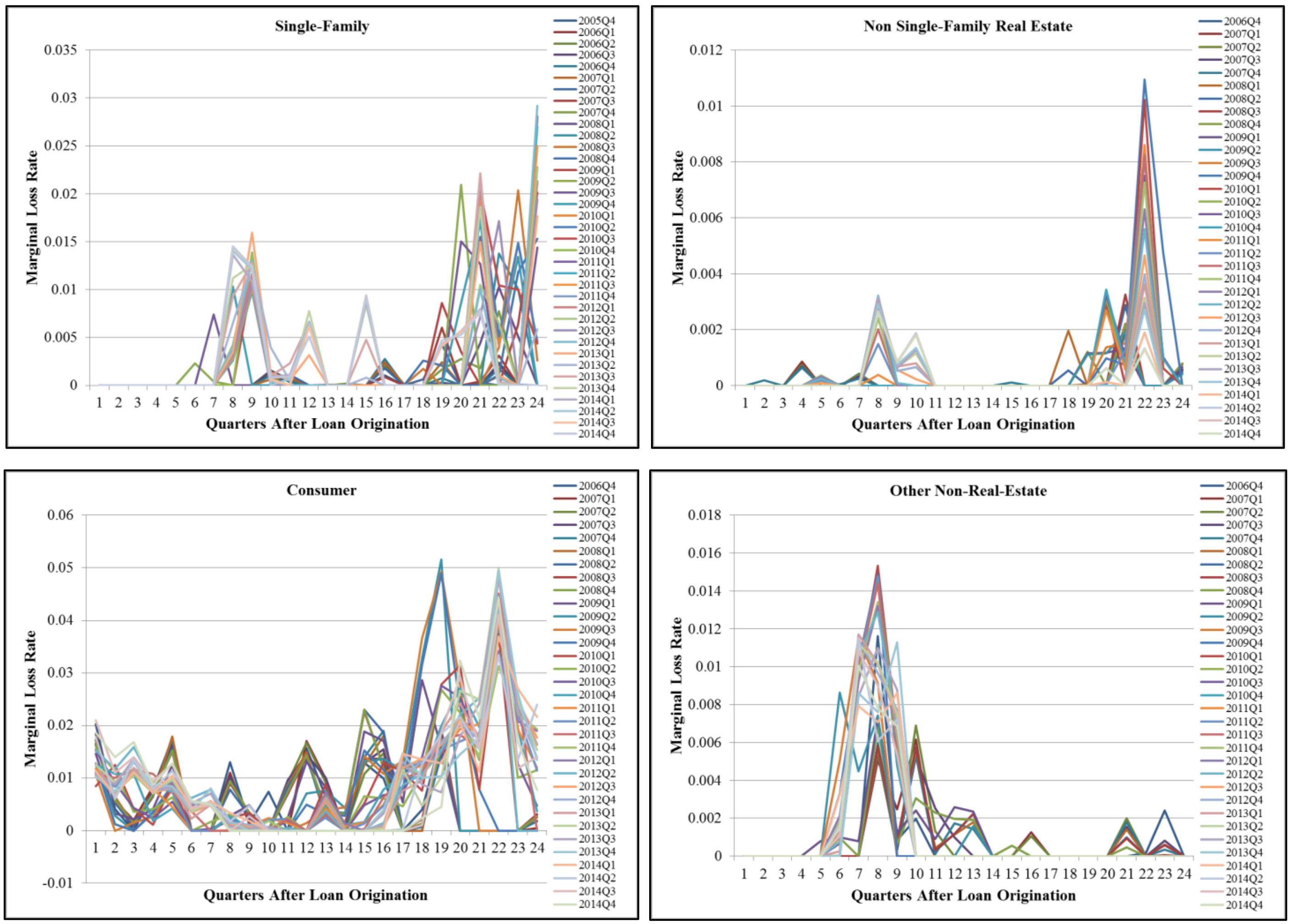
Wahlen, J. M. (1994). The nature of information in commercial bank loan loss disclosures. Accounting Review, 455-478.

White, L., Stovall, N. (2013). *The FASB and the furious*. SNL Financial. May 20, 2013.

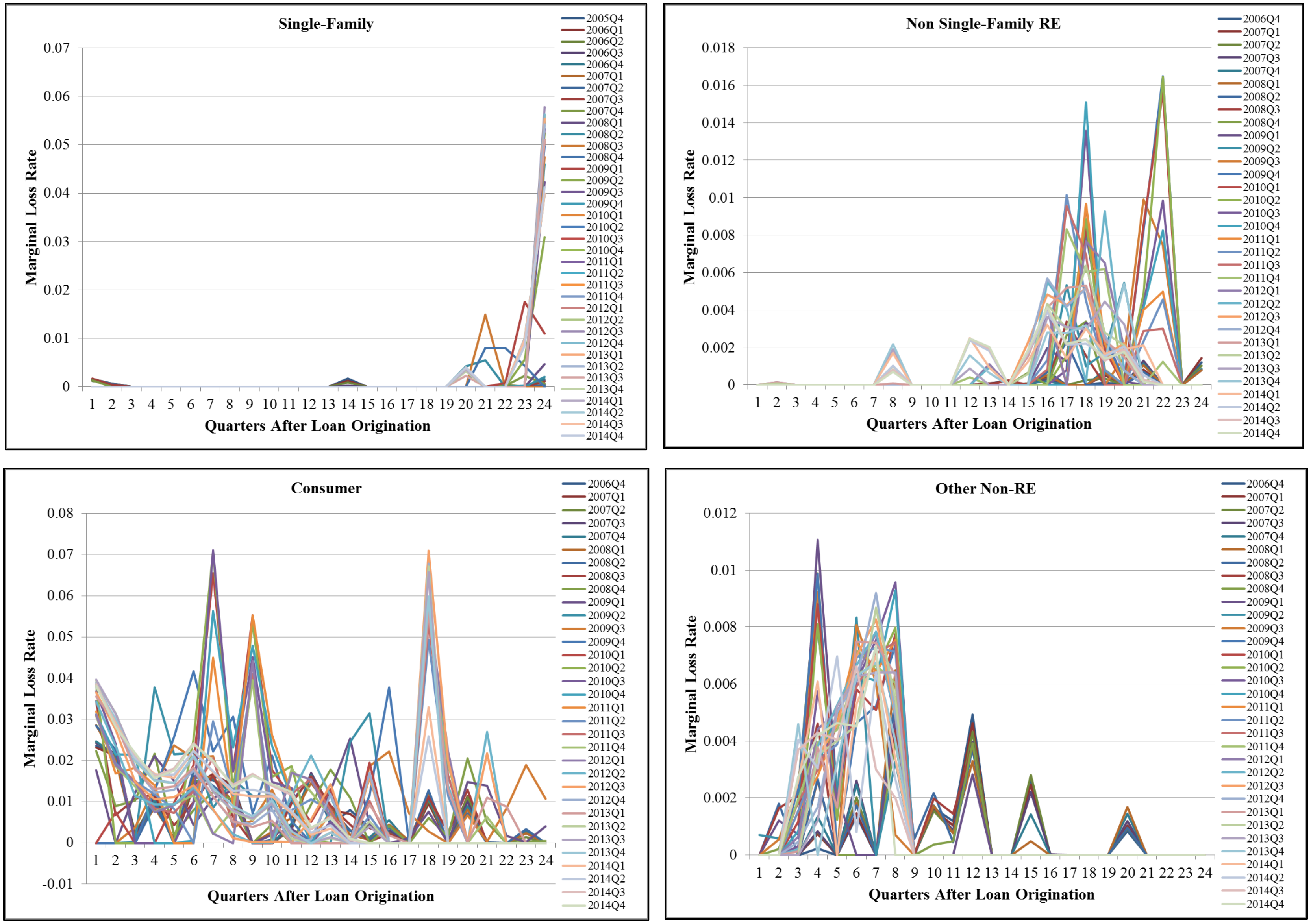
Figure 1
Example Loss Curves

The graphs below provide a visual depiction of the estimated loss emergence patterns of select banks obtained from estimating Eq. (2).

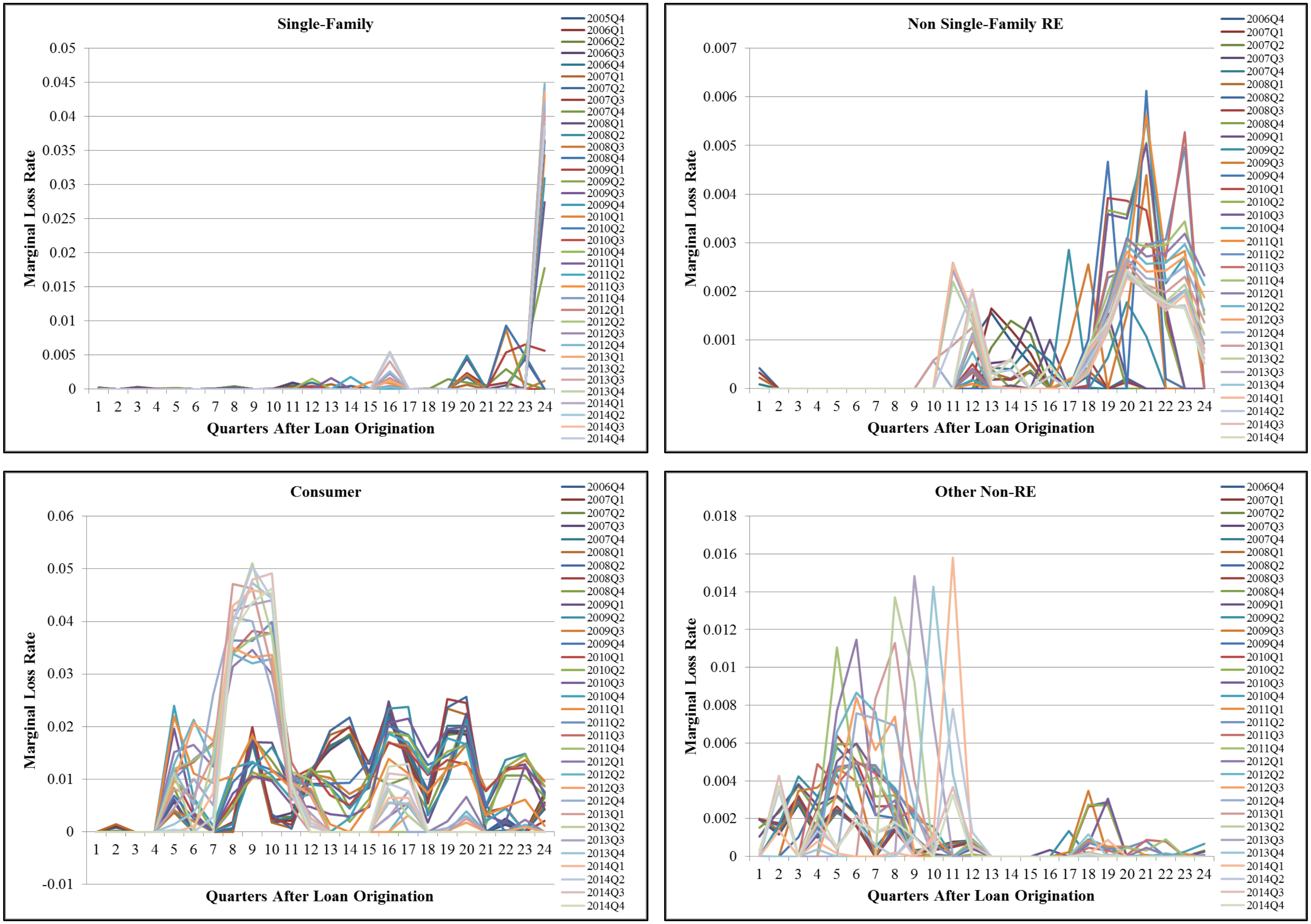
JPMorgan Chase & Co.



Bank of America Corporation



Wells Fargo and Company



Zions Bancorporation

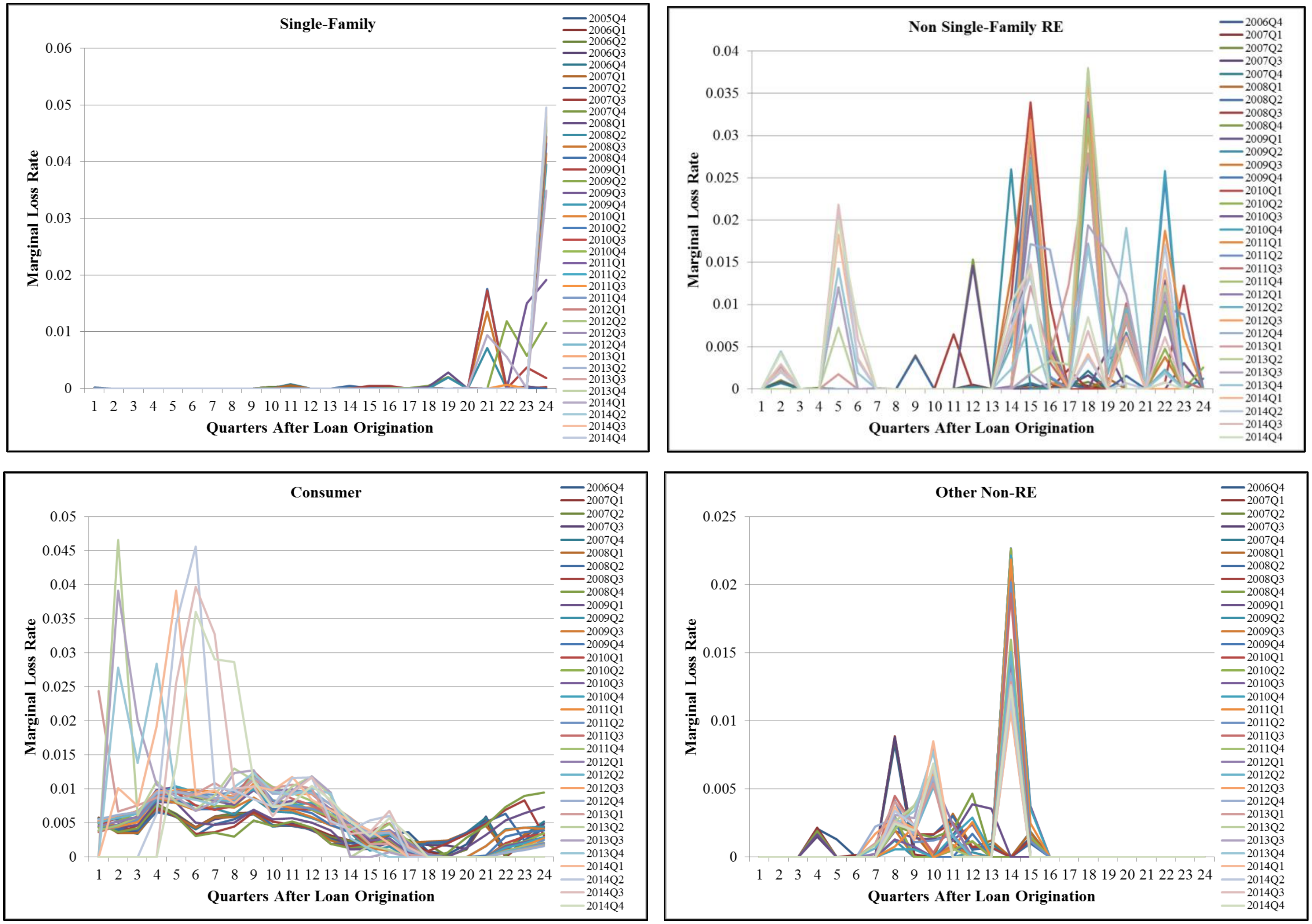


Table 1

Panel A: Descriptive Statistics

	N	*Mean*	*Std Dev*	*Min*	*5%*	*25%*	*Median*	*75%*	*95%*	*Max*
ALLL / Loans	8,107	0.018	0.008	0.005	0.009	0.012	0.015	0.021	0.036	0.050
ECL / Loans	8,107	0.031	0.031	0.001	0.003	0.010	0.021	0.040	0.098	0.160
ECLDIFF / Loans	8,107	0.013	0.026	-0.017	-0.011	-0.004	0.004	0.021	0.072	0.119
ECLDIFF / ALLL	8,107	0.834	12.215	-1.000	-0.736	-0.275	0.286	1.134	3.119	1,080.567
ECLDIFF / TA	8,107	0.009	0.020	-0.029	-0.007	-0.002	0.003	0.013	0.047	0.225
ECLDIFF / TCE	8,103	0.147	1.691	-73.270	-0.099	-0.032	0.037	0.174	0.698	73.488
Avg Cumulative Loss Rate	8,107	0.036	0.034	-0.145	0.004	0.012	0.026	0.050	0.106	0.356
Avg Interest / Loans	8,107	0.015	0.003	0.003	0.010	0.013	0.015	0.016	0.019	0.032
SFAS 5 Loans / Loans	8,107	0.977	0.028	0.858	0.919	0.967	0.986	0.998	1.000	1.000
RELoans / Loans	8,107	0.743	0.155	0.139	0.456	0.661	0.774	0.856	0.941	1.002
ConsLoans / Loans	8,107	0.058	0.074	0.000	0.002	0.011	0.027	0.075	0.209	0.383
RSA / BVE	8,107	3.844	1.905	0.623	1.318	2.473	3.601	4.829	7.412	10.678
MVE / BVE	8,107	1.146	0.596	0.153	0.296	0.726	1.086	1.457	2.283	3.113
WtdLags	8,107	14.6	4.1	1	7	12	15	18	21	24
Mat 5+ / Loans	8,096	0.056	0.074	0.000	0.002	0.013	0.033	0.069	0.184	0.460

Variable definitions are found in Appendix A.

Panel B: Comparison of Under- and Over-Reserved Bank Quarters

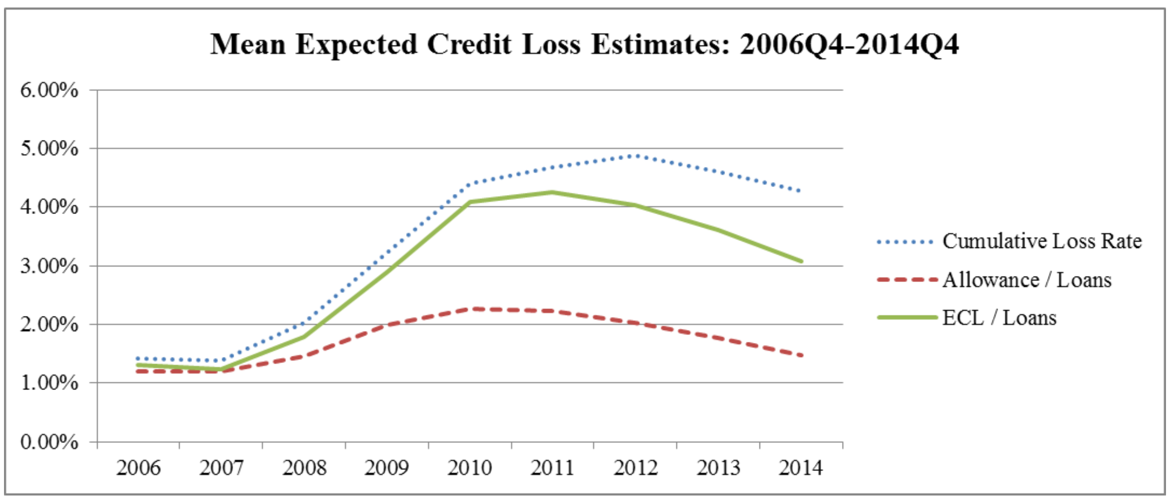
	Under-reserved	*Adequate*	*Over-reserved*	*Under vs. Over*	*Under vs. Over t-stat*	
ALLL / Loans	1.98%	1.43%	1.59%	0.39%	19.65	***
DALLL / Loans	-0.09%	-0.16%	0.07%	-0.16%	-4.97	***
ECL / Loans	4.70%	1.42%	0.86%	3.84%	78.19	***
ECLDIFF / Loans	2.70%	-0.01%	-0.71%	3.41%	84.43	***
ECLDIFF / ALLL	176.13%	-1.71%	-48.62%	224.75%	9.33	***
ECLDIFF / TA	1.87%	-0.01%	-0.47%	2.34%	69.72	***
ECLDIFF / TCE	29.70%	-0.12%	-6.26%	35.96%	10.77	***
MVE / BVE	1.00	1.26	1.36	-0.37	-24.59	***
TA	59,168,943	16,838,921	17,123,203	42,045,740	8.30	***
Avg Cumulative Loss Rate	5.26%	2.04%	1.35%	3.91%	63.57	***
Annualized Charge-off Rate	1.37%	0.63%	0.53%	0.84%	26.45	***
Avg Interest / Loans	1.45%	1.42%	1.47%	-0.03%	-4.03	***
σ(NIBP / TA)	0.25%	0.16%	0.15%	0.10%	19.82	***
SFAS 5 Loans / Loans	97.01%	98.40%	98.57%	-1.56%	-24.85	***
WtdLags	15.9	13.9	12.5	3.4	33.68	***
N	4,551	1,014	2,542			
%	56%	13%	31%			

This table presents descriptive statistics separately for under- and over-reserved bank quarters as well as "adequately" reserved banks. Banks are considered adequately reserved if *ECLDIFF / Loans* is between +/- 0.2%. Banks with *ECLDIFF / Loans* > 0.2% are considered under-reserved while banks with *ECLDIFF / Loans* < -0.2% are considered under-reserved. ***, **, and * indicate differences between the subsamples that are statistically significant at the 1%, 5%, and 10% levels, respectively.

Panel C: ALLL, ECL, and ECLDIFF by Year

Variable	*2006*	*2007*	*2008*	*2009*	*2010*	*2011*	*2012*	*2013*	*2014*
Allowance / Loans	1.20%	1.19%	1.45%	1.99%	2.26%	2.22%	2.03%	1.77%	1.47%
ECL / Loans	1.31%	1.24%	1.78%	2.90%	4.09%	4.25%	4.04%	3.61%	3.07%
ECLDIFF / Loans	0.09%	0.04%	0.33%	0.91%	1.81%	2.02%	1.98%	1.83%	1.59%
ECLDIFF / ALLL	16.85%	7.17%	19.67%	40.75%	196.37%	95.11%	104.11%	101.30%	115.15%
ECLDIFF / TA	0.07%	0.01%	0.23%	0.66%	1.33%	1.41%	1.41%	1.23%	1.07%
ECLDIFF / TCE	2.08%	0.37%	5.51%	22.71%	28.95%	24.59%	10.79%	15.04%	11.53%
Cumulative Loss Rate	1.43%	1.39%	2.03%	3.23%	4.40%	4.68%	4.88%	4.61%	4.26%
MVE / BVE	2.00	1.68	1.20	0.82	0.92	0.88	1.01	1.21	1.27
% Under-reserved	29%	28%	35%	49%	64%	67%	71%	70%	71%
% Adequately-reserved	19%	18%	17%	12%	9%	10%	10%	12%	12%
% Over-reserved	51%	54%	48%	39%	27%	23%	19%	19%	17%
Switch to under-reserved	na	1.5%	5.1%	7.5%	4.1%	2.3%	1.4%	1.3%	1.2%
Switch to over-reserved	na	1.0%	1.7%	2.4%	1.5%	1.3%	0.6%	1.6%	0.6%
N	249	941	973	995	992	1,018	988	976	975

This table presents mean statistics for each year during the sample period. 2006 contains only observations for the fourth quarter due to data constraints required to estimate *ECL*. See Appendix A for variable definitions.



Panel D: ALLL and ECLDIFF by Decile of ECL

ECL / Loans Decile	*ALLL / Loans*	*ECL / Loans*	*ECLDIFF / Loans*	*Annualized Charge-off Rate*	*Annualized Loss Rate*[a]	*Annualized Interest to Loans*[b]	*Spread*
1	1.21%	0.40%	-0.80%	0.22%	0.21%	5.64%	5.44%
2	1.39%	0.84%	-0.54%	0.38%	0.39%	5.76%	5.36%
3	1.51%	1.21%	-0.28%	0.52%	0.49%	5.84%	5.35%
4	1.62%	1.62%	0.02%	0.69%	0.63%	5.85%	5.22%
5	1.63%	2.03%	0.40%	0.83%	0.72%	5.90%	5.18%
6	1.75%	2.53%	0.78%	0.95%	0.78%	5.85%	5.07%
7	1.85%	3.18%	1.33%	1.07%	0.92%	5.79%	4.87%
8	2.04%	4.03%	1.99%	1.26%	1.01%	5.90%	4.89%
9	2.33%	5.56%	3.22%	1.71%	1.34%	5.99%	4.65%
10	2.53%	9.50%	6.81%	2.50%	1.96%	6.19%	4.23%

[a]Estimated by dividing the cumulative loss rate for a vintage (sum of all quarterly marginal loss rate coefficients) by the number of prior quarters of loans that explain charge-offs and multiplying by 4.

[b]Estimated by multiplying quarterly interest income by 4 and then dividing by the lagged loan balance.

Table 2
Correlation Matrix

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
(1)	*MVE / Share*		**0.74**	**0.28**	**0.05**	**-0.13**	**0.43**	**0.57**	**-0.33**	**-0.28**	**0.34**	**-0.39**	**0.18**	**-0.31**	**-0.19**	-0.01
(2)	*BVE / Share*	**0.68**		**0.64**	**0.32**	**0.04**	**0.70**	**0.78**	**-0.19**	**-0.18**	**0.15**	**-0.35**	**0.17**	**-0.17**	**-0.09**	-0.02
(3)	*ALLL / Share*	**0.15**	**0.55**		**0.63**	**0.26**	**0.76**	**0.62**	**0.19**	**0.06**	**-0.20**	**-0.13**	**0.17**	**0.15**	**0.10**	**-0.10**
(4)	*ECL / Share*	**-0.13**	**0.24**	**0.62**		**0.89**	**0.42**	**0.35**	**0.64**	**0.61**	**-0.23**	**-0.03**	**0.11**	**0.48**	**0.26**	**-0.07**
(5)	*ECLDIFF / Share*	**-0.27**	**-0.08**	**0.13**	**0.80**		**0.13**	**0.10**	**0.75**	**0.77**	**-0.21**	0.02	**0.07**	**0.56**	**0.28**	**-0.03**
(6)	*Avg Interest / Share*	**0.38**	**0.65**	**0.73**	**0.34**	**-0.06**		**0.71**	**-0.11**	**-0.13**	**0.09**	**-0.08**	**0.17**	**-0.16**	**-0.03**	**-0.05**
(7)	*RSA / Share*	**0.44**	**0.66**	**0.60**	**0.30**	**-0.02**	**0.72**		**-0.10**	**-0.10**	**0.11**	**-0.38**	**0.12**	**-0.11**	**-0.09**	**-0.19**
(8)	*ECL / Loans*	**-0.45**	**-0.20**	**0.24**	**0.82**	**0.88**	**-0.15**	**-0.11**		**0.97**	**-0.41**	**0.07**	**0.05**	**0.81**	**0.38**	**-0.06**
(9)	*ECLDIFF / Loans*	**-0.34**	**-0.17**	**0.06**	**0.76**	**0.95**	**-0.15**	**-0.10**	**0.92**		**-0.31**	**0.07**	**0.04**	**0.76**	**0.37**	**-0.03**
(10)	*SFAS5 Loans / Loans*	**0.34**	**0.08**	**-0.20**	**-0.35**	**-0.32**	**0.11**	**0.12**	**-0.46**	**-0.34**		**-0.20**	**0.09**	**-0.45**	**-0.23**	**0.18**
(11)	*RELoans / Loans*	**-0.35**	**-0.27**	**-0.11**	**-0.10**	**-0.04**	**-0.07**	**-0.26**	-0.01	-0.01	**-0.16**		**-0.46**	0.02	**0.24**	**0.14**
(12)	*ConsLoans / Loans*	**0.24**	**0.22**	**0.13**	**0.15**	**0.10**	**0.20**	**0.15**	**0.07**	**0.08**	**0.07**	**-0.48**		**0.05**	**-0.12**	**0.05**
(13)	*Avg Cumulative Loss Rate*	**-0.43**	**-0.19**	**0.20**	**0.72**	**0.77**	**-0.19**	**-0.12**	**0.91**	**0.81**	**-0.47**	**-0.04**	**0.06**		**0.20**	**-0.10**
(14)	*WtdLags*	**-0.22**	**-0.09**	**0.13**	**0.38**	**0.40**	**-0.04**	**-0.10**	**0.42**	**0.41**	**-0.25**	**0.24**	**-0.10**	**0.24**		**0.04**
(15)	*Mat 5+ / Loans*	**0.09**	**0.06**	**-0.11**	**-0.10**	**-0.04**	**-0.04**	**-0.22**	**-0.11**	**-0.04**	**0.14**	**0.12**	**0.15**	**-0.13**	**0.05**	

*Pearson (Spearman) correlations are shown below (above) the diagonal. Correlations in bold are significant at the 5% level or greater.

Table 3
H1: The ILM and Allowance Understatement

Dependent: ECLDIFF	Predicted sign	(1) Full Sample coeff	t-stat		(2) Under-Reserved coeff	t-stat		(3) Over-Reserved coeff	t-stat	
Intercept	?	-0.099	-3.40	***	-0.103	-2.92	***	-0.076	-2.77	***
SFAS5 Loans	+	0.079	2.91	***	0.082	2.54	**	0.065	2.66	***
WtdLags	+	0.001	8.69	***	0.002	6.15	***	0.000	4.61	***
ln(TA)	?	-0.001	-1.12		-0.001	-1.19		0.000	-0.43	
Cumulative Loss	?	0.566	13.43	***	0.560	11.51	***	0.318	7.10	***
Consumer Loans	?	0.012	0.99		0.011	0.75		0.009	0.59	
RE Loans	?	0.002	0.37		-0.001	-0.16		0.001	0.30	
Acquisition	+	0.001	0.64		0.000	0.20		0.001	1.51	
N		8,107			4,615			2,599		
Adj. R^2		63.3%			57.4%			35.7%		

This table presents results for tests of the relationship between proxies of the ILM and *ECLDIFF*. All variables expect for *WtdLags*, *ln(TA)*, and *Acquisition* are scaled by loans at the end of the quarter. Standard errors are clustered by bank. ***, **, and * indicate statistical significant at the 1%, 5%, and 10% levels, respectively.

Table 4
H2: Allowance Over / Understatement and Bank Market Value

Dependent: *lnMVE*	Pred. sign	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**Pooled**
Intercept	?	2.435 ***	2.201 ***	0.944 **	-0.834	-0.704	-0.499	-0.841	-0.939 *	-0.667 **	0.058
lnBVE	+	0.723 ***	0.871 ***	1.193 ***	1.264 ***	1.319 ***	1.339 ***	1.309 ***	1.195 ***	1.123 ***	1.241 ***
lnALLL	-	0.037	-0.095	-0.626 ***	-0.690 ***	-0.371 ***	-0.273 ***	-0.248 ***	-0.157 *	-0.006	-0.363 ***
ECLDIFF_RANK	-	-0.017 **	-0.029 ***	-0.052 ***	-0.051 ***	-0.045 ***	-0.056 ***	-0.040 ***	-0.027 ***	-0.021 **	-0.040 ***
lnAvgInt	+	0.239 *	0.309 ***	0.434 ***	-0.042	-0.156	-0.174	-0.190	-0.201	-0.203 **	0.045
lnRELoans	?	-0.264 ***	-0.329 ***	-0.245 ***	0.056	-0.006	-0.013	0.038	0.138	0.092	-0.063
lnConsLoans	?	0.007	0.021	0.112 ***	0.135 ***	0.077 ***	0.043 *	-0.002	-0.005	-0.022	0.041 **
lnRSA	?	0.012	0.000	-0.059	0.007	0.015	-0.058	0.020	0.042	0.064	-0.010
N		249	941	973	995	992	1,018	988	976	975	8,107
Adj R^2		61.0%	60.4%	56.6%	63.1%	70.2%	66.5%	69.8%	77.1%	82.3%	70.1%
Year Fixed Effects		N	N	N	N	N	N	N	N	N	Y

All regression variables are scaled by shares outstanding and then log-transformed. Standard errors are clustered by bank. ***, **, and * indicate statistical significant at the 1%, 5%, and 10% levels, respectively.

Table 5

Allowance Over / Understatement and Bank Market Value with Control for Discretionary ALLL

Panel A: Discretionary ALLL Model

Dependent = ln(ALLL / GBV)$_{it}$	*coeff*	*t-stat*
Intercept	-2.782	-21.77 ***
ln(CO / GBV)$_{it}$	0.166	8.45 ***
ln(Loans / GBV)$_{it}$	0.679	9.97 ***
ln(NPA / GBV)$_{it}$	0.092	5.35 ***
ln(1+(ΔNPA/GBV))$_{it+1}$	-0.183	-3.05 ***
N	7,919	
Adj R^2	60.3%	

Panel B

Dependent: *lnMVE*	Pred. sign	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**Pooled**
Intercept	?	2.522 ***	1.989 ***	0.545	-0.929	-1.385 **	-0.742	-1.242 **	-1.303 **	-1.018 ***	-0.358
lnBVE		0.680 ***	0.908 ***	1.577 ***	1.707 ***	1.472 ***	1.518 ***	1.344 ***	1.227 ***	1.096 ***	1.407 ***
lnNDALLL	-	-0.042	-0.275 ***	-0.774 ***	-0.732 ***	-0.446 **	-0.294	-0.227	-0.252 *	-0.282 **	-0.461 ***
lnDALLL	+/-	0.003	-0.017	-0.329 ***	-0.417 ***	-0.024	-0.162	-0.020	0.000	0.114 **	-0.116 *
ECLDIFF_RANK	-	-0.017 *	-0.018 **	-0.039 ***	-0.046 ***	-0.040 ***	-0.053 ***	-0.038 ***	-0.023 **	-0.012	-0.032 ***
N		239	925	959	984	973	1,003	985	969	882	7,919
Adj R^2		60.5%	60.9%	54.8%	61.4%	69.2%	66.0%	69.3%	76.9%	83.1%	69.5%
Year Fixed Effects		N	N	N	N	N	N	N	N	N	Y
Controls		Y	Y	Y	Y	Y	Y	Y	Y	Y	Y

All regression variables are scaled by shares outstanding and then log-transformed. Standard errors are clustered by bank. ***, **, and * indicate statistical significant at the 1%, 5%, and 10% levels, respectively.

Appendix A – Variable Definitions

Name	***Definition***
Annualized Charge-off Rate	Charge-offs (SNL Keyfield 216333) during the quarter times four divided by loans outstanding at the end of the quarter.
ALLL	The allowance for loan and lease losses at the end of the quarter (SNL Keyfield 215372).
Acquisition	An indicator equal to 1 if a bank acquired another bank in the current or prior year, 0 otherwise.
AvgInt	Average interest income on loans (SNL Keyfield 215406) for the prior eight quarters.
BrokDep	Brokered deposits (SNL Keyfield 216107).
BVE	Book value of equity excluding minority interest at the end of the quarter (SNL Keyfield 215404).
Cash	Total cash and amounts due from depository institutions (SNL Keyfield 215361).
CO	Gross charge-offs (SNL Keyfield 216333).
ConsLoans	Total consumer loans outstanding at the end of the quarter (SNL Keyfield 215813).
Cumulative Loss Rate	The average estimated lifetime loss rate for a loan origination vintage and calculated as the sum of the marginal loss coefficients obtained from estimating Eq. (2) for each bank-quarter.
DALLL	The "discretionary" portion of the allowance for loan and lease losses calculated as the residual from the following model, modified from Beaver and Engel (1996): $\ln(ALLL_{it}) = \alpha_0 \ln\left(\frac{1}{GBV}\right)_{it} + \alpha_1 \ln\left(\frac{CO}{GBV}\right)_{it} + \alpha_2 \ln\left(\frac{LOANS}{GBV}\right)_{it} + \alpha_3 \ln\left(\frac{NPA}{GBV}\right)_{it} + \alpha_4 \ln\left(1 + \frac{\Delta NPA}{GBV}\right)_{it+1} + \varepsilon_{it}$
ECL	My measure of expected credit losses (see Section IV and Appendix C for a discussion of how I measure ECL and an illustrative example, respectively).
ECLDIFF	*ECL – ALLL*
GAP	One year cumulative repricing gap, calculated as rate sensitive assets less rate sensitive liabilities (SNL Keyfield 215612).
Loans	Total loans outstanding at the end of the quarter excluding loans held for sale (SNL Keyfield 215830).
Mat 5+	Loans maturing in 5 years or more (SNL Keyfield 215839 + SNL Keyfield 215840 + SNL Keyfield 215846 + SNL Keyfield 215847).
MVE	Market value of equity at the end of the quarter, calculated from the CRSP monthly stock file as the price per share on the last trading day of the quarter (prc) times shares outstanding at the end of the quarter (shrout).
NIBP	Net income before taxes and the loan loss provision, calculated as net income before taxes (SNL Keyfield 215435) plus the provision for loan

	and lease losses (SNL Keyfield 215420).
NPA	*NPL* plus other real estate owned (SNL Keyfield 216505).
NPL	Nonperforming loans, equal to nonaccrual loans (SNL Keyfield 216483) plus loans past due 90 days or more but still accruing (SNL Keyfield 216442).
RELoans	Total real estate loans outstanding at the end of the quarter (SNL Keyfield 215807).
RSA	Rate-sensitive assets maturing within one year at the end of the quarter (SNL Keyfield 215609).
SFAS 5 Loans	*Loans* minus impaired loans gross of any allowance for impaired loans (SNL Keyfield 232988) at the end of the quarter. If impaired loans are blank, then impaired loans are set to zero prior to calculating *SFAS 5 Loans*.
SGL	Realized gains and losses from sales of securities (SNL Keyfield 215434).
TA	Total assets at the end of the quarter (SNL Keyfield 215382).
TCE	Tangible common equity, representing total equity capital excluding minority interest, adjusted for preferred stock, goodwill and other intangibles. Mortgage servicing rights are not treated as intangible assets (SNL Keyfield 216816).
Tier1Ratio	Tier 1 risk-based capital ratio (SNL Keyfield 215628).
WtdLags	Weighted lags, an estimate of the loan loss emergence period. This variable is the weighted average number of lags used to estimate Eq. (2) for each bank-quarter, where each lag number *n* is weighted by the estimated marginal loss rate for period *t-n*.

Appendix B
Loss Emergence Patterns and Allowance Understatement

The below example illustrates how differences in loss emergence assumptions in ALLL estimates and actual loss emergence patterns can result in ALLL understatement.

First, assume there are two banks, Bank A and Bank B, with identical loan originations:

Bank A		*Bank B*	
Year 1	100,000	Year 1	100,000
Year 2	105,000	Year 2	105,000
Year 3	110,000	Year 3	110,000
Year 4	115,000	Year 4	115,000

Next, assume that Bank A and Bank B realize the same ultimate credit losses but have different loss emergence patterns, such that all charge-offs for Bank A are realized within two years, while charge-offs are realized over three years for Bank B as follows:

Years After Origination	*Bank A*	*Bank B*
1	4%	2%
2	2%	3%
3	0%	1%
Total	6%	6%

The banks will have the following pattern of losses on loans originated in years 1 – 4:

Bank A	Year 2 Expected Charge Offs	Year 3 Expected Charge Offs	Year 4 Expected Charge Offs	Year 5 Expected Charge Offs	Year 6 Expected Charge Offs	Total
Year 1 Vintage	4,000	2,000				6,000
Year 2 Vintage		4,200	2,100			6,300
Year 3 Vintage			4,400	2,200		6,600
Year 4 Vintage				4,600	2,300	6,900
Total Bank A	4,000	6,200	6,500	6,800	2,300	25,800

Bank B	Year 2 Expected Charge Offs	Year 3 Expected Charge Offs	Year 4 Expected Charge Offs	Year 5 Expected Charge Offs	Year 6 Expected Charge Offs	Year 7 Expected Charge Offs	Total
Year 1 Vintage	2,000	3,000	1,000				6,000
Year 2 Vintage		2,100	3,150	1,050			6,300
Year 3 Vintage			2,200	3,300	1,100		6,600
Year 4 Vintage				2,300	3,450	1,150	6,900
Total Bank B	2,000	5,100	6,350	6,650	4,550	1,150	25,800

Finally, assume that each bank sets its ALLL at a level sufficient to cover either one year or two year of expected losses. Each bank's ALLL, ECL, and ALLL understatement relative to ECLs would be:

Bank A		Loss Emergence Period: 1 Year			Loss Emergence Period: 2 Years		
	ECL	ALLL	ALLL Under-statement	% Under-statement	ALLL	ALLL Under-statement	% Under-statement
Year 1	6,000	4,000	2,000	33%	10,200	-4,200	-70%
Year 2	8,300	6,200	2,100	25%	12,700	-4,400	-53%
Year 3	8,700	6,500	2,200	25%	13,300	-4,600	-53%
Year 4	9,100	6,800	2,300	25%			

Bank B		Loss Emergence Period: 1 Year			Loss Emergence Period: 2 Years		
	ECL	ALLL	ALLL Under-statement	% Under-statement	ALLL	ALLL Under-statement	% Under-statement
Year 1	6,000	2,000	4,000	67%	7,100	-1,100	-18%
Year 2	10,300	5,100	5,200	50%	11,450	-1,150	-11%
Year 3	11,800	6,350	5,450	46%	13,000	-1,200	-10%
Year 4	12,350	6,650	5,700	46%	11,200	1,150	9%

This example illustrates that when the assumed loss emergence period is 1 year, the bank with the greater difference between the assumed loss emergence period and actual loss emergence period, Bank B, is more significantly under-reserved relative to lifetime expected credit losses. Further, this example shows that it is possible to be over-reserved if the assumed loss emergence period is equal to (Bank A) or even less than (Bank B) the actual loss emergence period, depending on the pattern of loss emergence. In the case of overstatement, this overstatement is decreasing in the period of loss emergence. Thus, as actual loss emergence increases, the incidence (magnitude) of overstatement becomes less likely (smaller) and the incidence (magnitude) of understatement becomes more likely (larger).

Appendix C
ECL Estimation

To estimate expected credit losses each bank-quarter, I estimate the following model by bank:

$$CO_{ijt} = \beta_{ij1}LO_{ijt-1} + \cdots + \beta_{ijN}LO_{ijt-N} + \varepsilon_{it} \quad (2)$$

$$\text{s.t. } \beta_{ijn} \geq 0$$

where $N \in [1,24]$. Further, I assume initial parameter values of 0.001, 0.0025, 0.005, and 0.0075 for the iterative non-linear modeling process. Therefore for each bank-quarter, I estimate 96 (24 x 4) models. The model with the highest pseudo R^2 is then used to forecast expected credit losses at quarter end.

As an example, assume that a model with *N=4* provides the highest pseudo R^2 for Bank A for loan type *j* and results in the following coefficients:

$$CO_{ijt} = (0.005) * LO_{ijt-1} + (0.010) * LO_{ijt-2} + (0.020) * LO_{ijt-3} + (0.004) * LO_{ijt-4}$$

Each coefficient represents a marginal loss rate, and the sum of the coefficients provides the cumulative loss rate for each vintage (3.9% in this example). Further, assume the following loan originations by Bank A for loan type *j*:

Period	*Loan Originations*
t	100,000
t-1	110,000
t-2	90,000
t-3	85,000
t-4	95,000

The ECL calculation for Bank A and loan type *j* would be:

Origination Period	*Period of Charge-Off* *t+1*	*t+2*	*t+3*	*t+4*	*Total*
t	(100,000*0.005) = 500	(100,000*0.010) = 1,000	(100,000*0.020) = 2,000	(100,000*0.004) = 400	3,900
t-1	(110,000*0.010) = 1,100	(110,000*0.020) = 2,200	(110,000*0.004) = 440		3,740
t-2	(90,000*0.020) = 1,800	(90,000*0.004) = 360			2,160
t-3	(85,000*0.004) = 340				340
Total	3,740	3,460	2,440	400	10,140

Appendix D
Loan Origination Estimates

The following table provides detail on loan origination estimates for each bank-quarter. For each loan type *j* without direct loan origination data, I calculate loan originations each quarter *t* as:

$$LO_{jt} = Ending\ Balance_{jt} - Beginning\ Balance_{jt} + Estimated\ Repayments_{jt}$$

Loan Type	*Quarterly Repayment Assumption*	*Rationale*
1-4 Family: Closed-end	None	Direct origination data from HMDA
1-4 Family: Construction	None	Included in HMDA data
1-4 Family: HELOC	None	I assume that HELOC originations are included in 1-4 family HMDA data. Per the HMDA guide, inclusion of HELOC originations is optional if made "in part for the purpose of home improvement or home purchase."
Commercial & Farm	Variable	I assume that these loans follow the same repayment pattern as 1-4 family and multifamily loans based on the duration of such loans and the sensitivity of prepayments to changes in interest rates.
Multifamily	None	Direct origination data from HMDA
C&I	Variable	Based on data from the Federal Reserve's Survey of Terms of Business Lending from 1997-2015. I assume that repayment rates prior to Q1 2007 equal the repayment rate in Q1 2007. The Federal Reserve provides separate data for large and small commercial banks. I split banks into large and small groups each quarter based on median total assets and apply the relevant maturity assumption.
Consumer	5% of beginning quarterly balance	Consumer loans are comprised largely of credit card and auto loans. Analysis of static pool data on credit card securitizations of Discover, Capital One, Bank of America, and HSBC suggest average annual repayment rates ranging from 18% to 30%, with most between 18%-23%. Further, analysis of static pool data on Carmax securitizations shows an average annual loan repayment rate of 22% for securitized auto loans from 2011-2014. Data on auto loans securitized by Ally Bank suggest an average repayment rate on beginning loans of 10%-13%. Data gathered by credit agency Experian show that auto loan maturities have increased in recent years, with just over 40% of auto loans having an original maturity of 61-72 months. Given all of these factors, a 20% annual rate (5% quarterly) based on an average duration of 5 years appears reasonable.
Agriculture	25%	Survey data from the Federal Reserve System suggests that the average duration of non-real-estate farm loans from 1998-2010 was 12.5 months.
All other	None	I assume that, on average, other loans are immaterial.

Appendix E – Validation Tests of ECL Estimates

Table E1
Predictive Power Tests

Panel A: Full Sample

	NCO - 1-year ahead			NCO - 2-years ahead			NCO - 3-years ahead			NCO - 4-years ahead		
Intercept	0.01 ***	0.00 ***	0.00 ***	0.02 ***	0.01 ***	0.01 ***	0.03 ***	0.02 ***	0.02 ***	0.04 ***	0.03 ***	0.03 ***
ECL	0.11 ***		0.00	0.12 ***		-0.01	0.14 ***		0.01	0.21 ***		0.05
ALLL		0.65 ***	0.64 ***		0.73 ***	0.75 ***		0.73 ***	0.72 ***		0.97 ***	0.87 ***
N	7,062	7,062	7,062	5,818	5,818	5,818	4,626	4,626	4,626	3,517	3,517	3,517
Adj. R^2	8.26%	22.70%	22.69%	3.16%	9.70%	9.70%	2.09%	5.35%	5.33%	2.86%	5.68%	5.77%

	NCO - 5-years ahead			NCO - 6-years ahead			NCO - 7-years ahead		
Intercept	0.05 ***	0.03 ***	0.03 ***	0.06 ***	0.02 ***	0.02 ***	0.06 ***	0.03 ***	0.03 ***
ECL	0.42 ***		0.23 **	0.60 ***		0.43 ***	0.57 ***		0.48 ***
ALLL		1.65 ***	1.30 ***		3.25 ***	2.78 ***		3.40 ***	3.02 ***
N	2,548	2,548	2,548	1,671	1,671	1,671	881	881	881
Adj. R^2	5.70%	8.37%	9.70%	6.24%	10.07%	13.09%	4.02%	5.39%	8.17%

This table presents the results of tests comparing the ability of my measure of expected credit losses (ECL) and loan loss allowances (ALLL) to predict future cumulative net charge-offs. *ECL* is the ratio of expected credit losses to loans at the end of the quarter. *ALLL* is the ratio of ALLL to loans at the end of the quarter. The dependent measures are cumulative net charge-offs cumulated over the 1 to 7 years after the balance sheet date, scaled by loans outstanding at the balance sheet date. Standard errors are clustered by bank. ***, **, and * indicate statistical significant at the 1%, 5%, and 10% levels, respectively.

Panel B: Loss Emergence Greater Than 3 Years

	NCO - 1-year ahead			NCO - 2-years ahead			NCO - 3-years ahead			NCO - 4-years ahead		
Intercept	0.007 ***	-0.002 **	-0.002 **	0.017 ***	0.008 ***	0.008 ***	0.029 ***	0.020 ***	0.020 ***	0.040 ***	0.030 ***	0.030 ***
ECL	0.107 ***		0.002	0.124 ***		-0.001	0.142 ***		0.021	0.216 ***		0.078
ALLL		0.649 ***	0.645 ***		0.734 ***	0.735 ***		0.724 ***	0.679 ***		0.905 ***	0.743 ***
N	5,188	5,188	5,188	4,222	4,222	4,222	3,284	3,284	3,284	2,409	2,409	2,409
Adj. R^2	7.97%	21.82%	21.80%	3.61%	9.90%	9.88%	2.59%	5.62%	5.63%	3.40%	5.38%	5.61%

	NCO - 5-years ahead			NCO - 6-years ahead			NCO - 7-years ahead		
Intercept	0.047 ***	0.033 ***	0.034 ***	0.056 ***	0.024 ***	0.024 ***	0.066 ***	0.036 **	0.035 **
ECL	0.447 ***		0.281 **	0.647 ***		0.466 ***	0.521 **		0.429 **
ALLL		1.540 ***	1.068 ***		3.294 ***	2.640 ***		3.166 **	2.658 *
N	1,647	1,647	1,647	983	983	983	489	489	489
Adj. R^2	7.22%	7.94%	10.01%	7.75%	9.84%	13.43%	3.45%	3.75%	5.93%

This table presents the results of tests comparing the ability of my measure of expected credit losses (ECL) and loan loss allowances (ALLL) to predict future net charge-offs for bank-quarters with estimated loss emergence periods of more than three years (*WtdLags* > 12). Standard errors are clustered by bank. ***, **, and * indicate statistical significant at the 1%, 5%, and 10% levels, respectively.

Panel C: Loss Emergence of 3 Years or Less

	NCO - 1-year ahead			NCO - 2-years ahead			NCO - 3-years ahead			NCO - 4-years ahead		
Intercept	0.006 ***	-0.002 **	-0.002 *	0.018 ***	0.008 ***	0.008 ***	0.030 ***	0.020 ***	0.020 ***	0.040 ***	0.024 ***	0.024 ***
ECL	0.133 ***		0.006	0.119 *		-0.041	0.135		-0.024	0.174		-0.002
ALLL		0.646 ***	0.640 ***		0.774 ***	0.816 ***		0.828 ***	0.850 ***		1.224 ***	1.226 ***
N	1,874	1,874	1,874	1,596	1,596	1,596	1,342	1,342	1,342	1,108	1,108	1,108
Adj. R^2	5.12%	22.81%	22.78%	1.00%	8.59%	8.64%	0.51%	4.53%	4.48%	0.54%	5.75%	5.67%

	NCO - 5-years ahead			NCO - 6-years ahead			NCO - 7-years ahead		
Intercept	0.048 ***	0.025 ***	0.025 ***	0.055 ***	0.022 ***	0.020 ***	0.062 ***	0.027 **	0.023 **
ECL	0.255		0.103	0.405		0.315 *	0.637		0.584 **
ALLL		1.877 ***	1.817 ***		3.032 ***	2.898 ***		3.539 ***	3.381 ***
N	901	901	901	688	688	688	392	392	392
Adj. R^2	0.92%	7.91%	7.97%	2.17%	9.35%	10.60%	3.99%	7.35%	10.68%

This table presents the results of tests comparing the ability of my measure of expected credit losses (ECL) and loan loss allowances (ALLL) to predict future net charge-offs for bank-quarters with estimated loss emergence periods of three years or less ($Wtd\ Lags \leq 12$). Standard errors are clustered by bank. ***, **, and * indicate statistical significant at the 1%, 5%, and 10% levels, respectively.

Panel D: 2006-2007 Period Ends Only

	NCO - 1-year ahead			NCO - 2-years ahead			NCO - 3-years ahead			NCO - 4-years ahead		
Intercept	0.005 ***	-0.004 *	-0.004 **	0.020 ***	0.003	0.003	0.036 ***	0.014 **	0.014 **	0.048 ***	0.018 **	0.018 **
ECL	0.068 *		0.041 *	0.094		0.042	0.193		0.125	0.275		0.188
ALLL		0.806 ***	0.774 ***		1.493 ***	1.458 ***		2.056 ***	1.955 ***		2.778 ***	2.631 ***
N	1,175	1,175	1,175	1,129	1,129	1,129	1,073	1,073	1,073	995	995	995
Adj. R^2	1.80%	11.66%	12.25%	0.37%	4.96%	4.96%	0.90%	4.78%	5.10%	1.33%	6.12%	6.67%

	NCO - 5-years ahead			NCO - 6-years ahead			NCO - 7-years ahead		
Intercept	0.056 ***	0.024 **	0.023 **	0.062 ***	0.028 ***	0.027 **	0.064 ***	0.031 ***	0.029 ***
ECL	0.367		0.276	0.454 **		0.362 **	0.573 ***		0.484 ***
ALLL		3.075 ***	2.861 ***		3.310 ***	3.025 ***		3.395 ***	3.019 ***
N	956	956	956	919	919	919	881	881	881
Adj. R^2	1.97%	5.85%	6.90%	2.67%	5.59%	7.22%	4.02%	5.39%	8.17%

Panel E: 2008-2009 Period Ends Only

	NCO - 1-year ahead			NCO - 2-years ahead			NCO - 3-years ahead		
Intercept	0.010 ***	-0.004 ***	-0.004 ***	0.021 ***	0.003	0.003	0.030 ***	0.010 ***	0.010 ***
ECL	0.257 ***		0.073 **	0.371 ***		0.129 *	0.430 ***		0.172 *
ALLL		1.161 ***	1.040 ***		1.619 ***	1.418 ***		1.803 ***	1.535 ***
N	1,948	1,948	1,948	1,840	1,840	1,840	1,742	1,742	1,742
Adj. R^2	18.76%	41.06%	42.11%	14.05%	29.38%	30.58%	12.31%	23.37%	24.78%

	NCO - 4-years ahead			NCO - 5-years ahead			NCO - 6-years ahead		
Intercept	0.036 ***	0.014 ***	0.015 ***	0.040 ***	0.018 ***	0.019 ***	0.047 ***	0.006	0.006
ECL	0.474 ***		0.206 *	0.517 ***		0.259 **	0.775 ***		0.523 ***
ALLL		1.948 ***	1.623 ***		2.004 ***	1.601 ***		3.836 ***	3.193 ***
N	1,667	1,667	1,667	1,592	1,592	1,592	752	752	752
Adj. R^2	11.78%	20.89%	22.50%	12.08%	18.82%	21.05%	14.93%	23.55%	29.65%

Panel F: 2010-2011 Period Ends Only

	NCO - 1-year ahead			NCO - 2-years ahead		
Intercept	0.006 ***	-0.002 **	-0.002 *	0.012 ***	0.000	0.000
ECL	0.135 ***		0.051 ***	0.183 ***		0.066 *
ALLL		0.629 ***	0.519 ***		0.879 ***	0.740 ***
N	1,982	1,982	1,982	1,896	1,896	1,896
Adj. R^2	17.11%	27.95%	29.54%	13.90%	24.10%	25.26%

	NCO - 3-years ahead			NCO - 4-years ahead		
Intercept	0.015 ***	0.001	0.001	0.021 ***	0.003	0.004
ECL	0.205 ***		0.061	0.266 ***		0.066
ALLL		1.032 ***	0.903 ***		1.274 ***	1.129 ***
N	1,811	1,811	1,811	855	855	855
Adj. R^2	12.17%	23.28%	23.96%	13.61%	25.21%	25.64%

Panel G: 2012-2013 Period Ends Only

	NCO - 1-year ahead			NCO - 2-years ahead		
Intercept	0.002 ***	-0.003 ***	-0.003 ***	0.005 ***	-0.002	-0.002
ECL	0.063 ***		0.020	0.101 ***		0.033
ALLL		0.373 ***	0.331 ***		0.565 ***	0.499 ***
N	1,957	1,957	1,957	953	953	953
Adj. R^2	9.67%	21.04%	21.71%	9.93%	21.12%	21.79%

Table E2

Panel A: Enforcement Action Quarters by Decile of ECL

ECL Decile	Enforcement Action Quarters	Percent of Total	Cumulative Percentage
10	65	21%	21%
9	60	19%	40%
8	55	17%	57%
7	35	11%	68%
6	16	5%	73%
5	21	7%	80%
4	16	5%	85%
3	9	3%	88%
2	22	7%	95%
1	17	5%	100%
Total	316	100%	

Panel B: Expected Credit Loss Estimates and Regulatory Enforcement Actions

Pr(ENF$_{t+6}$)	Predicted sign	(1)	(2)	(3)	(4)
Intercept	?	-3.85 ***	-4.85 ***	-4.96 ***	-3.74 ***
High ECL	+	1.21 ***		0.66 ***	0.48 *
ALLL / Loans	+		77.76 ***	66.38 ***	22.30 *
NPL / Loans	+				24.11 ***
CO / Loans	?				-54.49 *
AvgInt / Loans	?				65.18 *
Tier 1 Ratio	-				-0.18 ***
NIBP / TA	-				11.27
SGL / TA	+				-7.48
Cash / TA	-				3.05
Brokered Deposits / TA	+				0.89
|Gap| / TA	+				-0.01
N		8,100	8,100	8,100	8,100
Pseudo R^2		3.95%	8.21%	9.12%	18.91%

HighECL is an indicator variable equal to 1 if a bank-quarter falls in the top four deciles of *ECL* scaled by loans and 0 otherwise. ***, **, and * indicate statistical significant at the 1%, 5%, and 10% levels, respectively. Standard errors are clustered by bank.

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EDUCATION AND PROFESSIONAL CERTIFICATION

Ph.D.	Accounting, Indiana University, Kelley School of Business	2017
M.B.	Indiana University, Kelley School of Business	2015
B.S.	Commerce, University of Virginia, McIntire School of Commerce	2002

Certified Public Accountant (Virginia)

RESEARCH

Interests: Financial accounting and the capital markets; disclosure; financial institutions; standard setting

Working Papers:

- Dissertation: "Do Investors Impound Information About Unrecognized Expected Credit Losses Into Bank Stock Prices?" Committee: Leslie Hodder (chair), Jim Wahlen, Brian Miller, and Greg Udell
- "Loan Loss Accounting and Procyclical Bank Lending: The Role of Direct Regulatory Intervention"
    - Accepted to and presented at the 2016 Conference on Financial Economics & Accounting (University of Toronto, Rotman School of Management)
- "Discretionary Loan Loss Allowances and Bank Regulation" with Leslie Hodder

Works in Progress:

- "Are smooth earnings informative about future bank performance?" with Allison Nicoletti

TEACHING EXPERIENCE

Teaching Interests: Financial accounting, Audit

Indiana University, Kelley School of Business
Average Rating: 6.25 / 7.0

- Instructor, Introduction to Financial Accounting – Summer 2016, 2 sections
- Teaching Assistant, Introduction to Financial Accounting – Fall 2015, 3 sections
- Teaching Assistant, Introduction to Financial Accounting – Fall 2013, 3 sections
- Instructor, Introduction to Financial Accounting – Summer 2013
- Teaching Assistant, Introduction to Financial Accounting – Spring 2013, 3 sections

Ernst & Young
Average Rating: 4.7 / 5.0

- Instructor Rotational Program – 2007

University of Virginia, McIntire School of Commerce

- Teaching Assistant, Ernst & Young "Your Master Plan" Program, University of Virginia – Summer 2002

Research Presentations

2017	George Washington University	Washington, DC
2017	University of Houston	Houston, TX
2017	Tulane University	New Orleans, LA
2017	Vanderbilt University	Nashville, TN
2016	Accounting PhD Rookie Recruiting and Research Camp	Miami, FL
2016	Conference on Financial Economics and Accounting	Toronto, Canada
2014	Midwest Doctoral Conference	Bloomington, IN

Conference Participation (* indicates by invitation only)

2016	Conference on Financial Economics and Accounting	Toronto, Canada
2016	AAA Annual Meeting (Discussant)	New York, NY
2016	FASB Doctoral Program*	Norwalk, CT
2016	Midwest Accounting Research Conference	State College, PA
2016	AAA FARS Mid-Year Meeting	Newport Beach, CA
2016	AAA Southeast Region Meeting	Atlanta, GA
2015	AAA Annual Meeting (Moderator)	Chicago, IL
2015	AAA FARS Mid-Year Meeting	Nashville, TN
2014	Dopuch Accounting Conference – Olin Business School*	St. Louis, MO
2014	Midwest Doctoral Conference	Bloomington, IN
2014	AAA FARS Mid-Year Meeting	Houston, TX
2013	AAA FARS Mid-Year Meeting	San Diego, CA

Professional Service

Ad-hoc reviewer for *European Accounting Review*

Awards and Honors

2017 Doctoral Student Research Productivity Award, Kelley School of Business

Professional Experience

- Franklin Federal Savings Bank – Vice President, Director of Accounting Policy and Shareholder Reporting, 2008 – 2012 (Richmond, VA)
    - Prepared offering documents in connection with the bank's initial public offering.
    - Prepared and filed bank 10-Q's and 10-K's with the SEC.
    - Analyzed and concluded on significant accounting policy issues and estimates, including the allowance for loan losses, other-than-temporary impairments, and troubled-debt restructurings.
    - Designed the bank's control system for compliance with Section 404 of the Sarbanes-Oxley Act.

- Ernst & Young LLP, Manager, 2002 – 2008 (McLean, VA; Richmond, VA)
    - Worked on audit engagements primarily in the financial services industry.
    - Performed assurance and agreed-upon procedures in connection with asset securitization and servicing activities.

REFERENCES

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