Recognizing Loan Losses in Banks: An Examination of Alternative Approaches

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Abstract

I investigate the accounting rules for loan loss recognition in banks. In June 2016 the FASB issued a new rule, effective in December 2019, that will replace current GAAP with a model that allows banks to use broader information to estimate loan loss allowances. To empirically examine current GAAP and the new model, I exploit differences in the information sets allowed under the old and the new rules. Using a methodology that combines micro data and machine learning techniques, I provide evidence that it is possible to construct a loan loss recognition model that outperforms the current GAAP without expanding the information set beyond that permitted under the current rule. I find that expanding this model's information set does not significantly improve its performance. My model's predicted allowances would have been materially larger at the outset of the financial crisis than actual reported bank estimates. The differences are due to that my model consistently assigns larger weights to certain input variables relative to current GAAP. I also find that weakly capitalized banks under-provision relative to well capitalized banks. My results provide a novel method to examine aspects of the new accounting rule before it comes into effect. The findings suggest that the way information is used, rather than the use of broader information set improves the estimates of loan loss allowance. (JEL G21, G28, M41)

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... so we're not trying to put up as little [loan loss reserves] as possible. You know me, I'd put up more if I could but accounting rules dictate what you can do.[1]

– Jamie Dimon, *CEO JPMorgan Chase, January 2016*

1 Introduction

The mortgage crisis has spurred an ongoing debate on the role of transparency in enhancing financial system stability. This has, in turn, revived the longstanding question among policymakers about how banks should account for loan losses on their held for investment loans (see Wall and Koch, 2000; Davenport, 2004). Current US GAAP employs the incurred loss model (ILM), which requires banks to accrue for losses only if there is objective evidence that it is "probable" that a loss event has occurred. The rule applied in practice restricts banks' ability to record losses that are expected, but do not yet meet the probable threshold, allowing use of only a subset of the available information. In June 2016 the FASB issued ASU 2016 – 13, a new accounting standard that replaces the ILM with a rule that (i) eliminates the "probable" threshold, and (ii) broadens the information considered when measuring credit losses to include forward-looking information, which are reasonable and supportable. This rule is referred to as the current expected credit loss methodology (CECL).[2]

In this paper, I empirically examine two questions related to the ILM and CECL models, focusing on the differences in the information sets that they allow and the way that the information is used. First, I evaluate whether it is possible to construct a predictor of future loan losses that performs better than the ILM approach, without expanding the information set beyond that permitted under that approach. Second, I assess the impact of expanding the information set to include data of the kind proposed under the CECL rule. Together, the empirical analyses contribute to our understanding of the trade-off between allowing for better use of existing information and allowing for broader information, and identifies areas where relevant accounting rules can be improved.

The CECL proposal is widely believed to be the "biggest change ever to bank accounting." [3] Given that allowance estimates directly influence the volatility of bank earnings, as well as the value at which loans are reported on the balance sheet, research on loan accounting rules has important implications. Better estimates of loan loss allowances can improve the efficiency of capital allocation. The catalyst for the CECL rule was criticism that the ILM delayed recognition of loan losses during the mortgage crisis until the losses were probable, thereby affecting the adequacy

[1] Response to question from analyst Mike Mayo's during JPMorgan Chase's Q4 2015 earnings call.

[2] See FASB (2016) for further discussion of the new rule.

[3] See letter from Rob Nichols, ABA President and CEO, to FASB Chairman Russell Golden available at http://www.aba.com/Advocacy/LetterstoCongress/Documents/RussellGolden-FASB-011316.pdf

of allowance estimates (Dugan, 2009). In the pre-crisis period, banks had unusually low levels of reserves against eventual loan losses. One possible explanation for this phenomenon is that the ILM limited banks' ability to record adequate provisions on loans that were performing, but that were eventually expected to become delinquent. Under this argument, provisions should have been recorded earlier than allowed by the ILM. However, whether loan loss allowances were untimely because of ILM remains an open empirical question.

Ideally, an evaluation of the performance of the two models would compare the estimated allowance under the CECL model to the allowance under the ILM to identify which is the better predictor of loan losses. While bank financial statements currently report allowances under ILM, there are no data available on the allowance under the CECL. Therefore, my paper uses a prediction model of future net-chargeoffs to obtain counterfactual estimates of allowances and use the root mean squared error to compare their performance. The root mean squared error is a measure of the difference between the actual realized loan loss and the model allowance.

For my first research question, I estimate allowances without expanding the information set beyond that allowed under the ILM. I consider the information that managers typically use under the ILM, but construct a prediction model by removing constraints on how managers use this information. I refer to this as the "limited information model" (LINM). I construct the limited information model in order to calibrate my estimates because one concern with the underperformance of the ILM, or with any accounting rule, is the opportunity for self-interested managers to affect its implementation, which may impact its performance. The limited information model uses the same information that is allowed in principle under the ILM, but estimates the allowance without any management judgment. If the limited information model outperforms the ILM, it would then serve as a baseline for further analysis.

It is not clear a priori how the estimates from my limited information model would perform relative to the ILM. On one hand, the ILM allowance may out perform the limited information model for at least two reasons: 1) banks possess private information, which they could use for their allowance estimation; and 2) each bank can use its own allowance model, which could improve the overall ILM estimates. On the other hand, my limited information model could outperform the ILM if the allowances from the ILM are biased due to agency problems or bounds on managers' information processing. Thus, comparing the performances of the limited information model and the ILM is ultimately an empirical question.

To preview the results from the first question, I find my limited information model outperforms the ILM. The limited information model hence serves as a credible baseline for the analysis of my second question.

For the second research question, on the impact of expanding the information set, I build on my limited information model from the first question, but extend the information set managers can use in estimating the allowance to also include non-bank economic information. This notion accords with the CECL, which will allow managers to use a broader set of data relative to the ILM. I refer to this model as the "full information model" (FINM). I then examine the value of incorporating broader information by comparing the performance of the expanded full information model to that of my limited information model. If there are material gains from using broader information, then I should find a significant difference between the performance of the full information model and limited information model – with the full information model having a significantly lower root mean squared error for predicting realized loan losses.

My empirical strategy uses quarterly data in the periods 1996 – 2012 to estimate the allowances under the limited and full information models. To answer my first research question on estimating allowances using the limited information model, I consider only historical bank data such as non-performing loans and loan portfolio compositions that managers use under ILM. I employ a technique from the machine learning literature – lasso – to predict future loan losses. The lasso is similar to OLS in the coefficients of input variables are estimated by minimizing squared-error. But the difference is that the lasso also imposes bounds on the sum of the absolute values of the coefficients. This constraint has the effect of shrinking the coefficients, where only a small number of predictors are chosen to have nonzero values, while the other coefficients are exactly zero. These smaller number of predictors reduce the variance of the predicted values and improve the overall out of sample prediction accuracy. Lasso also offers a feasible and objective approach to estimating allowances that could easily be implemented in practice. To predict allowances, I use a rolling-window out of sample technique, where I estimate the lasso in a particular period and then use the estimated model to predict out of sample one-quarter and two-quarters ahead. I assess if the estimated allowances from my limited information model have a lower root mean squared error than those using the reported ILM standard.

My estimation of bank loan loss allowances under the full information model hinges on my ability to proxy for the manager's information set available to be used in the estimates. To address this challenge, I construct a dataset focused on US banks that operate in only one county. This allows me to exploit variation in county business cycles and economic conditions to construct time varying proxies for the credit risk underlying the banks' loan portfolios. My dataset includes information on current county house prices, income, and other demographic variables that I anticipate managers could use under CECL.

To empirically estimate the allowances in the full information model, I build on my limited information lasso model, but expand the information it uses to include detailed county-level economic micro data. I use the rolling-window out of sample technique for the estimates. The lasso model is particularly well suited for the full information case because it identifies relevant information that predicts loan losses and incorporates them into the allowance estimates. I compare the accuracy of the allowance estimates from the full information model to that of the allowance from the limited information model using the root mean squared error.

My findings are as follows. Regarding the first question, I find that it is indeed possible to construct a prediction model that outperforms the ILM, without expanding the information set beyond that already considered under the ILM. I find that the allowance estimated from my limited information lasso model significantly outperforms the allowance under the ILM: the limited information model accurately predicts loan losses with a lower root mean squared error. The estimated allowances using the limited information model are economically meaningful and translate to an increase of 22% in allowances for the mean bank in my sample. Additionally, using the estimated allowance from the limited information model, banks would have recognized higher losses when entering the mortgage crisis beginning in 2006.

In answer to the second question, I find that expanding the information set provides no significant benefit in the model performance. The allowance estimated from the full information lasso model is directionally better than that of my limited information model, but is not substantially different (with only a slightly lower root mean squared error) from the limited information model.

Finally, I provide evidence on the drivers of the performance difference between the LINM and ILM. I find that my LINM outperforms because the model assigns larger weights to some input variables relative to the ILM. In contrast, the ILM systematically under-weights the input variables. I also find that my LINM recalibrates to incorporate current information better than ILM estimations. These two effects result in significantly higher allowance estimates for banks that operate in states with severe banking crises. In analyzing the inefficiency in the ILM and the incentives for managers to understate the losses, I find that weakly capitalized banks consistently under-provision relative to well capitalized banks. This suggests that the discretion afforded to managers under the ILM reduces the accuracy of the estimates.

Overall, the analysis suggests that improving the model specification, rather than broadening the information set, is the key to improving loan loss estimates. The findings that using a machine learning model with ILM inputs outperforms ILM is robust across different empirical specifications and samples. When I repeat my analysis using OLS, I consistently find that merely expanding the information set provides no significant benefit in performance accuracy. When I extend the analysis to a sample of large banks operating in multiple counties, I consistently find that the limited information model continues to outperform the ILM.

The results from my paper have several important implications for bank loan loss accounting rules and their implementation. Assessing the ILM seems to suggest that even with the limited information set, using a simpler, imminently feasible, and objective approach leads to outperforming the current GAAP. One explanation for this result is the possibility that managers were reluctant to use the information to which they had access under the ILM, and that judgment was not used in an unbiased way. These findings raise the question of whether judgment and discretion enhances the quality of accounting in my setting. Finally, my paper sheds light on where the accounting rules can be improved. Despite the stress on using a broader information set in the CECL, it is not clear that information alone will improve its performance. More guidance would be helpful on how managers should implement the accounting rule.

My paper contributes to the literature in several ways. First, while a large body of accounting and banking research investigates the factors that influence bank loan loss accounting, research that examines the role of the accounting standards is scarce (e.g., Beck and Narayanamoorthy, 2013). A unique feature of my paper is that it builds on the institutional details around bank loan losses, and focuses on the implementation aspects of the accounting rules. Second, I show that, in this setting, discretion reduces the quality of the accounting estimate. Third, I propose a way to implement the CECL rule by using objective and verifiable information, thereby examining aspects of the model before it goes into effect in December 2019. Finally, the machine learning techniques used in the paper open up opportunities for further research in accounting, particularly in scenarios where the objective is to build a prediction model and where causal inference is not the primary aim.

The rest of the study proceeds as follows. Section 2 discusses the motivation and background of the paper, while Section 3 lays out the empirical framework. Section 4 discusses details of the data. Section 5 provides the empirical results of my analysis and Section 6 discusses possible interpretations of the results. Section 7 concludes.

2 Motivation and Background

Loans held to maturity on banks' balance sheets are a gross asset that reports the remaining contractual principal on loans in the portfolio. The allowance for loan losses, a contra-asset account, has several components, but the largest consists of allowances for loans collectively evaluated for impairment that fall under FAS 5.[4] The current accounting rules from the FASB require banks to assess whether there is any objective evidence of a "loss event" that indicates that a loan or group of loans is impaired. If there is objective evidence of an impairment (probable condition), the amount

[4]FAS 5 refers to the original FASB pronouncement FAS 5, Accounting for Contingencies, which is included in the FASB Accounting Standards Codification (ASC) subtopic 450–20, Contingencies: Loss Contingencies. The other two components are: FAS 114 (Also known as ASC 310–10–35) for loans individually determined to be impaired and SOP 03–3 (ASC 310–30) for loans acquired with deteriorated credit.

of the loss incurred needs to be estimated (measurable condition). This methodology is referred to as the incurred loss model (ILM).

The notion of *incurred* is an application of the general requirement in GAAP that an accounting event (like loan delinquency) must occur for accounting recognition to occur. Therefore, under ILM, banks can recognize losses for an impaired asset only when a loss is probable based on past events. The rationale for these requirements is that it limits managers' ability to manipulate financial statements. Thus, FAS 5 prohibits firms from accruing for losses that are not currently incurred, even if those losses are expected or from possible future events (see Ryan, 2012).[5] Historically, the issue of whether allowances should be provided for potential or possible future losses has received the most attention from the SEC and bank regulators, leading to interpretive guidance and various publications related to the application of the ILM (Baskin, 1992; SEC, 1997). The application hinges on two key guidance releases, FRR28 and SAB102, both of which are faithful to the FAS 5 loss condition.[6]

During and after the financial crisis, concerns resurfaced that this aspect of GAAP did not allow banks to accrue adequate reserves, which delayed the reporting of losses and hence exacerbated the severity of economic downturns (Laeven and Majnoni, 2003; Dugan, 2009; Beatty and Liao, 2011). The criticism of the model was in limiting banks from recognizing loan losses that were expected, but did not yet meet the probable threshold based on past loan portfolio events. Indeed, in past downturns, realized loan losses were not adequately reflected in banks' provisions. And using historical loss rates for incurred losses, which were low in pre-crisis years, underestimated the provisions.

The ILM with its focus on using historical information for loan loss recognition is inherently backward-looking. Thus, banks are allowed to use only a subset of the available information to predict loan losses for the purpose of estimating allowances.

In discussing the severity of the issue in one of his addresses, Ben Bernanke, then Chairman of the Board of Governors of the Federal Reserve, stressed that "there is considerable uncertainty regarding the appropriate levels of loan loss reserves over the cycle. As a result, further review of accounting standards governing ... loan loss provisioning would be useful, and might result in modifications to the accounting rules that reduce their pro-cyclical effects without compromising the goals of disclosure and transparency" (Bernanke, 2009).

The procyclicality referred to by Bernanke is the consequence of the ILM preventing banks from

[5]Also, FAS 5 Paragraph 30 states that "... exposure to risks does not mean that an asset has been impaired or a liability has been incurred. The condition for accrual ... is not met with respect to loss ... that may occur after the date of an enterprise's financial statements. Losses of those types do not relate to the current or a prior period but rather to the future period in which they occur."

[6]See further discussions in Ryan and Keeley (2013).

recording adequate provisions during favorable periods in the economic cycle. As a result, incurred losses are lower than the long run average i.e., across the cycle. When the credit quality of bank loan portfolios deteriorate during downturns, banks must accrue excessive provisions, potentially magnifying the impact of the economic cycle on the loan loss allowance and reducing the bank's regulatory capital at times when it is expensive to raise capital (FSB, 2009).[7]

Bernanke's sentiment was echoed by the US GAO, who in their report and testimony to Congress examining bank failures (see GAO-US, 2013a,b) stated that the "Federal banking regulators have also noted that requiring management at failed banks to recognize loan losses earlier could have helped stem losses" and "potentially lessened the impact of the crisis, when banks had to recognize the losses through a sudden series of provisions to the loan loss allowance, thus reducing earnings and regulatory capital." The GAO also expressed these concerns about community banks, which are concentrated in their lending, and are hence more exposed to local shocks.

These events together have made the FASB and IASB reconsider the loan loss provision accounting rules to address the criticism. The FASB in its response issued a proposal for public comment for an alternative loan loss provisioning rule that would accommodate the use of more forward-looking information and stress on expected losses. After several years of deliberation, FASB issued a final standard as of June 2016 – the CECL. The IASB separately replaced IAS 39 with the guidance IFRS 9 for Financial Instruments, which is also based on an expected credit loss model, issuing a final standard in July 2014.

2.1 Current GAAP Rules – Implemention

The incurred loss model focuses on banks' discretion in identifying probable and quantifying estimable losses. FAS 5 defines "probable" as "the event or events are likely to occur" (paragraph 3). In practice, the threshold for probable is defined as 70% or more likely (see Ryan, 2012). When loans are underwritten, banks classify them into pools of loans with similar risk categories.[8] Once the loans are classified, the allowances are estimated by identifying trigger events for losses based on the severity of delinquency and payment status. The banks primarily use information on past due loans such as 30 days past due, 90 days past due, and non-accrual along with historic charge-off rates for the estimation (Balla and McKenna, 2009).[9] Banks also consider the composition of loans

[7] The world leaders during the G20 Washington Summit in their response to the crisis called for the development of "The IMF, expanded FSF, and other regulators and bodies should develop recommendations to mitigate procyclicality, including the review of how valuation and leverage, bank capital, executive compensation, and provisioning practices may exacerbate cyclical trends." (G20 Summit, 2008)

[8] These risk categories vary by banks. They fall broadly under pass, special mention, substandard, doubtful, or loss. The loans can move between loan categories during its term in the portfolio.

[9] See (Walter, 1991) for further explanation on how banks categorize defaults and estimate allowance.

in their portfolio in determining allowances. Thus, a limited set of information is used as the basis for estimating the incurred losses.

2.2 CECL Rule and the Use of Broader Information

The main objective of the CECL is to enhance transparency in reporting expected future loan losses, and therefore capture current risks in the banks' portfolio. It aims to achieve this objective by eliminating the "probable" threshold that exists under the ILM. Therefore, a trigger event would no longer be required to estimate the loan losses. It would also weaken the incurred condition that exists under the ILM (FASB, 2016; Acharya and Ryan, 2016).

Furthermore, the CECL rule alters the information set banks can use in estimating future expected losses, compared to the ILM. The rule broadens the information considered when measuring credit losses to include forward-looking information, to include a broader set of information about past events, current conditions, and "reasonable and supportable forecasts" relevant to assessing future credit losses.

The CECL model reflects a fundamental shift in estimating allowance compared to the incurred loss model. In contrast to the ILM, which requires recognizing losses only on delinquent loans, the CECL requires recognizing losses on all loans (including the ones that are in current standing). The CECL, in principle, should provide early warning signs of deterioration in the economic conditions relative to the ILM.

2.3 Evaluating the ILM and the CECL

My empirical focus is on examining the ILM and the CECL rules by developing prediction models for future loan losses to estimate allowances. I exploit the differences in the information sets allowed under these rules for the estimation. The current ILM rule not only limits the information managers can use, but also their discretion by constraining *how* this information is used. Therefore, my investigation of the models involves considering (i) an objective approach that would remove constraints on how the information is used, thus removing the discretion, and (ii) the information set the model has access to.

Assessing both the limited information model and full information model are necessary to answer my research question and to understand the implications of the ILM and CECL models. Documenting evidence of any performance difference between the full information model (i.e., my implementation of the CECL) and the ILM does not address whether the difference is from the better use of information, as captured by the model, or from the broader set of information used.

On the other hand, the limited information model provides a set of baseline results that can be used to gauge its performance relative to both the ILM and the full information model.

There is, however, a key limitation in evaluating the limited information and full information models. The allowances under CECL are not yet observed in the bank financial statements since the rule change goes into effect in the fiscal year beginning December 15, 2019. Consequently, I estimate counterfactual allowances under the two models by making out of sample predictions. The innovation lies in treating this as a prediction problem, rather than a problem of causal inference. Machine learning methods are better suited than traditional regression approaches for this purpose. I use lasso, which is widely used in the statistical and machine learning literature.[10] I discuss the lasso methodology in Section 3.4, and its implementation relevant to this paper in Section 3.6.

2.4 Research on Loan Loss Accounting

This study is related to several lines of research in accounting and banking. First, it contributes to the large body of research on the factors that influence bank loan loss accounting. Prior research documents the incentives of bank managers to smooth earnings, circumvent capital requirements, and reduce taxes (Ahmed et al., 1999; Wall and Koch, 2000; Beatty et al., 2002; Collins et al., 1995). But as argued in Ryan (2012), the results from this literature have been inconsistent. In my paper, I offer another view to the literature on the role of accounting standards, and emphasize that banks' loan loss estimates also depend on FAS 5 ILM. Indeed, as Dechow et al. (2010) state, a general problem researchers encounter in identifying income smoothing is the difficulty in disentangling (i) the fundamental earnings process (ii) the accounting rules and (iii) intentional earnings manipulation. A key aspect of my analysis is that I do not explicitly model agency problems, and the performance difference between my models and the ILM arises primarily due to the accounting rules.

Second, my work relates to the debate on the relationship between transparency and stability. This literature focuses on whether increasing transparency enhances or impairs stability. The arguments for the positive effects of transparency are that it enhances market discipline, increases timely regulatory intervention, and mitigates panics (Rochet, 1992; Ratnovski, 2013; Granja, 2013).[11] The opposing view argues that transparency can lead to bank runs that are driven by coordination failures, and can also lead to inefficient investment decisions (Morris and Shin, 2002; Goldstein and Sapra, 2014), while Dang et al. (2014) argue that bank opacity avoids adverse selection in the market, allowing the deposit mechanism to work better. There is a consensus,

[10]Note that the name "lasso" is an acronym for Least Absolute Selection and Shrinkage Operator.
[11]See also Bushman (2015) for a discussion of the topic.

however, that one of the primary channels by which bank financial reports can affect stability is by increasing public information about the risk and economic conditions to which banks are exposed (Acharya and Ryan, 2016). Loan loss allowance estimates reflect a fundamental aspect of the risk attributes of a loan portfolio. My study considers a specific setting to discuss how the new rule, whose objective is to enhance transparency, is likely to work in practice.

Third, this paper contributes to the policy discussion around accounting standard setting for loan loss provisions.[12] These discussions have been motivated by the need to use more forward-looking measures to mitigate the limitations of the ILM. Studies on forward-looking measures include Bushman and Williams (2012) that use a cross-country sample to argue that forward-looking provisions, if designed to smooth earnings increase risk taking in banks.[13] In modeling expected losses, Harris et al. (2017) develop a measure to capture one-year forward expected losses. They used cross-sectional regression analysis and find the measure performs well in predicting next year losses and contains incremental information relative to fair value disclosures in explaining future losses. The case of Spain provides useful data for studying the issue, as Spanish banks have employed an alternative approach in dynamic provisioning for loan losses since 2000 to reduce pro-cyclicality (see Fernández et al., 2000; Saurina, 2009a,b). Using this setting, Jiménez et al. (2012) examine the changes in credit availability after dynamic provisioning went into effect. The authors find that the growth in credit during upturns and credit supply contraction during downturns are significantly reduced after the implementation of the dynamic provisioning approach. Similarly, Pérez et al. (2011) study income-smoothing in Spanish banks around the implementation of dynamic provisioning, and find the effect only from 1988 to 1999. They find that between 2000 to 2004 when banks used dynamic provisions, transparency increased, but there was no evidence of income-smoothing. I add to this discussion by performing an empirical study to understand how forward-looking measures would have performed in a US setting.

Finally, my paper designs and implements a new approach to estimate allowances that incorporates more current information, as would be observed under CECL. To construct the information set for my analysis, I use detailed micro data to empirically build proxies that capture the credit risk in loan portfolios. To identify the credit risk, I build on work by Mian and Sufi (2009, 2011) who study the causes and consequences of the credit crisis by examining the role of household debt and defaults in the period. The implications to bank accounting arise from the fact that household debts are typically assets on banks' balance sheets. Thus, it is reasonable to posit that the factors that drive household debt defaults would be the information that managers would consider to

[12] See further discussion by Barth (2007) on the case for researchers to develop studies relevant to issues faced by the standard setters.

[13] Consistent with these results, Bushman and Williams (2015) find that U.S. banks that tend to delay loss provisioning are associated with contractions in their balance sheet, and contribute to systemic risk during periods of downturns.

predict future losses.

In implementing my estimation, I build on emerging research by economists (Mullainathan, 2014; Kleinberg et al., 2015) who argue for the value of using machine learning (ML) technique, which are primarily designed for prediction. The authors give examples of applying the tools to policy questions, which have prediction as an objective of interest. My approach to predict future losses, and estimating allowances, is a natural extension of prior accounting studies that have focused on using ML (referred to as an expert system or artificial intelligence) for human information processing and decision making.[14]

3 Empirical Framework

This section develops the statistical framework for predicting allowances in the limited information and full information model. I use this framework to motivate the empirical analysis, and discuss the various ingredients of the prediction technique. My framework builds on modeling the bank manager's decision by considering 1) the information she has access to and 2) the information that she is allowed to use given the rule. The assumption is that a manager uses the information set and the realized losses in prior periods to build a prediction model. The model would then be used to predict losses out of sample. If the bank maintains the allowance at this estimate, then the total loans, less the allowance, would be the best estimate of the collectible value of the loan at the evaluation date.

My empirical strategy in the paper follows a two-step procedure to estimate the allowance under the limited and full information models. I first use the information set allowed under the relevant rule, and build a prediction model of loan losses in an estimation period. The model is estimated every quarter, where I follow a rolling-window technique with the estimation period expanded every quarter to use information only up to that quarter. The rolling-window technique helps to avoid any hindsight bias. In the second step, I use the model developed in the estimation period to make predictions in the subsequent time period, the out of sample test period. The predictions in the test periods are then used to evaluate the model's performance. This algorithm is further discussed in Section 3.6.

Let the information set a manager has access to be denoted by $\mathscr{I}_t$, which could be used at time

[14]Some of these studies have used the lens model analysis (Zimmer, 1980; Kim and McLeod Jr, 1999). For other examples, see work by Libby (1976), Casey (1983) and Wright and Willingham (1997). In other works, Mengle (1990) discusses about the efforts from the accounting industry developing "expert systems" to capture the estimation of the quality of the loans and ascertaining the market values of loan loss reserves.

t to predict losses in estimating the bank's loan loss allowance LLA_t. The $\mathscr{I}_t$ refers to the vector

$$\mathscr{I}_t := \big[\{X_0, X_1, \ldots, X_t\}, \{M_0, M_1, \ldots, M_t\}\big],$$

where X captures bank-level variables, such as the portfolio loan balance, information on the delinquency status of the loans, net-chargeoffs. The set M contains macroeconomic indicators that affect the loan performance of the bank such as home prices, unemployment rates, and wages. Let $\mathscr{I}^{ilm}$ be the subset of $\mathscr{I}_t$ containing information that banks can use under the ILM. The set $\mathscr{I}_t$ also contains the broader information set allowed under CECL, which is denoted by $\mathscr{I}^{cecl}$. The $\mathscr{I}^{ilm}$ is hence the limited information set containing variables in X, while $\mathscr{I}^{cecl}$ is the full information set containing X and M.

I first estimate allowances using the limited information model. I then expand the information the limited information model uses for the full information model. The accuracy of each model is assessed by how well the estimated allowance captures actual net-chargeoffs. This idea is consistent with the accounting identity:

$$\begin{aligned} \text{LLA}_t &= \text{LLA}_{t-1} + \text{RECOV}_t - \text{CO}_t + \text{LLP}_t \\ &= \text{LLA}_{t-1} - \text{NCO}_t + \text{LLP}_t \end{aligned} \tag{3.1}$$

where LLA_t is allowance for loan losses at end of t, RECOV_t the amounts that have previously been charged off but are recovered during this time period, CO_t the gross amount of all loans charged off against the LLA losses. The income statement effect is captured by LLP, the loan loss provisions. Thus, the precision of the LLA_{t-1} is assessed by how well it predicts future net-chargeoffs ($\text{NCO}_t =$ CO_t – RECOV_t) at t.

3.1 Current US GAAP

I begin by studying the banks' loan loss estimation strategy using the ILM, which forms the motivation for my limited information model predictions. For the discussions around the relevant statements of the rule, refer to Appendix Section A.1. At time t, the LLA_t is estimated by predicting CO_{t+1}, using information from t, based on the subset of data that could be used i.e., $\mathscr{I}_t^{ilm}$. This timing notation captures the aspect under the ILM that even though the manager has access to larger information from t, she is only allowed to use a subset $\mathscr{I}_t^{ilm}$.In the discussions that follow, for simplicity I use charge-offs to motivate the prediction models, but my actual empirical estimates uses net-chargeoffs. I initially assume that the manager predicts CO one period ahead, such that LLA_t estimates cover CO_{t+1}. This assumption is relaxed to consider multi-period losses later in this section. Formally,

$$\text{LLA}_t = \mathbb{E}[\text{CO}_{t+1}|\mathscr{I}_t^{ilm}]. \tag{3.2}$$

At the evaluation date t, the manager uses historical data in the periods $\tau = 0, \ldots, t$ and uses information on delinquencies and nonperforming loans and their corresponding charge-offs to build a prediction model of CO. She then uses the model estimates to make out of sample predictions, with a new realization of information at t that she can use. If the bank manager uses an OLS model, then

$$\begin{aligned} \mathbb{E}[\text{CO}_{t+1}|\mathscr{I}_t^{ilm}] &= \mathbb{E}[\alpha + \beta * X_t + \epsilon|\mathscr{I}_t^{ilm}], \\ \text{CO}_{t+1} &= \alpha + \beta * X_t + \epsilon. \end{aligned} \tag{3.3}$$

Therefore, it follows that at time t

$$CO_t = \alpha + \beta * X_{t-1} + \epsilon, \tag{3.4}$$

where CO_t is the realized credit losses of the bank at t.

Estimates of α and β can be generated by regressing CO on X, where X is bank-level covariates defined earlier, and recover the estimates $\hat{\alpha}$ and $\hat{\beta}$. Substituting the parameter estimates in (3.2) and making predictions with the new realization X_t,

$$\begin{aligned} \hat{\alpha} + \hat{\beta} * X_t &= \widehat{CO_{t+1}} \\ &= \widehat{LLA}_{t(ilm)}. \end{aligned}$$

This forms the basis for estimating allowances under the limited information model. I use the lasso approach for predicting the allowances, which serves as my baseline to compare its performance, to the allowance from the ILM reported in the bank financial statements. I attribute the difference in performance to how the limited information model uses the information set while estimating the allowance, and attribute the effect to discretion in the ILM.

3.2 CECL Model

This section forms the motivation for my estimation in the full information model. The key feature of the expected loss model is that it alters the information set that banks can use while estimating their LLA, without having to wait for a triggering event.

Under the CECL, bank managers predict CO using a broader set of information that reflects current condition, and thus any deterioration of credit. Formally:

$$\text{LLA}_{t(cecl)} = \mathbb{E}[\text{CO}_{t+1}|\mathscr{I}_t^{cecl}] \tag{3.5}$$

over $\tau = 0, \ldots, t$. The manager as of evaluation date t incorporates all information up to that point in time. Similar to the derivation in Equation (3.3),

$$CO_t = \alpha_{cecl} + \beta_{cecl} * X_{t-1} + \gamma_{cecl} * M_{t-1} + \epsilon, \tag{3.6}$$

i.e., the bank predicts CO based on its information at t. This idea is empirically equivalent to regressing CO_t on X_{t-1}, but also includes county level economic information M. I then use the parameters from the predicted model, $\hat{\alpha}_{cecl}$ and $\hat{\beta}_{cecl}$, to estimate at period t

$$\begin{aligned} \hat{\alpha}_{cecl} + \hat{\beta}_{cecl} * X_t + \hat{\gamma}_{cecl} * M_t &= LLA_{t(cecl)} \\ &= \widehat{LLA}_{t(cecl)}. \end{aligned} \tag{3.7}$$

The $\widehat{LLA}_{t(cecl)}$ is my estimated allowance under full information model. The prediction model I use is the lasso. I interpret the analysis of the limited information model and the full information model under the maintained hypothesis that these estimated measures reflect an unbiased and knowledgeable party's estimate of future losses using the information. I attribute the difference in the performance of the limited information and full information model to the broader information incorporated in the full information model.

3.3 Measuring Loan Losses

In the above model, I assume the manager estimates LLA at time t to absorb loan losses NCO realized in future period $t+1$. In reality, the bank estimates LLA in (3.2) and (3.5) by developing a model predicting credit losses in multiple subsequent periods towards the maturity of the loans.

To expand the model's loss horizon, I follow Fillat and Montoriol-Garriga (2010) and consider the sum of rolling four quarter net chargeoffs, and add non-performing loans at the end of the rolling-window's fourth quarter. At time t the loss is measured as,

$$g = \sum_{\tau=t+1}^{t+4} NCO_\tau + NPL_{t+4},$$

where NPL is Non-performing loans, which is the sum of loans that are ninety-days past due and the loans that are in non-accrual. This broader measure of loan losses is the dependent variable in my lasso prediction model. This measure avoids any double-counting when non-performing loans become charged-offs in the future periods, as the ninety-days past due and the non-accrual are measured at the end of the fourth-quarter in the rolling window. This approach provides a more conservative estimate than what CECL will require.[15]

3.4 Lasso Approach

The above discussion highlights the importance of prediction to model estimates of loan loss allowance. Thus I use techniques from the machine learning literature as they are primarily developed for the purpose of making out of sample predictions with improved accuracy. I build on the framework provided in the economics literature by Kleinberg et al. (2015) for using tools from ML, particularly to empirical policy research (For further discussion of using ML methods in empirical social science research, see Mullainathan (2014); Einav and Levin (2014); Athey and Imbens (2015)).

The need to use ML techniques also arises from that OLS estimates, which are designed for causal inference, are meant to generate an unbiased estimate of $\hat{\beta}$ when used in sample. They do not usually yield the most accurate prediction $\widehat{Y}$. This is because the focus of OLS is to get an unbiased estimate in terms of in sample fit by minimizing the squared error, i.e.,

$$\min_{\beta \in \mathbb{R}^p} \left\{ \sum_{i=1}^{N} (Y_i - x_i^\top \beta)^2 \right\}.$$

Thus the OLS estimated model is likely to result in a very poor prediction out of sample because of overfitting, and are not useful for out of sample predictions (see Belloni et al., 2014).

I use the lasso predictor (Tibshirani, 1996), which is among the most widely used models under the class of regularization methods in ML. The lasso estimator minimizes:

$$\min_{\beta \in \mathbb{R}^p} \left\{ \sum_{i=1}^{N} (Y_i - x_i^\top \beta)^2 + \lambda \sum_{j=1}^{p} |\beta_j| \right\}.$$

This estimator is an extension to OLS. However, the second term, which is a function of λ and β,

[15] The OCC handbook OCC (1998) states that "Many banks consider coverage of one year's losses an appropriate benchmark of an adequate reserve for most pools of loans. ... A one-year coverage period is generally considered appropriate because the probable loss on any given loan in a pool should ordinarily become apparent in that time frame." Further, the Federal Reserve as part of the stress test argues that "The appropriate level of ALLL at the end of a given quarter is generally assumed to be the amount needed to cover projected loan losses over the next four quarters." http://www.federalreserve.gov/bankinforeg/stress-tests/2015-Appendix-B.htm

called a shrinkage penalty, is small when some of the β coefficients are close to zero. This term controls the overfitting concern by foregoing in-sample fit in exchange for improved out of sample fit. The $\sum_{j=1}^{p} |\beta_j|$ term has the effect of constraining some of the estimated β coefficients to be exactly equal to zero when the λ is sufficiently large (see further discussion in Tibshirani (1996); Hastie et al. (2009)).[16]

The key idea is that the parameter λ can be chosen using the data by a commonly used cross-validation technique. The lasso allows me to fit a model containing a large number of predictors with some of the coefficients that are equal to zero.

As discussed in Kleinberg et al. (2015), ML techniques are an extension of non-parametric statistics. Specific to my research question, they provide a disciplined way to pick a model that would map the information set to predict loan losses CO_t, while estimating allowances. The lasso offers an eminently feasible, simple, objective approach to implement the accounting rules. The lasso performs variable selection to include predictors that are a subset of the variables.

3.5 Predicting Loan Losses

Here I outline the functional form for predicting loan losses to model charge-offs CO in equations (3.2) and (3.5). Consider the future expected chargeoffs,

$$\mathbb{E}(\text{CO}) = \text{loan balance} * \text{pd} * \text{lgd},$$

where pd is the probability of default, and lgd is the percent-loss given default. The term pd * lgd can be set equal to historical charge-off rate (COrate). Estimating the expected loss is equivalent to predicting the charge-off rate, which is equal to:

$$= \text{loan balance}_{t-1} * \widehat{COrate}_t \tag{3.8}$$

The $\widehat{\text{COrate}}_t$ can be predicted from historical COrate_{t-1}, adjusting to incorporate new information for subsequent defaults. To illustrate, consider the unemployment rate at the county level, and then rewrite the estimate in a regression framework for a bank i that operates in county j in time t. In the actual empirical model used in the paper, I use a comprehensive set of macroeconomic indicators.

[16] Note that OLS is a special case where $\lambda = 0$.

$$\text{COrate}_{ijt} = \beta_1 * \text{COrate}_{it-1} + \beta_2 * \text{NPL}_{it-1} + \beta_3 * \Delta\text{unemprate}_{jt-1} + \\ \beta_3 * \mathbf{X}_{it-1} + \beta_4 * \mathbf{M}_{jt-1} + \text{fixed effects} + u_{ijt}. \tag{3.9}$$

Refer to Appendix Section B for further discussion of the empirical model. I use the specification from (3.9) to predict credit losses for my analysis with the time period t in quarters. This forms the basis for the variables used in my lasso model. The dependent variable I use is the sum of four quarter net charge offs and nonperforming loans. I use the predicted losses from the estimation as my $\widehat{LLA}_{t(cecl)}$. The data I use for the estimation comes from a cross sectional panel of banks with quarterly loan loss data between 2002Q1 and 2012Q4.

3.6 Predicting Allowance from Lasso

I obtain counterfactual allowances by estimating the lasso in a rolling-window estimation period, and then predicting allowances in a test period which are one-quarter and two quarter ahead out-of-sample.[17] The information used as inputs for predictions in my limited information model are the bank level variables, while the information used as inputs in my full information model are the bank and micro-economic variables. The variables are presented in appendix Table A.1.

As discussed in Section 3.4, to select a suitable value of λ, I perform a ten-fold cross validation using all the input variables, and loan loss measure, at each iteration of my lasso estimation. The cross validation method is commonly used in the ML literature (see Hastie et al., 2009).[18] The algorithm splits the historical data into 10-subsets (or folds). For a set of λ, the algorithm is estimated on the 9 folds and it then validates which value of λ produces the best prediction in the 10-th fold. This process is repeated until the model is tested on each of the 10 folds, which produces the cross-validated λ. In order for my model to have reasonable estimation window, I start my first predictions in 2002Q1, when the model is estimated using all data from 1996Q1 to 2002Q1. I then make predictions using the coefficients from the lasso one quarter and two quarters ahead. In the next iteration, I increase the window by a quarter, and include 2002Q2. I repeat the process until 2012Q4.

In evaluating the prediction accuracy of my lasso models and the ILM, I use the out-of-sample predictions, and use the root mean square error (RMSE) (see Hamilton, 1994, chap. 4).[19] This

[17]For example, to estimate allowance for 2007Q1, the estimation period ends at 2006Q4, while the one-quarter out-of-sample test period is 2007Q1.

[18]For my lasso estimates, I use the `glmnet` package in R that implements a class of regularization algorithms.

[19]The mean squared error is $\mathbb{E}(Y_{t+1} - \widehat{Y}_{t+1}|t)^2$ based on the estimated model at t. Here Y is the actual net-chargeoff

measure is the difference between the actual realized loan losses (measured as four quarter net-chargeoffs plus non-performing loans) for a bank in a quarter, and the corresponding estimated allowances in that quarter. I calculate the measure for each bank in each period. Then I square the difference, and the mean of this loss measure is the RMSE. I repeat this procedure to calculate the RMSE for the allowance under ILM and its performance relative to the actual realized losses. The model with the lower RMSE predicts realized loan losses more accurately, and is a better model.

4 Data

Estimating allowances for the full information model requires the information set of the manager that would be used to predict the credit risk in the banks' portfolio. This is not readily available for banks operating across a variety of geographic regions. As a result, I restrict the sample to banks that primarily do their lending in one county in the US for my analysis. I then obtain county data, such as housing prices and unemployment rates. The advantage of this research design is that it not only allows me to precisely identify the economic signals to predict future losses, but also to use a consistent sample for my limited information and full information models. Appendix Table A.2 provides definitions of all variables used in the paper.

4.1 Sample selection

I use the Summary of Deposit (SOD) statement from the FDIC to identify banks that operate in only one county. The SOD is the annual survey of branch office deposits for all FDIC-insured institutions. All institutions with branch offices are required to submit the survey, but institutions with only a main office are exempt. The data includes exact address of the branch offices, including the county. I aggregate the underlying branch data to the bank-county level and identify banks that have all their operations in the same county. The implicit assumption is that these banks do lending in the same county.[20]

To avoid misclassification, I merge the bank-county data with the list of banks the FDIC has designated as community banks for research purposes (FDIC, 2012). The FDIC's research definition

rate, while the value $\widehat{Y}_{t+1}$ is the model predicted allowance as a percentage of loans. For calculating the MSE under the incurred loss model, I consider a prediction model that takes loan loss allowance as the only independent variable. I use the predicted value from this estimated model as the allowance under ILM.

[20]My conversations with various bank regulators strengthen the reasonableness of this assumption. The SOD gives only deposit data at the branch level. I use deposits, aggregating them at the county level, to capture the geographic concentration of bank lending and to exploit the variation across the bank's loan portfolio. This assumption is reasonable as under section 109, banks are prohibited from opening, or acquiring branches outside their home state primarily for deposits. This limitation is under the Community Reinvestment Act (CRA) that was enacted by the Congress to ensure that the bank branches do not take deposits from a community without lending to the community (FDIC, 2014).

of a community bank fits my analysis well for two reasons. First, these banks have lending and deposit taking as their main business focus, and second, their business is fairly circumscribed in a geographic area. This identification helps me to tie the bank characteristics, and the demographics of the borrowers from these banks, with the assumption that both the bank (loans) and the borrowers are exposed to the same economic shocks at the county level. This level of abstraction allows me to model information that is not available in the call reports of the banks and to infer the quality of loans in the bank's portfolios.

Using the above criteria generates a sample of $306,666$ bank-county-quarter observations, for $7,086$ banks that operated in 1996 to 3,170 banks that operated in 2012, as shown in Table 1. Given the stringent restriction on one-county lending, this represents a significant number of banks for analysis and reflects a sizable economic activity. Together these banks represent 59% of all commercial banks in 1996 in number, decreasing to 43% of all banks in 2012. They operated in $2,337$ ($1,519$) counties in 1996 (2012). The US map in Figure 1 shows the distribution of the counties for 2002Q1 with banks that operate only in that county. Sample banks have a presence across the US, and are particularly concentrated in the Midwest, Northeast, mid-Atlantic, California, eastern Texas, and Washington. The mean number of one-county banks in the counties they operated was 2.56 in 2002, while the mean was 2.08 in 2012. Together, this information shows the diversity of the commercial banking in the US that allows me to run this quasi-experiment in exploiting economic cycles across counties.

4.2 County Data

I follow work by Mian and Sufi (2009, 2011) on building micro data on local economic shocks by county. I obtain monthly housing prices at the county level from a proprietary data set from Core Logic and supplement it with data from the Federal House Financing Agency (FHFA).[21] I use these data together to construct quarterly shocks to housing market performance for sample bank counties. The quarterly county-level unemployment rates are from the Bureau of Labor Statistics.

I also collect average adjusted gross income at the county level from the IRS. This data gives information on the income of residents living in that particularly county. The income numbers are based on county income data on the addresses reported on individual income tax returns filed with the IRS. I include data on wages from the Quarterly Census of Employment and Wages (QCEW) that tracks wage and employment statistics for individuals who work, but who do not necessarily live in that county. I include data on per capita income from the Bureau of Economic Analysis

[21] Both these sources use the same house repeat sales data to construct the home price index and are among the some of the best data sources on home prices (see Mian et al., 2013).

(BEA). I use data on the change in the number of private establishments to capture performance of business in the county come from the QCEW. To capture shocks in the agriculture sector, I use data on farming income at the county level from the BEA.

I obtain data on business/non business bankruptcies from the Administrative Office of the U.S. Courts. This source gives statistics on the number of bankruptcies filed at a county level. Finally, I obtain from the Census Bureau data on the demographics of various variables at the county level: of population, senior share, non-white share, the vacancy rate in housing, poverty levels of households, and the fraction of the population that has less than a high school education.

4.3 Bank Data and Summary Statistics

For the banks in my sample, I collect quarterly balance sheet information from the Bank's Quarterly Reports of Condition and Income (the "call reports"). Data on loan performance are the loans that are thirty days, ninety days or more past due and those that fall under non-accrual, all scaled by the outstanding loan balance. The size of the bank is measured as the natural logarithm of the bank's assets. As suggested by Ryan (2012), data on percentage of loans in real estate (RE) and commercial and industrial (CI) is collected to reflect variation in bank loan portfolio compositions. I further collect data on loan to asset ratio along with securities to asset ratio, where securities are the book value of all held to maturity securities.

I use other bank-level variables that are used in prior research to predict future loan losses. I use interest receivables for income accrued but not yet collected on loans (Prescott and Walter, 2015). Interest receivables also capture the difference between the sum of loans outstanding and the present value of contractually promised future payments on loans (Ryan, 2007). I capture loan yields on the loan portfolio, which should reflect the risk of default and the loss in the underlying risks in the portfolio. I define this measure as the ratio of tax-equivalent interest income divided by total loans at the end of the quarter following Jiang et al. (2016).

Table 2 reports summary statistics for the sample of bank-quarter-county in the period 1996 – 2012. The mean sample bank has \$104 million in total assets, while the median has \$64 million in assets. The median and mean of total loans are \$38 million and \$66 million respectively. The mean rolling four-quarter net-chargeoffs (NCO) is $\$269,000$, while the mean rolling four-quarter NCO + non-performing loans (NPL) at the end of the four quarters is \$1.4 million. The mean and the median loan loss allowance of the concentrated banks are $\$892,000$ and $\$483,000$ respectively.

The mean sample bank has about 0.4% in loans that are ninety day past due, and 1% in loans that are in non-accrual. The mean loan to asset percentage is 61%, while the median is 62% and shows the fact that the loans are a large percentage of these banks' assets. The mean percentage of real estate loans is 64%, while the mean percentage of commercial and industrial loans in the sample is 14%.

I measure all county variables in terms of quarterly changes. The mean housing price growth for the sample counties is 1.1%, and the mean unemployment rate in the sample is 5.5%. The change in farm earnings is a decrease of about 4.2%, while the mean wage growth in the county from the IRS 1.1%.[22] The mean and median of the ratio of all business bankruptcies to the establishments in the county are 62% and 44% respectively. The mean home price growth for the counties in the sample is 1.1%. The change in farm earnings is a decrease of about 4.2%.

5 Empirical Results

This section provides tests of the limited information model (section 5.1), full information model (section 5.2), magnitude of impact from using these models (section Section 5.3), and a discussion of the findings (section 5.4). I then discuss a setting where the accounting rules would have been particularly helpful in states that suffered from severe banking crisis (section 5.5), expand analysis of my limited information model to large banks (section 5.6).

5.1 Evaluation of the Limited Information Model

I present the results in a series of tables that report the RMSE of my lasso-estimated limited information model and the bank reported ILM. The variables used as predictors for my limited information model (LINM) are presented in appendix Table A.1. If the limited information model outperforms the ILM, I expect to observe its RMSE to be lower than the ILM. Intuitively, the RMSE measures the difference between the actual realized loan losses and the corresponding allowances estimated from my LINM, as a percentage of total loans. I present results by aggregating the quarterly RMSE at the yearly level. I report the cumulative RMSE, and the yearly RMSE of the models.[23]

The results for the performance evaluation between the limited information model allowance (LINM) and the ILM allowance are reported in Table 3 and Table 4. The key result is that the allowance from my limited information model predicts future loan losses more accurately, and outperforms the allowance from the ILM. The RMSE estimates in both one-quarter and two-quarters

[22] The IRS data are available only on annual basis. I follow Mian and Sufi (2011) in interpolating the IRS data in obtaining the quarterly data.

[23] The cumulative RMSE for year t in the table is cumulative means of RMSE for all years less than or equal to t. The yearly RMSE for t is the means of the RMSE for year t.

out-of-sample model estimates using my LINM are less than those of the ILM (summarized in top panel of Figure 2).

The cumulative RMSE for the one-quarter ahead and two-quarter ahead predictions are in panel A and panel B of Table 3, respectively (also shown in Figure 3). The RMSE for the limited information model (LINM) for the overall sample between 2002 and 2012 is 3.22 for one-quarter ahead, and 3.26 for two-quarters ahead. The RMSE for the ILM allowance in this period is 6.07 for one-quarter ahead, and 6.66 for two-quarters ahead. The interpretation is that my LINM model using one-quarter ahead predictions has an error of 3.26 (percentage of total loans) in predicting actual loan losses, while the ILM with one-quarter ahead predictions has an error of 6.07 (percentage of total loans) in predicting actual loan losses. The cumulative RMSE for the one-quarter ahead limited information model estimated for the sample ending in 2009 is 3.65, compared to the ILM which is 6.74.

The results in Table 4 show the one-quarter and two-quarter RMSE for estimates for the individual years (also illustrated in Figure 4). In contrast to Table 3, the RMSE in Table 4 are the aggregated values by year for the RMSE values. Overall, the results consistently show that the limited information model is more accurate than the ILM in predicting future loan losses. The performance of both the limited information model and the ILM suffer in 2008 during the mortgage crisis, but my LINM continues to outperform the ILM.

The evidence reported indicates that it is possible to construct a prediction model that outperforms the ILM without having to expand the information set. I interpret the performance difference attributed to using the lasso model, which relaxes any restrictions on how the information set can be used while estimating the allowances. The lasso model efficiently weighs the limited information set to improve the overall prediction accuracy. The implication is that an objective and simple approach using the lasso to estimate allowance brings performance gains to the ILM, without having to expand its information set.

5.2 Evaluation of the Full Information Model

The variables used as predictors for my full information model (FINM) are presented in appendix Table A.1. The results of the performance evaluation of the full information model (FINM) and the limited information model (LINM) are reported in Table 3 and Table 4. I use the limited information model as the baseline to evaluate the full information model's performance. If incorporating broader information in my LINM lasso model brings significant benefits in allowance estimation, I expect observing the RMSE of the full information model significantly differ from RMSE of the limited information model.

I find that the performance of the limited information model does not change significantly on expanding the information in the full information set. The RMSE for both the one-quarter and two-quarter out of samples do not exhibit significant differences. Nevertheless, the full information model (FINM) does outperform the ILM (summarized in bottom panel of Figure 2). The cumulative RMSE for the one-quarter ahead and two-quarters ahead predictions are in panel A and panel B of Table 3, respectively (illustrated in Figure 3). The RMSE for the full information model for the overall sample between 2002 and 2012 is 3.19 for one-quarter ahead, and 3.24 for two-quarters ahead. The RMSE for the limited information model is 3.22 for one-quarter ahead and 3.26 for two-quarters ahead.

The yearly estimates exhibit similar pattern as shown in Table 4. Panel A presents the one-quarter ahead RMSE, while panel B presents the two-quarters RMSE for the estimates aggregated by the year (illustrated in Figure 4). The one-quarter RMSE for the full information model in 2007 is 2.2, while the limited information model is 2.304. The magnitudes of these differences are similar in 2012 with the RMSE for the full information model being 1.85 and for the limited information model 1.89. Consistently, I find that the broader information does not does not bring performance gains to the full information model compared to the limited information model.

In summary, the evidence reported is consistent with expanding information set in estimating allowances to the limited information model, as suggested in the CECL, provides no significant benefit in model performance relative to the limited information lasso model. I attribute the result to the lasso approach that flexibly weighs the limited information set, as was available in the ILM, to produce an accuracy similar to that obtained using the full information set.

5.3 How much more Allowance?

My statistical tests of the allowance models thus far focused on the accuracy of the estimates to predict future loan losses. I now discuss the impact of the estimated allowance by measuring the magnitude of the difference between the actual loan loss allowances that were accrued by banks, and my model predicted allowance. I measure this difference expressed as a percentage of loans. I calculate this measure for each sample bank in each quarter, and aggregate it to the year. The intuition is that if managers had used my limited information model or full information model to estimate allowances, it is the difference that they would have adjusted their allowance recognition relative to their estimated ILM.

Figure 5 summarizes the results for the limited information model for the one-quarter (top panel) and two-quarters ahead (bottom panel) predictions. The difference in the allowances as percentage of loans in 2008 is 0.4%, and in 2009 is 0.8%. The mean bank in the sample accrues

1.5% of loans as allowance as presented in Table 2. I find that using the limited information model one-quarter ahead estimates in the periods between 2002 – 2012, the mean bank in the sample would have increased its allowance recognition by 22%, relative to actual allowances. This impact is economically meaningful.

In the period between 2002 – 2003, the limited information model predicts that banks would have increased allowances relative to ILM. Then for the periods from 2004 to 2005, this difference is negative, suggesting the banks would have lowered allowance using the limited information model relative to the ILM. But entering the crisis, beginning in 2006, the limited information model would have predicted higher allowances than what the banks had under the ILM. The limited information model predicts banks should have increased their allowance by 10% relative to what they had under ILM in 2007. I find similar results for the two-quarter ahead limited information model predictions.

In analysis not presented, I find similar economically meaningful results for allowances predicted by the full information model. On average, banks would have increased their allowance by 22% for the period between 2002 – 2012. However, in contrast to the limited information model, the full information model would have predicted lower allowances than that of the ILM during the early part of the analysis until about 2005. But similar to the lower information model, banks under the full information model would have increased their allowance entering the crisis beginning in 2006. Using the full information model, banks should have increased their allowance by 23% in 2007.

The predicted allowances from the limited information and full information model together suggest that using the ILM for allowances understated the value of sample banks' portfolios as presented in Figure 5. Moreover, this inaccurate level of allowance under the ILM has a direct impact on bank capital. The difference in the allowance estimates between the models presented in the figures reveal the unclear picture of how capital adequate the banks really were. These aspects suggest that with the shortcomings of the ILM allowance model, banks and its supervisors would have had a false sense of the risks in the bank balance sheets. As a result, banks could have continued to lend and, hold excessively risky loan positions on their balance sheets. Besides, the allowance estimates from the limited and full information models have the ability to provide early warning about changing economic conditions as seen in the increase in allowances beginning in 2006 for the financial crisis.

5.4 Discussion of the Limited and Full Information Models

This section explores the implications of my empirical results from the limited and full information models towards improving the current accounting rules. In particular, I consider two aspects of the

ILM and the CECL – the judgment allowed under the rule, and the information that can be used in allowance estimation.

The evidence that limited information model outperforms ILM raises the possibility that the managers were reluctant to use the information they had access to under the ILM. Their judgment seems to have not been exercised in an unbiased way. The limited information model implements a loan loss accounting rule without any constraints on how the information is used; but removes the judgment on the part of the managers relative to the ILM. Given that the limited information model predicts future loan losses more accurately, it raises the question of whether affording managers with more discretion in my setting, improves the quality of accounting and enhance transparency. My findings document the effect from the discretion.

The CECL rule stresses using broader information to estimate allowances. From the results of the full information model, it is not clear that broader information alone will improve the performance. As a result, more guidance would be helpful for managers on how to implement the accounting rule. The CECL, as issued, does not specify a single method for measuring the losses; and leaves it to the banks to develop methods that help in objectively applying the principles of the CECL.

In the analyses presented in the paper using the limited information and full information model, I show how to implement a CECL rule, and more broadly an allowance rule using the lasso approach. The lasso offers a simple, and objective approach that clearly outperforms current GAAP. By incorporating a broader set of county economic data, I show how a rule can be implemented, that is also verifiable and can be consistently applied over time. Furthermore, this approach can be easily implemented in practice. These findings will be of interest to standard setters, bank managers, and auditors.

5.5 Allowances in States that Suffered Severe Recession

In this section, I consider banks in states that suffered severe recession with a significant number of bank failures. I then examine the performance of the LINM, FINM, and ILM for these banks. The idea is to study how the accounting information in allowances could have played a larger role and provided early warning of the changing economic conditions. Hence, the allowance estimates from the models would possibly acted as a trigger and allowed bank supervisors to heed to the warning, and act on the risk accumulation in these banks thus mitigating the threat to financial stability.

For this analysis, I first identify states that suffered severe banking failures during the mortgage crisis. I use the list of states from Figure 6, which shows the distribution of failed banks in the US. I consider states with at least 10 bank failures in the period 2008 – 2011. The states that fall in this category are Arizona, California, Florida, Georgia, Illinois, Michigan, Minnesota, Missouri, Nevada, and Washington. For these severe crises states, I expect to observe larger effects in the performance difference between the ILM relative to the limited information model, and the full information model. I also hypothesize that the differences between estimated and actual reported loan loss allowances should be higher than those documented above for all sample banks. Note, the classification of the states happen based on ex post performance of the banks.

I estimate the allowances using the limited information model and the full information model for only the subsample of banks that operate in the identified states. I compare the RMSE for the models relative to the ILM. The results are reported in Table 5, and illustrated in Figure 7. Panel A in the table shows the RMSE for one-quarter ahead predictions, and panel B the two-quarters ahead predictions. The evidence suggests that the limited information model continues to outperform the ILM, and that adding new information does not bring significant benefits. However, the ILM severely underperforms thus widening the difference between the performance of the ILM and my estimated models.

The one-quarter cumulative RMSE of my limited information model in this sample in the period 2002 – 2012 is 4.479, while the RMSE for the ILM is 10.007. The RMSE for the full information model in this period is 4.574. The RMSE in the periods 2002 – 2008 for the limited information model is 3.691, and for the ILM is 8.658. The RMSE by year for the models are reported in Table 6 (shown in Figure 8).

These prediction accuracy estimates translate to large differences in the allowance amounts estimated by my models and the ILM's allowances. Similar to the analysis in Section 5.3, I calculate the difference between the actual loan losses and my model predicted allowances for each bank in the subsample in each quarter. I then aggregate the difference to the year. The findings are presented in Figure 9. I find the mean bank that operated in the states with severe banking crisis should have increased its allowances by 33% using the limited information model, relative to the actual allowance they had accrued in the period between 2002 – 2012. This increase is higher compared to the estimates based on a sample of all banks. Under the full information model, banks should have increased their loan loss recognition by 29%.

Furthermore, I find that using both the limited information model and full information model, banks would have started to increase their allowance beginning in 2006. For example, the limited information model predicts that the banks should have increased their allowance by 10% in 2007 entering the crisis. The full information model, on the other hand, would have predicted the banks to have increased by 35%. During the initial part of the estimation sample, there are no significant differences between the ILM allowance and the limited information model allowance. But in the same period, the allowance under the full information model would have suggested that the allowance be decreased.

Overall, the evidence presented for the subsample of banks that operated in states that suffered severe crisis is consistent with that a limited information model would have more accurately predicted the loan losses than the ILM, and that full information model does not bring considerable performance gains. However, even with my LINM allowance estimates, could have possibly allowed the bank regulators and supervisors to act timely in limiting some of the bank failures.

5.6 How does the Limited Information Model Perform for Large Banks?

The analysis thus far focuses on a sample of county banks, which allows me to map their the micro-economic information. A natural extension is to examine the performance of the limited information model relative to the ILM for a broader sample of larger banks. Not only do the larger banks differ in terms of how they are regulated, but also tend to have different loan portfolio compositions compared to the one-county banks. The larger banks also have a capacity for greater risk and could estimate loan loss allowances using more sophisticated models. Therefore it is not clear ex ante how my limited information model would perform, given the performance of the ILM observed is a function of the models used in the estimation, and the incentives of larger banks.

To examine the limited information model for larger banks, I consider banks that have more than $250 million in total assets (and operate in multiple counties).[24] I predict allowances for each sample bank in each quarter in the period 2002 – 2012, and compare the performance using the RMSE, as well as the magnitude difference between the estimated allowance and the actual loan loss allowance. The results from the out of sample RMSE are presented in Figure 10. I find the LINM continues to outperform the ILM and accurately predicts the loan losses. The RMSE for the LINM for the large banks for the overall sample between 2002 and 2012 is 2.12, while the RMSE for the ILM allowance in this period is 3.01. The cumulative RMSE for the one-quarter ahead (top panel) and two-quarter ahead predictions (bottom panel) are in Figure 11. The RMSE for the one-quarter ahead LINM estimated for the sample ending in 2009 is 2.03, compared to the ILM which is 3.04.

The magnitude differences between the LINM predicted allowance, and the actual allowance accrued by larger banks is presented in Figure 12. The LINM predicts that the larger banks would have decreased their allowance in 2005, relative to what they had actually recognized. But early in the crisis, the LINM predicts that the larger banks increased their allowance. The difference between the allowances in 2007 is 0.11% and in 2008 is 0.64%. These differences are economically meaningful. With the LINM one-quarter ahead estimates in the period between 2002 – 2012, the mean bank in the sample would have increased its allowance by 24% relative to actual allowances.

[24] The mean bank in the sample has total loans of about $2.3 billion.

The results are similar for the two-quarter ahead predictions.

The above analysis suggests that LINM continues to outperform the ILM for banks with larger loan portfolios. This is consistent with the earlier findings using the one-county bank sample, adding further validity of the performance gains from using the LINM model.

5.7 How Robust are the Horizon of Future Losses?

The analysis in the paper predicts allowance based on four-quarter rolling net charge-offs plus non-performing loans. This measure is the dependent variable used in the lasso approach to capture bank managers' estimate of future losses. In reality, the actual horizon the banks use in estimating the losses are not observable. To test the robustness of my assumption, I estimate the models by extending the loss horizon in the prediction model to two-years and three-years. I then repeat the analysis and evaluate the out of sample performance accuracy of the limited information model and full information models relative to the performance of the ILM. I find that the results are qualitatively the same, and the limited information model continues to outperform the ILM. And the difference between the full information model does not bring any significant benefits.

6 What Drives the Performance Difference between LINM and ILM?

A principal finding in this paper is that my LINM outperforms the bank's ILM. In this section I examine four explanations for the performance difference between the two models by 1) differences in the weights assigned to the variables in the models (section 6.1); 2) determining where the effects from the weights are large by exploiting variations in banks' losses (section 6.2), and 3) assessing whether using aggregate data in the analysis plays a role in the performance difference (section 6.3). In section 6.4, I explore 4) capital management incentives.

6.1 Examining the Weights on Input Variables by the LINM and ILM

The statistical tests to examine the performance difference between the LINM and the ILM models in this paper use the RMSE. To examine the differences in the RMSE arising from the statistical models, I explicitly consider the coefficients of the variables from the my LINM and the bank's ILM. The purpose of this analysis is to identify significant differences in the weights that each model assigns to the input variables, and the changes in these weights over time. I use the coefficients generated from my LINM model as its weights. For the coefficients of allowances under the ILM, I fit an OLS regression using the same set of variables from the limited information model, using recognized allowances as the dependent variable. I generate the coefficients estimated on various windows of my sample data split by year. Hence, this approach allows me to compare the coefficients directly to understand if the ILM systematically under-weights variables in the model and if managers ignore information they already possess.

The coefficients from my LINM lasso model are reported in Appendix Table C.1 and the coefficients from the ILM model are reported in Appendix Table C.2. I join the two tables and present them in Table 7. The columns in the tables refer to the window used to estimate the models. For example, the column 1996 – 2005 refers to the coefficients from the model estimated in the period between 1996 and 2005. I compare the magnitudes of the weights assigned to the variables. I focus on the sample ending in 2008 because this year is when the performance of my LINM, and the bank ILM begin to diverge.

Table 7 suggests that the outperformance of my LINM is driven by two effects. First, my LINM model consistently assigns larger weights than ILM to the 30 days past due, 90 days past due, and nonaccrual variables. In contrast, the ILM model systematically under-weights these variables, as observed across all of the windows. In the LINM model, the weight in 2008 for 30 days past due is 0.129, the weight for 90 days past due is 0.355, and the weight for nonaccrual is 0.406. The corresponding weights in the ILM are 0.030, 0.024, and 0.108.

Second, my LINM continuously recalibrates and updates to incorporate the underlying information while predicting allowances, unlike the ILM. This aspect is reflected in the difference in the magnitudes of the 30 days past due, 90 days past due, and nonaccrual variables between the LINM and ILM. The difference gradually increases across the period. Furthermore, the magnitudes of the coefficients of LINM for the 30 days past due, 90 days past due, and nonaccrual variables are higher in 2008 relative to 2002. To provide economic intuition, the sum of the absolute differences between the coefficients of the three variables in 2002 is 0.35 percent of loans. The sum of the absolute difference doubles in 2008 to 0.73 percent of loans.[25] Using these variables alone, my LINM would predict that banks would have increased their allowances by 0.73 times their loans in 2008.

The larger coefficients in 2008 for LINM occur because the model uses the experience in the period 1996 – 2008 to assign weights to the relevant input variables. An alternative explanation is that my LINM assigns larger weights to more recent data, while the ILM data assigns larger weights to historical data and smaller weights to recent data, which could improve its relative performance. To test this alternative explanation, I estimate the LINM and ILM models using only

[25]This number for 2008 is calculated as the sum of the following differences – for the 30 days PD: $(0.129-0.030)$, 90 days PD: $(0.355-0.024)$, and Nonaccrual PD: $(0.406-0.108)$.

the period 1996 – 2002 and predict the allowance in the period 2005 – 2012. I then compare the performance of the models relative to the full rolling window case. The cumulative RMSE for the models are presented in Appendix Figure C.1. I report the RMSE beginning only in 2005. LINM_2002 refers to the lasso model estimated using the sample in the period 1996 – 2002, while ILM_2002 refers to the ILM model estimated in the period 1996 – 2002. I find that my LINM consistently outperforms the LINM_2002. The difference between the LINM_2002 and the LINM is attributed to the LINM model's incorporation of current information and experience to update the coefficient estimates of the input variables, which improves its performance. However, the performance of the ILM_2002 does not improve, and continues to perform poorly relative to the ILM, and in turn the LINM. The ILM seems to partly ignore both recent and historical experience, as reflected in the under-weightings. Thus, the test results rule out an alternative explanation for the poor performance of the ILM.

6.2 Exploiting Variation in Banks Operating in States with Severe and Less Severe Crises

I now identify a setting where the weights assigned by the LINM and ILM models play a large role in driving a wedge between their relative performances. The findings from Figure 3 and Figure 4 reveal only modest differences in the LINM and the ILM models' performance until 2007. As discussed earlier, their performance diverges beginning in the year 2008. To examine this divergence, I partition the sample of all county banks into a subsample of banks that operate in states with severe crises, and another subsample comprising banks with less- severe crises.[26] The partition allows me to exploit variation and observe differences in banks depending on the severity of the loan defaults in the state. The idea is that the banks operating in the severe default states suffered larger losses or recognized lower allowances, or both, in the period of the study. Therefore, the weights assigned to the input variables by the LINM and ILM should have larger effects on the performance of the models. To study the performance, I fit the LINM and ILM models for the full sample of banks as in the main analysis.[27] I then decompose the RMSE from the LINM and ILM

[26] Given the focus here is to understand the differences in 2008, I classify states that suffered severe banking failures during the mortgage crisis by considering states that had at least 10 bank failures in the period 2008 – 2011. The states that are in the category are AZ, CA, FL, GA, IL, MI, MN, MO, NV, and WA. This classification is same as the one used in Section 5.5. The rest of the states comprise the category of less-crisis states. I use this classification for the entire period of my study.

[27] The difference between the analysis in the current section compared to the analysis in Section 5.5 is that in the current section I estimate one model using all sample banks, while in Section 5.5, I estimate separate model for the subsamples. The other difference between this section and Section 5.5 is that the key focus of analysis in Section 5.5 is to compare the performances of the ILM, LINM, and the FINM model. But in the current section, I specifically focus on the performance difference between my LINM and the ILM.

models (presented in the top panel of Figure 2) by using the estimates from the models to predict allowance, and estimate the RMSE separately for the subsamples of banks in states with severe and less-severe crises.

Figure 13 presents the out-of-sample cumulative RMSE for the two subsamples and the full sample. The RMSE are from the estimates of the LINM and ILM using the full sample. The RMSE for the sample of banks operating in the less-severe states (LINM_Less and ILM_Less) and severe states (LINM_Sev and ILM_Sev) are also shown. There is a significant increase in the RMSE of ILM_Sev relative to the baseline ILM. The RMSE of ILM is 6.07, while the RMSE of ILM_Sev is 10.03. The RMSE of ILM_Less is 2.17. Therefore, the RMSE of the ILM model is dominated by the RMSE of ILM_Sev. Hence, the findings suggest that the underperformance of the ILM relative to the LINM is driven by the performance of the banks operating in the severe crisis states.

Figure 14 presents the cumulative RMSE by year for the subsamples of banks in states with severe and less-severe crises. This analysis is similar to the analysis underlying Figure 3 for the full sample case. The top panel is for the sample of banks operating in less severe crisis states, and the bottom panel is for more severe crisis states. The LINM_Less outperforms ILM_Less, and the LINM_Sev outperforms ILM_Sev. There is a striking contrast between the figures in the top panel and the bottom panel. The difference in the models for the less severe banks is smooth and the performance in 2008 is not pronounced. The bottom panel for severe banks reveals the spike beginning in 2008 for the ILM, similar to the main analysis with the full sample case. The underperformance of the banks in severe crisis states has a punitive effect on the performance of the ILM. Overall, the evidence in Figures 13 and 14 suggests that the differences between the LINM and ILM, particularly beginning in 2008, are driven by banks operating in states with severe crises. The difference is attributable to the possibility that these banks possibly underprovisioned relative to the larger losses that they actually realized, as compared to the banks in less severe crisis states.

6.3 The Role of Aggregate Data in the LINM and ILM Models

My LINM model in this paper relies on using aggregate data on all county-level banks across the US to estimate allowances. One potential problem with this approach is that it may not be feasible in practice for a particular bank to use aggregate data across all banks. This is important because of the concern that using the aggregate data from the sample banks brings the performance gains in my LINM. There are two reasons this concern is mitigated to a certain extent in my setting. First, the data from bank balance sheets used in the study are public and accessible to all banks. Second, it is reasonable to posit that there are information flow between the auditors or regulators, and bank managers on the loan performance and allowance recognition of other banks.

Nevertheless, to directly address the concern, I repeat the analysis of the LINM and ILM by restricting them to all sample (one-county) banks operating within a specific geographic area, such as a single state or in a cluster of states. The LINM and ILM models are then estimated by restricting them to only these banks, and the performances are compared in each specific case. If the results of this analysis, focusing on subsamples of banks, are consistent with the full sample case (with my LINM outperforming the ILM), then the analysis provides direct evidence that my results are not driven by the use of aggregate data across all banks.

To test this premise, I consider states that have a large number of sample banks. The states that fall in this category are Illinois and Minnesota. I also focus on states with the mean and median numbers of sample banks: Arkansas and New Jersey. Finally, I consider Maine, which has a small number of sample banks. In addition, to include a larger subsample of banks, the analysis is repeated by focusing on clusters of states, as designated by the Bureau of Economic Analysis (BEA). The regions are New England, Mideast, Great Lakes, Plains, Southeast, Southwest, Rocky Mountain, and Far West.[28] Finally, I also include banks in California, a state that is classified as a severe crisis state. The selection of the specific states and the regions is for the sake of parsimony in reporting the findings.

Figure 15 and Figure 16 present the cumulative RMSE estimated on sample banks restricted to the corresponding single state. The cumulative model performances for sample banks restricted to BEA regions are presented in Figure C.2 and Figure C.3. For example, the RMSE for sample banks in Minnesota is LINM: 1.79 and ILM: 2.28. The RMSE of sample banks in the BEA-designated Far West region is LINM: 2.56 and ILM: 3.56. Across all the states and regions in the analysis, the LINM model continues to outperform the ILM. The RMSE of the LINM is lower than the RMSE of the ILM. There are differences in terms of the magnitude of the cumulative RMSE across the states. Overall, the evidence in the figures from across the model performances is consistent with the hypothesis that my LINM outperforms the ILM even when smaller subsamples are considered, and rules out the hypothesis that the results are driven by using a large sample of banks.

[28]The BEA regions and the states that capture the areas are as follows: New England Region – Connecticut, Maine, Massachusetts, New Hampshire, Rhode Island and Vermont; Mideast Region – Delaware, DC, Maryland, New Jersey, New York, Pennsylvania; Great Lakes Region – Illinois, Indiana, Michigan, Ohio, Wisconsin; Plains Region – Iowa, Kansas, Minnesota, Missouri, Nebraska, North Dakota, South Dakota; Southeast Region – Alabama, Arkansas, Florida, Georgia, Kentucky, Louisiana, Mississippi, North Carolina, South Carolina, Tennessee, West Virginia; Southwest Region – Arizona, New Mexico, Oklahoma, Texas; Rocky Mountain Region – Colorado, Idaho, Montana, Utah, Wyoming; Far West Region – Alaska, California, Hawaii, Nevada, Oregon, Washington.

6.4 Agency Issues in Recognizing Allowances

In this section, I consider agency issues in the performance gains of my LINM relative to the estimates of the managers. To investigate this inefficiency, I consider the incentives for managers to systematically understate the allowances as observed in the ILM. I focus on variation in incentives to manage regulatory capital in banks. I pick capital management for two reasons: first, due to my sample's limitations in identifying variations in other managerial incentives, and second, to build on prior research that studies the relationship between allowance recognition and bank capital (see Ryan, 2012, chapter 3).

To investigate whether managerial incentives to recognize allowances are different for well capitalized relative to weakly capitalized banks, I exploit variation in the sample of large banks discussed in Section 5.6. I split the sample into a subsample comprising banks whose capital ratios are above-median capital ratio in the year-quarter ("well capitalized"), and another subsample that comprises banks that are below-median capital ratio in the year-quarter ("weakly capitalized"). I then estimate the LINM and ILM separately for each of the two subsamples and compare the difference in the magnitude of allowance, and accuracy.

The model performance for the weakly capitalized bank subsample is presented in the top panel of Figure 17, and the model performance for the well capitalized bank subsample is presented in the bottom panel of Figure 17. The figures show the cumulative RMSE from each subsample in the period 2002 – 2012. I find that in each of the subsample, my LINM continues to outperform the ILM with a lower RMSE. The RMSE for the well-capitalized banks are LINM: 2.10 and ILM: 2.92. The RMSE for the weakly capitalized banks are LINM: 1.88 and ILM: 2.89. There are no significant differences in the RMSE, and model accuracy, across the two subsamples. However, the differences in the RMSE between LINM and ILM in the subsample of weakly capitalized banks is slightly higher compared to the difference in the RMSE between LINM and ILM in the subsample of well capitalized banks.

The magnitude of the difference in the allowances, as a percentage of loans, from the models for the two subsamples is presented in Figure 18. The top panel is the difference for weakly capitalized banks, while the bottom panel is the difference for well capitalized banks. The mean bank in the well capitalized bank subsample would have increased its allowance by 14%, the weakly capitalized subsample would have increased its allowance by 28%. This significantly larger increase for weakly capitalized banks is suggestive of their underprovisioning. In addition, the peak in the difference in magnitude for the below median capital firm is at 1.8 percent of loans, while the peak for the above median capital firm is about 1.2 percent of loans. The mean magnitude difference for the below median capital banks in the period 2007 – 2012 is 0.62 percent and the mean for the above median capital banks in the period 2007 – 2012 is 0.94 percent.

Overall, the findings of a larger increase in magnitude of allowances as predicted by my LINM for the weakly capitalized banks, along with a slightly higher difference in accuracy between the LINM and ILM models for these banks, provide evidence for the difference in provisioning between the subsamples. The evidence suggests that weakly capitalized banks exercise discretion, and underprovision relative to well capitalized banks.

7 Conclusion and Suggestions for Future Research

This paper contributes to our understanding of the role of information in financial reporting and transparency. I examine this notion in the context of how accounting rules influence bank loan loss allowances, where a longstanding debate exists among standard setters and regulators about the best way to account for loan losses. Current GAAP's incurred loss model delays loss recognition until a probable threshold is met. This aspect has been criticized for limiting bank's ability to recognize losses that are expected, but have not yet met the threshold. The mortgage crisis underscored some of these concerns, and the FASB responded by issuing a new accounting standard CECL, that would alter the information set banks can use in estimating allowances to include forward-looking information.

I examine whether it is possible to construct a predictor of future loan losses that outperforms the incurred loss model by using the same information that is typically allowed under the rule. I then examine the impact of expanding the information set to include data of the kind proposed in the CECL rule (The CECL rule will be effective beginning December 2019). I find that it is indeed possible to construct a prediction model – the limited information model – that performs better than the incurred loss model, without having to expand the information set beyond what is already used under the incurred loss model. I also find that expanding information to this model provides no significant performance gains. I document that using the predicted allowances from the limited information model, banks would have recognized higher allowances before entering the financial crisis. I also find that the performance gains from the limited information model is consistent for a sample of large banks.

I then examine the factors that drive the outperformance of the limited information model relative to the ILM. I find that the limited information model assigns larger weights to input variables, and continuously recalibrates incorporating the underlying information, unlike the ILM. I find that these translate to large differences in performance, particularly for banks that operated in states with severe crisis. In examining the incentives of managers to understate the losses in the ILM, I find evidence consistent with that weakly-capitalized banks underprovision, relative to the well-capitalized banks.

While a large stream of accounting and banking research examines the factors that influence bank loan loss accounting, there is a paucity of empirical research that examines the rules and its implementation. I find that even with a simpler and eminently feasible approach, implemented from the machine learning literature in lasso outperforms current GAAP.

I further use the CECL rule change as a setting to understand on two aspects of the rule, the discretion allowed, and the use of the information. My findings suggest that using broader information in allowance estimates is beneficial, but that primary benefits are from how the discretion is exercised in using the information, rather than the availability of broader information. I argue that this finding raises the question as to whether discretion improves accounting quality in my setting, and contributes towards the debate in standard setting, and financial reporting over affording managers discretion versus a uniformity in the rules.

The findings in this study suggests several avenues for future research. One natural question is to understand the form of inefficiency in the accounting rule. It would be an interesting study to extend the analysis to understand if the outperformance of the limited information model is driven by the biases from the models used by the banks, or other incentives of bank managers in applying the rule. Another area is to explore whether bank managers react to the limitations in the accounting rules through real actions such as raising capital or reducing risk or through other means. Finally, it would be interesting study to examine if the market understands the frictions arising from current GAAP, and if there are possible mispricing of risks. Understanding these questions would further increase our grasp of bank accounting choices, financial reporting, and more broadly to standard setting.

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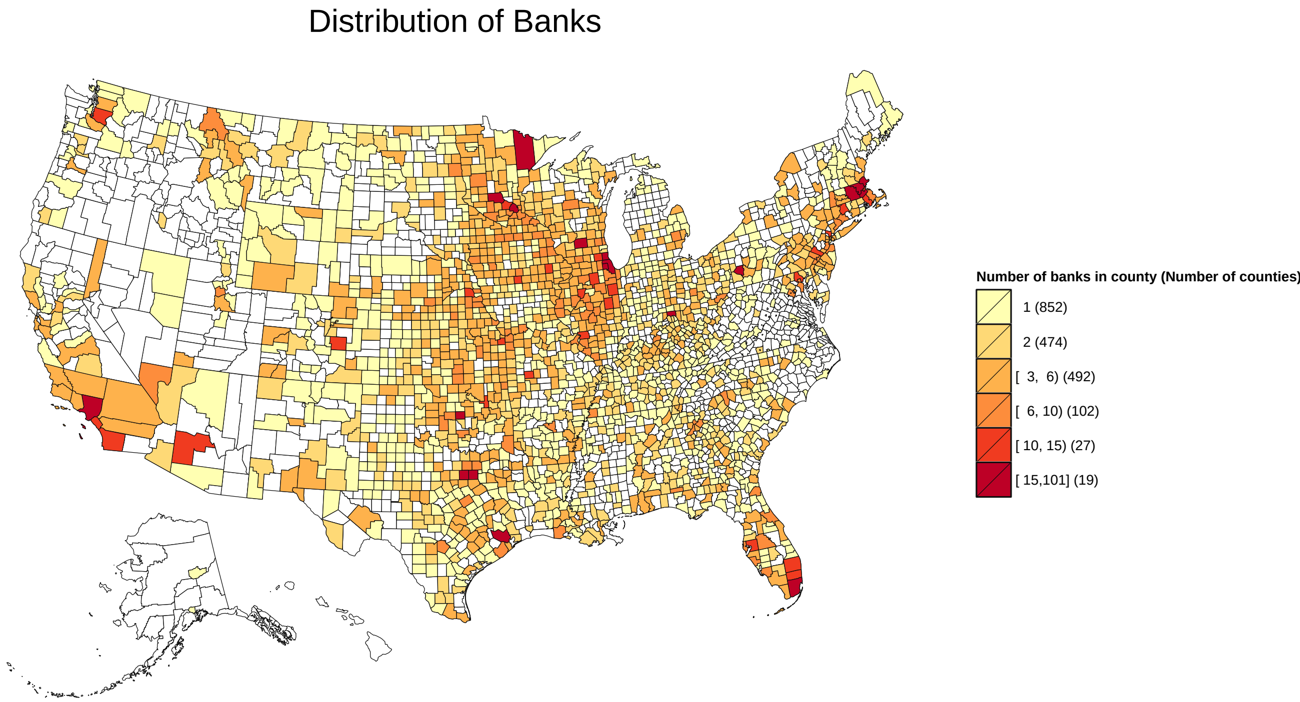


FIGURE 1: SAMPLE BANKS BY COUNTY

This figure presents the geographic distribution of sample banks in the US as of 2002Q1. The map shows the counties which have banks that are fully concentrated in the county, along with number of the concentrated banks operating in these counties.

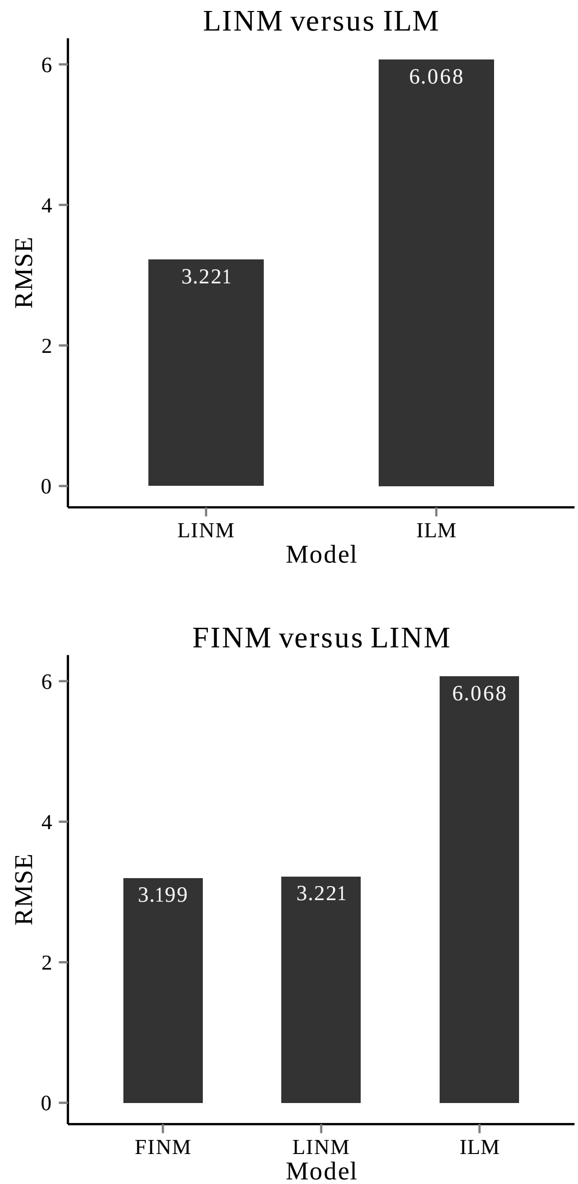


FIGURE 2: SUMMARY OF ALLOWANCE MODEL PERFORMANCE.

This figure presents evidence on the performance of the model predicted allowance relative to the current GAAP's ILM in their accuracy in predicting future losses. It shows the cumulative root mean squared error for the model estimated and tested out of sample in the period 2002–2012. LINM is the root mean squared error of the predicted allowance from the lasso model that takes the limited information as input. FINM is the root mean squared error of the predicted allowance from the lasso model that takes the full information as the input. ILM is the root mean squared error of allowance under current GAAP from the financial statements. Refer Figure 3 for further discussion on the models.

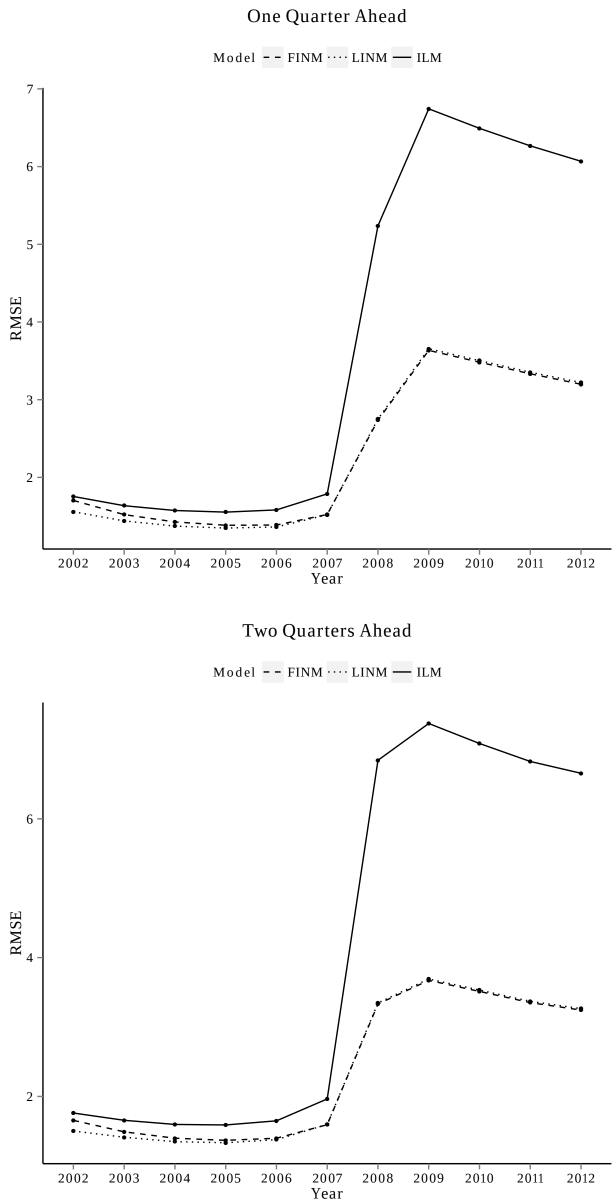


FIGURE 3: ALLOWANCE MODEL CUMULATIVE PERFORMANCE BY YEAR.

This figure presents evidence on the performance of the model predicted allowance relative to the current GAAP's ILM in their accuracy in predicting future losses. It shows the cumulative root mean squared error by year as reported in Table 3. LINM is the root mean squared error of the predicted allowance from the lasso model that takes the limited information as input. FINM is the root mean squared error of the predicted allowance from the lasso model that takes the full information as the input. ILM is the root mean squared error of allowance under current GAAP from the financial statements.

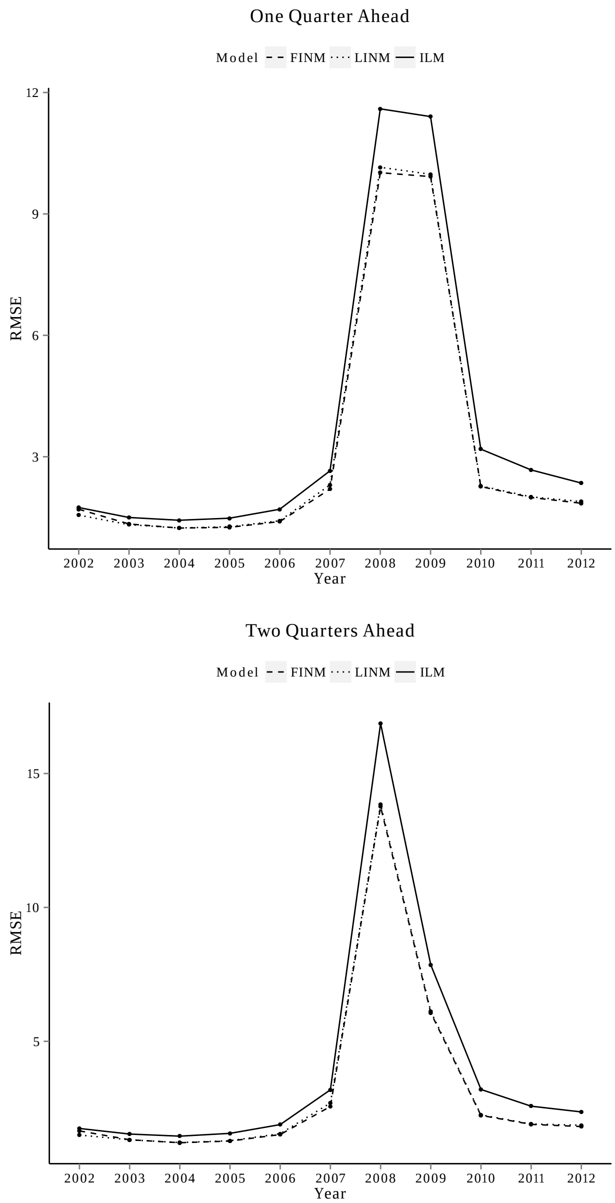


FIGURE 4: ALLOWANCE MODEL PERFORMANCE BY YEAR

This figure presents evidence on the performance of the model predicted allowance relative to the current GAAP's ILM in their accuracy in predicting future losses. It shows the root mean squared error by year as reported in Table 4. LINM is the root mean squared error of the predicted allowance from the lasso model that takes the limited information as input. FINM is the root mean squared error of the predicted allowance from the lasso model that takes the full information as the input. ILM is the root mean squared error of allowance under current GAAP from the financial statements.

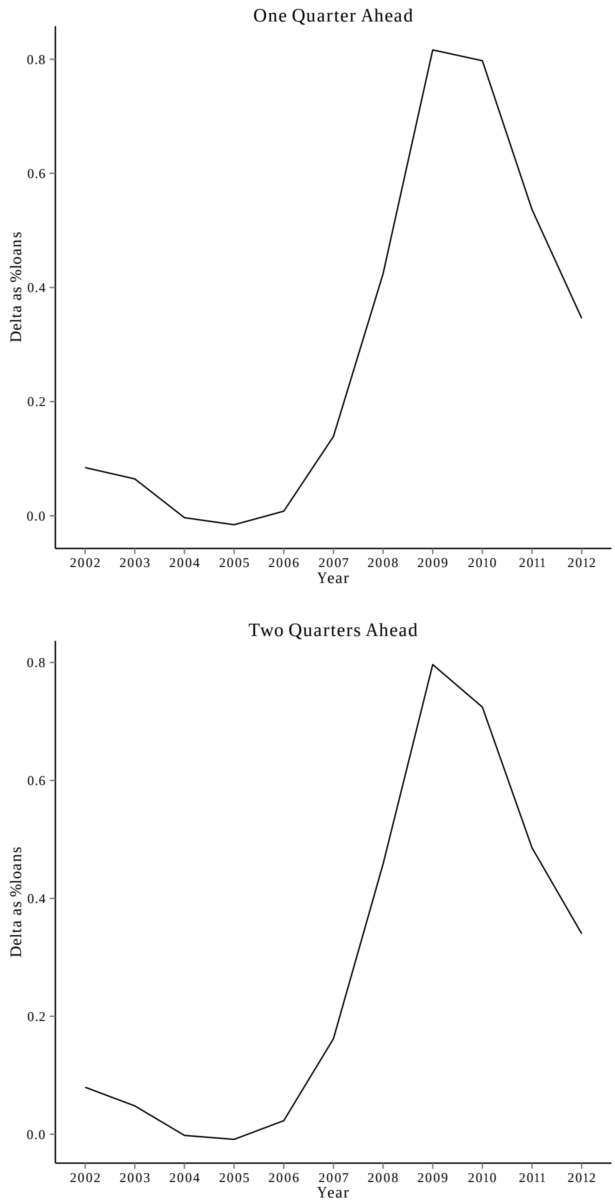


FIGURE 5: DIFFERENCE BETWEEN PREDICTED ALLOWANCE AND ACTUAL ALLOWANCE

This figure presents magnitude difference between the allowance estimated from the LINM and actual loan loss allowance from the bank's financial statements. The difference is calculated for each bank in the sample for each quarter, and mean difference is aggregated by year. The mean difference per year is plotted as a percentage of outstanding loans. LINM is the allowance model estimated from the lasso model that takes the limited information as the input.

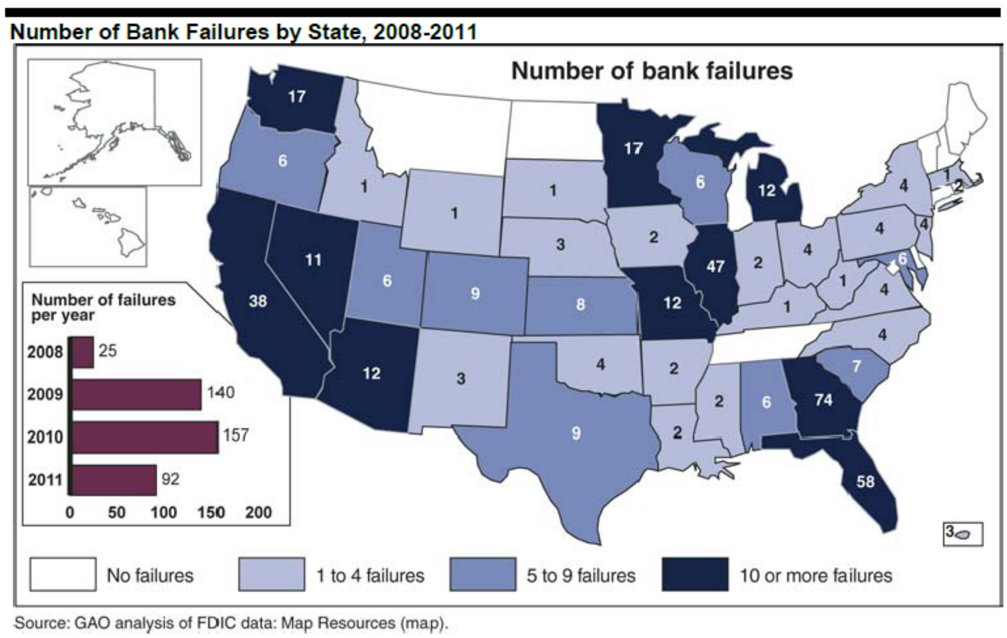


FIGURE 6: DISTRIBUTION OF FAILED BANKS IN THE US.

This figure shows the number of failed banks by state between 2008 – 2011.

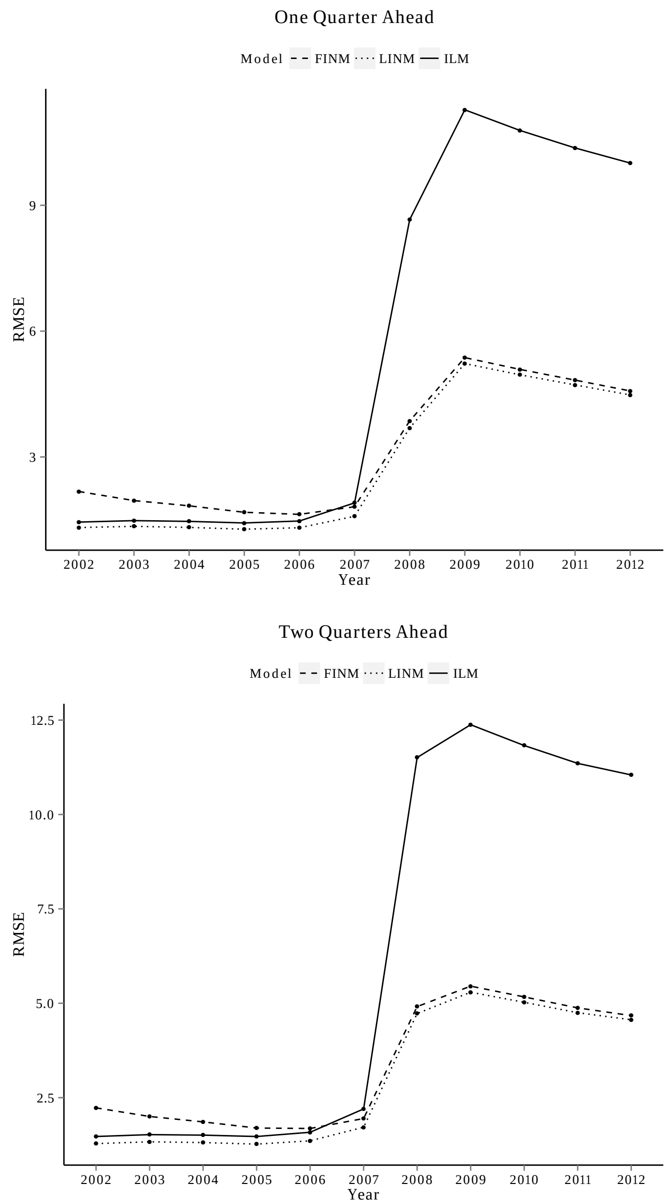


FIGURE 7: ALLOWANCE MODEL CUMULATIVE PERFORMANCE BY YEAR IN US STATES WITH SEVERE BANKING CRISIS

This figure presents evidence on the performance of the model predicted allowance relative to the current GAAP's ILM in their accuracy in predicting future losses in sample banks that operated in US states that suffered severe banking crisis. The states are identified by the ones that have more than 10 bank failures in the period 2008 – 2011. The figure shows the cumulative root mean squared error by year as reported in Table 5. LINM is the root mean squared error of the predicted allowance from the lasso model that takes the limited information as input. FINM is the root mean squared error of the predicted allowance from the lasso model that takes the full information as the input. ILM is the root mean squared error of allowance under current GAAP from the financial statements.

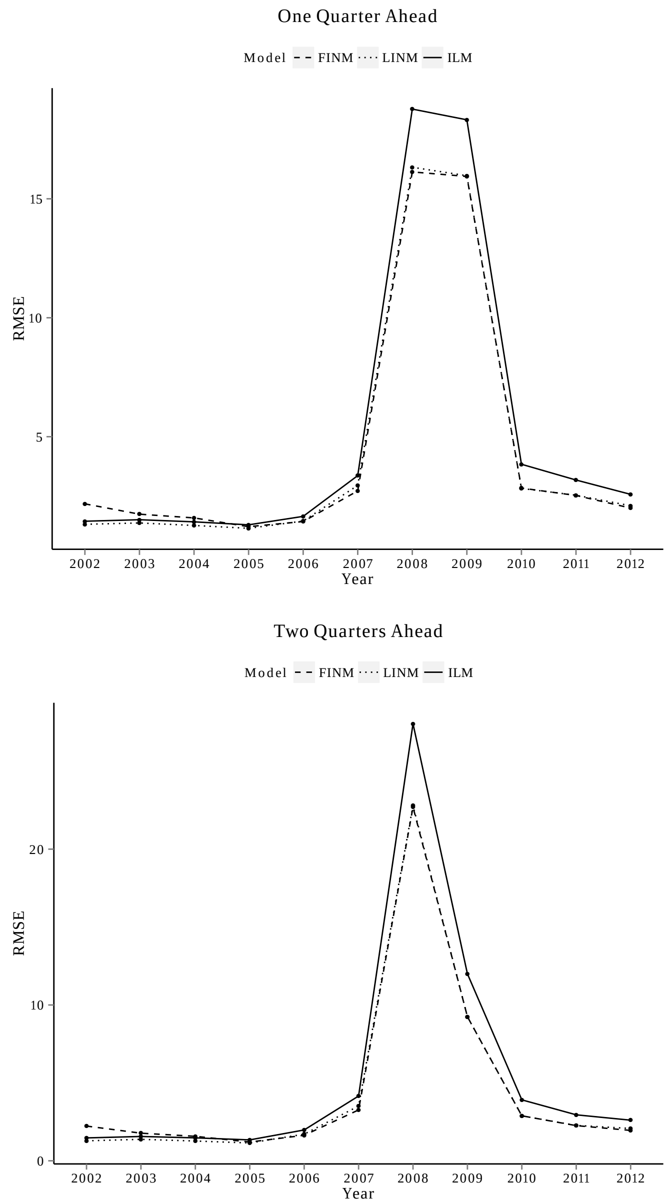


FIGURE 8: ALLOWANCE MODEL PERFORMANCE BY YEAR IN US STATES WITH SEVERE BANKING CRISIS

This figure presents evidence on the performance of the model predicted allowance relative to the current GAAP's ILM in their accuracy in predicting future losses in sample banks that operated in US states that suffered severe banking crisis. The states are identified by the ones that have more than 10 bank failures in the period 2008 – 2011. The figure shows the root mean squared error by year as reported in Table 6. LINM is the root mean squared error of the predicted allowance from the lasso model that takes the limited information as input. FINM is the root mean squared error of the predicted allowance from the lasso model that takes the full information as the input. ILM is the root mean squared error of allowance under current GAAP from the financial statements.

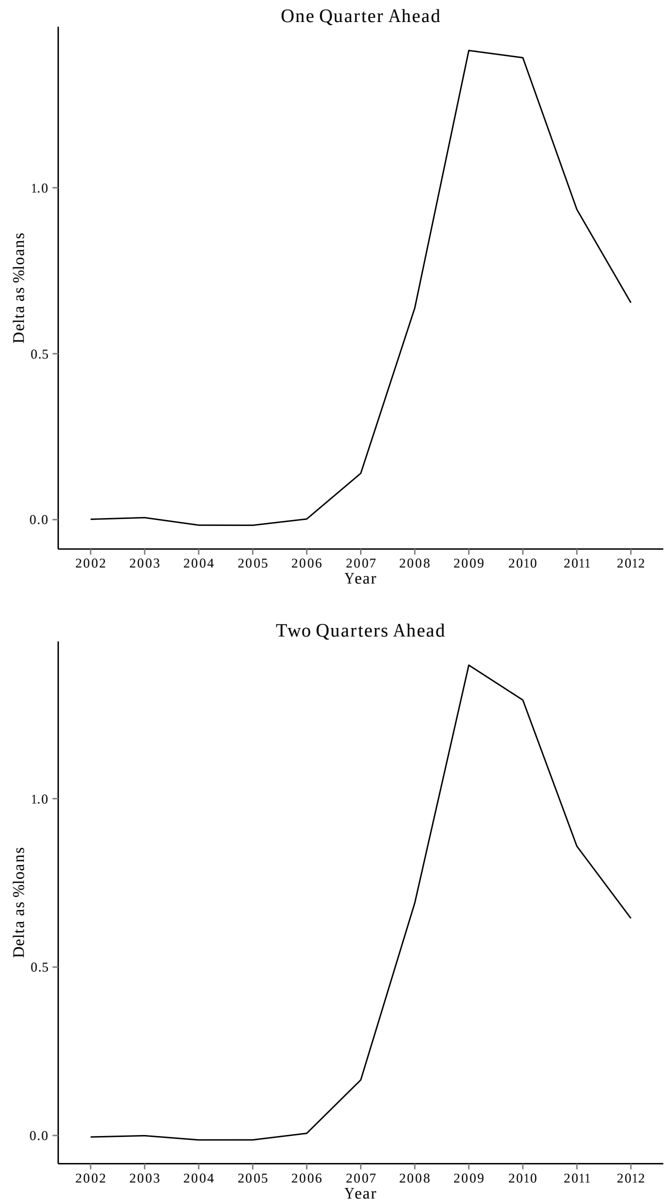


FIGURE 9: DIFFERENCE BETWEEN PREDICTED ALLOWANCE AND ACTUAL ALLOWANCE IN US STATES WITH SEVERE BANKING CRISIS

This figure presents magnitude difference between the allowance estimated from the LINM and actual loan loss allowance from the bank's financial statements. The figure shows the difference in sample banks that operated in US states that suffered severe banking crisis. The states are identified by the ones that have more than 10 bank failures in the period 2008 – 2011. The difference is calculated for each bank in the sample for each quarter, and mean difference is aggregated by year. The mean difference per year is plotted as a percentage of outstanding loans. LINM is the allowance model estimated from the lasso model that takes the limited information as the input.

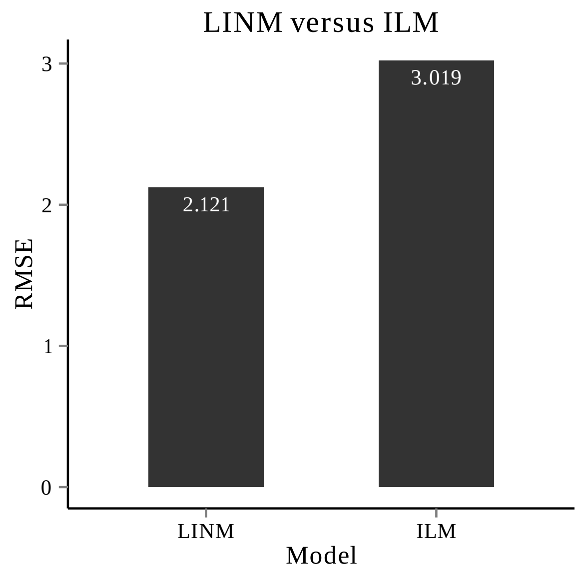


FIGURE 10: SUMMARY OF ALLOWANCE MODEL PERFORMANCE FOR LARGE BANKS

This figure presents evidence on the performance of the model predicted allowance relative to the current GAAP's ILM in their accuracy in predicting future losses for sample of large banks. The banks are identified with total assets greater than $250 million. It shows the cumulative root mean squared error for the model estimated and tested out of sample in the period 2002–2012. LINM is the root mean squared error of the predicted allowance from the lasso model that takes the limited information as input. ILM is the root mean squared error of allowance under current GAAP from the financial statements. Refer Figure 3 for further discussion on the models.

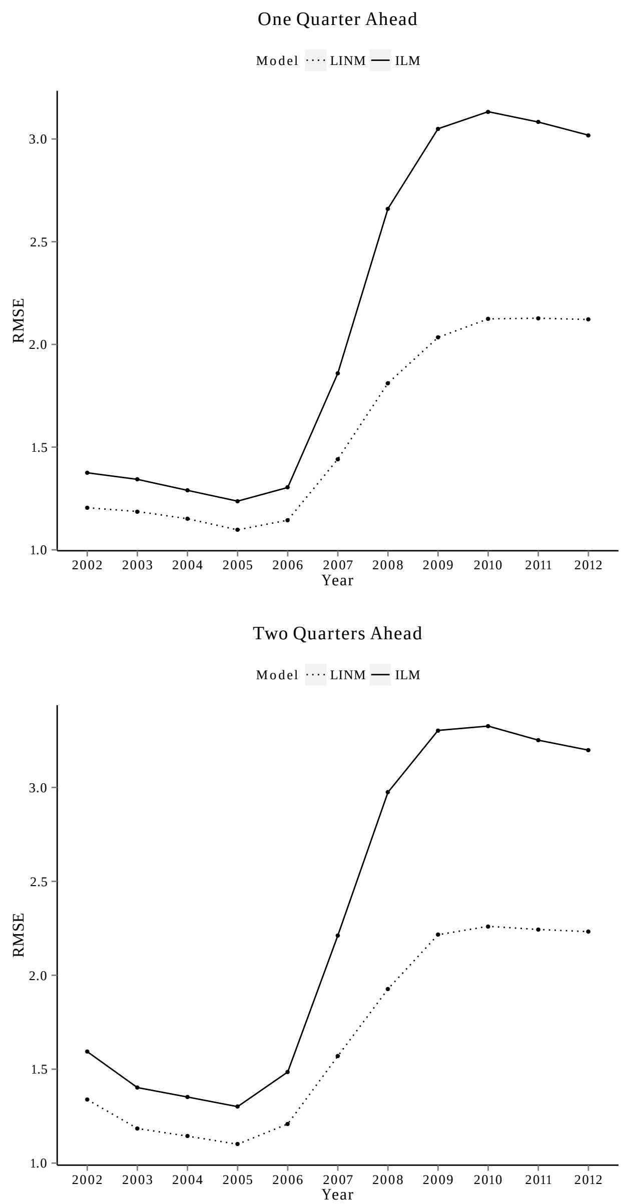


FIGURE 11: ALLOWANCE MODEL CUMULATIVE PERFORMANCE BY YEAR FOR LARGE BANKS

This figure presents evidence on the performance of the model predicted allowance relative to the current GAAP's ILM in their accuracy in predicting future losses for a sample of large banks. The banks are identified with total assets greater than $250 million. It shows the cumulative root mean squared error by year. LINM is the root mean squared error of the predicted allowance from the lasso model that takes the limited information as input. ILM is the root mean squared error of allowance under current GAAP from the financial statements.

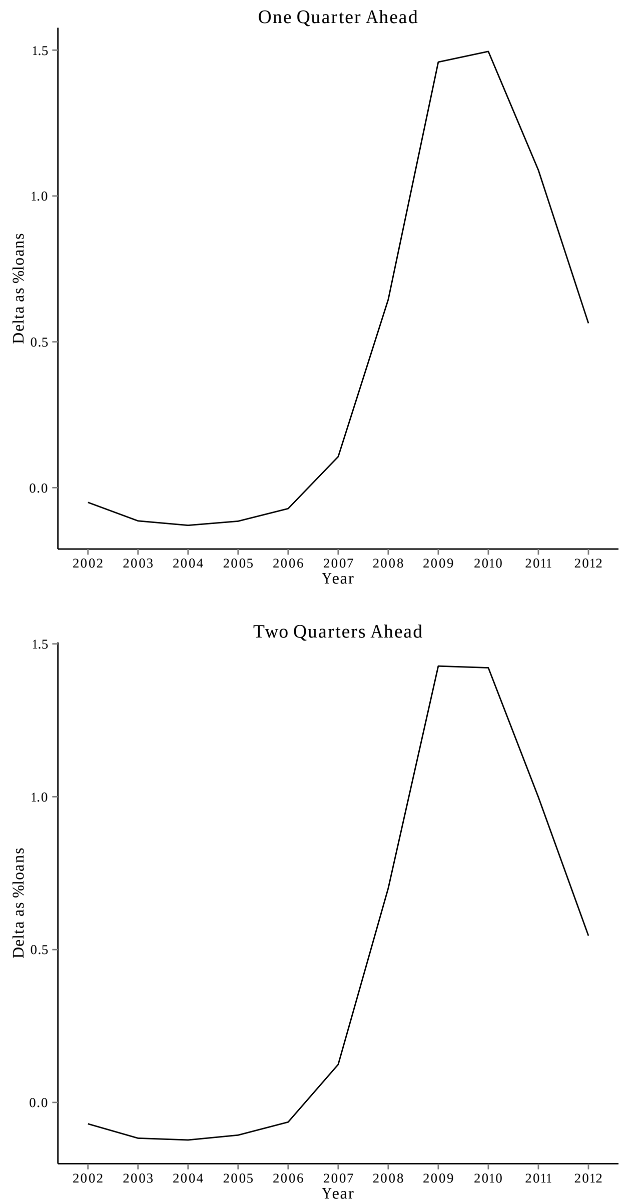


FIGURE 12: DIFFERENCE BETWEEN PREDICTED ALLOWANCE AND ACTUAL ALLOWANCE FOR LARGE BANKS

This figure presents magnitude difference between the allowance estimated from the LINM and actual loan loss allowance from the bank's financial statements. The figure shows the difference in sample of large banks. The banks are identified with total assets greater than $250 million. The difference is calculated for each bank in the sample for each quarter, and mean difference is aggregated by year. The mean difference per year is plotted as a percentage of outstanding loans. LINM is the allowance model estimated from the lasso model that takes the limited information as the input.

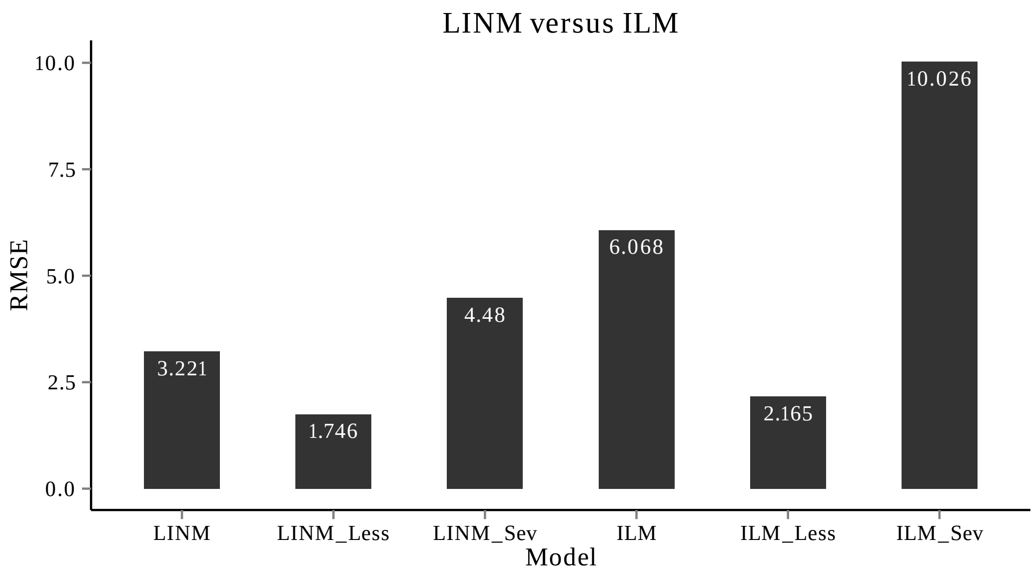


FIGURE 13: LINM VS ILM DECOMPOSED BY BANKS WITH SEVERE BANKING CRISIS STATES AND LESS SEVERE BANKING CRISIS STATES

This figure presents evidence on the performance drivers of the LINM model relative to the current GAAP's ILM. The bars represent the cumulative root mean squared error for the models estimated and tested out of sample in the period 2002–2012. The overall sample of banks are split into banks that operate in US states that suffered severe banking crisis (Sev), and in states that suffered less severe banking crisis (Less). The severe states are identified by the ones that have more than 10 bank failures in the period 2008 – 2011. LINM is the root mean squared error of the predicted allowance from the lasso model that takes limited information as input, while ILM is the root mean squared error (RMSE) of allowance under current GAAP from the financial statements. The LINM_Sev is the root mean squared from the LINM model for banks in the severe crisis states, and LINM_Less is the root mean squared from the LINM model for banks in less severe crisis states. The ILM_Sev is the root mean squared from the ILM model of banks in the severe crisis states, and ILM_Less is the root mean squared from the ILM model of banks in less severe crisis states. Refer Figure 3 for further discussion on the models.

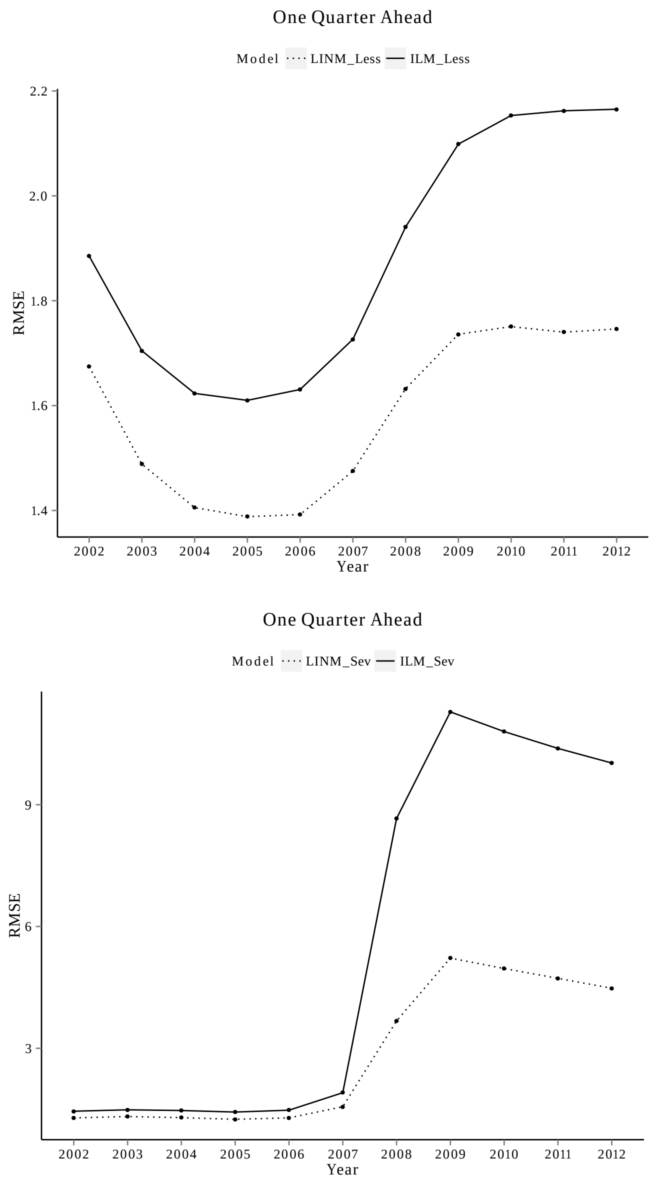


FIGURE 14: ALLOWANCE MODEL CUMULATIVE PERFORMANCE BY YEAR IN US STATES WITH LESS SEVERE AND SEVERE BANKING CRISIS

This figure presents evidence on the performance drivers of the LINM model relative to the current GAAP's ILM in their accuracy in predicting future losses. The overall sample of banks are split into banks that operate in US states that suffered severe banking crisis (Sev), and in states that suffered less severe banking crisis (Less). The severe states are identified by the ones that have more than 10 bank failures in the period 2008 – 2011. LINM is the root mean squared error of the predicted allowance from the lasso model that takes limited information as input, while ILM is the root mean squared error of allowance under current GAAP from the financial statements. The LINM_Sev is the root mean squared error from the LINM model for banks in the severe crisis states, and LINM_Less is the root mean squared from the LINM model for banks in less severe crisis states. The ILM_Sev is the root mean squared from the ILM model of banks in the severe crisis states, and ILM_Less is the root mean squared from the ILM model of banks in less severe crisis states.

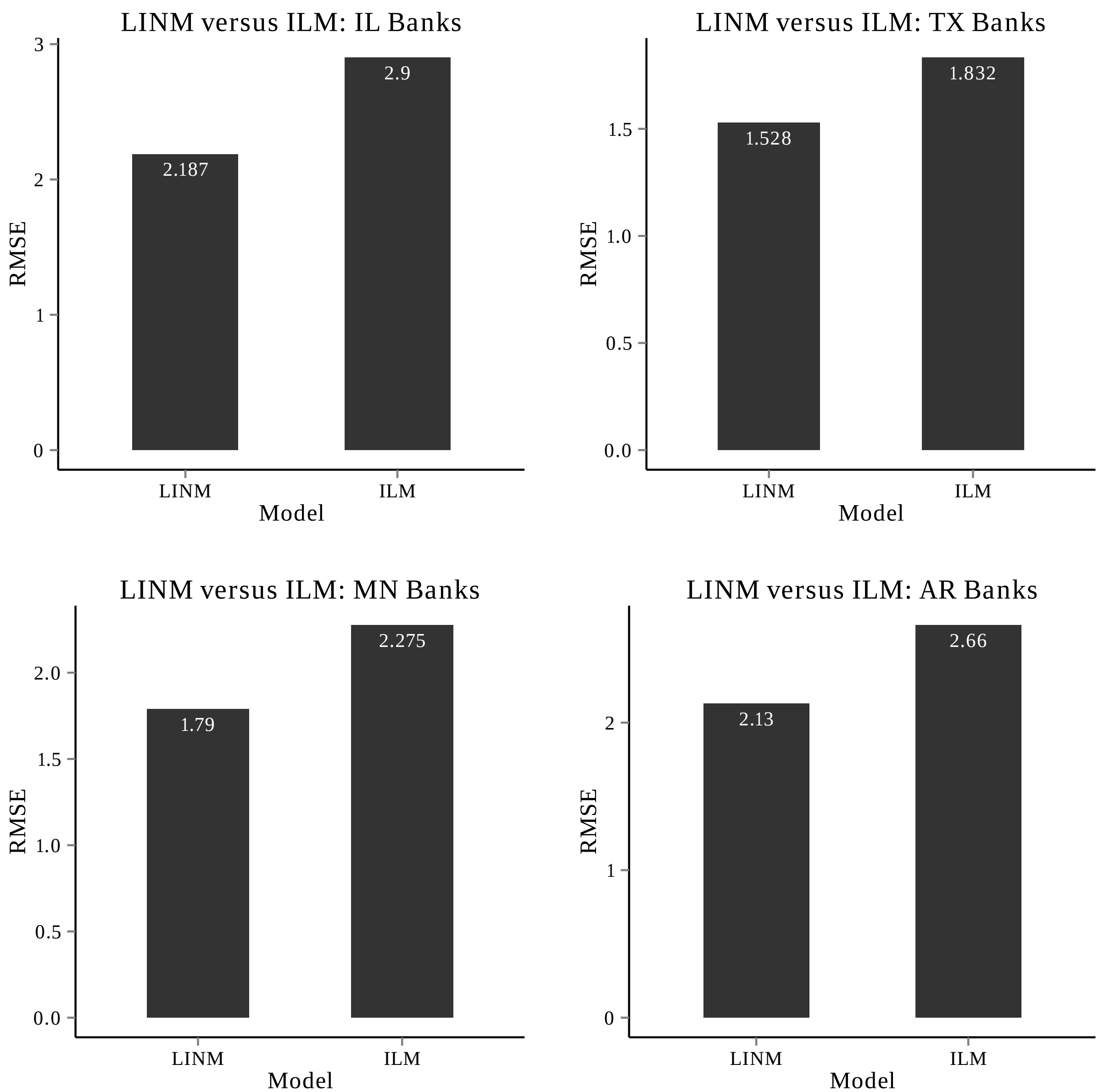


FIGURE 15: LINM VS ILM FOR SAMPLE COUNTY BANKS OPERATING IN STATES

This figure presents evidence on the difference in model performance based on sample banks that operate in particular states. The figures presents the performance of the LINM model predicted allowance relative to the current GAAP's ILM in their accuracy in predicting future losses. It shows the cumulative root mean squared error for the model estimated and tested out of sample in the period 2002–2012. LINM is the root mean squared error of the predicted allowance from the lasso model that takes the limited information as input. ILM is the root mean squared error of allowance under current GAAP from the financial statements. Each bargraph represents results from separate model estimations restricting on banks operating in the corresponding states.

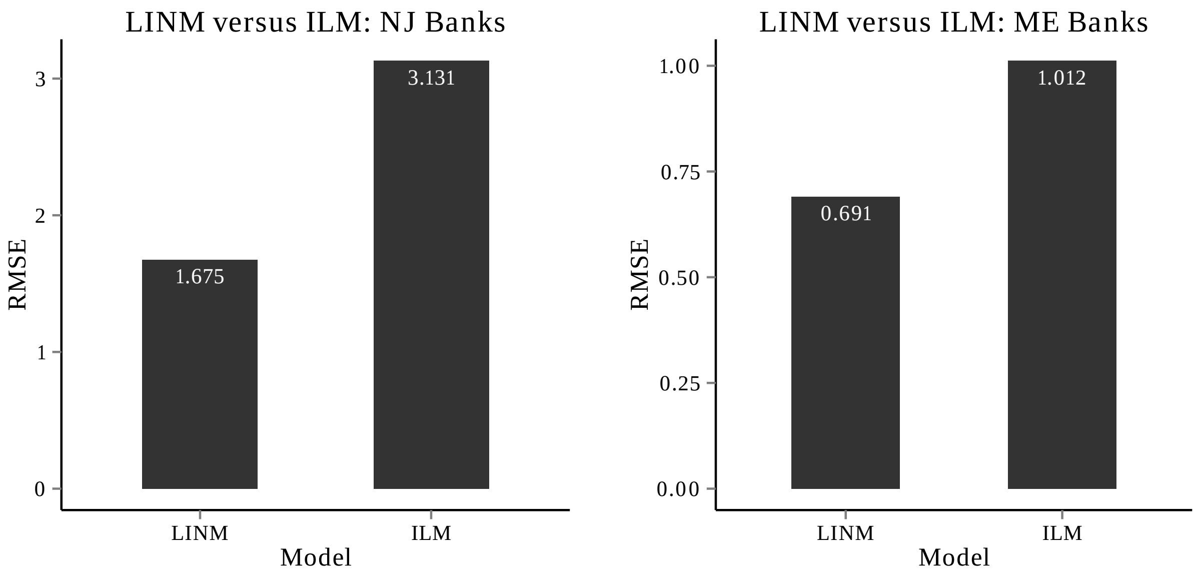
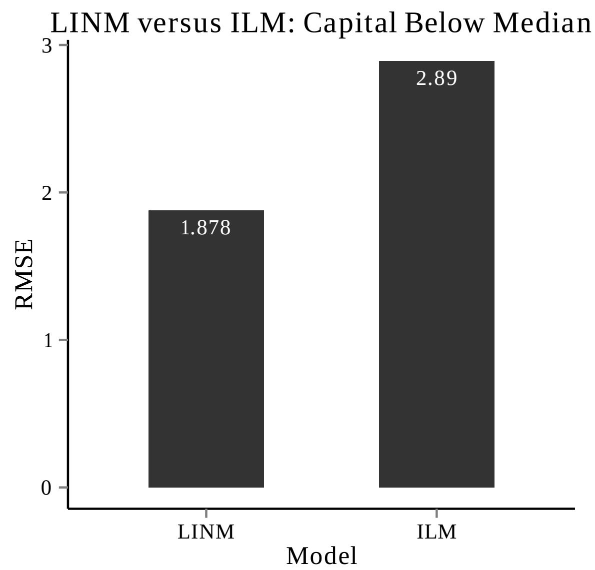


FIGURE 16: LINM VS ILM FOR SAMPLE COUNTY BANKS OPERATING IN STATES

This figure presents evidence on the difference in model performance based on sample banks that operate in particular states. The figures presents the performance of the LINM model predicted allowance relative to the current GAAP's ILM in their accuracy in predicting future losses. It shows the cumulative root mean squared error for the model estimated and tested out of sample in the period 2002–2012. LINM is the root mean squared error of the predicted allowance from the lasso model that takes the limited information as input. ILM is the root mean squared error of allowance under current GAAP from the financial statements. Each bargraph represents results from separate model estimations restricting on banks operating in the corresponding states.



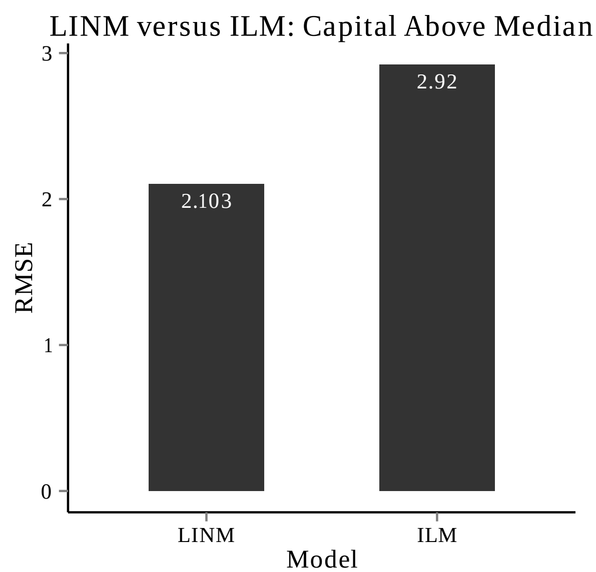


FIGURE 17: SUMMARY OF ALLOWANCE MODEL PERFORMANCE FOR LARGE BANKS THAT ARE ABOVE-MEDIAN ("WELL CAPITALIZED") AND BELOW-MEDIAN CAPITAL ("WEAKLY CAPITALIZED")

This figure presents evidence on the difference in model performance based on the degree of capital constrains for large banks. The figures presents the performance of the model predicted allowance relative to the current GAAP's ILM in their accuracy in predicting future losses. It shows the cumulative root mean squared error for the model estimated and tested out of sample in the period 2002–2012. LINM is the root mean squared error of the predicted allowance from the lasso model that takes the limited information as input. ILM is the root mean squared error of allowance under current GAAP from the financial statements. The sample of large banks are split based on if the bank's capital ratios are above or below median. The models are estimated separately for the sample above the median and below the median.

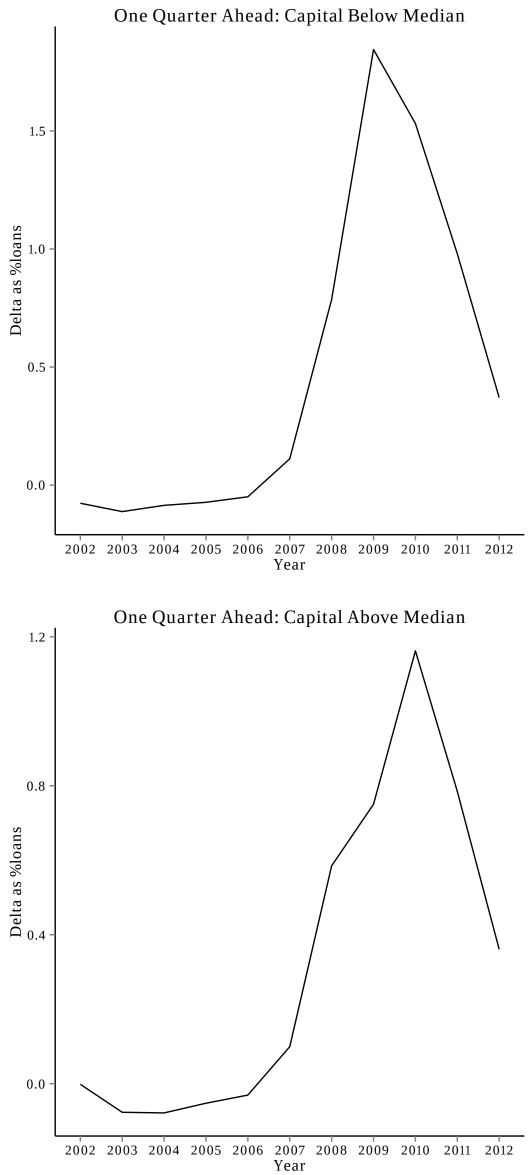


FIGURE 18: DIFFERENCE BETWEEN PREDICTED ALLOWANCE AND ACTUAL ALLOWANCE FOR LARGE BANKS BASED ON THEIR DEGREE OF CAPITAL CONSTRAIN

This figure presents magnitude difference between the allowance estimated from the LINM and actual loan loss allowance from the bank's financial statements. The analysis is based on the degree of capital constrains for large banks. The sample are split based on if the bank's capital ratios are above or below median. The models are estimated separately for the sample above the median and below the median. The difference, as a percentage of loans, is calculated for each bank in the sample for each quarter, and mean difference is aggregated by year. LINM is the allowance model estimated from the lasso model that takes the limited information as the input.

TABLE 1: SELECTION OF SAMPLE BANKS

Year	All US Banks	Number of Single-County Banks	Number of Counties
1996	12,047	7,086	2,337
1997	11,600	6,597	2,270
1998	11,079	6,081	2,199
1999	10,699	5,727	2,140
2000	10,430	5,500	2,089
2001	10,031	5,255	2,021
2002	9,690	5,031	1,966
2003	9,505	4,763	1,911
2004	9,313	4,599	1,874
2005	9,174	4,347	1,806
2006	9,033	4,148	1,743
2007	8,877	3,989	1,706
2008	8,635	3,828	1,658
2009	8,342	3,678	1,608
2010	8,018	3,518	1,577
2011	7,650	3,342	1,546
2012	7,377	3,170	1,519

This table shows yearly distribution of number of sample banks used in this study. The second column shows the number of all commercial banks regulated under FDIC. The third column shows the number of banks having hundred percent of their deposits in one county. The third column shows the number of different counties that these banks operate in. The sample is formed by merging the FDIC summary of deposits data along with the list of banks that are designated as community banks by the FDIC in the period.

TABLE 2: SUMMARY STATISTICS

Statistic	N	Mean	P25	Median	P75	St. Dev.
Bank-level data						
Assets	306,666	103,917.90	35,168.2	64,531	120,032	150,108.80
Total Loans	306,666	65,556.07	19,209	38,212	75,499	99,042.87
Pct Four-qtr NCOs + NPL	306,666	1.83	0.31	0.98	2.26	10.76
Four-qtr NCOs + NPL	306,666	1,359.48	92	359	1,038	10,795.08
Chargeoffs	306,666	157.40	1	20	94	761.38
Recoveries	306,666	30.53	0	5	24	146.21
Allowance	306,666	892.17	242	483	974	1,543.63
Pct Allowance	306,666	1.49	0.99	1.28	1.73	1.14
30 days PD	306,666	0.97	0.00	0.23	1.41	1.57
90 days PD	306,666	0.42	0.00	0.05	0.41	1.04
Nonaccrual	306,666	1.02	0.00	0.33	1.19	1.96
Delta 30 days PD	306,666	0.03	−0.08	0.00	0.13	1.29
Delta 90 days PD	306,666	0.00	−0.05	0.00	0.06	0.81
Delta Nonaccrual	306,666	0.02	−0.08	0.00	0.06	0.93
Pct RE Loans	306,666	64.47	49.36	65.98	81.24	21.95
Pct CI Loans	306,666	13.97	6.36	12.01	19.13	10.97
Loans to Assets	306,666	60.67	50.69	62.12	72.33	16.12
Securities to Assets	306,666	25.67	13.63	24.04	35.67	15.88
Interest Receivables	306,666	0.71	0.40	0.57	0.89	0.45
Loan Yields	306,666	7.95	6.75	7.95	9.06	1.63
County-level data						
County Unemployment	306,506	5.54	3.80	5.00	6.70	2.57
HPI	306,487	129.26	106.29	122.95	149.23	33.06
HPI Growth	306,487	0.01	0.00	0.01	0.02	0.02
Establishments	306,666	0.00	−0.00	0.00	0.01	0.02
Wage Growth	305,896	0.01	0.00	0.01	0.02	0.02
Farm Earnings	302,229	−4.24	−7.00	−0.11	8.67	1,396.92
Per Capita	305,882	1.01	0.46	0.99	1.50	1.20
Bus Bankr	306,666	0.62	0.24	0.44	0.78	0.68

This table presents summary statistics for sample bank-level and county-level variables. The variables are in the period between 1996 and 2012. These variables are used in the limited information model and full information model. The data sources are identified in the appendix Table A.1.

Table 3: Allowance Model Cumulative Performance By Year

Panel A: One Quarter Ahead

Year	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012
FINM	1.703	1.521	1.427	1.384	1.387	1.522	2.736	3.635	3.482	3.333	3.199
LINM	1.558	1.440	1.373	1.348	1.362	1.519	2.752	3.656	3.503	3.354	3.221
ILM	1.755	1.636	1.574	1.553	1.581	1.788	5.238	6.743	6.492	6.267	6.068

Panel B: Two Quarters Ahead

Year	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012
FINM	1.655	1.490	1.398	1.368	1.398	1.593	3.331	3.673	3.513	3.352	3.245
LINM	1.502	1.412	1.348	1.333	1.377	1.597	3.346	3.692	3.533	3.371	3.266
ILM	1.761	1.656	1.597	1.589	1.649	1.964	6.843	7.373	7.085	6.826	6.656

This table presents evidence on the performance of the model predicted allowance relative to the current GAAP's ILM in their accuracy in predicting future losses. It shows the cumulative root mean squared error by year. LINM is the root mean squared error of the predicted allowance from the lasso model that takes the limited information as input. FINM is the root mean squared error of the predicted allowance from the lasso model that takes the full information as the input. ILM is the root mean squared error of allowance under current GAAP from the financial statements. The error are generated from rolling-window predictions and measured as the accuracy of the allowance estimates to predict future net-chargeoffs. Panel A examines the prediction allowance using one-quarter out of sample. Panel B examines the predicted allowances using two-quarter out of sample.

Table 4: Allowance Model Performance By Year

Panel A: One Quarter Ahead

Year	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012
FINM	1.703	1.339	1.238	1.256	1.398	2.200	10.019	9.923	2.264	1.993	1.851
LINM	1.558	1.321	1.240	1.272	1.418	2.304	10.152	9.980	2.280	2.009	1.893
ILM	1.745	1.499	1.431	1.482	1.703	2.653	11.597	11.405	3.188	2.675	2.350

Panel B: Two Quarters Ahead

Year	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012
FINM	1.655	1.325	1.214	1.276	1.519	2.567	13.762	6.063	2.235	1.899	1.818
LINM	1.502	1.322	1.220	1.288	1.551	2.697	13.843	6.114	2.254	1.913	1.867
ILM	1.747	1.538	1.459	1.564	1.891	3.190	16.868	7.854	3.203	2.578	2.364

This table presents evidence on the performance of the model predicted allowance relative to the current GAAP's ILM in their accuracy in predicting future losses. It shows the root mean squared error by year. LINM is the root mean squared error of the predicted allowance from the lasso model that takes the limited information as input. FINM is the root mean squared error of the predicted allowance from the lasso model that takes the full information as the input. ILM is the root mean squared error of allowance under current GAAP from the financial statements. The error are generated from rolling-window predictions and measured as the accuracy of the allowance estimates to predict future net-chargeoffs. Panel A examines the prediction allowance using one-quarter out of sample. Panel B examines the predicted allowances using two-quarter out of sample.

TABLE 5: ALLOWANCE MODEL CUMULATIVE PERFORMANCE BY YEAR IN US STATES WITH SEVERE BANKING CRISIS

Panel A: One Quarter Ahead

Year	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012
FINM	2.176	1.960	1.835	1.681	1.631	1.813	3.858	5.369	5.088	4.832	4.574
LINM	1.317	1.346	1.320	1.277	1.313	1.586	3.691	5.226	4.959	4.717	4.479
ILM	1.447	1.482	1.464	1.427	1.473	1.904	8.658	11.277	10.785	10.367	10.007

Panel B: Two Quarters Ahead

Year	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012
FINM	2.229	2.001	1.858	1.695	1.683	1.947	4.911	5.453	5.168	4.877	4.673
LINM	1.282	1.330	1.310	1.269	1.357	1.716	4.728	5.292	5.025	4.750	4.563
ILM	1.471	1.520	1.507	1.470	1.583	2.201	11.509	12.378	11.827	11.354	11.048

This table presents evidence on the performance of the model predicted allowance relative to the current GAAP's ILM in their accuracy in predicting future losses in sample banks that operated in US states that suffered severe banking crisis. The states are identified by the ones that have more than 10 bank failures in the period 2008 – 2011. The table shows the cumulative root mean squared error by year. LINM is the root mean squared error of the predicted allowance from the lasso model that takes the limited information as input. FINM is the root mean squared error of the predicted allowance from the lasso model that takes the full information as the input. ILM is the root mean squared error of allowance under current GAAP from the financial statements. The error are generated from rolling- window predictions and measured as the accuracy of the allowance estimates to predict future net-chargeoffs. Panel A examines the prediction allowance using one-quarter out of sample. Panel B examines the predicted allowances using two-quarter out of sample.

Table 6: Allowance Model Performance by Year in US States with Severe Banking Crisis

Panel A: One Quarter Ahead

Year	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012
FINM	2.176	1.743	1.586	1.218	1.434	2.721	16.130	15.941	2.840	2.530	2.001
LINM	1.317	1.374	1.269	1.149	1.454	2.951	16.326	15.970	2.825	2.540	2.097
ILM	1.446	1.510	1.421	1.295	1.650	3.364	18.772	18.321	3.842	3.179	2.577

Panel B: Two Quarters Ahead

Year	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012
FINM	2.229	1.773	1.571	1.205	1.637	3.265	22.700	9.245	2.889	2.258	1.951
LINM	1.282	1.378	1.269	1.145	1.709	3.512	22.802	9.242	2.887	2.270	2.076
ILM	1.469	1.561	1.472	1.343	1.980	4.157	28.048	12.000	3.912	2.951	2.607

This table presents evidence on the performance of the model predicted allowance relative to the current GAAP's ILM in their accuracy in predicting future losses in sample banks that operated in US states that suffered severe banking crisis. The states are identified by the ones that have more than 10 bank failures in the period 2008 – 2011. The table shows the root mean squared error by year. LINM is the root mean squared error of the predicted allowance from the lasso model that takes the limited information as input. FINM is the root mean squared error of the predicted allowance from the lasso model that takes the full information as the input. ILM is the root mean squared error of allowance under current GAAP from the financial statements. The error are generated from rolling-window predictions and measured as the accuracy of the allowance estimates to predict future net-chargeoffs. Panel A examines the prediction allowance using one-quarter out of sample. Panel B examines the predicted allowances using two-quarter out of sample.

Table 7: Coefficients from the LINM and ILM Model of Sample Banks

	1996 – 2002		1996 – 2005		1996 – 2006		1996 – 2007		1996 – 2008		1996 – 2010	
	LINM	ILM	LINM	ILM	LINM	ILM	LINM	ILM	LINM	ILM	LINM	ILM
30 days PD	0.077	0.028	0.090	0.030	0.089	0.029	0.095	0.028	0.129	0.030	0.167	0.032
90 days PD	0.183	0.013	0.268	0.013	0.304	0.017	0.324	0.020	0.355	0.024	0.388	0.026
Nonaccrual PD	0.223	0.088	0.274	0.102	0.291	0.104	0.318	0.104	0.406	0.108	0.522	0.126
30 days PD (t-3)	0	−0.013	−0.011	−0.017	−0.009	−0.017	−0.006	−0.016	−0.017	−0.016	−0.023	−0.016
90 days PD (t-3)	0	−0.007	−0.034	−0.007	−0.052	−0.010	−0.058	−0.012	−0.058	−0.015	−0.064	−0.016
Nonaccrual PD(t-3)	0.034	−0.030	0.051	−0.038	0.045	−0.041	0.039	−0.041	0.044	−0.039	0.002	−0.048
Loan to Asset	0	−0.015	0.004	−0.015	0.005	−0.015	0.007	−0.015	0.013	−0.014	0.010	−0.014
Securities to Asset	0	0.002	−0.000	0.002	−0.001	0.002	−0.001	0.002	−0.000	0.002	−0.005	0.001
Pct RE Loans	−0.007	0.000	−0.018	0.002	−0.018	0.001	−0.017	−0.000	−0.014	−0.001	−0.009	−0.002
Pct CI Loans	0	−0.003	−0.006	−0.003	−0.008	−0.004	−0.008	−0.004	−0.009	−0.005	−0.010	−0.006
Log Assets	0.088	−0.156	0.029	−0.149	0.077	−0.150	0.264	−0.147	0.600	−0.152	0.832	−0.138
Net-Chargeoffs$_t$	0	−0.033	0.133	−0.049	0.157	−0.046	0.160	−0.044	0.211	−0.026	0.334	0.003
Net-Chargeoffs$_{t-3}$	0.007	−0.005	0.119	0.000	0.129	0.007	0.127	0.013	0.180	0.019	0.253	0.057
Net-Chargeoffs$_{t-6}$	0.006	0.053	0.105	0.056	0.112	0.058	0.110	0.063	0.108	0.071	0.152	0.103
Net-Chargeoffs$_{t-9}$	0	0.074	0.053	0.075	0.062	0.075	0.057	0.080	0.044	0.081	0.073	0.109

This table presents the coefficients of the LINM model, and from the ILM model from implicit regression on allowances recognized by banks. The table presents combined coefficients from Table C.1 and Table C.2. The columns represent coefficients from LINM and ILM models run between the periods 1996 – 2002, 1996 – 2005, 1996 – 2006, 1996 – 2007, 1996 – 2008 and 1996 – 2010 for sample banks. See Section A.3 for variable definitions.

A Appendix

A.1 Current GAAP Rules

The two statements relevant to bank loan loss accounting are FAS 5 ("Accounting for Contingencies"), and FAS 114 ("Accounting by Creditors for Impairment of a Loan"). FAS 5 (paragraph 8) requires that both the following requirements be met to recognize a loss in the bank's financial statements:

a. Information available prior to issuance of the financial statements indicates that it is probable that an asset had been impaired or a liability had been incurred at the date of the financial statements. It is implicit in this condition that it must be probable that one or more future events will occur confirming the fact of the loss.

b. The amount of loss can be reasonably estimated.

This is commonly referred to as the incurred loss model. The allowance is to cover loan losses that are "probable" and "estimable" on the date of the evaluation.

A.2 Data Sources

TABLE A.1: DATA SOURCES

Data	Source
Bank balance sheet	FDIC Call Reports
Location information	FDIC Summary of Deposits
Home price growth	Corelogic/FHFA
Unemployment rate	Bureau of Labor Statistics
Income from tax returns	IRS
Business/Nonbusiness bankruptcies	Administrative Office of the U.S. Courts on behalf of the Federal Judiciary
Establishments - Number and Wages	QCEW/Bureau of Labor Statistics
Farm Income	Bureau of Economic Analysis
Per Capita Income	Bureau of Economic Analysis
County controls:	
Poverty rate	Census Bureau
High school	Census Bureau
Population demographics	Census Bureau

This table presents the list of data and their sources for variables used in the paper. All economic variables are identified at the county level.

A.3 Variable Definitions

TABLE A.1: VARIABLES USED IN THE MODELS

LINM	FINM
30 days PD	30 days PD
90 days PD	90 days PD
Nonaccrual PD	Nonaccrual PD
30 days PD (t-3)	30 days PD (t-3)
90 days PD (t-3)	90 days PD (t-3)
Nonaccrual PD (t-3)	Nonaccrual PD (t-3)
Loans to Assets	Loans to Assets
Securities to Assets	Securities to Assets
Pct RE Loans	Pct RE Loans
Pct CI Loans	Pct CI Loans
Log Assets	Log Assets
NCO_t	NCO_t
NCO_{t-3}	NCO_{t-3}
NCO_{t-6}	NCO_{t-6}
NCO_{t-9}	NCO_{t-9}
	Loan Yields
	Interest Receivables
	Unemp $Rate_t$
	Unemp Rate (t-3)
	Unemp Rate (3-6)
	Unemp Rate (6-9)
	Unemp Rate (9-12)
	HPI Growth (t-3)
	HPI Growth (3-6)
	HPI Growth (6-9)
	HPI Growth (9-12)
	Establishments (t-3)
	Establishments (3-6)
	Establishments (6-9)
	Establishments (9-12)
	Wage growth (t-3)
	Wage growth (3-6)
	Wage growth (6-9)
	Wage growth (9-12)
	Farm Earnings (t-3)
	Farm Earnings (3-6)
	Farm Earnings (6-9)
	Farm Earnings (9-12)
	Per Capita (t-3)

(*Continued*)

Table A.1 – *Continued*

LINM	FINM
	Per Capita (3-6)
	Per Capita (6-9)
	Per Capita (9-12)
	Bus Bankr (t-3)
	Bus Bankr (3-6)
	Bus Bankr (6-9)
	Bus Bankr (9-12)

This table reports the variables that are used for the prediction models developed in the paper. The LINM column shows variables used in the limited information model, and the FINM column shows variables used in the full information model. The subscript in the variables refer to lags, while the parenthesis show the difference in variable between the time periods specified. For example, NCO_{t-3} is the one-quarter lag in the NCO, HPI Growth (t-3) is the three quarter housing price growth between the periods t and $t-3$, HPI Growth (3-6) is the quarter housing price growth between three months and six months prior to when HPI Growth is measured. Refer to appendix table Table A.2 for variable definitions.

TABLE A.2: VARIABLE DEFINITIONS

Variable Name	Definition
Bank Variables	
Log Assets	Log of Total Assets
Total Loans	Total loans in banks portfolio
NCO	Net-chargeoffs
Four-qtr NCO + NPL	Sum of rolling four-quarter net-chargeoffs plus ninety-days past due and non-accrual loans at the end of the rolling window's fourth-quarter
Pct Four-qtr NCO + NPL	Four-qtr NCO + NPL scaled by total loans at the beginning of the quarter.
Chargeoffs	Amount that is charged-offs
Recoveries	Amount recovered in previously charged-off loans
Allowance	Loan Loss Allowance
Pct Allowance	Loan Loss Allowance scaled by total loans at the beginning of the quarter.
30 days PD	Loans that are 30-days past due scaled by total loans at the beginning of the quarter.
90 days PD	Loans that are 90-days past due scaled by total loans at the beginning of the quarter.
Nonaccrual	Loans that are in Nonaccrual scaled by total loans at the beginning of the quarter.
Delta 30 days PD	Change in loans 30 days past due divided by total loans at the beginning of the quarter.
Delta 90 days PD	Change in loans 90 days past due divided by total loans at the beginning of the quarter.
Delta Nonaccrual	Change in loans Non-accrual loans divided by total loans at the beginning of the quarter.
Pct RE Loans	Real estate loans as a percentage of total loans.
Pct CI Loans	Commercial and Industrial loans as a percentage of total loans.
Loans to Assets	Ratio of loans to assets
Securities to Assets	Ratio of the securities to assets
Interest Receivables	Income accrued but not yet collected on loans
Loan Yields	The ratio of tax-equivalent interest income divided by total loans
County Variables	
Unemp Rate	County unemployment rate
HPI	Home price index
HPI Growth	Home price growth in the county
Establishments	Change in the number of business establishments in the county
Wage Growth	Change in adjusted gross income at the county
Farm Earnings	Change in farm earnings at the county
Per Capita	Per capita income at the county
Bus Bankr	Change in the ratio of business bankruptcies to all establishments in the county

This table presents the definitions for the variables used in the paper.

B Empirical Model Appendix

To estimate future losses $\mu_t = \mathbb{E}(CO_t|\mathscr{I}_{t-1})$, where $\mathscr{I}_{t-1}$ contains all information up to and including time $t-1$. For e.g., CO_{t-1} , $COrate_{t-1}$, and macro measures M at $t-1$. Let $\Delta M_{t-1} = M_{t-1} - M_{t-2}$.

To estimate μ_t, the bank uses historical loan information, and estimate the $COrate$. That is,

$$\mu_t = \text{loan balance}_{t-1} * \widehat{COrate}_t \tag{B.1}$$

The estimates for $\widehat{COrate}_t$ can be obtained by considering historical chargeoff rates, and adjusting for the change in the macro economic information and hence can recovered by estimating $\widehat{COrate}_t = COrate_{t-1} + \beta \Delta M_{t-1}$. To illustrate let M be unemployment at a county level. Substituting in Equation (B.1),

$$\mathbb{E}(CO_{i,t}) = \text{loan balance * COrate}_{i,t-1} + \text{loan balance *}\Delta\text{unemprate}_t \tag{B.2}$$

Dividing by the loan balance at $t-1$,

$$\frac{\mathbb{E}(CO_{i,t})}{\text{loan balance}_{i,t-1}} = \text{COrate}_{i,t-1} + \Delta\text{unemprate}_{t-1}$$
$$\text{COrate}_{i,t} = \text{COrate}_{i,t-1} + \Delta\text{unemprate}_{t-1}$$

In my data, bank i operates only in county j. Rewriting to include the subscripts,

$$\text{COrate}_{ijt} = \text{COrate}_{it-1} + \Delta\text{unemprate}_{jt-1}$$

Estimating the above

$$\begin{aligned}\text{COrate}_{ijt} = \beta_1 * \text{COrate}_{it-1} + \beta_2 * \Delta\text{unemprate}_{jt-1} + \\ \beta_3 * \mathbf{X}_{it-1} + \beta_4 * \mathbf{M}_{jt-1} + u_{ijt}.\end{aligned} \tag{B.3}$$

where **X** are bank-level controls, and **M** are county-level controls.

The loan losses are driven by shocks to the county and the type of loans that the banks hold.

To estimate unobserved heterogeneity, I introduce for fixed effects for bank α_i and rewrite the equation as,

$$\text{COrate}_{ijt} = \beta_1 * \text{COrate}_{it-1} + \beta_2 * \Delta\text{unemprate}_{jt-1} + \beta_3 * \mathbf{X}_{it-1} + \beta_4 * \mathbf{M}_{jt-1} + \alpha_i + u_{ijt}. \tag{B.4}$$

This is a panel with about 2000 banks and with quarterly loan loss data. So, $N \gg T$ where T is from $2002Q1$ to $2012Q4$.

C Supplementary Tables and Figures

TABLE C.1: COEFFICIENTS FROM THE LINM LASSO MODEL

	1996 – 2002	1996 – 2005	1996 – 2006	1996 – 2007	1996 – 2008	1996 – 2010
(Intercept)	0.002	0.002	−0.004	−0.016	−0.021	0.001
30 days PD	0.077	0.090	0.089	0.095	0.129	0.167
90 days PD	0.183	0.268	0.304	0.324	0.355	0.388
Nonaccrual PD	0.223	0.274	0.291	0.318	0.406	0.522
30 days PD (t-3)	0	−0.011	−0.009	−0.006	−0.017	−0.023
90 days PD (t-3)	0	−0.034	−0.052	−0.058	−0.058	−0.064
Nonaccrual PD(t-3)	0.034	0.051	0.045	0.039	0.044	0.002
Loan to Asset	0	0.004	0.005	0.007	0.013	0.010
Securities to Asset	0	−0.000	−0.001	−0.001	−0.000	−0.005
Pct RE Loans	−0.007	−0.018	−0.018	−0.017	−0.014	−0.009
Pct CI Loans	0	−0.006	−0.008	−0.008	−0.009	−0.010
Log Assets	0.088	0.029	0.077	0.264	0.600	0.832
Net-Chargeoffs$_t$	0	0.133	0.157	0.160	0.211	0.334
Net-Chargeoffs$_{t-3}$	0.007	0.119	0.129	0.127	0.180	0.253
Net-Chargeoffs$_{t-6}$	0.006	0.105	0.112	0.110	0.108	0.152
Net-Chargeoffs$_{t-9}$	0	0.053	0.062	0.057	0.044	0.073

The table shows coefficients from the LINM model estimates for the sample banks. The LINM is the allowance prediction lasso model that takes the limited information as input. The coefficients of the variables are from lasso model estimated at bank-quarter level. Each columns represent coefficients from separate lasso models run between the periods 1996 – 2002, 1996 – 2005, 1996 – 2006, 1996 – 2007, 1996 – 2008 and 1996 – 2010 for sample banks. See Section A.3 for variable definitions.

TABLE C.2: IMPLICIT COEFFICIENTS FROM THE ILM MODEL

	Allowances					
	1996 – 2002	1996 – 2005	1996 – 2006	1996 – 2007	1996 – 2008	1996 – 2010
30 days PD	0.028***	0.030***	0.029***	0.028***	0.030***	0.032***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
90 days PD	0.013***	0.013***	0.017***	0.020***	0.024***	0.026***
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Nonaccrual PD	0.088***	0.102***	0.104***	0.104***	0.108***	0.126***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
30 days PD (t-3)	−0.013***	−0.017***	−0.017***	−0.016***	−0.016***	−0.016***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
90 days PD (t-3)	−0.007***	−0.007***	−0.010***	−0.012***	−0.015***	−0.016***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Nonaccrual PD (t-3)	−0.030***	−0.038***	−0.041***	−0.041***	−0.039***	−0.048***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Loan to Asset	−0.015***	−0.015***	−0.015***	−0.015***	−0.014***	−0.014***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Securities to Asset	0.002***	0.002***	0.002***	0.002***	0.002***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Pct RE Loans	0.000	0.002***	0.001***	−0.000	−0.001***	−0.002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Pct CI Loans	−0.003***	−0.003***	−0.004***	−0.004***	−0.005***	−0.006***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Log Assets	−0.156***	−0.149***	−0.150***	−0.147***	−0.152***	−0.138***
	(0.006)	(0.005)	(0.005)	(0.005)	(0.004)	(0.004)
Net-Chargeoffs$_t$	−0.033***	−0.049***	−0.046***	−0.044***	−0.026***	0.003
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Net-Chargeoffs$_{t-3}$	−0.005	0.000	0.007*	0.013***	0.019***	0.057***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Net-Chargeoffs$_{t-6}$	0.053***	0.056***	0.058***	0.063***	0.071***	0.103***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Net-Chargeoffs$_{t-9}$	0.074***	0.075***	0.075***	0.080***	0.081***	0.109***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Observations	153,001	204,576	220,074	234,937	249,336	276,693
Adjusted R^2	0.837	0.798	0.781	0.763	0.748	0.718

Notes: ***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

This table shows OLS regressions to obtain coefficient of ILM for sample banks. The dependent variable is the allowances deflated by the beginning period loan balance. The coefficients are the implicit weights from the allowances recognized by banks. Each columns represent coefficients from separate regression models run between the periods 1996 – 2002, 1996 – 2005, 1996 – 2006, 1996 – 2007, 1996 – 2008 and 1996 – 2010 for sample banks. The regressions are at the bank-quarter level. All standard errors clustered at the county level. See Section A.3 for variable definitions.

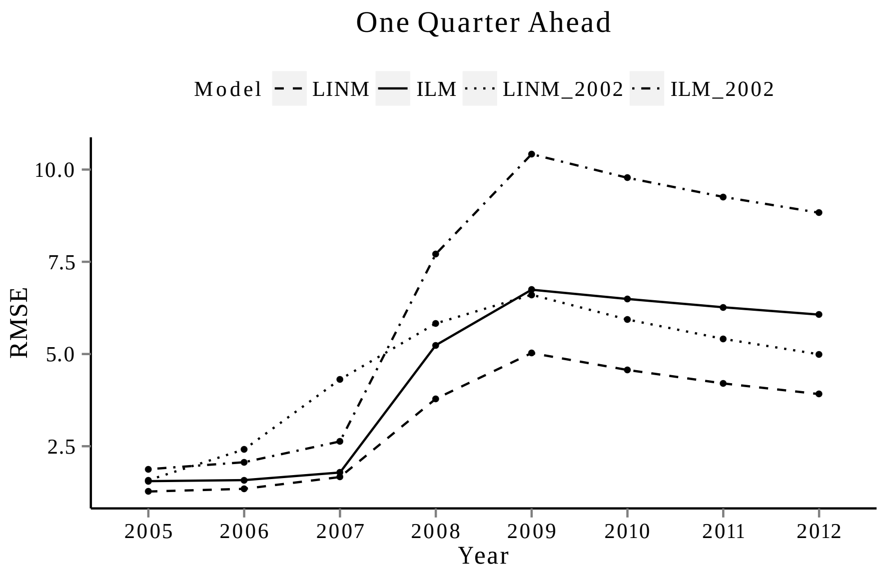


FIGURE C.1: ALLOWANCE MODEL CUMULATIVE PERFORMANCE BY YEAR.

This figure presents evidence on the performance of the model predicted allowance relative to the current GAAP's ILM in their accuracy in predicting future losses. LINM is the root mean squared error, based on one-quarter out of sample, of the predicted allowance from the lasso model that takes the limited information as input. ILM is the root mean squared error, based on one-quarter out of sample, of allowance under current GAAP from the financial statements. LINM_2002 is the model estimated using the sample between 1996 – 2002 and ILM_2002 is the ILM model estimated using the sample between 1996 – 2002.

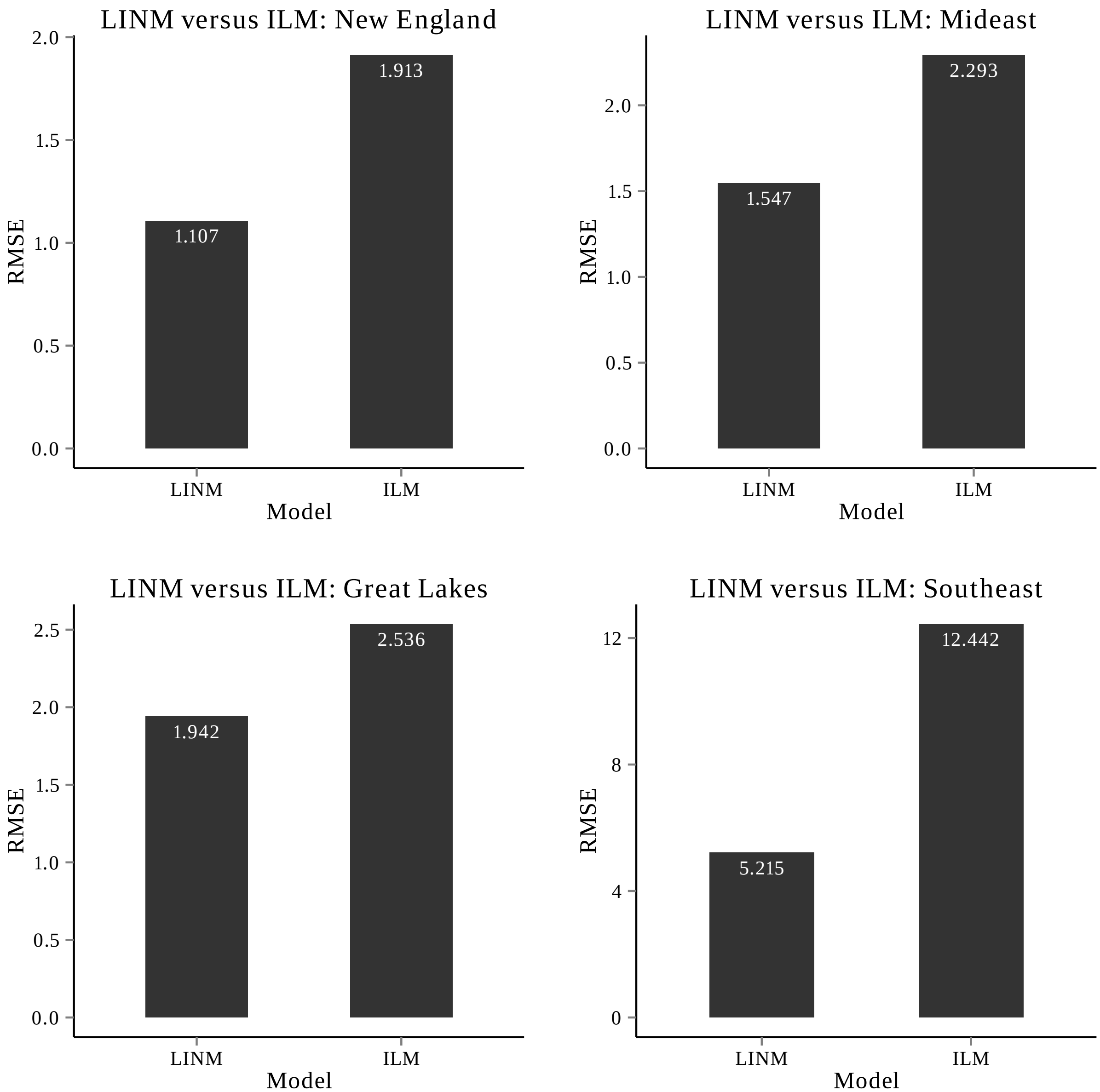


FIGURE C.2: LINM VS ILM FOR COUNTY BANKS IN BEA REGION STATES

This figure presents evidence on the difference in model performance based on sample banks that operate in particular states. The figures presents the performance of the LINM model predicted allowance relative to the current GAAP's ILM in their accuracy in predicting future losses. It shows the cumulative root mean squared error for the model estimated and tested out of sample in the period 2002–2012. LINM is the root mean squared error of the predicted allowance from the lasso model that takes the limited information as input. ILM is the root mean squared error of allowance under current GAAP from the financial statements. Each bargraph represents results from separate model estimations restricting to banks that operate in the corresponding BEA regions.

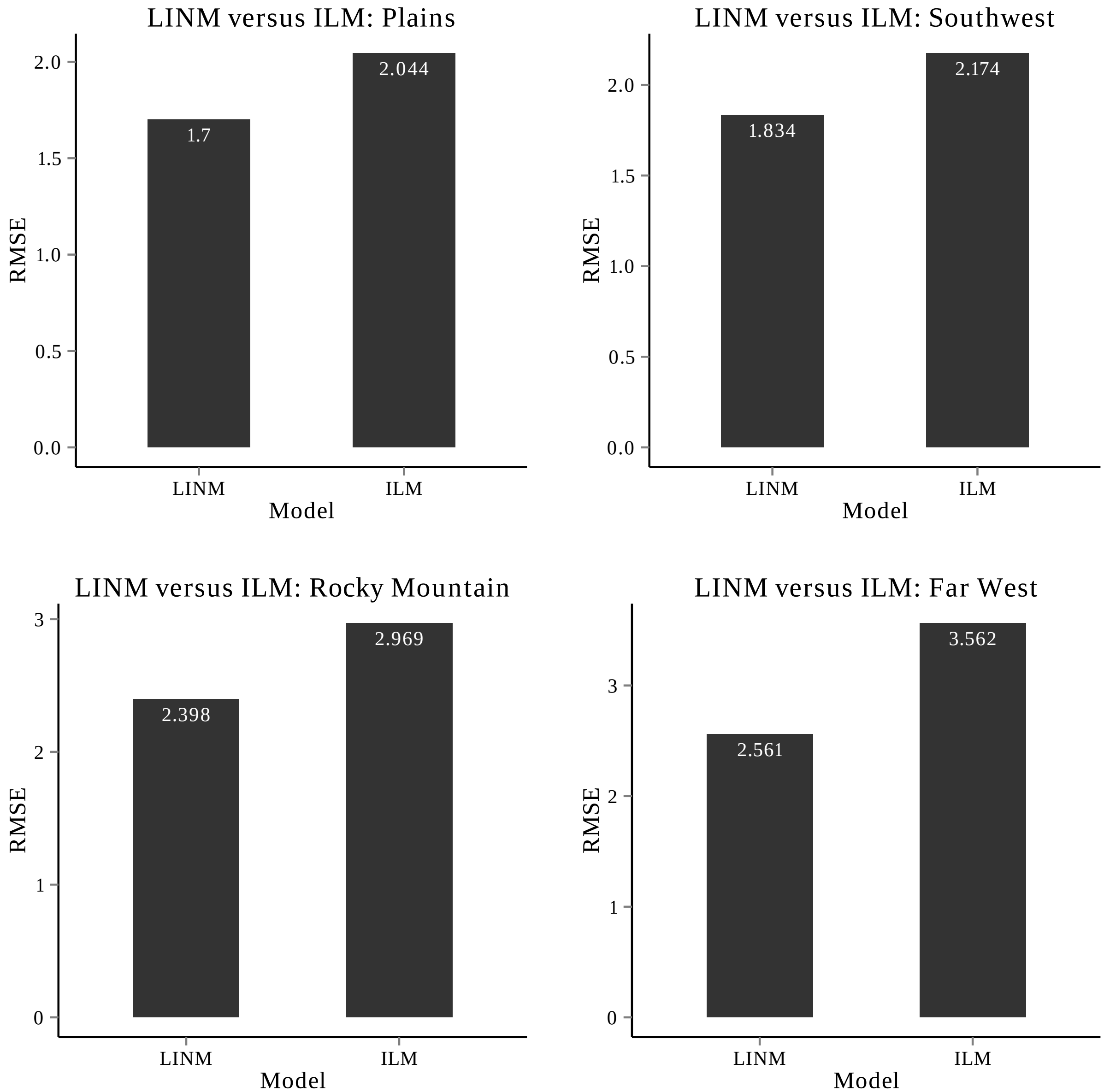


FIGURE C.3: LINM VS ILM FOR COUNTY BANKS IN BEA REGION STATES

This figure presents evidence on the difference in model performance based on sample banks that operate in particular states. The figures presents the performance of the LINM model predicted allowance relative to the current GAAP's ILM in their accuracy in predicting future losses. It shows the cumulative root mean squared error for the model estimated and tested out of sample in the period 2002–2012. LINM is the root mean squared error of the predicted allowance from the lasso model that takes the limited information as input. ILM is the root mean squared error of allowance under current GAAP from the financial statements. Each bargraph represents results from separate model estimations restricting to banks that operate in the corresponding BEA regions.