CHICAGO BOOTH
The University of Chicago Booth School of Business

Working Paper No. 19-11

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First version: November 2017
This version: February 2019

*We gratefully acknowledge financial support from the University of Chicago Booth School of Business. We thank Karthik Balakrishnan, John Gallemore, Sudarshan Jayaraman, Thomas Rauter, Stephen Ryan, Sehwa Kim, Joanna Wu, and seminar participants at London Business School, Ohio State University, and Yale Accounting Summer Conference for helpful comments.

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Abstract

Recently introduced accounting standards require that financial institutions provision for expected losses on their loan portfolios. Understanding the economic consequences of provisioning for expected losses is of significant interest to academics and regulators. We develop an empirical model of expected loan loss provisioning and use it to construct a bank-year measure of under-provisioning for expected losses. The model relies on forward-looking bank- and macro-economic indicators of future losses. The estimated expected losses are substantially more informative in explaining realized losses as compared to the reported numbers. Unlike the reported provisions, the estimated provisions for expected losses behave in a counter-cyclical fashion. Using our measure of under-provisioning, we find evidence consistent with under-provisioning for expected losses distorting banks' lending, financing, and dividend decisions. While in practice banks need not provision in the way predicted by the model, we provide a useful benchmark to evaluate provisioning under the new accounting rules.

Keywords: Expected loss model; loan loss provisioning; under-provisioning; bank decisions.

JEL Classification: G21, M40, M41.

1. Introduction

Loan loss provisioning is at the heart of bank accounting and has been the subject of a long-standing policy debate because of its effect on banks' regulatory capital. Untimely reporting of loan losses overstates a bank's true economic capital and increases the pro-cyclicality of banks' lending (Laeven and Majnoni 2003). Until recently, financial institutions followed the FAS 5 incurred loss approach to account for losses on their loan portfolios. Under FAS 5, losses are recorded when they become probable, i.e., after a loss impairment event has occurred. This practice became the subject of significant controversy in the wake of the 2008 financial crisis as it arguably limited banks' ability to record losses that had not met the probable threshold, causing untimely reporting. To address this issue, the Financial Accounting Standards Board has recently made a historic change in the way financial institutions provision for loan losses, effective as of the end of 2019 (ASC 326-20). The new standard requires that financial institutions provision for expected losses over the lifetime of loans in their portfolio. Similar changes in loan loss accounting are taking place internationally, with the adoption of IFRS 9.

Understanding the economic consequences of expected vs. incurred loan loss provisioning is of significant interest to academics, accounting standard setters, and bank regulators (Dugan 2009, Acharya and Ryan 2016). Does the recognition of expected vs. incurred losses on a bank's portfolio affect banks' behavior outside of recessionary periods? Does expected loan loss provisioning dampen the severity of economic downturns? Are provisions for expected losses that are reported under the new standard more likely to lead to regulatory capital manipulations? A number of studies have emerged over the past decade addressing the links between the timeliness of loan loss provisioning and banks' risk-taking behavior (Beatty and Liao 2011; Bushman and Williams 2012, 2015). To progress further in this area, however, researchers need to be able to evaluate the timeliness of provisioning relative to an expected loss benchmark. This requires developing an empirical model of expected loan loss provisioning.

It is important to note that the timeliness of loan loss provisioning under the incurred loss approach is distinct from that under the expected loss approach (a bank can be timely in recognizing incurred losses but untimely with respect to expected losses). Under the incurred loss approach, the timeliness of reported provisions is judged relative to an *incurred* loss benchmark, i.e., expected losses *conditional* on loans being subject to adverse credit events. Accordingly, it is measured by the extent to which provisions reflect the current and one-period-ahead non-performing loans, i.e., the proxies for incurred losses (Beatty and Liao 2011). This approach is not suitable for measuring the timeliness of expected provisioning, as the later requires estimating and using a benchmark for *expected* losses.[1]

We develop an empirical model of expected loan losses and loan loss provisioning. Based on this model, we also construct a bank-year measure of the degree to which banks' reported numbers under-provision for expected losses and hence overstate their real economic capital. We begin with the notion that under the expected loss approach, the balance sheet allowance must reflect the present value of future expected losses on the existing loans over their lifetime, conditional on the forward-looking information available to accountants at that time. Provision for expected losses, in turn, equals realized losses plus the change in expected losses in a given period. We estimate long-run expected loan losses by modeling future expected default rates on a

[1] When measured over a relatively long period, non-performing loans or future realized losses cannot be used as a proxy for expected losses without assuming perfect foresight. Consequently, the inability of future non-performing loans (or realized losses) to explain current provisions is directly linked to the predictability of future losses, i.e., uncertainty (predictability is clearly different from timeliness as it has little to do with accounting measurement). When one regresses LLP on future loan losses or future non-performing loans, a low regression coefficient (or low incremental R-squared) does not imply poor timeliness (or a failure to incorporate information about expected losses); it is consistent with provisions rationally incorporating all available forward-looking information about future losses, but with losses being difficult to predict.

given portfolio of loans as a function of concurrent bank-specific and macro-economic forward-looking indicators.[2] We apply the estimated default rates to expected loan balances, adjusted for attrition due to defaults, to estimate future expected losses. Subsequently, we calculate their present value to determine the estimated allowance and provision for expected losses. We acknowledge that our approach relies on several assumptions, which are discussed more fully in Section 2. One such assumption is that, conditional on the information at a given point in time, expected loan losses over our prediction horizon are (on average) uncorrelated with changes in loan portfolio composition.[3]

We estimate the model and perform two sets of tests to validate its performance. First, we show that the estimated allowance for expected losses is significantly more effective at anticipating medium run losses than is the reported allowance, which has very little power to predict loan losses measured over extended horizons. Second, we show that the estimated allowance and provision for expected losses contains significant value-relevant information not reflected in the reported numbers. We also observe that the estimated provision for expected loan losses is counter-cyclical (in contrast to the pro-cyclical reported provision for incurred losses) and exhibits a more pronounced "income smoothing" property – a positive correlation between earnings before provision and the estimated provisions for expected loan losses. The latter, by design, cannot be attributed to earnings manipulations, but is a property of expected loan loss provisioning. These findings are in line with expected loss provisions being timelier as compared to the current reporting practice.

[2] We estimate long-run expected losses following FASB's ASC 326-20, which requires that "an entity shall estimate expected credit losses over the contractual term of the financial asset(s)."

[3] The reader needs to bear this assumption in mind when interpreting the results. Ryan and Keeley (2013) show that portfolio composition changes over time. However, the assumption that portfolio composition is relatively stable at a given bank over five year periods (which are our prediction horizons) is a useful approximation, and is a necessary compromise given our goal of estimating long-run expected loan losses (this is discussed further in Section 8).

To assess the timeliness of provisioning relative to expected losses, we use a bank-year measure of under-reserving (under-provisioning) for expected loan losses: the difference between expected and reported allowance for loan losses computed at a given balance-sheet date. To validate this proxy, we perform three sets of tests. First, we show that banks with a higher degree of under-reserving report lower earnings and capital levels in the subsequent three years. Second, we show that banks with a greater degree of under-reserving for expected losses at the end of 2007 suffered significantly lower stock performance and loan growth during the financial crisis of 2008. Finally, we show that under-provisioning for expected losses is associated with lower banks' viability, i.e., a higher probability of failure in the subsequent years.

Our last set of tests applies the proposed bank-year measure to further our understanding of the real effects of insufficient provisioning relative to the level of expected loan losses. First, we explore the association between expected loss under-provisioning and banks' key decisions. We take the perspective that managers of financial institutions understand expected losses on their loan portfolios, even if they are not required to report them (Benston and Wall 2005). Thus, banks' lending and financing decisions should be based on the level of expected losses, not just on the portion of losses that banks are required to report under FAS 5. For example, greater expected losses translate into lower economic capital and should adversely affect banks' willingness to extend new loans. However, holding the amount of real capital constant, does the degree of under-reserving for expected losses explain banks' decisions? Since capital requirements are based on reported, not expected, numbers, under-reserving for expected losses (which amounts to overstating real capital) gives a bank incentive (and opportunity) to expand its balance sheet by issuing more loans and taking more risks outside of recessionary periods (Bertomeu, Mahieux, and Sapra 2018). In line with this argument, we show that, controlling for the amount of expected losses, the degree of under provisioning for expected losses is associated with an increase in new loans issuance, an increase in banks' liabilities, and a higher level of dividend payouts in the subsequent year. Second, we supplement these results by testing whether under-reserving for expected losses is associated with an increase in banks' cost of capital, as measured by market beta. In line with increased risk-taking incentives, we observe that the degree of under-reserving is significantly and positively associated with banks' future market beta. Overall, while our evidence is not causal, it is consistent with the idea that the lack of timely provisioning for *expected* losses distorts banks behavior.

As a caveat, it needs to be noted that the main analysis presented in our paper is deliberately based on in-sample tests. We make this choice because we have a relatively short time series (after requiring 5 years of lagged time series, our sample period is 1991-2017, i.e. we have 26 years of data), whereas the model is, in part, identified based on time-series variation in macro-economic indicators. Nevertheless, to test whether our findings are sensitive to this research design choice, we perform a sensitivity test (described in more detail in Section 8). We find that our results are overall similar in the out-of-sample tests and our conclusions remain unchanged.

We contribute to the literature in several ways. First, provisioning for loan losses is one of the primary determinants of the informativeness and transparency of banks' financial statements (Bushman 2016). We develop and validate an empirical model of expected loan losses, which can be used as a benchmark to evaluate the adequacy and timeliness of expected loan loss provisioning. Our study is related to Harris, Khan, and Nissim (2018), that models short-term expected loan losses (the expected loss rate over a 12-month period) and finds they predict realized losses and bank failures. Our study adds to their work in several important ways:

(1) our focus is on modeling long-term losses, which requires a combination of predictive regressions and a structural approach to estimate the present value of long-run (life-time) expected losses; (2) our model incorporates business-cycle macroeconomic indicators to address the pro-cyclicality of loan loss provisioning; and (3) we construct, validate, and apply a bank-year measure of banks' under-reserving relative to the expected loss benchmark.

We also contribute to the literature by exploring the links between under-provisioning for expected losses (under the current reporting practice) and the distortion of banks' investment, financing, and payout decisions. Under-provisioning banks appear to be more aggressive in their lending and financial policies. These results complement recent evidence that forward-looking provisioning reduces risk taking and improves bank stability (Beatty and Liao 2011; Bushman and Williams 2012, 2015). The key distinction is that these studies investigate the timeliness of forward-looking provisioning for incurred/probable losses (i.e., the losses reflected in the changes to the current and subsequent periods' non-performing loans) and do not evaluate the timeliness of provisioning relative to *expected* loan losses. The latter is a different construct, as timely provisioning for incurred losses can be, at the same time, rather untimely relative to the expected losses.

Our study should be of interest to regulators and accounting standard setters. We show that a simple model generates significantly timelier provisions as compared to the current reporting practice. Additionally, our evidence supports the view that provisioning for expected loan losses exhibits lower pro-cyclicality and is in fact counter-cyclical. In line with this finding, our evidence also indicates that reserves insufficient to cover expected loan losses lead to pro-cyclical bank decisions. It is important to note that the adoption of the new rule itself need not automatically lead to a more forward-looking provisioning practice by banks, as implied by our model, because reporting incentives are a primary factor in determining provisioning behavior (Bischof, Laux and Leuz, 2018). In fact, the more forward-looking provisioning rule could give bank managers even more discretion, with economic incentives potentially playing an even greater role than before. Thus, our results should not be viewed as a prediction about what will actually happen to banks' provisioning behavior, but rather a counterfactual (or benchmark) useful in evaluating banks' provisioning under the new rule.

The rest of the paper is organized as follows. Section 2 lays out the model. Section 3 describes the data and implementation. Section 4 validates the model and explores expected loss pro-cyclicality. Section 5 explores the pro-cyclicality of expected loan loss provisioning. Section 6 constructs and validates the measure of under-reserving for expected losses. Section 7 explores the possible economic consequences of under-reserving on banks' decisions and risk-shifting behaviors. Section 8 describes out-of-sample tests. Section 9 concludes.

2. Modeling expected loan losses.

In this section, we lay out our empirical approach to modeling expected loan losses. Subsequently, we discuss how this approach reconciles with prior models that measure the timeliness and forward-looking nature of loan loss provisioning.

2.1. A model of expected loan losses.

Expected losses, EL_t, on portfolio of loans, w_t, can be written as:

$$EL_t = \mathrm{E}_t[L_t^{t+1} + L_t^{t+2} + L_t^{t+3} \ldots | I_t], \tag{1}$$

where L_t^{t+k} are losses on the portfolio of loans in place at the end of period t realized during the period $t + k$, and where I_t is the information available at time t. Expected losses on a loan portfolio are not the same as expected (net) charge-offs, NCO_{t+k}:

$$\mathrm{E}_t[L_t^{t+1} + L_t^{t+2} + L_t^{t+3} \ldots | I_t] \neq \mathrm{E}_t[NCO_{t+1} + NCO_{t+2} + NCO_{t+3} \ldots | I_t].$$

This is because NCO_{t+k} is associated with portfolio w_{t+k}, which reflects changes in the portfolio w_t due to new issuance, defaults, or repayments. The two sides of the above equation are only equal if a bank continues to hold its current portfolio, allowing loans to default or mature (and does not issue any new loans).

To model expected losses, it is thus necessary to fix the portfolio of loans in place at time t and to only allow for changes due to attrition (accumulation of defaults) and maturities. This necessitates using elements of a structural approach. We begin by assuming that $L_t^{t+k} = NCO_{t+k}$ for $k = 1$ since portfolio changes within the year $t + 1$ are unlikely to cause defaults within the same year and are relatively small. Thus, we can compute the following default (loss) rate:

$$p_{t+1} \equiv \frac{L_t^{t+1}}{B_t} = \frac{NCO_{t+1}}{B_t}$$

This rate is useful because it allows us to model the *expected* default rate, $p_{t+1|t} = E\left(\frac{L_t^{t+1}}{B_t} \middle| I_t\right) = E\left(\frac{NCO_{t+1}}{B_t} \middle| I_t\right)$, as well as the future expected default rate, $p_{t+k|t} = E\left(p_{t+k|t+k-1} \middle| I_t\right) = E\left(\frac{NCO_{t+k}}{B_{t+k-1}} \middle| I_t\right)$, as a function of information I_t. We apply these expected default rates to the gross book value of loans in the portfolio, B_t, in order to obtain the following estimates of expected losses:

$$E[L_t^{t+1}|I_t] = p_{t+1|t}B_t, \tag{2a}$$

$$E[L_t^{t+2}|I_t] = p_{t+2|t}(B_t - E[L_t^{t+1}|I_t]) = p_{t+2|t}(1 - p_{t+1|t})B_t, \tag{2b}$$

$$E[L_t^{t+3}|I_t] = p_{t+3|t}(B_t - E[L_t^{t+1}|I_t] - E[L_t^{t+2}|I_t]) = p_{t+3|t}(1 - p_{t+2|t})(1 - p_{t+1|t})B_t,$$

$$\ldots \tag{2c}$$

$$E[L_t^{t+k}|I_t] = p_{t+k|t}(1 - p_{t+k-1|t}) \times \ldots \times (1 - p_{t+1|t})B_t, \tag{2d}$$

where $p_{t+k|t} = E\left[\frac{NCO_{t+k}}{B_{t+k-1}}\middle|I_t\right]$ is an expected future default rate for the period $t + k$, conditional on the information at time t.

This formulation is intuitive. Expected losses in period $t + k$ are equal to the corresponding expected default rates multiplied by the beginning-of-period loan balance adjusted for prior expected defaults.

An important assumption embedded in the equations above is that the expected default rates, $p_{t+k|t}$, can be applied multiplicatively to the current portfolio book value B_t adjusted for expected defaults. This assumes that the composition of loans in a bank's portfolio remains systematically unchanged over the prediction horizon k, which would be the case if changes in loan portfolios were non-systematic or proportional so that the composition stays, on average, the same over time. Relaxing this assumption would require adjusting the expected default rates for expected changes in portfolio composition. However, implementing such adjustments is not currently feasible as it would require observability of loan losses by loan vintages *and* type (which is not currently a reporting requirement). The reader needs to bear this limitation in mind when interpreting the results.

The model of expected loan losses allows us to define and calculate the allowance for expected losses:

$$ALLE_t = E\left[\frac{L_t^{t+1}}{1+r_t} + \frac{L_t^{t+2}}{(1+r_t)^2} + \frac{L_t^{t+3}}{(1+r_t)^3} + \cdots + \frac{L_t^{t+T}}{(1+r_t)^T} \,|I_t\right], \tag{3}$$

where T is the average remaining time to maturity for the loans in the current portfolio. For practical considerations, we set T to five years (estimating expected losses over longer horizons is likely unreliable and we do not explore this here).

Once we have estimated expected losses at a given time, we can also estimate the provision for expected losses $LLPE_t$, defined as losses realized over a period plus an increase (decrease) in the present value of expected loan losses:

$$LLPE_t = L_{t-1}^t + E\left[\frac{L_t^{t+1}}{1+r_t} + \frac{L_t^{t+2}}{(1+r_t)^2} \ldots |I_t\right] - E\left[\frac{L_{t-1}^t}{1+r_{t-1}} + \frac{L_{t-1}^{t+1}}{(1+r_{t-1})^2} \ldots |I_{t-1}\right]$$

$$\equiv NCO_t + ALLE_t - ALLE_{t-1}, \tag{4}$$

In order to implement the model, we need to estimate the bank-specific expected loss rate $p_{it+k|t}$. Suppose that the information set I_{it}, available to accountants when estimating losses, consists of a vector of variables, y_{it}. We model expected default probabilities by running the following non-linear regression for subsamples of different bank sizes:

$$p_{it+k} = p_{it+k|t} + \epsilon_{it+k} = \exp(y_{it}\beta_k) / (1 + \exp(y_{it}\beta_k)) + \epsilon_{it+k}, \tag{5}$$

where $p_{it+k} = NCO_{it+k}/B_{it+k-1}$ is the realized charge-offs rate, $k = 1,2, \ldots, T$. We use the estimated regression coefficients to calculate expected future default probabilities conditional on the information available at time t:

$$p_{it+k|t} = E[p_{it+k}|I_{it}] = \exp\left(y_{it}'\hat{\beta}_k\right) / \left(1 + \exp\left(y_{it}'\hat{\beta}_k\right)\right). \tag{6}$$

We now substitute the quantities from equations (2a)-(2d) into equation (3) in order to calculate future expected losses and their present value, $ALLE_{it}$. To measure the discount rate, we use the concurrent interest rate on the loans in portfolio r_t.[4] Subsequently, we use equation (4) to estimate $LLPE_{it}$.

We include the following variables in the information set used to estimate the model:

$$y_{it}' = (p_{it}, \Delta p_{it}, IntRate_{it}, \Delta IntRate_{it}, NAL_{it}, Pastdue90_{it}, \Delta Loan_{it}, \Delta GDP_t,$$

[4] Since we do not observe the interest rate on the loans, we approximate it by calculating the ratio of interest revenue less loan loss provision to the sum of total loans, held-to-maturity securities, available-for-sales securities, and trading assets.

$Unemployment_t, \Delta Unemployment_t, CSRet_t$),

where $p_{it} = \frac{Net\ Charge-offs_{it}}{Loan_{it-1}}$ is the current default rate, $\Delta p_{it} = p_{it} - p_{it-1}$ is the change in current default rates, $IntRate_{it} = \frac{Interest\ revenue_{it}}{Loan_{it-1}}$ is the interest rate, $\Delta IntRate_{it} = IntRate_{it} - IntRate_{it-1}$ is the change in the interest rate, $NAL_{it} = \frac{Non-accrual\ loans_{it}}{Loan_{it-1}}$ is the non-accrual loans ratio, $Pastdue90_{it} = \frac{Loans\ past\ due\ 90\ days_{it}}{Loan_{it-1}}$ the fraction of past due loans, $\Delta Loan_{it}$ is the percentage change in total loans outstanding, *ΔGDP* is the real GDP growth in the US, $\Delta Unemployment_t$ is the annual change in unemployment in the US, and $CSRet_t$ is the percentage change in the Case-Shiller real estate index.

To construct a bank-year measure of under-reserving for expected losses, we use the difference between the reported allowance for loan losses, $ALLR_{it}$, and $ALLE_{it}$:

$$UNDERR_{it} = ALLE_{it} - ALLR_{it}, \tag{7}$$

The higher the value of $UNDERR_{it}$, the less timely a bank is in recording expected losses in year t.

2.2. Conceptual differences from prior models.

Prior literature does not offer a model of provisioning for expected loan losses, but measures the degree to which provisions reflect information about future losses using a different approach (see Beatty and Liao 2014). This approach relies on estimating the following regression model (with some variation in model specification in the literature):

$$LLPR_t = \alpha_0 + \alpha_1 \Delta NPL_{t+1} + \alpha_2 \Delta NPL_t + Other\ Determinants_t + \varepsilon_t \tag{8}$$

where $LLPR_t$ is the current provision and where ΔNPL_{t+1} and ΔNPL_t are future and current changes in non-performing loans that aim to proxy for incurred (probable) losses. The incremental R-squared from the first two regressors in this model and/or the magnitude of the coefficient α_1 have been used in the literature to measure the timeliness of provisioning for expected losses (e.g., Bushman and Williams 2015).

There are two important considerations behind this approach. First, the model given by equation (8) assumes that at time t, the managers (accountants) know or can accurately estimate the changes in non-performing loans realized in the future (at $t+1$). Second, non-performing loans is a proxy for incurred losses and thus only reflect the losses that are likely to be realized within a relatively short period of time (i.e., they do not capture losses to be realized over longer horizons). These two considerations render this approach unsuitable to modeling expected long-term losses or measuring the timeliness of loan loss provisioning under the new accounting rules. Instead, it measures the timeliness of (expected) losses conditional on such losses being probable (probable losses and expected losses are different and need not be positively correlated).

Equation (8) could be modified to incorporate some measure of non-performing loans or realized losses over a number of periods (i.e., $t+2$, $t+3$, $\ldots$). However, in such a modification, the assumption that a manager knows future non-performing loans (i.e., predicts realized losses) would no longer be plausible. As a result, low incremental R-squared would become a proxy for a portfolio's loan loss predictability instead of timeliness. For this reason, measuring the timeliness of loan loss provisioning under the expected loss approach is conceptually distinct from the notion of timeliness under the incurred loss model and requires a different model, one that models expected losses as a first step and subsequently considers their mapping onto reported numbers.

3. Data and sample selection.

Our data come from several sources. We obtain accounting information for bank holding companies and commercial banks from FR Y-9C reports and Call Reports, which are available on the Federal Reserve Bank of Chicago website. We use annual data to construct the variables used in our analysis. We obtain monthly stock returns (for listed bank holding corporations) from the Center for Research in Security Prices (CRSP). Finally, data on bank failure come from the Federal Deposit Insurance Corporation (FDIC) website.

Our sample covers the period of 1986-2017, the years for which the data are available. We require bank holding companies to have at least 15 years of available data during this sample period to ensure enough historical data to estimate expected loan losses, i.e., to determine the estimated allowance (*ALLE*) and provision (*LLPE*) for expected loan losses. The exception to this requirement is the bank failure tests, where we do not restrict data availability by year. We scale the (estimated and reported) allowance and provision for loan losses by the lagged gross amount of loans. To reduce the impact of extreme observations, we truncate the top and bottom 1% of observations for all the variables that appear in our regressions, except for macroeconomic and bank failure variables. The model is estimated on the resulting sample.

Table 1 presents the descriptive statistics for the variables used in our analysis. Banks in our sample have average total assets (*Asset*) of $7.7 billion and average total loans (*Loans*) of $4 billion. The reported allowance of loan losses (*ALLR*) is 1.6% of lagged total loans, which is about three times larger than the provision for loan losses (*LLPR*). Descriptive statistics are similar to those used in other studies that use US bank holding company data (e.g., Beatty and Liao 2011, Bushman and Williams 2015, Laux and Rauter 2017).

4. Baseline tests.

4.1 Descriptive analysis of model estimated variables.

We use the methodology in Section 2 to estimate the allowances (*ALLE*) and provisions (*LLPE*) for expected loan losses and scale them by the lagged total loans. The estimated coefficients for the prediction model are reported in the Appendix (Table A1). The model is estimated separately for the largest banks (top 33%) and the remaining banks (bottom 67%) to accommodate possible differences in specification due to the scale of business. The estimates indicate that default ratios exhibit an intuitive relation with concurrent information in firm and macro indicators. They are significantly positively associated with historical losses, past-due and non-accrual loans, growth in the interest rates, growth in unemployment, and real GDP growth. Default rates exhibit negative associations with interest rates, unemployment, and the return of the Case-Shiller Home Price Index. The positive association between future default probability and GDP growth and the negative association with unemployment is an indication of banks' lending pro-cyclicality, i.e., banks adopt a more liberal credit policy in good times, extending loans to lower quality borrowers. Better market conditions lead to new, lower quality loans being extended, which results in a higher default frequency in the future. The results also point to the presence of bank-specific effects in loan losses, which means that high default rate or low-asset-quality banks are more likely to default in the future.

Table 2 presents the percentiles for the distribution of the estimated allowances and provisions for loan losses, and contrasts them with the distribution of the reported numbers. The distributions can also be seen in Figure 1. *ALLE* has a mean of 0.019 and a median of 0.017. Both quantities are somewhat larger than the corresponding quantities based on the reported allowance *ALLR*, which are 0.016 and 0.015 respectively. However, the differences are moderate in economic magnitude. In part, this is due to the fact that reported allowance is relatively high on average. In fact, the reported allowance is large enough to cover three years' worth of reported provisions. This is not generally expected under the application of incurred loss model, as incurred losses are likely to be realized within a year. As expected, the mean and median level of *UNDERR* is positive, in line with the expectation that on average, the current reporting practice under-reserves for expected loan losses.

4.2 Model performance and validation.

We begin by validating the model and contrasting its performance to the reported numbers. First, we explore the predictive ability of the estimated allowance for expected losses (*ALLE*) to explain future realized losses and compare it to the predictive power of the reported allowance (*ALLR*). We focus on the medium run because it is plausible that the reported allowance will have power to predict losses in the medium run but not in the longer run. Recall that the level of reported allowance is sufficient to cover three to four years of provisions or realized losses. Second, we explore the value relevance of the estimated expected vs. reported loan loss allowances and provisions.

4.2.1 Predictive ability tests.

We regress the cumulative net charge-offs measured over the following three years (*Future losses*) on the current year allowance for expected vs. reported loan losses:

$$Future\ losses_{i,t+3} = \beta_0 + \beta_1 Allowance_{i,t} + \varepsilon_{i,t},$$

where *Allowance* is either *ALLE* (allowance for expected losses) or *ALLR* (reported allowance). Since *ALLE* incorporates forward-looking information, we expect it to be a significantly better predictor of loan losses than *ALLR*.

Table 3 presents the results of this comparison. Columns 1 and 2 show that the coefficient (t-statistic) on *ALLE* is more than twice (three times) as large as on *ALLR*. Importantly, while both allowance measures are significant predictors of future loan losses, the explanatory power of *ALLE* is an order of magnitude higher than that of *ALLR*. When we include both *ALLE* and *ALLR* in the regression (column 3), both the coefficient and t-statistics on *ALLR* drop significantly, while the coefficient on *ALLE* (and its level of statistical significance) remains unchanged; R-squared also remains largely unchanged. As we control for past realized (historical) losses (*NCO*) in columns 4-6, the coefficients and t-statistics on reported allowance, *ALLR*, deteriorate further, whereas those on the allowance for estimated losses, *ALLE*, remain largely unchanged. Unlike in the case of reported allowances, adding *NCO* as a control does not add much incremental information to that contained in our measure of expected loan losses. Overall, the ability of the reported allowance to predict future losses over a medium-term horizon is strikingly low.

These findings indicate that the reported allowance for loan loss is mainly driven by historical loss experience and not by forward-looking information. In contrast, the estimated allowance for expected losses contains a large amount of relevant forward-looking information that is not reflected in the reported numbers or historically realized losses. These results suggest that our model is reasonably effective at estimating expected loan losses.

4.2.2 Value relevance tests.

We next evaluate the value relevance of the estimated allowance and provision for expected losses. If *ALLE* is better at anticipating future losses than *ALLR*, it should also be more value relevant with respect to contemporaneous banks' stock prices. To test value relevance, we use the following model on a subsample of publicly traded banks:

$$Price_{i,t} = \beta_0 + \beta_1 Allowance_{i,t} + \beta_2 Controls_{i,t} + \varepsilon_{i,t},$$

where *Price* is the closing stock price at the end of April of the following year scaled for consistency by lagged loans per share (total loans scaled by the number of shares outstanding in April of the current year).[5] This ensures that the dependent and independent variables are both scaled by the same deflator. *Allowance* is either *ALLE* or *ALLR*; $Controls$ are capital ratio, *CapR*, and the natural log of total assets, *Size*.

The results are presented in columns 1 and 2 of Table 4. In line with our expectations, we find that the estimated allowance *ALLE* has a negative and statistically significant (at the less than 1% level) association with *Price*. In contrast, *ALLR* is positively associated with *Price*, and the effect is not significant. In columns 3 and 4, we run the return-based version of the analysis above, using stock returns as the dependent variable and replacing allowances with provisions:

$$Ret_{i,t} = \beta_0 + \beta_1 Provision_{i,t} + \beta_2 Controls_{i,t} + \varepsilon_{i,t},$$

where *Ret* is the current year buy-and-hold stock return, measured over the period starting the end of April of the current year and going to the end of April of the following year. In this specification, *Provision* is either *LLPE* or *LLPR*, and $Controls$ are net income scaled by lagged total loans, *NI*, and the natural log of total assets, *Size*.

The results, reported in columns 3 and 4, are analogous to those in the levels-based specifications (columns 1 and 2). We find that expected loan loss provision *LLPE* exhibits a statistically significant negative association with *Ret* at the 5% level. While *LLPR* also exhibits a negative relation with returns, it is only significant at the 10% level.

[5] We assume that a bank's annual accounting information with a December fiscal year-end is publically available by the end of April of the following year.

As in the predictive ability tests, the results here indicate that the estimated allowances and provisions based on our model contain more information about the performance of a bank's loan portfolios than the reported numbers.

5. Pro-cyclicality of expected vs. reported loan loss provisioning.

One of key criticisms of the incurred loss approach to loan loss provisioning is its pro-cyclicality (Laeven and Majnoni 2003, Dugan 2009, FSF Report 2009). Laeven and Majnoni (2003) provide evidence that many banks around the world delay provisioning until too late, thereby amplifying the impact of the economic cycle on banks' earnings and capital. The pro-cyclicality of loan loss provisioning arguably leads to lending pro-cyclicality and the banking system's vulnerability to financial crisis (Beatty and Liao 2011; Bushman and Williams 2012, 2015; GAO 2013).

While the adoption of the expected loan loss approach aims to address the pro-cyclicality in loan loss provisioning, it is not yet well understood whether (and to what extent) this will happen (Acharya and Ryan 2016). In fact, it is possible to envision scenarios where the expected loss approach will increase pro-cyclicality. In particular, it is possible that expected losses are even smaller in periods of economic booms and greater in periods of economic downturns as compared to reported losses.

To provide some preliminary evidence on this, we explore the pro-cyclicality of expected loan losses from the model and compare it to the reported numbers. As argued by Laeven and Majnoni (2003), the pro-cyclicality of loan loss provisioning is manifested in (1) a negative association of provisions and GDP growth, (2) a negative association between provisions and loan growth, and (3) a negative association of loan loss provisions and bank's earnings before provisions.[6] We start exploring the association between provisioning and GDP growth by running the following regression:

$$Depvar_{i,t} = \beta_0 + \beta_1 \Delta GDP_{i,t} + \beta_2 Controls_{i,t} + \beta_3 FE_{i,t} + \varepsilon_{i,t},$$

where the dependent variable, $Depvar$, is either the reported allowance (provision), *ALLR (LLPR)*, or the allowance (provision) for expected loan losses, *ALLE* (*LLPE*). *ΔGDP* is the real GDP growth. *Controls* are the natural log of total assets, *Size*. *FE* represents bank fixed effects.

The results are presented in Table 5, Panel A. In line with the increased pro-cyclicality of loan loss provisioning under the incurred loss approach, columns 1 and 3 indicate a pronounced *negative* association of the reported loan loss provisions and allowances with changes in GDP. In contrast, columns 2 and 4 indicate that estimated provisions and allowances based on the expected loss approach exhibit a significant *positive* association with GDP growth. In other words, the allowances for expected losses, absent earnings manipulations, behave in a counter-cyclical way. This evidence supports the intended effect of the new provisioning standard.

As an alternative, we also investigate pro-cyclicality by examining loan growth:

$$Depvar_{i,t} = \beta_0 + \beta_1 \Delta Loans_{i,t} + \beta_2 Controls_{i,t} + \beta_3 FE_{i,t} + \varepsilon_{i,t},$$

where the dependent variable, $Depvar$, is either the reported allowance (provision), *ALLR (LLPR)*, or the allowance (provision) for expected loan losses, *ALLE* (*LLPE*). *ΔLoans* is the percentage change in total loans outstanding. *Controls* are the natural log of total assets, *Size*. *FE* represents bank fixed effects.

The results in Table 5, Panel B are similar to the case of GDP growth (Panel A). Columns 1 and 3 indicate significant pro-cyclical behavior by the reported loan loss provisions and allowances, i.e., they exhibit negative associations with loan growth. In contrast, columns 2 and

[6] Laeven and Majnoni (2003) find evidence in support of pro-cyclicality based on predictions (1) and (2) but not prediction (3). The latter is consistent with earnings management smoothing earnings over time.

4 indicate that estimated provisions and allowances based on the expected loss approach switch to counter-cyclical behavior and exhibit a *positive* association with loan growth, also in line with the intended effect of the new standard.

5.1. Income smoothing

Another way to investigate the pro-cyclicality of loan loss provisioning is to examine the income smoothing of expected vs. reported provisions for loan losses (Laeven and Majnoni 2003). Because losses are not recognized in a sufficiently timely manner under the incurred loss approach, companies are incentivized to smooth earnings by over (under) provisioning during periods of high (low) revenues in order to protect themselves against adverse economic shocks to future earnings (Liu and Ryan 2006). This, however, need not be a manifestation of timely provisioning for future losses, but can be explained by general earnings management practice. In line with this idea, Bushman and Williams (2012) find that income smoothing dampens discipline over risk taking. To investigate whether accounting for expected loan losses also generates income smoothing, we run the following regression (Collins, Shackelford, and Wahlen 1995; Beatty, Chamberlain, and Magliolo 1995):

$$Depvar_{i,t} = \beta_0 + \beta_1 EBP_{i,t} + \beta_2 Controls_{i,t} + \beta_3 FE_{i,t} + \varepsilon_{i,t},$$

where $Depvar$ is either the reported provision, *LLPR*, or the provision for expected losses, *LLPE*. *EBP* is earnings before provision scaled by lagged total loans. *Controls* include *NCO*, *Size*, *ΔGDP*, *CapR*, and last-period *EBP*. *FE* represents bank fixed effects.

Table 6 reports the estimates from this model. Columns 1 and 2, which do not include any controls, indicate that the coefficient on *EBP* in the case of the expected provision, *LLPE,* is similar to the case of reported losses, *LLPR*. Note that by design, *LLPE* is not subject to earnings management. When we add *NCO* as the control variable in columns 3 and 4, and the other controls in Models 5 and 6, the coefficient on *EBP* which corresponds to LLPE is either similar or greater than the one corresponding to *LLPR*. The evidence suggests that in the absence of earnings management, provisioning for expected loan losses also exhibits an income smoothing property. This result is similar to what one would expect when matching higher revenues with higher expenses. Overall, the evidence is in line with the counter-cyclical behavior of expected loan losses.

6. Bank-year proxy for under-reserving.

While prior research shows that forward-looking provisioning benefits capital markets and improves the stability of the financial sector (Beatty and Liao 2011; Bushman and Williams 2012, 2015; Acharya and Ryan 2016), the models used to measure forward looking provisioning do not answer a number of questions. First, we still do not understand the implications of provisioning for *expected* losses on bank behavior. Under current rules, reported provisions have a limited scope to reflect expected losses (as is also suggested by our analysis in Section 2) and only can speak to the forward-looking nature of provisioning with respect to short run (probable) losses. Furthermore, provisions for incurred losses are likely to differ substantially from the provisions for expected loan losses at a given point in time, and need not be positively correlated. Second, most of the measures are estimated at a bank or even country (region) level, and do not allow us to answer questions related to a specific point in time, e.g., the lack of sufficient provisioning right before the financial crisis.

To address these challenges and evaluate provisioning relative to an expected loss benchmark, we measure the degree of under-reserving for expected loan losses at a given point in time. We use the estimated allowance for expected losses, *ALLE*, as a benchmark against which the adequacy of the reported reserves is measured:

$$UNDERR_{i,t} = ALLE_{i,t} - ALLR_{i,t}.$$

Higher (lower) *UNDERR* indicates a higher (lower) degree of under-reserving, i.e., a less timely reporting of loan losses at a given point in time.

We validate this measure in several ways. First, we investigate whether a bank's future performance and capital is predictable based on the current degree of under-reserving. Second, we examine whether under-provisioning explains the amplitude of the effect of financial crisis on banks' stock prices and lending behavior. Third, we examine whether under-provisioning predicts bank failure.

6.1 Under-reserving and future accounting performance.

We start by showing that our proxy for under-reserving, a timelier indicator for future losses, is a significant predictor of future accounting indicators: reported provisions, net income, and capital ratio. To do this, we run the following regressions:

$$Depvar_{i,t+s} = \beta_0 + \beta_1 UNDERR_{i,t} + \beta_2 Controls_{i,t} + \beta_3 FE_{i,t} + \varepsilon_{i,t},$$

where *Depvar* is either *LLPR*, *NI* (net income), or *CapR* (capital ratio); and *s*=1,2,3. *Controls* are *NCO*, *CapR*, *ΔGDP*, and *Size*. *FE* represents bank fixed effects.

Table 7 reports the results of this analysis. Columns 1-3 show that *UNDERR* is significantly, positively associated with reported loan loss provisions in the following year, and significantly, negatively associated with the following year's net income and capital ratio. Furthermore, columns 4-6 and 7-9 demonstrate that these results persist to years t+2 and t+3, respectively. Overall, as expected, under-reserving banks exhibit predictable changes in future performance and capital ratios under the current reporting practice and hence captures the lack of timeliness in banks' financial reporting.

6.2 Under-reserving and the effect of the financial crisis of 2008.

We expect that financial markets are able to see through a lack of reserves for expected losses. Thus, a valid proxy for under-provisioning should be able to explain a bank's reaction to an *unanticipated* financial sector shock. For example, Bushman and Williams (2012) provide evidence that less forward-looking reporting of loan losses increases the risk of contraction in the bank's assets. We use the 2008 financial crisis as a shock and examine how banks' stock returns and lending behavior change in response to the shock depending on their level of under-reserving:

$$Depvar_{2008} = \beta_0 + \beta_1 UNDERR_{2007} + \beta_2 Controls_{2007} + \varepsilon_{i,t},$$

where $Depvar_{2008}$ is either a buy-and-hold return over the 12-month period from the end of April, 2008 to the end of April, 2009, $Return_{2008}$, or the change in total loans over the year 2008, $\Delta Loans_{2008}$; *Controls* include *ALLR*, *Size*, and *CapR*.

Table 8 reports the results. As expected, when controlling for reported losses, banks with a higher degree of under-reserving at the end of 2007 show significantly lower stock market returns and loan growth during the crisis year.

6.3 Under-reserving and bank failure.

Finally, we investigate whether banks that under-reserve for expected losses exhibit a higher probability of failure in subsequent years. If under-reserving creates expected-loss overhang and distorts banks' risk-taking decisions, one should expect that under-reserved banks are more likely to fail in the future. We test whether under-reserving explains the probability of bank failure in the subsequent three years. Given that bank failures happen primarily at the commercial bank level, we use commercial bank-level data for this test and estimate the following model:

$$Fail\ in\ N\ years_t = \beta_0 + \beta_1 UNDERR_t + \beta_2 Controls_t + \varepsilon_t,$$

where *Fail in N years* equals 1 if a commercial bank fails in the next *N* years, and zero otherwise; $UNDERR$ is our measure of past under-reserving; and *Controls* are *Size*, *ALLR*, and *CapR*.

Table 10 reports the result of these tests. We find that, controlling for the level of reported loan loss reserve, the coefficients on *UNDERR* are all positive and significant at the 1% level for both *N*=3 and 5. That is, current under-reserving is positively associated with the likelihood of bank failure in the next 3 or 5 years.

In sum, our results in this section show that our proxy for under-reserving for expected loan losses behaves as a valid proxy should.

7. The real effects of under-reserving.

In our final section, we take a step towards understanding the real effects of the current reporting practice as compared to expected loan loss provisioning. Can under-provisioning for expected losses explain banks' real investment and financing decisions? Does under-provisioning for expected losses affect banks' risk-shifting behaviors? These are important questions that have yet to be answered. Here, we take the perspective that bank managers understand their banks' expected loan losses, even if they are not required to report them. In a world with agency problems and capital requirements, banks' investment and financing decisions should depend not only on the true losses that banks expect, i.e., on the level of real economic capital, but also on the wedge between expected and reported losses. Indeed, in a world where capital requirements written on accounting numbers aim to control banks' risk-taking behavior, the measurement of loan losses will affect bank decisions (Bertomeu, Mahieux, and Sapra 2018). Therefore, when holding expected losses constant, the under-reporting of these losses should significantly influence banks' decisions and risk-taking behavior. Specifically, when reported capital understates banks' real capital and relaxes banks' capital constraints, banks are incentivized to expand their balance sheets by issuing more loans and levering up.

In the next subsections, we explore the association between under-reserving and the following key decisions: loan growth, leverage, liability growth, and dividend payouts. Then we directly test whether under-reserving is followed by increased risk-shifting, i.e. an increased market beta of banks.

7.1. Under-reserving and banks' investment and financing decisions.

First, we examine the prediction that for a given amount of a bank's expected loan losses, the degree of under-reserving for such losses is positively associated with increased loan growth, the growth of leverage and liabilities, and dividend payments in the subsequent year. To accomplish this, we run the following regression:

$$Depvar_t = \beta_0 + \beta_1 UNDERR_{t-1} + \beta_2 ALLE_{t-1} + \beta_3 OtherControls + \beta_4 FE_i + \varepsilon_t,$$

where *Depvar* is *ΔLoan*, *ΔLeverage*, *ΔLiability*, or *Dividends* measured over year *t*; *OtherControls* are ΔGDP_t, $CapR_{t-1}$, and $Size_{t-1}$; *FE* is bank fixed effects.

Table 10 reports the results of this analysis. The coefficients on the proxy for expected losses, *ALLE*, are negative for *ΔLoan*, *ΔLiability*, and *Dividends*, which is in line with the expectation that higher expected losses should lead to more conservative lending policies. We find, however, that under-reserving measured at the end of the previous year has a significantly positive association with loan growth, leverage and liability growth, and dividend payout decisions. By design, *UNDERR*'s positive contribution to balance sheet expansion cannot be attributed to higher expected losses and appears to come from the 'slack' in the bank's capital which is introduced by the current incurred loss-based approach.

7.2 Under-reserving and banks' market beta.

Finally, we investigate whether, holding the level of real capital (expected losses) constant, under-reserving predicts banks' future market beta, and hence banks' cost of capital. If under-reserving banks make more aggressive decisions because of the 'slack' in their reported capital, as our analysis suggests, then these banks will be riskier than similar banks that do not under-reserve. Therefore, we test whether under-reserving banks exhibit higher market betas in the subsequent years. To test this prediction, we sort banks into quintiles based on current-year *UNDERR* and examine market betas across the quintiles estimated over the following three years.

Table 11, Panel A shows that portfolio betas increase monotonically with the level of *UNDERR*; the increase is significant both statistically and economically. Specifically, the portfolio betas of banks with the highest *UNDERR* quintile are 0.04 to 0.10 higher than those with the lowest *UNDERR* quintile; this is significant at the 1%-10% level.

To test the relationship between *UNDERR* and banks' market betas (while controlling for the level of expected losses and other determinants), we run the following regression at the individual bank level:

$$Beta_{t+k} = \beta_0 + \beta_1 UNDERR_t + \beta_2 ALLE_t + \beta_3 OtherControls + \beta_4 FE_i + \varepsilon_t,$$

where $Beta_{t+k}$ is individual banks' market beta in year $t+k$, k=1,2,3; *OtherControls* are $CapR_t$, and $Size_t$; *FE* is bank fixed effects.

Table 11, Panel B reports the results of this analysis. Current year *UNDERR* is significantly, positively associated with betas in years t+2 and t+3, although it is not statistically significant when explaining next year's beta. This is generally consistent with our prediction that under-reserving banks take on more risks, which leads to higher market beta. The insignificant relationship between current year *UNDERR* and next year's beta is likely due to a time lag between banks' increased risk-shifting and the market's response.

In sum, our results in this section are consistent with the measurement of loan-loss provisioning having real effects on banks' behavior.

8. Robustness checks: Out-of-sample tests.

The analysis presented above relies on the model in Equation (6) to estimate expected losses. In our main analysis, the model's coefficients are estimated on the entire sample period, which generates a set of "time-invariant" coefficients, $\hat{\beta}_k$. We make this choice for two related reasons. First, our model requires a sufficiently long time-series of economy-wide, forward-looking indicators to reliably estimate expected losses. Second, having one set of time-invariant coefficients, $\hat{\beta}_k$, reduces the risk of over-fitting the model (for example, compared to a case where a time-varying version, $\hat{\beta}_{t,k}$, is estimated using the most recent 3 or 5 years' data). This is particularly important for our goal of estimating long run expected loan losses.

The downside for using the full sample to estimate $\hat{\beta}_k$ is that it contains information about the future and is potentially subject to a look-ahead bias. To alleviate this concern, we conduct an out-of-sample test. In particular, we use the data from 1991 to 2005 to estimate $\hat{\beta}_k$ coefficients. We then use the pre-estimated model to calculate *ALLE*, *LLPE*, and *UNDERR* for 2006-2017. By doing this, we are able to avoid using future information in estimating the model. Finally, we rerun all the tests in Tables 3-11 for the period of 2006-2017. Despite the much shorter horizon used to estimate $\hat{\beta}_k$, the results in this out-of-sample tests are largely consistent with our main results and are available upon request. To preserve space, we do not tabulate them here. Given that the out-of-sample tests generate similar conclusions, it is unlikely that our results are driven by look-ahead bias. Furthermore, this analysis implies that our model is robust and can be used out of sample.

9. Conclusion.

Loan loss provisioning has been the subject of a long-standing policy debate among academics and regulators. The lack of timely provisioning for loan losses overstates banks' capital and has been argued to have a detrimental effect on the stability of financial sector. Recently, FASB introduced a historic change to the standards for accounting for loan losses by mandating the use of the expected loss approach to provisioning for future loan losses. This approach sharply contrasts with the incurred-loss provisioning (FAS 5) that is currently in place. Despite the importance of timely provisioning to bank regulators and accounting standard setters, the literature has made limited progress in understanding the economic implications of expected loan loss provisioning. We argue that the existing approach to measuring the timeliness (forward-looking nature) of loan loss provisioning under the incurred loss framework is not suitable for understanding the timeliness of expected loan loss provisioning. Given this, and given the unobservable nature of expected losses, a model of expected loan loss provisioning is needed.

We propose, implement, and validate an empirical model of expected loan loss provisioning as a function of concurrent forward-looking information about bank and macro-economic conditions. While our model relies on several strong assumptions, it considerably outperforms the current reporting practice at anticipating future loan losses and also exhibits significant value-relevant information not reflected in the reported numbers. While reported provisions under the incurred loss approach exhibit pro-cyclical behavior, the estimated provisions and allowances for expected loan losses are counter-cyclical.

We also provide and validate a measure of under-provisioning for loan losses in a given bank-year. This measure is a proxy for the untimely reporting of banks' profitability and capital, and is predictably associated with the adverse effect of the financial crisis on under-reserved banks. We use the measure of under-reserving to shed some light on the real effects of loan-loss provisioning relative to expected losses. We find that, holding the amount of expected loan losses constant, slack in reported capital gives banks the incentive and opportunity to expand their balance sheets by issuing loans and increasing leverage, as well as to increase dividend distributions. We further show that under-reserving for expected losses is associated with a higher cost of capital (as measured by market beta) in the subsequent years.

Our study should be of interest to accounting standard setters and bank regulators. It suggests that expected loan losses can be successfully measured in a way that is superior to the current reporting practice. Our evidence suggests that expected loan loss provisioning has important implications for the pro-cyclicality of banks' capital and for banks' investment and financing decisions that ultimately affect their viability.

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Figure 1. Distributions of reported vs. expected allowance and provisions.

ALLR (*ALLE*) is the reported (estimated) allowance of loan losses scaled by lagged total loans. *LLPR* (*LLPE*) is the reported (estimated) provision of loan losses scaled by lagged total loans. The sample covers annual US bank holding companies' observations for the period from 1986 to 2017 that have at least 15 years of available data during the sample period. The top and bottom 1% observations are truncated. Bank fundamentals are obtained from FR Y-9C reports available on the Federal Reserve Bank of Chicago's website.

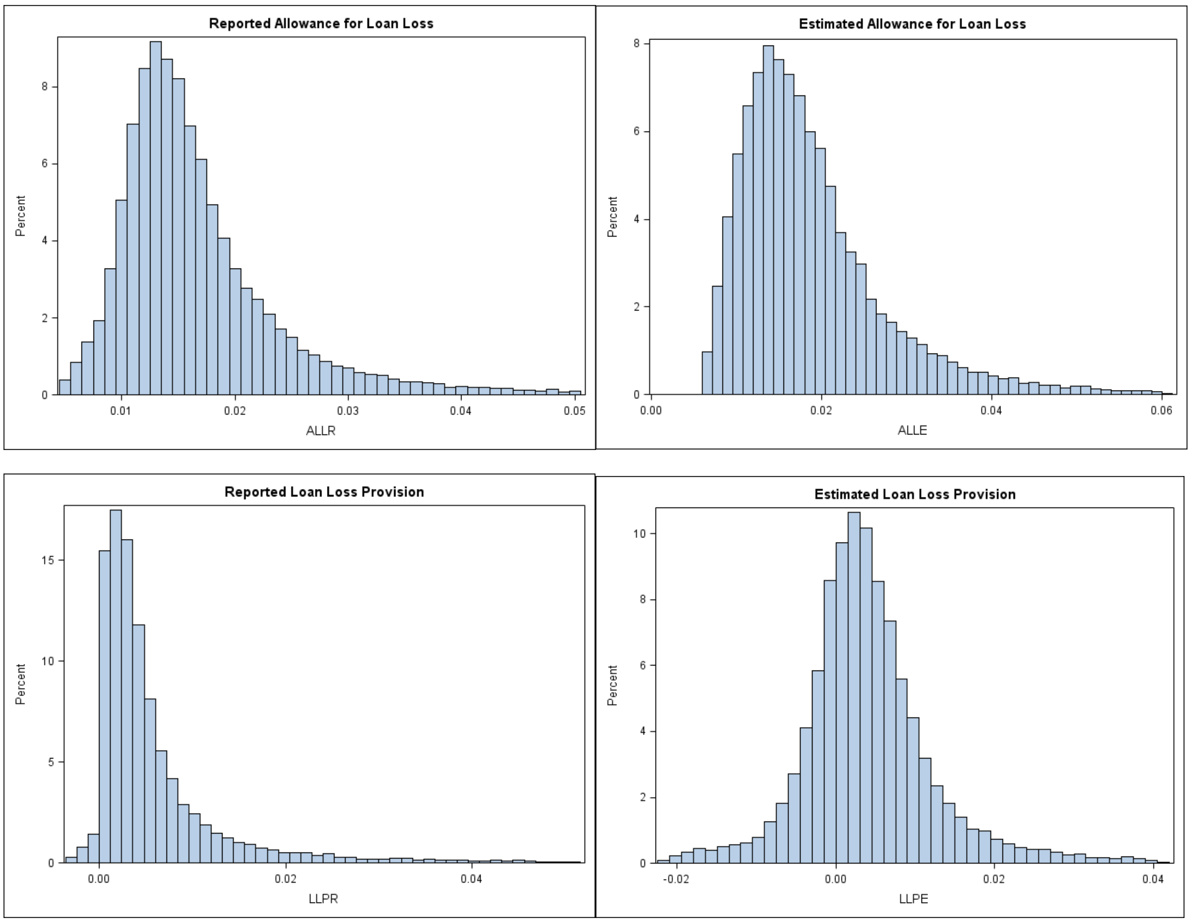

Table 1: Descriptive statistics

This table reports descriptive statistics for the sample. NCO is net charge-offs scaled by lagged total loans. EBP is earnings before provisions (net income plus loan loss provision) scaled by lagged total loans. NI is net income scaled by lagged total loans. $CapR$ is the ratio of total equity to total assets. $\Delta Leverage$ is the absolute change in leverage, where leverage is the ratio of total assets to total equity. $\Delta Loan$ is the percentage change in total loans outstanding. $\Delta Liability$ is the percentage change in total liability outstanding. $ALLR$ is the reported allowance of loan losses scaled by lagged total loans. $LLPR$ is the reported loan loss provision scaled by lagged total loans. NAL is non-accrual loans scaled by lagged total loans. $Loan$ is total loans outstanding (billion USD). $Asset$ is total assets (billion USD). *IntRate* is total interest income scaled by lagged total loans. The sample covers all annual US bank holding companies' observations for the period from 1986 to 2017 that have at least 15 years of available data during the sample period. The top and bottom 1% observations are truncated for all the variables constructed based on banks' financial reports that appear in our regressions. Bank fundamentals are obtained from FR Y-9C reports available on the Federal Reserve Bank of Chicago's website.

	count	mean	sd	p25	p50	p75
NCO	28,208	0.004	0.006	0.001	0.002	0.005
EBP	28,832	0.023	0.011	0.016	0.021	0.027
NI	28,867	0.017	0.012	0.012	0.017	0.023
CapR	31,189	0.089	0.026	0.071	0.086	0.102
ΔLeverage	28,406	-0.111	1.492	-0.759	-0.162	0.462
ΔLoan	28,843	0.097	0.130	0.022	0.081	0.152
ΔLiability	28,366	0.087	0.117	0.018	0.065	0.126
ALLR	28,909	0.016	0.006	0.012	0.015	0.019
LLPR	28,849	0.005	0.007	0.002	0.003	0.006
NAL	27,033	0.011	0.013	0.003	0.006	0.013
Loan	32,131	3.984	36.246	0.135	0.287	0.753
Asset	32,131	7.698	82.866	0.220	0.460	1.148
IntRate	28,313	0.110	0.042	0.078	0.104	0.134

Table 2: Descriptive statistics of the reported vs. estimated variables

This table compares the model-estimated variables with the reported numbers. *ALLR* (*ALLE*) is the reported (estimated) allowance of loan losses scaled by lagged total loans. *LLPR* (*LLPE*) is the reported (estimated) provision of loan losses scaled by lagged total loans. *UNDERR* equals *ALLE* minus *ALLR*. This is our measure of under-reserving; the higher the measure, the more under-reserving the bank. The sample covers annual US bank holding companies' observations for the period from 1986 to 2017 that have at least 15 years of available data during the sample period. The top and bottom 1% observations are truncated. Bank fundamentals are obtained from FR Y-9C reports available on the Federal Reserve Bank of Chicago's website.

	count	mean	sd	p1	p10	p25	p50	p75	p90	p99
ALLR	28909	0.016	0.006	0.006	0.010	0.012	0.015	0.019	0.024	0.040
ALLE	22407	0.019	0.008	0.007	0.010	0.013	0.017	0.022	0.030	0.049
LLPR	28849	0.005	0.007	-0.001	0.001	0.002	0.003	0.006	0.012	0.035
LLPE	19403	0.004	0.008	-0.017	-0.004	-0.000	0.003	0.008	0.013	0.031
UNDERR	22301	0.003	0.010	-0.019	-0.008	-0.003	0.002	0.008	0.015	0.031

Table 3. Predictive power of the reported vs. estimated allowance

This table reports the estimates from the OLS regressions of cumulative future charge-offs on the reported and estimated allowances for the period from 1986 to 2017. The sample covers all US bank holding companies that have at least 15 years of available data during the sample period. The top and bottom 1% observations are truncated for the dependent and independent variables. *Future losses* is the sum of net charge-offs in the next three years scaled by lagged total loans. *ALLR* (*ALLE*) is the reported (estimated) allowance of loan losses scaled by lagged total loans. *NCO* is net charge-offs scaled by lagged total loans. Bank fundamentals are obtained from FR Y-9C reports available on the Federal Reserve Bank of Chicago's website. Standard errors are clustered by bank. Robust *t*-statistics are in parentheses. ***, **, * indicate statistical significance at less than 1, 5, and 10%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Future losses	Future losses	Future losses	Future losses	Future losses	Future losses
ALLR	0.493***		0.351***	0.167***		0.189***
	(11.23)		(9.219)	(4.570)		(5.309)
ALLE		0.934***	0.912***		0.808***	0.810***
		(38.51)	(38.55)		(32.52)	(32.70)
NCO				1.143***	0.700***	0.623***
				(24.18)	(13.56)	(11.81)
Observations	16,127	16,127	16,127	16,127	16,127	16,127
R-squared	0.030	0.268	0.283	0.131	0.306	0.309
Clustering Level	Bank	Bank	Bank	Bank	Bank	Bank

Table 4. Value relevance of the reported vs. estimated allowances and provisions for loan losses

This table reports the average Fama and MacBeth (1973) regression estimates from cross-sectional regressions of prices and returns on the reported and estimated allowances and provision. The regressions are estimated annually using data from 1986 to 2017. The sample covers all listed US bank holding companies that have at least 15 years of available data during the sample period. The top and bottom 1% observations are truncated for the dependent and independent variables. *Price* is the closing price at the end of April of the next year and is scaled by loan per share. Loan per share is the lagged total loans divided by the number of shares for the month in which the stock price is measured. *Ret* is the buy-and-hold return over the period from the end of April of the current year to the end of April of the next year. *ALLR* (*ALLE*) is the reported (estimated) allowance of loan losses scaled by lagged total loans. *LLPR* (*LLPE*) is the reported (estimated) provision of loan losses scaled by lagged total loans. *CapR* is the ratio of total equity to total assets. *NI* is net income scaled by lagged total loans. *Size* is the natural log of total assets. Bank fundamentals are obtained from FR Y-9C reports available on the Federal Reserve Bank of Chicago's website. Monthly stock returns for listed bank holding corporations are obtained from the Center for Research in Security Prices (CRSP). Standard errors are based on the Fama-MacBeth procedure; *t*-statistics are in parentheses. ***, **, * indicate statistical significance at less than 1, 5, and 10%, respectively.

VARIABLES	(1) Price	(2) Price	(3) Ret	(4) Ret
ALLR	1.012			
	(1.310)			
ALLE		-1.667***		
		(-3.691)		
LLPR			-2.651*	
			(-2.008)	
LLPE				-1.324**
				(-2.587)
CapR	2.124***	2.063***		
	(13.05)	(12.41)		
NI			1.996***	2.366***
			(3.001)	(2.918)
Size	0.0256***	0.0274***	-0.00169	-0.00241
	(12.61)	(12.76)	(-0.239)	(-0.343)
Observations	5,866	5,866	5,457	5,457
R-squared	0.223	0.235	0.098	0.091
Number of groups	27	27	27	27

Table 5. Pro-cyclicality of the reported vs. estimated allowances and provisions for loan losses

This table reports the estimates from the OLS regressions of the reported and estimated allowances and provisions on GDP growth and loan growth for the period from 1986 to 2017. The sample covers all US bank holding companies that have at least 15 years of available data during the sample period. The top and bottom 1% observations are truncated for the dependent and independent variables (except the macroeconomic variables). *ALLR* (*ALLE*) is the reported (estimated) allowance of loan losses scaled by lagged total loans. *LLPR* (*LLPE*) is the reported (estimated) provision of loan losses scaled by lagged total loans. *ΔGDP* is the real GDP growth rate. *ΔLoan* is the percentage change in total loans outstanding. *Size* is the natural log of total assets. Bank fundamentals are obtained from FR Y-9C reports available on the Federal Reserve Bank of Chicago's website. Standard errors are clustered by bank. Robust *t*-statistics are in parentheses. ***, **, * indicate statistical significance at less than 1, 5, and 10%, respectively.

Panel A: Response to GDP growth

VARIABLES	(1) ALLR	(2) ALLE	(3) LLPR	(4) LLPE
ΔGDP	-0.0325***	0.0464***	-0.104***	0.116***
	(-14.54)	(12.20)	(-29.00)	(25.19)
Size	-0.000741***	0.00352***	-0.000607***	0.00244***
	(-5.491)	(24.22)	(-6.578)	(21.43)
Constant	0.0271***	-0.0309***	0.0176***	-0.0346***
	(14.93)	(-15.67)	(13.74)	(-21.58)
Observations	22,278	22,278	19,306	19,306
R-squared	0.507	0.302	0.390	0.162
Bank Fixed Effect	YES	YES	YES	YES
Clustering Level	Bank	Bank	Bank	Bank

Panel B: Response to loan growth

VARIABLES	(1) ALLR	(2) ALLE	(3) LLPR	(4) LLPE
ΔLoan	-0.00105**	0.0227***	-0.00880***	0.0233***
	(-2.097)	(33.98)	(-17.69)	(31.69)
Size	-0.000474***	0.00365***	0.000146	0.00189***
	(-3.482)	(24.21)	(1.581)	(15.10)
Constant	0.0220***	-0.0326***	0.00326***	-0.0239***
	(12.06)	(-16.04)	(2.611)	(-14.01)
Observations	22,278	22,278	19,306	19,306
R-squared	0.499	0.377	0.315	0.200
Bank Fixed Effect	YES	YES	YES	YES
Clustering Level	Bank	Bank	Bank	Bank

Table 6. Income smoothing of the reported vs. estimated provisions for loan losses

This table reports the estimates from the OLS regressions of the reported and estimated provision on earnings before provisions for the period from 1986 to 2017. The sample covers all US bank holding companies that have at least 15 years of available data during the sample period. The top and bottom 1% observations are truncated for the dependent and independent variables (except the macroeconomic variables). *LLPR* (*LLPE*) is the reported (estimated) provision of loan losses scaled by lagged total loans. *EBP* is earnings before provision (net income plus loan loss provision) scaled by lagged total loans. *NCO* is net charge-offs scaled by lagged total loans. *Size* is the natural log of total assets. *ΔGDP* is the real GDP growth rate. *CapR* is the ratio of total equity to total assets. Bank fundamentals are obtained from FR Y-9C reports available on the Federal Reserve Bank of Chicago's website. Standard errors are clustered by bank. Robust *t*-statistics are in parentheses. ***, **, * indicate statistical significance at less than 1, 5, and 10%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	LLPR	LLPE	LLPR	LLPE	LLPR	LLPE
EBP	0.0539***	0.0528***	0.0700***	0.0648***	0.0946***	0.149***
	(4.530)	(4.275)	(11.43)	(5.929)	(11.77)	(8.780)
NCO			0.954***	0.709***	0.893***	0.980***
			(90.81)	(31.11)	(84.54)	(44.99)
Size					-0.000105**	0.00255***
					(-2.139)	(26.07)
ΔGDP					-0.0361***	0.196***
					(-20.47)	(50.65)
CapR					-0.0292***	0.0103***
					(-14.24)	(2.591)
EBP_{t-1}					-0.00836	-0.185***
					(-1.220)	(-10.94)
Constant	0.00317***	0.00274***	-0.000451***	4.99e-05	0.00520***	-0.0434***
	(11.92)	(9.914)	(-3.233)	(0.195)	(7.491)	(-31.32)
Observations	19,207	19,207	19,207	19,207	19,024	19,024
R-squared	0.281	0.102	0.768	0.204	0.787	0.344
Bank Fixed Effect	YES	YES	YES	YES	YES	YES
Clustering Level	Bank	Bank	Bank	Bank	Bank	Bank

Table 7. Predictive power of under-reserving

This table reports the estimates from the OLS regressions of banks' future performance on the level of under-reserving for the period from 1986 to 2017. The sample covers all US bank holding companies that have at least 15 years of available data during the sample period. The top and bottom 1% observations are truncated for the dependent and independent variables (except the macroeconomic variables). *LLPR* is the reported provision of loan losses scaled by lagged total loans. *NI* is net income scaled by lagged total loans. *CapR* is the ratio of total equity to total assets. *UNDERR* is *ALLE* minus *ALLR*, where *ALLR* (*ALLE*) is the reported (estimated) allowance of loan losses scaled by lagged total loans. *NCO* is net charge-offs scaled by lagged total loans. *ΔGDP* is the real GDP growth rate. *Size* is the natural log of total assets. Bank fundamentals are obtained from FR Y-9C reports available on the Federal Reserve Bank of Chicago's website. Standard errors are clustered by bank. Robust *t*-statistics are in parentheses. ***, **, * indicate statistical significance at less than 1, 5, and 10%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
VARIABLES	$LLPR_{t+1}$	NI_{t+1}	$CapR_{t+1}$	$LLPR_{t+2}$	NI_{t+2}	$CapR_{t+2}$	$LLPR_{t+3}$	NI_{t+3}	$CapR_{t+3}$
$UNDERR_t$	0.191***	-0.273***	-0.105***	0.268***	-0.306***	-0.153***	0.233***	-0.253***	-0.128***
	(24.71)	(-24.28)	(-9.708)	(28.54)	(-22.83)	(-8.809)	(27.04)	(-18.82)	(-6.216)
NCO_t	0.283***	-0.364***	0.0941***	-0.0529***	-0.0329	0.184***	-0.238***	0.142***	0.247***
	(17.07)	(-14.73)	(3.945)	(-2.923)	(-1.217)	(4.836)	(-13.66)	(5.152)	(5.303)
$CapR_t$	-0.0145***	0.0519***	0.761***	-0.0158***	0.0235***	0.544***	-0.0152***	0.00998	0.365***
	(-4.193)	(7.023)	(85.64)	(-3.529)	(2.730)	(38.74)	(-3.184)	(1.064)	(20.38)
ΔGDP_t	-0.0878***	0.0792***	-0.00213	-0.0568***	0.0436***	-0.0196***	0.00313	-0.0171***	-0.0159*
	(-25.61)	(17.28)	(-0.481)	(-16.91)	(8.758)	(-2.768)	(0.985)	(-3.552)	(-1.865)
$Size_t$	-0.000909***	-0.00236***	0.00215***	-0.000230**	-0.00347***	0.00356***	0.000931***	-0.00473***	0.00475***
	(-10.38)	(-11.75)	(10.88)	(-2.024)	(-15.00)	(10.41)	(7.154)	(-17.67)	(10.43)
Constant	0.0208***	0.0430***	-0.00646***	0.0113***	0.0609***	-0.00485	-0.00649***	0.0810***	-0.00471
	(17.35)	(16.01)	(-2.599)	(7.529)	(19.91)	(-1.074)	(-3.711)	(22.74)	(-0.772)
Observations	19,795	19,795	19,795	17,932	17,932	17,932	16,275	16,275	16,275
R-squared	0.450	0.627	0.878	0.395	0.592	0.803	0.380	0.579	0.756
Bank Fixed Effect	YES	YES	YES	YES	YES	YES	YES	YES	YES
Clustering Level	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank

Table 8. Under-reserving banks' performance during the financial crisis of 2008

This table reports the estimates from the OLS regressions of bank returns and loan growth in 2008 on the level of under-reserving in 2007. The sample covers all listed US bank holding companies that have at least 15 years of available data during the full sample period of 1986-2017. The top and bottom 1% observations are truncated for the dependent and independent variables. $Return_{2008}$ is the buy-and-hold return over the period from the end of April in 2008 to the end of April in 2009. $\Delta Loan$ is the percentage change in total loans outstanding. $UNDERR_{2007}$ is $ALLE_{2007}$ minus $ALLR_{2007}$, where $ALLR_{2007}$ ($ALLE_{2007}$) is the reported (estimated) allowance of loan losses at the end of 2007 scaled by total loans at the end of 2007. $Size_{2007}$ is the natural log of total assets at the end of 2007. $CapR_{2007}$ is the ratio of total equity to total assets at the end of 2007. Bank fundamentals are obtained from FR Y-9C reports available on the Federal Reserve Bank of Chicago's website. Monthly stock returns for listed bank holding corporations are obtained from the Center for Research in Security Prices (CRSP). *T*-statistics are in parentheses. ***, **, * indicate statistical significance at less than 1, 5, and 10%, respectively.

	(1)	(2)
VARIABLES	$Return_{2008}$	$\Delta Loan_{2008}$
$UNDERR_{2007}$	-9.248***	-1.444**
	(-3.672)	(-2.485)
$Size_{2007}$	0.00285	0.00277
	(0.183)	(0.673)
$CapR_{2007}$	1.140	0.138
	(1.327)	(0.766)
$ALLR_{2007}$	-24.71***	-5.183***
	(-5.447)	(-4.756)
Constant	0.0146	0.130**
	(0.0632)	(2.174)
Observations	246	681
R-squared	0.136	0.034

Table 9. Probability of failure for under-reserving banks

This table reports the estimates from the probit regressions of future bank failures (in 3 or 5 years) on previous levels of under-reserving for the period from 1986 to 2017 at the commercial bank level. *Fail in n years* equals 1 if a commercial bank fails in the next *n* years of a given year, 0 otherwise. *UNDERR* is *ALLE* minus *ALLR*, where *ALLR* (*ALLE*) is the reported (estimated) allowance of loan losses scaled by lagged total loans. Commercial bank level *ALLE* is estimated in the same way as the bank holding company level one, except for removing *NAL* and *Pastdue90* from the estimation model due to data limitation. *Size* is the natural log of total assets. *CapR* is the ratio of total equity to total assets. Commercial bank fundamentals are obtained from Call Reports available on the Federal Reserve Bank of Chicago's website. Commercial bank failure data comes from the Federal Deposit Insurance Corporation (FDIC) website. Standard errors are clustered by bank. Robust *t*-statistics are in parentheses. ***, **, * indicate statistical significance at less than 1, 5, and 10%, respectively.

VARIABLES	(3) Fail in 3 years	(4) Fail in 5 years
$UNDERR_t$	16.75***	18.65***
	(12.79)	(15.12)
$Size_t$	0.161***	0.169***
	(11.67)	(12.20)
$ALLR_t$	31.16***	25.73***
	(17.79)	(15.58)
$CapR_t$	-4.596***	-2.377***
	(-5.678)	(-3.943)
Observations	226,612	226,612
Clustering Level	Bank	Bank

Table 10. Real effects of the current provisioning rule: Under-reserving distorts bank decisions

This table reports the estimates from the OLS regressions of the changes in loan, leverage, liability, and the level of dividend on the level of under-reserving for the period from 1986 to 2017. The sample covers all US bank holding companies that have at least 15 years of available data during the sample period. The top and bottom 1% observations are truncated for the dependent and independent variables (except the macroeconomic variables). *ΔLoan* is the percentage change in total loans outstanding. *ΔLeverage* is the absolute change in leverage and *leverage* is the ratio of total assets to total equity. *Δliability* is the percentage change in total bank liabilities. *Dividend* is cash dividends declared on common stock scaled by lagged total loans. *UNDERR* is *ALLE* minus *ALLR*, where *ALLR* (*ALLE*) is the reported (estimated) allowance of loan losses scaled by lagged total loans. *ΔGDP* is the real GDP growth rate. *CapR* is the ratio of total equity to total assets. *Size* is the natural log of total assets. Bank fundamentals are obtained from FR Y-9C reports available on the Federal Reserve Bank of Chicago's website. Standard errors are clustered by bank. Robust *t*-statistics are in parentheses. ***, **, * indicate statistical significance at less than 1, 5, and 10%, respectively.

	(1)	(2)	(3)	(4)
VARIABLES	$\Delta Loan_t$	$\Delta Leverage_t$	$\Delta Liability_t$	$Dividend_t$
$UNDERR_{t-1}$	3.198***	14.13***	2.786***	0.115***
	(9.688)	(3.722)	(10.80)	(7.848)
ΔGDP_t	1.258***	4.121***	0.472***	0.0242***
	(21.19)	(5.556)	(8.541)	(11.33)
$CapR_{t-1}$	0.641***	31.46***	1.195***	0.0511***
	(7.197)	(26.87)	(14.70)	(10.80)
$Size_{t-1}$	-0.0371***	-0.201***	-0.0512***	0.000541***
	(-12.90)	(-7.707)	(-19.46)	(4.654)
$ALLE_{t-1}$	-3.726***	4.729	-2.158***	-0.137***
	(-10.30)	(1.105)	(-7.648)	(-9.147)
Constant	0.538***	-0.543	0.678***	-0.00498***
	(14.00)	(-1.586)	(19.58)	(-3.147)
Observations	19,905	19,916	19,857	19,918
R-squared	0.276	0.191	0.277	0.635
Bank Fixed Effect	YES	YES	YES	YES
Clustering Level	Bank	Bank	Bank	Bank

Table 11. Under-reserving banks' future market beta

Panel A: Descriptive statistics of portfolio-specific market betas

This table reports the time series average of market betas of portfolios formed based on the *UNDERR* quintile. *UNDERR* is *ALLE* minus *ALLR*, where *ALLR* (*ALLE*) is the reported (estimated) allowance of loan losses scaled by lagged total loans. Portfolios are formed annually by assigning banks into quintiles based on the level of *UNDERR*. Portfolio beta of portfolio x in year $t+n$ is the average of the $Beta_{t+n}$ of all banks whose *UNDERR* are in the x^{th} quintile in year t. Larger x corresponds to higher *UNDERR*. $Beta_t$ is market beta of individual banks calculated using the daily stock returns of individual banks and the value-weighted market returns in the 250 trading days leading to the last trading day in April of year $t+1$. The sample covers all listed US bank holding companies for the period from 1986 to 2017 that have at least 15 years of available data. Bank fundamentals are obtained from FR Y-9C reports available on the Federal Reserve Bank of Chicago's website. Daily stock returns for listed bank holding corporations and the value-weighted market returns are obtained from the Center for Research in Security Prices (CRSP). The Newey-West *t*-statistics are in parentheses. ***, **, * indicate statistical significance at less than 1, 5, and 10%, respectively.

	UNDERR quintile	Low	2	3	4	High	H-L
Year of portfolio beta							
t+1		0.58	0.62	0.63	0.66	0.68	0.10***
		(5.62)	(5.51)	(5.41)	(5.37)	(6.10)	(3.51)
t+2		0.61	0.65	0.67	0.67	0.68	0.07***
		(5.69)	(5.63)	(6.22)	(5.67)	(6.61)	(2.89)
t+3		0.64	0.68	0.68	0.71	0.68	0.04*
		(6.62)	(5.91)	(5.75)	(6.65)	(6.56)	(1.99)

Panel B. Predictive power of under-reserving and future market beta

This table reports the estimates from the OLS regressions of banks' future market beta on the level of under-reserving for the period from 1986 to 2017. The sample covers all listed US bank holding companies that have at least 15 years of available data during the sample period. The top and bottom 1% observations are truncated for the independent variables. $Beta_{t+n}$ is market beta of individual banks calculated using the daily stock returns of individual banks and the value-weighted market returns in the 250 trading days leading to the last trading day in April of year $t+n+1$, $n=1,2,3$. *UNDERR* is *ALLE* minus *ALLR*, where *ALLR* (*ALLE*) is the reported (estimated) allowance of loan losses scaled by lagged total loans. *CapR* is the ratio of total equity to total assets. *Size* is the natural log of total assets. Bank fundamentals are obtained from FR Y-9C reports available on the Federal Reserve Bank of Chicago's website. Daily stock returns for listed bank holding corporations and the value-weighted market returns are obtained from the Center for Research in Security Prices (CRSP). Standard errors are clustered by bank. Robust *t*-statistics are in parentheses. ***, **, * indicate statistical significance at less than 1, 5, and 10%, respectively.

	(4)	(5)	(6)
VARIABLES	$Beta_{t+1}$	$Beta_{t+2}$	$Beta_{t+3}$
$UNDERR_t$	0.464	5.842***	9.107***
	(0.248)	(2.908)	(4.458)
$CapR_t$	1.508**	0.873	-0.290
	(2.472)	(1.352)	(-0.434)
$Size_t$	0.447***	0.454***	0.461***
	(22.51)	(21.09)	(20.43)
$ALLE_t$	4.221**	-2.480	-8.105***
	(2.067)	(-1.182)	(-3.718)
Constant	-6.048***	-5.932***	-5.788***
	(-22.47)	(-20.33)	(-18.83)
Observations	5,422	5,098	4,743
R-squared	0.633	0.630	0.640
Bank Fixed Effect	YES	YES	YES
Clustering Level	Bank	Bank	Bank

Appendix

Table A1: Regressions that predict loan default probability

This table reports the results of regression (5) that predicts default probability in the next five years. The regressions are separately conducted on the smallest 67% banks and largest 33% banks, sorted by assets each year. The sample covers all US bank holding companies that have at least 15 years of available data during the sample period of 1986-2017. The top and bottom 1% observations of the dependent and independent variables (except the macroeconomic variables) are truncated. The dependent variables are the default probability in the next five years $p_{t+1} \sim p_{t+5}$, where p is net charge-offs scaled by lagged total loans. NAL is non-accrual loans scaled by lagged total loans. *Pastdue90* is loans past due over 90 days scaled by lagged total loans. *ΔLoan* is the percentage change in total loans outstanding. $Unemployment$ is the unemployment rate in the US. *ΔUnemployment* is the annual change in the unemployment rate. $IntRate$ is total interest income scaled by lagged total loans. *ΔIntRate* is the change in interest rate. *ΔGDP* is the real GDP growth rate. $CSRet$ is the return of the Case-Shiller Home Price Index. Bank fundamentals are obtained from FR Y-9C reports available on the Federal Reserve Bank of Chicago's website. Standard errors are clustered by bank. Robust *t*-statistics are in parentheses, and significance is indicated by: $*** <$ 0.01, $** < 0.05$, $* < 0.10$.

Panel A: Smallest 67% firms

	(1)	(2)	(3)	(4)	(5)
	p_{t+1}	p_{t+2}	p_{t+3}	p_{t+4}	p_{t+5}
$Constant_t$	-5.243***	-4.737***	-4.086***	-3.940***	-4.547***
	(-48.98)	(-42.84)	(-31.05)	(-24.15)	(-25.88)
NAL_t	12.71***	10.10***	8.767***	8.821***	7.855*
	(12.07)	(8.31)	(5.46)	(4.00)	(2.55)
$Pastdue90_t$	22.24***	21.35***	23.63***	16.59**	14.43*
	(5.98)	(6.07)	(5.26)	(2.73)	(2.05)
$\Delta Loan_t$	0.0627	0.668***	1.121***	1.728***	1.796***
	(0.41)	(4.64)	(7.08)	(11.11)	(9.27)
$Unemployment_t$	-0.0896***	-0.163***	-0.263***	-0.263***	-0.164***
	(-7.90)	(-13.13)	(-18.39)	(-14.54)	(-8.26)
$\Delta Unemployment_t$	0.129***	0.259***	0.363***	0.329***	0.389***
	(3.56)	(6.38)	(9.07)	(7.26)	(8.60)
$\Delta IntRate_t$	-2.581*	3.200*	7.040***	11.57***	11.04***
	(-2.39)	(2.40)	(4.31)	(6.58)	(5.98)
$IntRate_t$	-1.165	-4.443***	-10.03***	-16.63***	-18.73***
	(-1.78)	(-6.15)	(-11.61)	(-16.30)	(-15.93)
p_t	42.18***	39.33***	34.98***	32.25***	25.92***
	(12.04)	(10.18)	(7.73)	(5.10)	(3.57)
Δp_t	-5.063	-5.285	-9.533*	-4.077	-7.405
	(-1.61)	(-1.36)	(-2.23)	(-0.74)	(-1.30)
ΔGDP_t	1.158	8.838***	20.41***	30.43***	33.05***
	(0.52)	(3.85)	(8.97)	(13.22)	(13.61)
$CSRet_t$	-4.971***	-6.321***	-6.756***	-4.861***	-0.836
	(-20.27)	(-26.53)	(-25.00)	(-14.79)	(-1.96)
Observations	15495	13151	11225	9674	8448
adj. R-squared	0.601	0.509	0.448	0.424	0.432

Panel B: Largest 33% firms

	(1)	(2)	(3)	(4)	(5)
	p_{t+1}	p_{t+2}	p_{t+3}	p_{t+4}	p_{t+5}
Constant_t	-5.063^{***}	-3.948^{***}	-3.674^{***}	-3.880^{***}	-6.746^{***}
	(-40.96)	(-28.94)	(-18.76)	(-18.42)	(-23.13)
NAL_t	8.474^{***}	6.551^{***}	-0.0111	2.267	-6.956
	(5.28)	(4.73)	(-0.00)	(0.67)	(-1.63)
Pastdue90_t	21.96^{***}	31.61^{***}	24.14^{**}	7.458	-0.545
	(4.82)	(7.27)	(2.87)	(0.84)	(-0.05)
ΔLoan_t	0.0521	0.305^{**}	0.812^{***}	1.110^{***}	1.086^{***}
	(0.43)	(2.60)	(5.99)	(8.54)	(6.81)
Unemployment_t	-0.127^{***}	-0.269^{***}	-0.328^{***}	-0.237^{***}	0.0720^{**}
	(-8.93)	(-15.46)	(-13.28)	(-11.63)	(2.64)
$\Delta\text{Unemployment}_t$	0.161^{***}	0.160^{***}	0.116^{*}	0.186^{***}	0.294^{***}
	(4.39)	(3.64)	(2.03)	(3.61)	(5.85)
$\Delta\text{IntRate}_t$	-2.426^{*}	1.841	4.104^{**}	11.21^{***}	7.414^{***}
	(-2.24)	(1.85)	(2.74)	(7.37)	(5.48)
IntRate_t	0.291	-3.093^{**}	-8.019^{***}	-17.20^{***}	-10.59^{***}
	(0.41)	(-3.17)	(-5.86)	(-13.71)	(-6.49)
p_t	51.53^{***}	53.48^{***}	52.26^{***}	45.29^{***}	51.55^{***}
	(14.03)	(15.24)	(8.59)	(5.04)	(5.87)
Δp_t	-10.11^{**}	-16.78^{***}	-17.45^{**}	-14.09^{*}	-11.16
	(-2.92)	(-4.66)	(-2.81)	(-2.32)	(-1.82)
ΔGDP_t	2.482	4.017	17.30^{***}	28.98^{***}	30.57^{***}
	(1.25)	(1.65)	(5.72)	(10.52)	(11.98)
CSRet_t	-5.886^{***}	-6.794^{***}	-7.861^{***}	-4.014^{***}	4.501^{***}
	(-23.05)	(-23.20)	(-22.60)	(-11.06)	(6.70)
Observations	9153	8473	7802	7130	6575
adj. R-squared	0.695	0.602	0.499	0.457	0.481