Asymmetric Loan Loss Provisioning

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Abstract

Banks' loan loss provisions have a V-shaped relation with changes in nonperforming loans, i.e., nonperforming loan *decreases* are associated with loan loss provision increases. Loan charge-offs contribute to this asymmetry, and modeling this contribution can change inferences about the presence of earnings management and the effects of delayed loan loss recognition in prior papers that assume linearity. Loan loss provision asymmetry is greater for banks with more heterogeneous loans, during economic downturns and in the fourth quarter, and for public banks, consistent both with loan loss impairment standards varying across loan types and with litigation incentives for conditional conservatism.

Keywords: loan collectibility, misspecification, delayed loan loss recognition, conditional conservatism

JEL Codes: G21, G28, M41, M48

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1. Introduction

Banks reserve for future losses when reporting their loan portfolio values. End-of-period adjustments to the loan loss allowance (a contra-asset) are made through a loan loss provision, like how nonfinancial firms adjust bad debt expense at period end to reflect unexpected changes in accounts receivable collectibility. Since the loan loss provision typically is a large expense (averaging more than a quarter of a bank's net income) and involves much managerial judgment, researchers have studied banks' loan loss provisions intensely. The typical approach (cf. Beatty and Liao 2014) models loan loss provision as an increasing *linear* function of observable credit risk indicators such as nonperforming loan changes and calls the residuals "discretionary." Empirically, we find a piecewise linear relation between loan loss provisions and nonperforming loan changes, explore why this *asymmetry* arises, and propose simple ways to reduce predictable biases in estimated "normal" loan loss provisions and loan loss recognition delays.

Figure 1 plots mean quarterly loan loss provisions against mean quarterly nonperforming loan changes (both deflated by beginning loans) in 20 equal-frequency bins (sorted on the X-axis) for all U.S. bank holding companies during 2000Q1–2018Q4. Loan loss provisions have a V-shaped relation (blue) with nonperforming loan changes that differs markedly from the OLS line (red), whose misspecification causes wide 95% confidence intervals. Consistent with the typical model, loan loss provisions increase almost linearly with increases in nonperforming loans. However, when nonperforming loans decrease, the relation slopes *down* instead of up. Piecewise linear regressions show that the slope coefficient for loan loss provision on nonperforming loan increases (decreases) is reliably positive (negative). Importantly, the 95% confidence interval for the OLS line does not overlap with much of the data at the tails and in the middle of the distribution, leading to predictable over- or under-estimation in standard models.

The negative slope for nonperforming loan decrease seems at odds with bank supervisory guidance that the loan loss provision be "directionally consistent with changes in the factors, taken as a whole, that evidence credit losses" (Interagency Policy Statement *on the Allowance for Loan and Lease Losses,* December 2006). If nonperforming loan decreases reflect better loan quality, as assumed implicitly in standard models, then loan loss provisions should decrease.

We argue that loan charge-offs (net of recoveries) are a major source of the V-shaped relation. Loan loss provisions are accrual adjustments for future loan charge-offs, and actual charge-offs reduce both nonperforming loans and loan loss allowances. Large decreases in nonperforming loans likely capture large net loan charge-offs rather than loan portfolio quality improvements. If large charge-offs reflect a decrease in loan portfolio quality, then managers must reserve more for additional loan losses, causing the downward sloping portion of Figure 1. This logic likely applies to bad debts, sales returns and warranties that use similar allowances.

We explore a few ways to better model loan loss provisions. First, we sum net loan charge-offs and nonperforming loan change to measure loan performance. Second, we include net charge-offs separately as a linear variable and nonperforming loan change as a piecewise linear variable, unlike our first approach that forces equal piecewise linear coefficients on these two variables. Both approaches reduce loan loss provision asymmetry. Under the second approach, loan loss provisions fall when nonperforming loans fall, suggesting that a large portion of the asymmetry in loan loss provisions arises from a confounding effect of net charge-offs.

Next, we assess the potential bias in estimated discretionary loan loss provisions in the earnings management context. Residual plots and simulations indicate that not modeling loan loss provision asymmetry and charge-offs results in over-rejections in favor of positive (negative) discretionary loan loss provisions in samples with extreme (moderate) nonperforming loan change.

We also examine the implications of omitting asymmetry for measuring delayed loan loss recognition—the additional explanatory power (i.e., incremental adjusted R^2) associated with the lead and current changes in nonperforming loans (e.g. Beatty and Liao 2011). Correlations between the incremental R^2s from linear models and our parallel piecewise linear models are as low as 53%, suggesting large measurement errors. We replicate parts of Beatty and Liao (2011) and Bushman and Williams (2015), which show that banks that delay loan loss recognition less suffer less capital crunch (i.e., lower sensitivity of lending growth to capital adequacy) and less downside tail risk during recessions. We find that these results weaken and even flip signs once we control for piecewise linearity and/or net charge-offs in first-stage loan loss provision models.

Even after better modeling net charge-offs, loan loss provisions go up more when nonperforming loans rise than they fall when nonperforming loans fall. Since banks report conditionally conservatively (e.g. Lim, Lee, Kausar and Walker 2014; Black, Chen, and Cussatt 2018), we explore conditional conservatism (e.g. Basu 1997; Watts 2003a) as a cause of the residual asymmetry. Because prescribed impairment recognition varies across loan types, nonperforming status means different things for different loan types (Ryan and Keeley 2013). We find that the residual asymmetry is related to the varying speeds of loan impairments for homogenous and heterogeneous loans, reflecting variation in mandatory conservatism (Lawrence, Sloan and Sun 2013). In 1999, the Securities Exchange Commission (SEC) and banking regulators stepped up enforcement of the incurred loss model (e.g., Joint Interagency Letter, July 1999), likely slowing down loan impairments since many banks' practices were closer to an expected loss model (Camfferman 2015). We find no change in asymmetry around this mandatory conservatism change, which suggests that the current expected credit loss (CECL) model, proposed by the Financial Accounting Standards Board (FASB), will not affect our main findings much.

We also explore litigation incentives for conditional conservatism and find that the residual asymmetry is greater in the fourth quarter, for public banks, and during recessions, when assets are impaired and charged off most often (e.g., Basu 1997; Watts 2003a). The residual asymmetry during the 2007–2012 crisis is greater for real estate loans that are impaired more quickly, consistent with mandatory conservatism playing a role. We also show that loan loss provisions are more sensitive to negative stock returns than to positive stock returns, consistent with conditional conservatism being a likely source of the residual asymmetry.

We contribute by showing that the standard loan loss provision models, which do not allow for asymmetry, are misspecified. We extend prior research on the "normal" accrual accounting process (e.g. Jones 1991; Dechow 1994; Dechow and Dichev 2002; Nikolaev 2018), conditional conservatism (e.g., Basu, 1997; Ball and Shivakumar 2006; Byzalov and Basu 2016), and loan loss provision timeliness (e.g., Nichols, Wahlen, and Wieland 2009; Beatty and Liao 2011, 2014; Bushman and Williams 2012, 2015). Our results suggest that researchers should model loan charge-offs and asymmetry when predicting loan loss provisions, which will improve inferences.

2. Institutional Background and Hypothesis Development

U.S. GAAP and bank regulatory guidance codify longstanding reporting practices for bank loan portfolios. As banks issue loans, they estimate potential loan losses and record the amounts in loan loss allowances, which are contra-asset accounts that are netted against loans outstanding on the balance sheet. Under U.S. GAAP, loans are impaired using an "incurred loan loss model," under which allowances are provided for losses that are incurred, probable and reasonably estimable based on management's existing data about the loan portfolio on the balance sheet date.[1]

[1] In June 2016, the FASB issued Accounting Standards Update (ASU) 2016-13, Financial Instruments - Credit Losses (Topic 326): *Measurement of Credit Losses on Financial Instruments*, which replaces the existing incurred loss impairment methodology with a current expected credit loss (CECL) methodology. CECL will be effective in 2020 for SEC registrant banks, and 2023 for SEC registrants that meet the definition of "smaller reporting companies" and

When loans are confirmed to be uncollectible in whole or in part, banks reduce the corresponding loan balances and allowances dollar-for-dollar via charge-offs that do not directly affect net income. The allowance accounts are adjusted with end-of-period loan loss provisions to reflect management's estimates of probable losses.

Theoretically, the allowance for loan losses should be the difference between the present values of the contractual and expected receipts (including those from the disposal of collateral or the exercise of various contingent options such as performance pricing and/or creditor control of the firm under bankruptcy). In a world with complete information, measurement is straightforward. However, introducing risk and uncertainty (Knight 1921), agency problems (Jensen and Meckling 1976), financial contagion (e.g. Allen and Gale 2000; Plantin, Sapra and Shin 2008), income taxes, bank regulations, and other frictions makes estimation difficult and prone to manipulation.

Two U.S. accounting standards govern loan loss accruals. Accounting Standards Code (ASC) 450-20, *Contingencies - Loss Contingencies* (formerly SFAS 5 (FASB 1975)), provides general guidance for loss accruals on (pools of) homogeneous loans and on (individual) unimpaired heterogeneous loans. ASC 310, *Receivables* (formerly SFAS 114 (FASB 1993)), defines impairment for heterogeneous loans and provides specific guidance for credit losses on impaired heterogeneous loans. Longstanding bank regulatory guidance requires that banks use a systematic, consistently applied, and well-documented process for determining loan losses in accordance with GAAP (e.g., Staff Accounting Bulletin No. 102 (SEC 2001); Interagency Policy Statement on the *Allowance for Loan and Lease Losses*, 2006). We analyze the implications of differing accounting rules for different types of loans in Section 6.1.

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for private banks (as proposed by FASB on August 15, 2019, after legislation was introduced in Congress to delay the implementation of CECL until one year after a quantitative impact study is conducted by the SEC; see H.R. 3182– CECL Consumer Impact and Study Bill of 2019). Because the effects of charge-offs and conditional conservatism will persist, we expect an asymmetry to remain. We analyze the possible impact of CECL further in Section 6.2.

We study the sensitivity of loan loss provisions to changes in nonperforming loans for three reasons. First, nonperforming loans are a relatively nondiscretionary credit quality indicator (Liu and Ryan 2006), which fits our goal of modeling the “normal” process of loan loss accruals absent accounting manipulation. Nonperforming loans must be disclosed in banks’ regulatory reports (e.g., Schedule HC-N of bank holding company Y-9C reports) and financial statements filed with the SEC (Industry Guide 3). Second, outstanding loans are classified as nonperforming when they are deemed severely delinquent (usually at 90 days past due), which is usually also when loan losses are deemed probable under FASB’s incurred loan loss approach. Third, the extant loan loss provision models assume a linear relation with nonperforming loan change, which is problematic if researchers ignore the effects of net loan charge-offs on period-end loan loss provisions.

The usual loan loss metrics—loan loss provisions (*LLP*), net loan charge-offs (*NCO*), allowance for loan losses (*ALL*), and nonperforming loans (*NPL*)—are connected by the following (simplified) accounting equations for *ALL* (Credit) and *NPL* (Debit).

$$ALL_t = ALL_{t-1} + LLP_t - NCO_t \tag{1}$$

$$NPL_t = NPL_{t-1} + NetNewNPL_t - NCO_t \tag{2}$$

In equation (1), the ending balance of *ALL* is increased by *LLP* and decreased by *NCO* dollar-for-dollar. *LLP*, which is like bad debt expense, decreases period *t*’s net income directly while *NCO* does not. In equation (2), the nonperforming loan component of total loans outstanding is reduced dollar-for-dollar by net loan charge-offs, assuming that the uncharged-off portions of the loans stay classified as nonperforming.[2] In this simplified scenario, *NCO* has the same dollar amounts in equations (1) and (2), but it is usually a debit in (1) and a corresponding credit in (2).

[2] Nonperforming loans may decrease by more than the charge-off amount if, say because of a troubled debt restructuring, the carrying value of the remaining loan is reclassified as performing. We discuss this complication further in section 6.1.2. and report exploratory empirical analyses in the online appendix (Figure A1 and Table A8).

The ending balance of *NPL* increases as loans become severely delinquent and are classified as nonperforming, which we label *NetNewNPL*. Because a loan can be reclassified as performing if borrowers catch up on overdue payments, this variable captures the net flow of performing loans to nonperforming loans.

Rearranging equations (1) and (2), we obtain expressions for the two flow variables *LLP* and *NCO*, which reflect loan performance during the period:

$$LLP_t = ALL_t - ALL_{t-1} + NCO_t \tag{3}$$

$$NCO_t = NetNewNPL_t - (NPL_t - NPL_{t-1}) \tag{4}$$

Consistent with equation (3), Figure 2 shows that *LLP* increases close to linearly with *NCO*. Substituting (4) into (3) and denoting ($NPL_t - NPL_{t\text{-}1}$) as ΔNPL_t gives:

$$LLP_t = ALL_t - ALL_{t-1} + NetNewNPL_t - \Delta NPL_t \tag{5}$$

In equation (5), periodic *LLP* increases with new nonperforming loans, $NetNewNPL_t$, its primary theoretical driver. The minus sign before ΔNPL_t suggests that using the *reported* nonperforming loan change—and not controlling for the effect of net loan charge-offs—would bias downward the estimated coefficient for the 'true' change in loan performance, but that would not induce a V-shaped relation. Equation (4) shows that *NCO* creates a gap between *NetNewNPL* and *ΔNPL*, and sufficiently large *NCO* could decrease *NPL* (equation (2)) while increasing *LLP* (equation (3)). Intuitively, unexpectedly large loan charge-offs can reduce reported nonperforming loans and render allowances inadequate. In response, management must increase provisions at period end to reserve for additional loan losses stemming from the underlying loan performance deterioration. Thus, we hypothesize that the V-shaped relation loan loss provisions have with nonperforming loan change is due largely to not controlling for the effects of large net loan charge-offs when using reported *ΔNPL* to proxy for the unobserved true change in loan performance, $NetNewNPL_t$. We can estimate $NetNewNPL_t$ by rearranging equation (2) as:

$$NetNewNPL_t = \Delta NPL_t + NCO_t \tag{6}$$

***H1*:** Loan loss provisions vary asymmetrically with respect to increases versus decreases in nonperforming loans because of large net loan charge-offs.

3. Regression Models

While much prior research has studied banks' loan loss provisions, there is no consensus on a best model. Beatty and Liao (2014, Table 1) review nine representative regression models that combine explanatory variables differently. Eight of these models include nonperforming loan change as an explanatory variable, reflecting its critical role in estimating loan loss provisions.

3.1. Baseline linear model (*Model 1*)

Our starting point is the model that, based on Beatty and Liao's (2014) review, best detects serious loan loss provision manipulation as reflected by accounting restatements and SEC comment letter receipts (Model (a) in their Table 4). This model is applied in many recent studies (e.g., Jiang, Levin, and Lin 2016; Nicoletti 2018) and is used to derive the incremental adjusted R^2 measure of loan loss provision opacity (Beatty and Liao 2011; Bushman and Williams 2015). We write the model as follows (bank subscript *i* is omitted for brevity):

Model 1:
$$LLP_t = \alpha_1 \Delta NPL_t + \alpha_2 \Delta NPL_{t-1} + \alpha_3 \Delta NPL_{t-2} + \alpha_4 SIZE_{t-1} + \alpha_5 \Delta LOAN_t + Bank\ FE + Quarter\ FE + \epsilon_t,$$

where:

LLP_t	=	Loan loss provision in quarter *t*, scaled by end-of-quarter *t*-1 total loans
ΔNPL_t	=	Change in nonperforming loans in quarter *t*, scaled by end-of-quarter *t*-1 total loans; nonperforming loans are defined as loans (a) no longer accruing interest, or (b) past due 90 days or more and still accruing interest.
$SIZE_{t-1}$	=	Logarithm of assets at end of quarter *t*-1
$\Delta LOAN_t$	=	Change in loans in quarter *t*, scaled by end-of-quarter *t*-1 total loans

We adjust Beatty and Liao's specification in several ways. We use quarter fixed effects in place of the macroeconomic variables in Beatty and Liao (2014) to more fully control for macroeconomic conditions. We add bank fixed effects to absorb systematic variation in loan loss provisions across banks. Unlike Beatty and Liao (2014), we exclude lead *ΔNPL* for two reasons. First, under the current incurred loss model, the loan loss allowance should reflect probable credit losses that are *incurred*, and hence, current loan loss provisions should have limited predictive power for future delinquencies if the losses have not yet been incurred. Second, by excluding lead *ΔNPL*, our model reflects only loan loss data known to managers at the period end.[3] Because all later models include the same bank controls, bank and quarter fixed effects, we suppress them in the equations. Standard errors are clustered by both bank and quarter unless otherwise noted.

3.2. Replacing linear ΔNPL with linear ΔNPLNCO (*Model 2*)

We adjust for the impact of net loan charge-offs by adding net loan charge-offs back to nonperforming loan change. This measure equals *NetNewNPL*, nonperforming loan change before charge-offs (equation (6) of section 2), if net loan charge-offs reduce nonperforming loans dollar-for-dollar. We replace *ΔNPL* in Model 1 with *ΔNPLNCO*:

Model 2: $$LLP_t = \alpha_1 \Delta NPLNCO_t + \alpha_2 \Delta NPLNCO_{t-1} + \alpha_3 \Delta NPLNCO_{t-2} + \epsilon_t,$$

where $\Delta NPLNCO_t$ is the sum of nonperforming loan change and net loan charge offs in quarter t scaled by quarter t-1 total loans. As discussed in section 2, we expect the slope coefficient α_1 in Model 2 to be larger than in Model 1. In section 6.1.2, we propose a measure of *NetNewNPL* that lets nonperforming loans fall by more than the amount of net charge-offs as some nonperforming loan balances may be reclassified to performing.

[3] In Table A1 of the online appendix, we add lead *ΔNPL* in both linear and piecewise-linear forms, and our inferences are unaltered. Alternatively, we include current changes in less severe delinquency loans, i.e., loans 30-89 days past due, that management knows at the quarter end, can predict quarter-ahead *NPL*, and thus can yield *LLP*. As Table A2 in the online appendix shows, our results remain unchanged. We also find that lead change in nonperforming loans and current changes in loans 30-89 days past due have similar explanatory power for current loan loss provisions.

3.3. Adding a piecewise linear term for ΔNPL (*Model 3*)

The V-shaped relation of *LLP* with *ΔNPL*, as plotted in Figure 1, suggests that a piecewise linear regression that allows separate coefficients for *NPL* increases and decreases should fit better:

Model 3:
$$LLP_t = \alpha_1 \Delta NPL_t + \boldsymbol{\alpha_2 D\Delta NPL_t} \times \boldsymbol{\Delta NPL_t} + \alpha_3 D\Delta NPL_t + \alpha_4 \Delta NPL_{t-1} + \alpha_5 \Delta NPL_{t-2} + \epsilon_t \,,$$

where *DΔNPL* is an indicator equal to one if $\Delta NPL<0$, and zero otherwise. Based on Figure 1, the coefficient on nonperforming loan increases (α_1) should be positive, while the coefficient on nonperforming loan decreases ($\alpha_1+\alpha_2$) and *a fortiori* the incremental coefficient on nonperforming loan decreases (α_2) should be negative.

3.4. Adding a piecewise linear term for ΔNPLNCO (*Model 4*)

We replace *ΔNPL* in Model 3 with *ΔNPLNCO*:

Model 4:
$$LLP_t = \alpha_1 \Delta NPLNCO_t + \boldsymbol{\alpha_2 D\Delta NPLNCO_t} \times \boldsymbol{\Delta NPLNCO_t} + \alpha_3 D\Delta NPLNCO_t + \alpha_4 \Delta NPLNCO_{t-1} + \alpha_5 \Delta NPLNCO_{t-2} + \epsilon_t,$$

where $D\Delta NPLNCO_t$ is an indicator equal to one if $\Delta NPLNCO_t < 0$, and zero otherwise. To the extent that adding back concurrent net loan charge-offs to change in nonperforming loans alleviates the confounding asymmetric effect of net loan charge-offs, H1 predicts that the incremental slope coefficient α_2 in Model 4 is less negative than in Model 3.

3.5. Adding piecewise-linear ΔNPL and linear NCO (Model 5)

We next add net loan charge-offs separately to Model 3, isolating the variation in *LLP* that is orthogonal to *NCO*. This method lets *NCO* and *ΔNPL* have different slope coefficients, instead of forcing equal coefficients as in our combined variable *ΔNPLNCO*. While early studies (e.g., Beaver and Engel 1996; Kim and Kross 1998) include net loan charge-offs, recent studies (e.g., Beatty and Liao 2011; Bushman and Williams 2012) do not. Because loan loss provisions should precede net loan charge-offs (Beatty, Liao, and Zhang 2019), including *NCO* in an *LLP* model could suggest that previous provisions were inadequate, which is a reason why prior research does not always control for *NCO* in estimating non-discretionary *LLP*.[4] Another reason for omitting *NCO* is that *NCO* can subsume too much variation in *LLP* given the high correlation between the two (Beatty and Liao 2014).

We argue that banks adjust end-of-period valuation allowances not because past provisions are inadequate *ex ante* but to cover unexpected loan losses that occur *ex post* (especially during recessions), like how non-financial firms use a percentage-of-(aged)-receivables allowance to reflect their clients' economic condition. As the accounting equations in Section 2 illustrate, net loan charge-offs decrease both nonperforming loans and loan loss allowances, affecting end-of-period loan loss provisions. Not incorporating the effects of net charge-offs makes nonperforming loan change a poor measure of the true change in loan portfolio quality and creates a correlated omitted variable problem (see the online appendix for a numerical example). Since there are costs and benefits to including net charge-offs in the regressions, we report results using both approaches and let future research identify contexts when each method is more appropriate.

Model 5 is written as follows:

Model 5:
$$\begin{aligned} LLP_t = {} & \alpha_1 \Delta NPL_t + \boldsymbol{\alpha_2 D\Delta NPL_t \times \Delta NPL_t} + \alpha_3 D\Delta NPL_t + \alpha_4 \Delta NPL_{t-1} \\ & + \alpha_5 \Delta NPL_{t-2} + \boldsymbol{\alpha_6 NCO_t} + \epsilon_t, \end{aligned}$$

where NCO_t is loan charge-offs, net of recoveries, for quarter *t* scaled by end-of-quarter *t*-1 loans. Since Figure 2 indicates that *LLP* and *NCO* are linearly related, we include a linear term for *NCO*. H1 predicts that the incremental slope coefficient α_2 in Model 5 is less negative than in Model 3.

[4] Liu and Ryan (2006) report charge-off recovery patterns consistent with banks' smoothing income through loan loss provisions. One interpretation is that the timing of net loan charge-offs is not always non-discretionary and may be altered to help conceal managements' discretionary loan loss provisioning behavior.

4. Data and Results

4.1. Sample

We use Federal Reserve Bank FR Y-9C Reports, which provide consolidated quarterly income statement and balance sheet data for U.S. bank holding companies. We find similar results if we instead use the Reports of Condition and Income (Call Reports) for chartered banks or Compustat Bank data for publicly listed banks. Our primary sample is an unbalanced panel of 85,690 bank-quarters from 2,795 bank holding companies during 2000Q1 to 2018Q4. The Appendix defines our main variables. We log bank size to reduce right skewness and winsorize all the other continuous variables at the top and bottom 1% to mitigate the influence of outliers.

4.2. Summary statistics

Table 1 Panel A reports descriptive statistics for our main variables. Quarterly loan loss provision scaled by start-of-quarter loan balance (*LLP*) has a mean of 0.14% with a standard deviation of 0.25%. Net charge-off scaled by start-of-quarter loan balance (*NCO*) averages 0.11% with a standard deviation of 0.23%. The mean ΔNPL_t is 0.02% with a standard deviation of 0.55%, and the mean $\Delta NPLNCO_t$ is 0.14% with a standard deviation of 0.61%. The natural logarithm of banks' total assets (in thousands of dollars) averages 13.77 with a standard deviation of 1.46. Banks' quarterly loan growth rate ($\Delta LOAN$) averages 2.06%.

Panel B reports Pearson (Spearman) correlations between the variables below (above) the diagonal. Large differences in these correlation coefficients for the same variable pairs suggest strong nonlinearity. The Pearson (Spearman) correlation between *LLP* and ΔNPL_t is (0.144) 0.086. *LLP* also correlates positively with the two lagged ΔNPLs. *LLP* and *NCO* are highly positively correlated, with Pearson (Spearman) correlation equal to 0.801 (0.614). Although constructed as their sum, $\Delta NPLNCO$ is more highly correlated with ΔNPL than *NCO*, with Pearson (Spearman) correlations of 0.899 (0.892) and 0.375 (0.244), respectively, reflecting the much higher standard deviation of *ΔNPL* (Panel A). In untabulated analyses, we find that the correlation between *ΔNPLNCO* and *ΔNPL* is higher for positive *ΔNPL* (Pearson = 0.935; Spearman = 0.919) than for negative *ΔNPL* (Pearson = 0.729; Spearman = 0.742). This difference is driven by the negative (positive) correlation between *ΔNPL* and *NCO* for negative (positive) *ΔNPL*, with Pearson correlations of -0.301 (0.250) and Spearman correlations of -0.314 (0.284), respectively (untabulated).

4.3. Model comparisons

We report the results of estimating the five alternative models in Table 2. We begin with the baseline linear specification, Model 1. Consistent with prior research, the coefficients on the current and two lagged changes in nonperforming loans are similarly positive (coefficients = 0.043, 0.044 and 0.040). The adjusted R^2 is 0.437, and the adjusted within R^2, which captures model explanatory power excluding the fixed effects, is 0.050. As expected, adding net loan charge-offs to the nonperforming loan change results in better model fit; the adjusted within R^2 of Model 2 is more than three times as large as that of Model 1. The slope coefficients on *ΔNPLNCO* for all three periods in Model 2 are consistently larger than those in Model 1, with current-period *ΔNPLNCO* having the largest coefficient of 0.111.

The estimates from Model 3 confirm and extend the graphical evidence in Figure 1. Loan loss provision exhibits severe asymmetry with respect to increases versus decreases in nonperforming loans, even after including many control variables. The slope coefficient for nonperforming loan increases (coefficient on ΔNPL_t) is 0.131, and the slope coefficient for nonperforming loan decreases (the sum of the coefficients on ΔNPL_t and $D\Delta NPL_t \times \Delta NPL_t$) is -0.079. On average, a one percent increase (decrease) in *ΔNPL* corresponds to a 13.1 basis point increase (7.9 basis point *increase*) in *LLP*. The adjusted (within) R^2 is about 6 (84) percent higher than that in baseline Model 1, suggesting that allowing for asymmetry increases explanatory power considerably.[5]

The Model 4 estimates suggest that combining nonperforming loan change with net loan charge-offs reduces, but does not remove, the V-shaped pattern. The coefficient on decreases in *NPLNCO* is much smaller and less significant than the coefficient on decreases in *NPL* in Model 3 (coefficient = -0.012 vs. -0.079; p = 0.073 vs. 0.000). The adjusted within R^2 of Model 4 increases over its linear version, Model 2 (0.210 vs. 0.182). Figure 3 plots mean *LLP* against mean $\Delta NPLNCO$ across 20 equal-frequency bins sorted on $\Delta NPLNCO$. Consistent with the regression estimates, the negative slope for decreases in $\Delta NPLNCO$ is flatter, but the V-shaped relation is still visible, suggesting an incomplete correction.

Model 5 includes *NCO* as an additional explanatory variable. The coefficient on *NCO* is 0.730 (t-statistic = 37.36), which is ten times that on ΔNPL (0.072), showing that requiring equal coefficient in Models 2 and 4 was overly restrictive. Consequently, Model 5's adjusted within R^2 is five times as big as that of Model 3 and more than double that of Model 4. The slope coefficient for *NPL* decreases, 0.043, is significantly positive. Thus, after controlling for *NCO*, the residual loan loss provision moves in the same direction as the change in ΔNPL, that is, the V-shaped pattern disappears. Furthermore, consistent with a better specified model, the coefficient on change in total loans flips from negative to the predicted positive sign because more loans should lead to higher loan loss provisions on average. However, some asymmetry remains, as loan loss provisions are nearly twice as sensitive to nonperforming loan increases as to decreases. Our inferences do

[5] In Table A1 of the online appendix, we show that piecewise linear effects for lagged ΔNPL_{t-1} and ΔNPL_{t-2} are also statistically significant with incremental slope coefficients that are approximately half those on concurrent $\Delta NPL_{t.}$ Adding lead ΔNPL_{t+1} in a piecewise linear form yields an incremental slope coefficient that is approximately half that on current ΔNPL_t and increases adjusted R^2 moderately.

not change if we additionally control for beginning-of-period allowances, $ALL_{t\text{-}1}$, which accounting equation (5) of section 2 predicts has a negative coefficient.[6]

We perform several diagnostic tests to evaluate the implications of not modelling the effects of asymmetry or net loan charge-offs for the properties of model residuals. First, we run the Wooldridge (2002, pp. 282-3) test for serial correlation in residuals. The results reported in Table 2 indicate that only residuals from Model (5) are not serially correlated.[7] We also evaluate whether the residuals are Normally distributed. The test statistics reported in the bottom rows of Table 2 reject the null hypothesis that the skewness or kurtosis of residuals are equal to those of a Normal distribution for all five models.

Second, in Figure 4 we plot the mean residuals from each of the five models against mean *ΔNPL* (*ΔNPLNCO* for Models 2 and 4) divided into 100 equal-frequency bins. Well-specified residuals should be randomly dispersed around zero across nonperforming loan change bins. However, the residuals from Models 1 and 2 exhibit a V-shaped relation with *ΔNPL* (*ΔNPLNCO*); the residuals are too large when *ΔNPL* (*ΔNPLNCO*) is extreme, but too small when *ΔNPL* (*ΔNPLNCO*) is close to zero. Thus, if researchers do not model the asymmetry related to *ΔNPL* when estimating normal loan loss provisions, they would erroneously infer positive (negative) discretionary accruals (i.e., model residuals) for extreme (moderate) ΔNPL_t. In section 5.1, we quantify this misspecification using simulation tests with random samples.

[6] The results are similar if we also control for Tier1 risk-based capital ratio, earnings before loan loss provisions, and lead and lagged net loan charge-offs.

[7] Serial correlation between residuals does not influence the unbiasedness or consistency of the coefficient estimate, but biases the standard errors and causes the coefficient estimates to be less efficient. The Wooldridge (2002) auto-correlation test for panel data tests the null of $E|\epsilon_{is}\epsilon_{it}| = 0$ for $s \neq t$, where *i* denotes banks, and *s* and *t* denote quarters. In a panel data set of large N (observations) and small T (the number of time periods), robust clustering, as used in all our models, should address both heteroscedasticity and serial correlation among residuals (see Stata manual for Xtreg command).

Third, we regress the residuals from each of the five models on linear, squared, and cubic terms of *ΔNPL* (*ΔNPLNCO*). If the residuals are randomly distributed, we expect these residual regressions to yield little explanatory power. As Table A3, Panel A in the online appendix shows, while the coefficients on the polynomial terms of nonperforming loan changes (except the squared term in model 5) are significant for all five residual regressions, the adjusted R^2 for the residuals of Models 3, 4, and 5 (0.0005, 0.0014, and 0.0003 respectively) are much smaller than the adjusted R^2 for the residuals of Models 1 and 2 (0.034 and 0.027). This finding reinforces the notion that modeling net charge-offs in loan loss provision models yields residuals that are less misspecified.

Last, we test for functional misspecification using the Harvey-Collier (1977) test (which is essentially a *t t*est of the recursive residuals), the rainbow test (Utts 1982), and a Lagrange Multiplier test comparing restricted (linear) and unrestricted (piecewise linear) models. As Table A3, Panel B in the online appendix shows, Models 3, 4, and 5 all reduce the misspecification in linear models. Model 3 exhibits the least misspecification according to the rainbow test, and Model 5 performs the best in the Harvey-Collier and Lagrange Multiplier tests.

In short, our Table 2 results extend and generalize Figure 1. Loan loss provisions have a V-shaped relation with concurrent changes in reported nonperforming loans, i.e., a larger fall in nonperforming loans is associated with a greater increase in loan loss provisions, after controlling for many standard determinants. Our analysis shows that the effect of net loan charge-offs is the major source of this asymmetry. Simple methods such as summing net loan charge-offs with nonperforming loan change or separately including net loan charge-offs substantially reduce or eliminate the V-shaped pattern but leave some residual asymmetry.[8]

[8] In Table A4 of the online appendix, we add squared *ΔNPL* to each of the five models. We find that the incremental slope coefficient for nonperforming loan decreases remains negative in Models (1) through (4). Interestingly, adding squared *ΔNPL* to Model 5 yields positive coefficients on both the incremental slope coefficient and the squared term. This result makes sense because, as reported in Table 2, column (5), including *NCO* eliminates the V-shaped pattern;

5. Implications for the extant banking literature

Figure 4 showed that the estimated discretionary loan loss provisions (model residuals) from standard models are nonrandom and systematically related to nonperforming loan changes. We evaluate the potential consequences of omitting asymmetry in tests of discretionary loan loss provisions. We first estimate the magnitude and direction of the potential bias induced by the five alternative models in Table 2 using simulations like those in Kothari, Leone, and Wasley (2005). We then illustrate systematic errors in measuring delayed loan loss recognition—the incremental R^2 obtained by including lead and current nonperforming loan change as explanatory variables in loan loss provisions models. We replicate sections of Beatty and Liao (2011) and Bushman and Williams (2015) that use delayed loan loss recognition measures and examine whether their inferences change after modeling the effect of net loan charge-offs.

5.1. Specification tests of alternative discretionary loan loss provision models

We start by randomly selecting 100 bank-quarter observations from the full sample (Kothari et al., 2005). Since these bank-quarters are randomly selected, we can reasonably assume that there is no systematic earnings management through loan loss provisions in the subsample, i.e., the null hypothesis of no directional loan loss provisions is true. Findings of large mean discretionary *LLP* would suggest model misspecification. We estimate each model using the full sample and test for provision management in the selected subsample. Since Model 1 and 2 residuals are empirically piecewise linear in *ΔNPL*, we also analyze stratified subsamples, where

as a result, the residual asymmetry is adequately captured by either a piecewise-linear or quadratic functional form. We find that adding the piecewise-liner term, the squared term, and both yield nearly identical model adjusted R^2, suggesting that these functional forms are equally effective in capturing the residual asymmetry.

100 bank-quarter observations are drawn from a specific *ΔNPL* quintile.[9] We repeat this sampling procedure 250 times with replacement.

Table 3 summarizes the simulation results. Panel A (B) reports the frequency with which the null hypothesis of no discretionary *LLP* is rejected at the 5% level against the alternative of positive (negative) discretionary *LLP*. With 250 trials, there is a 95% probability that the rejection rate lies between 2.4% and 8.0% if the discretionary *LLP* measures are well-specified and the null hypothesis is true. Panel A reports tests for positive discretionary *LLP*. When observations are drawn from the full sample, all models are relatively well-specified, i.e., they have a low probability of committing a Type I error. This finding is expected because biases within *ΔNPL* partitions cancel out when samples are randomly drawn across the entire distribution of *ΔNPL*.

Models 1 and 2 (the linear specifications) have excessively high rejection rates (54% and 79.2%) for observations in the bottom quintile of *ΔNPL* and *ΔNPLNCO*, respectively, and moderately high rejection rates (26.8% and 9.6%) for observations in the top quintile of *ΔNPL* and *ΔNPLNCO*. The high rejections rates for extreme values of *ΔNPL* (*ΔNPLNCO*) suggest that researchers would likely conclude that provisions had been managed upwards for cases of unusually large changes in loan performance (such as during economic recessions). The two models never reject in quintiles 2, 3, and 4, which contain cases where loan quality changes were moderate. Simply summing net charge-off and nonperforming loan change, as in Model 2, does not fully address the bias because net charge-offs and nonperforming loan changes have very different relations with loan loss provisions (Figures 1 and 2). In contrast, Models 3, 4 and 5 (the piecewise linear specifications) all have rejection rates within reasonable bounds. The sole

[9] Following Collins, Pungaliya, and Vijh (2017), we also randomly select 2,000 observations, half of which come from a given nonperforming loan change partition and the other half from the remainder of the sample. This approach makes the random sample only partially over-populated with firms from a given nonperforming loan change partition and thus is closer to the real data. The untabulated results are similar to those reported in Table 3.

exception is that Model 4 rejects the null hypothesis 15.2% of the time in quintile 3 of *ΔNPLNCO*. A potential explanation is that quintile 3 is the only partition in which the mean *ΔNPLNCO* (0.041%) and mean *ΔNPL* (-0.008%) have opposite signs, so the coefficient on the summed variable masks the different contributions of the two components.

Panel B reports tests for negative discretionary *LLP*. Models 1 and 2 over-reject in the middle three quintiles of *ΔNPL* (*ΔNPLNCO*), with Model 1's rejection rate reaching 80.8% in quintile 3. Model 1 rejects too infrequently in the bottom and top quintiles of *ΔNPL*. The takeaway is that in situations where nonperforming loan change is close to zero (for example, when loan performance is stable), not incorporating asymmetry would lead researchers to infer downward provision management—or equivalently, upward earnings management—even though there may be none. As in Panel A, Models 3, 4, and 5 all have acceptable rejection rates with just a few exceptions where the rejection rate is moderately high. Thus, incorporating asymmetry and the effect of charge-offs considerably reduces bias in tests for discretionary loan loss provisions.[10]

5.2. Implications for measuring delayed loan loss recognition (incremental adjusted R^2)

We next explore the implications of our findings for recent research that uses the difference in model adjusted R^2 as a proxy for delayed loan loss recognition or opacity (e.g., Beatty and Liao 2011; Bushman and Williams 2015). We start with the Bushman and Williams (2015) models:

$$LLP_t = \beta_1 \Delta NPL_{t-1} + \beta_2 \Delta NPL_{t-2} \quad \text{(a)}$$

$$LLP_t = \beta_1 \Delta NPL_{t-1} + \beta_2 \Delta NPL_{t-2} + \beta_3 \Delta NPL_t + \beta_4 \Delta NPL_{t+1} \quad \text{(b)}$$

[10] We also compare the models' power to detect earnings management. We randomly draw 100 bank-quarters from either the full sample or from a given *ΔNPL* (*ΔNPLNCO*) quintile, and induce earnings management in those bank-quarters by seeding positive or negative discretionary *LLP* that are 1 or 3 bps of lagged loans. We conduct 250 trials and record the frequency with which the models reject the null of no discretionary *LLP* using one-tailed *t*-tests. As Table A5 in the online appendix shows, Model 5 generally has the greatest power in detecting seeded earnings management, while Models 1 and 2 perform the worst in the tail (middle) of the *ΔNPL* distribution when negative (positive) *LLP* are seeded.

Model (a) includes two lagged *ΔNPL*s, and Model (b) adds current and lead *ΔNPLs*. Both models include Tier1 risk-based capital ratio and earnings before provisions scaled by lagged loans as explanatory variables, which we suppress for parsimony when writing out the equations. Following Beatty and Liao (2011) and Bushman and Williams (2015), we run the models for each bank-quarter using a 12-quarter rolling window. A higher (lower) incremental adjusted R^2 of model (b) relative to that of model (a) is interpreted as timelier (delayed) recognition of expected loan losses. We call this measure *R2Diff*.

As we have shown, omitting loan loss provision asymmetry and charge-offs induces model misspecification and poor fit. Consequently, the incremental adjusted R^2 from adding the change in current and lead *ΔNPL* (without controls for asymmetry and net charge-offs) likely contains substantial measurement errors relative to a better-specified model. We propose three alternative incremental R^2s computed from pairs of models that are based on Models 3 to 5 in Table 2:

$$LLP_t = \gamma_1 \Delta NPLPOS_t + \gamma_2 \Delta NPLNEG_t + \gamma_3 \Delta NPL_{t+1} + \gamma_4 \Delta NPL_{t-1} + \gamma_5 \Delta NPL_{t-2} \tag{c}$$

$$LLP_t = \gamma_1 \Delta NPLNCO_{t-1} + \gamma_2 \Delta NPLNCO_{t-2} \tag{d}$$

$$\begin{aligned} LLP_t = {} & \gamma_1 \Delta NPLNCOPOS_t + \gamma_2 \Delta NPLNCONEG_t + \gamma_3 \Delta NPLNCO_{t+1} + \gamma_4 \Delta NPLNCO_{t-1} \\ & + \gamma_5 \Delta NPLNCO_{t-2} \end{aligned} \tag{e}$$

$$LLP_t = \gamma_1 \Delta NPL_{t-1} + \gamma_2 \Delta NPL_{t-2} + \gamma_3 NCO_t \tag{f}$$

$$LLP_t = \gamma_1 \Delta NPLPOS_t + \gamma_2 \Delta NPLNEG_t + \gamma_3 \Delta NPL_{t+1} + \gamma_4 \Delta NPL_{t-1} + \gamma_5 \Delta NPL_{t-2} + \gamma_6 NCO_t \tag{g}$$

First, we modify model (b) by splitting the coefficient on *ΔNPL* into separate slope coefficients for nonperforming loan increases and decreases. *ΔNPLPOS* (*ΔNPLNEG*) equals *ΔNPL* when $\Delta NPL \geq 0$ ($\Delta NPL < 0$), and zero otherwise. This approach is like adding a piecewise linear term but omits the incremental dummy variable to save one degree of freedom, which matters in rolling regressions with only 12 observations. We calculate the incremental adjusted R^2 of model (c) over model (a), which we call *R2Diff_Asym*. Second, we modify models (a) and (c) by replacing *ΔNPL*s with *ΔNPLNCO*s. We subtract the adjusted R^2 of model (d) from that of model (e) and call the difference *R2Diff_Asym_NetNewNPL*. Third, we calculate the incremental R^2 of model (g) over model (f), which we call *R^2Diff_Asym_NCO*.

The Pearson (Spearman) correlations between *R^2Diff* and *R2Diff_Asym*, *R2Diff_Asym_NetNewNPL*, and *R2Diff_Asym_NCO* are 0.811 (0.776), 0.687 (0.635), and 0.577 (0.529), respectively. Figure 5 plots *R2Diff* against each of the three new measures. Both the correlation tables and the scatter plots suggest that modeling asymmetry in loan loss provisions can affect inferences drawn from the standard incremental R^2 measure. In the first comparison, almost none of the points are above the 45% line, suggesting that *R^2Diff_Asym* is almost always greater than or equal to *R2Diff*, i.e., the latter is systematically downward biased.

Motivated by the univariate evidence of downward bias and error in *R2Diff*, we reexamine two prior studies to check if modeling the loan loss provision asymmetry changes inferences.

5.3. Delayed loan loss recognition and capital crunch

Beatty and Liao (2011) examine the effect of banks' delayed loan loss recognition on the capital crunch hypothesis, i.e., that bank lending is more sensitive to capital adequacy during economic downturns. The positive correlation between bank capital adequacy and lending growth during recessions weakens when banks delay recognizing expected loan losses less (i.e. have a higher *R2Diff*), which they attribute to timelier loan loss recognition alleviating capital crunch. Since banks charge off many loans during and after recessions, asymmetry arising from large loan charge-offs can systematically bias *R2Diff*.

Following Beatty and Liao (2011), we obtain public bank quarterly financial data from Compustat Banks for 1993Q3-2009Q2. We estimate the following model:

Model 7:

$$\begin{aligned} \Delta Loan \ &= \delta_0 + \delta_1 Recession + \delta_2 Capital\,R1 + \delta_3 Capital\,R1 \times Recession \\ &+ \delta_4 < Delay + \delta_5 Recession \times < Delay + \delta_6 Capital\,R1 \times \\ &< Delay + \delta_7 Capital \times Recession \times < Delay + Controls + \epsilon, \end{aligned}$$

where *ΔLoan* is the change in the natural log of loans; *Capital R*1 is lagged Tier1 risk-based capital ratio; *Recession* is an indicator equal to one for quarters between 2001Q2 and 2001Q4 inclusive, and quarters between 2008Q1 and 2009Q2 inclusive, and zero otherwise. < *Delay* is an indicator equal to one for bank-quarters with lagged *R2Diff* above the median. The coefficient of interest is δ_7, which captures the effect of less loan loss recognition delay on capital crunch. Beatty and Liao (2011) define all the control variables in detail, so we do not repeat them here.

Table 4, column (1) presents the estimation results.[11] The first two rows report the δ_7 coefficients in Beatty and Liao (2011, Table 5, column 1) and our replication, which are fairly close (δ_7 = -0.138 vs. -0.090; *t*-statistic = -1.75 vs. -1.66). We repeat the test using *R2Diff_Asym* to identify bank-quarters with less loan-loss-recognition delay. The estimate is one-third smaller (δ_7 = -0.064 vs -0.090) than in row (2) and insignificant (*t*-statistic = -0.58). Row (4) reports the results from using *R2Diff_Asym_NetNewNPL* as the explanatory variable. The coefficient turns positive (0.021) but is still insignificant (*t*-statistic = 0.41). Finally, we partition using *R^2Diff_Asym_NCO*. The coefficient estimate is now positive (0.153) and statistically significant (*t*-statistic = 2.41), opposite to what Beatty and Liao (2011) report.[12] In summary, the mitigating effect of timelier loan loss recognition on capital crunch documented in Beatty and Liao (2011) is

[11] Beatty and Liao (2011) use a one-tailed *t*-test to evaluate the statistical significance of δ_7. To facilitate comparison, we report a one-tailed *t*-test when replicating their finding. We report two-tailed *t*-tests when using alternative incremental R^2 measures because the coefficient sign changes in some cases.

[12] Beatty and Liao (2011) hypothesize that banks with timely recognition may take other actions, such as accumulating capital during good times, that would reduce the cyclicality of their lending and thus lead to less pro-cyclical lending behavior. The results in row 5 of Table 5 suggest that banks with timelier loss recognition do not take enough actions to mitigate this effect, experiencing larger capital constraint effects during recessions than do banks with more delayed loan loss recognition. We believe that the effect of a small delay in loan loss recognition, when measured correctly, on capital crunch is an empirical question. Our goal is to test whether prior results based on incremental R^2 are sensitive to whether asymmetry and net charge-offs are incorporated in first-stage loan loss provision models. We hope that researchers will be more cautious in using the traditional incremental R^2 measures when drawing inferences. It is beyond the scope of our paper to flesh out the precise mechanism(s) that change previous results using our models.

weakened and even reversed if the effects of net loan charge-offs are incorporated in first-stage loan loss provisions models.

5.4. Delayed expected loss recognition and downside risk

Bushman and Williams (2015) examine the effect of banks' delayed loan loss recognition on downside tail risk. They find that banks with less delay in loan loss recognition have less downside tail risk during recessions. Like Beatty and Liao (2011), Bushman and Williams (2015) use *R2Diff* to measure loan loss recognition timeliness, which can be problematic when banks' underlying loan performance is more volatile (e.g., during recessions).[13]

We follow Bushman and Williams (2015) and estimate the following model:

Model 8: $$VaR_t = \eta_0 + \eta_1 DELR_{t-1} + Controls + Year\ FE + \epsilon$$

Where *VaR* is the estimated value at risk at the 1% quantile derived from a quantile regression of banks' weekly returns on a series of lagged macroeconomic state variables. A more negative *VaR* indicates larger individual bank downside risk. Like Bushman and Williams (2015), we retrieve bank-quarter observations from the intersection of Computstat Banks, FR Y-9C reports, and CRSP. Detailed definitions of *VaR* as well as the control variables are provided in their paper, so we do not repeat them here. *DELR* is an indicator equal to one for observations below the median *R2Diff* in the quarter, and zero otherwise. Because Bushman and Williams (2015) find a significant coefficient on *DELR* only during recessionary periods, we restrict our replication to those periods.

Table 4, column (2) reports the results. The first two rows report the coefficients on *DELR* in Bushman and Williams (2015, Table 3, column 3) and our replication, which are very close (η_1 = -0.082 vs -0.083; *t*-statistic = -2.49 vs -2.87). In row (3), we use *R2Diff_Asym* to identify bank-

[13] When replicating Bushman and Williams (2015), we follow their specifications exactly and add lagged bank size to models (a) to (g) to facilitate direct comparison. Beatty and Liao (2011) do not include lagged bank size in their loan loss provision models, so we exclude it when replicating their tests to be comparable.

quarters with delayed loan loss recognition. η_1 falls by about 15% relative to row (2), and is no longer statistically significant (*t*-statistic = -1.58). When R^2*Diff_Asym_NetNewNPL* is used as the partitioning variable in row (4), η_1 turns positive (0.011) but is statistically insignificant (*t*-statistic = 0.19). Last, we use *R2Diff_Asym_NCO* as the partitioning variable, and η_1 is again negative (-0.051) and statistically insignificant (*t*-statistic = -1.00). In sum, the results suggest that inferences about the effect of delayed loan loss recognition on downside tail risk during recessions can change when researchers model the effects of net loan charge-offs on loan loss provision.

6. Sources of the residual asymmetry

We next explore potential factors that could explain the residual loan loss provision asymmetry after removing the confounding effects of net loan charge-offs (Table 2, column 5). The piecewise linear relation between loan loss provisions and nonperforming loan change resembles the asymmetric earnings-return relation, which Basu (1997) attributes to conditional conservatism. Given that conditional conservatism is longstanding and pervades the normal accrual process (Watts 2003a; Ball and Shivakumar 2006; Byzalov and Basu 2016), it is plausible that loan loss accruals' asymmetrically greater sensitivity to nonperforming loan increases (a proxy for bad news about loan performance) is partially driven by conditional conservatism. Lawrence et al. (2013) observe that some conditional conservatism is mandatory and caused by accounting standards. For example, SFAS 141 and 142 (FASB 2000a, 2000b) jointly increased the frequency and magnitude of goodwill impairments by stopping goodwill amortization and requiring annual goodwill impairment tests. Holding standards constant, conditional conservatism also varies predictably across firms, countries, and business cycles based on managerial incentives (e.g. Ball, Kothari, and Robin 2000; Watts 2003a; Jenkins, Kane, and Velury 2009; Gunn, Khurana, and Stein 2018). We first examine mandatory conservatism as reflected in differences in impairment standards for different loan types as well as changes in SEC and FASB interpretation of loan loss standards around 1998. The July 1999 interagency letters issued by the SEC and banking regulators stress that financial institutions should have "prudent, conservative, but not excessive, loan loss allowances that fall within an acceptable range of estimated losses." We next explore litigation incentives for time-series and cross-sectional variation in conservatism holding standards constant.

6.1. Effects of differing accounting standards for impairment recognition by loan type

We posit that the residual asymmetry can be attributed to the different accounting standards (ASC 310 vs ASC 450) governing different loan types. Smaller-balance homogenous loans—e.g., residential real estate loans and consumer loans—are grouped into pools of loans with similar risk characteristics and collectively evaluated for losses under ASC 450. Losses are accrued if they are "probable" and can be "reasonably estimated." Banks establish allowances for homogenous loans at inception and adjust provisions *incrementally* as the loans become more delinquent using statistical models, so that falling into a severe delinquency status (e.g., nonperforming) is not the initial trigger for loan loss accruals (Ryan and Keeley 2013).

Larger-balance heterogeneous loans such as construction loans are individually evaluated for impairment under ASC 310. A loan is considered impaired if "based on available data, it is probable that a creditor cannot collect all contractually due interest and principal payments." Because ASC 450's probable and reasonable estimated requirements for loan loss accruals are easier to meet at the pool level than at the individual asset level, banks tend to record appreciably large allowances for heterogeneous loans (by charging higher provisions) when they first become nonperforming and switch from ASC 450 to ASC 310 for impairment, not before (Ryan and Keeley 2013). This induces a disproportionally large increase in loan loss provisions when nonperforming loans increase. Thus, the residual asymmetric loan loss provisions can be caused by the differing accounting standards governing and the resulting differential speed of loan loss accruals for homogenous loans and heterogeneous loans.

6.1.1. Mandatory conservatism by loan type and during the real estate crisis

To test this argument, we classify loans into four types: construction loans, non-construction commercial loans (commercial real estate loans plus commercial and industrial loans), residential mortgages, and consumer loans (e.g., credit card loans). Construction loans are quite heterogeneous and cyclical, while residential mortgages and consumer loans are mostly homogenous. Non-construction commercial loans are somewhat to very heterogeneous, depending on the size and characteristics of the loan. We sort bank-quarter observations into deciles according to the proportion of a bank's total loans made up of a specific loan type. On average, construction loans comprise 9.4% of the loan portfolio, while commercial loans, residential mortgages, and consumer loans make up 47.2%, 27.1%, and 7% of total loan balance, respectively.[14] We predict that loan loss provision asymmetry is greater (less) for banks with more heterogeneous (homogenous) loans in their loan portfolios. We estimate an expanded version of Model 5:

Model 9:

$$\begin{aligned} LLP_t = {} & \alpha_1 \Delta NPL_t + \alpha_2 \Delta NPL_t \times D\Delta NPL_t + \alpha_3 \Delta NPL_t \times PART + \boldsymbol{\alpha_4 D\Delta NPL_t} \\ & \boldsymbol{\times \Delta NPL_t \times PART} + \alpha_5 D\Delta NPL_t \times PART + \alpha_6 PART + \alpha_7 D\Delta NPL_t \\ & + \alpha_8 \Delta NPL_{t-1} + \alpha_9 \Delta NPL_{t-2} + \alpha_{10} NCO_t + \alpha_{11} SIZE_{t-1} + \alpha_{12} \Delta LOAN_t \\ & + \epsilon_t, \end{aligned}$$

where *PART* represents one of the four loan portfolio composition decile rank variables. The coefficient α_4 on the interaction $D\Delta NPL \times \Delta NPL \times PART$ estimates the impact of the proportion of loans made up of a given type on loan loss provision asymmetry. We obtain similar results using Model 4 as the baseline for cross-sectional analyses (Tables A6 and A7 in the online appendix)

[14] Those ratios do not add to one because banks also hold agricultural loans, loans to foreign governments and other loans that collectively represent a small share of total loan balance.

Table 5, Panel A, columns (1) to (4) display the results. As predicted, the asymmetry is greater for banks with more heterogeneous construction loans (α_4 = -0.012; *t*-statistic = -5.33), and less for banks with more homogenous residential mortgages (α_4 = 0.005; *t*-statistic = 2.62) and consumer loans (α_4 = 0.007; *t*-statistic = 2.81). We do not find significant differences in asymmetry conditioned by banks' holdings of non-construction commercial loans, presumably because this loan type can be either homogenous or heterogeneous, and thus, the direction of its net effect is not obvious. Overall, consistent with our prediction, the differing speed of loan loss provisions across loan types due to accounting standard variation partly explains the residual asymmetry.

We also examine whether the asymmetry was more pronounced during the 2007-2012 real estate crisis, which saw a prolonged and significant decline in real estate prices. Because a lot of heterogeneous real estate loans became nonperforming and were switched to ASC 310 (for impairment) during the crisis, deteriorating collateral values would have triggered much larger loan loss provisions and charge-offs, exacerbating the asymmetry. To test this argument, we estimate Model 9 coding *PART* equal to one for the 2007–2012 real estate crisis, and zero otherwise. As Table 5, Panel A, column (5) shows, the α_4 triple-interaction coefficient is -0.095 (*t*-statistic = -5.66). We then explore whether the variation in loan loss provision asymmetry by loan type also holds during the real estate crisis. We restrict the sample to 2007-2012 and re-estimate Model 9. Table 5, Panel B reports the results. The α_4 coefficient is -0.012 with a *t*-statistic of -3.43, confirming that loss provision asymmetry was greater when banks had many construction loans that were impaired during the real estate crisis. To sum up, our findings are consistent with the differing loan loss impairment accounting standards for homogenous and heterogeneous loans driving at least partly the residual asymmetry.

6.1.2. An alternative measure of nonperforming loan change before charge-offs

Previously, we combined net loan charge-offs and nonperforming loan change to capture loan performance, while assuming that net loan charge-offs reduce nonperforming loans dollar-for-dollar. This assumption may not hold for individually impaired loans under ASC 310; nonperforming loans may decrease by more than the amount of net loan charge-offs when the net realizable values of the loans are returned to performing status. Per regulatory guidance, when a bank charges off a portion of a nonperforming loan, the uncharged-off portion can be returned to performing status if 1) the bank expects repayment of the remaining contractual principal and interest or 2) when the loan is well-secured and in the process of collection (see FR Y-9C instructions on *restoration to accrual status*).

Beginning with the 2013 Q1 FR Y-9C reports, banks disclose separately the amount of loans impaired under ASC 310 and ASC 450, as well as the associated allowances. We rely on the fact that banks' allowance decisions, as specified by GAAP, reflect banks' best estimate of the loan values after charge-offs and estimate the amount of nonperforming loans restored to performing after partial charge-offs. The online appendix provides more detailed measurement of the variable, *ΔNPLNCOadj*. Because the data necessary to construct this measure only became available after 2012 for banks with more than $1 billion in total assets, generalizability is a concern.

In Table A8 of the online appendix, we estimate the piecewise linear specification (Model 3) over 2013-2018, replacing *ΔNPL* with *ΔNPLNCOadj*. The slope coefficients for *NPLNCOadj* increases and decreases are both positive (coefficients = 0.101 and 0.040), suggesting that this approach removes the V-shaped pattern. Some asymmetry remains, as reflected in the negative coefficient (= -0.061) on the interaction term. Figure A1 of the online appendix plots the mean residuals of the model against *ΔNPLNCOadj* partitioned into 100 equal-frequency bins and shows that the residuals are close to randomly dispersed. Overall, the findings suggest that differences in loss recognition standards across loan types affect the relation between net charge-offs and nonperforming loans, contributing to loan loss provision asymmetry.

6.2. Incurred loss model vs expected loss model

On August 15, 2019, FASB proposed that ASC 326-20 (originally ASU 2016-13, FASB 2016) would take effect in 2020 for SEC registrant banks and 2023 for SEC registrants that meet the definition of "smaller reporting companies" and for private banks. ASC 326-20 mandates a current expected credit loss (CECL) model, under which banks must use forward looking information to provide "life of loan" estimates of losses at loan inception. Conceptually, the total amount of credit losses is the same under CECL and the incurred loss model, but loan loss provisions will be recorded earlier under CECL. Since CECL aims to forecast average losses rather than maximum losses, it is unlikely to avoid large loan charge-offs during crisis periods. To the extent that the effect of charge-offs and conditional conservatism persist, we expect loan loss provision asymmetry to remain.[15]

Although we cannot directly examine this prediction today using U.S. data, we note that historically the distinction between the incurred and expected loss approaches was blurry. In the late 1990s, the SEC and bank regulators emphasized that banks should strictly follow the incurred loss approach, which had always been required by the accounting standards, mainly to curb over-provisioning of expected loan losses (Camfferman 2015). SEC chairman, Arthur Levitt (1998), famously criticized public firms for creating cookie jar reserves to manage earnings. Banks were criticized next for reporting excessive loan loss allowances (see SEC Review of SunTrust 1998,

[15] Under current GAAP, when loans are individually impaired under ASC 310 (including troubled debt restructurings, banks forecast all future cash flows to measure impairment, similar to an expected loss model. For collateral-dependent loans evaluated under ASC 310, banks can calculate loan losses using the fair value of the collateral (less cost to sell), which also reflects the present value of future cash flows.

Levitt 1999; Beck and Narayanamoorthy 2013). Examining the relation between loan loss provisions and nonperforming loan change before 1998 when loan loss accounting implementation resembled an expected loss model (Camfferman 2015) can shed some light on the implications of the proposed CECL model for our findings.

Figure 6 plots mean loan loss provisions against mean nonperforming loan change partitioned into 20 equal-frequency bins over the period 1986–1998. Loan loss provisions have a distinct V-shaped relation with nonperforming loan change, like that in Figure 1. We fit Model 5 using pre-1998 data and report the results in Table 6, column (1). Like our main inferences, this out-of-sample test suggests that controlling for net loan charge-offs eliminates the V-shaped pattern, but that loan loss provisions increase more when nonperforming loans increase than they drop when nonperforming loans decrease. We then examine whether the residual asymmetry is stronger or weaker after 1999, when the trends toward an incurred loss model arguably accelerated (Camfferman 2015). We interact a *POST* dummy variable with ΔNPL, $D\Delta NPL$, and $\Delta NPL \times D\Delta NPL$. The residual asymmetry did not change much around 1999, as the coefficient on $D\Delta NPL \times \Delta NPL \times POST$ in column (2) is statistically insignificant (t-statistic = -0.96). This finding suggests that the loan loss provisioning asymmetry is likely to persist after CECL becomes effective. The implications of CECL for loan loss provision asymmetry can be studied better when U.S. firms adopt CECL or by using data from IASB jurisdictions where expected credit loss recognition is already in force.

6.3. Litigation incentives for conditional conservatism holding standards constant

We make two additional predictions based on litigation exposure incentives for conditional conservatism. First, Basu, Hwang, and Jan (2002) and others show that fourth quarter earnings exhibit greater asymmetric timeliness of bad news recognition due to auditors' legal liability exposure. Loan loss provisions likely exhibit similarly greater asymmetric timeliness in the fourth quarter if conditional conservatism is at play. Second, public banks are scrutinized by equity holders, the SEC and shareholder class-action lawsuits, so demand for conditional conservatism is greater for public banks than for private banks (Ball and Shivakumar 2005, 2008; Nichols et al. 2009; Hope, Thomas, and Vyas 2013).

We estimate Model 9, coding *PART* equal to one for the fourth quarter or publicly traded banks. Table 7 reports the results. Consistent with our prediction, the coefficient α_4 is negative and significant in both columns, suggesting greater asymmetry in settings where condition conservatism is most pervasive, i.e., in fourth quarters and for public banks. In Figure A2 of the online appendix, we show that the fourth quarter effect on loan loss provision asymmetry was the largest during the 2007-2012 real estate crisis, even after controlling for the large charge-offs.[16] As a validation check for conditional conservatism, we conduct a piecewise linear regression of loan loss provisions on contemporaneous stock returns for public banks, similar to the earnings-return relation in Basu (1997) and the operating accrual-return relation in Ball and Shivakumar (2006) and Collins, Hribar and Tian (2014). As Table 8 shows, loan loss provisions are significantly more responsive to negative returns than to positive returns, consistent with the effect of conditional conservatism.[17]

[16] In a similar analysis (untabulated) we interact the asymmetric term, $\Delta NPL(NCO) \times D\Delta NPL(NCO)$, with Q4 dummy and real estate crisis dummy in Models 4 and 5. The four-way interaction term is negative and significant, suggesting that the fourth quarter effect on loan loss provision asymmetry was most pronounced during recessions.

[17] Managers could exercise greater discretion over net charge-offs in fourth quarters, for public banks, and during recessions to create cookie jar reserves or take a "big bath," similar to write-offs of long-lived assets (e.g., Elliott and Hanna 1996; Riedl 2004). However, it is unclear why this behavior would systematically influence loan loss provision *asymmetry* per se. For example, the big baths in fourth quarters, if any, can be plausibly addressed in linear models that allow a steeper slope for nonperforming loan change in the fourth quarters and/or a positive intercept for a fourth quarter dummy (unconditionally large net charge-off in fourth quarters). Managers' discretion in net charge-offs in fourth quarters is unlikely to be sustainable since regulators require that the loan loss allowance be *consistently* determined in accordance with GAAP. Unusually large charge-offs or provisions will likely reverse in future, which attracts regulatory scrutiny. The higher correlation of loan loss provisions with concurrent stock returns suggest that these accruals reflect public information, more consistent with conditional conservatism than earnings management (Watts, 2003b)

To summarize, our findings suggest that the residual loan loss provision asymmetry is driven by both mandatory conservatism embedded in accounting standards for different loan types and litigation incentives for conditional conservatism. We think it unlikely that alternative explanations such as cost stickiness (e.g. Anderson, Banker, Janakiraman 2003; Banker, Basu, Byzalov and Chen, 2016) or liquidation options (e.g. Lawrence, Sloan and Sun, 2017) would bias our loan loss provision model estimates, but we leave this for future research to explore.

7. Conclusion

Researchers typically model loan loss provisions as linear functions of changes in loan performance metrics (i.e., changes in nonperforming loans). An implicit assumption is that loan loss provisions change proportionally to nonperforming loan changes. The data reveal a V-shaped relation, where a large drop in nonperforming loans is associated with an *increase* in loan loss provisions. A piecewise linear model that accommodates this asymmetry fits much better and reduces the bias in the estimates of discretionary loan loss provisions (i.e., model residuals).

We show that net loan charge-offs are a major source of the V-shaped pattern. After modeling the effects of net loan charge-offs, loan loss provisions move in the same direction as nonperforming loan change, with loan loss provisions being more sensitive to nonperforming loan increases than to decreases. We replicate parts of two recent studies that use the difference in adjusted R^2 between standard linear models as a measure of delayed loan loss recognition. We show that the inferences change when the first-stage loan loss provision models incorporate asymmetry and net loan charge-offs. The residual asymmetry after modeling net loan charge-offs is at least partly due to variation in mandatory loan loss recognition standards across loan types and litigation incentives for conditional conservatism (and any interactions).

More broadly, our paper demonstrates the large benefits of plotting data. Relying solely on regression estimates leads even trained econometricians to infer incorrectly (Anscombe, 1973; Soyer and Hogarth, 2012). Easton (1999) emphasized that the major asymmetries in the return-earnings relation identified by Hayn (1995) and Basu (1997) could have been detected decades earlier if researchers routinely plotted their data; our paper shows that this argument also applies to banking research on loan loss provision timeliness.

We suggest several future research directions. First, our attempt to measure nonperforming loan change before net loan charge-offs can be improved upon by using more detailed data (for example, loan receivables aging schedule, loan-to-value ratios) or alternative ways of estimating the amount of loans restored to performing status as a result of charge-offs. A second opportunity is to study whether and how the CECL model affects loan loss provision asymmetry by running our models after CECL is adopted in the U.S. or with data from jurisdictions following IASB standards that have already implemented expected credit loss recognition rules.

Third, including net charge-offs as a standalone explanatory variable can throw the baby out with the bath water and does not account for settings where net loan charge-offs are jointly determined with loan loss provisions (Beatty, Chamberlain, and Magliolo 1995; Liu and Ryan 2006). Future research can compare the costs and benefits of including net charge-offs in different contexts. Fourth, future research could explore contracting and tax demands for conservatism and/or the other asymmetry sources such as cost stickiness, earnings management and liquidation options. Fifth, our findings suggest asymmetry in expenses tied to contra-asset allowances such as bad debts, sales returns, and warranties, and thus can apply far beyond banking. Our takeaway is that researchers still have much to learn about the empirical effects of the methods taught in Introductory Accounting.

Appendix

Variable Definitions

Variable	Definition
LLP	Loan loss provisions (BHCK4230) scaled by lagged loans (BHCK2122)
ΔNPL	Change in nonperforming loans (BHCK5525+BHCK5526) scaled by lagged loans
SIZE	Logarithm of lagged total assets (BHCK2170)
ΔLOAN	Change in loan (BHCK2122) scaled by lagged loans
ALL	Allowance for loan losses (BHCK3123) scaled by lagged loans
NCO	Net charge-offs (BHCK4635-BHCK4605) scaled by lagged loans
ΔNPLNCO	Change in nonperforming loans (BHCK5525+BHCK5526) plus net charge-offs (BHCK4635-BHCK4605) scaled by lagged loans
TIER1CAP	Tier1 capital (BHCK8274) divided by risk weighted assets (BHCKA223)
EBP	Earnings before provisions (BHCK4301 + BHCK4230) scaled by lagged loans (BHCK2122)
CONSTRUCTION	The ratio of construction loans (BHCKF158+BHCKF159) to total loans (BHCK2122)
COMMERCIAL	The ratio of non-construction commercial loans (BHCK1460+BHCK1763+BHCK1764) to total loans (BHCK2122)
RESIDENTIAL REAL ESTATE	The ratio of residential real estate mortgage loans (BHCK1797+BHCK5367+BHCK5368) to total loans
CONSUMER	The ratio of consumer loans (BHCKB538+BHCKB539+BHCKK137+BHCKK207) to total loans
QTR4	An indicator for fourth quarter
PUBLIC	An indicator for public banks, defined as those whose equity shares are traded on U.S. stock exchanges. Public banks are identified via the RSSD (bank regulatory identification number)-PERMCO (permanent company number used by CRSP) link table provided by Federal Reserve Bank of New York.
RET	Market adjusted quarterly stock returns
NEG	An indicator variable equal to one if *RET*<0, and zero otherwise

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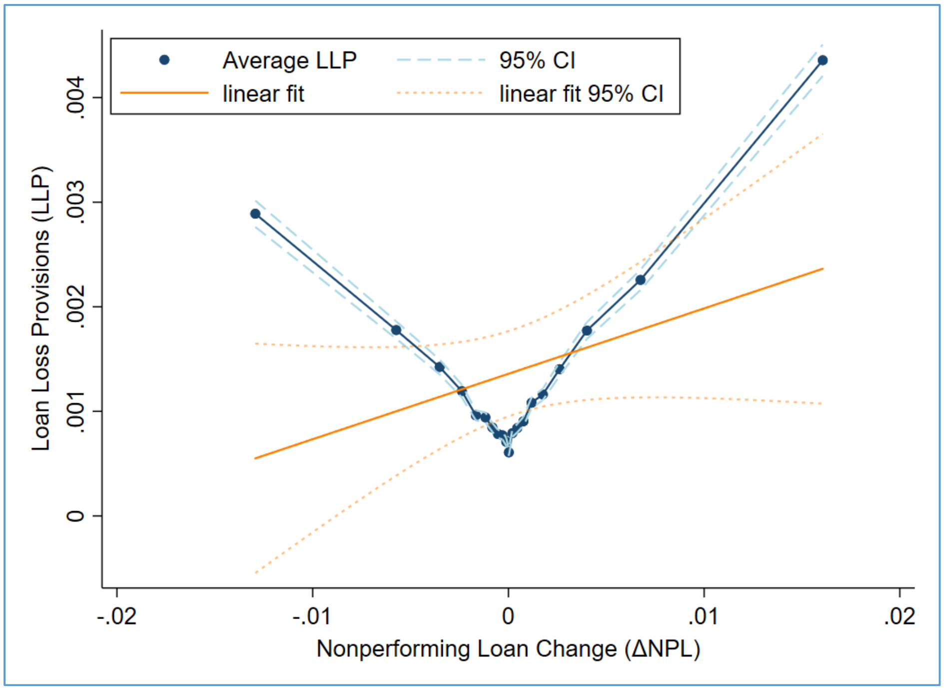
FIGURE 1

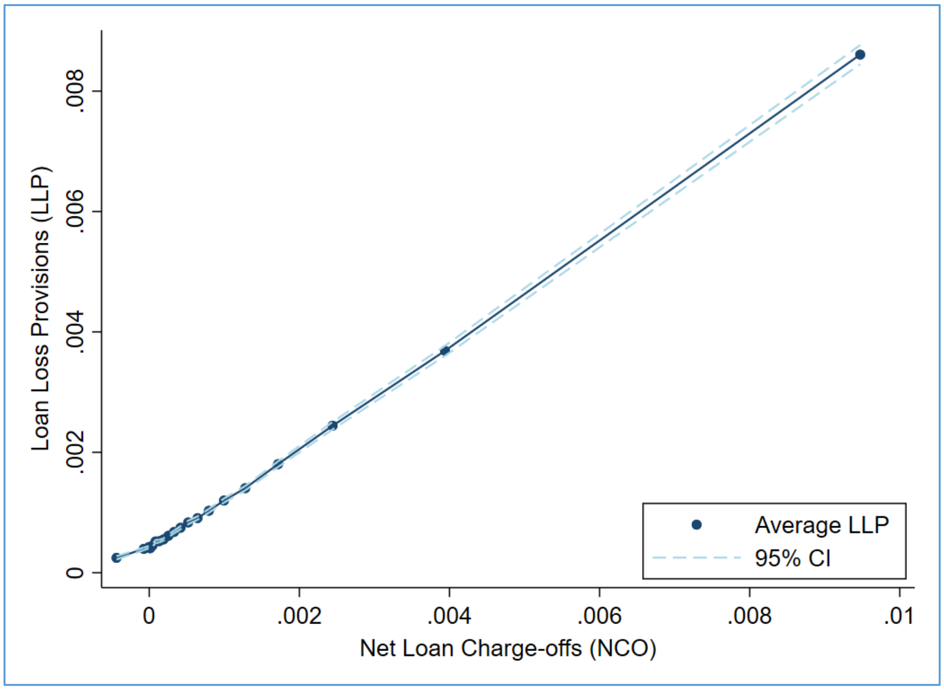
Unconditional Relation Between LLP and ΔNPL (Raw Data)



This figure plots the relationship between quarterly loan loss provisions and quarterly change in nonperforming loans, both scaled by beginning loans. We divide quarterly change in nonperforming loan into 20 equal-frequency bins and plot the mean loan loss provisions versus the mean change in nonperforming loans for each bin (blue circles connected by solid blue line). The dashed blue lines represent the 95% confidence interval of loan loss provisions within each bin. The solid red line represents the OLS estimate for the same data, and the dashed red lines represent the 95% confidence interval for the OLS line.

FIGURE 2

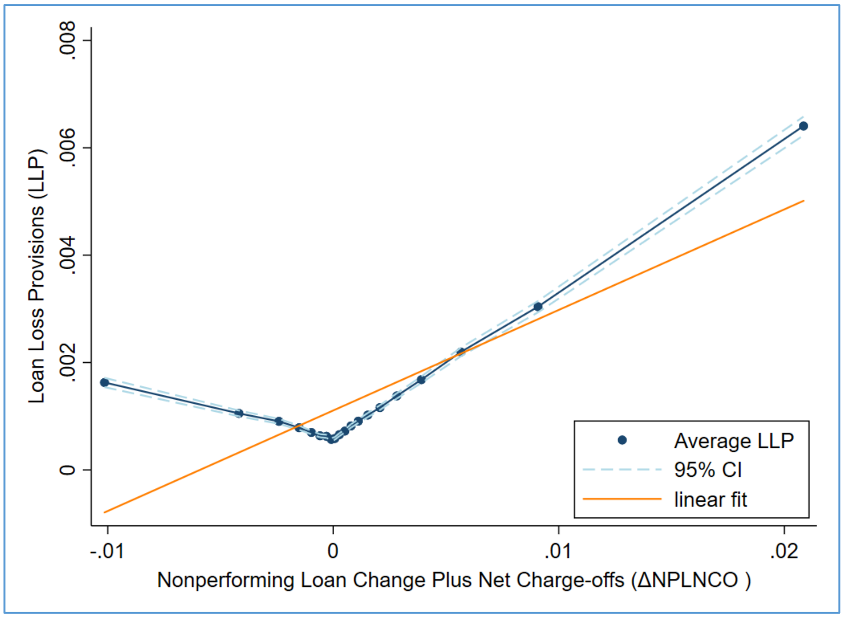
Unconditional Relation Between LLP and NCO (Raw Data)



This figure plots the relationship between quarterly loan loss provisions and net loan charge-offs, both scaled by beginning loans, sorted on net loan charge-offs into 20 equal-frequency bins. The solid blue line connects the mean loan loss provision and mean loan charge-offs in each bin (indicated as blue circles), while the dashed blue line represents the 95% confidence interval for mean loan loss provision in each bin.

FIGURE 3

Nonperforming Loan Change Plus Net Loan Charge-offs (ΔNPLNCO)



This figure plots mean loan loss provisions against mean nonperforming loan changes plus current net loan charge-offs (both deflated by beginning-of-the-quarter loans) across 20 equal-frequency bins sorted by nonperforming loan change plus loan charge-offs (indicated as blue circles connected by solid blue lines). The dashed blue lines represent the 95% confidence interval of loan loss provisions within each bin. The solid red line represents the OLS estimate for the same data.

FIGURE 4

Model Residuals and Nonperforming Loan Change

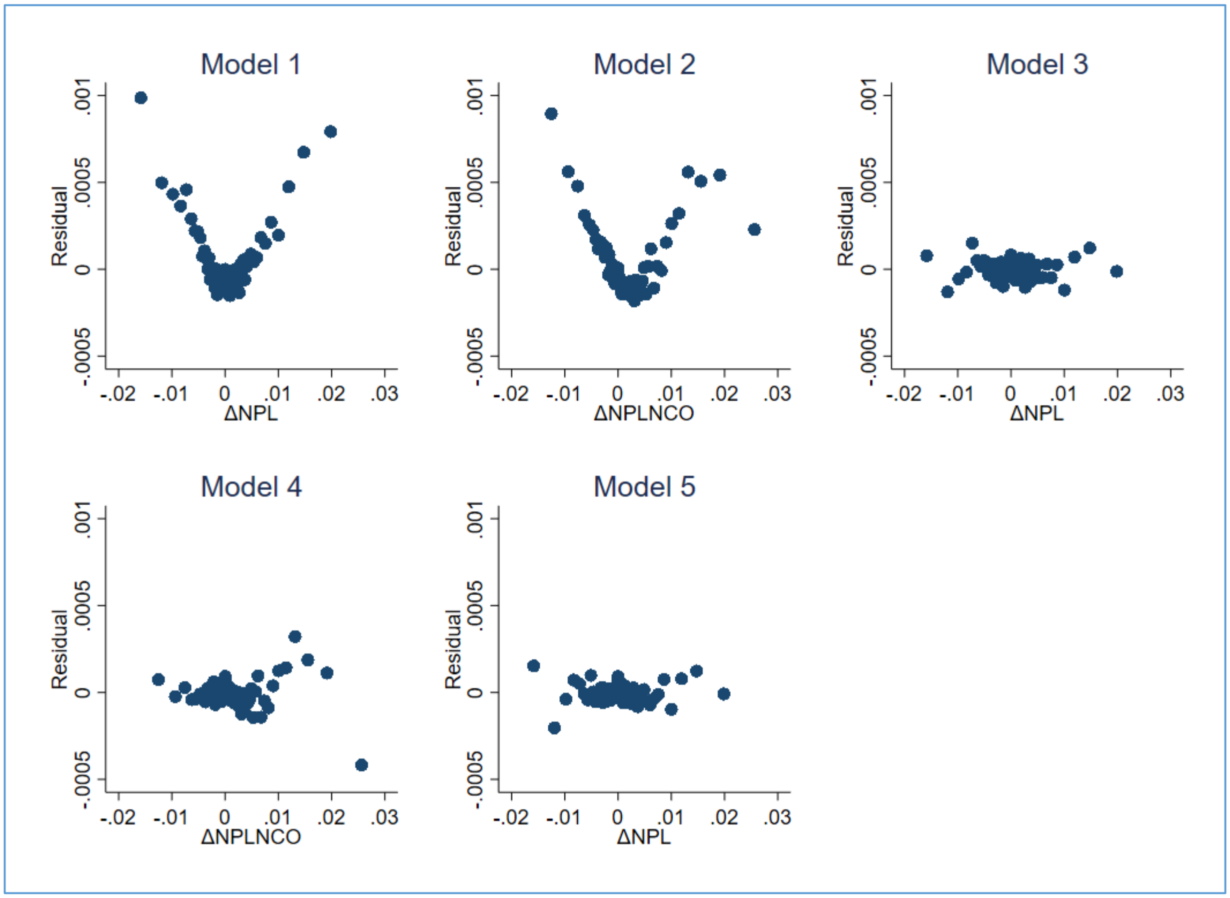
Model 1: $LLP_t = \alpha_1 \Delta NPL_t$

Model 2: $LLP_t = \alpha_1 \Delta NPLNCO_t$

Model 3: $LLP_t = \alpha_1 \Delta NPL_t + \alpha_2 D\Delta NPL_t \times \Delta NPL_t + \alpha_3 D\Delta NPL_t$

Model 4: $LLP_t = \alpha_1 \Delta NPLNCO_t + \alpha_2 D\Delta NPLNCO_t \times \Delta NPLNCO_t + \alpha_3 D\Delta NPLNCO_t$

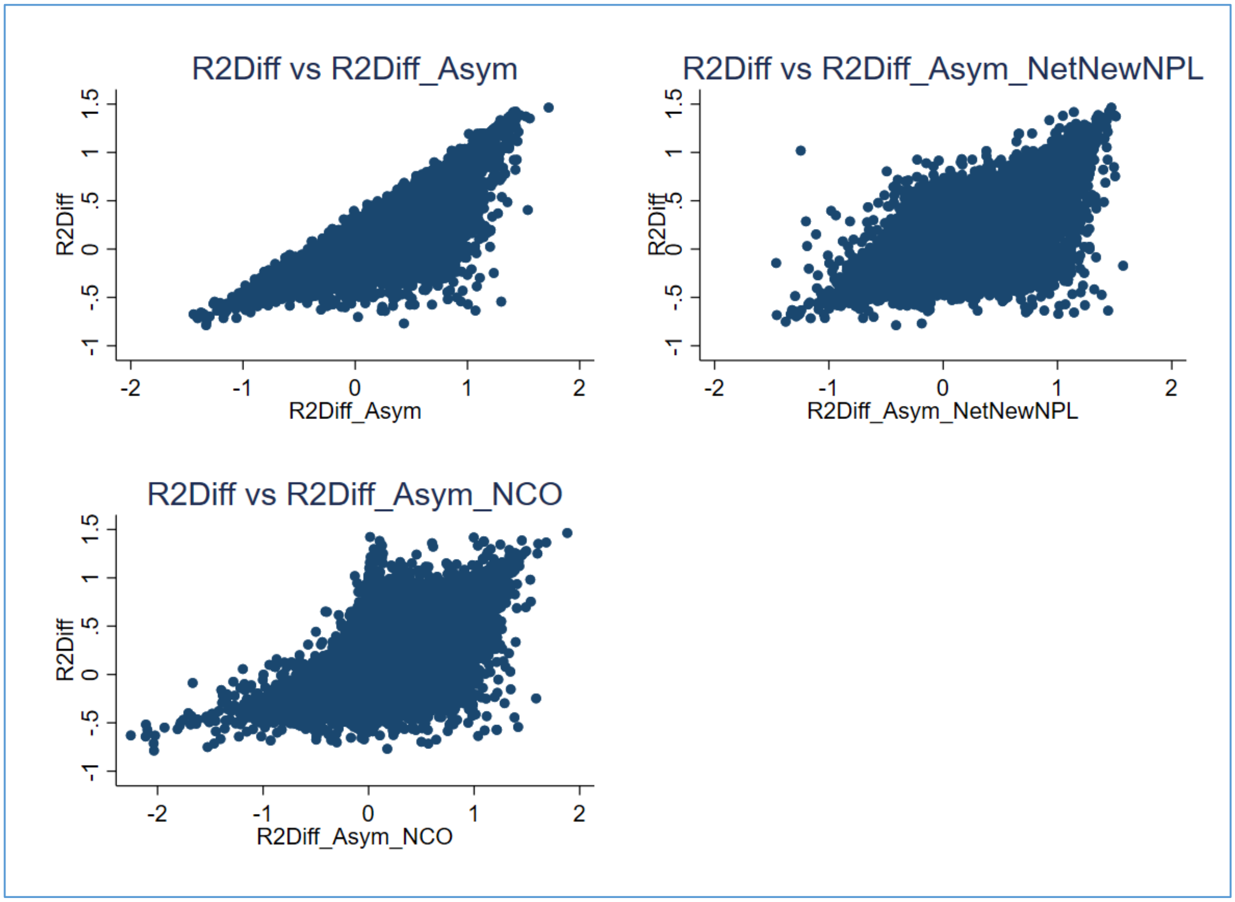
Model 5: $LLP_t = \alpha_1 \Delta NPL_t + \alpha_2 D\Delta NPL_t \times \Delta NPL_t + \alpha_3 D\Delta NPL_t + \alpha_4 NCO_t$



The figures plot the mean residuals from each of the five models in Table 2 against mean quarterly *ΔNPL* (mean *ΔNPLNCO* for Models 2 and 4). Bank-quarter observations are divided into 100 equal-frequency bins sorted on *ΔNPL* (*ΔNPLNCO*), and the mean residuals from each of the five models are plotted against the mean *ΔNPL* (*ΔNPLNCO*) in each bin.

FIGURE 5

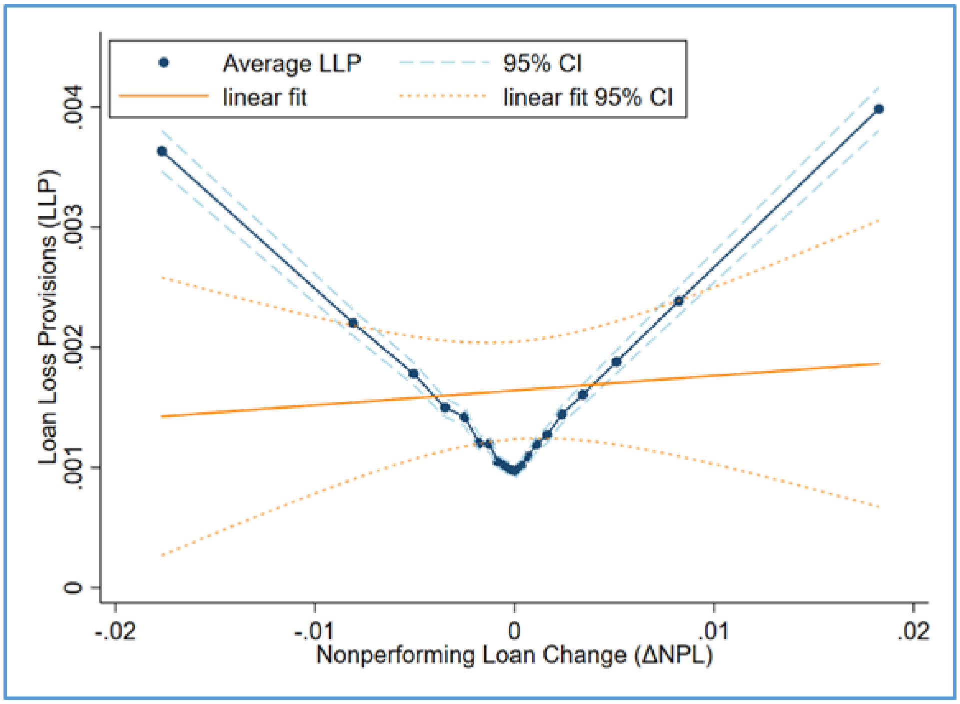
Correlations between Incremental R^2 Measures



The figures depict the correlation between the incremental adjusted R^2 (a proxy for loan loss recognition timeliness) derived from standard linear models, called *R2Diff*, and the incremental adjusted R^2 derived from alternative specifications that incorporate piecewise linearity and the effect of net charge-offs. Section 5.2 in the main text provides the model specifications. *R2Diff_Asym* is the incremental adjusted R^2 of model (c) over model (a); *R2Diff_Asym_NetNewNPL* is the incremental adjusted R^2 of model (e) over model (d); *R2Diff_Asym_NCO* is the incremental adjusted R^2 of model (g) over model (f). The incremental R^2 measures of each bank-quarter are obtained by running the models for each bank-quarter using a rolling window of 12 bank-quarters, as in prior studies (Beatty and Liao 2011; Bushman and Williams 2015).

FIGURE 6

Unconditional Relation between LLP and ΔNPL over the period 1986-1998



This figure plots the relationship between quarterly loan loss provisions and quarterly changes in nonperforming loans, both scaled by beginning loans, over the period 1986-1998. We divide quarterly changes in nonperforming loans into 20 equal-frequency bins and plot the mean loan loss provisions versus the mean changes in nonperforming loans for each bin (blue circles connected by solid blue line). The dashed blue lines represent the 95% confidence interval of loan loss provisions within each bin. The solid red line represents the OLS estimate for the same data, and the dashed red lines represent the 95% confidence interval for the OLS line.

TABLE 1

Summary Statistics

Panel A: Descriptive Statistics (N = 85,690)

	Mean	Std	p25	Median	p75
LLP_t	0.14%	0.25%	0.03%	0.07%	0.14%
ΔNPL_t	0.02%	0.55%	-0.14%	0.00%	0.14%
ΔNPL_{t-1}	0.03%	0.55%	-0.14%	0.00%	0.15%
ΔNPL_{t-2}	0.03%	0.54%	-0.14%	0.00%	0.15%
NCO_t	0.11%	0.23%	0.01%	0.04%	0.11%
$\Delta NPLNCO_t$	0.14%	0.61%	-0.08%	0.04%	0.24%
$\Delta LOAN_t$	2.06%	4.55%	-0.40%	1.59%	3.81%
$SIZE_{t-1}$	13.77	1.46	12.75	13.46	14.31

Panel B: Pearson and Spearman correlations

	LLP_t	ΔNPL_t	ΔNPL_{t-1}	ΔNPL_{t-2}	NCO_t	$\Delta NPLNCO_t$	$\Delta LOAN_t$	$SIZE_{t-1}$
LLP_t		**0.086**	**0.117**	**0.123**	**0.614**	**0.300**	**-0.077**	**0.070**
ΔNPL_t	**0.144**		**-0.011**	**0.036**	**-0.062**	**0.892**	**0.069**	0.003
ΔNPL_{t-1}	**0.170**	**0.024**		**-0.014**	**0.077**	**0.010**	-0.007	0.007
ΔNPL_{t-2}	**0.172**	**0.050**	**0.017**		**0.078**	**0.057**	**-0.038**	0.005
NCO_t	**0.801**	**-0.027**	**0.121**	**0.136**		**0.244**	**-0.249**	**0.158**
$\Delta NPLNCO_t$	**0.464**	**0.899**	**0.071**	**0.100**	**0.375**		**-0.026**	**0.062**
$\Delta LOAN_t$	**-0.152**	**0.088**	**-0.020**	**-0.050**	**-0.233**	**-0.009**		**-0.047**
$SIZE_{t-1}$	**0.099**	0.006	0.008	0.006	**0.118**	**0.049**	**-0.017**	

This table presents summary statistics for the variables used in the main regression analyses. The sample comprises 85,690 bank-quarter observations over the period 2000Q1 to 2018Q4. Panel A reports the descriptive statistics of the variables and Panel B reports the Pearson (Spearman) correlations between the variables below (above) the diagonal. Bold face indicates significance level at the 1% level in two-tailed tests. Variable definitions are in the Appendix.

TABLE 2

Model Comparison

Model 1: $LLP_t = \alpha_1 \Delta NPL_t + \alpha_2 \Delta NPL_{t-1} + \alpha_3 \Delta NPL_{t-2} + \alpha_4 SIZE_{t-1} + \alpha_5 \Delta LOAN_t + \epsilon_t$

Model 2: $LLP_t = \alpha_1 \Delta NPLNCO_t + \alpha_2 \Delta NPLNCO_{t-1} + \alpha_3 \Delta NPLNCO_{t-2} + \alpha_4 SIZE_{t-1} + \alpha_5 \Delta LOAN_t + \epsilon_t$

Model 3: $LLP_t = \alpha_1 \Delta NPL_t + \alpha_2 \Delta NPL_{t-1} + \alpha_3 \Delta NPL_{t-2} + \alpha_4 D\Delta NPL_t \times \Delta NPL_t + \alpha_5 D\Delta NPL_t + \alpha_6 SIZE_{t-1} + \alpha_7 \Delta LOAN_t + \epsilon_t$

Model 4: $LLP_t = \alpha_1 \Delta NPLNCO_t + \alpha_2 \Delta NPLNCO_{t-1} + \alpha_3 \Delta NPLNCO_{t-2} + \alpha_4 D\Delta NPLNCO_t \times \Delta NPLNCO_t + \alpha_5 D\Delta NPLNCO_t + \alpha_6 SIZE_{t-1} + \alpha_7 \Delta LOAN_t + \epsilon_t$

Model 5: $LLP_t = \alpha_1 \Delta NPL_t + \alpha_2 \Delta NPL_{t-1} + \alpha_3 \Delta NPL_{t-2} + \alpha_4 D\Delta NPL_t \times \Delta NPL_t + \alpha_5 D\Delta NPL_t + \alpha_6 NCO_t + \alpha_7 SIZE_{t-1} + \alpha_8 \Delta LOAN_t + \epsilon_t$

		Model				
		1	2	3	4	5
ΔNPL_t	+	0.043***		0.131***		0.072***
		(6.63)		(12.51)		(10.59)
ΔNPL_{t-1}	+	0.044***		0.035***		0.021***
		(7.99)		(7.49)		(10.18)
ΔNPL_{t-2}	+	0.040***		0.035***		0.016***
		(8.37)		(8.31)		(9.39)
$D\Delta NPL_t \times \Delta NPL_t$	-			-0.210***		-0.029***
				(-12.50)		(-4.04)
$\Delta NPLNCO_t$	+		0.111***		0.164***	
			(15.07)		(17.54)	
$\Delta NPLNCO_{t-1}$	+		0.067***		0.057***	
			(13.46)		(13.04)	
$\Delta NPLNCO_{t-2}$	+		0.055***		0.048***	
			(11.89)		(11.68)	
$D\Delta NPLNCO_t \times \Delta NPLNCO_t$	-				-0.176***	
					(-13.12)	
NCO_t						0.730***
						(37.36)
$SIZE_{t-1}$		0.000***	0.000***	0.000***	0.000***	0.000***
		(4.80)	(3.08)	(5.55)	(3.94)	(6.55)
$\Delta LOAN_t$		-0.004***	-0.003***	-0.003***	-0.003***	0.001***
		(-4.96)	(-5.17)	(-4.60)	(-4.84)	(5.45)
F-test: $\Delta NPL_t + D\Delta NPL_t \times \Delta NPL_t = 0$				-0.079***		0.043***
F-test: $\Delta NPLNCO_t + D\Delta NPLNCO_t \times \Delta NPLNCO_t = 0$					-0.012*	
Bank, quarter FE		Yes	Yes	Yes	Yes	Yes
Adj. R^2		0.437	0.515	0.462	0.532	0.706
Adj. within R^2		0.050	0.182	0.092	0.210	0.504
Wooldridge test for autocorrelation		16.82***	7.29***	13.90***	5.82**	0.53
Residual Skewness		2.97***	2.58***	2.77***	2.41***	1.61***
Residual Kurtosis		20.03***	19.37***	19.43***	19..32***	25.14***

This table presents the results of estimating the five competing models of loan loss provisions as laid out above and in section (3) of the main text. All models include bank and quarter fixed effects. The sample comprises 85,690 bank-quarter observations over the period 2000Q1 to 2018Q4. *t*-statistics are reported in parentheses based on standard errors clustered at both the bank and quarter level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels (two-tail). See the Appendix for definitions of all variables in the regressions. The standalone *DΔNPL* and *DΔNPLNCO* are included in the corresponding regressions. Since the coefficients on these variables are close to zero and insignificant, we do not report them to conserve space.

TABLE 3

Specification Tests of Earnings Management through LLP (Type I Error)

Model 1: $LLP_t = \alpha_1 \Delta NPL_t + \alpha_2 NPL_{t-1} + \alpha_3 \Delta NPL_{t-2}$

Model 2: $LLP_t = \alpha_1 \Delta NPLNCO_t + \alpha_2 \Delta NPLNCO_{t-1} + \alpha_3 \Delta NPLNCO_{t-2}$

Model 3: $LLP_t = \alpha_1 \Delta NPL_t + \alpha_2 \Delta NPL_{t-1} + \alpha_3 \Delta NPL_{t-2} + \alpha_4 D\Delta NPL_t \times \Delta NPL_t + \alpha_5 D\Delta NPL_t$

Model 4: $LLP_t = \alpha_1 \Delta NPLNCO_t + \alpha_2 \Delta NPLNCO_{t-1} + \alpha_3 \Delta NPLNCO_{t-2} + \alpha_4 D\Delta NPLNCO_t \times \Delta NPLNCO_t + \alpha_5 D\Delta NPLNCO_t$

Model 5: $LLP_t = \alpha_1 \Delta NPL_t + \alpha_2 \Delta NPL_{t-1} + \alpha_3 \Delta NPL_{t-2} + \alpha_4 D\Delta NPL_t \times \Delta NPL_t + \alpha_5 D\Delta NPL_t + \alpha_6 NCO_t$

Panel A: H1: Discretionary LLP>0

		ΔNPL (*ΔNPLNCO*) quintile				
	All banks	Bottom	Q2	Q3	Q4	Top
Model 1	*1.6*	**54.0**	*0.0*	*0.0*	*0.0*	**26.8**
Model 2	*1.6*	**79.2**	*0.0*	*0.0*	*0.0*	**9.6**
Model 3	2.8	*2.0*	*1.6*	2.4	2.4	*1.6*
Model 4	3.6	2.4	2.0	**15.2**	*1.2*	3.6
Model 5	4.4	5.6	2.8	4.8	3.2	3.6

Panel B: H1: Discretionary LLP<0

		ΔNPL (*ΔNPLNCO*) quintile				
	All banks	Bottom	Q2	Q3	Q4	Top
Model 1	**8.8**	*0.0*	**59.6**	**80.8**	**56.4**	*1.2*
Model 2	5.2	*0.0*	**46.0**	**73.2**	**54.4**	2.8
Model 3	7.2	8.0	**14.0**	**10.0**	**8.8**	**11.6**
Model 4	6.0	**8.4**	8.0	*1.2*	6.4	8.0
Model 5	4.8	5.6	**9.2**	*2.0*	5.6	**14.0**

This table compares the frequency with which the null hypothesis of zero discretionary *LLP* is rejected at the 5% level against the alternative of positive (negative) discretionary *LLP* in Panel A (B) under each of the five competing models laid out above and in section (3) of the main text. All models include the quarterly change in loans, lagged logged bank assets, and bank and quarter fixed effects, which are suppressed for parsimony. For each trial, 100 bank-quarters are randomly drawn from either the aggregate sample of 85,690 bank-quarter observations or from each of the five quintiles of bank-quarters ranked by *ΔNPL* (*ΔNPLNCO* for Models 2 and 4). We report the percentage of 250 trials for which the null hypothesis of zero discretionary *LLP* is rejected at the 5% level using a one-tailed *t*-test. Rejection rates that are significantly less than the nominal significance level (below 2.4%) are in italics, and rejection rates that are significantly more than the nominal significance level (above 8%) are in bold.

TABLE 4

Biases in Research Using Incremental R^2 from Linear Loan Loss Provision Models

Model (a): $LLP_t = \Delta NPL_{t-1} + \Delta NPL_{t-2}$

Model (b): $LLP_t = \Delta NPL_t + \Delta NPL_{t+1} + \Delta NPL_{t-1} + \Delta NPL_{t-2}$

Model (c): $LLP_t = \Delta NPLPOS_t + \Delta NPLNEG_t + \Delta NPL_{t+1} + \Delta NPL_{t-1} + \Delta NPL_{t-2}$

Model (d): $LLP_t = \Delta NPLNCO_{t-1} + \Delta NPLNCO_{t-2}$

Model (e): $LLP_t = \Delta NPLNCOPOS_t + \Delta NPLNCONEG_t + \Delta NPLNCO_{t+1} + \Delta NPLNCO_{t-1} + \Delta NPLNCO_{t-2}$

Model (f): $LLP_t = \Delta NPL_{t-1} + \Delta NPL_{t-2} + NCO_t$

Model (g): $LLP_t = \Delta NPLPOS_t + \Delta NPLNEG_t + \Delta NPL_{t+1} + \Delta NPL_{t-1} + \Delta NPL_{t-2} + NCO_t$

	Difference in models' adjusted R^2
R2Diff:	Model (b) - Model (a)
R2Diff_Asym:	Model (c) - Model (a)
R2Diff_Asym_NetNewNPL:	Model (e) - Model (d)
R2Diff_Asym_NCO:	Model (g) - Model (f)

Replication and extension of prior studies

	Capital crunch (Beatty and Liao 2011, Table 5, column 1)	Downside tail risk (Bushman and Williams 2015, Table 3, column 3)
(1) *Original result (R2Diff)*	-0.138**	-0.082**
	(-1.75)	(-2.49)
(2) *Replication (R2Diff)*	-0.090**	-0.083**
	(-1.66)	(-2.87)
(3) *R2Diff_Asym*	-0.064	-0.072
	(-0.58)	(-1.58)
(4) *R2Diff_Asym_NetNewNPL*	0.021	0.011
	(0.41)	(0.19)
(5) *R2Diff_Asym_NCO*	0.153**	-0.051
	(2.41)	(-1.00)

This table presents the results of replicating parts of Beatty and Liao (2011) and Bushman and Williams (2015), which use the incremental R^2 from adding lead and current changes in nonperforming loans over and above lagged changes in nonperforming loans. *R2Diff* is derived from linear models, computed by subtracting the adjusted R^2 of model (a) from model (b). *R2Diff_Asym* is the incremental adjusted R^2 of model (c) over model (a). *R2Diff_Asym_NetNewNPL* is computed by subtracting the adjusted R^2 of model (d) from that of model (e). *R2Diff_Asym_NCO* is the incremental adjusted R^2 of model (g) over model (f). Following prior literature, all models include lagged tier1 capital ratio (*TIER1CAP*) and earnings before loan loss provisions scaled by lagged loans (*EBP*), which are suppressed for parsimony. When replicating Bushman and Williams (2015), we also include lagged bank size as an additional control variable in all models to facilitate direct comparison. For each bank-quarter, we run the models using a 12-quarter rolling window and obtain the corresponding adjusted model R^2s for that bank-quarter. In models (c) and (g), *ΔNPLPOS* (*ΔNPLNEG*) equals *ΔNPL* when *ΔNPL*>=0 (*ΔNPL*<0), and zero otherwise. This approach is similar to adding a piecewise linear term as in the main specification, but saves one degree of freedom (by omitting the standalone dummy variable), which matters in rolling regressions with only 12 observations. Likewise, in model (e), *ΔNPLNCOPOS (ΔNPLNCONEG)* equals *ΔNPLNCO* when *ΔNPLNCO*>=0 (*ΔNPLNCO*<0*)*, and zero otherwise.

TABLE 5

Variations in Loan Loss Accounting Standards

$$LLP_t = \alpha_1 \Delta NPL_t + \alpha_2 \Delta NPL_t \times D\Delta NPL_t + \alpha_3 \Delta NPL_t \times PART + \boldsymbol{\alpha_4 \Delta NPL_t \times D\Delta NPL_t \times PART} + \alpha_5 D\Delta NPL_t \times PART + \alpha_6 PART + \alpha_7 D\Delta NPL_t + \alpha_8 \Delta NPL_{t-1} + \alpha_9 \Delta NPL_{t-2} + \alpha_{10} NCO_t + \alpha_{11} SIZE_{t-1} + \alpha_{12} \Delta LOAN_t + \epsilon_t$$

Panel A: Variation in loan loss provision asymmetry during the full sample period of 2000-2018

	PART =				
	(1)	(2)	(3)	(4)	(5)
	Construction	Commercial	Residential Real Estate	Consumer	Real Estate Crisis
ΔNPL_t	0.019**	0.066***	0.084***	0.093***	0.033***
	(2.26)	(6.27)	(8.11)	(8.35)	(6.39)
$D\Delta NPL_t \times \Delta NPL_t$	0.051***	-0.017	-0.054***	-0.060***	0.021***
	(4.06)	(-1.27)	(-3.70)	(-4.01)	(2.69)
$\Delta NPL_t \times PART$	0.008***	0.001	-0.003**	-0.005***	0.065***
	(4.78)	(0.73)	(-2.08)	(-3.01)	(5.94)
$D\Delta NPL_t \times \Delta NPL_t \times PART$	-0.012***	-0.002	0.005**	0.007***	-0.095***
	(-5.33)	(-0.99)	(2.62)	(2.81)	(-5.66)
ΔNPL_{t-1}	0.020***	0.021***	0.021***	0.021***	0.020***
	(9.81)	(10.06)	(10.11)	(10.18)	(10.12)
ΔNPL_{t-2}	0.015***	0.016***	0.015***	0.016***	0.015***
	(9.08)	(9.53)	(9.33)	(9.41)	(8.87)
NCO_t	0.726***	0.730***	0.729***	0.728***	0.724***
	(37.59)	(37.48)	(37.45)	(37.20)	(36.93)
$SIZE_{t-1}$	0.000***	0.000***	0.000***	0.000***	0.000***
	(6.22)	(6.58)	(6.43)	(6.43)	(6.53)
$\Delta LOAN_t$	0.001***	0.001***	0.001***	0.001***	0.001***
	(6.12)	(5.47)	(5.52)	(5.85)	(5.73)
Observations	85,681	85,644	85,665	85,499	85,690
Bank, quarter FE	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.707	0.706	0.706	0.706	0.708
Adj. within R^2	0.506	0.504	0.504	0.504	0.507

Panel B: Variation in loan loss provision asymmetry during the 2007-2012 real estate crisis

	PART =			
	(1)	(2)	(3)	(4)
	Construction	Commercial	Residential Real Estate	Consumer
ΔNPL_t	0.045**	0.083***	0.095***	0.094***
	(2.69)	(6.35)	(6.80)	(6.43)
$D\Delta NPL_t \times \Delta NPL_t$	0.046*	-0.012	-0.080***	-0.070***
	(1.95)	(-0.52)	(-3.54)	(-3.07)
$\Delta NPL_t \times PART$	0.005**	0.000	-0.002	-0.002
	(2.12)	(0.11)	(-1.21)	(-0.92)
$D\Delta NPL_t \times \Delta NPL_t \times PART$	-0.012***	-0.005	0.008**	0.007
	(-3.43)	(-1.29)	(2.50)	(1.60)
ΔNPL_{t-1}	0.018***	0.020***	0.019***	0.019***
	(7.66)	(8.26)	(8.18)	(8.30)
ΔNPL_{t-2}	0.013***	0.015***	0.014***	0.015***
	(4.87)	(5.54)	(5.14)	(5.35)
NCO_t	0.736***	0.741***	0.741***	0.741***
	(37.80)	(38.58)	(38.50)	(38.56)
$SIZE_{t-1}$	0.001***	0.001***	0.001***	0.001***
	(5.61)	(5.90)	(5.82)	(5.83)
$\Delta LOAN_t$	0.001*	0.001	0.001	0.001*
	(1.81)	(1.66)	(1.63)	(1.74)
Observations	23,102	23,102	23,102	23102
Bank, quarter FE	Yes	Yes	Yes	Yes
Adj. R^2	0.698	0.697	0.697	0.697
Adj. within R^2	0.489	0.487	0.488	0.488

This table examines the impact of differential accounting standards across loan types on the residual loan loss provision asymmetry after controlling for net loan charge-offs. Panel A presents the results of estimating the effect of loan portfolio composition and real estate crisis on the asymmetry. In columns (1) to (4), the partitioning variable *PART* represents the proportion of a bank's loans that is made up of a given loan type, transformed into a decile rank variable. In column (5), *PART* is an indicator for the 2007-2012 real estate crisis. Panel B reports the estimation of the variation in residual loan loss provision asymmetry for bank-quarter observations in the 2007-2012 real estate crisis. *DΔNPL* and *DΔNPL×PART* are included in the regressions. Because the coefficients on those variables are close to zero and insignificant, we do not report them to conserve space. *t*-statistics are reported in parentheses based on standard errors clustered at both the bank and quarter level *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels (two-tail).

TABLE 6

Would an Expected Loan Loss Approach Affect Asymmetry?

$$LLP_t = \alpha_1 \Delta NPL_t + \alpha_2 \Delta NPL_t \times D\Delta NPL_t + \alpha_3 \Delta NPL_t \times POST + \boldsymbol{\alpha_4 \Delta NPL_t} \times \boldsymbol{D\Delta NPL_t} \times \boldsymbol{POST} + \alpha_5 D\Delta NPL_t \times POST + \alpha_6 POST + \alpha_7 D\Delta NPL_t + \alpha_8 \Delta NPL_{t-1} + \alpha_9 \Delta NPL_{t-2} + \alpha_{10} NCO_t + \alpha_{11} SIZE_{t-1} + \alpha_{12} \Delta LOAN_t + \epsilon_t$$

	(1)	(2)
	Pre-1998	Pre vs. Post 1998
ΔNPL_t	0.059***	0.056***
	(9.39)	(8.77)
$D\Delta NPL_t \times \Delta NPL_t$	-0.038***	-0.027***
	(-5.40)	(-3.41)
$\Delta NPL_t \times POST$		0.016
		(1.57)
$D\Delta NPL_t \times \Delta NPL_t \times POST$		-0.013
		(-0.96)
ΔNPL_{t-1}	0.018***	0.020***
	(6.97)	(12.03)
ΔNPL_{t-2}	0.015***	0.016***
	(7.08)	(11.96)
NCO_t	0.655***	0.707***
	(35.55)	(48.50)
$SIZE_{t-1}$	0.001***	0.000***
	(7.11)	(9.15)
$\Delta LOAN_t$	-0.000	0.000
	(-1.01)	(1.47)
F-test: $\Delta\ \Delta NPLt + D\Delta NPLt \times \Delta NPLt = 0$	0.021***	0.029***
F-test: $\Delta\ \Delta NPLt + D\Delta NPLt \times \Delta NPLt + D\Delta NPL_t \times \Delta NPL_t \times POST$		0.016
Observations	60,245	152,803
Bank, quarter FE	Yes	Yes
Adj. R^2	0.597	0.660
Adj. within R^2	0.405	0.469

This table presents an out-of-sample test using data between 1986 and 1998. Column (1) reports the results of fitting Model 5 over the period 1986-1998. Column (2) reports the results of comparing the residual loan loss provision asymmetry before and after 1998. *POST* is an indicator variable equal to for bank-quarters after 1998, and zero otherwise. The standalone *POST* is subsumed by quarter fixed effects. *DΔNPL* and *DΔNPL×POST* are included in the regressions but suppressed in the table to conserve space. *t*-statistics are reported in parentheses based on standard errors clustered at both the bank and quarter level *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels (two-tail).

TABLE 7

Incentives for Conditional Conservatism

$$LLP_t = \alpha_1 \Delta NPL_t + \alpha_2 \Delta NPL_t \times D\Delta NPL_t + \alpha_3 \Delta NPL_t \times PART + \boldsymbol{\alpha_4 \Delta NPL_t} \times \boldsymbol{D\Delta NPL_t} \times \boldsymbol{PART} + \alpha_5 D\Delta NPL_t \times PART + \alpha_6 PART + \alpha_7 D\Delta NPL_t + \alpha_8 \Delta NPL_{t-1} + \alpha_9 \Delta NPL_{t-2} + \alpha_{10} NCO_t + \alpha_{11} SIZE_{t-1} + \alpha_{12} \Delta LOAN_t + \epsilon_t$$

	PART =	
	QTR4	*PUBLIC*
ΔNPL_t	0.059***	0.057***
	(7.48)	(8.77)
$D\Delta NPL_t \times \Delta NPL_t$	-0.009	-0.010
	(-0.98)	(-1.45)
$\Delta NPL_t \times PART$	0.051***	0.049***
	(2.95)	(6.71)
$D\Delta NPL_t \times \Delta NPL_t \times PART$	-0.080***	-0.060***
	(-3.04)	(-5.97)
ΔNPL_{t-1}	0.021***	0.021***
	(10.06)	(10.13)
ΔNPL_{t-2}	0.016***	0.015***
	(9.33)	(9.34)
NCO_t	0.727***	0.728***
	(38.29)	(37.46)
$SIZE_{t-1}$	0.000***	0.000***
	(6.60)	(6.51)
$\Delta LOAN_t$	0.001***	0.001***
	(5.40)	(4.79)
Observations	85,690	85,690
Bank, quarter FE	Yes	Yes
Adj. R^2	0.707	0.707
Adj. within R^2	0.506	0.506

This table estimates the incremental effect of fourth quarter and public banks on the residual loan loss provision asymmetry after controlling for net loan charge-offs. In column (1), the partitioning variable *PART* is *QTR4*, which equals one for fourth quarter loan loss provisions, and zero otherwise. The standalone *QTR4* is subsumed by quarter fixed effects. In column (2), the partitioning variable is *PUBLIC*, which equals one if the bank is publicly listed, and zero otherwise. The standalone *PUBLIC* is subsumed by bank fixed effects. *t*-statistics are reported in parentheses based on standard errors clustered at the bank and quarter level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels (two-tail).

TABLE 8

Loan Loss Provisions-Stock Return Relation

	Dependent variable = *LLP*				
	(1)	(2)	(3)	(4)	(5)
RET_t	0.001**	0.001**	0.001***	0.001***	0.000
	(2.32)	(2.53)	(3.16)	(2.75)	(1.03)
$RET_t \times NEG_t$	-0.008***	-0.008***	-0.007***	-0.006***	-0.002***
	(-9.71)	(-9.85)	(-9.09)	(-8.79)	(-5.93)
$SIZE_{t-1}$		0.001***	0.000***	0.000***	0.000***
		(4.96)	(4.14)	(4.60)	(4.61)
$\Delta LOAN_t$		-0.001**	-0.002***	-0.002***	0.001***
		(-2.48)	(-3.50)	(-3.81)	(3.05)
ΔNPL_t			0.060***	0.165***	0.093***
			(6.12)	(14.09)	(9.81)
ΔNPL_{t-1}			0.049***	0.042***	0.020***
			(6.58)	(5.89)	(5.60)
ΔNPL_{t-2}			0.052***	0.047***	0.017***
			(6.94)	(6.65)	(4.81)
$\Delta NPL_t \times D\Delta NPL_t$				-0.275***	-0.041***
				(-12.89)	(-3.49)
NCO_t					0.804***
					(42.94)
Bank, quarter FE	Yes	Yes	Yes	Yes	Yes
Observations	26,720	26,720	26,720	26,720	26,720
Adj. R^2	0.445	0.450	0.476	0.505	0.755
Adj. within R^2	0.055	0.063	0.107	0.156	0.583

This table presents the results of estimating piecewise linear regressions of loan loss provisions on stock returns for public banks over the sample period of 2000Q1-2018Q4. Columns (1) through (5) incrementally add control variables to the regressions, all of which include bank and quarter fixed effects. *LLP* is loan loss provisions deflated by lagged total loans. *RET* is market adjusted quarterly stock return. *NEG* is an indicator variable for *RET*<0, and zero otherwise. *t*-statistics are reported in parentheses based on standard errors clustered at both the bank and quarter level *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels (two-tail). All regression variables are defined in the appendix.