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The Implications of Credit Risk Modeling for Banks' Loan Loss Provisions and Loan-Origination Procyclicality

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Abstract. Economic policymakers express concern that procyclical lending by banks imperils financial stability. Prior research finds that banks that record timelier loan loss provisions originate more loans during downturns, consistent with loan loss–provision timeliness mitigating loan-origination procyclicality. Motivated by this concern and research, we examine whether banks' credit risk modeling disciplines both their loan loss provisions and loan origination. We identify two forms of credit risk modeling from banks' financial report disclosures: statistical modeling of the drivers of past loan losses and stress testing of future loan losses to adverse scenarios. We show that banks' credit risk–modeling disclosures are positively associated with their loan loss–provision timeliness, with the ability of their provisions to predict future loan charge-offs, and with their loan origination during downturns. We further show that these associations vary in predictable ways across the two forms of credit risk modeling when we distinguish homogeneous from heterogeneous loans and stable periods from downturns.

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Keywords: credit risk modeling • loan loss provisions • timeliness • procyclicality • financial crisis • disclosure

1. Introduction

Banks primarily assume credit risk by originating and holding loans. Banks engage in credit risk modeling to understand and manage loan credit risks as well as to satisfy the requirements of FAS 5's incurred loss model (including related SEC and bank regulatory guidance) for the accrual of credit losses on loans.[1] In this paper, we argue that credit risk modeling increases the timeliness and range of banks' information about loan losses, thereby disciplining their loan loss provisions and loan originations. We identify two distinct but nonmutually exclusive and complementary forms of credit risk modeling from disclosures in banks' 1995–2009 Form 10-K filings: statistical modeling of the drivers of past loan losses (statistical modeling) and stress testing of future loan losses to severely adverse scenarios (stress testing).

We empirically examine the associations of banks' credit risk–modeling disclosures with their loan loss–provision timeliness, the ability of their loan loss provisions to predict future net loan charge-offs, and their loan-origination procyclicality. Two related conjectures motivate these analyses. First, policymakers often claim that banks delay loan loss provisions during stable periods and, thus, must record larger provisions in downturns, reducing their regulatory capital adequacy and causing them to cut back on loan originations (Dugan 2009, Curry 2013).[2] We conjecture that limitations of banks' credit risk modeling, not just the conditions that must be met to accrue for loan losses under FAS 5, may delay loan loss provisions. If so, policies that improve banks' credit risk modeling should mitigate policymakers' concern. Second, we conjecture that variation in the quality of credit risk modeling across banks may help explain Beatty and Liao's (2011) finding that banks that record timelier loan loss provisions issue more capital during both stable periods and downturns, allowing them to originate more loans during downturns (Ryan 2017). That is, better credit risk modeling may improve a bank's understanding of the credit risks of its loans, and this understanding may yield both timelier loan loss provisions and less procyclical loan originations.

Banks' credit risk–modeling disclosures, particularly about stress testing, are limited in extent and frequency. These limitations make it difficult to rank disclosures based on quality and to distinguish banks' usage of credit risk modeling from their disclosure of that usage. We cope with these limitations in three ways. First, we assume that nondisclosure of a particular form of credit risk modeling implies only that a bank uses a less extensive or sophisticated approach, not that it does not use the form. Second, we conduct our primary empirical analyses using an ordinal measure of credit risk–modeling disclosures that equals the sum of indicator variables for bank-year disclosures of statistical modeling and stress testing. Third, we conduct these analyses using two distinct two-stage approaches that attempt to distinguish banks' usage of credit risk modeling from their disclosure of that usage. The first and primary approach is two-stage least squares (2SLS) using a measure of bank sophistication as the instrument for usage. Prior research provides evidence that more sophisticated banks are more likely to engage in risk modeling (e.g., Liu et al. 2004, Pérignon and Smith 2010), indicating that this instrument is relevant. Our use of this instrument assumes that bank sophistication does not directly affect the dependent variables in our second-stage models. To corroborate the 2SLS approach, similar to Bhat and Ryan (2015), we also use a second two-stage approach that statistically decomposes credit risk–modeling disclosures into a usage component explained by bank sophistication and a disclosure component explained by proxies for the external demand for and banks' voluntary choice to supply credit risk–modeling disclosures drawn from the prior literature.

We conduct these primary analyses for banks' entire loan portfolios and the overall sample period. Following prior banking research, we conduct these analyses controlling for many observable bank characteristics and macroeconomic variables. In some models, we also include bank fixed effects to capture unobservable, time-invariant bank characteristics.

We also conduct descriptive empirical analyses using the statistical modeling and stress-testing indicators. Based on our expectations as to when these forms of credit risk modeling are most likely to be effective, these analyses distinguish the primary homogeneous loan type (real estate loans) from the primary heterogeneous loan type (commercial and industrial loans) and/or stable periods from downturns. Given the limited frequency of banks' credit risk–modeling disclosures, particularly for stress testing, we do not attempt to distinguish banks' usage of specific forms of credit risk modeling from their disclosure of that usage.

Statistical modeling provides estimates of banks' credit losses on existing loans based on historical data about loan characteristics, loan performance, and economic conditions. As for all forms of statistical analysis, the availability of larger samples of observations of more similar phenomena improves the specification and power of statistical modeling. Larger samples of observations of more similar phenomena are available for homogeneous loans in stable periods than for this type of loan in downturns or for heterogeneous loans in any type of period.[3] Hence, we expect statistical modeling to be most effective for homogeneous loans during stable periods.

Statistical modeling is the form of credit risk modeling most often disclosed by banks. This likely occurs because homogeneous loans on average constitute over three quarters of banks' loans; banks can conduct statistical modeling at varying levels of sophistication and cost; and statistical modeling yields measures of loan losses that meet FAS 5's requirements to accrue only for losses that are incurred, probable, and reasonably estimable.

Stress testing involves the development and estimation of the effects of low probability but currently relevant adverse scenarios that, were they to occur, would sharply increase banks' credit losses on loans. To develop relevant scenarios, banks engaging in stress testing must pay close attention to current loan characteristics, loan performance, and the economic conditions that drive credit losses on loans. These economic conditions vary across loan types. For example, real estate prices, which follow long cycles, drive credit losses on real estate loans[4] while shorter business cycles drive credit losses on commercial and industrial loans.[5] We expect banks engaging in stress testing for a loan type to be more aware of the potential for loan losses to rise in downturns in the economic conditions that affect that type and, thus, to originate that type of loan more sensibly during stable periods. We also expect these banks to diagnose deterioration in loan performance and economic conditions on a timelier basis and to manage loans more effectively when such deterioration occurs. We expect stress testing to be effective for all loan types but particularly for commercial and industrial loans, the loan type for which credit losses vary most strongly with the business cycle (Ryan 2007, pp. 113–114; Caouette et al. 2008).

Relatively few banks disclose stress testing. This likely occurs because stress testing requires sophistication and involves nontrivial costs and because loan losses that arise if *low-probability* scenarios occur in the *future* do not meet FAS 5's requirements for loss accruals.[6]

While we expect statistical modeling and stress testing to be most effective for distinct loan types and economic conditions, we do not expect them to be useless in other circumstances. To illustrate this subtle point, assume that a severe drop in real estate prices causes a sharp rise in loss rates on real estate loans and that these loss rates gradually stabilize at a higher level. When the severe drop in real estate prices occurs, stress testing is most effective as this is the sort of occurrence that stress testing evaluates. Meanwhile, statistical modeling is less effective but not useless because estimated historical loss rates continue to have some association with current loss rates. The effectiveness of statistical modeling gradually increases over time as historical loss rates incorporate banks' experience of the higher loss rates. Meanwhile, stress testing is less effective but again not useless as the likelihood that conditions remain stable rises but never attains certainty. These roughly contemporaneous changes in the effectiveness of statistical modeling and stress testing are associated but not causally related. Stress testing gains effectiveness when real estate prices drop and statistical modeling gains effectiveness as loss rates stabilize, not because the other form of credit risk modeling loses effectiveness, but because the two forms of credit risk modeling primarily capture different loan types, economic conditions, and moments of the distribution of loan losses.[7]

We conduct three sets of empirical analyses. First, we examine the associations of the credit risk–modeling variables with a measure of the timeliness of banks' loan loss provisions, the association of banks' quarterly loan loss provisions with their next-quarter changes in nonperforming loans. Following prior literature, we infer greater loan loss–provision timeliness when this association is more positive. We find that the ordinal credit risk–modeling variable is positively associated with this measure during our overall sample period. We find that the statistical-modeling indicator is positively associated with this measure for real estate loans during stable periods but not for this type of loan during downturns or for commercial and industrial loans during any period. We find that the stress-testing indicator is positively associated with this measure for commercial and industrial loan types during downturns but not for this type of loan during stable periods or for real estate loans during any period.[8]

Second, we examine the associations of the credit risk–modeling variables with the ability of banks' quarterly loan loss provisions to predict their net loan charge-offs over the following two and four quarters, windows suggested by bank regulatory guidance. We find that the ordinal credit risk–modeling variable is positively associated with this ability during our overall sample period. We find that the statistical-modeling indicator is positively associated with this ability for real estate loans during stable periods but not for this loan type during downturns or for commercial and industrial loans during any period. We find that the stress-testing indicator is positively associated with this ability for both real estate and commercial and industrial loans during downturns but not during stable periods.

Third, we examine the associations of the credit risk–modeling variables with three measures of banks' loan-origination procyclicality. The first is the association between banks' quarterly loan loss provisions and their loan growth over the current and next three quarters. Following Laeven and Majnoni (2003), we infer reduced procyclicality when this association is less negative. We find that the ordinal credit risk–modeling variable is associated with less procyclical total loan originations during the overall sample period. We find that the statistical-modeling indicator is associated with less procyclical originations of real estate loans during stable periods but not of this type of loans during downturns or of commercial and industrial loans during any period. We find that the stress-testing indicator is associated with less procyclical originations of commercial and industrial loans during downturns but not of this type of loan during stable periods or of real estate loans during any period.

The second loan-origination procyclicality measure is the association between an indicator for negative current quarterly growth in gross domestic product (GDP) and total loan growth over the current and next three quarters. Banks' behavior during downturns drives this procyclicality measure more strongly than the first measure. Following Bikker and Metzemakers (2005), we infer reduced procyclicality when this association is less negative. We find that the ordinal credit risk–modeling variable is associated with less procyclical total loan originations during our overall sample period.

The third procyclicality measure is a modification of the second measure that better captures the primary driver of credit losses on real estate loans over the current and following three quarters. This measure is the association of the cumulative decline in the subprime mortgage–related ABX index from its inception in January 2006 to the current quarter with growth in real estate loans. We find that the ordinal credit risk–modeling variable is associated with less procyclical real estate loan originations during the financial crisis period.

This study contributes to two empirical literatures. The first identifies bank characteristics, such as loan portfolio composition and health-related incentives to exercise discretion, that are associated with the timeliness or predictive ability for future net loan charge-offs of banks' loan loss provisions (e.g., Liu and Ryan 1995, 2006; Nichols et al. 2009; Bhat et al. 2016). Understanding the determinants of these attributes of banks' loan loss provisions is important because these provisions are the primary accrual estimates for most banks. We find that our credit risk–modeling variables are positively associated with the timeliness and predictive ability for future net loan charge-offs of banks' loan loss provisions. The second literature examines the associations of loan loss–provision timeliness with banks' loan-origination procyclicality and overall risk taking (e.g., Beatty and Liao 2011; Bushman and Williams 2012, 2015). Because of the recent financial crisis, procyclicality is of deep policy interest (Bank for International Settlements 2008; Financial Stability Forum 2009a, b; United States Treasury 2009). We find that our credit risk–modeling variables are associated with reduced loan-origination procyclicality.

2. Credit Risk Modeling

2.1. Additional Details About Statistical Modeling and Stress Testing

In this section, we provide additional details about statistical modeling and stress testing, trying not to repeat the lengthy descriptions of these forms of credit risk modeling in Section 1. In particular, we describe how banks vary considerably in their credit risk modeling usage. We base this description on various public sources[9] and one author's litigation experience.

Statistical modeling typically corresponds to banks' modeling of loan credit risk in terms of two primary parameters, the probability of default and the loss given default, under the approach developed for regulatory capital purposes in the Basel II Agreement. Banks typically estimate these credit–loss parameters using one or more of the following types of information: (1) initial loan attributes, such as loan type, maturity, and loan-to-value ratio; (2) initial borrower attributes, such as credit score and loan-to-income ratio; (3) current payment statuses and payment histories, such as number of days past due and number of payments made, respectively; and (4) current relevant economic conditions, such as house prices and GDP.

Sophisticated banks develop and estimate customized multivariate statistical models of loan credit–loss parameters as functions of rich sets of all four types of variables. Less sophisticated banks estimate these parameters using similarly extensive but generic vendor-supplied models, simple spreadsheet models that capture a few key underwriting criteria and loan performance status buckets, or other approaches that involve intermediate levels of customization and complexity.

Sophisticated banks "back test" their statistical modeling–generated loan credit loss parameter estimates. That is, they compare prior period estimates to realized values to date to identify trends in the parameters. These banks also conduct various other forms of model validation and calibration.

Banks often base stress-testing scenarios on adverse events that have occurred previously. The available historical events upon which to base these scenarios change over time. For example, banks conducting stress testing now likely use the financial crisis as the most adverse credit loss/illiquidity scenario, whereas prior to the crisis banks likely used the much less severe Russian debt/hedge fund crisis in the second half of 1998 as the corresponding scenario. Banks also may base stress scenarios on expert judgment about events that have not previously occurred but that conceivably might occur. Because stress testing requires risk-modeling expertise and involves nontrivial cost, banks conducting stress testing usually are large and sophisticated.

In addition to bank size and sophistication, banks' credit risk modeling usage likely is correlated with banks' loan portfolio composition, credit risk, financial health, and other characteristics. Prior research finds that many of these bank characteristics are also associated with loan loss–provision timeliness and the ability of loan loss provisions to predict future net loan charge-offs. To mitigate the possibility that our results reflect correlated bank characteristics, in each of the primary empirical analyses we control for a large number of these characteristics.

2.2. Credit Risk–Modeling Disclosure Variables

We hand-collected disclosures of statistical modeling of the drivers of past loan losses and stress testing of future loan losses to adverse scenarios from the 1995–2009 Form 10-K filings of commercial bank holding companies (banks) using 10-K Wizard.[10] Using the Adobe Acrobat Pro search function, we searched each filing for disclosures of statistical modeling using terms such as "model," "historical loss experience," "statistical," and "credit migration" as well as related terms using the stemming option. We searched each filing for disclosures of stress testing using individual terms such as "stress," "scenario," and "backtest" as well as related terms and pairs of "stress" and "test" or "analysis" occurring within 10 or 25 words of each other. We read through each search result and manually coded the indicator variable *MODEL* (*STRESS*) as 1 if the bank discloses that it employs statistical modeling (stress testing) in a year and 0 otherwise.[11] These indicators take value of 0, for example, in filings where banks discuss how they might be required to conduct stress tests rather than that they perform those tests. The ordinal variable *CRM* is the sum of *MODEL* and *STRESS*. In the empirical analyses, we use the values of the credit risk–modeling variables from the most recent prior year to ensure that the corresponding form of credit risk modeling is predetermined and used during the year examined.[12]

Appendix A provides representative examples of banks' disclosures of statistical modeling and stress testing. These sample disclosures and the descriptive analyses reported in Table 1 indicate that the disclosures are relatively infrequent and usually terse when made. Since banks must engage in at least a minimal level of credit risk modeling to make loan decisions and calculate loan loss provisions, they do not appear to disclose their credit risk modeling fully. This may reflect the absence of disclosure requirements or well-established disclosure practices during our sample period as well as the considerable difficulty involved in developing and validating credit risk modeling. It is unlikely to be attributable to banks being concerned about proprietary costs given the voluminous information they are required to provide about their estimated and realized credit losses under GAAP, SEC Industry Guide 3, and bank regulatory reporting requirements. Moreover, banks' credit risk–modeling disclosures are too high level and aggregated to reveal proprietary information.

3. Credit Risk–Modeling Disclosures and Discipline Over Loan Loss Accruals

In this section, we develop and estimate the empirical models used to test for the associations of the credit risk–modeling variables with banks' loan loss–provision timeliness and the ability of their loan loss provisions to predict future net loan charge-offs.

3.1. Loan Loss–Provision Timeliness

We base our measure of loan loss–provision timeliness on prior research, which typically evaluates the timeliness of loan loss provisions relative to changes in nonperforming loans. Specifically, following Liu and Ryan (1995), Nichols et al. (2009), Beatty and Liao (2011) and others, we deem quarterly loan loss provisions to be timelier when they are more positively associated with the next-quarter change in nonperforming loans. For reasons discussed in Section 1, we expect the ordinal credit risk–modeling variable (*CRM*) to be positively associated with this measure of loan loss–provision timeliness during the overall sample period. We expect the statistical-modeling indicator (*MODEL*) to be positively associated with this provision timeliness measure for real estate loans during stable periods. We expect the stress-testing indicator (*STRESS*) to be positively associated with the measure for all loan types, particularly commercial and industrial loans, during downturns.

To estimate this measure of loan loss–provision timeliness, we regress the loan loss provision for the current quarter divided by prior quarter total loans (LLP_t) on (1) the change in nonperforming loans from quarter-end $t-2$ to quarter-end t divided by quarter $t-1$ total loans ($\Delta NPL_{t-2,t}$) and the change in nonperforming loans for quarter $t+1$ divided by quarter t total loans (ΔNPL_{t+1}); (2) either *CRM* or *MODEL* and *STRESS* for the prior year, both separately and interacted with ΔNPL_{t+1}; and (3) an extensive set of control variables:

$$LLP_t = \beta_0 + \beta_1 \Delta NPL_{t-2,t} + \beta_2 \Delta NPL_{t+1} + \beta_3 CRM + \beta_4(\Delta NPL_{t+1} \times CRM) + \sum_{j\geq 5} \beta_j controls + \varepsilon_t \quad (1)$$

$$LLP_t = \beta_0 + \beta_1 \Delta NPL_{t-2,t} + \beta_2 \Delta NPL_{t+1} + \beta_{3M} MODEL + \beta_{3S} STRESS + \beta_{4M}(\Delta NPL_{t+1} \times MODEL) + \beta_{4S}(\Delta NPL_{t+1} \times STRESS) + \sum_{j\geq 5} \beta_j controls + \varepsilon_t. \quad (1MS)$$

In Equation (1), we expect the coefficient β_4 on $\Delta NPL_{t+1} \times CRM$ to be positive, consistent with credit risk modeling increasing loan loss–provision timeliness. In Equation (1MS), we expect the coefficient β_{4M} on $\Delta NPL_{t+1} \times MODEL$ to be positive for real estate loans during stable periods and the coefficient β_{4S} on $\Delta NPL_{t+1} \times STRESS$ to be positive for both types of loans, particularly commercial and industrial loans, during downturns. Throughout, we suppress time subscripts except where necessary for clarity.

Equation (1) includes a large number of control variables motivated by the prior banking literature (Liu and Ryan 1995, 2006; Laeven and Majnoni 2003; Beatty and Liao 2011; Bushman and Williams 2012, 2015; Bhat and Ryan 2015; Bhat et al. 2016). We control for the following bank characteristics: the natural logarithm of prior quarter total assets (*SIZE*) to capture banks' resources and sophistication, an indicator for above-median commercial and industrial loans divided by total loans for the year (*C&I_High*) to capture banks' loan portfolio composition, the Tier 1 capital ratio (*TIER*1) to capture banks' solvency, earnings before the provision for loan losses divided by prior quarter assets (*EBP*) to capture banks' profitability, net loan charge-offs divided by prior quarter loans (*NCO*) to capture banks' realized credit losses on loans, prior quarter allowance for loan losses divided by prior quarter loans (ALL_{t-1}) to capture banks' cumulative prior loan loss accruals, prior quarter loans divided by prior quarter assets ($LOANS_{t-1}$) to capture banks' asset composition, and the percentage change in total loans in quarter t ($\%\Delta LOANS$) to capture banks' loan growth. Following Bhat and Ryan (2015), we include two variables to capture banks' disclosure of noncredit risks. The ordinal variable *MktRisk* takes a value from zero to five based on the extensiveness of banks' market risk disclosures; this variable increases by one as banks disclose each of repricing gap, market risk sensitivity, value at risk, back-testing of market risk models, and stress testing of these models. The indicator variable *OpRisk* takes a value of 1 if the bank discloses details about operational risk management. We control for macroeconomic conditions and uncertainty using the change in the unemployment rate for the quarter ($\Delta UNRATE$) (Beatty and Liao 2011) and the end-of-quarter CBOE volatility index (*VIX*), respectively.

We estimate Equation (1) for the overall sample period 1996–2010 using five approaches: pooled OLS for the models without and with the test variables; with fixed bank effects to capture unobservable, time-invariant bank characteristics; and two distinct two-stage approaches with first stages that attempt to distinguish banks' credit risk–modeling usage from their disclosure of that usage. The first and primary of these approaches is two-stage least squares (2SLS). We use a measure of bank sophistication as the instrument for credit risk–modeling usage based on prior research evidence that, consistent with economic intuition, more sophisticated banks engage in (higher quality) risk modeling (e.g., Liu et al. 2004, Pérignon and Smith 2010), indicating that the instrument is relevant.[13]

We emphasize that our use of this instrument is valid only under the difficult-to-test assumption that bank sophistication affects the dependent variables in our second-stage models (loan loss provisions, net loan charge-offs, and loan growth) only through its effect on banks' credit risk–modeling usage (the exclusion restriction). That is, bank sophistication cannot affect these dependent variables directly or through unobserved variables, conditional on the other explanatory variables included in the second-stage models. We view the assumption as reasonable because, to the best of our knowledge, no prior empirical study uses bank sophistication as a direct determinant of any of our dependent variables. Moreover, the other explanatory variables included in these models control for banks' size, financial health, asset composition, loan credit risk, loan growth, and voluntary disclosures of market and operating risks. However, the possibility that this assumption is not satisfied remains.

To corroborate the 2SLS approach, similar to Bhat and Ryan (2015), we also use a second two-stage approach that statistically decomposes the indicators for banks' credit risk–modeling disclosures into a usage component explained by bank sophistication and a disclosure component explained by four proxies for the external demand for and banks' voluntary choice to supply credit risk modeling disclosures. These proxies are (1) banks' pre-LLP return on assets, which empirically appears primarily to capture the benefits of voluntary disclosure (Lang and Lundholm 1993, Leuz and Verrecchia 2000), but it could also capture the proprietary costs of voluntary disclosure (Healy and Palepu 2001); (2) net loan charge-offs, a primary predictor of future credit losses (Harris et al. 2018), which we expect to be positively associated with the demand for credit risk modeling disclosures; (3) banks' voluntary disclosures of operating risk, which we expect to capture their propensity to disclose any form of risk modeling;[14] and (4) an indicator for big N auditors, who we expect to have higher bank industry expertise and reputational incentives and, thus, to encourage banks to provide higher overall disclosure quality (Dunn and Mayhew 2004).

Bank sophistication is a multidimensional construct. Hence, in both of the two-stage approaches, we proxy for bank sophistication (*SOPHIST*) as the first principal component of four variables: indicator variables for a complex bank holding company according to the Federal Reserve and for disclosure of the employment of a chief risk officer in the most recent Form 10-K filing, and the natural logarithms of the total notional amounts of derivatives and of the dollar amount of sponsored securitizations reported by Asset-Backed Alert.

In the 2SLS approach, first-stage OLS models regress *CRM* or $\Delta NPL_{t+1} \times CRM$ on *SOPHIST* and $\Delta NPL_{t+1} \times SOPHIST$ with all the control variables in Equation (1) included in both models. As discussed in Section C.2 of Appendix C, the Cragg–Donald F-statistic indicates that *SOPHIST* and $\Delta NPL_t \times SOPHIST$ are strong instruments in the first-stage models for Equation (1) and the subsequent equations in the paper. The predicted values of *CRM* and $\Delta NPL_{t+1} \times CRM$ from the estimations of the first-stage models, which are reported in Table C.1, panel A, replace the corresponding variables in the second-stage model. To satisfy the exclusion restriction, *SOPHIST* and $\Delta NPL_{t+1} \times SOPHIST$ are excluded from the second-stage model.

In the decomposition approach, a first-stage probit model regresses *CRM* on *SOPHIST* to capture credit risk–modeling usage and on four variables that we expect to be positively associated with banks' disclosure of credit risk modeling but relatively uncorrelated with their usage of credit risk modeling: *EBP*, *NCO*, *OpRisk*, and indicator for an auditor in the top four or six, depending on the year (*BigN*).[15] Based on the estimation of this model reported in Table C.1, panel B,

Table 1. Sample Selection and Descriptive Statistics

Panel A: Sample selection

Firm-quarter observations with Bank Compustat data in 1996:Q1–2010:Q4, nonzero total assets, and valid GVKEY	41,527
Firm-quarter observations also with most recent prior year credit risk–modeling disclosure variables	19,108
Firm-quarter observations also with all Equation (1) variables	16,282

Panel B: Frequency credit risk–modeling disclosures by year

Year	Number of observations: *CRM* = 1	Number of observations: *CRM* = 2
1995	7	0
1996	12	0
1997	16	0
1998	24	0
1999	57	0
2000	72	0
2001	114	4
2002	149	3
2003	173	4
2004	189	4
2005	213	4
2006	236	4
2007	236	8
2008	254	16
2009	277	29
Total	2,029	76

Table 1. (Continued)

Panel C: Descriptive statistics for overall sample ($N = 16,282$)

	Mean	Std. dev	25%	Median	75%
LLP	0.002	0.003	0.000	0.001	0.002
$\Delta NPL_{t-2,t}$	0.002	0.007	−0.001	0.000	0.003
ΔNPL_{t+1}	0.001	0.005	−0.001	0.000	0.002
CRM	0.134	0.354	0	0	0
$MODEL$	0.115	0.319	0	0	0
$STRESS$	0.019	0.138	0	0	0
$SIZE$	7.634	1.562	6.488	7.284	8.433
$C\&I\_High$	0.491	0.500	0	0	1
$MktRisk$	1.667	0.567	1	2	2
$OpRisk$	0.142	0.349	0	0	0
$TIER1$	11.751	2.916	9.900	11.320	13.080
EBP	0.005	0.002	0.003	0.005	0.006
LLA_{t-1}	0.015	0.006	0.012	0.014	0.017
$LOANS_{t-1}$	0.661	0.114	0.601	0.673	0.736
$\%\Delta LOAN_t$	0.028	0.061	−0.001	0.019	0.041
NCO	0.001	0.002	0.000	0.001	0.001
$\Delta UNRATE$	1.341	5.697	−2.3	0.0	3.8
VIX	21.932	8.039	16.23	21.53	25.61

Panel D: Descriptive statistics for subsamples based on credit-risk-modeling disclosure values

	$CRM = 0$ ($N = 14,177$)		$CRM = 1$ ($N = 2,029$)		$CRM = 2$ ($N = 76$)	
	Mean	Median	Mean	Median	Mean	Median
LLP	0.002	0.001	0.003	0.001	0.006	0.004
$\Delta NPL_{t-2,t}$	0.002	0.000	0.003	0.001	0.001	0.000
ΔNPL_{t+1}	0.001	0.000	0.001	0.000	0.000	0.000
$SIZE$	7.447	7.164	8.822	8.569	10.900	11.958
$C\&I\_High$	0.479	0.000	0.557	1.000	0.789	1.000
$MktRisk$	1.655	2.000	1.727	2.000	2.303	2.000
$OpRisk$	0.115	0.000	0.319	0.000	0.434	0.000
$TIER1$	11.870	11.420	10.954	10.600	10.783	9.890
EBP	0.005	0.005	0.004	0.005	0.005	0.006
LLA_{t-1}	0.015	0.014	0.017	0.014	0.023	0.022
$LOANS_{t-1}$	0.664	0.674	0.642	0.665	0.635	0.636
$\%\Delta LOAN_t$	0.030	0.020	0.017	0.010	0.004	−0.008
NCO	0.001	0.001	0.002	0.001	0.005	0.004
$\Delta UNRATE$	1.236	0.000	2.041	0.000	2.208	0.500
VIX	21.941	21.530	21.800	19.520	23.833	23.210

we decompose CRM into three components: its predicted value based on $SOPHIST$ (CRM_{usage}), its predicted value based on the four disclosure variables (CRM_{disc}), and the residual (CRM_{resid}), which could capture either credit risk–modeling usage or disclosure. We substitute these components for CRM in the second-stage estimation of Equation (1).

We estimate Equation (1MS) using pooled OLS for four subsamples of bank quarters in our overall 1996–2010 period: above-median real estate loans and stable conditions, above-median real estate loans and downturns, above-median commercial and industrial loans and stable conditions, and above-median commercial and industrial loans and downturns. We define downturns as the NBER-determined recessions 2001:Q2–Q4 and 2007:Q4–2009:Q2, in each case removing the last quarter, by which time the return of economic stability was evident.

3.2. Sample Selection and Descriptive Statistics

Table 1, panel A, describes the sample selection process. For a bank-year observation to be included in the full sample, we require the observation (1) to be publicly traded on NYSE, AMEX, or NASDAQ; (2) to have assets above \$150 million; (3) to have Form 10-K filings available on 10K Wizard for the most recent prior year (to hand-collect the credit risk–modeling disclosures); and (4) to have quarterly financial data available on Bank Compustat. The sample period is 1996:Q1 to 2010:Q4, a period that according to the National Bureau of Economic Research (NBER) encompasses two booms (1996:Q1–2001:Q1 and 2003:Q1–2007:Q4), two recessions (2001:Q2–Q4 and 2008:Q1–2009:Q2), and two slow-growth periods following recessions (2002:Q1–Q4 and 2009:Q3–2010:Q4). These requirements yield 16,282 bank-quarter observations for 479 unique banks for the estimation of Equation (1).

Table 1, panel B, reports the frequencies with which *CRM* takes values of one or two for the overall sample and for each year from 1995 to 2009. For the overall sample, *CRM* takes a value of one (two) for 2,029 (76) observations, indicating that in the vast majority of cases banks disclose at most one form of credit risk modeling. The number of observations with nonzero *CRM* rises considerably over time from seven observations in 1995 to 277 observations in 2009. These increasing frequencies reflect the fact the vast majority of banks that disclose a form of credit risk modeling in a year also disclose that form in the next year.[16]

Table 1, panel C, provides descriptive statistics for the variables in Equation (1). The mean of *CRM* is 0.134, reflecting the relatively low frequency of banks' credit risk–modeling disclosures, particularly in the earlier sample years. The bulk of the sample observations are well capitalized and profitable. The means of ΔNPL and $\Delta UNRATE$ are positive, owing to the financial crisis in the last four years of the sample period.

Table 1, panel D, reports variable means and medians for the subsamples of observations taking each of the three values of *CRM*. The means and medians of *SIZE*, *MktRisk*, and *OpRisk* increase monotonically with *CRM*, consistent with banks that are larger or disclose more about their noncredit risks being more likely to disclose credit risk modeling. The means and medians of *LLP*, *NCO*, and $\Delta UNRATE$ increase monotonically with *CRM*, reflecting banks' increased disclosure of credit risk modeling when loan performance and economic conditions deteriorate.

Table 2 reports Pearson correlations of the variables. In line with the descriptive statistics reported in Table 1, panel D, *CRM* is significantly positively correlated with *SIZE*, *MktRisk*, and *OpRisk*. *CRM* is also significantly positively correlated with *LLP*, *C&I_High*, *NCO*, $\Delta UNRATE$, and *VIX*, consistent with banks that accept higher credit risk or operate under less favorable economic conditions being more likely to disclose credit risk modeling.

Consistent with prior research, *LLP* is significantly positively correlated with the credit loss–related variables ΔNPL, *C&I_High*, *NCO*, $\Delta UNRATE$, and *VIX*. The latter two (macroeconomic) variables are highly positively correlated (57%); consequently, these variables in some cases are individually insignificant (but generally are collectively significant) in the empirical models.

Table 2. Pearson Correlations

	LLP	$\Delta NPL_{t-2,t}$	ΔNPL_{t+1}	*CRM*	*SIZE*	*C&I_High*	*MktRisk*	*OpRisk*	*TIER1*	*EBP*	*ALL*	*LOANS*	*%ΔLOAN*	*NCO*	$\Delta UNRATE$
$\Delta NPL_{t-2,t}$	**0.359**														
ΔNPL_{t+1}	**0.148**	**0.174**													
CRM	**0.164**	**0.042**	**0.023**												
SIZE	**0.171**	0.011	−0.001	**0.323**											
C&I_High	**0.081**	−0.004	−0.006	**0.0624**	**0.270**										
MktRisk	**0.028**	−0.011	−0.005	**0.067**	**0.272**	**0.072**									
OpRisk	**0.207**	**0.071**	**0.037**	**0.201**	**0.359**	**0.137**	**0.106**								
TIER1	**−0.086**	**−0.061**	**−0.035**	**−0.105**	**−0.306**	**−0.192**	**−0.092**	**−0.095**							
EBP	**−0.198**	**−0.172**	**−0.092**	−0.006	**0.216**	**0.106**	**0.068**	**−0.033**	**0.030**						
ALL	**0.390**	**0.043**	**−0.064**	**0.107**	**0.183**	**0.147**	0.013	**0.132**	0.001	−0.011					
LOANS	**0.074**	**0.139**	**0.114**	**−0.063**	**−0.220**	0.002	**−0.099**	**−0.097**	**−0.323**	−0.018	**−0.083**				
%ΔLOAN	**−0.131**	−0.003	−0.007	**−0.075**	**−0.038**	−0.001	0.009	**−0.066**	**−0.043**	**0.100**	**−0.152**	**0.025**			
NCO	**0.822**	**0.210**	**0.062**	**0.163**	**0.191**	**0.080**	**0.025**	**0.209**	**−0.063**	**−0.176**	**0.509**	**0.022**	**−0.179**		
$\Delta UNRATE$	**0.222**	**0.276**	**0.222**	**0.047**	0.011	0.005	−0.012	**0.075**	**−0.050**	**−0.172**	**−0.045**	**0.094**	**−0.096**	**0.133**	
VIX	**0.251**	**0.217**	**0.167**	0.001	0.012	−0.001	0.008	**0.026**	0.001	**−0.086**	**0.104**	0.001	**−0.087**	**0.191**	**0.572**

Note. Correlations significant at the 5% level using a two-tailed test are in boldface font.

3.3. Loan Loss–Provision Timeliness Estimations Equation (1)

Table 3, panel A, reports the estimation of Equation (1) for the overall sample period. Column (1) ((2)) reports the estimation of the base model without (with) the interactive test variable $\Delta NPL_{t,t+1} \times CRM$. Column (3) reports the estimation of the base model adding fixed bank effects. Column (4) reports the estimation of the second-stage of the 2SLS approach; Appendix C develops the first-stage models and Table C.1, panel A, reports the pooled OLS estimation of these models. Column (5) reports the pooled OLS estimation of the model replacing *CRM* with its components CRM_{usage}, CRM_{disc}, and CRM_{resid}; Appendix C develops the first-stage probit model used to estimate these components, and the model estimation is reported in Table C.1, panel B. Throughout, we report standard errors calculated clustering observations by bank and quarter for panel regressions and heteroskedasticity-robust standard errors for cross-sectional regressions.[17]

We first discuss the coefficients on the control variables. Most of these coefficients are consistently significant or not across most or all of the five estimations, so for brevity, we discuss only the coefficients in the base model without the test variables reported in column (1). Consistent with extensive prior research on the bank-specific and macroeconomic determinants of loan loss provisions (Wahlen 1994, Beatty and Liao 2011, Bhat et al. 2016), the coefficients on $\Delta NPL_{t-2,t}$, $\Delta NPL_{t,t+1}$, *NCO*, *LOANS*, *%ΔLOANS*, *ΔUNRATE*, and *VIX* are positive and significant at the 1% level. Consistent with larger and more sophisticated banks assuming greater credit risk, the coefficients on *CRM* and *OpRisk* are positive and significant at the 1% level although the coefficient on *SIZE* is insignificant. Consistent with more profitable banks experiencing lower credit losses, the coefficient on *EBP* is significantly negative at the 5% level.

The coefficient β_4 on the interactive test variable $\Delta NPL_{t,t+1} \times CRM$ is significantly positive at the 5% level in the base model reported in column (2) and the fixed effects model reported in column (3), indicating that credit risk–modeling disclosures are associated with increased loan loss–provision timeliness.[18] Consistent with these results being attributable to banks' credit risk–modeling usage rather than to their disclosure of that usage, β_4 is significant at the 5% level in the 2SLS model reported in column (4), and the coefficient on $\Delta NPL_{t,t+1} \times CRM_{usage}$ is significant at the 10% level in the decomposition model reported in column (5). The coefficient on $\Delta NPL_{t,t+1} \times CRM_{resid}$ is also significant at the 10% level.

Equation (1MS). Table 3, panel B, reports the estimations of Equation (1MS) for four subsamples of bank quarters: above-median real estate loans and stable conditions (column (1)), above-median real estate loans and downturns (column (2)), above-median commercial and industrial loans and stable conditions (column (3)), and above-median commercial and industrial loans and downturns (column (4)). For brevity, we do not discuss the coefficients on the control variables, which usually are similar to those reported in panel A and similar across the four subsamples.

As expected, the coefficient β_{4M} on $\Delta NPL_{t+1} \times MODEL$ is significantly positive at the 5% level in the above-median real estate loan and stable period subsample reported in column (1), consistent with statistical modeling enhancing loan loss–provision timeliness for this subsample. This coefficient is insignificant in the other subsamples. As expected, the coefficient β_{4S} on $\Delta NPL_{t+1} \times STRESS$ is significantly positive at the 1% level in the above-median commercial and industrial loans and downturn subsample reported in column (4), consistent with stress testing enhancing loan loss–provision timeliness for this subsample. Unexpectedly, β_{4S} is insignificant in the above-median real estate loans and downturn subsample reported in column (2). This coefficient is insignificant in the stable period subsamples reported in columns (1) and (3).[19]

In summary, the results reported in Table 3 suggest that banks' use of statistical modeling enhances banks' loan loss–provision timeliness on average across our sample period as well as for real estate loans during stable periods. These results suggest that banks' use of stress testing enhances banks' loan loss–provision for commercial and industrial loans during downturns.

3.4. Ability of Loan Loss Provisions to Predict Future Net Loan Charge-Offs

In this section, we develop a model of the ability of quarterly loan loss provisions to predict future net loan charge-offs that is similar to the models in Wahlen (1994) and Bhat et al. (2016). We deem quarterly loan loss provisions that are more positively associated with net loan charge-offs over the following two and four quarters, denoted $NCO_{t+1,t+s}$, for s equal to two or four, to be better predictors. Under bank regulatory guidance for homogeneous loans, loan loss provisions should predict future net loan charge-offs over these windows.[20] We expect credit risk modeling to increase the ability of banks' quarterly loan loss provisions to predict future net loan charge-offs on average over our sample period. We expect statistical modeling to increase the ability of banks' quarterly loan loss provisions to predict future net loan charge-offs for real estate loans (*NCOREAL*) during stable periods. We expect stress testing to increase the ability of banks' quarterly loan loss provisions to predict future net loan charge-offs for all loan types, particularly commercial and industrial loans (*NCOC&I*), during downturns.

This model regresses $NCO_{t+1,t+s}$ or $NCOREAL_{t+1,t+s}$ and $NCOC\&I_{t+1,t+s}$ on (1) *LLP*; (2) *CRM* or *MODEL* and

Table 3. Association of Credit Risk–Modeling Disclosures with the Timeliness of Quarterly Loan Loss Provisions Relative to Next-Quarter Change in Nonperforming Loans

Panel A: Pooled estimations of Equation (1) for the overall sample period

Variables	(1) Restricted base model	(2) Full base model	(3) Fixed effects	(4) Second-stage 2SLS	(5) Second-stage decomposition
$\Delta NPL_{t-2,t}$	0.059***	0.059***	0.057***	0.058***	0.058***
	[11.31]	[11.27]	[15.12]	[14.63]	[11.24]
ΔNPL_{t+1}	0.027***	0.022***	0.018***	0.011	−0.024
	[3.66]	[2.94]	[3.08]	[1.18]	[−0.89]
CRM	0.000***	0.000***	0.000***	0.001*	
	[3.19]	[2.72]	[2.59]	[1.95]	
CRM_{usage}					0.000
					[1.61]
CRM_{disc}					0.000
					[1.56]
CRM_{resid}					0.000*
					[1.75]
$\Delta NPL_{t+1} \times CRM$		0.029**	0.031**	0.097**	
		[2.40]	[2.15]	[2.11]	
$\Delta NPL_{t+1} \times CRM_{usage}$					0.082*
					[1.67]
$\Delta NPL_{t+1} \times CRM_{disc}$					0.019
					[0.68]
$\Delta NPL_{t+1} \times CRM_{resid}$					0.010*
					[1.89]
$SIZE$	0.000	0.000	0.000	−0.000	0.000
	[1.55]	[1.58]	[1.44]	[−0.44]	[0.70]
$C\&I\_High$	0.000***	0.000***	0.000	0.000***	0.000***
	[2.87]	[2.81]	[1.63]	[2.95]	[2.72]
$TIER1$	0.000	0.000	0.000	0.000	0.000
	[0.23]	[0.29]	[0.93]	[0.51]	[0.18]
EBP	−0.032**	−0.032**	−0.063***	−0.029**	−0.031**
	[−2.35]	[−2.37]	[−4.53]	[−2.57]	[−2.26]
ALL_{t-1}	−0.005	−0.005	−0.018***	−0.005	−0.005
	[−1.10]	[−1.09]	[−3.36]	[−1.15]	[−1.06]
$LOANS_{t-1}$	0.001***	0.001***	0.001***	0.001***	0.001***
	[3.81]	[3.84]	[3.31]	[4.58]	[3.83]
$\%\Delta LOAN$	0.001***	0.001***	0.000	0.001***	0.001***
	[3.08]	[3.05]	[0.70]	[3.08]	[3.10]
$MktRisk$	0.000	0.000*	−0.000*	0.000	0.000*
	[1.64]	[1.68]	[−1.90]	[1.31]	[1.94]
$OpRisk$	0.000***	0.000***	0.000**	0.000*	0.000***
	[2.97]	[3.02]	[2.47]	[1.75]	[2.64]
NCO	0.872***	0.872***	0.859***	0.865***	0.872***
	[33.59]	[33.42]	[45.02]	[45.94]	[33.30]
$UNRATE$	0.000**	0.000**	0.000**	0.000***	0.000**
	[2.24]	[2.20]	[2.18]	[3.42]	[2.18]
VIX	0.000***	0.000***	0.000***	0.000***	0.000***
	[4.08]	[4.04]	[9.08]	[7.43]	[4.02]
Constant	−0.001**	−0.001**	−0.001	−0.000*	−0.001***
	[−2.31]	[−2.35]	[−1.45]	[−1.87]	[−2.65]
No. of observations	16,282	16,282	16,282	16,282	16,282
Adjusted R^2 (%)	72.45	72.49	73.25	71.52	72.49

Table 3. (Continued)

Panel B: Pooled estimations of Equation (1) for subsamples with above-median real Estate or commercial and industrial loans and stable or downturn subperiods

Variables	(1) Stable *Real_High* = 1	(2) Downturn *Real_High* = 1	(3) Stable *C&I_High* = 1	(4) Downturn *C&I_High* = 1
$\Delta NPL_{t-2,t}$	0.055***	0.073***	0.068***	0.060***
	[6.10]	[6.47]	[6.31]	[7.34]
ΔNPL_{t+1}	0.014	0.040***	0.031***	0.022**
	[1.11]	[3.97]	[3.45]	[2.43]
MODEL	0.000	−0.000	−0.000	0.001*
	[0.15]	[−0.03]	[−0.37]	[1.72]
STRESS	0.000***	−0.000	0.000**	−0.000
	[6.15]	[−0.37]	[2.44]	[−0.30]
$\Delta NPL_{t+1} \times MODEL$	0.043**	0.057	0.011	0.059
	[2.35]	[1.43]	[0.53]	[1.11]
$\Delta NPL_{t+1} \times STRESS$	−0.019	0.087	−0.013	0.127***
	[−0.60]	[1.62]	[−0.44]	[5.19]
SIZE	0.000	0.000***	−0.000	0.000***
	[1.03]	[2.96]	[−0.56]	[2.95]
*TIER*1	−0.000	−0.000	−0.000	0.000
	[−1.32]	[−0.41]	[−0.04]	[1.26]
EBP	−0.060***	−0.038	0.001	−0.069***
	[−3.28]	[−1.60]	[0.07]	[−3.99]
ALL_{t-1}	−0.003	−0.036**	−0.007	−0.015
	[−0.59]	[−2.32]	[−0.96]	[−0.67]
$LOANS_{t-1}$	0.001***	0.001***	0.001**	0.001*
	[2.82]	[2.80]	[2.15]	[1.81]
$\Delta LOANS$	0.001	−0.000	0.001*	0.004**
	[1.51]	[−0.20]	[1.75]	[2.17]
MktRisk	0.000	−0.000	0.000*	−0.000
	[1.20]	[−1.14]	[1.91]	[−1.39]
OpRisk	0.000	−0.000*	0.000**	0.000
	[1.21]	[−1.88]	[2.56]	[0.78]
NCO	0.838***	0.919***	0.909***	0.989***
	[20.92]	[30.96]	[26.57]	[15.85]
Constant	0.000	−0.001	0.000	−0.002*
	[0.11]	[−1.05]	[0.14]	[−1.70]
No. of observations	6,843	1,036	6,944	1,043
Adjusted R^2 (%)	71.08	67.05	74.67	71.67

Notes. Panel A reports pooled estimations of Equation (1) for the overall sample of 16,282 bank-quarter observations from 1996Q1–2010Q4. These estimations associate the ordinal credit risk–modeling variable *CRM* with the timeliness of banks' quarterly loan loss provisions (LLP_t) measured relative to the next-quarter change in nonperforming loans (ΔNPL_{t+1}). Equation (1) regresses LLP_t on (1) ΔNPL_{t+1}; (2) *CRM*, both separately and interacted with ΔNPL_{t+1}; and (3) control variables, including the change in nonperforming loans over the current and prior quarter ($\Delta NPL_{t-2,t}$). Column (1) ((2)) reports the OLS estimation of Equation (1) excluding (including) the test variable $\Delta NPL_{t+1} \times CRM$. Column (3) reports the estimation of the equation, including bank fixed effects. Column (4) reports the second stage of a 2SLS estimation of the equation; the estimations of the first-stage models are reported in panel A of Table C.1. Column (5) reports the OLS estimation of the equation replacing *CRM* with three components estimated based on the probit estimation reported in panel B of Table C.1: the predicted value of *CRM* based on *SOPHIST*, a proxy for bank sophistication (CRM_{usage}); the predicted value of *CRM* based on *EBP*, *NCO*, *OpRisk*, and *BigN*, proxies for bank disclosure (CRM_{disc}); and the residual (CRM_{resid}). Panel B reports pooled OLS estimations of Equation (1MS)—which is Equation (1) replacing *CRM* with the credit risk–modeling indicator variables, *MODEL* and *STRESS*—for subsamples of the overall sample with above-median real estate loans (*Real_High* = 1) or above-median commercial and industrial loans (*C&I_High* = 1) and in stable periods or downturns. Columns (1) and (2) report the estimations for *Real_High* = 1 and the stable and downturn, respectively, subperiods of the overall sample period. Columns (3) and (4) report the estimations for *C&I_High* = 1 and the stable and downturn, respectively, subperiods. All variables are defined in Appendix B. Continuous variables are winsorized at the top and bottom 1% of their distributions. Standard errors for OLS regressions are calculated clustering observations by bank and quarter. Standard errors for the fixed effects and 2SLS analyses are calculated clustering observations by bank. Coefficient t-statistics are reported in square brackets.

***, **, and * denote significance at the 1%, 5%, and 10%, levels, respectively, using two-tailed tests.

STRESS; (3) *LLP* times *CRM* or *MODEL* and *STRESS*; and (4) control variables:

$$NCO_{t+1,t+s} = \delta_0 + \delta_1 LLP_t + \delta_2 CRM + \delta_3 LLP_t \times CRM + \sum_{j \geq 4} \delta_j controls + \varepsilon_t \quad (2)$$

$$NCOREAL_{t+1,t+s} \text{ or } NCOC\&I_{t+1,t+s} = \delta_0 + \delta_1 LLP_t + \delta_{2M} MODEL + \delta_{2S} STRESS + \delta_{3M} LLP_t \times MODEL + \delta_{3S} LLP_t \times STRESS + \sum_{j \geq 4} \delta_j controls + \varepsilon_t. \quad (2MS)$$

In Equation (2), we expect the coefficient δ_3 on $LLP_t \times CRM$ to be positive, consistent with credit risk modeling increasing the ability of loan loss provisions to predict future net loan charge-offs. In Equation (2MS), we expect the coefficient δ_{3M} on $LLP_t \times MODEL$ to be positive for real estate loans during stable periods and the coefficient δ_{3S} on $LLP_t \times STRESS$ to be positive for all types of loans, particularly commercial and industrial loans, during downturns.

The control variables in Equations (2) and (2MS) are the same as those in Equation (1) except that we include NPL_{t-1} as an additional control given its predictive power over future net loan charge-offs (Wahlen 1994, Bhat et al. 2016). We estimate Equation (2) over the overall sample period using the same five approaches used to estimate Equation (1). We estimate Equation (2MS) using pooled OLS for the same four subsamples of bank quarters used to estimate Equation (1MS).

3.5. Ability of Loan Loss Provisions to Predict Future Net Loan Charge-Off Estimations

Table 4, panel A, reports the estimations of Equation (2) with the dependent variable defined as $NCO_{t+1,t+2}$ for the overall sample period; to conserve space, we do not tabulate or discuss the directionally identical but statistically slightly weaker results obtained with the dependent variable defined as $NCO_{t+1,t+4}$. The five columns of the panel reflect the estimations using the same approaches as in panel A of Table 3.

We first discuss the coefficients on the control variables. For brevity, we again discuss only the coefficients in the base model reported in column (1). The coefficient on *SIZE* is positive and significant at the 1% level, likely reflecting the fact that large banks write more consumer loans, which exhibit consistently high net loan charge-offs (Ryan and Keeley 2013), although the coefficient on *C&I_High* is positive and significant at the 10% level. Not surprisingly, the coefficients on *LLP*, *NCO*, ΔNPL_t, NPL_{t-1}, and *LOANS* are positive and significant, and the coefficient on *GDP* is negative and significant, all at the 1% level. The coefficient on $\%\Delta LOANS$ is negative and significant at the 1% level, likely reflecting the fact that it takes time for new loans to be charged off. The coefficient on *CRM* is positive and significant at the 5% level, consistent with firms that engage in credit risk modeling experiencing higher credit losses.

As expected, the coefficient δ_3 on the interactive test variable $LLP \times CRM$ is positive and significant at the 5% level in the base model reported in column (2) and at the 1% level in the fixed effects model reported in column (3), indicating that credit risk–modeling disclosures are positively associated with the ability of loan loss provisions to predict future loan charge-offs.[21] Consistent with these results being attributable to banks' credit risk–modeling usage rather than to their disclosure of that usage, δ_3 is positive and significant at the 1% level in the 2SLS model reported in column (4), and the coefficient on $LLP \times CRM_{usage}$ is positive and significant at the 1% level in the decomposition model reported in column (5).

Table 4, panel B, reports the estimations of Equation (2MS). The estimations reported in columns (1) and (2) of the panel are for the model with dependent variable $NCOREAL_{t+1,t+2}$ and are estimated over the stable and downturn, respectively, subperiods. The estimations reported in columns (3) and (4) are for the model with dependent variable $NCOC\&I_{t+1,t+2}$ and are estimated over the stable and downturn, respectively, subperiods. We do not discuss the coefficients on the control variables, which are generally similar to those for the overall sample period estimations with the dependent variable defined as $NCO_{t+1,t+2}$.

In the $NCOREAL_{t+1,t+2}$ model estimations, as expected, the coefficient δ_{3M} on $LLP \times MODEL$ is positive and significant at the 1% level in column (1), consistent with statistical modeling enhancing the ability of banks' loan loss provisions to predict future charge-offs of real estate loans during stable periods. This coefficient is insignificant in column (2) for downturns. Also as expected, the coefficient δ_{3S} on $LLP \times STRESS$ is positive and significant at the 5% level in column (2), consistent with stress testing enhancing the ability of banks' loan loss provisions to predict future charge-offs of real estate loans during downturns. This coefficient is insignificant in column (1) for stable periods.

In the $NCOC\&I_{t+1,t+2}$ model estimations, as expected, the coefficient δ_{3S} on $LLP \times STRESS$ is positive and significant at the 1% level in column (4), consistent with stress testing enhancing the ability of banks' loan loss provisions to predict future charge-offs of commercial and industrial loans during downturns. This coefficient is insignificant in column (3) for stable periods. The coefficient δ_{3M} on $LLP \times MODEL$ is insignificant in both columns.[22]

Table 4. Association of Credit Risk–Modeling Disclosures with the Ability of Quarterly Loan Loss Provisions to Predict Net Loan Charge-Offs Over the Next Two Quarters

Panel A: Pooled estimations of Equation (3) for the overall sample period

Variables	(1) Restricted base model	(2) Full base model	(3) Fixed effects	(4) Second-stage 2SLS	(5) Second-stage decomposition
LLP	0.605***	0.574***	0.504***	0.373***	0.127
	[13.50]	[10.72]	[10.56]	[4.10]	[1.10]
CRM	0.000**	0.000	−0.000*	0.002	
	[2.22]	[0.54]	[−1.71]	[1.49]	
CRM_{usage}					−0.001
					[−1.28]
CRM_{discl}					0.001**
					[2.50]
CRM_{resid}					0.000
					[1.28]
$LLP \times CRM$		0.095**	0.132***	0.600**	
		[1.97]	[2.63]	[2.37]	
$LLP \times CRM_{usage}$					1.135***
					[4.76]
$LLP \times CRM_{disc}$					−0.364
					[−1.53]
$LLP \times CRM_{resid}$					−0.005
					[−0.23]
SIZE	0.000***	0.000***	0.001***	0.000	0.000***
	[7.49]	[7.40]	[6.71]	[0.34]	[5.56]
C&I_High	−0.000	−0.000	−0.000	0.000	0.000
	[−0.05]	[−0.09]	[−0.39]	[0.62]	[0.10]
*TIER*1	0.000	0.000	0.000	0.000	0.000
	[1.44]	[1.23]	[1.62]	[0.78]	[0.91]
EBP	0.005	0.009	0.002	0.048	0.000
	[0.19]	[0.34]	[0.07]	[1.26]	[0.01]
ALL_{t-1}	0.076***	0.075***	0.091***	0.072***	0.065***
	[5.01]	[4.99]	[5.16]	[5.01]	[4.78]
$LOANS_{t-1}$	0.002***	0.002***	0.002***	0.002***	0.002***
	[3.90]	[3.84]	[3.05]	[3.64]	[4.12]
%Δ*LOANS*	−0.001***	−0.001***	−0.001***	−0.001	−0.001***
	[−2.84]	[−2.86]	[−2.64]	[−0.76]	[−3.09]
OpRisk	0.000***	0.000***	0.001***	0.000	0.000**
	[3.20]	[3.13]	[3.42]	[0.53]	[2.41]
MktRisk	−0.000	−0.000	−0.000	−0.000	0.000
	[−0.04]	[−0.14]	[−1.11]	[−0.03]	[0.21]
NCO_t	0.138**	0.140**	−0.031	0.140**	0.116**
	[2.55]	[2.56]	[−0.67]	[2.28]	[2.31]
ΔNPL_t	0.119***	0.120***	0.121***	0.122***	0.125***
	[9.61]	[9.59]	[9.81]	[8.72]	[10.26]
NPL_{t-1}	0.060***	0.060***	0.077***	0.062***	0.067***
	[6.69]	[6.69]	[8.09]	[6.89]	[7.39]
UNRATE	0.000***	0.000***	0.000***	0.000***	0.000***
	[3.17]	[3.18]	[8.44]	[4.05]	[2.97]
VIX	0.000	0.000	0.000***	0.000***	0.000
	[1.47]	[1.42]	[6.38]	[3.39]	[1.61]
Constant	−0.005***	−0.005***	−0.008***	−0.003***	−0.004***
	[−5.87]	[−5.71]	[−7.45]	[−4.31]	[−5.36]
No. of observations	14,694	14,694	14,694	14,694	14,694
Adjusted R^2 (%)	59.54	59.64	63.72	47.23	60.54

Table 4. (Continued)

Panel B: Pooled OLS estimations of Equation (3) by loan type for the stable and downturn subperiods

Variables	(1) Stable	(2) Downturn	(3) Stable	(4) Downturn
	Dep var = $NCOREAL_{t+1,t+2}$		Dep var = $NCOC\&I_{t+1,t+2}$	
LLP	0.349***	0.483***	0.573***	0.580***
	[6.77]	[4.61]	[8.07]	[8.64]
MODEL	−0.000	−0.000	0.000	0.001
	[−1.03]	[−1.00]	[1.53]	[0.89]
STRESS	0.001*	0.000	−0.000	−0.001
	[1.81]	[0.23]	[−1.12]	[−0.89]
$LLP \times MODEL$	0.167***	0.103	0.173	0.046
	[2.71]	[1.20]	[1.56]	[0.21]
$LLP \times STRESS$	0.121	0.204**	−0.086	0.549***
	[1.04]	[2.52]	[−0.78]	[3.41]
SIZE	0.000***	0.001***	0.000	0.000
	[3.92]	[2.66]	[1.17]	[1.30]
*TIER*1	0.000***	0.000	−0.000	0.000
	[3.35]	[1.02]	[−0.60]	[0.54]
EBP	−0.077***	−0.033	0.002	−0.041
	[−4.05]	[−0.94]	[0.04]	[−0.98]
ALL_{t-1}	0.025**	0.102***	0.048**	0.025
	[2.12]	[2.86]	[2.36]	[0.61]
$LOANS_{t-1}$	0.003***	0.005***	0.002***	0.006***
	[5.00]	[4.30]	[2.97]	[2.86]
$\%\Delta LOANS$	−0.002***	−0.002	−0.003***	−0.004**
	[−5.75]	[−1.17]	[−3.07]	[−2.17]
MktRisk	−0.000	−0.000**	0.000	0.001***
	[−0.48]	[−2.28]	[0.89]	[2.86]
OpRisk	0.000***	0.001**	−0.000	0.000
	[3.35]	[2.31]	[−0.74]	[0.28]
NCO_t	−0.245***	−0.831***	−0.298***	−0.528***
	[−3.65]	[−7.40]	[−3.89]	[−4.24]
$NCOREAL_t$	0.659***	1.049***		
	[8.49]	[7.20]		
$NCOCOMML_t$		0.285***	0.441***	
			[6.90]	[5.76]
ΔNPL_t	0.100***	0.170***	0.164***	0.066***
	[6.17]	[8.96]	[8.10]	[3.12]
NPL_{t-1}	0.055***	0.082***	0.081***	0.038*
	[7.11]	[5.76]	[5.06]	[1.75]
Constant	−0.004***	−0.008***	−0.002	−0.005*
	[−4.15]	[−3.48]	[−1.44]	[−1.81]
No. of observations	12,324	1,911	12,361	1,917
Adjusted R^2 (%)	54.47	62.13	21.64	18.17

Notes. Panel A reports pooled estimations of Equation (2) for the 14,694 bank-quarter observations in the overall sample from 1996Q1–2010Q4 with the necessary data. These estimations associate the ordinal credit risk–modeling variable *CRM* with the ability of banks' quarterly loan loss provisions (LLP_t) to predict net loan charge-offs over the following two quarters ($NCO_{t+1,t+2}$). Equation (2) regresses $NCO_{t+1,t+2}$ on (1) LLP_t; (2) *CRM*, both separately and interacted with LLP_t; and (3) control variables. Columns (1)–(5) report estimations of Equation (2) using five approaches that are described in the notes to Table 3 regarding the same columns of panel A of that table. Panel B reports pooled OLS estimations of Equation (2MS), which is Equation (2) replacing *CRM* with the credit risk–modeling indicator variables, *MODEL* and *STRESS*, and replacing $NCO_{t+1,t+2}$ with net charge-offs over the next two quarters of either real estate loans ($NCOREAL_{t+1,t+2}$) or commercial and industrial loans ($NCOC\&I_{t+1,t+2}$), for the stable period or downturn subperiods of the overall sample. Columns (1) and (2) report estimations of the model with dependent variable $NCOREAL_{t+1,t+2}$ for the stable and downturn, respectively, subperiods. Columns (3) and (4) report estimations of the model with dependent variable $NCOC\&I_{t+1,t+2}$ for the stable and downturn, respectively, subperiods. All variables are defined in Appendix B. Continuous variables are winsorized at the top and bottom 1% of their distributions. Standard errors for OLS regressions are calculated clustering observations by bank and quarter. Standard errors for the fixed effects and 2SLS analyses are calculated clustering observations by bank. Coefficient t-statistics are in square brackets.

***, **, and * denotes significance at the 1%, 5%, and 10% levels, respectively, using two-tailed tests.

4. Credit Risk–Modeling Disclosures and Loan-Origination Procyclicality

We expect banks that engage in credit risk modeling to exhibit less procyclical loan originations for three related reasons. First, evidence provided in Section 3 indicates that credit risk–modeling disclosures are associated with enhanced loan loss–provision timeliness and ability of provisions to predict future net loan charge-offs. Second, prior research argues and shows empirically that banks that record timelier loan loss provisions build larger regulatory capital cushions that enable them to originate more loans during downturns. Specifically, Laeven and Majnoni (2003) and Dugan (2009) argue that banks that record larger allowances for loan losses during stable times are able to absorb the higher level of net loan charge-offs that occur during downturns. Beatty and Liao (2011) provide evidence that banks that record timelier loan loss provisions issue more capital during both stable periods and recessions and originate more loans during recessions. Third, we expect banks that engage in credit risk modeling to have better understandings of the adequacy of their allowances for loan losses and, thus, the ability of their reported capital cushions to absorb future net loan charge-offs.

4.1. Loan-Origination Procyclicality Measures

In this section, we develop three measures of loan-origination procyclicality and related models and expectations.

4.1.1. First Measure. Laeven and Majnoni (2003, p. 184) hypothesize that "a bank shows imprudent loan loss provisioning behavior—susceptible to have procyclical effects on banks' capital—if. . . . Loan loss provisions are negatively related to loan growth." Laeven and Majnoni test this hypothesis by regressing loan loss provisions on contemporaneous loan growth. We instead reverse the relationship and regress the natural logarithm of banks' one plus loan growth during the current and three future quarters ($LOANGR_{t-1,t+3}$) on quarterly loan loss provisions. We do this in part to be able to interact our credit risk–modeling variables with loan loss provisions and in part because loan growth is the more natural dependent variable in the analysis of loan-origination procyclicality. We infer reduced procyclicality when the association of banks' quarterly loan loss provisions and this loan growth measure is less negative, that is, when banks decrease loan originations less as loan loss provisions increase.

We expect credit risk modeling to reduce this loan-origination procyclicality measure during our overall sample period. We expect statistical modeling to reduce this procyclicality measure for growth in real estate loans ($REALGR_{t-1,t+3}$) during stable periods. We expect stress testing to reduce this measure for all loan types, particularly growth in commercial and industrial loans ($C\&IGR_{t-1,t+3}$), during downturns. We test these expectations using the following models:

$$LOANGR_{t-1,t+3} = B_0 + B_1 LLP_t + B_2 CRM + B_3(LLP \times CRM) + \sum_{j\geq 4} B_j controls_j + \varepsilon_{t-1,t+3}. \quad (3)$$

$$REALGR_{t-1,t+3} \text{ or } C\&IGR_{t-1,t+3} = B_0 + B_1 LLP_t + B_{2M} MODEL + B_{2S} STRESS + B_{3M}(LLP_t \times MODEL) + B_{3S}(LLP_t \times STRESS) + \sum_{j\geq 4} B_j controls_j + \varepsilon_{t-1,t+3}. \quad (3MS)$$

In Equation (3), we expect the coefficient B_3 on $LLP_t \times CRM$ to be positive, consistent with credit risk modeling increasing the ability of loan loss provisions to predict future net loan charge-offs. In Equation (3MS), we expect the coefficient B_{3M} on $LLP_t \times MODEL$ to be positive for growth in real estate loans during stable periods. We expect the coefficient B_{3S} on $LLP_t \times STRESS$ to be positive for growth in all types of loans, particularly commercial and industrial loans, during downturns.

The control variables in Equations (3) and (3MS) include all the controls in Equation (1) except $\%\Delta LOANS$, which we exclude owing to its overlap with the dependent variable. These equations also include *ALL/NPL* to capture the adequacy of banks' allowance for loan losses (Beatty and Liao 2011), and *DEMAND*, the percentage of bank officers reporting stronger loan demand during the quarter in the Federal Reserve's Senior Loan Officer Opinion Survey on Bank Lending Practices (Lown and Morgan 2006), to capture loan demand. Controlling for loan demand enables the coefficients on the test variables to better capture loan supply (Acharya and Ryan 2016).

We estimate Equation (3) over the overall sample period using the same five approaches used to estimate Equation (1). We estimate Equation (3MS) using pooled OLS for the same four subsamples of bank quarters used to estimate Equation (1MS).

4.1.2. Second Measure. Following Bikker and Metzemakers (2005), we also evaluate procyclicality in terms of the association between an indicator for negative quarterly GDP growth (*GDPDECR*) and $LOANGR_{t-1,t+3}$, inferring reduced procyclicality when this association is less negative. We expect credit risk modeling to reduce this loan-origination procyclicality measure. We test this expectation using the following model:

$$LOANGR_{t-1,t+3} = C_0 + C_1 CRM + C_2 GDPDECR_t + C_3(GDPDECR_t \times CRM) + \sum_{j\geq 4} C_j controls_j + \varepsilon_{t-1,t+3}. \quad (4)$$

We expect the coefficient C_3 on $GDPDECR_t \times CRM$ to be positive. The control variables are the same as in Equation (3) except that we exclude $\Delta UNRATE$, *VIX*, and *DEMAND* to avoid multicollinearity with *GDPDECR*. We estimate Equation (4) only for the overall sample because partitioning on stable versus downturn periods would eliminate variation in *GDPDECR*.

4.1.3. Third Measure. Bikker and Metzemakers's (2005) use of negative GDP growth as a proxy for downturns is more appropriate for commercial and industrial loans than for real estate loans. Accordingly, we modify Bikker and Metzemakers's approach to evaluate the procyclicality of banks' origination of real estate loans by replacing *GDPDECR* with the cumulative decrease in the subprime mortgage–related ABX index, averaging across all tranches, from the inception of the index in January 2006 to the current quarter (*ABXDECR*). The ABX index is highly sensitive to declines in real estate prices, which drive losses on real estate loans. We measure procyclicality as the association between *ABXDECR* and $REALGR_{t-1,t+3}$:

$$\begin{aligned} REALGR_{t-1,t+3} = D_0 &+ D_1 CRM + D_2 ABXDECR_t \\ &+ D_3(ABXDECR_t \times CRM) \\ &+ \sum_{j \geq 4} D_j controls_j + \varepsilon_{t-1,t+3}. \end{aligned} \tag{5}$$

We expect the coefficient D_3 on $ABXDECR \times CRM$ to be positive. The control variables are the same as in Equation (4). We estimate Equation (5) over the quarters from 2007:Q1 to 2008:Q2, the period over which the (junior) tranches of the ABX index lost the (vast) majority of their value, for which *ABXDECR* should have high signal value.

4.2. Loan-Origination Procyclicality Estimations

Equation (3). Table 5, panel A, reports the estimation of Equation (3) for the overall sample period. The five columns of the panel reflect the estimations using the same approaches as in panels A of Tables 3 and 4.

We first discuss the coefficients on the control variables. For brevity, we again discuss only the coefficients in the base model reported in column (1). The coefficient on *CRM* is significantly negative at the 5% level, indicating that credit risk–modeling disclosures are, on average, associated with reduced loan origination. The coefficients on *SIZE* and *LOANS* are significantly negative at the 1% and 10% level, respectively, perhaps because it is harder for larger banks that hold more loans to grow their loan portfolios. The coefficient on *C&I_ High* is significantly positive at the 5% level. The coefficient on *TIER*1 is significantly negative at the 1% level perhaps because loan growth reduces capital ratios or because banks with higher capital ratios are more risk averse.[23] The coefficient on *EBP* (*NCO*) is significantly positive (negative) at the 1% level, indicating higher loan growth for more profitable (lower credit loss) banks. The coefficient on *ALL/NPL* is significantly positive at the 1% level, consistent with better reserved banks being more willing to extend loans. The coefficient on *DEMAND* is significantly positive at the 1% level, indicating higher loan growth when loan demand is higher. The inclusion of *DEMAND* swamps the effects of the other macroeconomic variables, rendering the coefficients on $\Delta UNRATE$ and *VIX* insignificant.

As expected, the coefficient B_3 on $LLP \times CRM$ is significantly positive at the 10% level in the pooled OLS estimation of the base model reported in column (2) although it is insignificant in the fixed effects estimation reported in column (3), providing weak and inconsistent evidence that credit risk–modeling disclosures are associated with reduced loan-origination procyclicality.[24] Providing evidence that is both stronger and consistent with this result being attributable to banks' credit risk–modeling usage rather than to their disclosure of that usage, B_3 is significant at the 1% level in the 2SLS estimation reported in column (4), and the coefficient on $LLP \times CRM_{usage}$ is significantly positive at the 1% level in the decomposition approach reported in column (5). Moreover, the coefficient on $LLP \times CRM_{disc}$ is significantly *negative* at the 10% level in column (5); this negative coefficient likely explains the weak and inconsistent results in columns (2) and (3).

The following calculation gives a sense for the economic significance of the positive coefficient B_3 on $LLP \times CRM$ in the base model estimation reported in column (2). A one standard deviation increase in LLP yields 0.75% higher loan growth when *CRM* equals one than when it equals zero, holding all other explanatory variables constant at their means.

4.2.1. Equation (3MS). Columns (1) and (2) of panel B of Table 5 report estimations of Equation (3MS) with dependent variable *REALGR* for the stable and downturn subperiods, respectively, of the overall sample. Columns (3) and (4) of the panel report estimations of Equation (3MS) with dependent variable *C&IGR* for the stable and downturn subperiods, respectively. For brevity, we do not discuss the coefficients on the control variables, which are similar to those reported in Table 5, panel A.

As expected, the coefficient B_{3M} on $LLP \times MODEL$ is significantly positive at the 10% level in the regression with dependent variable *REALGR* for stable periods reported in column (1), consistent with statistical modeling mitigating the procyclical relationship between loan loss provisions and real estate loan growth during stable periods. This coefficient is insignificant in the other subsamples. As expected, the coefficient B_{3S} on $LLP \times STRESS$ is significantly positive at the 10% level in the regression with dependent variable *C&IGR* during downturns reported in column (4), consistent with stress testing mitigating the procyclical relationship between loan loss provisions and commercial

Table 5. Association of Credit Risk–Modeling Disclosures with Loan-Origination Procyclicality Measured as the Association of Loan Loss Provisions with Loan Growth

Panel A: Pooled estimations of Equation (3) for the overall sample period

Variables	(1) Restricted base model	(2) Full base model	(3) Fixed effects	(4) Second-stage 2SLS	(5) Second-stage decomposition
LLP	−0.708	−1.479	−3.923***	−6.906***	−11.417***
	[−0.58]	[−1.12]	[−3.68]	[−3.61]	[−2.76]
CRM	−0.018**	−0.026***	−0.011	−0.114	
	[−2.31]	[−2.95]	[−1.13]	[−1.57]	
CRM_{usage}					−0.101***
					[−2.83]
CRM_{discl}					−0.060***
					[−3.46]
CRM_{resid}					−0.008**
					[−2.09]
$LLP \times CRM$		2.876*	0.527	24.196***	
		[1.87]	[0.31]	[3.29]	
$LLP \times CRM_{usage}$					30.736***
					[3.83]
$LLP \times CRM_{discl}$					−12.693*
					[−1.65]
$LLP \times CRM_{resid}$					−0.136
					[−0.17]
SIZE	−0.009***	−0.009***	−0.087***	−0.007	−0.005**
	[−3.61]	[−3.66]	[−12.91]	[−1.64]	[−1.97]
C&I_High	0.011**	0.011**	0.015**	0.010*	0.013***
	[2.29]	[2.29]	[2.40]	[1.88]	[2.58]
*TIER*1	−0.004***	−0.004***	0.001	−0.004***	−0.004***
	[−3.34]	[−3.43]	[1.12]	[−3.98]	[−3.42]
EBP	11.400***	11.441***	7.519***	11.531***	10.263***
	[8.07]	[8.08]	[7.28]	[8.49]	[7.72]
ALL_{t-1}	−2.293***	−2.333***	−4.062***	−2.615***	−2.388***
	[−4.46]	[−4.52]	[−9.35]	[−5.76]	[−4.58]
$LOANS_{t-1}$	−0.055*	−0.056*	−0.217***	−0.065**	−0.048
	[−1.65]	[−1.70]	[−5.50]	[−2.13]	[−1.49]
OpRisk	−0.006	−0.006	0.019**	−0.005	0.002
	[−0.86]	[−0.88]	[2.23]	[−0.62]	[0.32]
MktRisk	0.004	0.004	0.004	0.002	0.003
	[0.86]	[0.82]	[0.60]	[0.47]	[0.64]
NCO	−8.060***	−7.980***	−3.460***	−7.282***	−8.113***
	[−4.36]	[−4.29]	[−2.66]	[−4.83]	[−4.41]
ΔNPL	0.507	0.540	1.056***	0.774**	0.587
	[1.22]	[1.31]	[4.02]	[2.41]	[1.43]
ALL/NPL	0.002***	0.002***	0.002***	0.002***	0.002***
	[5.38]	[5.37]	[5.50]	[5.22]	[5.35]
UNRATE	−0.000	−0.000	0.001**	−0.000	−0.000
	[−0.36]	[−0.37]	[2.10]	[−0.87]	[−0.49]
VIX	0.000	0.000	−0.000*	0.000	0.000
	[0.48]	[0.46]	[−1.95]	[0.30]	[0.21]
DEMAND	0.001***	0.001***	0.001***	0.001***	0.001***
	[6.28]	[6.31]	[10.44]	[11.62]	[6.35]
Constant	0.234***	0.238***	0.931***	0.262***	0.290***
	[5.99]	[6.21]	[14.63]	[6.45]	[7.67]
No. of observations	15,879	15,879	15,879	15,879	15,879
Adjusted R^2 (%)	18.6	18.6	38.8	14.8	19.6

Table 5. (Continued)

Panel B: Pooled OLS estimations of Equation (3MS) by loan type for the stable and downturn subperiods

Variables	(1) Stable	(2) Downturn	(3) Stable	(4) Downturn
	Dep var = $REALGR_{t-1,t+3}$		Dep var = $C\&IGR_{t-1,t+3}$	
LLP	−4.605**	2.449	−5.458**	−1.871
	[−2.34]	[0.73]	[−2.34]	[−0.43]
MODEL	−0.035***	0.001	−0.018	0.005
	[−2.94]	[0.07]	[−1.02]	[0.18]
STRESS	−0.061**	−0.045	−0.042*	−0.078*
	[−2.55]	[−1.48]	[−1.79]	[−1.72]
$LLP \times MODEL$	4.037*	−1.537	−2.907	−4.954
	[1.66]	[−0.51]	[−0.92]	[−1.06]
$LLP \times STRESS$	0.874	8.553	1.391	13.384*
	[0.26]	[1.09]	[0.36]	[1.77]
SIZE	−0.012***	−0.006	0.003	0.002
	[−4.85]	[−0.72]	[0.95]	[0.40]
*TIER*1	−0.004***	−0.004**	−0.002	−0.003
	[−3.85]	[−2.32]	[−1.22]	[−0.82]
EBP	12.906***	6.633***	12.009***	5.871***
	[7.81]	[2.70]	[6.00]	[2.60]
LLA_{t-1}	−1.947***	−1.822	−2.906***	−4.899***
	[−3.25]	[−1.34]	[−3.28]	[−2.78]
$LOANS_{t-1}$	−0.081**	−0.072	−0.021	−0.010
	[−2.15]	[−1.40]	[−0.42]	[−0.11]
MarketRisk	0.009*	0.017**	−0.005	−0.013
	[1.75]	[1.98]	[−0.82]	[−1.20]
OpRisk	−0.011	−0.006	−0.021*	0.003
	[−1.26]	[−0.48]	[−1.75]	[0.17]
NCO	−5.796**	−12.578***	−8.120***	−9.721
	[−2.49]	[−4.55]	[−2.91]	[−1.62]
ΔNPL	0.616	−1.582	−0.605	−0.913
	[1.26]	[−1.41]	[−0.78]	[−1.36]
ALL/NPL	0.003***	0.003***	0.002***	0.001
	[5.11]	[3.15]	[3.28]	[0.47]
Constant	0.279***	0.206***	0.114**	0.126
	[7.15]	[2.78]	[1.97]	[1.26]
No. of observations	13,197	1,902	13,796	2,051
Adjusted R^2 (%)	12.60	10.12	7.86	6.38

Notes. Panel A reports pooled estimations of Equation (3) for the 15,879 bank-quarter observations in the overall sample from 1996Q1–2010Q4 with the necessary data. These estimations associate the ordinal credit risk–modeling variable *CRM* with the association of quarterly loan loss provisions (LLP_t) with loan growth from the end of quarter $t-1$ to the end of quarter $t+3$ ($LOANGR_{t-1,t+3}$). Following Laeven and Majnoni (2003), we infer (greater) loan-origination procyclicality from a (more) negative association of LLP_t with $LOANGR_{t-1,t+3}$. Equation (3) regresses $LOANGR_{t-1,t+3}$ on (1) LLP_t; (2) *CRM*, both separately and interacted with LLP_t; and (3) control variables. Columns (1)–(5) report estimations of Equation (2) using five approaches that are described in the notes to Table 3 regarding the same columns of panel A of that table. Panel B reports pooled OLS estimations of Equation (3MS), which is Equation (3) replacing *CRM* with the credit-risk-modeling indicator variables, *MODEL* and *STRESS*, and replacing $LOANGR_{t+1,t+2}$ with four-quarter growth of either real estate loans ($REALGR_{t+1,t+2}$) or commercial and industrial loans ($C\&IGR_{t+1,t+2}$), for the stable period or downturn subperiods of the overall sample. Columns (1) and (2) report estimations of the model with dependent variable $REALGR_{t+1,t+2}$ for the stable and downturn, respectively, subperiods. Columns (3) and (4) report estimations of the model with dependent variable $C\&IGR_{t+1,t+2}$ for the stable and downturn, respectively, subperiods. All variables are defined in Appendix B. Continuous variables are winsorized at the top and bottom 1% of their distributions. Standard errors for OLS regressions are calculated clustering observations by bank and quarter. Standard errors for the fixed effects and 2SLS analyses are calculated clustering observations by bank. Coefficient t-statistics are in square brackets.

***, **, and * denotes significance at the 1%, 5%, and 10% levels, respectively, using two-tailed tests.

and industrial loan growth during downturns. Unexpectedly, B_{3S}, while positive, is insignificant in the regression for real estate loan growth and downturns reported in column (2). This coefficient is insignificant in the regressions for both loan types during stable periods reported in columns (1) and (3).[25]

4.2.2. Equation (4). Column (1) of Table 6 reports the pooled OLS estimation of Equation (4) for the overall sample period. We again do not discuss the coefficients on the control variables, which are similar to those reported in Table 5, panel A. Consistent with the findings of Bikker and Metzemakers (2005), the coefficient on *GDPDECR* is significantly negative at the 1% level, consistent with loan growth being lower when GDP growth is negative; that is, on average, loan origination is procyclical. As expected, the coefficient C_3 on $GDPDECR \times CRM$ is significantly positive at the 5%

Table 6. Association of Credit Risk–Modeling Disclosures with Loan-Origination Procyclicality Measured as the Association of Decreases in GDP or the ABX Index With Loan Growth

Dep var = *MACRODECR* = Variables	(1) $LOANGR_{t-1,t+3}$ *GDPDECR*	(2) $REALGR_{t-1,t+3}$ *ABXDECR*
LLP	−1.681 [−1.25]	0.941 [0.49]
CRM	−0.023*** [−2.69]	−0.076*** [−3.81]
MACRODECR	−0.053*** [−4.97]	−0.000 [−1.24]
MACRODECR × *CRM*	0.027** [2.40]	0.001** [2.47]
SIZE	−0.008*** [−3.31]	−0.002 [−0.44]
C&I_High	0.011** [2.16]	0.013 [1.42]
*TIER*1	−0.004*** [−3.38]	−0.003 [−0.94]
EBP	11.490*** [7.30]	4.553** [2.17]
LLA_{t-1}	−2.099*** [−3.94]	−1.320 [−1.17]
$LOANS_{t-1}$	−0.057 [−1.62]	0.021 [0.27]
MktRisk	0.004 [0.86]	0.022** [2.44]
OpRisk	−0.009 [−1.22]	−0.008 [−0.53]
NCO	−8.944*** [−4.79]	−14.457*** [−8.81]
Δ*NPL*	0.285 [0.66]	−1.798*** [−3.70]
ALL/NPL	0.003*** [5.33]	0.001 [1.08]
Constant	0.222*** [6.00]	0.125 [1.32]
No. of observations	15,879	1,581
Adjusted R^2 (%)	15.90	7.00

Notes. Column (1) reports the pooled OLS estimation of Equation (4) for the 15,879 bank-quarter observations in the overall sample from 1996Q1–2010Q4 with the necessary data. This estimation associates the ordinal credit risk–modeling variable *CRM* with the association of an indicator for negative quarterly GDP growth ($GDPDECR_t$) and loan growth from the end of quarter $t-1$ to the end of quarter $t+3$ ($LOANGR_{t-1,t+3}$). Following Bikker and Metzemakers (2005), we infer (greater) procyclicality from a more negative assocation of $GDPDECR_t$ and $LOANGR_{t-1,t+3}$. Equation (4) regresses $LOANGR_{t-1,t+3}$ on: (1) $GDPDECR_t$; (2) *CRM*, both separately and interacted with $GDPDECR_t$; and (3) control variables. Column (2) reports the pooled OLS estimation of Equation (5) for the 1,581 bank-quarter observations in the overall sample from 2007Q1–2008Q2 with the necessary data. This estimation associates *CRM* with the association of the cumulative decline in the ABX index from its inception in January 2006 to quarter t (*ABXDECR*) and $LOANGR_{t-1,t+3}$. We infer (greater) procyclicality from a (more) negative assocation of $ABXDECR_t$ and$LOANGR_{t-1,t+3}$. Equation (5) regresses $LOANGR_{t-1,t+3}$ on: (1) $ABXDECR_t$; (2) *CRM*, both separately and interacted with $ABXDECR_t$; and (3) control variables. The 2007Q1–2008Q2 period is when changes in the ABX index had significant signal value. All variables are defined in Appendix B. Continuous variables are winsorized at the top and bottom 1% of their distributions. Standard errors are calculated clustering observations by bank and quarter. Coefficient *t*-statistics are in square brackets.

***, **, and * denotes significance at the 1%, 5%, and 10% levels, respectively, using two-tailed tests.

level, indicating that credit risk–modeling disclosures are associated with reduced loan-origination procyclicality.

The following calculation gives a sense for the economic significance of the positive coefficient C_3 on *GDPDECR* × *CRM*. *GDPDECR* taking a value of 1 rather than 0 yields 2.60% higher loan growth when *CRM* equals 1 than when it equals 0, holding all other explanatory variables constant at their means.

4.2.3. Equation (5). Table 6, column (2) reports the pooled OLS estimation of Equation (5) for the overall sample period. We again do not discuss the coefficients on the control variables, which are similar to those reported in Table 5, panel A. As expected, the coefficient D_3 on *ABXDECR* × *CRM* is significantly positive at the 5% level, indicating that credit risk–modeling disclosures are associated with reduced loan-origination procyclicality.

The following calculations give a sense for the economic significance of the positive coefficient D_3 on *ABXDECR*×*CRM*. *ABXDECR* taking a value of 1 rather than 0 yields 0.08% higher growth in real estate loans when *CRM* equals 1 than when *CRM* equals 0, holding all other explanatory variables constant at their means. This economically modest incremental growth may reflect the problematic state of the real estate market during the 2007:Q1–2008:Q2 estimation period.

5. Conclusion

In this study, we provide evidence that banks' financial report disclosures of credit risk modeling are associated with enhanced loan loss–provision timeliness, enhanced ability of loan loss provisions to predict future net loan charge-offs, and reduced loan-origination procyclicality on average for our overall sample from 1996:Q1 to 2010:Q4. We employ two approaches that provide evidence suggesting that these findings are attributable to banks' credit risk–modeling usage rather than to their disclosure of that usage. We emphasize, however, that banks' credit risk–modeling disclosures are limited in their frequency and extent, which makes it difficult to distinguish banks' usage of credit risk modeling from their disclosure of that usage.

We further examine how the documented associations vary for disclosures of two distinct forms of credit risk modeling (statistical modeling of historical loan losses and stress tests of future loan losses), two subperiods of the overall sample (stable periods and downturns), and two types of loans (homogeneous real estate loans and heterogeneous commercial and industrial loans). We find that statistical modeling has significant desirable effects for real estate loans during stable periods while stress testing has significant desireable effects during downturns, particularly for commercial and industrial loans.

Our results raise two questions for future research. First, would bank regulatory requirements for improved credit risk modeling or financial reporting requirements for enhanced credit risk–modeling disclosures help mitigate policymakers' concern that delay in banks' loan loss provisions during stable periods requires banks to record larger provisions in downturns, reducing their regulatory capital adequacy and causing them to cut back on loan originations (Dugan 2009, Curry 2013)? Second, does variation in banks' credit risk modeling explain Beatty and Liao's (2011) finding that banks that record timelier loan loss provisions issue more capital during both stable periods and downturns, allowing banks to originate more loans during downturns (Ryan 2017)? We believe the answers to both questions are likely to be yes. However, because we identify banks' credit risk modeling based on their existing, largely voluntary disclosures in financial reports, we cannot draw direct inferences about potentially desirable requirements for credit risk modeling or related disclosures from our results.

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Appendix A. Credit Risk–Modeling Disclosure Indicator Variables

		No. of firms (firm quarters) with scores of 1	Sample disclosures
MODEL = 0 or 1	Does the bank disclose the use of statistical modeling?	78 firms (1,226 firm-quarters)	Bank of America Corporation 10K 2009 We use proprietary models to measure the capital requirements for credit, country, market, operational, and strategic risks. Statistical models are built using detailed behavioral information from external sources, such as credit bureaus and/or internal historical experience. These models are a component of our consumer credit risk management process and are used, in part, to help determine both new and existing credit decisions, portfolio management strategies, including authorizations and line management, collection practices and strategies, determination of the allowance for loan and lease losses, and economic capital allocations for credit risk.
STRESS = 0 or 1	Does the bank disclose the use of stress testing?	39 firms (353 firm-quarters)	Zions Bancorporation 10K 2009 The company periodically stress tests its CRE loan portfolio. This testing is back-tested, and the results of the testing are reviewed regularly with the management, rating agencies, and various banking regulators. The stress-testing methodology includes a loan-by-loan Monte Carlo simulation, which is an approach that measures potential loss of principal and related revenues. The Monte Carlo simulation stresses the probability of default and loss given default for CRE loans based on a variety of factors including regional economic factors, loan grade, loan-to-value, collateral type, and geography.

Notes. We hand-collected banks' disclosures in their Form 10-K filings from 1995–2009 about two credit risk–modeling activities: statistical modeling of the drivers of past loan losses (*MODEL*) and stress testing of future loan losses to adverse scenarios (*STRESS*). Each activity is scored 1 or 0. We chose the sample disclosures randomly.

Appendix B. Variable Definitions

Variable	Definition
Credit Risk Modeling (CRM) Variables:	
MODEL	Indicator variable that takes a value of 1 if the bank discloses the use of statistical modeling of the drivers of past loan losses in its most recent Form 10-K filing
STRESS	Indicator variable that takes a value of 1 if the bank discloses the use of stress tests of future loan losses to adverse scenarios in its most recent Form 10-K filing
CRM	*MODEL* plus *STRESS*. An ordinal variable with a minimum value of zero and a maximum value of two
Loan Loss Accrual Variables:	
LLP	Loan loss provision divided by prior quarter total loans
ALL/NPL	Allowance for loan losses divided by nonperforming loans
ALL_{t-1}	Prior quarter allowance for loan losses divided by prior quarter total loans
Nonperforming Loan (NPL) Variables:	
NPL	Nonperforming loans divided by prior quarter total loans
ΔNPL	Change in nonperforming loans divided by quarter $t-1$ total loans
$\Delta NPL_{t-2,t}$	ΔNPL from quarter-end $t-2$ to quarter-end t
ΔNPL_{t+1}	ΔNPL for quarter $t+1$
Net Loan Charge-off (NCO) Variables:	
$NCO_{t+1,t+s}$	Net loan charge-offs for quarters $t+1$ to $t+s$ divided by quarter $t-1$ total loans
$NCOREAL_{t+1,t+s}$	Net charge-offs of real estate loans for quarters $t+1$ to $t+s$ divided by quarter $t-1$ real estate loans
$NCOC\&I_{t+1,t+s}$	Net charge-offs of commercial and industrial loans for quarters $t+1$ to $t+s$ divided by quarter $t-1$ commercial and industrial loans
Bank Characteristics:	
SIZE	Natural logarithm of prior quarter total assets
C&I_High	Indicator variable that takes a value of one for above-median commercial and industrial loans divided by total loans for the bank-year
MktRisk	Ordinal variable that takes a value from zero to five, increasing by one if the bank discloses each of repricing GAP, market risk sensitivity, value at risk, back-testing of market risk models, and stress testing of market risk models in its most recent Form 10-K filing
OpRisk	Indicator variable that takes a value of 1 if the bank discloses details about its operational risk management in its most recent Form 10-K filing
TIER1	Tier 1 risk-adjusted capital ratio for prior quarter
EBP	Pretax earnings before the loan loss provision divided by prior quarter total assets
NCO	Net loan charge-offs divided by prior quarter total loans
NPL_{t-1}	Nonperforming loans divided by prior quarter total loans
$LOANS_{t-1}$	Prior quarter loans divided by prior quarter total assets
$\%\Delta LOANS$	Change in total loans divided by prior quarter total loans
Loan Growth Variables:	
LOANGR	Natural logarithm of one plus growth in total loans from end of quarter $t-1$ to end of quarter $t+3$
REALGR	Natural logarithm of one plus growth in real estate loans from end of quarter $t-1$ to end of quarter $t+3$
C&IGR	Natural logarithm of one plus growth in commercial and industrial loans from end of quarter $t-1$ to end of quarter $t+3$
Macroeconomic Variables:	
$\Delta UNRATE$	Percentage change in the nationwide unemployment rate from the U. S. Department of Labor
VIX	Chicago Board Options Exchange (CBOE) Volatility Index®
ABXDECR	Decline in the price of the ABX index (average of all tranches) from its inception in January 2006 to the end of the current quarter
DEMAND	The average of the net percentages of bank loan officers reporting stronger demand for commercial and industrial loans and for consumer loans in the Federal Reserve's quarterly Senior Loan Officer Opinion Survey on Bank Lending Practices
GDP	Growth in U.S. gross domestic product
GDPDECR	Indicator variable that takes a value of one for quarters with negative GDP growth
Two-Stage Least Squares and Decomposition Approaches Variables:	
BigN	An indicator variable that takes a value of one if the bank's auditor for the year is one of Arthur Andersen, Coopers and Lybrand, Ernst and Young, Deloitte and Touche, KPMG, and PriceWaterhouseCoopers
COMPLEX	An indicator variable that takes a value of one if the Federal Reserve's Bank Holding Company Complexity Indicator (RSSD9057) equals 1 or 3–8

Appendix B. (Continued)

Variable	Definition
Two-Stage Least Squares and Decomposition Approaches Variables:	
LOG_NOTIONAL	The natural logarithm of the total notional amount of derivatives
LOG_SEC_VOL	The natural logarithm of the total dollar amount of securitizations sponsored by the bank during the sample period reported by Asset-Backed Alert
CRO	An indicator variable that takes a value of one if the bank discloses the employment of a chief risk officer in its most recent Form 10-K filing
SOPHIST	The first principal component of *COMPLEX*, *LOG_NOTIONAL*, *LOG_SEC_VOL*, and *CRO*. Used as an instrumental variable for the 2SLS analysis

Note. Undeflated variables and the numerators of deflated variables other than percentage change or growth variables are measured during the current quarter (t) for flow (including percentage change and growth) variables or as of the end of that quarter for stock variables unless indicated otherwise.

Appendix C. First-Stage Models in the Two-Stage Least Squares and Decomposition Approaches

C.1. Description

As discussed in Section 1, we observe banks' financial report disclosures of their credit risk modeling, not their usage of credit risk modeling. Moreover, banks relatively infrequently provide these disclosures. In the primary analyses discussed in the text, we employ two approaches to attempt to provide evidence as to whether our results are driven by banks' credit risk–modeling usage or their disclosure of that usage: (1) two-stage least squares (2SLS) with a measure of bank sophistication as the instrument for usage; and (2) a statistical decomposition of credit risk–modeling disclosures into a usage component explained by bank sophistication and a disclosure component explained by proxies for the external demand for and banks' voluntary choice to supply credit risk modeling disclosures, similar to Bhat and Ryan (2015). In this appendix, we develop the first-stage models in the 2SLS and decomposition approaches, and we discuss the estimations of these models.

Prior research provides evidence that more sophisticated banks are more likely to engage in (higher quality) risk modeling (e.g., Liu et al. 2004, Pérignon and Smith 2010). Accordingly, we expect that more sophisticated banks are more likely to engage in credit risk modeling. The first-stage models in both approaches incorporate this expectation. Because bank sophistication is a multidimensional construct, in both the two-stage approaches, we use a measure of bank sophistication (*SOPHIST*) that equals the first principal component of four proxies for the construct: (1) an indicator variable derived from the Federal Reserve's bank holding company complexity indicator RSSD9057 that takes a value of 1 for complex banks (RSSD9057 equal to 1 or 3–8) and 0 otherwise (*COMPLEX*);[26] (2) the natural logarithm of the notional amount of derivatives (*LOG_NOTIONAL*); (3) the natural logarithm of securitization deal volume from Asset-Backed Alert (*LOG_SEC_VOL*); and (4) an indicator for banks that report the employment of a chief risk officer in their Form 10-K that year (*CRO*).

C.2. 2SLS Approach

In this approach, for each of the second-stage models—Equations (1)–(3), whose estimations are reported in column (3) of panel A of Tables 3–5, respectively—we estimate first-stage models that predict the ordinal credit risk–modeling disclosure variable *CRM* (another variable times *CRM*) in terms of an instrument for credit risk–modeling usage (the other variable times the instrument) and the control variables in the second-stage model. We use *SOPHIST* as the instrument for credit risk–modeling usage. We emphasize that our use of this instrument is valid only under the difficult-to-test assumption that bank sophistication affects the (loan loss provision, net loan charge-off, and loan origination procyclicality) dependent variables in our second-stage models only through its effect on banks' credit risk modeling usage, that is, not directly or through unobserved variables, conditional on the other explanatory variables in the second models. We view this assumption as reasonable because the other explanatory variables included in these models control for banks' size, financial health, asset composition, loan credit risk, loan growth, and voluntary disclosures of market and operating risks. Moreover, to the best of our knowledge prior literature has not used bank sophistication as a direct determinant of any of our dependent variables.

In each of the second-stage models, we replace *CRM* as well as the other variable times *CRM* with their predicted values from the first-stage models. *SOPHIST* is not included in the second-stage models to satisfy the exclusion restriction.

As the estimations of the first-stage models for the various second-stage models yield similar results, to conserve space, we tabulate and discuss only the estimated first-stage models for the second-stage model Equation (1). These first-stage models explain *CRM* and $\Delta NPL_{t+1} \times CRM$:

$$\begin{aligned} &CRM \text{ or } (\Delta NPL_{t+1} \times CRM) \\ &\quad = a + b_1 SOPHIST + b_2(\Delta NPL_{t+1} \times SOPHIST) \\ &\qquad + \sum_{s\geq 3} b_s \text{second-stage controls} + e. \end{aligned} \tag{C.1}$$

(The first-stage models for Equations (2) and (3) explain *CRM* and $LLP_t \times CRM$.) We expect the coefficient on *SOPHIST* to be positive when *CRM* is the dependent variable and the coefficient on $\Delta NPL_t \times SOPHIST$ to be positive when $\Delta NPL_{t+1} \times CRM$ is the dependent variable. We evaluate the collective strength of *SOPHIST* and $\Delta NPL_t \times SOPHIST$ as instruments for *CRM* and $\Delta NPL_{t+1} \times CRM$ using the Cragg–Donald F-statistic (Sanderson and Windmeijer 2016).

Panel A of Table C.1 reports the pooled OLS estimations of Equation (C.1), suppressing the coefficients on the control variables to conserve space. In first-stage model for *CRM*, the coefficient on *SOPHIST* is significant at the

Table C.1. First-Stage Models

Panel A: Two-stage least squares approach: First-stage models for Equation (1)

Variables	(1) Dep var = *CRM*	(2) Dep var = $\Delta NP_{t+1} \times CRM$
SOPHIST	0.0361***	0.000
	[3.55]	[−0.73]
$\Delta NP_{t+1} \times SOPHIST$	0.235	0.0747***
	[0.35]	[5.13]
Include controls from second-stage model	Yes	Yes
# observations	16,282	16,282
Cragg Donald F-statistic	132.1	
Stock-Yogo weak instrument test critical value: 10% maximal size	7.03	

Panel B: Credit- risk–modeling disclosure decomposition approach: First-stage model

Variables	*CRM*
EBP	−22.436
	[−1.17]
NCO	4.522
	[0.24]
OpRisk	0.189
	[1.44]
BigN	0.521***
	[4.84]
SOPHIST	0.198***
	[6.64]
Constant	−1.368***
	[−11.63]
Observations	17,282
Pseudo R-squared (%)	13.53

Notes. Panel A reports the pooled OLS estimations of Equation (C.1), the first-stage models for the second-stage model Equation (1) in the two-stage least squares approach, whose estimation is reported in column (3) of panel A of Table 3. These models include SOPHIST and $\Delta NP_{t+1} \times SOPHIST$ as instruments for CRM and $\Delta NP_{t+1} \times CRM$. The coefficients on the control variables from the second-stage model are not tabulated. Panel B of the table reports the probit estimation of Equation (C.2), the first-stage model in the credit risk–modeling disclosure decomposition approach similar to Bhat and Ryan (2015). This estimation is used to decompose *CRM* into the components associated with credit risk–modeling usage (the projection based on *SOPHIST*), credit risk–modeling disclosure (the projection based on *EBP*, *NCO*, *OpRisk*, and *BigN*), and the residual. Continuous variables are winsorized at the top and bottom 1%. Standard errors are calculated clustering observations by bank in panel A and by bank and quarter in panel B. Coefficient t-statistics in panel A and Z-statistics in panel B are reported in square brackets. All variables are defined in Appendix B. The two-stage least squares and decomposition approaches are described in Appendix C.

***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively, using two-tailed tests.

1% level. In first-stage model for $\Delta NPL_{t+1} \times CRM$, the coefficient on $\Delta NPL_{t+1} \times SOPHIST$ is also significant at the 1% level. The Cragg–Donald F-statistic for the collective strength of the instruments in the two models equals 132.1, which far exceeds the Stock and Yogo (2005) critical value of 7.03. Hence, *SOPHIST* and $\Delta NPL_t \times SOPHIST$ appear to be collectively strong instruments.[27]

C.3. Decomposition Approach

This approach statistically decomposes *CRM* into three components: (1) the projection based on *SOPHIST*, which we expect to capture banks' credit risk–modeling usage; (2) the projection based on four variables that we expect to proxy for the external demand for and banks' voluntary choice to supply credit risk–modeling disclosures but to be relatively uncorrelated with their usage of credit risk modeling; and (3) a residual. In each of the second-stage models, we replace *CRM* with its three component projections from the first-stage models.

The four predictors of credit risk–modeling disclosure are (1) banks' pre-LLP return on assets, which empirically appears to capture the benefits of voluntary disclosure (Lang and Lundholm 1993, Leuz and Verrecchia 2000) but could also capture the proprietary costs of voluntary disclosure (Healy and Palepu 2001); (2) net loan charge-offs, a primary predictor of future credit losses (Harris et al. 2018) that we expect to be positively associated with the demand for credit risk–modeling disclosures; (3) banks' voluntary disclosures of operating risk, which we expect to capture their propensity to disclose any form of risk modeling;[28] and (4) an indicator for big N auditors, who we expect to have higher bank industry expertise and reputational incentives and, thus, to encourage banks to provide higher overall disclosure quality (Dunn and Mayhew 2004). This yields the following model:

$$CRM = a + b_1 EBP + b_2 NCO + b_3 OpRisk + b_4 BigN + b_5 SOPHIST + e. \tag{C.2}$$

We expect the coefficients on all the explanatory variables in Equation (C.2) to be positive.

Panel B of Table C.1 reports the probit estimation of Equation (C.2). The model fit is reasonably good with a pseudo R^2 of 13.5%. As expected, the coefficients on *BigN* and *SOPHIST* are positive and significant at the 1% level; the coefficient on the other explanatory variables are insignificant.

Endnotes

[1] FAS 5, *Accounting for Contingencies*, specifies loss accrual only for loss contingencies that are incurred, probable of realization, and capable of reasonable estimation (Ryan 2011, Section 3.1.2). SAB 102, *Selected Loan Loss Allowance Methodology and Documentation Issues*, requires banks to estimate loan loss allowances under FAS 5 using systematic and consistently applied processes (Beck and Narayanamoorthy 2013). Bank regulators provide extensive guidance regarding the application of FAS 5 for homogeneous loan types (Ryan 2011, Section 3.1.3). We refer to FAS 5, SAB 102, and bank regulatory guidance collectively as FAS 5 or the incurred loss model.

[2] Dugan (2009, p. 2) states that

> in the booming part of the economic cycle in the earlier part of this decade, the ratio of loan loss reserves to total loans went down, not up—even though there was broad recognition that the cycle would soon have to turn negative. Conversely, when the turn finally did come, and the tidal wave of losses began hitting shore, banks have had to recognize losses through a sudden series of increased provisions to the loan

> loss reserve, which in turn has more than offset earnings and eaten into precious capital. Stated differently, rather than being counter-cyclical, loan loss provisioning has become decidedly pro-cyclical, magnifying the impact of the downturn.

To remedy this alleged problem, Dugan (2009, p. 8) asks "whether there ought to be changes made to the incurred loss model." Similarly, Curry (2013) states that the "financial crisis revealed a distinct flaw in the incurred loss model. By requiring banks to wait for an 'incurred' loss event to recognize the resulting impairment, the model precludes banks from taking appropriate provisions for emerging risks that the bank can reasonably anticipate to occur."

[3] This helps explain why banks primarily accrue for loan losses on homogeneous loans at the loan pool level and on heterogeneous loans at the individual loan level (Ryan 2011, Section 3.1.4).

[4] Federal Reserve data indicate that banks' annualized percentage net loan charge-offs of real estate loans averaged 1.91% during the financial crisis and its aftermath in 2007:Q3–2010:Q4, about 15 times the 0.13% rate during the generally favorable 1995:Q1–2007:Q3.

[5] Federal Reserve data indicate that banks' annualized percentage net loan charge-offs of commercial and industrial loans averaged 1.95% from 2008:Q4 to 2010:Q4 and 1.67% from 2001:Q3 to 2003:Q2, that is, during two recessions and their aftermaths, over six times the 0.25% rate during the generally favorable 2005:Q1–2006:Q3 and 1994:Q1–1998:Q3 periods.

[6] For example, FAS 5 defines "probable" as "likely to occur," which EITF Topic No. D-80 (ASC 310-10-35-19) clarifies is "a higher level of likelihood than more likely than not." In practice, firms often define probable as 70% or more likely (Ryan 2011, Section 3.1.2). Hence, FAS 5 requires a far higher probability threshold for loss recognition than the low-probability events examined in stress testing.

[7] The discussion in this paragraph further motivates our use of the ordinal credit risk–modeling variable in the primary empirical analyses. This discussion also partly explains why we do not tabulate or discuss tests of the differences in the coefficients on the test variables in the descriptive empirical analyses using the statistical modeling and stress-testing indicators. (The other reason is the infrequency of banks' stress-testing disclosures.) For completeness, however, we footnote the results of these tests.

[8] In prior drafts, we also examined a second measure of loan loss–provision timeliness: the percentage of banks' cumulative loan loss provisions from 2007 to 2010 that they record from the beginning of 2007 to three points in time during the financial crisis, the year-ends of 2007 (i.e., early), 2008 (i.e., middle), and 2009 (i.e., late). Following Vyas (2011), we infer greater loan loss–provision timeliness when a bank records a higher percentage of its cumulative loan loss provision by a point in time, controlling for the percentage of the bank's economic loan losses it has experienced up to that point. We find that stress testing is positively associated with this measure early in the crisis (2007) when highly adverse conditions abruptly arose. We find that statistical modeling is positively associated with this measure late in the crisis (2009) after banks had experienced elevated loss rates for sufficient time to revise their loss estimates upward reliably.

[9] Variation in banks' use of credit risk modeling for loan loss reserving and credit risk management purposes is well documented in bank industry surveys (KPMG 2013, McGladrey 2013), bank regulatory research and policy documents around the formulation and implementation of the Basel II agreement (Jones and Mingo 1998, Basel Committee on Banking Supervision 1999), articles in trade publications (Novikov-Jank et al. 2008, Wisnewski 2013), credit rating agency documents (Moody's 2011), and documentation of vendor models (CoreLogic's extensive documentation of its models and data for residential mortgages at www.corelogic.com). The relatively recent and rapid development of sophisticated credit risk models (Duffie and Singleton 2003, Lando 2004) helps explain this variation.

[10] We examine statistical modeling and stress testing because they are the most common forms of historically focused and forward-looking, respectively, credit risk modeling disclosed by banks. Moreover, banks can apply both of these forms of credit risk modeling each period to all types of loans. Banks disclose two additional forms of credit risk modeling: (1) credit scoring to inform the credit granting decision, typically for homogeneous loans; and (2) credit risk rating, typically for heterogeneous loans. We do not examine credit scoring, as it occurs only at the credit granting decision, or credit risk rating, as it is subject to incentive problems for loan officers and credit rating agencies that yield lags and biases in these ratings (Udell 1989, Berger and Udell 2002, Kraft 2015, Bessis 2011).

[11] Appendix B provides the definitions of all model variables.

[12] Given the limitations of banks' credit risk–modeling disclosures discussed in Section 1, we conduct specification tests for the primary analyses in which we redefine the credit risk–modeling variables assuming that a bank that discloses statistical modeling or stress testing in any year during the sample period enagages in that form of credit risk modeling throughout the sample period. We footnote the results of these specification tests.

[13] Our use of bank sophistication as an instrument for credit risk–modeling can also be justified from practitioner sources. For example, Zazzara (2016), S&P Global Head of Risk Services Europe, states,

> According to Mark Carey of the Federal Reserve Board of Governors, 'in the last 20 years models have crept into accounting,' and the only way to get a forward looking measure of credit losses is via the use of credit models. Currently, several *sophisticated* Banks rely on a 'centralized' credit risk modelling and data framework, which is then adjusted to serve specific capital requirements, stress testing and accounting needs. (Emphasis added)

[14] The broad voluntary disclosure literature shows that firm characteristics are associated with firms' propensity to make voluntary disclosures of various types (e.g., Lang and Lundholm 1993). A number of studies, mostly examining samples from specific countries, show similar associations for risk disclosures. For example, Elshandidy et al. (2013) find that riskier firms and firms with higher compliance with mandatory risk disclosures are more likely to make voluntary disclosures.

[15] The number of large auditing firms diminishes from six to four over our sample period because of the 1998 merger of Price Waterhouse and Coopers and Lybrand and the 2002 dissolution of Arthur Andersen.

[16] Taking into account the loss of sample banks over time as a result of mergers and acquisitions and other reasons, only 17 (6) banks stop disclosing statistical modeling (stress testing) across our 15-year sample period.

[17] The results of our primary analyses are robust to including time effects or linear time trends in the empirical models.

[18] To mitigate concerns about changes in the frequency of banks' credit risk–modeling disclosures over the sample period, we repeat the OLS estimation reported in column (2) redefining *CRM* under the assumption that a bank that discloses statistical modeling or stress testing in any year during the sample period engages in that form of credit risk modeling throughout the sample period. The results are robust to this redefinition; the coefficient β_4 on $\Delta NPL_{t,t+1} \times CRM$ is positive and significant at the 5% level.

[19] The difference between the coefficients β_{4M} on $\Delta NPL_{t+1} \times MODEL$ in columns (1) and (2) is statistically insignificant. The difference between the coefficients β_{4S} on $\Delta NPL_{t+1} \times STRESS$ in columns (3) and (4) is statistically significant at the 1% level.

[20] Bank regulatory guidance for consumer loans and residential mortgages loans requires banks (1) to charge off these loans at no

later than 120 or 180 days past due and (2) to accrue loan loss allowances sufficient to cover expected net loan charge-offs over the period that incurred losses are expected to emerge, which this guidance suggests is 12 months for performing loans (Ryan 2011, Section 3.1.3).

[21] To mitigate concerns about changes in the frequency of banks' credit risk–modeling disclosures over the sample period, we repeat the OLS estimation reported in column (2), redefining *CRM* under the assumption that a bank that discloses statistical modeling or stress testing in any year during the sample period enagages in that form of credit risk modeling throughout the sample period. The results are robust to this redefinition; the coefficient δ_3 on $LLP \times CRM$ is positive and significant at the 5% level.

[22] The difference in the coefficients δ_{3M} on $LLP \times MODEL$ in columns (1) and (2) is statistically insignificant. The difference in the coefficients δ_{3S} on $LLP \times STRESS$ in columns (3) and (4) is statistically significant at the 1% level.

[23] A bivariate regression of *LOANGR* on *TIER*1 yields a positive and significant coefficient.

[24] To mitigate concerns about changes in the frequency of banks' credit risk–modeling disclosures over the sample period, we repeat the OLS estimation reported in column (2) redefining *CRM* under the assumption that a bank that discloses statistical modeling or stress testing in any year during the sample period enagages in that form of credit risk modeling throughout the sample period. The results are not robust to this redefinition; the coefficient B_3 on $LLP \times CRM$ is positive but not significant (t-stat = 1.03).

[25] The differences in the coefficients B_{3M} on $LLP \times MODEL$ in columns (1) and (2) and in the coefficients B_{3S} on $LLP \times STRESS$ in columns (3) and (4) are statistically insignificant.

[26] RSSD9057 is defined on the Federal Reserve Board's Research, Statistics, Supervision and Regulation, and Discount and Credit Database. See http://www.federalreserve.gov/apps/mdrm/data-dictionary/search/item?keyword=9057&show_short_title=False&show_conf=False&rep_status=All&rep_state=Opened&rep_period=Before&date_start=99991231&date_end=99991231.

[27] The Cragg–Donald F-statistic for the collective strength of the instruments in the two first-stage models for Equation (2) [(3)] equals 77.4 [106.4].

[28] The broad voluntary disclosure literature shows that firm characteristics are associated with firms' propensity to make voluntary disclosures of various types (e.g., Lang and Lundholm 1993). A number of studies, mostly examining samples from specific countries, show similar associations for risk disclosures. For example, Elshandidy et al. (2013) find that riskier firms and firms with higher compliance with mandatory risk disclosures are more likely to make voluntary disclosures.

References

Acharya V, Ryan S (2016) Banks' financial reporting and financial system stability. *J. Accounting Res.* 54(2):277–340.

Bank for International Settlements (2008) Addressing financial system procyclicality: A possible framework. Note for the FSF Working Group on Market and Institutional Resilience. Available at: http://www.fsb.org/wp-content/uploads/r_0904e.pdf (last accessed October 16, 2018).

Basel Committee on Banking Supervision (1999) Credit risk modeling: Current practices and applications (April). Available at https://www.bis.org/publ/bcbs49.pdf (last accessed October 15, 2018).

Beatty A, Liao S (2011) Do delays in expected loss recognition affect banks' willingness to lend? *J. Accounting Econom.* 52(1):1–20.

Beck P, Narayanamoorthy G (2013) Did the SEC impact banks' loan loss reserve policies and their informativeness? *J. Accounting Econom.* 56(2–3):42–65.

Berger A, Udell G (2002) Small business credit availability and relationship ending: The importance of bank ownership structure. *Econom. J.* 112(477):F32–F53.

Bessis J (2011) *Risk Management in Banking*, 3rd ed. (John Wiley & Sons, Hoboken, NJ).

Bhat G, Ryan S (2015) The impact of risk modeling on the market perception of banks' estimated fair value gains and losses for financial instruments. *Accounting Organ. Soc.* 46:81–95.

Bhat G, Lee J, Ryan S (2016) Utilizing loan loss indicators by loan type to sharpen the evaluation of the determinants and implications of banks' loan loss accruals. Working paper, Southern Methodist University, Dallas.

Bikker J, Metzemakers P (2005) Bank provisioning behavior and procyclicality. *J. Internat. Financial Markets, Institutions Money* 15(2):141–147.

Bushman R, Williams C (2012) Accounting discretion, loan loss provisioning, and discipline of banks' risk-taking. *J. Accounting Econom.* 54(1):1–18.

Bushman R, Williams C (2015) Delayed expected loss recognition and the risk profile of banks. *J. Accounting Res.* 53(3):511–553.

Caouette J, Altman E, Narayanan P, Nimmo R (2008) *Managing Credit Risk: The Great Challenge for Global Financial Markets* (John Wiley & Sons: Hoboken, NJ).

Curry T (2013) Remarks before the AICPA banking conference, Washington, D.C. (September 16).

Duffie D, Singleton K (2003) *Credit Risk: Pricing, Measurement, and Management* (Princeton University Press, Princeton, NJ).

Dugan J (2009) Remarks before the Institute of International Bankers, Loan loss provisioning and pro-cyclicality (March 2).

Dunn K, Mayhew B (2004) Audit firm industry specialization and client disclosure quality. *Rev. Accounting Stud.* 9(1):35–58.

Elshandidy T, Fraser I, Hussainey K (2013) Aggregated, voluntary, and mandatory risk disclosure incentives: Evidence from UK FTSE all-share companies. *Internat. Rev. Financial Anal.* 30: 320–333.

Financial Stability Forum (2009a) Report of the FSF working group on provisioning (March).

Financial Stability Forum (2009b) Report of the Financial Stability Forum on addressing procyclicality in the financial system (April 2).

Harris T, Khan U, Nissim D (2018) The expected rate of credit losses on banks' loan portfolios. *Accounting Rev.* 93(5):245–271.

Healy P, Palepu K (2001) Information asymmetry, corporate disclosure, and the capital markets: A review of the empirical disclosure literature. *J. Accounting Econom.* 31(1–3):405–440.

Jones D, Mingo J (1998) Industry practices in credit risk modeling and internal capital allocations: Implications for a models-based regulatory capital standard. *FRBNY Econom. Policy Rev.* 4(3): 53–60.

KPMG LLP (2013) Credit risk management practices: 2012 survey on the allowance for loan and lease losses (May), https://assets.kpmg.com/content/dam/kpmg/pdf/2013/09/survey-allowance-loan-lease-losses-2012.pdf. Last accessed on October 10, 2018.

Kraft P (2015) Do rating agencies cater? Evidence from rating-based contracts. *J. Accounting Econom.* 59(2–3):264–283.

Laeven L, Majnoni G (2003) Loan loss provisioning and economic slowdowns: Too much, too late? *J. Financial Intermediation* 12(2):178–197.

Lando D (2004) *Credit Risk Modeling: Theory and Applications* (Princeton University Press, Princeton, NJ).

Lang M, Lundholm R (1993) Cross-sectional determinants of analyst ratings of corporate disclosure. *J. Accounting Res.* 31(2): 246–271.

Leuz C, Verrecchia R (2000) The economic consequences of increased disclosure. *J. Accounting Res.* 38(Supplement):91–124.

Liu C, Ryan S (1995) The effect of bank loan portfolio composition on the market reaction to and anticipation of loan loss provisions. *J. Accounting Res.* 33(1):77–94.

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

Liu C, Ryan S, Tan H (2004) How banks' value-at-risk disclosures predict their total and priced risk: Effects of bank technical sophistication and learning over time. *Rev. Accounting Stud.* 9(2–3): 265–294.

Lown C, Morgan D (2006) The credit cycle and the business cycle: New findings using the loan officer opinion survey. *J. Money, Credit, Banking* 38(6):1575–1597.

McGladrey LLP (2013) McGladrey loan loss reserve survey. http://mcgladrey.com/content/dam/mcgladrey/pdf/2013_loan_loss_survey.pdf. Last accessed on October 10, 2018.

Moody's (2011) Modeling commercial real estate loan credit risk: An overview, Version 2.0. https://www.moodysanalytics.com/-/media/whitepaper/2011/11-03-05-modeling-cre-loan-credit-risk-an-overview.pdf. Last accessed on October 10, 2018.

Nichols C, Wahlen J, Wieland M (2009) Publicly traded versus privately held: Implications for conditional conservatism in bank accounting. *Rev. Accounting Stud.* 14(1):88–122.

Novikov-Jank A, Mandapaka R, Josephal S (2008) Allowance for loan and lease loss reserves: Modeling challenges and recommendations. *RMA J.* 91(3):48–53.

Pérignon C, Smith D (2010) The level and quality of value-at-risk disclosure by commercial banks. *J. Bus. Finance* 34(4): 362–377.

Ryan S (2007) *Financial Instruments and Institutions: Accounting and Disclosure Rules*, 2nd ed. (John Wiley and Sons, Hoboken, NJ).

Ryan S (2011) Financial reporting for financial instruments. *Foundations Trends Accounting* 6(3–4):187–354.

Ryan S (2017) Do the effects of accounting requirements on banks' regulatory capital adequacy undermine financial stability? *Annual Rev. Financial Econom.* 9:1–20.

Ryan S, Keeley J (2013) Discussion of "Did the SEC impact banks' loan loss reserve policies and their informativeness?" *J. Accounting Econom.* 56(2–3):66–78.

Sanderson E, Windmeijer F (2016) A weak instrument *F*-test in linear IV models with multiple endogenous variables. *J. Econometrics* 190(2):212–221.

Stock J, Yogo M (2005) Testing for weak instruments in linear IV regression. Andrews D, Stock J, eds. *Identification and Inference for Econometric Models: Essays in Honor of Thomas Rothenberg* (Cambridge University Press, New York), 80–108.

Udell G (1989) Loan quality, commercial loan review, and loan officer contracting. *J. Banking Finance* 13(3):367–382.

United States Treasury (2009) *Financial Regulatory Reform, A New Foundation: Rebuilding Financial Supervision and Regulation*. http://www.treasury.gov/initiatives/Documents/FinalReport_web.pdf.

Vyas D (2011) The timeliness of accounting write-downs during the recent financial crisis. *J. Accounting Res.* 49(3):823–860.

Wahlen J (1994) The nature of information in commercial bank loan loss disclosures. *Accounting Rev.* 69(3):455–478.

Wisnewski M (2013) Case study: MidSouth finds way to tame "monster" reporting process. *Amer. Banker* (May 2).

Zazzara C (2016) Risk insight: Internal default risk models—Alive and kicking? (October 12), https://marketintelligence.spglobal.com/blog/risk-insight-internal-default-risk-models-alive-and-kicking.