The Implications of Banks' Credit Risk Modeling for their Loan Loss Provision Timeliness and Loan Origination Procyclicality

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Abstract

We examine the implications of banks' credit risk modeling (CRM) for the timeliness of their loan loss provisions (LLP) and the procyclicality of their loan originations. We identify two distinct types of CRM from disclosures in banks' financial reports: (1) overall credit risk measurement modeling, typically statistical analysis of loan performance statuses and underwriting criteria (MODEL); and (2) stress testing of credit losses to possible adverse future events (STRESS). We expect these two CRM activities to have different implications, because MODEL is primarily historically focused whereas STRESS is primarily forward-looking. Statistical analysis of historical data places discipline on banks' loan loss reserving during stable economic times and for homogeneous loans, but is limited at sharp turns in economic cycles and for heterogeneous loans, when forward-looking CRM becomes essential. We predict and find that MODEL is associated with timelier LLPs on average across our 2002-2010 sample period and late in the financial crisis after banks had experienced heightened credit losses for a period of time, and that STRESS is associated with timelier LLPs early in the financial crisis.

We argue that CRM enhances LLP timeliness because it yields informationally richer LLPs that are less sensitive to summary underwriting criteria. Consistent with this argument, we find that MODEL reduces the reliance of banks' LLPs on the loan-to-income ratio (estimated using disclosures required under the Home Mortgage Disclosure Act) for their homogeneous single-family mortgages.

Following Beatty and Liao (2011), we expect banks with higher LLP timeliness to exhibit lower loan origination procyclicality. We find that MODEL is associated with less procyclical loan originations, particularly for homogeneous loans, and that STRESS is associated with less procyclical originations of heterogeneous loans.

JEL: G21**,** G28, M41, M48

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The Implications of Banks' Credit Risk Modeling for their Loan Loss Provision Timeliness and Loan Origination Procyclicality

1. Introduction

We examine the implications of publicly traded U.S. commercial bank holding companies' credit risk modeling (CRM) for the timeliness of their loan loss provisions (LLPs) and the procyclicality of their loan originations. Our study has two primary motivations. First, Leaven and Majnoni (2003), Dugan (2009), and others argue that the incurred loss model of FAS 5, *Accounting for Contingencies*, tends to delay banks' LLPs during economic good times, causing banks to record larger increases in LLPs in economic downturns. This contributes to procyclicality in banks' loan originations to the extent that banks currently are or believe they might become capital constrained. Second, Beatty and Liao (2011) provide evidence that banks with timelier LLPs exhibit higher loan growth during recessions. We argue that banks' CRM enhances their LLP timeliness and confidence in these accrual estimates, thereby reducing their loan origination procyclicality. As described in detail below, we distinguish historically focused CRM, which works well for homogeneous loans and in stable economic times, from forward-looking CRM, which is essential for heterogeneous loans and at sharp turns in economic cycles.

We identify banks' CRM from disclosures in their Form 10-K filings that we hand collected for the years 2001-2009. We identify two primary types of CRM: (1) overall credit risk measurement modeling, typically statistical analysis of loan performance statuses and underwriting criteria (MODEL); and (2) stress testing of estimated credit losses to possible adverse future events (STRESS).[1] Because disclosing banks' descriptions of MODEL and

[1] In the prior draft of the paper (February 2012, presented at the March 2012 JAR/NY Fed mini-conference, available on SSRN), we also identified and analyzed two additional types of CRM: (1) credit scoring to inform the credit granting decision, typically for homogeneous consumer and real estate loans (SCORE); and (2) credit risk

STRESS do not exhibit sufficient variation across observations to allow for meaningful gradation based on quality, we employ indicator variables for these CRM activities for each bank-year in the empirical analyses.

The most important difference between the two CRM activities is that MODEL is primarily historically focused whereas STRESS is primarily forward-looking. Specifically, MODEL uses historical data on loan performance statuses (e.g., current versus delinquency buckets based on number of days past due) and underwriting criteria (e.g., credit scores and loan-to-value ratios) to estimate the future probabilities of default and losses given default on loans. STRESS estimates the effects of possible adverse future events on banks' credit losses.

Historically focused and forward-looking CRM have complementary strengths and weaknesses. Statistical analysis of historical data provides discipline on banks' LLPs that mitigates the tendency of FAS 5's incurred loss model to delay banks' LLPs. Such analysis generally works well for homogeneous loans, for which banks reserve for loan losses at the loan-pool level, and in stable periods when credit loss parameters change relatively little from the estimation period to the balance sheet date. However, it is of limited use for heterogeneous loans, for which banks reserve for loan losses at the individual-loan level, or when credit loss parameters change rapidly, as occurred to a nearly unprecedented degree during the early stages of the financial crisis beginning in 2007.

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rating, typically for heterogeneous commercial and industrial loans (RATE). We dropped these CRM activities from this draft for two reasons. First, unlike for MODEL and STRESS, we did not make hypotheses about SCORE and RATE, because these CRM activities apply to specific loan types, occur only at the credit granting decision in the case of SCORE, and are subject to incentive problems for loan officers and credit rating agencies that yield lags and biases in credit risk ratings in the case of RATE (see Udell 1989 and Berger and Udell 2002 regarding loan officers' incentives, Kraft 2011 regarding credit rating agencies' incentives, and Bessis 2011 regarding the stickiness of credit risk ratings across the business cycle). See pp. 10-13 of the prior draft for further discussion. Second, in the current draft we conduct propensity score matching on MODEL and STRESS that would be cumbersome to perform and discuss with additional CRM variables. None of our results for MODEL and STRESS are sensitive to the exclusion of SCORE and RATE from the empirical models.

Forward-looking CRM, while highly judgmental, is essential for heterogeneous loans and at sharp turns in economic cycles when credit loss parameters change rapidly. Forward-looking CRM provides banks with better ability to diagnose and respond to these turns. This is why U.S. and international bank regulators conducted stress tests of banks during the financial crisis.[2]

For these reasons, we predict that the historically focused MODEL enhances the timeliness of LLPs on average during our 2002-2010 sample period and late in the financial crisis after banks had experienced heightened credit losses for a period of time. In contrast, we predict that the forward-looking STRESS is associated with timelier LLPs when credit loss parameters increased rapidly early in the financial crisis.

We examine two measures of LLP timeliness. First, in pooled analysis across our sample period 2002-2010, we examine the association of quarterly LLPs with the change in non-performing loans for the current and subsequent quarter. Following Beatty and Liao (2011), we infer enhanced LLP timeliness when this association is more positive. Consistent with our predictions, we find that MODEL is associated with enhanced LLP timeliness based on this measure.

Second, for each of three points in time during the financial crisis—the ends of 2007 (i.e., early), 2008 (i.e., middle), and 2009 (i.e., late)—we examine the percentage of the bank's cumulative LLP from 2007-2010 that it recorded from the beginning of 2007 up to that point in time. Following Vyas (2011), we infer enhanced LLP timeliness when a bank records a higher percentage of its cumulative LLP by a point in time, controlling for the percentage of the bank's economic loan losses that it had experienced up to that point. Consistent with our predictions,

[2] This point is also consistent with Dugan's (2009) recommendation that banks' loan loss reserving reflect more judgmental forward-looking factors and with the widespread use of non-performing loans as a forward-looking benchmark for banks's loan loss reserving (Liu and Ryan 1995 and 2006 and Beck and Narayanamoorthy 2011).

we find that STRESS is associated with enhanced LLP timeliness based on this measure early in the financial crisis (in 2007) and that MODEL is associated with enhanced LLP timeliness only after banks had experienced heightened credit losses for a period of time (in 2009).

We conduct the following analysis to provide insight into the mechanism by which CRM enhances LLP timeliness. We argue that this enhancement occurs because CRM yields informationally richer LLPs that rely less on summary underwriting criteria. In general, we cannot observe banks' underwriting criteria. However, the Home Mortgage Disclosure Act of 1975 (HMDA) requires mortgage lenders to publicly disclose information about the characteristics of their mortgage originations. Using these disclosures, we estimate the average initial loan-to-income ratio for a bank's mortgages, homogeneous loans for which MODEL is the most relevant form of CRM. Mortgage lenders that engage in MODEL typically employ multivariate statistical models with many loan performance statuses and underwriting criteria to estimate credit losses on their loans, yielding informationally rich LLPs. Other mortgage lenders typically estimate credit losses using a few summary loan performance and underwriting criteria variables—often including loan-to-income ratios—yielding LLPs that are highly dependent on these summary variables. We predict and find that MODEL reduces the association of banks' average loan-to-income ratios with their LLPs.

Laeven and Majnoni (2003) find that banks with larger LLPs exhibit lower loan growth on average, consistent with banks' loan loss provisioning contributing to loan origination procyclicality. As mentioned above, Beatty and Liao (2011) find that banks with timelier LLPs exhibit higher loan growth during recession periods, consistent with these banks having less procyclical loan originations. Motivated by these findings, we measure loan origination procyclicality in terms of the association between banks' LLPs and future loan growth, inferring reduced procyclicality when this association is less negative. We examine loan growth for the overall loan portfolio and for each of consumer (most homogeneous), real estate (fairly homogeneous), and commercial and industrial (most heterogeneous) loans. We predict and find that MODEL is associated with reduced procyclicality based on this measure, particularly for homogeneous consumer and real estate loans. We predict and find that STRESS is associated with reduced procyclicality for heterogeneous commercial and industrial loans.

Our study raises two problems of inference that we attempt to address as best as possible with the available data. First, banks' use of CRM likely is correlated with their technical sophistication, financial health, credit risk, and other characteristics. These characteristics are in principle observable. To increase the likelihood that that we capture the effects of CRM rather than correlated firm characteristics, in each or our empirical analyses we control for bank size, profitability, capital, loan portfolio composition, and frequency of mergers and acquisitions.[3] In addition, we conduct specification analyses using propensity score matching on the more relevant CRM activity, MODEL or STRESS. We calculate the propensity scores using probit regressions of the two CRM activities on a broad set of explanatory variables that capture banks' technical sophistication, financial health, credit risk, and market and operating risk disclosures, as well as time.

Second, while our focus is on the implications of banks' CRM, we can only observe these activities through banks' financial report disclosures. Many banks disclose nothing about CRM and those that make such disclosures often do so tersely. This suggests that banks may have incentives not to (fully) disclose their CRM, although there is no obvious proprietary or other

[3] The implications of banks' CRM also likely vary across time depending on macroeconomic conditions. In the LLP timeliness analysis and loan origination procyclicality analyses for the pooled sample of quarters from 2001-2010, we control for three macroeconomic variables: the change in the unemployment rate, a recession indicator variable, and the level of the VIX index.

cost to these high-level, aggregate disclosures, particularly given extensive required disclosures of credit losses and risk in banks' financial and regulatory reports. These incentives are likely to be significantly unobservable. To mitigate the possibility that (non)disclosure incentives influence our results, for each of our empirical analyses we conduct two specification analyses. First, we eliminate banks with assets over $100 billion, because we expect these banks to have sophisticated CRM regardless of what they disclose about CRM. Second, we employ Heckman's (1979) two-stage approach that controls in the second stage for inverse Mills ratios generated by the same first-stage probit regressions described above for the propensity score matching.

Our empirical results are robust to these and other specification analyses. Moreover, we believe the most convincing reason to conclude that our results reflect banks' CRM rather than other bank characteristics or disclosure incentives is the overall coherence of the results for the distinct CRM activities, MODEL and STRESS, across the LLP timeliness and loan origination procyclicality analyses. The simplest and most natural interpretation of the results is that banks' disclosures of MODEL and STRESS reflect meaningful and distinct CRM activities that enhance banks' understanding of their credit losses. In particular, these activities reduce banks' reliance on summary underwriting criteria in loan loss provisioning and loan origination, as shown in the HMDA analysis.

This study contributes to four empirical literatures in accounting, finance, and banking. First, a longstanding literature examines the cross-sectional and time-series determinants of banks' LLP timeliness, such as loan portfolio composition and market, contractual, and regulatory incentives for bank managers to exercise discretion over LLPs (e.g., Liu and Ryan 1995 and 2006). This research documents significant variation in the timeliness of banks' LLPs.

Understanding the determinants of LLP timeliness is important because the LLP is the most important accrual estimate for most banks.

Second, several recent studies examine the effects of the timeliness or other attributes of LLPs on banks' loan origination procyclicality or other economic consequences (e.g., Beatty and Liao 2011 and Bushman and Williams 2012). Due to the severe financial crisis that began in 2007 and still looms over the global economy today, procyclicality is of deep current policy interest (Bank for International Settlements 2008, Financial Stability Form 2009a,b, United States Treasury 2009).

Third, several studies use the timeliness or other attributes of banks' LLPs as a proxy for their transparency or disclosure quality (e.g., Bushman and Williams 2012 and Ng and Rusticus 2011). Fourth, Bhat (2012) examines the economic consequences of an index of banks' disclosure quality that in part captures the CRM activities examined in this paper. Both of these literatures speak to the role of financial reporting in enhancing banks' corporate governance and economic decision-making, also an area of deep current policy interest.

The rest of this paper is organized as follows. Section 2 describes the complementary features of historical focused and forward-looking CRM and develops our hypotheses. Section 3 describes the sample selection, variables, and empirical models and methods. Section 4 presents the empirical results. Section 5 concludes.

2. CRM Activities and Hypothesis Development

In Sections 2.1 and 2.2, we expand on the discussion of the complementary natures of historically focused and forward-looking CRM activities and our MODEL and STRESS indicator variables in the introduction, endeavoring not to repeat that prior discussion. We formally state our hypotheses regarding the distinction associations of MODEL and STRESS with banks' LLP timeliness and loan origination procyclicality in Sections 2.3 and 2.4, respectively.

2.1. Description of Historically Focused and Forward-Looking CRM Activities

Banks' historically focused CRM typically involves activities that correspond to the modeling of credit risk for regulatory capital purposes first developed by the Basel Committee with Basel II and refined since. Using historical data compiled for some prior period, banks conduct statistical analyses attempting to explain the level of and trends in the probability of default and loss given default on outstanding loans. Banks conduct these analyses to estimate their LLPs and for general credit risk management purposes. They attempt to explain these credit loss parameters in terms of three sets of variables: (1) current loan performance statuses such as number of payments made and number of days past due; (2) initial loan attributes such as loan types, maturities, and loan-to-value ratios; and (3) initial borrower attributes such as credit scores and loan-to-income ratios. Loan performance status generally is meaningful only for seasoned loans. We refer to items 2 and 3 collectively as underwriting criteria, because they are available at the credit granting decision.

Banks vary in how they use loan performance statuses and underwriting criteria in these analyses. They can do so using statistical approaches that are simple, e.g., calculating the means of credit loss parameters for cells formed based on partitions of a few of the variables, or sophisticated, e.g., estimating multivariate hazard or regression models with many explanatory variables. Banks with a healthy appreciation for the limitations of historically focused CRM "back test" their parameter estimates—i.e., compare estimates from prior periods to realized values to date—in order to identify trends in the parameters.

To provide meaningful discipline over LLPs, banks' historically focused CRM generally requires both a sufficiently large sample of historical data and sufficient stability of credit loss parameters. These requirements are most likely to be satisfied for homogeneous consumer and real estate loans during periods of relative economic stability. Statistical analysis of historical data is much less feasible for heterogeneous commercial and industrial loans or during periods of economic instability. In these cases, forward-looking CRM is essential for the evaluation of banks' credit losses.

Banks' forward-looking CRM typically involves considerable judgment to identify and model the relevant possible drivers of future credit losses given current economic conditions. The most forward-looking CRM activity is stress testing credit loss parameter estimates to possible adverse future events. Banks usually base stress tests on adverse events that either have occurred previously or that they believe might occur based on economic forecasts. Stress testing is essential for heterogeneous loans—particularly for cyclical commercial and industrial loans that default at much higher rates in economic downturns than in booms (Caouette et al. 2008)—and at turning points in economic cycles.

Banks' use of CRM likely is correlated with their technical sophistication, financial health, credit risk, and other characteristics. As discussed in the introduction, we control for these bank characteristics through the inclusion of control variables and the use of propensity score matching in the empirical analyses.

2.2. CRM Activity Indicator Variables

We hand collected banks' disclosures of their CRM activities from their annual Form 10-K filings for 2001-2009. We identify and analyze one primarily historically focused activity, the use of credit risk measurement models, and one primarily forward-looking activity, stress testing of estimated credit losses to potential adverse future events. MODEL takes a value of 1 if the bank discloses that it uses credit risk measurement models in a year and 0 otherwise. STRESS takes a value of 1 if the bank discloses that it employs stress testing in its CRM that year and 0 otherwise. In the empirical analyses, we use the values of MODEL and STRESS from the most recent prior year to ensure these activities are predetermined and present throughout the fiscal periods examined. Appendix A provides representative examples of banks' disclosures of MODEL and STRESS. See Bhat (2012) for further details.

The introduction discusses our predictions about the implications of MODEL and STRESS for banks' LLP timeliness and loan origination procyclicality. To summarize, due to the discipline provided by statistical analysis of historical data, we predict that the historically focused MODEL enhances the timeliness of LLPs on average during our 2002-2010 sample period and late in the financial crisis after heightened credit losses had been experienced for a period of time. Due to the limitations of statistical analysis of historical data when credit loss parameters change rapidly, we predict that the forward-looking STRESS is positively associated with LLP timeliness early in the financial crisis.

Our expectations for loan origination procyclicality follow from our expectations for LLP timeliness. We argue that CRM reduces loan origination procyclicality in part because it enhances banks' LLP timeliness and in part because it enhances banks' confidence in these accrual estimates. We predict that MODEL reduces the procyclicality of loan originations, particularly for homogeneous consumer and real estate loans. We predict that STRESS reduces the procyclicality of heterogeneous commercial and industrial loan originations.

Obviously, we can only know banks' CRM activities from what they disclose about those activities in their financial reports. As discussed below, the sample disclosures provided in Appendix A and descriptive analysis reported in Table 1 indicate that these disclosures are relatively infrequent and often terse when they exist. These facts suggest that banks may have incentives not to (fully) disclose their CRM. In our base models, we assume that cross-sectional variation in banks' CRM activities corresponds at least to some degree with variation in banks' CRM activities and their use of the resulting information to estimate their LLPs. This assumption is reasonable in the sense that anything that banks disclose about CRM in their financial reports likely reflects their actual practices. Moreover, it is not clear what incentives would lead banks to suppress information about their CRM, particularly given the voluminous information they are required to provide about their estimated and realized credit losses under GAAP and SEC Industry Guide 3, and the fact that CRM disclosures invariably are too high level and aggregated to reveal meaningful proprietary information.

As discussed in the introduction, we address the possibility of selective disclosure by conducting two specification analyses for each empirical analysis: eliminating from the sample banks with assets greater than $100 billion that are likely to use CRM even if they do not disclose it and a two-stage Heckman (1979) selection model approach.

2.3. Hypotheses about Banks' LLP Timeliness

We examine two measures of LLP timeliness. First, following Beatty and Liao (2011), we judge quarterly LLPs to be timelier when they are more positively associated with the change in non-performing loans (NPLs) for the current and subsequent quarters. We estimate this measure in two ways discussed in Section 3.3, both of which measure LLP timeliness across the quarters of 2002-2010, a period that reflects a boom (2003 to mid-2007), a recession (late-2007 to early-2009), and two gradual transition periods after recessions (2002 and mid-2009 to 2010). For reasons discussed in the introduction and Section 2.2, we expect MODEL to be positively associated with LLP timeliness based on this measure. We formally state this expectation in the following alternative hypothesis:

> [H1] MODEL yields more positive associations of quarterly LLPs with the change in NPLs over the current and subsequent quarter.

Second, following Vyas (2011), we judge cumulative LLPs from the beginning of 2007 to at any point during the financial crisis to be timelier when they are a larger percentage of the cumulative LLP from 2007-2010. We examine three specific points in time during the crisis: year-end 2007 (i.e., early), 2008 (i.e., middle), and 2009 (i.e., late). We control for a bank's economic loan losses using the percentage of its change in non-performing loans from 2007-2010 that it experiences from the beginning of 2007 up to that point in time. We expect STRESS to be associated with timelier LLPs early in the crisis, when forward looking CRM is essential to cope with the rapid increases in credit loss parameters. We expect MODEL to have no association with LLPs early in the crisis, when historical data has little power to explain credit loss parameters, but to have an increasingly positive association with LLP timeliness as time passes during the crisis and data is accumulated about the heightened levels of credit loss parameters. We formally state these expectations as the following alternative hypotheses:

> [H2] STRESS is positively associated with the percentage of the cumulative LLP from 2007-2010 that banks record from the beginning of 2007 to points in time early in the financial crisis.

> [H3] MODEL is positively associated with the percentage of the cumulative LLP from 2007-2010 that banks record from the beginning of 2007 to points in time later in the financial crisis.

As discussed in the introduction, we expect banks that engage in CRM to have informationally richer LLPs that depend less on a few summary underwriting criteria. We argue that dependence on summary underwriting criteria yields untimely and fragile LLPs. This is particularly likely if the implications of the summary underwriting criteria for loan default depend on context or if the criteria are misrepresented or otherwise mismeasured. Ryan (2008) discusses how both of these problems existed prior to the financial crisis. For example, subprime mortgages defaulted at low rates prior to the crisis because of easy refinancing opportunities and at high rates during the crisis when these opportunities vanished. Stated income mortgages were subject to fraudulent representation of mortgagors' income that became apparent once the mortgages defaulted during the crisis.

Unfortunately, we generally cannot observe the summary underwriting criteria that banks use in estimating LLPs. Using HMDA data, however, we can estimate loan-to-income ratios for single family mortgages, a homogeneous type of loan. For these loans, MODEL is the most relevant form of CRM, and so we limit our hypothesis to MODEL. We expect MODEL to reduce the association of banks' average loan-to-income ratios for mortgages with their LLPs. We formally state this expectation as the following alternative hypothesis:

> [H4] MODEL reduces the association of banks' average loan-to-income ratios for mortgages with their LLPs.

Were we able to observe banks' summary underwriting criteria for commercial and industrial loans, we would propose an analogous hypothesis for STRESS.[4]

2.4. Hypotheses about Banks' Loan Origination Procyclicality

We evaluate the procyclicality of banks' loan originations in terms of the association between their LLPs and future loan growth. We infer reduced procyclicality when this association is less negative. As discussed in the introduction and Section 2.2, we expect MODEL to be associated with reduced procyclicality, particularly for homogeneous consumer and real estate loans. We expect STRESS to be associated with reduced procyclicality for heterogeneous commercial and industrial loans. We formally state these expectations as the following alternative hypothesis:

> [H5] MODEL yields a less negative association between banks' LLPs and their future loan growth, particularly for their homogeneous consumer and real estate loans.
>
> [H6] STRESS yields a less negative association between banks' LLPs and the future growth of their heterogeneous commercial and industrial loans.

3. Sample Selection, Variable Definitions, and Empirical Models and Methods

3.1. Sample Selection

Table 1 describes the sample selection process. We obtain quarterly accounting data from the first quarter of 2001 to the fourth quarter of 2010 from banks' Y-9C regulatory filings available on the Federal Reserve Bank of Chicago website, which yields 17,959 initial bank-quarter observations. The availability of hand-collected CRM disclosures for the most recent

[4] We obtained and attempted to use data on underwriting criteria for (somewhat heterogeneous) commercial mortgage originations from Commercial Mortgage Alert, but were unable to develop sufficient observations matched to our commercial bank sample.

prior year described in Section 2.2 and Appendix A reduces the number of observations to 10,955. The availability of other explanatory variables described in Sections 3.3 and 3.4 and in Appendix B limits the final full sample to 10,562 observations for 394 unique banks.

3.2. HMDA Data and Loan-to-Income Ratio

We compute the average initial loan-to-income ratio for a bank's single family real estate mortgages using mortgage-level data from the Federal Financial Institutions Examination Council's (FFIEC) HMDA database available at www.ffiec.gov/hmda/. The HMDA requires mortgage lenders with assets or mortgage originations that exceed fairly low thresholds determined annually by the Federal Reserve to disclose information about their individual mortgage applications and originations. This information primarily pertains to types of mortgages and the demographics of mortgagors. However, this information also includes the loan amounts and mortgagors' incomes, which allows us to estimate loan-to-income ratios for a bank's mortgages. To the best of our knowledge, this ratio is the only important underwriting criterion that we can reliably estimate across banks during our sample period.

We collected HMDA data for the top 800 mortgage originators based on number of mortgage applications for which they made credit granting decisions over the period 2005-2007. We matched 134 of these originators to 103 of the banks in our sample using the FFIEC's National Information Center website (www.ffiec.gov/nicpubweb/nicweb/SearchForm.aspx), 100 of which had the necessary data on other model variables. For each of these banks each year from 2005-2007, we drew a random sample of 1,000 mortgage loan applications. We computed each bank's average loan-to-income ratio for the approved loans within the 3000 sampled loans for the three-year period 2005-2007, denoted LOAN_INC.

3.3. LLP Timeliness Models and Variables

We test hypothesis H1 using measures of LLP timeliness motivated by Beatty and Liao (2011, p. 8), who estimate this construct at the bank level using time-series regressions of quarterly LLPs on the current quarter, next quarter, and prior two quarter changes in NPLs, as well as Tier 1 regulatory capital ratio and earnings before the provision for loan losses. Beatty and Liao measure LLP timeliness as the incremental R^2 attributable to inclusion of the current and next quarter changes in NPL in the model. This measure is bank specific and conceptually tightly tied to LLP timeliness, but it likely is measured with considerable error due to the limited number of time-series observations per bank. We use two approaches to mitigate this measurement error.

In the first approach, we estimate LLP timeliness within the same pooled regression model in which we estimate the effect of MODEL and STRESS on LLP timeliness. The presence of many cross-sectional observations in the pooled sample increases our ability to estimate LLP timeliness accurately. Specifically, in equation (1A) below we regress quarterly LLPs on MODEL and STRESS, both separately and interacted with Beatty and Liao's (2011) changes in NPL (for simplicity, we combine the current and next quarter changes in NPL into a single variable and also the prior two quarter changes in NPL into a single variable), as well as on an extensive set of control variables. The coefficients on the interactions of MODEL and STRESS with the NPL change for the current and next quarter capture the effect of these CRM activities on LLP timeliness. The main limitation of this approach is that the model's interactive structure makes control either limited (if control variables are added only linearly) or cumbersome (if control variables are added both linearly and interactively). Trading off these issues, we add all control variables linearly and in specification analyses add the most important control variable, bank size, interactively as well.

In the second approach, we estimate LLP timeliness for each bank using time-series regressions for rolling 12 quarter periods as described in Beatty and Liao (2011). To mitigate measurement error, we coarsify this estimate into an indicator variable for above and below median LLP timeliness, denoted B&L. In equation (1B) below, we regress this indicator variable on MODEL, STRESS, and control variables. While we expect this approach to be less powerful than the first, it allows for simpler and more flexible control.

The regression model used in the first approach is:

$$\begin{aligned} LLP_t = {} & \beta_0 + \beta_1 \Delta NPL_{t-2,t-1} + \beta_2 \left(\Delta NPL_{t-2,t-1} \times MODEL \right) + \beta_3 \left(\Delta NPL_{t-2,t-1} \times STRESS \right) \\ & + \beta_4 \Delta NPL_{t,t+1} + \beta_5 \left(\Delta NPL_{t,t+1} \times MODEL \right) + \beta_6 \left(\Delta NPL_{t,t+1} \times STRESS \right) \\ & + \beta_7 MODEL + \beta_8 STRESS + \beta_9 SIZE + \beta_{10} C\ \&\ I + \beta_{11} TIER1 + \beta_{12} EBP \\ & + \beta_{13} M\ \&\ A + \beta_{14} \Delta UNRATE + \beta_{15} RECESSION + \beta_{16} VIX + \varepsilon_t . \end{aligned} \tag{1A}$$

We estimate equation (1A) as an OLS panel regression for the full sample of 10,562 observations from 2002:1Q-2010:4Q, clustering standard errors by firms and quarters. All of the variables in equation (1A) are measured at the firm-quarter level except for MODEL and STRESS, which are measured at the firm-most recent prior year level. In this and subsequent equations, we suppress time subscripts except where necessary for clarity.

The dependent variable in equation (1A) is the quarterly loan loss provision divided by prior quarter total loans, denoted LLP_t. $\Delta NPL_{t,t+1}$ denotes the average of the change in non-performing loans in quarters t and t+1 divided by prior quarter total loans. MODEL and STRESS are defined in Section 2.2 and Appendix A. We include the most recent prior MODEL and STRESS directly and interacted with $\Delta NPL_{t,t+1}$. Hypothesis H1 predicts a positive coefficient β_5 on the interaction of $\Delta NPL_{t,t+1}$ with MODEL. To ensure that the interactions of the CRM activities are with the current and next quarter ΔNPLs (i.e., that they capture LLP timeliness) and not with past two quarter ΔNPLs (i.e., that they do not capture LLP untimeliness), we also include the average of the change in non-performing loans in quarters t-2 and t-1 divided by prior quarter total loans, denoted $\Delta NPL_{t-2,t-1}$, and interact this variable with MODEL and STRESS.

We also control for the following additional variables. Because size is the bank characteristic we expect to be most associated with banks' CRM activities, we control for the natural logarithm of prior quarter total assets, denoted SIZE. To capture the differential timeliness of LLPs for homogeneous and heterogeneous loans (Liu and Ryan 1995 and 2006), we include commercial and industrial loans divided by total loans, denoted C&I.[5] To capture banks' financial health, we include the prior quarter tier 1 capital ratio, denoted TIER1, and earnings before the provision for loan losses divided by prior quarter total assets, denoted EBP. To capture the fact that banks that make frequent acquisitions may have problems integrating their loan loss provisioning or CRM systems, we include the number of acquisitions from 1990 to 2010, denoted M&A. We include three variables to capture macroeconomic downturns or uncertainty: the change in the unemployment rate during the quarter, denoted ΔUNRATE; an indicator variable for the recessionary quarters 2008:1Q-2009:2Q, denoted RECESSION; and the level of the VIX index at the end of the quarter, denoted VIX.[6]

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[5] In untabulated analysis, we also interact C&I with the ΔNPL variables; the coefficients on these variables are insignificant and the inclusion of these variables has no substantive effect on the coefficients on the other included variables.

[6] Alternatively, we included the Philadelphia Federal Reserve's "Anxious" index (the mean and median of professional economic forecasters' four-quarter-ahead recession probability forecasts) instead of VIX, with no substantive effect on the empirical results.

As discussed in Section 2.2, we conduct specification analyses adding interactions of SIZE with $\Delta NPL_{t,t+1}$ and $\Delta NPL_{t-2,t-1}$ to equation (1A), propensity score matching on based on the predicted value of MODEL (the CRM activity specified in hypothesis H1) from a probit model, eliminating observations with assets greater than $100 billion, and using a Heckman (1979) selection model approach that adds inverse Mills ratios from first-stage probit models to the equation. We describe the probit models used in the propensity score matching and Heckman analyses in Section 3.6.

The regression model used in the second approach is:

$$\begin{aligned} B\&L = \beta_0 + \beta_1 MODEL + \beta_2 STRESS + \beta_3 SIZE + \beta_4 C\&I + \beta_5 TIER1 + \beta_6 EBP \\ + \beta_7 M\&A + \beta_8 \Delta UNRATE + \beta_9 RECESSION + \beta_{10} VIX + \varepsilon_t. \end{aligned} \tag{1B}$$

We estimate equation (1B) in the same fashion described above for equation (1A), although we lose observations due to the requirement that 12 consecutive quarterly time-series observations exist to estimate B&L for a bank. Because of the greater flexibility to add control variables allowed by the non-interactive structure of equation (1B), in specification analysis we decompose MODEL into two separate indicator variables that capture the length of time that banks have engaged in that CRM activity: MODEL_EXP takes a value of 1 if the bank has engaged in MODEL both in 2000 (i.e., the first year we collected this variable) and the period under consideration and zero otherwise; MODEL_NEXP takes a value of 1 if the bank did not engage in MODEL in 2000 but did in the period under consideration and zero otherwise. Because the effectiveness of banks' CRM should increase with the time they have engaged in it, we expect B&L to be more positively associated with MODEL_EXP than with MODEL_NEXP.

To test hypotheses H2 and H3, we estimate the following base model at three fiscal year ends during the financial crisis, s= 2007 (early), 2008 (middle), and 2009 (late):

$$\begin{aligned} CUMLLP\_PCT_s &= \gamma_0 + \gamma_1 CUM\Delta NPL\_PCT_s + \gamma_2\left(CUM\Delta NPL_s\_PCT \times MODEL_{2006}\right) \\ &+ \gamma_3\left(CUM\Delta NPL\_PCT_s \times STRESS_{2006}\right) + \gamma_4 MODEL_{2006} + \gamma_5 STRESS_{2006} \\ &+ \gamma_6 SIZE + \gamma_7 C\,\&\,I + \gamma_8 TIER1 + \gamma_9 EBP + \gamma_{10} M\,\&\,A_t + \eta_s. \end{aligned} \tag{2}$$

We estimate equation (2) using cross-sectional OLS regressions for the full sample in each of the three years with heteroskedasticity-corrected standard errors.

Following Vyas (2011), the dependent variable in equation (2) is the cumulative LLP from the beginning of 2007 to the end of the year s divided by the cumulative LLP over the entire 2007-2010 period, denoted $CUMLLP\_PCT_s$. We control for economic loan losses using the analogously defined ΔNPL from the beginning of 2007 to the end of the year s divided by the ΔNPL over the entire 2007-2010 period, denoted $CUM\Delta NPL\_PCT_s$. We interact $CUM\Delta NPL\_PCT_s$ with MODEL and STRESS for 2006. Hypothesis H2 predicts that the coefficient γ_3 on $CUM\Delta NPL\_PCT_s \times STRESS_{2006}$ is positive early in the financial crisis, e.g., for s=2007. Hypothesis H3 predicts that the coefficient γ_2 on $CUM\Delta NPL\_PCT_s \times MODEL_{2006}$ becomes positive later in the crisis, e.g., for s=2009.

The control variables in equation (2) are defined above and included in the equation for the same reasons as in prior equations. There are no macroeconomic variables in the equation because it is cross-sectional. In specification analyses, we also estimate equation (2) adding an interaction of SIZE with $CUMLLP\_PCT_s$ to the base model, using propensity score matching based on the predicted value of STRESS (the CRM activity specified in hypothesis H2) in the 2007 regression and based on the predicted value of MODEL (the CRM activity specified in hypothesis H3) in the 2008 and 2009 regressions, eliminating observations with assets greater than $100 billion, and as a second-stage Heckman model.

To test hypothesis H4, we estimate the following base model:

$$
\begin{aligned}
CUMLLP_{2005-07} = {} & b_0 + b_1 LOAN\_INC + b_2 \left(LOAN\_INC \times MODEL_{2004} \right) \\
& + b_3 \left(LOAN\_INC \times STRESS_{2004} \right) + b_4 MODEL_{2004} + b_5 STRESS_{2004} \\
& + b_6 SIZE_{2004} + b_7 REAL\_SF_{2004} + b_8 TIER1_{2004} + b_9 EBP_{2004} + b_{10} M \,\&\, A \\
& + b_{11} NPL_{2004} + e.
\end{aligned}
\tag{3}
$$

We estimate equation (3) as a cross-sectional OLS regression with heteroskedasticity-corrected standard errors.

The dependent variable in equation (3) is the sum of the LLP for the 2005-2007 period divided by 2004 total loans, denoted $CUMLLP_{2005\text{-}07}$. The estimated average loan-to-income ratio for 2005-2007, denoted LOAN_INC, is described in Section 3.2. LOAN_INC is included directly and interacted with the CRM activities for 2004. Hypothesis H4 predicts a negative coefficient b_2 on the interaction of LOAN_INC and MODEL. Equation (3) also includes the 2004 values of MODEL, STRESS, SIZE, single family real estate loans divided by total loans, denoted REAL_SF, TIER1, EBP, M&A, and NPL. As for prior equations, we also estimate equation (3) adding an interaction of SIZE with LOAN_INC to the base model, using propensity score matching based on MODEL (the CRM activity specified in hypothesis H4), eliminating observations with assets greater than $100 billion, and as a second-stage Heckman model.

3.4. Loan Origination Procyclicality Models and Variables

To test Hypotheses H5 and H6, we estimate the following base model:

$$
\begin{aligned}
LOANGR_{t-1,t+3} = {} & B_0 + B_1 LLP_t + B_2\left(LLP_t \times MODEL\right) + B_3\left(LLP_t \times STRESS\right) \\
& + B_4 MODEL + B_5 STRESS + B_6 SIZE + B_7 C\ \&\ I + B_8 TIER1 + B_9 EBP \\
& + B_{10} M\ \&\ A + B_{11}\Delta UNRATE + B_{12} RECESSION + B_{13} VIX + E_t .
\end{aligned} \tag{4}
$$

We estimate equation (4) using pooled OLS regressions, clustering standard errors by firms and quarters.

The primary dependent variable in equation (4) is the natural logarithm of one plus the total loan growth measured over the four-quarter period from quarter t-1 to t+3, denoted $LOANGR_{t-1,t+3}$. We also estimate the equation with analogously defined dependent variables for the growth rates in consumer loans, denoted $CONSGR_{t-1,t+3}$, real estate loans, denoted $REALGR_{t-1,t+3}$, and commercial and industrial loans, denoted $C\&IGR_{t-1,t+3}$. The other explanatory variables in the equation have a similar structure to those in equation (1A), except that the ΔNPL variables in the latter equation are replaced with LLP_t. Hypothesis H5 predicts a positive coefficient B_2 on the interaction between LLP_t and MODEL with $LOANGR_{t-1,t+3}$ as the dependent variable. Hypothesis H6 predicts a positive coefficient B_2 with growth in either type of homogeneous loan, $CONSGR_{t-1,t+3}$ or $REALGR_{t-1,t+3}$, as the dependent variable. Hypothesis H6 also predicts a positive coefficient B_3 on the interaction between LLP_t and STRESS with growth in heterogeneous commercial and industrial loans, $C\&IGR_{t-1,t+3}$, as the dependent variable.

We also estimate equation (4) with LOANGR as the dependent variable adding an interaction of SIZE with LLP_t to the base model, using propensity score matching based on MODEL (the CRM activity specified in hypothesis H5), eliminating banks with assets greater than $100 billion, and as a second-stage Heckman model. To conserve space, we do not perform these specification analyses for estimations of equation (4) with CONSGR, REALGR, and C&IGR as the dependent variables, although the empirical results for these models are similarly robust to these specification analyses.

3.5. Propensity Score Matching

As discussed in the introduction, in specification analyses we use propensity score matching in addition to linear inclusion of observable bank characteristics to control for the associations between the CRM activities and those characteristics. Propensity score matching efficiently pairs each treatment observation with a single control observation based on multiple characteristics without relying on a linear or any other specific functional form (Rosenbaum and Rubin 1983, Dehejia and Wahba 2002, Li and Prabhala 2007). However, propensity score matching reduces sample size, particularly when treatment observations are infrequent relative to the available set of pre-matched control observations, as is the case in this study, and so can reduce statistical power and generalizability to the full population (Cram et al. 2009).

We match each bank-quarter with a value of one for MODEL or STRESS, i.e., treatment observations, with control observations based on the estimated probability of usage of that type of CRM, called the "propensity score". The propensity scores are based on probit estimation of equation (5) discussed in the following section. We choose the control observation with the closest propensity score to the treatment observation, requiring the absolute difference of the propensity scores of each matched pair of observations to be less than a pre-specified proportion of the standard deviation of propensity scores of treatment observations, referred to as the "caliper distance". To ensure that the treatment and control samples are well matched, we use a narrow caliper distance of 0.01. If no control observations have propensity scores within the caliper distance, then the treatment observation is left unmatched and excluded from the matched sample. After matching, we check that there are no significant differences in the average bank characteristics for the treatment and control samples (Armstrong et al. 2011).

Most of our hypotheses pertain to MODEL, and so in most cases we match on the propensity scores for that CRM activity. In this case the resultant matched pooled sample, subject to availability of control variables, is 1,531 observations, less than one-sixth of the overall sample. Matching based on propensity scores for STRESS yields even greater sample attrition. Matching in cross-sections yields relatively few observations. For completeness, we report the results of propensity score matching in the cross-sectional analyses, but we caution the reader against overinterpreting these results, despite the fact that they usually provide support for the hypotheses.

3.6. Models for Propensity Score Matching and the First-Stage of the Heckman Selection Model

To develop propensity scores for matching purposes and inverse Mills ratios from the first stage of the Heckman selection model approach, we explain each of MODEL and STRESS, collectively denoted CRMScore, using the following model:

$$CRMScore = \eta_t + \eta_1 SIZE + \eta_2 MktRiskDis + \eta_3 OperRiskDis + \eta_4 NLCO_{t-1} + \eta_5 EBP + \xi_t. \qquad (5)$$

For simplicity, we use the same models for the propensity score matching and the Heckman selection model approach. We kept equation (5) fairly simple because adding further explanatory variables (in particular, the C&I, Tier1, and M&A variables in the primary empirical models) adds virtually nothing to the explanatory power of the model and has no effect on the results of the Heckman selection model approach but makes propensity score matching more difficult.

We include fixed time effects η_t in equation (5) to capture the increase in CRM activities over time attributable to banks' adoption of Basel II and other reasons. We include SIZE because it is the bank characteristic we expect to be most highly associated with CRM activities.

We include two variables for banks' other risk disclosures that we hand collected from their financial reports. MktRiskDis is an ordinal variable that takes a value from 0 to 5 based on the existence and extensiveness of banks' market risk disclosures. MktRiskDis increases by one if the bank makes disclosures about each of repricing GAP, market risk sensitivity, Value at Risk, backtesting of market risk models, and stress testing of these models. OperRiskDis is an indicator variable that takes a value of 1 for banks that disclose details about their operational risk management.

We include the ratio of net loan charge-offs to total loans in the prior quarter, denoted $NLCO_{t-1}$, to capture the level of credit losses. This variable uses net loan charge-offs rather than the level or change in non-performing loans in the numerator and is lagged one quarter to mitigate the possibility that it is tautologically related to our test variables. We include EBP to capture banks' disclosure incentives related to financial health.

Notice that MktRiskDis, OpRiskDis, and $NLCO_{t-1}$ do not appear in our primary empirical models (equation (1A)-equation (4)). Hence, these variables can be viewed as instrumental variables that yield identification in the Heckman selection model approach without relying on the nonlinear functional form of the inverse Mills ratios.

In conducting the Heckman analysis, for simplicity we include the inverse Mills ratios from the estimations of equation (5) with both MODEL and STRESS as the dependent variables in the empirical models. This joint inclusion is strictly correct only if MODEL and STRESS are independent;[7] in fact, the two CRM activities are slightly positively correlated, as discussed in Section 4.1. The empirical results are not significantly affected by including the inverse Mills ratios separately.

4. Empirical Results

To be conservative, we evaluate significance using two-tailed tests despite the fact that all of our hypotheses are one-tailed. Naturally, 10% significance in a two-tailed test corresponds to 5% significance in a one-tailed test.

4.1. Descriptive Statistics and Correlations

Table 1, Panel B provides descriptive statistics for the variables in equation (1A) and for the key additional or distinct variables in the other equations. Inspection of the panel reveals that the average values of MODEL and STRESS are 0.088 and 0.035, respectively, reflecting the relatively low frequency of disclosures of these CRM activities discussed above. The bulk of the sample observations are well-capitalized and profitable. The ΔNPL and ΔUNRATE variables are on average positive, primarily due to the financial crisis in the last four years of the sample period.

By construction, the $CUMLLP\_PCT_s$ variables increase as s rises from 2007 to 2009. The annual LLP as a percentage of the cumulative LLP from 2007-2010 averages 10.1% in 2007, 18.0% in 2008, 38.3% in 2009, and 33.6% in 2010, reflecting the peak of LLPs in the third quarter of 2009 and the very slow recovery afterwards.

[7] We thank Bill Greene for explaining this point and numerous other aspects of the Heckman selection model and propensity score matching to us.

Table 2 reports the Pearson correlations of the equation (1A) variables. MODEL and STRESS are positively significantly positively correlated, but at the relatively low level of 6.1%, indicating that they are substantially distinct CRM activities. MODEL and STRESS are both strongly positively correlated with SIZE and also with M&A (which not surprisingly is very highly correlated with SIZE). These correlations are consistent with SIZE proxying for banks' technical sophistication and with sophisticated banks being more likely to engage in these CRM activities. These CRM activities are also strongly positively correlated with LLP. This could result from banks that accept more credit risk being more likely to engage in and disclose CRM and/or banks that use CRM more fully incorporating credit losses in their LLPs.

Consistent with prior research, LLP is strongly positively correlated with the NPL changes, strongly negatively correlated with LOANGR, and strongly positively correlated with the three macroeconomic variables, ΔUNRATE, RECESSION, and VIX.

These macroeconomic variables are all very highly positively correlated. As a consequence of these high correlations, they tend not to be individually significant in the empirical models, although they often would be if included individually.

4.2. Results of the Estimations of the Matching/First-Stage Model

Table 3 reports probit estimations of equation (5) with MODEL and STRESS as the dependent variable. The fit of both models are good based on pseudo R^2s of 24.1% for the MODEL regression and 21.6% for the STRESS regression.

The untabulated fixed time effects increase over time, consistent with both CRM activities increasing over time. The coefficient on SIZE is positive and significant at the 1% level in the MODEL regression and at the 10% level in the STRESS regression, consistent with larger banks having greater desire or ability to engage in these CRM activities. The coefficient on MktRiskDis is positive and significant at the 1% level for the STRESS regression, consistent with banks being consistent in their modeling of the two primary types of risk. In contrast, the coefficient on OperRiskDis is negative and significant at the 1% level for the STRESS regression. While we did not expect this negative coefficient, it likely reflects the fact that operational risk rises primarily with banks' transactions volume, not with their credit risk. The coefficients on NLCO and EBP are insignificant in both regressions. Overall, these results indicate that a limited and straightforward set of bank characteristics are associated with banks' CRM activities.

4.3. Results of LLP Timeliness Estimations

Table 4, Panel A reports five estimation approaches for equation (1A): the base model in column 1, the base model with interactions of SIZE with the NPL change variables in column 2, propensity score matching based on MODEL in column 3, the base model for observations with less than $100 billion of assets in column 4, and the Heckman second-stage model in column 5. The results of the five estimations generally are consistent, with the variation across the columns apparently being primarily attributable to the important but distinct roles of SIZE in the approaches.

We first discuss the control variables, several of which are significant across multiple estimation approaches. The coefficient on $\Delta NPL_{t-2,t-1}$ is positive and significant at the 5% level or better in all but the model with interactions of SIZE with the NPL change variables, consistent with banks' LLPs reflecting their loan performance.

The coefficient on STRESS is positive and significant at the 10% level or better across all five estimation approaches. The coefficient on MODEL is positive and significant at the 10% level or better in the base model and the base model with interactions of SIZE with the NPL change variables. These results indicate that banks that engage in these CRM activities record larger/more conservative LLPs and/or assume greater credit risk.

The coefficient on SIZE is significantly positive at the 5% level or better in all but the propensity score matching and Heckman approaches, perhaps because SIZE is the primary variable involved in the matching or construction of the inverse Mills ratios. These results are consistent with larger banks recording larger/more conservative LLPs.

The coefficient on TIER1 is significantly negative at the 10% level in all but the propensity score matching approach, consistent with better capitalized banks experiencing lower credit losses.

Consistent with hypothesis H1, the coefficient on $\Delta NPL_{t,t+1}\times$MODEL is significantly positive at the 5% level in the base model, at the 10% level in the model with interactions of SIZE with the NPL change variables, the propensity score matching, and the base model with the sample of observations with less than $100 billion of assets, and at the 1% level in the Heckman selection model approach. These results indicate that banks engaging in historically focused CRM record timelier LLPs. In contrast, none of the interactions of $\Delta NPL_{t-2,t-1}$ with MODEL or of either ΔNPL variable with STRESS or SIZE are significant.

Table 4, Panel B reports five estimations of equation (1B): the base model in column 1, propensity score matching based on MODEL in column 2, the base model for observations with less than $100 billion of assets in column 3, the Heckman second-stage model in column 4, and the base model breaking MODEL into MODEL_EXP and MODEL_NEXP in column 5. Despite the considerably lower power of this equation compared to equation (1A) attributable to the measurement error in the dependent variable, as reflected in pseudo R^2s from 0.2%-0.6%, the results generally are consistent across columns.

We first discuss the control variables, several of which are significant across multiple estimation approaches. The coefficient on SIZE is significantly positive at the 10% level in the base model, propensity score matching, and MODEL breakdown approaches, again consistent larger banks recording larger/more conservative LLPs. Unlike in Panel A, the coefficient on M&A is significantly negative at the 5% level or better in all but the base model for observations with less than $100 billion of assets. This may reflect acquiring banks' difficulties in integrating acquired banks' legacy loan loss provisioning systems. Also unlike in Panel A, the coefficient on EBP is significantly negative at the 10% level or better in all estimation approaches. This may reflect the presence of EBP in the time-series estimations underlying B&L.

Consistent with hypothesis H1, the coefficient on MODEL is significantly positive at the 5% level in the base model and the Heckman selection model approach, at the 1% level in the propensity score matching, and at the 10% level in the base model with the sample of observations with less than $100 billion of assets. These results are consistent with the finding in Panel A that banks engaging in historically focused CRM record timelier LLPs. In contrast, the coefficient on STRESS is insignificant in four of the five estimation approaches; this coefficient is significantly positive at the 10% level in the Heckman selection model approach.

In the MODEL breakdown approach, the coefficient on MODEL_EXP is positive and significant at the 10% level and about twice as large as the insignificant coefficient on MODEL_NEXP. The difference of the two coefficients is insignificant, however. This provides weak evidence that the effects of MODEL are stronger when banks have more experience with this CRM activity.

Table 5 reports the estimation of equation (2) for each the three years examined in the financial crisis, s=2007, 2008, and 2009. Panel A reports the results for the base model in columns 1-3. To accommodate the volume of specification analyses, these analyses are reported in Panels B and C of the table with the columns numbered consecutively across Panels A-C. Panel B reports the results for the models with interactions of SIZE with $CUM\Delta NPL\_PCT_s$ in columns 4-6 and for the propensity score matching in columns 7-9. Reflecting the CRM activity specified in hypotheses H2 and H3, propensity score matching is based on STRESS in column 7 and on MODEL in columns 8 and 9. Because the regressions in this table are cross-sectional at a point in time, not pooled, propensity score matching yields fairly few observations, particularly when it is based on STRESS. Panel C reports the results for the base model on sample observations with below $100 billion assets in columns 10-12 and the Heckman second-stage estimation in columns 13-15.

EBP is the only control variable with a fairly reliably significant coefficient for all three points in time during the financial crisis and across all five estimation approaches. The negative coefficients on this variable suggest that more profitable banks were less affected by the financial crisis. The coefficient on $CUM\Delta NPL\_PCT_s \times SIZE_{2006,}$ it is significantly positive at the 10% level for s=2009 in the estimation with this interactive variable.

Consistent with hypothesis H2, the coefficient on $CUM\Delta NPL\_PCT_s \times STRESS_{2006}$ is positive and significant at the 1% level for s=2007 in all estimations except for the propensity score matching, which yields few observations as noted above. These results support the idea that forward-looking CRM provides banks with better ability to diagnose and respond to changing credit loss parameters at sharp turns in economic cycles such as occurred in 2007. In contrast, none of the interactions of CUMΔNPL_PCT$_s$ with MODEL is significant for s=2007.

Consistent with hypothesis H3, the coefficient on CUMΔNPL_PCT$_s$×MODEL$_{2006}$ is significantly positive at the 1% level for s=2009 in all estimations except for the propensity score matching. This supports the idea that, while historically focused CRM performs poorly when credit loss parameters change, this form of CRM recovers its usefulness once data pertinent to the new credit loss parameters are accumulated for a period of time.

There is weak evidence that MODEL started regaining usefulness in 2008. The coefficient on CUMΔNPL_PCT$_s$× MODEL$_{2006}$ is significantly positive at the 10% level for s=2008 in the estimation of the base model on sample observations with below $100 billion assets.

In summary, the results reported in Tables 4 and 5 indicate that MODEL enhanced banks' LLP timeliness on average across our sample period and late in the financial crisis. STRESS enhanced banks' LLP timeliness early in the financial crisis.

4.4. Results of HMDA Loan-to-Income Ratio Estimations

Table 6 reports the estimations of equation (3) for the usual five approaches. The coefficients on both MODEL$_{2004}$ and STRESS$_{2004}$ are significantly positive at the 1% level for all approaches (except that the coefficient on STRESS$_{2004}$ cannot be estimated in the propensity score matching due to the limited cross-sectional observations). These results are consistent with these CRM activities being associated with banks recording larger/more conservative LLPs greater credit risk and/or assuming greater credit risk.

Consistent with hypothesis H4, we find that the coefficients on both $LOAN\_INC \times MODEL_{2004}$ and $LOAN\_INC \times STRESS_{2004}$ are significantly negative at the 1% level in all estimation approaches (again except that the coefficient on $LOAN\_INC \times STRESS_{2004}$ cannot be estimated in the propensity score matching due to the limited cross-sectional observations). This supports the idea that banks with better historically focused and forward-looking CRM rely on an informationally richer array of credit risk factors, and so their LLPs are less dependent on summary underwriting criteria such as loan-to-income ratios.

4.5. Results of Loan Origination Procyclicality Estimations

Table 7, Panel A reports the estimation of equation (4) with total loan growth, $LOANGR_{t-1,t+3}$, as the dependent variable for the usual five estimation approaches. The results for the control variables are as expected based on the prior literature. Consistent with Laeven and Majnoni's (2003) findings, the coefficient on LLP is significantly negative in all estimations, indicating that higher LLPs are associated with reduced loan growth. This finding, combined with the fact that LLPs increase during downturns, suggests that LLPs contribute to procyclical loan originations. The coefficient on EBP is significantly positive in all estimations, indicating higher loan growth for more profitable banks. Despite the high positive correlations of the macroeconomic variables, the frequent significantly negative coefficients on ΔUNRATE, RECESSION, and VIX indicate that bank lending declines during macroeconomic downturns and uncertainty.

Consistent with hypothesis H5, the coefficient on LLP×MODEL is significantly positive at the 5% level or better in all estimation approaches. This supports the idea that historically focused CRM mitigates loan origination procyclicality associated with LLPs. In contrast, the interactions of LLP with STRESS are all insignificant.

Panel B of Table 7 reports similar analyses by loan type. The first (second) [third] column of the panel reports the estimation with consumer loan growth, $CONSGR_{t-1,t+3}$, (real estate loan growth, $REALGR_{t-1,t+3}$) [commercial and industrial loan growth, $C\&IGR_{t-1,t+3}$] as the dependent variable.

Consistent with hypothesis H6, the coefficients on LLP×MODEL are significantly positive at the 1% level in the $CONSGR_{t-1,t+3}$ regression and at the 10% level in the $REALGR_{t-1,t+3}$ regression, indicating that historically focused CRM mitigates the procyclical relationship between LLP and loan growth for homogeneous consumer and real estate loans. Also consistent with hypothesis H6, the coefficient on LLP×STRESS is significantly positive at the 10% level in the $C\&IGR_{t-1,t+3}$ regression, indicating that the forward looking stress tests mitigate the procyclical association between LLPs and loan growth for heterogeneous commercial and industrial loans.

5. Conclusion

In this study, we provide evidence that banks' historically focused credit risk measurement modeling (MODEL) and forward-looking stress tests of their estimated credit losses (STRESS) are distinctly associated with enhanced LLP timeliness and reduced loan origination procyclicality. Regarding LLP timeliness, we predict and find that MODEL is associated with timelier LLPs across our entire 2002-2010 sample period and also later in the financial crisis after banks had experienced heightened credit losses for a period of time (in 2009). This finding supports the idea that statistical analysis of historical data provides discipline on banks' loan loss reserving. We also predict and find that STRESS is associated with timelier LLPs early in the financial crisis (in 2007). This finding indicates the limitations of statistical analysis of historical data and the essential role of forward-looking credit risk modeling during sharp turns in economic cycles.

We provide insight into the mechanism by which CRM enhances LLP timeliness, providing evidence that CRM reduces banks' reliance on summary underwriting criteria. In particular, we predict and find that MODEL yields informationally richer LLPs with less reliance on banks' average loan-to-income ratios for mortgages, a type of homogeneous loan for which MODEL is the most relevant form of CRM.

Regarding loan origination procyclicality, we predict and find that MODEL is associated with reduced procyclicality as evidenced by a less negative association between LLPs and loan growth, particularly growth in homogeneous consumer and real estate loans for which statistical analysis of historical data is most feasible. We predict and find that STRESS is associated with reduced procyclicality as reflected in a less negative association between LLPs and growth in heterogeneous commercial and industrial loans, the loan type for which statistical analysis of historical data is least feasible.

In summary, our empirical results are consistent with MODEL and STRESS having significantly positive but distinct effects on banks' loan loss reserving and loan origination procylicality. The results are logically coherent and explained by CRM reducing banks' reliance on summary underwriting criteria in loan origination. They also are consistent across five different estimation approaches that control for bank's other characteristics as well as their disclosures incentives regarding their CRM.

An open policy question for future research suggested by our study is whether financial and regulatory reporting policymakers should expand required or encourage voluntary disclosures of banks' CRM activities. While we identify banks' CRM activities based on their existing financial report disclosures, and so cannot draw direct inferences about potentially desirable disclosures from our results, we conjecture that additional CRM disclosure requirements would induce banks to undertake additional CRM activities and to pay more attention to their existing activities. If this conjecture is correct, then our results imply that imposing such disclosure requirements would increase banks' LLP timeliness and thereby reduce their loan origination procyclicality. This outcome would be highly desirable for bank regulators and other economic policymakers charged with the responsibility to mitigate the severity of future economic downturns. It is also something for the FASB and IASB to consider in their current joint project to improve the financial reporting for loan losses, and it is consistent with Ryan's (2012) recommendation that financial reporting policymakers expand required disclosures of firms' risk modeling in financial reports.

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APPENDIX A
Credit Risk Modeling Disclosure Indicator Variables

We hand collected banks' disclosures in their Form 10-K filings from 2001-2009 about two credit risk modeling activities: credit risk measurement modeling (MODEL) and stress tests (STRESS). Each activity is scored 1 or 0. We chose the sample disclosures randomly.

		# of firms (firm quarters) with scores of 1	**Sample disclosures**
MODEL =0 or 1	Does the bank disclose the use of credit risk measurement models?	59 firms (936 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?	38 firms (388 firm-quarters)	Bank of Hawaii 10K 2009 In addition, the Company uses a variety of other tools to estimate probable credit losses including, but not limited to, a rolling quarterly forecast of asset quality metrics; stress testing; and performance indicators based on the Company's own experience, peers, or other industry sources.

APPENDIX B
Variable Definitions

Variable	Definition
Loan Loss Provision Variables:	
LLP	Loan loss provision for the quarter divided by total loans for the prior quarter
$CUMLLP\_PCT_s$	Cumulative LLP from 2007:Q1 to the quarter under consideration divided by cumulative LLP from 2007:Q1-2010:Q4
$CUMLLP_{2005\text{-}07}$	Cumulative LLP for 2005-2007 divided by total loans for 2004:4Q
B&L	An indicator variable equal to one if Beatty and Liao's (2011) LLP timeliness measure is greater than the sample median for the prior quarter. Their timeliness measure is the incremental adjusted R_2 in model (2) versus the nested model (1) below. $LLP_t=\alpha_0+\alpha_1\Delta NPL_{t-2}+\alpha_2\Delta NPL_{t-1}+\alpha_3 TIER1+\alpha_4 EBP+\varepsilon_t$ (1) $LLP_t=\alpha_0+\alpha_1\Delta NPL_{t-2}+\alpha_2\Delta NPL_{t-1}+\alpha_3\Delta NPL_t+\alpha_4\Delta NPL_{t+1}+\alpha_5 TIER1 +\alpha_6 EBP+\varepsilon_t$ (2) We estimate each model in time-series by bank over rolling 12 quarter periods, requiring complete data availability within those periods.
Loan Variables:	
LOANGR	Natural logarithm of one plus growth in total loans from quarter t-1 to t+3
REALGR	Natural logarithm of one plus growth in real estate loans quarter t-1 to t+3
C&IGR	Natural logarithm of one plus growth in commercial and industrial loans from quarter t-1 to t+3
CONSGR	Natural logarithm of one plus growth in consumer loans from quarter t-1 to t+3
LOAN_INC	Average loan-to-income ratio of single family mortgages originated between 2005 and 2007 from the HMDA database
Credit Risk Modeling (CRM) Variables:	
MODEL	0-1 indicator variable that takes a value of 1 if the bank discloses the use of credit risk measurement modeling in its most recent Form 10-K filing
STRESS	0-1 indicator variable that takes a value of 1 if the bank discloses the use of stress tests in its most recent Form 10-K filing
MODEL_EXP	0-1 indicator variable that takes a value of 1 if the bank discloses the use of credit risk measurement modeling in its most recent and 2000 Form 10-K filings
MODEL_NEXP	0-1 indicator variable that takes a value of 1 if the bank discloses the use of credit risk measurement modeling in its most recent Form 10-K filing *but not* in its 2000 filing

Non-performing Loan Variables:	
NPL	Non-performing loans
$\Delta NPL_{t-2,t-1}$	Average of the change in NPL divided by prior quarter total loans for the prior two quarters
$\Delta NPL_{t,t+1}$	Average of the change in NPL divided by prior quarter total loans for the current and subsequent quarters
$CUM\Delta NPL\_PCT_s$	*ΔNPL* from 2007 to the quarter under consideration divided by *ΔNPL* from 2007-2010
Bank Characteristics:	
SIZE	Natural logarithm of prior quarter total assets
C&I	Commercial and industrial loans divided by total loans
REAL	Real estate loans divided by total loans
REAL_SF	Single family real estate loans divided by total loans
CONSUMER	Consumer loans divided by total loans
TIER1	Tier 1 risk-adjusted capital ratio for prior quarter divided by 100
EBP	Pre-tax earnings before loan loss provision divided by prior quarter total assets
M&A	Number of M&A transactions between 1990 and 2010 for which a given bank is listed as an acquirer in the SDC Platinum database
Macroeconomic Variables:	
ΔUNRATE	Percent change in nationwide unemployment rate for quarter from the U. S. Department of Labor
RECESSION	0-1 indicator variable that takes a value of 1 for the 2008Q1-2009Q2 recessions
VIX	Quarter-end level of the Chicago Board Options Exchange Volatility Index
Probit Model Explanatory Variables and Estimation Outputs:	
MktRiskDis	Ordinal variable that takes a value from 0 to 5 based on the existence and extensiveness of banks' market risk disclosures. Increases by one if the bank discloses each of repricing GAP, market risk sensitivity, Value at Risk, backtesting of market risk models, and stress testing of market risk models
OperRiskDis	0-1 indicator variable that takes a value of 1 for banks that disclose details about their operational risk management
NLCO	Net loan charge-offs divided by loans
IMR_MODEL	Inverse Mills ratio from the probit estimation of the first stage model (equation (5)) with MODEL as the dependent variable
IMR_STRESS	Inverse Mills ratio from the probit estimation of the first stage model (equation (5)) with STRESS as the dependent variable

TABLE 1
Sample Selection and Descriptive Statistics

Panel A: Sample Selection

Firm-quarter observations with Y-9C filings in 2002:Q1-2010:Q4 with non-zero total assets and valid PERMCO	17,959
Firm-quarter observations also with prior firm-year CRM disclosure scores	10,955
Firm-quarter observations also with control variables for Table 3 regressions	10,562

Panel B: Descriptive Statistics

	N	MEAN	STD. DEV	25%	MEDIAN	75%
LLP	10,562	0.004	0.007	0.001	0.002	0.004
$\Delta NPL_{t-2,t-1}$	10,562	0.001	0.008	-0.002	0.000	0.003
$\Delta NPL_{t,t+1}$	10,562	0.001	0.006	-0.001	0.000	0.003
B&L	9,655	0.493	0.500	0.000	0.000	1.000
SIZE	10,562	14.820	1.531	13.685	14.456	15.564
ΔUNRATE	10,562	1.396	5.717	-2.200	0.000	3.200
VIX	10,562	20.835	8.926	13.340	18.000	25.610
MODEL	10,562	0.088	0.283	0.000	0.000	0.000
STRESS	10,562	0.035	0.184	0.000	0.000	0.000
C&I	10,562	0.160	0.097	0.093	0.143	0.201
REAL_SF	10,562	0.264	0.146	0.155	0.257	0.352
REAL	10,530	0.572	0.197	0.427	0.580	0.734
CONSUMER	10,562	0.068	0.076	0.016	0.040	0.094
TIER1	10,562	0.117	0.029	0.099	0.112	0.128
EBP	10,562	0.010	0.008	0.005	0.009	0.015
M&A	10,562	3.496	6.841	0.000	1.000	4.000
LOANGR	9,743	0.092	0.142	0.012	0.078	0.154
REALGR	9,699	0.152	0.268	0.007	0.084	0.206
C&IGR	9,703	0.066	0.230	-0.059	0.063	0.174
CONSGR	9,723	-0.031	0.279	-0.160	-0.028	0.093
$CUMLLP\_PCT_{2007}$	295	0.101	0.183	0.027	0.054	0.089
$CUMLLP\_PCT_{2008}$	282	0.281	0.165	0.182	0.250	0.334
$CUMLLP\_PCT_{2009}$	276	0.664	0.158	0.575	0.668	0.764
$CUMLLP_{2005\text{-}07}$	100	0.011	0.013	0.004	0.007	0.012
LOAN_INC	100	1.682	0.555	1.287	1.667	2.045

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TABLE 2
Pearson Correlations

	LLP	*LOANGR*	$\Delta NPL_{t-2,t-1}$	$\Delta NPL_{t,t+1}$	*MODEL*	*STRESS*	*C&I*	*SIZE*	*TIER1*	*EBP*	$\Delta UNRATE$	*RECESSION*	*VIX*	*M&A*
LLP														
LOANGR	-0.325*													
$\Delta NPL_{t-2,t-1}$	0.171*	-0.154*												
$\Delta NPL_{t,t+1}$	0.174*	-0.033*	0.015											
MODEL	0.126*	-0.026*	0.030*	0.037*										
STRESS	0.125*	-0.057*	0.031*	0.032*	0.061*									
C&I	0.014	-0.002	-0.030*	-0.054*	0.105*	0.021*								
SIZE	0.137*	-0.031*	0.034*	0.031*	0.397*	0.131*	0.156*							
TIER1	-0.097*	0.059*	-0.063*	-0.050*	-0.127*	-0.035*	-0.148*	-0.199*						
EBP	-0.051*	0.163*	-0.096*	-0.024*	0.076*	-0.036*	0.051*	0.166*	0.104*					
$\Delta UNRATE$	0.258*	-0.258*	0.218*	0.294*	0.036*	0.042*	0.001	0.041*	-0.084*	-0.148*				
RECESSION	0.346*	-0.274*	0.182*	0.221*	0.016	0.031*	0.029*	0.019	-0.063*	-0.116*	0.619*			
VIX	0.313*	-0.246*	0.166*	0.206*	0.024*	0.052*	0.017	0.019	-0.036*	-0.113*	0.664*	0.673*		
M&A	0.075*	-0.013	0.001	-0.006	0.254*	0.179*	0.102*	0.641*	-0.216*	0.133*	0.000	0.005	0.005	
B&L	0.036*	-0.048*	0.033*	0.048*	0.040*	0.020*	-0.015	0.015	-0.002	-0.030*	0.007	0.001	0.006	-0.026*

TABLE 3
Model for Propensity Score Matching
and First-Stage of Heckman Selection Model

	MODEL	**STRESS**
	(1)	(2)
SIZE	0.312***	0.144*
	(5.407)	(1.794)
NLCO	6.317	9.684
	(0.884)	(1.434)
MktRiskDis	0.178*	0.540***
	(1.827)	(4.801)
OperRiskDis	0.165	-0.773***
	(1.013)	(-2.994)
EBP	8.176	-7.280
	(1.328)	(-0.928)
Intercept	-6.970***	-5.123***
	(-8.574)	(-4.345)
Year FE	Yes	Yes
# of Observations	11,147	11,147
Pseudo R^2	0.241	0.216

This table presents the probit estimations for MODEL and STRESS (equation (5)). These estimations are used in the Propensity Score Matching and in the first-stage of the Heckman selection models. Column 1 (2) presents the results for the MODEL (STRESS) estimation. We estimate the models using OLS for the years 2001-2009 with standard errors are calculated clustering observations by firm only due to the inclusion of time fixed effects. Continuous variables are winsorized at the top and bottom 1%. Coefficient *z*-statistics are in square brackets. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively, using two-tailed tests. All variables are defined in Appendix B.

TABLE 4
The Effect of CRM Disclosures on the Timeliness of Quarterly Loan Loss Provisions

Panel A: The Effect of CRM Disclosures on the Association between Quarterly LLPs and the Change in NPL over the Current and Subsequent Quarter

VARIABLES	**Base Model** (1)	**Base Model with SIZE Interactions** (2)	**PSM for MODEL** (3)	**Base Model with SIZE <$100 Billion** (4)	**Heckman Second-Stage Model** (5)
$\Delta NPL_{t-2,t-1}$	0.088**	-0.153	0.161***	0.083**	0.068**
	(2.564)	(-0.766)	(3.321)	(2.479)	(2.007)
$\Delta NPL_{t-2,t-1}\times MODEL$	0.066	0.029	-0.053	0.067	0.079
	(0.968)	(0.365)	(-1.139)	(0.893)	(1.254)
$\Delta NPL_{t-2,t-1}\times STRESS$	0.114	0.104	0.056	0.146	0.116
	(1.109)	(1.017)	(0.271)	(1.444)	(1.178)
$\Delta NPL_{t-2,t-1}\times SIZE$		0.017			
		(1.098)			
$\Delta NPL_{t,t+1}$	0.095*	-0.114	0.068	0.096*	0.060
	(1.854)	(-0.400)	(0.778)	(1.887)	(1.088)
$\Delta NPL_{t,t+1}\times MODEL$	0.204**	0.177*	0.273*	0.167*	0.223***
	(2.514)	(1.897)	(1.878)	(1.944)	(2.925)
$\Delta NPL_{t,t+1}\times STRESS$	0.090	0.076	-0.168	0.081	0.134
	(0.713)	(0.626)	(-0.356)	(0.596)	(1.226)
$\Delta NPL_{t,t+1}\times SIZE$		0.014			
		(0.652)			
MODEL	0.001*	0.001**	0.000	0.001	0.001
	(1.868)	(2.039)	(0.343)	(1.380)	(0.882)
STRESS	0.003**	0.003**	0.005*	0.004**	0.002**
	(2.397)	(2.463)	(1.866)	(2.367)	(2.159)
SIZE	0.001**	0.000**	0.000	0.001***	-0.003***
	(2.351)	(2.104)	(0.384)	(2.590)	(-3.243)
C&I	-0.001	-0.001	0.001	-0.001	-0.001
	(-0.636)	(-0.618)	(0.493)	(-0.753)	(-0.830)
TIER1	-0.012*	-0.012*	0.010	-0.015**	-0.014**
	(-1.688)	(-1.708)	(0.886)	(-2.085)	(-1.993)
EBP	-0.012	-0.012	0.074	-0.032	-0.022
	(-0.212)	(-0.208)	(1.137)	(-0.524)	(-0.413)
M&A	-0.000	-0.000	-0.000	-0.000***	0.000
	(-1.177)	(-1.206)	(-0.259)	(-2.679)	(0.350)
VIX	0.000	0.000	-0.000	0.000	0.000**
	(1.043)	(1.047)	(-0.882)	(1.049)	(2.111)
$\Delta UNRATE$	0.004	0.004	0.009**	0.004	0.004
	(1.126)	(1.123)	(2.101)	(1.107)	(1.575)
RECESSION	-0.000	-0.000	0.000	-0.000	-0.000
	(-0.338)	(-0.355)	(0.101)	(-0.391)	(-1.235)
IMR_MODEL					-0.012***
					(-3.611)
IMR_STRESS					0.002***
					(3.452)
Intercept	-0.005	-0.005	-0.000	-0.006*	0.063***
	(-1.619)	(-1.380)	(-0.047)	(-1.807)	(3.199)
Observations	10,562	10,562	1,531	10,135	10,395
Adjusted R-squared	0.185	0.186	0.299	0.176	0.262

Table 4 (continued)

Panel B: The Effect of CRM Disclosures on the Timeliness of Quarterly LLPs using Beatty and Liao's (2011) Time-Series Estimation Approach

VARIABLES	**Base Model** (1)	**PSM for MODEL** (2)	**Base Model with SIZE <$100 Billion** (3)	**Heckman Second-Stage Model** (4)	**Breakdown MODEL by Experience** (5)
MODEL	0.295**	0.381***	0.231*	0.320**	
	(2.061)	(2.684)	(1.722)	(2.229)	
STRESS	0.255	0.105	0.281	0.353*	0.293
	(1.413)	(0.362)	(1.503)	(1.870)	(1.597)
MODEL_EXP					0.468*
					(1.892)
MODEL_NEXP					0.228
					(1.412)
SIZE	0.065*	0.106*	0.039	0.048	0.061*
	(1.794)	(1.857)	(0.864)	(0.734)	(1.655)
C&I	-0.424	0.323	-0.432	-0.526	-0.226
	(-0.924)	(0.442)	(-0.920)	(-1.142)	(-0.503)
TIER1	0.063	2.245	0.218	0.293	0.340
	(0.041)	(0.639)	(0.140)	(0.186)	(0.217)
EBP	-7.745**	-16.827**	-7.121*	-10.173***	-8.748**
	(-2.200)	(-2.276)	(-1.954)	(-2.811)	(-2.259)
M&A	-0.019**	-0.029***	-0.013	-0.019**	-0.018**
	(-2.455)	(-2.772)	(-1.196)	(-2.360)	(-2.327)
VIX	0.002	0.012	-0.000	0.003*	0.001
	(0.796)	(1.341)	(-0.078)	(1.770)	(0.473)
ΔUNRATE	0.000	-0.003	0.002	-0.001	0.000
	(0.007)	(-0.173)	(0.580)	(-0.238)	(0.105)
RECESSION	-0.047	-0.248	-0.043	-0.034	-0.048
	(-1.441)	(-1.571)	(-1.448)	(-1.129)	(-1.102)
IMR_MODEL				-0.157	
				(-0.787)	
IMR_STRESS				0.216**	
				(2.162)	
Intercept	-0.838	-1.883*	-0.456	-0.835	-0.830
	(-1.395)	(-1.910)	(-0.653)	(-0.687)	(-1.362)
Observations	9,655	1,467	9,266	9,614	8,803
Pseudo R2	0.002	0.002	0.006	0.006	0.004

Table 4 (continued)

Panel A presents analyses of the effect of CRM disclosures on the association between quarterly loan loss provisions and the change in non-performing loans (NPL) over the current and subsequent quarter. The dependent variable is quarterly loan loss provision divided by total loans (*LLP*). Column 1 presents the results of the base model (equation (1)). Column 2 presents the results including interactions of SIZE with the NPL changes in the base model. Column 3 presents the results for a propensity score matched sample for MODEL. Column 4 presents the results of the base model eliminating observations with assets above $100 billion. Column 5 presents the results of estimating the second-stage Heckman model, which includes the two inverse Mills ratios from the estimation of equation (5) reported in Table 3. Panel B reports the results of the regression using B&L as the dependent variable, which is an indicator variable based on Beatty and Liao's (2011) LLP timeliness measure. We estimate the models using OLS for the quarters of 2002-2010 with standard errors calculated clustering observations by firm and quarter. Continuous variables are winsorized at the top and bottom 1% levels. Coefficient *t*-statistics are in square brackets. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively, using two-tailed tests. All variables are defined in Appendix B.

TABLE 5
The Association between CRM Disclosures and LLP Timeliness during 2007-2010

Panel A: Base Model

	Base Model		
	2007	2008	2009
VARIABLES	(1)	(2)	(3)
$CUM\Delta NPL\_PCT_s$	0.032***	0.009	0.009
	(2.671)	(1.013)	(0.889)
$CUM\Delta NPL\_PCT_s \times MODEL_{2006}$	0.194	0.033	0.116***
	(0.847)	(1.648)	(3.649)
$CUM\Delta NPL\_PCT_s \times STRESS_{2006}$	0.909***	0.128	-0.043
	(15.467)	(0.641)	(-0.415)
$MODEL_{2006}$	-0.018	-0.020	-0.109**
	(-0.766)	(-0.608)	(-2.257)
$STRESS_{2006}$	-0.100***	-0.005	0.064
	(-4.362)	(-0.067)	(0.563)
SIZE	0.009	0.014	0.020**
	(0.723)	(1.210)	(2.145)
C&I	-0.078	-0.077	0.089
	(-1.004)	(-0.836)	(0.977)
TIER1	0.114	-0.227	-1.096***
	(0.195)	(-0.286)	(-2.763)
EBP	-2.783*	-3.379***	-2.496***
	(-1.787)	(-3.016)	(-2.632)
M&A	-0.002	-0.002	-0.001
	(-1.017)	(-1.407)	(-1.117)
Intercept	0.005	0.145	0.499***
	(0.027)	(0.707)	(3.593)
Observations	295	282	276
Adjusted R-squared	0.105	0.043	0.121

Table 5 (continued)

Panel B: Base Model with Size Interaction and Propensity Score Matching (PSM)

	Base Model with Size Interaction			PSM on STRESS	PSM on MODEL	
	2007	2008	2009	2007	2008	2009
VARIABLES	(4)	(5)	(6)	(7)	(8)	(9)
$CUM\Delta NPL\_PCT_s$	-0.332	-0.081	-0.141*	-0.248***	0.001	0.037*
	(-0.901)	(-0.670)	(-1.791)	(-2.181)	(0.078)	(1.701)
$CUM\Delta NPL\_PCT_s \times MODEL_{2006}$	0.151	0.022	0.101***	0.382	0.028	0.073
	(0.630)	(0.895)	(2.977)	(1.542)	(0.754)	(1.431)
$CUM\Delta NPL\_PCT_s \times STRESS_{2006}$	0.922***	0.122	-0.055	0.382	0.198	-2.050**
	(14.766)	(0.607)	(-0.523)	(1.591)	(1.393)	(-2.015)
$CUM\Delta NPL\_PCT_s \times SIZE$	0.026	0.006	0.011*			
	(0.963)	(0.750)	(1.969)			
$MODEL_{2006}$	-0.011	-0.013	-0.091*	-0.141*	-0.040	-0.037
	(-0.468)	(-0.387)	(-1.760)	(-1.774)	(-0.909)	(-0.454)
$STRESS_{2006}$	-0.097***	-0.001	0.078	-0.046	-0.061	2.740**
	(-4.033)	(-0.009)	(0.674)	(-1.763)	(-0.895)	(2.012)
SIZE	0.004	0.010	0.004	0.021***	0.014	0.004
	(0.368)	(0.750)	(0.270)	(3.152)	(0.766)	(0.251)
C&I	-0.066	-0.082	0.100	-0.161	-0.038	0.094
	(-0.856)	(-0.901)	(1.097)	(-1.761)	(-0.174)	(0.598)
TIER1	0.096	-0.234	-1.103***	0.269	1.267	0.424
	(0.167)	(-0.293)	(-2.727)	(0.694)	(0.961)	(0.522)
EBP	-2.675*	-3.411***	-2.350**	-2.860**	0.348	-3.194*
	(-1.784)	(-3.048)	(-2.469)	(-2.251)	(0.154)	(-1.914)
M&A	-0.002	-0.002	-0.001	0.001	-0.002	-0.001
	(-1.022)	(-1.412)	(-0.814)	(1.282)	(-1.224)	(-0.426)
Intercept	0.077	0.206	0.725***	-0.185*	-0.053	0.543**
	(0.457)	(0.912)	(3.488)	(-1.842)	(-0.163)	(2.284)
Observations	295	282	276	24	64	69
Adjusted R-squared	0.116	0.043	0.127	0.317	-0.050	0.079

Table 5 (continued)

Panel C: Base Model with Assets < $100 Billion and Heckman Second-Stage Model

	Base Model with Assets<$100 Billion			**Heckman Second-Stage Model**		
	2007	2008	2009	2007	2008	2009
VARIABLES	(10)	(11)	(12)	(13)	(14)	(15)
$CUM\Delta NPL\_PCT_s$	0.031**	0.008	0.008	0.031***	0.009	0.009
	(2.586)	(0.828)	(0.766)	(2.654)	(0.975)	(0.865)
$CUM\Delta NPL\_PCT_s \times MODEL2006$	0.253	0.038*	0.132***	0.158	0.033	0.118***
	(0.924)	(1.808)	(3.469)	(0.647)	(1.565)	(3.528)
$CUM\Delta NPL\_PCT_s \times STRESS_{2006}$	0.936***	0.149	-0.041	0.920***	0.155	-0.041
	(16.068)	(0.738)	(-0.381)	(15.212)	(0.778)	(-0.398)
$MODEL_{2006}$	-0.028	-0.045	-0.112**	-0.025	-0.020	-0.109**
	(-0.952)	(-1.249)	(-2.166)	(-0.936)	(-0.648)	(-2.240)
$STRESS_{2006}$	-0.120***	-0.029	0.064	-0.111***	0.000	0.074
	(-4.625)	(-0.388)	(0.558)	(-3.845)	(0.001)	(0.651)
SIZE	0.021	0.023	0.015	-0.021	-0.000	0.017
	(1.196)	(1.521)	(1.176)	(-1.011)	(-0.008)	(1.614)
C&I	-0.113	-0.100	0.096	-0.089	-0.083	0.085
	(-1.278)	(-1.033)	(0.976)	(-1.157)	(-0.930)	(0.938)
TIER1	0.102	-0.078	-1.117***	0.148	-0.337	-1.091***
	(0.174)	(-0.100)	(-2.737)	(0.260)	(-0.441)	(-2.812)
EBP	-2.899*	-3.815***	-2.456**	-4.672**	-3.862***	-2.651***
	(-1.704)	(-3.180)	(-2.479)	(-2.439)	(-3.376)	(-2.776)
M&A	-0.005	-0.005*	-0.000	-0.002	-0.002	-0.002
	(-1.618)	(-1.747)	(-0.085)	(-1.139)	(-1.483)	(-1.131)
IMR_MODEL_{2006}				-0.127**	-0.058**	-0.015
				(-2.083)	(-2.036)	(-0.975)
IMR_STRESS_{2006}				0.000	0.036**	0.021
				(0.019)	(2.324)	(1.289)
Intercept	-0.150	0.011	0.569***	0.723*	0.395	0.517***
	(-0.597)	(0.046)	(3.081)	(1.656)	(1.520)	(2.944)
Observations	280	269	263	295	282	276
Adjusted R-squared	0.112	0.055	0.113	0.115	0.067	0.121

This table presents an analysis of the relation between CRM activities and the timeliness of loan loss provisions (LLPs) relative to changes in nonperforming loans (NPLs) during the financial crisis beginning in 2007. The dependent variable $CUMLLP\_PCT_s$ is the cumulative LLP from the beginning of 2007 to the end of the firm-year under consideration divided by the total cumulative LLP over the entire 2007-2010 period. The CRM disclosure scores are for the end of fiscal year 2006 (pre-crisis). Panel A presents the results of OLS estimations of the base model (equation (2)) in columns 1-3. The various specification analyses are reported in Panels B and C and the columns are numbered consecutively across Panels A-C. Panel B presents the results for the base model including interactions of SIZE with the cumulative change in NPL variable in

Table 5 (continued)

columns 4-6 and for the propensity score matching (PSM) in columns 7-9. PSM is conducted on STRESS in column 7 and on MODEL in columns 8 and 9. Panel C presents the results eliminating observations with assets above $100 billion in columns 10-12 and the results of the second-stage Heckman model in columns 13-15. The Heckman model includes the two inverse Mills ratios from the estimation of equation (5) with MODEL and STRESS as the dependent variable reported in Table 3. We estimate OLS regressions at the end of 2007-2009. Standard errors are heteroskedasticity-robust (White 1980). Continuous variables are winsorized at the top and bottom 1% levels. Coefficient *t*-statistics are in brackets. ***, **, and * denotes significance at the 1%, 5%, and 10% levels, respectively, using two-tailed tests. All variables are defined in Appendix B.

TABLE 6
The Effect of CRM Disclosures on the Association between Banks' Average Mortgage Loan-to-Income Ratio and LLPs during 2005-2007

VARIABLES	**Base Model** (1)	**Base Model with Size Interaction** (2)	**PSM for Model** (3)	**Base Model With Assets <$100 Billion** (4)	**Heckman Second-Stage Model** (5)
LOAN_INC	0.005**	-0.001	0.002	0.005**	0.005**
	(2.081)	(-0.033)	(0.523)	(2.000)	(2.158)
LOAN_INC×MODEL$_{2004}$	-0.019***	-0.019***	-0.023***	-0.023***	-0.019***
	(-2.862)	(-2.942)	(-3.329)	(-3.122)	(-2.707)
LOAN_INC×STRESS$_{2004}$	-0.030***	-0.030***		-0.031***	-0.033***
	(-6.370)	(-6.024)		(-7.818)	(-5.224)
LOAN_INC×SIZE$_{2004}$		0.000			
		(0.200)			
MODEL$_{2004}$	0.032***	0.033***	0.035***	0.034***	0.032**
	(2.748)	(2.952)	(3.311)	(2.792)	(2.508)
STRESS$_{2004}$	0.065***	0.066***		0.068***	0.068***
	(6.827)	(6.936)		(8.745)	(5.596)
SIZE$_{2004}$	0.004***	0.003	0.010***	0.003***	-0.002
	(2.878)	(0.720)	(4.164)	(2.899)	(-0.438)
REAL_SF$_{2004}$	0.009	0.009	-0.001	0.010*	0.012
	(1.391)	(1.407)	(-0.069)	(1.849)	(1.635)
TIER1$_{2004}$	-0.115**	-0.116**	-0.101*	-0.098*	-0.094*
	(-2.091)	(-2.038)	(-2.035)	(-1.770)	(-1.858)
EBP$_{2004}$	0.161	0.166	-0.135	0.266*	0.149
	(0.966)	(0.938)	(-0.756)	(1.710)	(0.971)
M&A	-0.000*	-0.000*	-0.001***	-0.001***	-0.000
	(-1.771)	(-1.677)	(-4.186)	(-2.820)	(-1.563)
NPL$_{2004}$	0.152	0.151	0.150	0.059	0.152
	(1.300)	(1.261)	(1.443)	(0.760)	(1.400)
IMR_MODEL$_{2004}$					-0.019
					(-1.414)
IMR_STRESS$_{2004}$					-0.000
					(-0.106)
Intercept	-0.049**	-0.038	-0.143***	-0.041**	0.065
	(-2.339)	(-0.581)	(-3.924)	(-2.416)	(0.819)
Observations	101	101	22	92	100
Adjusted R-squared	0.310	0.303	0.813	0.194	0.336

This table presents an analysis of the effect of CRM disclosures on the association between banks' total loan loss provisions from 2005-2007 and their average loan-to-income ratio for mortgages originated during this period. Column 1 reports OLS estimation of the base model (equation (3)), column 2 reports estimation of the base model including the interaction of SIZE with the loan-to-income ratio, column 3 reports the results for a propensity score matched sample for MODEL, column 4 reports the results of the base model eliminating observations with assets above $100 billion, and column 5 reports the estimation of the second-stage Heckman model, which includes the four inverse Mills ratios from the estimation of equation (5) reported in Table 3. Loan-to-income ratio data are obtained from the Federal Financial Institution Examination

Table 6 (continued)

Council's Home Mortgage Disclosure Act database. CRM disclosure scores and other control variables are for the end of fiscal year 2004. Standard errors are heteroskedasticity-robust (White 1980). Continuous variables are winsorized at the top and bottom 1% levels. Coefficient *t*-statistics are in square brackets. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively, using two-tailed tests. All variables are defined in Appendix B.

TABLE 7
The Effect of CRM Disclosures on the Association between LLPs and Loan Growth

Panel A: Total Loan Growth

VARIABLES	**Base Model** (1)	**Base Model with Size Interaction** (2)	**PSM for MODEL** (3)	**Base Model with Assets <$100 Billion** (4)	**Heckman Second-Stage Model** (5)
LLP	-6.261***	-9.632***	-5.444***	-6.265***	-5.404***
	(-11.279)	(-4.607)	(-7.916)	(-11.532)	(-9.508)
*LLP*MODEL*	4.378***	3.867***	3.548**	3.557**	3.863***
	(3.903)	(3.629)	(2.280)	(2.557)	(3.849)
*LLP*STRESS*	1.238	1.085	2.265	0.947	1.264
	(1.220)	(1.081)	(1.031)	(0.883)	(1.339)
*LLP*SIZE*		0.207*			
		(1.929)			
MODEL	-0.022*	-0.020	-0.015	-0.026*	-0.016
	(-1.658)	(-1.478)	(-1.014)	(-1.814)	(-1.345)
STRESS	-0.021	-0.020	-0.045	-0.023	-0.013
	(-0.923)	(-0.870)	(-1.179)	(-0.954)	(-0.671)
SIZE	-0.001	-0.002	0.008	-0.003	0.027***
	(-0.289)	(-0.515)	(1.457)	(-0.669)	(3.818)
C&I	0.013	0.014	0.004	0.026	0.019
	(0.315)	(0.351)	(0.062)	(0.641)	(0.510)
TIER1	0.064	0.058	0.591***	0.048	0.061
	(0.482)	(0.431)	(2.808)	(0.357)	(0.462)
EBP	2.544***	2.556***	2.373***	2.543***	2.547***
	(3.912)	(3.950)	(4.038)	(3.826)	(4.572)
M&A	-0.000	-0.000	0.000	-0.001	-0.000
	(-0.140)	(-0.224)	(0.255)	(-0.995)	(-0.447)
VIX	-0.001	-0.001	0.000	-0.001	-0.002***
	(-1.081)	(-1.078)	(0.029)	(-1.107)	(-2.588)
ΔUNRATE	-0.002***	-0.002***	-0.003**	-0.002***	-0.000
	(-2.774)	(-2.715)	(-2.446)	(-2.872)	(-0.390)
RECESSION	-0.021*	-0.020*	-0.028*	-0.021*	-0.024*
	(-1.676)	(-1.653)	(-1.895)	(-1.736)	(-1.935)
IMR_MODEL					0.102***
					(4.828)
IMR_STRESS					-0.013*
					(-1.762)
Intercept	0.118**	0.131**	-0.091	0.146**	-0.467***
	(2.099)	(2.288)	(-1.014)	(2.321)	(-3.237)
Observations	9,743	9,743	1,510	9,351	9,607
Adjusted R-squared	0.165	0.166	0.164	0.176	0.184

Table 7 (continued)

Panel B: Loan Growth by Loan Type

VARIABLES	**CONSGR** (1)	**REALGR** (2)	**C&IGR** (3)
LLP	-4.016***	-5.365***	-7.407***
	(-3.827)	(-4.311)	(-7.961)
*LLP*MODEL*	6.493***	2.872*	2.261
	(2.833)	(1.665)	(1.496)
*LLP*STRESS*	-1.243	0.857	2.772*
	(-0.707)	(0.574)	(1.850)
*LLP*SIZE*			
MODEL	-0.034	-0.017	-0.022
	(-1.287)	(-0.803)	(-1.204)
STRESS	0.015	0.013	-0.012
	(0.647)	(0.350)	(-0.402)
SIZE	0.010	0.007	0.005
	(1.056)	(1.279)	(0.649)
CONSUMER	0.267***		
	(3.166)		
REAL		-0.162	
		(-1.209)	
C&I			-0.084
			(-1.365)
TIER1	0.057	0.014	0.082
	(0.279)	(0.055)	(0.356)
EBP	1.665**	1.703	2.912***
	(2.506)	(0.734)	(3.703)
M&A	0.001	-0.002**	-0.000
	(0.793)	(-1.998)	(-0.187)
VIX	-0.003***	-0.007**	-0.001
	(-4.037)	(-2.194)	(-1.567)
ΔUNRATE	-0.000	0.004	-0.002
	(-0.253)	(1.053)	(-1.548)
RECESSION	-0.016	-0.018	-0.039**
	(-1.258)	(-0.422)	(-2.251)
Intercept	-0.153	0.296	0.039
	(-1.127)	(1.545)	(0.354)
Observations	9,723	9,682	9,703
Adjusted R-squared	0.043	0.119	0.104

Table 7 (continued)

This table presents an analysis of the effect of CRM disclosures on the relation between quarterly loan loss provisions and loan growth. The dependent variables are four-quarter loan growth measured over the window t-1 to t+3. Panel A reports the results using aggregate loan growth (LOANGR) as a dependent variable. Column 1 of this panel reports OLS estimation of the base model (equation (4)), column 2 reports estimation of the base model including the interaction of SIZE and LLP, column 3 reports the results for a propensity score matched sample for MODEL, column 4 reports the results of the base model eliminating observations with assets above $100 billion and the column 5 reports the estimation of the second-stage Heckman model, which includes the two inverse Mills ratios from the estimation of equation (5) reported in Table 3. Panel B reports analogous analyses with loan growth for consumer loans (CONSGR) in Column 1, real estate loans (REALGR) in column 2, and commercial and industrial loans (C&IGR) in column 3 as the dependent variables only for the base model, and with size interaction variable estimation in columns 4 to 6. We estimate the models using OLS pooling observations across the quarters of 2002-2010, with standard errors calculated clustering observations by firm and quarter. Continuous variables are winsorized at the top and bottom 1% levels. Coefficient *t*-statistics are in square brackets. ***, **, and * denotes significance at the 1%, 5%, and 10% levels, respectively, using two-tailed tests. All variables are defined in Appendix B.