Loan Loss Reserves Underprovisioning in U.S. Banks: Managerial Preferences for Gambling

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Abstract

We investigate why bank managers understate loan loss reserves (LLR) and the long-term consequences of this activity on solvency and bank fundamentals. We view underprovisioning as a gambling-type behavior cutting down on expenses for timely recognition at the risk of incurring higher future losses. Given the analogy with self-insurance avoidance, we test whether factors associated with insurance demand predict a greater LLR mismatch. Based on listed U.S. banks over 2001-2019, we find that the propensity of bank managers to leave troubled loans without reserve-funded coverage is greater for banks (1) having a risk culture with more tolerance for gambling; (2) facing recent poor performance or distress; (3) exhibiting systemic characteristics; and (4) having greater managerial discretion. The long-term consequences of this activity include a greater likelihood of future losses, higher volatility, lower transparency, eroded solvency, and reduced lending ability.

Keywords: Loan Loss Reserves, Underprovisioning, Gambling, Delayed Expected Recognition, Expected Losses.

JEL classifications: G11, G12, G21, G28.

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1 Introduction

Leading up to the 2007-2009 financial crisis, U.S. banks engaged in speculative activities that resulted in substantial nonperforming loans. Many lending firms expanded their balance sheets aggressively without setting aside adequate loan loss reserves (LLR henceforth). Late recognition of credit losses during the crisis cut into earnings and regulatory capital, increasing counterparty risk in the banking sector and disrupting the interbank market. Public authorities intervened to prevent the collapse of the financial system leading to the largest bailout in the financial industry in history.

In this paper, we examine the reasons underlying bank managers' decisions to understate LLR relative to the size of the credit portfolio at risk and discuss the long-term consequences of this behavior. Undoubtedly, the legal and regulatory environment, including tax legislation and accounting rules, have created structural incentives for managers to misstate LLR.[1] Yet, the full set of motives behind delaying expected credit loss recognition is less clear. Provisioning for LLR involves a form of "self-insurance" or operational hedging policy (Smith and Stulz [1985]) to contain the impact of future uncertain credit losses. Analogous to a conscious decision to save on insurance costs by cutting down on self-insurance or hedging coverage, we view loan loss reserve underprovisioning (LLRU henceforth) as a speculative behavior meant to cut down the immediate costs associated with early credit loss recognition at the risk of exposing the bank to potentially higher future losses in

[1] Historically, the main systematic driver of loan loss provisions in the U.S. was tax management (see Walter [1991] for a review). Before the Tax Reform Act of 1986, loan loss provisions were treated as tax deductible expenses provided LLR did not exceed a certain threshold. As a result, banks used to build up reserves close to the maximum level seeking to maximize tax shields. The Tax Reform Act of 1986 tied the amount of tax deductible expenses to the actual size of charge-offs for banks with assets over $500 million, thereby eliminating tax incentives for large banks. After this reform, accounting standards seem to have been the main systematic driver of credit loss provisions. For instance, backward-looking accounting methods, such as the Incurred Loss model, contributed to systematically foster a "too little, too late" problem in credit risk recognition (Financial Stability Forum [2009]).

adverse conditions; see, among others, Laeven and Majnoni [2003], Beatty and Liao [2011], and Bushman and Williams [2012, 2015]. Like other forms of gambling, LLRU might be linked to moral hazard and is more likely to occur under conditions of financial distress. Bailout assistance programs and government guarantees create incentives for risk shifting (Demirgüç-Kunt and Detragiache [1998], Gropp et al. [2014]) which may also interfere with setting appropriate loan loss provisions (LLP henceforth). While previous literature has examined how moral hazard encourages risk taking in investing activities, operational decisions such as credit loss provisioning have received much less attention. The analogy of LLRU with self-insurance avoidance offers a novel perspective in understanding the set of managerial drivers behind the delayed recognition of expected credit losses.

We hypothesize that the propensity of bank managers to understate LLR is driven by (1) managerial preferences for risk taking embedded in a bank's corporate risk culture, (2) bank-specific and market-wide factors that determine the cost-benefit trade-off of self-insurance and (3) insurance-type costs and idiosyncratic characteristics associated with moral hazard. These premises are supported by general considerations underlying the demand for self-insurance and hedging (Ehlrich and Becker [1972], Stulz [1984], Smith and Stulz [1985], Dionne and Eeckhoudt [1985], Briys and Schlesinger [1990], Schlesinger [2013]) and by incentives for risk shifting associated with moral hazard (Jensen and Meckling [1976]). To test these hypotheses, we examine a broad sample of publicly traded U.S. banks in the period 2001-2019 involving 23,258 quarter-bank observations from 748 firms. LLRU is measured as the mismatch between the bank's credit portfolio at risk (both nonperforming and underperforming loans) and LLR. We conduct two sets of analyses.

First, we determine the main drivers of LLRU by means of predictive panel-data regressions at horizons from one quarter to one year. Since corporate risk and gambling preferences are not directly observable, we use geographic variation in the ratio of Catholic to Protestant population in the U.S. county in which a bank is headquartered to proxy for corporate risk culture (Kumar [2009], Kumar et al. [2011], Chen et al. [2014]). Other predictive variables include bank-specific characteristics associated with performance, financial health, systemic importance and discretionary LLP, as well as market-wide indicators capturing environmental conditions. Our findings lend support to the gambling-behavior prediction for LLRU. Banks with greater proclivity for speculative risk and especially those facing more adverse economic conditions are more prone to understate LLR relative to troubled loans. Our most significant predictors include strong preferences for risk taking and gambling, low past bank profitability and poor recent market performance, high idiosyncratic volatility and skewness, and high bank managerial discretion in LLP. Stress conditions in the financial markets and the real economy such as low or negative real GDP growth and high state unemployment rates are also significant predictors of greater LLRU. The role of moral hazard in this class of operational decisions is evident via bank size and short-term wholesale liquidity over-reliance.

Second, we examine the long-term consequences of LLRU on operational risk, bank insolvency, accounting transparency, and bank lending ability. We hypothesize that greater LLRU will result in lower asset quality leading to greater long-term risk exposure and eroded lending ability; see Beatty and Liao [2011] and Bushman and Williams [2012, 2015]. To test this prediction, we carry out panel-data regressions examining the forecasting ability of LLRU on the above performance measures over a three-year horizon controlling for idiosyncratic and market-wide variables. We find that greater divergence between troubled loans and LLP is a significant predictor of a higher likelihood of future bank losses, greater insolvency risk, lower accounting earnings quality and a greater volatility in stock returns.

Greater LLRU is also a robust predictor of lower future bank lending activity. This evidence complements and extends the results of Beatty and Liao [2011] and Bushman and Williams [2015] from a different theoretical and methodological perspective.

The remainder of the paper is organized as follows. Section 2 develops the arguments for the gambling-type nature of LLRU, reviews the related literature and states our main hypotheses. Section 3 describes the main variables. Section 4 details our methodological approach and discusses our main empirical results. Section 5 summarizes and concludes. An appendix discusses the theoretical link between loan loss provisioning and risk preferences.

2 Literature and hypothesis development

2.1 Background and related literature

LLR represent the size of currently expected losses from uncollectible loans based on the assessment of bank managers. From a regulatory perspective, LLR provide a cushion against *expected* losses, playing a complementary role to regulatory capital which provides a buffer for *unexpected* losses (Laeven and Majnoni [2003]).

While charges against earnings are the most direct consequence of LLR, provisioning credit losses can also have economic implications on the firm's value.[2] Under the risk-based capital regulatory framework, additions to LLR reduce core capital, which may force a bank in distress to raise new equity to restore capital adequacy. Unanticipated increments in LLP may also induce negative announcement effects if market investors interpret this as a negative revision of the bank's expectations (Docking et al. [1997], Blose [2001]). In

[2]The costly nature of LLR has been outlined in the previous literature; see, among others, Beaver et al. [1989], Ahmed et al. [1999], Kanagaretnan et al. [2005] and references therein.

turn, stock price declines in the context of deteriorating bank performance and asymmetric information may increase concerns over bank failure, leading to tighter monitoring and related costs, higher FDIS insurance cost premia and bank runs; see, for example, Akins et al. [2017]. Consequently, the total economic cost associated with LLR depends on firm-specific as well as market-wide circumstances and may well exceed the size of the direct charge against earnings.

As these costs increase, bank managers have stronger incentives to conceal private expectations. As loans are opaque assets, banks can hide expected losses more effectively than other firms (Morgan [2002]). Leaving uncollectible loans without adequate reserve coverage can, however, have dire consequences because it is likely that hidden expected credit losses will have to be recognized in the future. Consequently, understating LLR not only erodes accounting credibility and increases informational asymmetry (overstating the bank's asset quality and earnings potential), but it also creates loss overhangs that may impair the bank's ability to withstand unexpected future losses. As a result, the eventual realized costs associated with delayed expected loss recognition may well exceed the initial cost-saving benefits from cutting down on self-insurance coverage, particularly if the bank is forced to recognize loss overhangs during an economic downturn when earnings are low, market volatility is high and raising equity is more costly (Laeven and Majnoni [2003], Beatty and Liao [2011], Bushman and Williams [2015]).

Given that bank managers are aware of these risks, purposely understating LLR amounts to a speculative decision that aims to save on the costs associated with self-insurance and timely credit loss recognition at the risk of exposing the bank to much higher future losses from delayed recognition. The effectiveness of this managerial gambling behavior depends on the occurrence of credit default and, thus, LLRU is a managerial bet against this hazard event. Even though late recognition is a likely outcome, the allure of LLRU is that it also embeds a gambling-type benefit (namely, a chance that default will not eventually materialize and loan losses will not occur). Essentially, though, this practice buys time before likely default materializes. This "wait-and-see" incentive for delayed loss recognition, already recognized by regulators (European Commission [2018]), makes a bank's decision to leave troubled loans without adequate LLR coverage analogous to a decision not to fully take out self-insurance against a hazardous event.

As a result, LLRU involves aspects commonly associated with speculative risk and gambling behavior. Thus, bank managers are more likely to engage in this activity when they have strong preferences for risk taking and especially when the bank faces dire economic circumstances, which also makes building up LLR coverage more costly. Public bailout guarantees may further encourage LLRU even when the expected cost from delayed recognition exceeds the current benefits due to risk shifting and moral hazard. We further elaborate on this hypothesis in the next subsection.

LLRU may take several forms. Previous work emphasized the role played by earnings management in the discretionary setting of LLP; see Balboa et al. [2013] for a discussion. Understating LLR with the aim of reducing the volatility of reported earnings (i.e., earnings smoothing) is a form of LLRU. More evidently, when banks are close to failure, bank managers have the strongest incentives to hide incurred but as yet unrealized credit losses as part of gambling for resurrection (Acharya and Ryan [2016]). This form of accounting-type speculative activity represents the most pervasive manifestation of LLRU as it increases risk shifting and the likelihood of future bank failure.

Our paper is more closely related to two main strands of the literature. First, in the empirical accounting and regulatory banking literature, there is considerable interest in addressing the consequences of LLR inadequacy on financial stability (see Beatty and Liao [2014] for an overview). Within the broader accounting literature, our paper is closely related to Beatty and Liao [2011] and Bushman and Williams [2015]. Beatty and Liao [2011] analyze the consequences of delayed loan loss recognition on future lending activity under the credit crunch hypothesis. The authors use various proxies to capture delay, including a dummy variable signaling values below the median of the reserve coverage ratio. Our study builds on a similar accounting information foundation but our methodological approach and scope are substantially different. Bushman and Williams [2015] analyze the effects of delayed recognition on individual and systemic risk measures, employing a flow measure given by the incremental gain in R^2 from two time-shifted regressions; see also Beatty and Liao [2011]. We rely on accounting ratios that are directly observable. Additionally, while Bushman and Williams [2015] focus on the consequences of delayed recognition on systemic risk, we show that moral hazard increases the propensity to delay expected losses in banks with systemic characteristics.

Second, there is a great interest in corporate finance and asset pricing to understand the role played by managerial risk attitudes in financial decisions. According to this literature, local attitudes toward risk can help explain a greater predisposition by firms to engage in managerial decisions involving greater risk taking; see, among others, Hilary and Hui [2009], Shu et al. [2012], Chen et al. [2014], and Adhikari and Agrawal [2016]. Within this literature, our paper is closely related to Christensen et al. [2018] who show that banks headquartered in areas in which gambling is more socially acceptable have a greater predisposition for intentional accounting misreporting. Our study shows that banks in such areas are more likely to understate LLR.

2.2 Main hypotheses

Given the analogy with a conscious decision not to take out self-insurance against a hazardous event to save on insurance costs, our main hypothesis is that the key drivers for managerial gambling attitudes concerning expected loan loss recognition in banks should be related to the demand for insurance and hedging. As discussed previously, moral hazard further interferes in this context. Accordingly, we develop three interrelated hypotheses that involve risk preferences.

H$_1$: (**Risk attitudes**) *Banks with a corporate risk culture characterized by stronger tolerance for gambling will, all else being equal, hold a greater proportion of troubled loans not covered with LLR, thus more actively engaging in LLRU.*

Corporate risk culture represents a set of attitudes toward risk and uncertainty shared by the corporation's leaders (Pan et al. [2017]). Because of the speculative connotations associated with LLRU, banks characterized by a corporate risk culture more tolerant to speculative risk-taking (or less strict concerning risk control and supervision) will have a stronger propensity to understate LLR. H$_1$ is supported by theoretical arguments concerning self-insurance given in Ehlrich and Becker [1972], Dionne and Eeckhoudt [1985], Briys and Schlesinger [1990], Konrad and Skaperdas [1993], and Machina [2013]. Similarly, Stulz [1984] and Smith and Stulz [1985] show the relevance of managerial preferences in operational hedging, which can be readily extended to our context since LLR coverage provides an operational hedge. In line with these arguments, we show in the appendix that a decrease in the bank's level of risk aversion increases its propensity to engage in LLRU.

H_2: (**Coverage costs**) *LLRU is influenced by bank-specific and market-wide economic conditions that determine the current cost of building up LLR. The greater the relative costs of purchasing self-insurance, all else being equal, the greater the LLR deficit.*

Two interrelated arguments support H_2. First, the cost of building up LLR is influenced by firm-specific and market-wide conditions which determine the market's assessment of the quality of the bank's loan portfolio (Walter [1991]). Like insurance premia, this cost is greater in distress (when the hazard event is more likely to occur). Hence, we expect a greater propensity to leave troubled loans without reserve coverage in more adverse conditions, precisely when building up LLR is more costly.[3] Second, consistent with H_1 above, poverty conditions and financial distress may further increase the propensity for gambling (Kumar [2009], Kumar et al. [2011]). Accordingly, we assert that bank managers are more likely to understate LLR when the bank is facing distress conditions. Delaying credit loss recognition not only conceals negative information but it also represents a speculative activity attempting to improve the bank's financial condition by taking on greater operational risks. This gambling-type behavior extends beyond LLP and can affect the overall quality of financial reporting; see, for instance, Christensen et al. [2018].

H_3: (**Moral hazard**) *Banks that are more likely to benefit from public bailout guarantees owing to their systemic relevance are, all else being equal, more prone to understate LLR relative to troubled loans.*

[3]Ehlrich and Becker [1972] show that a risk averse expected utility maximizer will engage in self-insurance strategies. The optimal coverage depends on the cost of the self-insurance policy. If this cost exceeds its fair market value, the agent will optimally decide to leave some risks uninsured and take out only partial coverage, consistent with Mossin's theorem.

A greater mismatch between LLR and troubled loans may reflect managerial "optimism" about future bank conditions, which manifests in a conservative appraisal of the probability of default and/or the size of future losses. While several factors may underlie such views, in close connection to H_1 and H_2 above, the existence of public bailout guarantees may further exacerbate the bank's propensity to take on operational risks and understate LLR owing to moral hazard. Banks whose systemic characteristics make them too big or too interconnected to fail have a higher expectation of benefiting from public guarantees (Farhi and Tirole [2012]). Therefore, they have greater incentives for delaying credit loss recognition as they can shift negative consequences onto outsiders. H_4 is directly supported by the literature on moral hazard and risk-shifting (Jensen and Meckling [1976]). H_4 is also supported by the theoretical considerations relating to the demand for self-insurance. Public bailout guarantees and subsidies reduce the size of expected losses borne by shareholders, hence reducing the cost of self-insurance. In close connection to H_1 and H_2, a risk averse bank manager will optimally accept greater exposure to uninsured risk in the presence of public bailout guarantees, particularly when the current cost of self-insurance is high.

The following two hypotheses concern the main channel that facilitates LLRU activity and address the long term consequences of this form of managerial gambling, respectively:

H_4: (**Channel**) *Given that bank managers can use their discretion to set LLR, greater accounting discretion, all else being equal, would increase LLRU.*

H_5: (**Long-term consequences**) *Over the long term, LLRU behavior increases asymmetric information and reduces asset quality and solvency, thereby eroding the bank's ability to lend.*

Bank managers can manipulate earnings and engage in LLRU activity using accounting discretion in LLP. According to H_1, this establishes a causal link between LLR and risk preferences. Greater accounting discretion, enabling greater ability to set lower LLR, allows bank managers to engage in LLRU more actively. Further, since the discretionary component of LLP represents the size of manipulated earnings, it also reflects the size of the insurance-like premium associated with LLRU in terms of earnings write-downs. Hence, consistent with H_2, we expect a positive relation (in absolute terms) between the discretionary component of LLP and LLRU activity. H_5 arises as a direct consequence of the pervasive nature of LLRU. Since currently unrecognized expected loan losses are likely to be recognized down the road, they create loss overhangs that loom over future bank profitability and capital adequacy (Bushman and Williams [2015]). According to the credit-crunch hypothesis, banks in distress are likely to cut down on lending to preserve capital adequacy. Hence, we expect LLRU to reduce loan supply.

3 Data

Our primary source of data is the Bank Regulatory Database of the Federal Reserve Bank of Chicago. This comprises quarterly data obtained from required regulatory forms filed for supervisory purposes by regulated depository financial institutions. We focus on publicly-traded bank holding companies and commercial banks during the period 2001-2019 and collect data on a number of bank-specific variables from the balance sheet and income statements. The choice of the sample period is solely dictated by data availability, since data on underperforming loans, Tier 2 Capital and excess allowance for loan and lease losses are not available before 2001.[4] Additionally, we use a range of variables obtained from different sources. All stock market data come from CRSP database on WRDS. Market-wide variables related to macroeconomic and financial conditions, such as real GDP growth at the state level, local unemployment rates, and yield spreads are obtained from FRED database at Federal Reserve Bank of St. Louis. We also use geographic variation in religious composition across U.S. counties to capture differences in local gambling risk attitudes. These data, compiled by the Glenmary Research Center, are available from the American Religion Data Archive (ARDA).

Subsection A below describes our measures for LLRU. Subsections B to E describe the set of bank-specific and market-wide variables used to address hypotheses H_1 to H_4. Finally, subsection F describes the variables associated with different accounting and bank fundamentals used to address H_5.

A. Measures of LLRU

The difference between the numbers reported in the balance sheet of a bank and the "true" size of uncollectible loans given managerial expectations is unobservable to outsiders. Following Beatty and Liao (2011), we consider an observable accounting ratio directly related to the imbalance between LLR and defaulting loans. For the i-th bank at quarter t, we define:

$$logRC_{it} = log\left(\frac{LLR_{it}}{UPL_{it} + NPL_{it}}\right)$$

[4]More specifically, the Federal Financial Institutions Examination Council (FFIEC) established a charge-off policy for open-end credit at 180 days delinquency and closed-end credit at 120 days delinquency with guidelines for re-aging, extending, deferring, or rewriting past due accounts. The implementation date for these changes was extended to December 31, 2000. Since the charge-off policy affects nonperforming loans, our sample begins in 2001 to ensure regulatory homogeneity in the data.

where LLR is the bank's allowance for loans and lease losses reserves, and UPL and NPL are the size of underperforming and nonperforming loans, respectively.[5] LLR relative to NPL, usually referred to as the reserve coverage (RC henceforth) ratio, is an important accounting metric used in financial analysis and accounting reporting in the banking industry; see, for example, European Commission [2018]. This ratio has been the subject of specific regulation in the European Union requiring a common minimum loss coverage level for nonperforming loans. Higher values of LLR relative to the bank's loan portfolio at risk is generally associated with a better ability to absorb future loan losses and a lower delay in credit loss recognition; see, for example, Beatty and Liao [2011] and Akins et al. [2017]. We include UPL in the denominator of this ratio since defaulting loans at an early stage of delinquency may also affect the understating of LLR. The usual logarithmic transformation is used to smooth extreme observations in the upper tail of the distribution and induce homoskedasticity in the regression residuals, rendering the analysis of LLRU determinants more reliable.[6] The resulting variable, logRC, is our main measure of LLRU and is used to address hypotheses H_1 to H_5 in Section 4.

For robustness, we also consider the *credit loss uncovered exposure* (CLUE) ratio:

$$CLUE_{it} = \frac{UPL_{it} + NPL_{it} - LLR_{it}}{LOANS_{it}},$$

[5]Loans are classified as nonperforming if the debtor has made zero payments of interest or principal within 90 days or is 90 days past due. Underperforming is a previous stage in which the time reference is 30 days.

[6]The ratio LLR/(UPL+NPL) exhibits a massive degree of right skewness (6.89) and kurtosis (59.87) even after winsorization owing to the presence of extreme outliers on the upper tail of the distribution. While logRC is still right-skewed (0.76) and leptokurtic (4.85), parameter estimation in the regression analysis of this variable can be conducted without the influence of extreme outliers.

This variable measures the LLR imbalance relative to the size of the loan portfolio scaling by the size of outstanding loans (LOANS).[7] This scaled variant of the RC ratio can predict more accurately the long-term consequences of LLRU in addressing H_5 as it is more informative about the size of the risk exposure involved. A larger proportion of troubled loans not covered by LLR relative to the total loan portfolio is more likely to indicate that provision expenses are insufficient and credit losses are more likely to be realized in the future. A comparative drawback of this variable in addressing H_1 to H_4, however, is that its domain includes both positive and negative values, which prevents us from implementing the usual logarithmic transformation on the dependent variable. As in Beatty and Liao [2011], we alternatively consider a dummy variable indicating values of the CLUE ratio greater than the cross-sectional median at a specific quarter. The resulting variable, termed I(CLUE), is associated with banks that are more likely to engage in aggressive LLRU policies. We rely on this indicator to characterize the representative profile of banks speculating with reserves in Section 4 as an alternative measure to logRC in the analysis of H_1 to H_4 for the sake of robustness.

[Insert Figure 1 around here: logCR and CLUE]

Figure 1 shows the time-series dynamics of the 10th, 50th and 90th percentiles of the quarterly cross-sectional distribution of the LLR/(UPL+NPL) and CLUE ratios over the sample period. Since the two measures are closely related but the latter is somewhat more informative, we discuss here the main sample features exhibited by CLUE. On average, defaulting loans not covered with LLR represent a small portion of outstanding loans. The mean value of CLUE over the whole period is 0.869% but this ratio displays substantial

[7] The ratio CLUE exhibits strong non-Gaussian features, given by right-skewness (3.04) and kurtosis (15.97). Unfortunately, the log-transform is not feasible in this case because about 48% of observations of this variable are negative).

cross-sectional dispersion and pro-cyclical variability. Before the 2007-2009 financial crisis, banks appear to follow a prudent accounting policy holding LLR that exceed the size of their loan portfolios at risk (about 53% of observations in the CLUE ratio during this period are negative). However, this changes radically during the 2007-2009 crisis. Over this period, bad loans not covered with LLR represent a sizable 1.81% of total loans. Furthermore, the propensity to keep an excess of LLR over defaulting loans decreases dramatically: the large increment in the size of the credit portfolio at risk is not matched with LLR. For example, about 93% of the quarterly observations of the CLUE ratio during 2009 are positive, indicating a greater likelihood of LLR deficits. In the post-crisis period, the relative size of uncovered loans mean-reverts to average levels similar to those before 2007. Figure 1 also reveals a strong cyclical pattern in our LLRU measures. Common accounting practices fostering delayed recognition of credit losses under the prevailing Incurred Loss model are, to a large extent, responsible for this pattern. Nevertheless, the strong cross-sectional dispersion observed suggests that a number of firm-specific factors beyond common regulatory drivers must have intervened in the decision to leave troubled loans uncovered.

B. Corporate risk culture

To test H_1, we proxy (unobservable) managerial risk attitudes with variables that reflect local risk culture in the geographic area in which the bank is headquartered. Existing literature provides two main reasons why local risk attitudes shape corporate risk culture. On the one hand, the distinctive values of local culture influence the profile of corporate professionals, attracting managers and other employees who share a similar background and views as the firm. On the other, managers and other employees interact with the local environment, adopting personal behaviors that conform to the social norms of the surrounding community, even if these norms do not necessarily correspond to their personal views; see Shu et al. [2012], Christensen et al. [2018] and references therein for a review. Following previous research (Kumar [2009], Kumar et al. [2011]), we use geographical variation in the logarithm of the Catholic to Protestant Ratio (LOGCPR) at the county level to proxy for local corporate risk culture. A higher proportion of Catholic relative to Protestant population has been associated with stronger preferences for risk.[8]

C. Insurance cost determinants, global conditions and other factors

To address H_2, we consider several firm-specific and industry-wide environmental variables. Bank-specific variables include: (1) the bank's profitability (or management quality), measured by return on assets (ROA); (2) risk exposure in the real estate lending market (REXP), measured as the ratio of real estate loans to total loans; (3) the bank's book to market (BM) ratio; (4) Tier 1 capital (TIER1); (5) Tier II capital management (TIER2CM) as per Ng and Roychowdhury (2014), proxied by a dummy variable indicating if LLR are below 1.25% of gross risk-weighted assets;[9] (6) local contagion or local distress conditions (CONTAGION), measured by the sum of all losses (in absolute value) generated by all bank failures in the same state in a given quarter based on data from FDIC failures file; (7) stock market performance, measured by quarterly stock return (RETURN); (8) idiosyncratic volatility (IV) and (9) idiosyncratic skewness (IS), defined as the sample standard deviation and sample skewness of the residuals based on the 3-factor Fama-

[8]We construct this variable considering the number of adherents to the Catholic Church relative to adherents to Anglican and Mainline Protestant Churches at the county level using data from ARDA. Data at the county level in this database are only available for the years 1980, 1990, 2000 and 2010. Following previous studies, we linearly interpolate the available data to obtain missing observations between 2001 and 2010 and keep the values from 2010 constant for the last part of our sample as in Shu et al. [2012]).

[9]It is zero for those banks above this threshold and for banks using internal ratings as the limit of gross risk-weighted assets does not apply to them.

French model estimated with daily data for each quarter, respectively. We also include market-wide environmental variables reflecting macroeconomic and financial time-varying economic conditions that are common for all banks in a certain area, captured by (10) the unemployment rate (UNEM) at the state level, (11) real GDP growth (GDPG) at the state level, and (12) yield spread (YIELDSP), measured as the spread between the U.S. Treasury benchmark 10-year bond and the U.S. 3-month T-bill. Under H_2, we expect that distress and poor bank performance will predict a greater propensity to understate LLR.

The remaining variables (REXP, CONTAGION, TIER1 and TIER2CM) represent firm-specific controls. REXP proxies for credit risk and also helps control for risk appetite. CONTAGION reflects distress in the local geographic area and proxies for local incentives to engage in accounting manipulation. Previous literature has also underlined the incentives associated with capital management in LLP, TIER1 and TIER2CM control for this effect. Depending on prevailing incentives to use LLP to manage core capital or total capital, TIER1 can be positively or negatively related to LLR (Ahmed et al. [1999]). Previous evidence yields mixed results; see, for example, Beatty and Liao [2011]) and Balboa et al. [2013] for a review.

D. Moral hazard

To address H_3, we proxy for the influence of moral hazard with bank size, measured by the natural logarithm of total assets (SIZE), and systemic interconnectedness, measured by the ratio of short-term wholesale funding to total assets (STWF) capturing the extent of short-term liquidity over-reliance. Both variables are major drivers of systemic importance and increase the expectation of benefiting from implicit government bailout guarantees (see, López-Espinosa et al. [2012] and references therein).

E. Discretionary loan loss provisioning

To address H_4, we estimate the discretionary component of loan loss provisions (DLLP) in each quarter as the residuals from a cross-sectional regression of LLP deflated by total assets on a number of non-discretionary variables (nonperforming loans, underperforming loans, change in nonperforming loans, change in underperforming loans, loans over total assets, and loan loss reserves over underperforming and nonperforming loans lagged one quarter). In these cross-sectional regressions, we rely exclusively on information available up to a specific quarter to ensure that results are not driven by forward-looking bias. According to H_4, DLLP should be positively related (in absolute value) to LLRU.

F. Long-term consequences of LLRU

Since LLRU increases the probability of loss overhangs that will have to be recognized in the future, a greater proportion of troubled loans not covered with LLR should predict bank distress. These practices also imply reduced accounting transparency and reductions in the loan supply because a distressed bank is likely to cut on loans to preserve capital adequacy (Beatty and Liao [2011]). We test H_5 analyzing the predictability of logRC and CLUE on the following bank performance measures, computed over subsequent 12-quarter rolling-window periods: (1) the likelihood of realized losses ($LOSSES$), defined as the natural logarithm of one plus the relative frequency of negative earnings; (2) operational uncertainty, measured by the volatility of ROA and ROE, denoted as $\sigma(ROA)$ and $\sigma(ROE)$, respectively; (3) market volatility, measured by the volatility of quarterly stock returns, $\sigma(RET)$; (4) accounting transparency, measured by the volatility of DLLP, denoted as $\sigma(DLLP)$; (5) insolvency risk, measured by the natural logarithm of Altman's Z-score, determined as $log((E+AROA)/\sigma(ROA))$, with E denoting the equity to total assets ratio at the end of the period and $AROA$ the average ROA; and (6) changes in the loan supply ($\Delta LOAN$), measured by the average quarterly change in bank loans over the period.

4 Regression models and results

This section is divided into two subsections. In Subsection 4.1, we discuss the main results from testing H_1 to H_4 based on predictive regressions of logRC and I(CLUE) as measures of LLRU at different horizons from one to four quarters. According to previous literature, the RC ratio and related measures can be predicted on the basis of current information (Beatty and Liao [2011]). Thus, we identify the main drivers that, given current macroeconomic and bank-specific conditions, may cause a greater mismatch between LLR and troubled loans. In Subsection 4.2 we discuss the main results from testing H_5, assessing the ability of logRC and CLUE to predict a set of accounting and financial measures associated with accounting quality, operational risk and solvency in Section 3.1.F. This is of particular interest from a bank regulatory perspective as it allows early warning signals of bank distress.

4.1 Predicting LLRU

To test hypotheses H_1 to H_4, we estimate the following regression model:

$$\begin{aligned} logRC_{it+h} \;=\; & \alpha + \delta_i + \beta_1 LOGCPR_{it} + \beta_2 DLLP_{it} + \beta_3 REEXP_{it} + \beta_4 ROA_{it} + \\ & \beta_5 RETURN_{it} + \beta_6 IV_{it} + \beta_7 IS_{it} + \beta_8 SIZE_{it} + \beta_9 BM_{it} + \\ & \beta_{10} TIER1_{it} + \beta_{11} TIER2CM_{it} + \beta_{12} CONTAGION_{it} + \beta_{13} STWSF_{it} + \\ & \beta_{14} YIELDSP_t + \beta_{15} UNEMP_{it} + \beta_{16} GDPG_{it} + \varepsilon_{it} \qquad (1) \end{aligned}$$

at horizons of $h = 1, 2, 3, 4$ quarters ahead. The right-hand side variables are as described in Section 3.1, ε_{it} denotes a random error obeying standard assumptions, δ_i captures individual bank fixed effects, and $(\alpha, \beta_1, ..., \beta_{16})'$ are unknown parameters. Equation (1) is estimated using panel-data regressions with fixed effects at the bank level and two-way cluster-robust standard errors accounting for bank and quarter. All variables are winsorized at the top and bottom 0.5% to reduce the influence of extreme values. Table 1 presents descriptive statistics of the man variables involved at the firm-quarter level.

[**Insert Table 1 around here: Descriptive statistics**]

The sample mean of logRC is -0.149 (1.357 in the original scale), showing that most banks implement prudent policies, keeping reserves in excess of troubled loans. This variable exhibits a strong degree of volatility (0.826) resulting from both serial and cross-sectional variation. The mean value of LOGCPR is -0.464 (1.93 in the original scale), showing that publicly traded U.S. banks are mainly located in areas with a relatively high proportion of Catholic population. The average annualized idiosyncratic volatility is 28.46% and the average annualized return is 8.08%.

4.1.1 Main results

The main results from estimation of model (1) are reported in Table 2. Several observations are noteworthy. First, consistent with H_1, LOGCPR is a strongly significant predictor of logRC at all the considered horizons. Accordingly, managers of banks headquartered in geographic areas with more social tolerance for gambling, proxied by a greater proportion of Catholics relative to the Protestant population, maintain lower LLR relative to the size of the credit portfolio at risk and actively delay credit risk recognition. Estimates of the elasticity coefficient β_1 across different horizons h decrease as h increases, exhibiting significant predictive ability. This evidence is consistent with underlying risk preferences having little temporal variability leading to persistent LLR policies over time.

[Insert Table 2 around here: Predictive regression logRC]

Further, as posited in H_2, bank managers are more likely to understate LLR relative to troubled loans under distress conditions when the relative costs associated with building up LLR rise (and so do the incentives for deferring credit loss recognition). In particular, at the firm level, lower accounting (ROA) and market (RETURN) performance, as well as greater idiosyncratic volatility (IV) are significant predictors of LLRU at all horizons. Idiosyncratic skewness (IS), usually associated with extreme but infrequent movement in stock prices, exhibits short-term predictive ability for logRC. Accordingly, quarters in which stock prices experience extreme idiosyncratic drops are generally followed by a significant reduction of LLR relative to troubled loans over the next two quarters. As anticipated from the strong cyclical time series dynamics of Figure 1, market-wide conditions associated with economic and financial distress are also powerful predictors of LLRU, as evident by the significance of related environmental variables (GDPG, YIELDSP, and UNEMP).

While most banks seem to opt for a prudent policy regarding credit loss recognition during good times, some allow LLR to fall relative to the size of the portfolio at risk during bad times when reserve coverage is most needed. This supports the claim that purchasing LLR coverage is relatively cheap during good times but becomes increasingly expensive during bad times.

Third, after controlling for firm-specific characteristics and general macroeconomic conditions, larger bank size and greater interconnectedness manifested in greater reliance on short-term wholesale funding (STWSF) are significant predictors of LLRU at all horizons. Since bank size and interconnectedness are major drivers of systemic risk, this is also consistent with the hypothesis that LLRU is a manifestation of risk shifting and moral hazard, as posited in H_3. Accordingly, the presence of public guarantees gives managers of banks with systemic characteristics enhanced incentives for gambling with credit loss recognition.

Fourth, the current estimate of the discretionary component of loan loss provisions (DLLP) is a significant predictor of logRC at all horizons. DLLP is estimated with cross-sectional information available up to a particular quarter. The estimated coefficients on DLLP are positive, indicating that discretionary reductions in current expenses for loan provisions (i.e, negative values of DLLP) predict subsequent reductions in logRC over the following quarters. Because negative values of DLLP capture the current estimate of unrecognized future expected losses, they provide a rational expectation of the size of loss overhangs that need to be recognized in the future. Consequently, this evidence also lends support to H_2.

Concerning the remaining control variables, the coefficient estimates on TIER1 are negative. This is consistent with evidence reported in Ahmed et al. [1999], Laeven and Majnoni [2003], and Bikker and Metzemakers [2005] and suggests bank managers use loan loss provisions to manage total capital. Similarly, the coefficients on TIER2CM are negative and highly significant. Greater risk exposure in the real estate sector (REEXP) is negatively associated with logRC but it is statistically significant only in long-term forecasts. Variables CONTAGION and BM do not add incremental predictive power.

These findings help understand better the cross-sectional disparity exhibited by the logRC ratio. While the Incurred Loss model promotes the late recognition of expected losses and is a major driver underlying the pro-cyclical dynamics exhibited by CLUE, the above analysis uncovers additional incentives at the bank-level that exacerbate LLRU.

4.1.2 Characteristic profile of bank gambling behavior

I(CLUE), taking value one for observations of CLUE higher than the cross-sectional median in a given quarter, identifies banks that are more likely to engage in aggressive LLRU and delay more recognizing expected losses; see Beatty and Liao [2011] for a similar identification strategy. We characterize here the average profile of such banks by regressing I(CLUE) on the right-hand side variables of model (1).[10] This analysis also provides robustness to the main results of the previous analysis with an alternative proxy of LLRU and a slightly different methodological approach.

[Insert Table 3 around here: I(CLUE) analysis]

Table 3 reports the main results, which agree with the main qualitative picture discussed previously. The most representative features underlying large LLR deficits relative to total loans are banks i) with large capitalization (SIZE is a positive and highly significant predictor at all horizons), ii) facing distressed conditions reflected in low profitability and large drops in share value (significant coefficients on ROA, RETURN and BM), and iii) headquartered in geographic areas with more tolerant views on gambling (LOGCPR is positive and significant). Whereas certain differences arise with the results reported in the previous section, the main conclusions are similar.[11]

[10]Because the dependent variable is discrete, we could alternatively use a logistic regression. As in Christensen et al. [2018], we opt for the linear regression model to be able to deal with fixed effects and because linear regression still produces consistent estimates in this context.

[11]For example, LOGCPR is significant at horizons of 1, 2 and 3 quarters ahead, but loses predictive ability at longer horizons. Also, BM is more important as a measure of bank-specific distress than IV.

4.1.3 Gambling incentives under distress

H_1 and H_2 suggest that managerial incentives for speculating with the recognition of credit losses are stronger in banks that have a more tolerant risk culture and face distress conditions. This suggests that the interaction of local risk preferences and bank-specific distress is associated with stronger incentives for managerial gambling activity. A priori, a variable to capture distress at the bank level is idiosyncratic volatility (IV). We build a proxy of strong incentives for gambling using the interaction of LOGCPR and IV, denoted INCTGAMB. An advantage of this uncertainty-related measure is that it eases the interpretation of results. Because the largest values of INCTGAMB come from high values of IV and LOGCPR, under H_1 and H_2 the coefficient associated with this variable must be negative in the predictive regression of logRC and positive in the predictive regression of I(CLUE). In contrast, the sign of the coefficient associated with the interaction of LOGCPR and ROE, for example, is unclear as these variables are expected to generate opposite effects on LLRU.

We thus consider the regression model:

$$Y_{it+h} = \alpha + \delta_i + \beta' X_{it} + \xi \ INCTGAMB_{it} + u_{it} \tag{2}$$

with Y_{it+h} being logRC or I(CLUE), X_{it} the vector of predictive variables on the right-hand side of model (1), β a conformable vector of parameters, and u_{it} the error term. The results from the estimation of model (2) are presented in Table 4.

[Insert Table 4 around here: Gambling incentives]

The results on the role played by risk preferences can be summarized as follows. First, the coefficient of INCTGAMB exhibits the expected sign under the posited hypotheses, i.e., it is significantly negative in predicting logRC and positive for I(CLUE) at all horizons. Second, compared with model (1), the inclusion of the interaction term INCTGAMB reduces the statistical significance of LOGCPR, yielding mixed evidence on the unconditional role played by risk preferences. In the predictive regression of logRC, the coefficient on LOGCPR is negative for all horizons, but here it is marginally significant (90% confidence level) in one-side testing at $h = 1$ and non-significant at the remaining horizons. This suggests that risk preferences for gambling on LLR are manifested mostly during periods of distress. In periods of low idiosyncratic volatility, geographical differences in CPR do not lead to significant changes in the propensity to understate LLR. On the other hand, in the predictive regression on I(CLUE), the coefficient on LOGCPR is positive and significant at the 99% and 95% levels at horizons of one- and two-quarters ahead, respectively. This suggests that risk preferences lead bank managers in areas with high CPR to set lower LLR even during periods of low idiosyncratic volatility. During periods of high volatility, this effect is more pronounced. The remaining variables are not affected by the inclusion of INCTGAMB.

In sum, INCTGAMB, capturing both local risk preferences and bank-specific distress condition via idiosyncratic volatility, is one of the most significant variables in predicting LLRU activity. While the role played by risk preferences directly is not conclusive, this analysis provides strong support to the central hypothesis that LLRU is a speculative activity most pronounced in periods of distress and in geographic areas characterized by a local risk culture which is more permissive to gambling behavior.

4.1.4 Risk preferences and LLR

In this subsection, we examine further the empirical link between risk preferences and troubled loans. To this end, note that logRC can be rewritten as:

$$logRC_{it} = log\left(\frac{LLR_{it}}{LOANS_{it}}\right) - log\left(\frac{UPL_{it} + NPL_{it}}{LOANS_{it}}\right)$$

reflecting the difference of the natural logarithms of the LLR to loans ratio and the defaulting loan ratio. We refer to these components as logLLR and logDR, respectively. While our hypotheses do not imply any restriction on logDR, a testable restriction under H_1 and H_4 is that risk preferences exhibit predictive power on LLR and, hence, on logLLR as there is a persistent causal link between these variables. Table 5 reports the results from a panel data regression of logLLR on the lagged values of the predictive variables on the right-hand side of regression (1). Our main interest focuses on the coefficient on LOGCPR. For completeness, Table 5 also reports results from the predictive regressions of logDR. Although our hypotheses do not impose restrictions on this ratio, it is interesting to compare these results and gain insight into the sources of predictability of logRC.

[**Insert Table 5 around here: Risk preferences and LLR**]

As expected under H_1 and H_4, LOGCPR is a strongly significant predictor of logLLR at all horizons. In contrast, LOGCPR shows little or no predictive ability on logDR at $h = 1$ and $h = 2$ quarters ahead. Consequently, the evidence of predictability of LOGCPR on logRC at short horizons is mainly driven by the empirical connection between LLR and local risk preferences.

The results associated with other variables offer further insight into the predictability of logRC. Firstly, SIZE is highly significant in predicting both logLLR and logDR across different horizons. Notably, such estimates take on opposite signs in the regressions: greater SIZE predicts lower LLR holdings and a larger proportion of defaulting loans. A likely explanation is that both features represent different manifestations of moral hazard driving large banks to excessive risk-taking. This may explain why SIZE is a good predictor of logRC, as expected under H_3, as both effects are subsumed and aligned in the same direction by logRC. A similar effect is observed in other significant variables, such as DLLP.

In some cases, the right-hand side variables exhibit predictive power on the two components of logRC, with the estimated coefficient having the same sign. Such is the case, for example, for IV, which is positively related to logLLR and logDR; and for LOGCPR, which is negatively associated to both variables at long horizons. In this case, the regression of logRC reveals which source of information is most relevant for the prediction of LLRU. Thus, the negative coefficient on IV in the regression of logRC indicates that the prevailing source of information originates in defaulting loans. Similarly, the overall negative coefficient of LOGCPR on logRC suggests that the most important source of information originates in LLR. In the case of REEXP and BM, the coefficients take the same sign, leading to offsetting effects. While these variables are significant in predicting each of the components separately, their joint effect is partially offset and the coefficient in the regression of logRC is not significant.

4.2 Long-term consequences of LLRU

To assess the long-run consequences of LLRU activity, we estimate the following panel data regression model:

$$\begin{aligned} Y_{i,[t+1,h]} \quad = \quad & \alpha + \delta_i + \psi_t + \gamma LLRU_{it} + \theta_1 LOGCPR_{it} + \theta_2 REEXP_{it} + \theta_3 RETURN_{it} + \\ & \theta_4 IV_{it} + \theta_5 BM_{it} + \theta_6 TIER1_{it} + \theta_7 TIER2CM_{it} + \theta_8 STWSF_{it} + \\ & \theta_9 YIELDSP_t + \theta_{10} GDPG_{it} + u_{it} \end{aligned} \tag{3}$$

$Y_{i,[t+1,h]}$ are some of the performance variables described in Section 3.1.G above, measured over the interval $[t+1, t+h]$ with $h = 12$ quarters. The set of explanatory variables on the right-hand side includes a subset of the most important regressors in model (1), here used as controls, with u_{it} denoting an error term.[12] The variable $LLRU_{it}$ on the right-hand side is proxied either by logRC or CLUE. Our main interest here is on the coefficient γ associated with $LLRU_{it}$. Table 6 presents descriptive statistics of the right-hand side variables at the firm-quarter level.

[Insert Table 6 around here: Descriptive statistics]

4.2.1 Main results

Model (3) is estimated with panel-data regressions with fixed individual and time effects. Standard errors are computed according to Driscoll-Kraay's nonparametric covariance

[12] Including all the variables as controls do not lead to different qualitative interpretations in the main results. We rely on a subset of predictive variable selected parsimoniously using information criteria.

matrix estimator for robustness against unknown heteroskedasticity and h-th order autocorrelation due to overlapping.[13] Table 7 reports the main regression outcomes.

[Insert Table 7 around here: Long-term consequences]

In line with prior literature (Beatty and Liao [2011], Bushman and Williams [2015]), our findings show that a greater mismatch between LLR and troubled loans is a significant predictor of future bank distress. The picture that emerges from logRC and CLUE is remarkably similar, though some differences support a somewhat better forecasting ability for the latter. In particular, logRC predicts all the performance measures analyzed over the 3-year horizon, with the only exception being the Z-score for distress. The CLUE ratio is a significant predictor of all risk measures analyzed. This evidence confirms the pervasive long-term effects of LLRU activity, showing that unrecognized losses are most likely to materialize within the following three years.

More specifically, over a 3-year horizon, the estimates of model (3) with either logRC or CLUE show that late recognition of credit losses for banks that engage more aggressively in LLRU leads to a significant rise in the likelihood of losses and a greater volatility of earnings as measured by $\sigma(ROA)$ and $\sigma(ROE)$. Notably, greater LLRU activity is also associated with significant degradation in accounting transparency, as reflected in greater variability in the discretionary component of loan loss provisions, $\sigma(DLLP)$. A direct implication is that banks with larger LLR imbalances have a greater likelihood of losses and disclose less reliable accounting figures in their financial statements, thereby increasing informational asymmetry. Given that LLRU is related to risk preferences, this lends support, from a

[13] Driscoll-Kraay's estimator is a panel-data generalization of the well-known Newey-West's heteroskedasticity and autocorrelation consistent estimator which, furthermore, ensures robustness against spatial (i.e., cross-sectional) correlation. As in the literature of predictive regressions on overlapped data in time series, we use this correction to ensure robustness against h-th order autocorrelation.

different perspective, to the results in Christensen et al. [2018] who show that banks located in high CPR areas have a greater incidence of intentional misreporting.

The consequences of LLRU are not limited to deteriorating accounting transparency but also affect stock returns through a rise in volatility, $\sigma(RET)$. Market investors in banks that are more prone to LLRU activity will more likely face greater uncertainty over the following years. According to Bushman and Williams (2015), banks with a greater propensity to delay recognition are also more likely to have a weaker loan supply as they face greater funding costs originating in greater illiquidity; see also Beatty and Liao [2011]. Our evidence aligns with these arguments because stock return volatility and market illiquidity are direct consequences of asymmetric information. The link between LLRU and volatility also supports the empirical connection between lower timeliness in credit loss recognition and greater downside risk (Bushman and Williams [2015]).

The CLUE ratio is also a significant predictor of future insolvency over a 3-year horizon, as reflected in a significant deterioration in the Z-score implying an increase in the probability of bank failure. From a regulatory perspective, this evidence is most relevant as bank regulators are particularly concerned about bank failure and the stability of the financial system. Finally, consistent with Beatty and Liao [2011], greater holdings of uncovered troubled loans are a significant predictor of reductions in the loan supply. This evidence supports the credit-crunch hypothesis, positing that banks in distress are likely to cut back on lending to preserve capital adequacy.

5 Conclusion and policy implications

The main goal of this study was to shed light on the motivations that may lead U.S. bank managers to understate loan loss reserves in relation to the size of troubled loans. While previous literature has emphasized structural incentives driven mainly by accounting models, the main focus of this paper is on variables that affect the behavior of bank managers at the firm level. To this end, we have adopted a risk-based perspective leveraging on an analogy between understating LLR in relation to the size of the credit portfolio at risk and not taking adequate self-insurance against a hazard event.

The overall findings are consistent with the premise that such managerial behavior is akin to a gambling-type strategy that aims to avoid the insurance-type costs associated with early credit loss recognition at the risk of exposing the bank to higher future losses and related adverse long-term consequences. This speculative activity is more pronounced in banks with a corporate risk culture more prone to taking on excessive risks, and in circumstances that manifest distress conditions. Both features are directly related to the fundamental drivers of the demand for self-insurance and hedging. Similarly, banks with systemic characteristics are more likely to understate LLR in line with moral hazard concerns. Finally, a greater divergence between LLR and troubled loans relative to total loans is a significant predictor of a greater likelihood of future bank losses, greater bank insolvency risk, lower accounting earnings quality and greater volatility in stock returns. LLR underprovisioning is also a robust predictor of lower future lending activity.

Our findings are of particular relevance for bank regulators, supervisors and accounting standard setters. The existence of fundamental drivers at the bank level encouraging bank managers to understate LLR raises concerns on whether the new accounting standards aimed to promote early recognition of credit losses through the Expected Credit Loss model may actually achieve their intended goals. Bank managers may use their discretion to manipulate loan loss provisions via activities that represent a gamble on a default event, leading to LLR undeprovisioning. This suggests the need for tighter supervisory mechanisms and closer monitoring of banks with strong incentives to engage in LLR underprovisioning. In this regard, this study provides warning-sign indications on specific related bank characteristics, confirming the important role played by idiosyncratic factors associated with bank management quality and corporate risk culture.

The results in this paper support recent public initiatives aimed to reduce the size of uncovered losses relative to nonperforming loans. As recently as April 17th 2019, the EU Council adopted a set of new rules as an amendment to Capital Requirements Regulation 575/2013. These changes introduce a “prudential backstop” setting minimum common provisioning levels for nonperforming loan exposures. The main aim of the new rules is to reduce nonperforming loans and improve financial resilience in European banks but the minimum levels are also likely to help reduce LLR deficits. The empirical evidence in this study provides support for this recent regulatory initiative.

Appendix

In this technical appendix, we formally show that bank managers with more aggressive risk preferences will optimally decide to leave a greater proportion of troubled loans without reserve-based coverage. To this end, we build on the self-insurance theoretical setting of Ehrlich and Becker [1972], Dionne and Eeckhoudt [1985], Briys and Schlesinger [1990], and Machina [2013]. We adapt and extend this framework to the specific characteristics of LLR.

More specifically, we consider a single-period model. At the beginning of the period, t_0, a bank holds a portfolio composed of zero-coupon bonds with face value D. The initial market value of the bank's shares is S and we assume the bank has no previous loan loss reserves. Bonds fully mature at the end of the period, t_1, and default occurs with probability $0 < p < 1$. The market value of shares in the defaulting scenario at the end of the period is $S_{1,d}$ and $S_{2,nd}$ otherwise. At t_0, the bank manager must chose the level of LLR to be held over the period $[t_0, t_1]$, denoted LLR_0. This decision is partially driven by a non-discretionary policy, resulting in an exogenous amount $0 \leq LLR_{EX} < D$, and the manager's personal choice, $y \geq 0$, reflected in the possibility of increasing reserves arbitrarily. Thus, the total allowance is given by $LLR_0 = LLR_{EX} + y$, given the constraints $0 \leq LLR_0 \leq D$ and $y \geq 0$. We make the following assumptions:

(i) Increasing provisions arbitrarily over LLR_{EX} is costly, as reflected in a reduction in the market value of shares, $S_0 = S - c(y)$, with c denoting a monotonically increasing function such that $c(y) = 0$ and $c' > 0$.
(ii) The bank manager chooses y to maximize an expected utility function given the market value of shares at t_1. Preferences are given by a twice differentiable von Neumann-Morgenstern utility function $X(S_{t_1})$, such that $X' > 0$ and $X'' < 0$.
(iii) The two states of the economy are determined exogenously and may lead to different stock growth rates, namely, r_d (default) and r_{nd} (non-default). Furthermore, $0 < S_{1,d}(y) < S_{1,nd}(y)$ uniformly on y.
(iv) If default occurs, the market value of shares suffers a reduction (loss) given by $L\,(y) \geq 0$, with $L'\,(y) < 0$.
(v) If default does not occur, the bank can write off provisions totally or partially, which

will affect the market value of shares in an amount $d(y)$, with $d'(y) < c'(y)(1+r_{nd})$ for all y.

Some brief comments on these assumptions follow. Conditions (i) to (iv) are standard in the theoretical literature on self-insurance, which stresses the straightforward similarities of LLRU and insurance policies; see, for instance, Dionne and Eeckhoudt [1985] and Briys and Schlesinger [1990]. In our context, the wealth variable is measured by the market value of shares. Assumption (v) is similar in spirit to (i) and (iv) and attempts to capture price reactions at t_1 if default does not occur. The term $d(y)$ can more generally be seen as the salvage market value of the initial self-insurance investment at the end of the period. This term could be positive, null, and even negative (in the case stock prices react negatively). We only impose the restriction $d'(y) < c'(y)(1 + r_{nd})$, requiring marginal benefits not to offset initial costs. Otherwise, any rational agent would trivially set $y^* = D - LLR_{EX}$ such that $LLR_0 = D$, since purchasing insurance implies some form of net profit with probability one.

Proposition. *Let $y^*_{\mathcal{A}}$ and $y^*_{\mathcal{C}}$ denote the choices of y that maximize a bank manager's expected utility given two alternative sets of preferences $\mathcal{A}$ (aggressive) and $\mathcal{C}$ (conservative), respectively, with $\mathcal{C}$ characterizing uniformly more risk-averse preferences than $\mathcal{A}$. Then, under the assumptions considered, $y^*_{\mathcal{C}} \geq y^*_{\mathcal{A}}$ with strict inequality unless $y^*_{\mathcal{A}} + LLR_{EX} = D$ or $y^*_{\mathcal{C}} = 0$.*

Proof. In the default scenario, the market value of stocks at t_1 may be written as $S_{1,d}(y) = [S_0 - c(y)](1 + r_d) - L(y)$. Similarly, in the non-defaulting scenario, the market value of stocks may be written as $S_{1,nd}(y) = [S_0 - c(y)](1 + r_{nd}) + d(y)$. Then, the expected utility of a bank manager with utility function $X \in \{\mathcal{A}, \mathcal{C}\}$ is:

$$EU_X(y) = pX(S_{1,d}(y)) + (1-p)X(S_{1,nd}(y))$$

Consequently, $y^*_{\mathcal{A}}$ and $y^*_{\mathcal{C}}$ are the solution to the first-order condition equations $\partial EU_{\mathcal{A}}(y)/\partial y|_{y=y^*_{\mathcal{A}}} = 0$ and $\partial EU_{\mathcal{C}}(y)/\partial y|_{y=y^*_{\mathcal{C}}} = 0$, respectively. For instance, $y^*_{\mathcal{A}}$ solves:

$$-p\mathcal{A}'(S_{1,d}(y))[c'(y)(1+r_d) + L'(y)] - (1-p)\mathcal{A}'(S_{1,nd}(y))[c'(y)(1+r_{nd}) - d'(y)] = 0$$

Note that, under the assumptions considered, $c'(y^*_{\mathcal{A}})(1+r_d) + L'(y^*_{\mathcal{A}}) < 0$ for a positive $y^*_{\mathcal{A}}$, i.e., the marginal reduction in the future expected loss, $L'(y^*_{\mathcal{A}})$, is greater than the end-of-period value of the marginal costs associated with increasing provisions at the beginning of the period, a well-known result in the self-insurance literature. Similarly, the assumption of strict concavity in the utility function $X'' < 0$ ensures the second-order condition for a maximum.

If $\mathcal{C}$ characterizes uniformly more risk-averse preferences than $\mathcal{A}$, there exists a strictly concave function k such that $\mathcal{C} = k(\mathcal{A})$, with $k' > 0$ and $k'' < 0$ (Pratt [1964]). Hence,

$$\begin{aligned} \partial EU_{\mathcal{C}}(y)/\partial y|_{y=y^*_{\mathcal{A}}} &= -p\mathcal{A}'(S_{1,d}(y^*_{\mathcal{A}}))\left[c'(y^*_{\mathcal{A}})(1+r_d) + L'(y^*_{\mathcal{A}})\right]k'(\mathcal{A}(S_{1,d}(y^*_{\mathcal{A}}))) \\ &\quad -(1-p)\mathcal{A}'(S_{1,nd}(y^*_{\mathcal{A}}))\left[c'(y^*_{\mathcal{A}})(1+r_{nd}) - d'(y^*_{\mathcal{A}})\right]k'(\mathcal{A}(S_{1,nd}(y^*_{\mathcal{A}}))) \end{aligned}$$

Define $\delta_1(y^*_{\mathcal{A}}) = -p\mathcal{A}'(S_{1,d}(y^*_{\mathcal{A}}))\left[c'(y^*_{\mathcal{A}})(1+r_d) + L'(y^*_{\mathcal{A}})\right]$, and similarly consider the term $\delta_2(y^*_{\mathcal{A}}) = (1-p)\mathcal{A}'(S_{1,nd}(y^*_{\mathcal{A}}))\left[c'(y^*_{\mathcal{A}})(1+r_{nd}) - d'(y^*_{\mathcal{A}})\right]$ in the previous expression. Since $\partial EU_{\mathcal{A}}(y)/\partial y|_{y=y^*_{\mathcal{A}}} = \delta_1(y^*_{\mathcal{A}}) - \delta_2(y^*_{\mathcal{A}}) = 0$, it follows that $\delta_1(y^*_{\mathcal{A}}) = \delta_2(y^*_{\mathcal{A}})$ and we can write

$$\partial EU_{\mathcal{C}}(y)/\partial y|_{y=y^*_{\mathcal{A}}} = \delta_1(y^*_{\mathcal{A}})\left[k'(\mathcal{A}(S_{1,d}(y^*_{\mathcal{A}}))) - k'(\mathcal{A}(S_{1,nd}(y^*_{\mathcal{A}})))\right]$$

where $\delta_1(y^*_{\mathcal{A}}) > 0$ in view that $c'(y^*_{\mathcal{A}})(1+r_d) + L'(y^*_{\mathcal{A}}) < 0$. Finally, since $\mathcal{A}(S_{1,d}(y^*_{\mathcal{A}})) < \mathcal{A}(S_{1,nd}(y^*_{\mathcal{A}}))$ under the assumptions considered, it follows that $k'(\mathcal{A}(S_{1,d}(y^*_{\mathcal{A}}))) > k'(\mathcal{A}(S_{1,nd}(y^*_{\mathcal{A}})))$ necessarily because $k'' < 0$. Consequently:

$$\partial EU_{\mathcal{C}}(y)/\partial y|_{y=y^*_{\mathcal{A}}} > 0$$

and hence we can generally conclude that $y^*_{\mathcal{C}} > y^*_{\mathcal{A}}$, with $y^*_{\mathcal{C}} = y^*_{\mathcal{A}}$ holding true at the boundary points $y^*_{\mathcal{C}} = 0$ and $y^*_{\mathcal{A}} = D - LLR_{EX}$ in case the constraints are active. ■

Remark. The problem can be stated more generally in terms of a risk-averse manager who attempts to maximize expected utility given an equity-based compensation package, say $C = f(S_1)$, where f is some positive, non-decreasing function. Such a compensation package would include stock options. It can be shown that as long as $f(S_{1,d}(y)) < f(S_{2,nd}(y))$ uniformly on y, the main conclusions remain unaffected. In this case, the design of the compensation package may clearly condition the arbitrary choice of LLR, suggesting an interesting question for further research.

References

ACHARYA, V.V., and S.G. RYAN. 'Banks' Financial Reporting and Financial System Stability.' Journal of Accounting Research 54 (2016):277-340.

ADHIKARI B.K., and A. AGRAWAL. 'Does Local Religiosity Matter for Bank Risk-Taking?' Journal of Corporate Finance 38 (2016):272-293.

AHMED, A.S., TAKEDA, C., and S. THOMAS. 'Bank Loan Loss Provisions: A Re-examination of Capital Management, Earnings Management and Signalling Effects.' Journal of Accounting and Economics 28 (1999):1-25.

AKINS, B., DOU, Y., and J. NG. 'Corruption in Bank Lending: The Role of Timely Loan Loss Recognition.' Journal of Accounting and Economics 63 (2017):454-478.

BALBOA, M., LOPEZ-ESPINOSA, G., and A. RUBIA. 'Nonlinear Dynamics in Discretionary Accruals: An Analysis of Bank Loan-Loss Provisions.' Journal of Banking and Finance 37 (2013):5186-5207.

BEAVER, W., EGER, C., RYAN, S., and M. WOLFSON. 'Financial Reporting, Supplemental Disclosures, and Bank Share Prices.' Journal of Accounting Research 27 (1989):157–178.

BEATTY, A., and S. LIAO. 'Do Delays in Expected Loss Recognition Affect Banks' Willingness to Lend?' Journal of Accounting and Economics 52 (2011):1-20.

BEATTY, A., and S. LIAO. 'Financial Accounting in the Banking Industry: A Review of the Empirical Literature.' Journal of Accounting and Economics 58 (2014):339-383.

BIKKER, J.A., and P.A. METZEMAKERS. 'Bank Provisioning Behaviour and Procyclicality.' Journal of International Financial Markets, Institutions and Money 15 (2005):141-157.

BLOSE, L.E. 'Information Asymmetry, Capital Adequacy, and Market Reaction to Loan Loss Provision Announcements in the Banking Industry.' The Quarterly Review of Economics and Finance 41 (2001):239-258.

BUSHMAN, R., and C. WILLIAMS. 'Accounting Discretion, Loan Loss Provisioning, and Discipline of Banks' Risk-taking.' Journal of Accounting and Economics 54 (2012):1-18.

BUSHMAN, R., and C. WILLIAMS. 'Delayed Expected Loss Recognition and the Risk Profile of Banks.' Journal of Accounting Research 53 (2015):511-553.

BRIYS, E., and H. SCHLESINGER. 'Risk Aversion and the Propensities for Self-Insurance and Self-Protection'. Southern Economic Journal 57 (1990):458-467.

CHEN Y., PODOLSKI, E., RHEE, G., and M. VEERARAGHAVAN. 'Local Gambling Preferences and Corporate Innovative Success.' Journal of Financial and Quantitative Analysis 49 (2014):77-106.

CHRISTENSEN, D.M., JONES, K.L., and D.G. KENCHINGTON. 'Gambling Attitudes and Financial Misreporting.' Contemporary Accounting Research 35 (2018):1229-1261.

DEMIRGUC-KUNT, A., and E. DETRAGIACHE. 'The Determinants of Banking Crises in Developing and Developed Countries.' IMF Staff Papers 45 (1998):81-109.

DIONNE, G., and L. EECKHOUDT. 'Self-Insurance, Self-Protection and Increased Risk Aversion.' Economics Letters 17 (1985):39-42.

DOCKING, D.S., HIRSCHEY, M., and E. JONES. 'Information and Contagion Effects of Bank Loan-Loss Reserve Announcements.' Journal of Financial Economics 43 (1997):219-40.

EHRLICH, I., and G.S. BECKER. 'Market Insurance, Self-Insurance, and Self-Protection.' The Journal of Political Economy 80 (1972):623-648.

EUROPEAN COMMISSION (2018). Commission staff working document impact assessment, accompanying the document "Proposal for a regulation of the European Parliament and of the Council amending regulation (EU) No 575/2013 as regards minimum loss coverage for non-performing exposures". European Commission SWD 73.

FARHI, E., and J. TIROLE. 'Collective Moral Hazard, Maturity Mismatch and Systemic Bailouts.' American Economic Review 102 (2012):60-93.

FINANCIAL STABILITY FORUM (2009). Report of the Financial Stability Forum on Addressing Procyclicality in the Financial System, April.

GROPP, R., GRUENDL, C., and A. GUETTLER. 'The Impact of Public Guarantees on Bank Risk-Taking: Evidence from a Natural Experiment.' Review of Finance 18 (2014):457-488.

HILARY, G., and K.W. HUI. 'Does Religion Matter in Corporate Decision Making in America?' Journal of Financial Economics 93 (2009):455-473.

JENSEN, M.C., and W.H. MECKLING. 'Theory of the Firm: Managerial Behavior, Agency Costs and Ownership Structure.' Journal of Financial Economics 3 (1976):305-360.

KANAGARETNAM, K., LOBO, G., and D. YANG. 'Determinants of Signaling by Banks Through Loan Loss Provisions.' Journal of Business Research 58 (2005):312-320.

KONRAD, K., and S. SKAPERDAS. 'Self-insurance and Self-Protection: a Non-expected Utility Analysis.' The Geneva Papers on Risk and Insurance Theory 18 (1993):131-146.

KUMAR, A. 'Who Gambles in the Stock Market?' Journal of Finance 64 (2009):1889-1933.

KUMAR, A, PAGE, J., and O. SPALT. 'Religious Beliefs, Gambling Attitudes, and Financial Market Outcomes.' Journal of Financial Economics 102 (2011):671-708.

LAEVEN, L., and G. MAJNONI. 'Loan Loss Provisioning and Economic Slowdowns: Too Much, Too Late?' Journal of Financial Intermediation 12 (2003):178–197.

LOPEZ-ESPINOSA, G., MORENO, A., RUBIA, A., and L. VALDERRAMA. 'Short-term Wholesale Funding and Systemic Risk: A Global CoVaR Approach.' Journal of Banking and Finance 36 (2012):3150-3162.

LOUBERGE, H. Developments in Risk and Insurance Economics: The Past 40 Years, in Handbook of Insurance. 2nd Edition. Springer, 2013.

MACHINA, M.J. Non-Expected Utility and the Robustness of the Classical Insurance Paradigm, in Handbook of Insurance. 2nd Edition. Springer, 2013.

MORGAN, D.P. 'Rating Banks: Risk and Uncertainty in an Opaque Industry.' American Economic Review 92 (2002):874–888.

NG, J., and S. ROYCHOWDHURY. 'Do Loan Loss Reserves Behave Like Capital? Evidence from Recent Bank Failures.' Review of Accounting Studies 19 (2014):1234-1279.

PAN, Y., SIEGEL, S., and T.W. WANG. 'Corporate Risk Culture.' Journal of Finance and Quantitative Analysis 52 (2017):2327-2367.

PRATT, J.W. 'Risk Aversion in the Small and in the Large.' Econometrica 32 (1964):122-136.

SCHLINGER, H. The theory of Insurance Demand, in Handbook of Insurance. 2nd Edition. Springer, 2013.

SHU, T., SULAEMAN, J., and P.E. YEUNG. 'Local Religious Beliefs and Mutual Fund Risk-Taking Behaviors.' Management Science 58 (2012):1779–1796.

SMITH, C.W., and R.M. STULZ. 'The Determinants of Firms' Hedging Policies.' The Journal of Financial and Quantitative Analysis 20 (1985):391-405.

STULZ, R.M. 'Optimal Hedging Policies.' Journal of Financial and Quantitative Analysis 19 (1984):127-140.

WALTER, J.R. 'Loan loss Reserves.' Economic Review Federal Reserve Bank of Richmond 77 (1991):20-30.

Figures and Tables

Figure 1. Quarterly fluctuation in the cross-sectional percentiles of the ratios LLR/(NPL+UPL) (top) and CLUE=(UPL+NPL-LLR)/LOANS (bottom) over the period 2001-2019. The figure shows the 10th percentile (bottom blue line), 50th percentile (middle red line), and 90th percentile (top yellow line) computed cross-sectionally on each quarter in the sample. Overlayed shaded recession band corresponds to NBER economic recession (2007:Q4-2009:Q2).

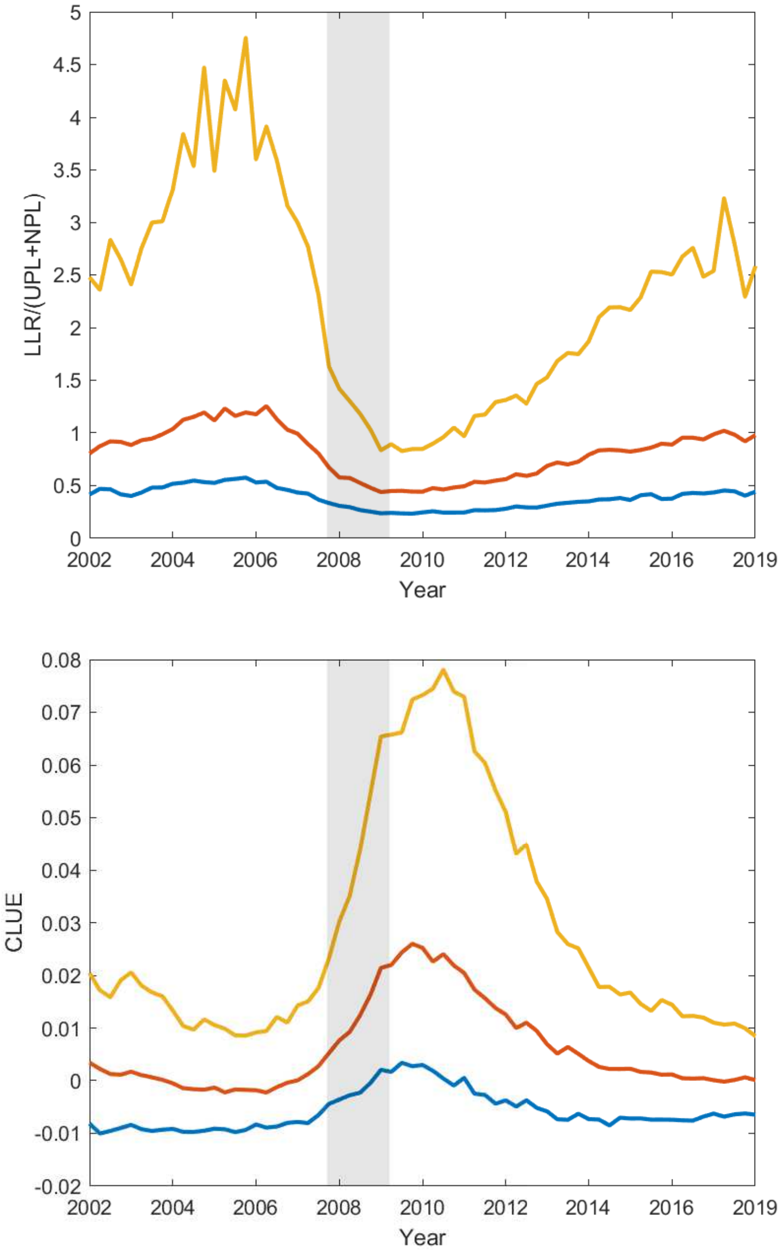

Table 1. Descriptive statistics (mean, quartiles and standard deviation) at the bank-quarter level of the variables in model (1); see Section 3 for a detail description of these variables.

Variables	Mean	Median	Q1	Q3	Std.Dev.
LogRC	-0.149	-0.219	-0.677	0.279	0.826
LOGCPR	-0.464	-0.378	-1.549	0.707	1.493
DLLP	1.38E-05	-9.08E-05	-4.09E-04	2.10E-04	0.001
REEXP	0.728	0.766	0.654	0.851	0.179
ROA	0.002	0.002	0.001	0.003	0.003
RETURN	0.022	0.019	-0.05	0.095	0.159
IV	0.018	0.013	0.01	0.02	0.015
IS	0.229	0.152	-0.207	0.555	0.936
SIZE	14.906	14.545	13.735	15.693	1.653
BM	0.952	0.721	0.523	0.988	0.892
TIER1	0.13	0.121	0.106	0.143	0.042
TIER2CM	0.138	0	0	0	0.345
CONT	0.62	0	0	0	2.607
STWF	0.07	0.055	0.026	0.099	0.062
YIELDSP	0.019	0.021	0.012	0.027	0.011
UNEMP	0.061	0.056	0.047	0.07	0.02
GDPG	0.016	0.018	0.006	0.027	0.021

Table 2. Main regression outcomes (parameter estimates and two-way clustered robust t-statistics in parenthesis) from the estimation of the predictive regression model (1) at the h-quarter ahead horizon. The dependent variable is $logRC_{it+h}$. The description of the right-hand side variables in the first column are detailed in section 3.1. Statistical significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Variable	Predictive horizon $h = 1$	$h = 2$	$h = 3$	$h = 4$
LOGCPR	-0.081***	-0.070***	-0.062**	-0.062**
	(-3.700)	(-2.924)	(-2.462)	(-2.554)
DLLP	56.390***	46.685***	43.348***	44.919***
	(12.089)	(10.000)	(9.797)	(11.063)
REEXP	-0.126	-0.186	-0.307**	-0.418***
	(-1.080)	(-1.550)	(-2.540)	(-3.491)
ROA	20.591***	16.937***	14.718***	13.177***
	(6.021)	(4.724)	(4.425)	(3.915)
RETURN	0.241***	0.282***	0.305**	0.378***
	(2.776)	(2.732)	(2.500)	(3.081)
IV	-9.412***	-10.839***	-11.350***	-11.493***
	(-7.998)	(-7.134)	(-6.483)	(-6.770)
IS	0.015**	0.015**	0.013	0.007
	(2.340)	(2.033)	(1.579)	(0.822)
SIZE	-0.304***	-0.288***	-0.283***	-0.271***
	(-14.296)	(-12.356)	(-11.428)	(-10.469)
BM	-0.008	0.001	0.009	0.016
	(-0.551)	(0.073)	(0.589)	(1.301)
TIER1	-1.366***	-1.162***	-1.038***	-0.853***
	(-6.150)	(-5.015)	(-4.320)	(-3.809)
TIER2CM	-0.106***	-0.121***	-0.127***	-0.136***
	(-5.279)	(-6.328)	(-6.045)	(-6.528)
CONTAGION	-0.004	-0.002	-0.001	-0.005**
	(-1.483)	(-0.681)	(-0.430)	(-2.280)
STWSF	-0.346**	-0.427**	-0.621***	-0.771***
	(-2.126)	(-2.530)	(-3.374)	(-4.379)
YIELDSPREAD	0.020	0.046**	0.074***	0.109***
	(1.210)	(2.388)	(3.373)	(4.931)
UNEMP	-0.118***	-0.113***	-0.109***	-0.105***
	(-15.106)	(-12.868)	(-10.215)	(-9.407)
GDPG	0.016***	0.021***	0.023***	0.023***
	(3.441)	(3.951)	(4.048)	(3.879)
Constant	5.448***	5.166***	5.100***	4.889***
	(14.691)	(13.128)	(12.370)	(11.639)
Observations	23,255	22,503	21,769	21,052
R-squared	0.279	0.262	0.245	0.233

Table 3. Main regression outcomes (parameter estimates and two-way clustered robust t-statistics in parenthesis) from the panel data regression of the variable I(CLUE) on the right-hand variables in model (1) at the h-quarter ahead horizon. Statistical significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

	Predictive horizon			
Variables	$h = 1$	$h = 2$	$h = 3$	$h = 4$
LOGCPR	0.049***	0.039***	0.030**	0.023
	(3.840)	(2.857)	(2.158)	(1.609)
DLLP	-12.369***	-9.573***	-6.302*	-7.085*
	(-3.226)	(-2.675)	(-1.672)	(-1.904)
REEXP	-0.045	-0.009	0.028	0.084
	(-0.798)	(-0.151)	(0.513)	(1.524)
ROA	-15.069***	-10.932***	-9.342***	-9.644***
	(-7.960)	(-6.244)	(-5.130)	(-6.005)
RETURN	-0.059***	-0.060**	-0.055**	-0.085***
	(-2.640)	(-2.569)	(-2.110)	(-3.024)
IV	-0.042	0.132	0.258	-0.092
	(-0.086)	(0.287)	(0.587)	(-0.179)
IS	-0.004	-0.004	-0.006**	-0.006*
	(-1.139)	(-1.077)	(-2.018)	(-1.840)
SIZE	0.093***	0.101***	0.111***	0.119***
	(8.051)	(8.791)	(9.377)	(9.811)
BM	0.043***	0.039***	0.031***	0.023***
	(7.134)	(6.988)	(5.542)	(3.283)
TIER1	0.136	0.108	0.106	0.012
	(1.063)	(0.810)	(0.693)	(0.083)
TIER2CM	0.002	0.012	0.011	0.013
	(0.170)	(1.035)	(0.872)	(0.962)
CONTAGION	0.001	0.002	0.001	-0.001
	(0.580)	(1.016)	(0.452)	(-0.356)
STWSF	0.060	0.076	0.127*	0.219***
	(1.047)	(1.113)	(1.723)	(2.894)
YIELDSPREAD	-0.004	-0.001	0.001	0.002
	(-0.632)	(-0.169)	(0.201)	(0.407)
UNEMP	-0.008**	-0.007**	-0.007*	-0.004
	(-2.147)	(-2.111)	(-1.895)	(-1.275)
GDPG	-0.010***	-0.010***	-0.010***	-0.008***
	(-3.898)	(-4.418)	(-4.567)	(-3.967)
Constant	-0.788***	-0.954***	-1.140***	-1.306***
	(-3.951)	(-4.892)	(-5.726)	(-6.509)
Observations	23,259	22,507	21,771	21,053
R-squared	0.040	0.035	0.032	0.030

Table 4. Main regression outcomes (parameter estimates and two-way clustered robust t-statistics in parenthesis) of model (2) with dependent variable logRC (Panel A) and I(CLUE) (Panel B) at different predictive horizons h. The variable INCTGAMB is the interaction between LOGCPR and IV. Statistical significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

	Panel A: logRC				Panel B: I(CLUE)			
Variables	$h = 1$	$h = 2$	$h = 3$	$h = 4$	$h = 1$	$h = 2$	$h = 3$	$h = 4$
LOGCPR	-0.035	-0.019	-0.008	-0.011	0.039***	0.029**	0.018	0.013
	(-1.594)	(-0.799)	(-0.323)	(-0.435)	(3.040)	(2.122)	(1.303)	(0.891)
INCTGAMB	-2.146***	-2.363***	-2.437***	-2.293***	0.464***	0.482***	0.536***	0.446***
	(-9.245)	(-11.734)	(-11.995)	(-8.445)	(3.784)	(3.542)	(3.667)	(2.838)
DLLP	56.290***	46.594***	43.237***	44.959***	-12.350***	-9.550***	-6.277*	-7.091*
	(12.197)	(10.228)	(9.974)	(11.158)	(-3.219)	(-2.674)	(-1.665)	(-1.912)
REEXP	-0.159	-0.219*	-0.337***	-0.445***	-0.038	-0.002	0.035	0.090
	(-1.372)	(-1.834)	(-2.789)	(-3.700)	(-0.677)	(-0.031)	(0.639)	(1.623)
ROA	20.235***	16.702***	14.523***	13.005***	-14.995***	-10.877***	-9.299***	-9.610***
	(5.952)	(4.685)	(4.414)	(3.908)	(-7.862)	(-6.152)	(-5.096)	(-5.995)
RETURN	0.240***	0.281***	0.305**	0.377***	-0.059***	-0.060**	-0.055**	-0.085***
	(2.870)	(2.830)	(2.572)	(3.172)	(-2.639)	(-2.575)	(-2.132)	(-3.068)
IV	-11.099***	-12.723***	-13.322***	-13.337***	0.323	0.516	0.692	0.266
	(-9.553)	(-8.495)	(-7.420)	(-7.504)	(0.665)	(1.102)	(1.562)	(0.516)
IS	0.016**	0.016**	0.013	0.006	-0.004	-0.004	-0.006**	-0.006*
	(2.526)	(2.157)	(1.635)	(0.797)	(-1.199)	(-1.115)	(-2.027)	(-1.822)
SIZE	-0.307***	-0.291***	-0.287***	-0.274***	0.093***	0.102***	0.111***	0.120***
	(-14.371)	(-12.490)	(-11.597)	(-10.654)	(8.046)	(8.758)	(9.348)	(9.796)
BM	-0.007	0.002	0.010	0.018	0.042***	0.039***	0.031***	0.022***
	(-0.525)	(0.172)	(0.746)	(1.452)	(7.262)	(7.179)	(5.645)	(3.341)
TIER1	-1.306***	-1.091***	-0.967***	-0.787***	0.124	0.094	0.091	-0.000
	(-5.895)	(-4.726)	(-4.050)	(-3.564)	(0.965)	(0.706)	(0.592)	(-0.003)
TIER2CM	-0.104***	-0.118***	-0.124***	-0.133***	0.002	0.012	0.011	0.013
	(-5.209)	(-6.288)	(-5.962)	(-6.392)	(0.135)	(0.990)	(0.822)	(0.915)
CONTAGION	-0.003	-0.001	-0.000	-0.004*	0.001	0.001	0.001	-0.001
	(-1.115)	(-0.333)	(-0.041)	(-1.894)	(0.428)	(0.878)	(0.332)	(-0.460)
STWSF	-0.276*	-0.355**	-0.555***	-0.718***	0.044	0.062	0.112	0.208***
	(-1.763)	(-2.225)	(-3.204)	(-4.307)	(0.774)	(0.891)	(1.510)	(2.770)
YIELDSPREAD	0.021	0.047**	0.075***	0.110***	-0.004	-0.001	0.001	0.002
	(1.264)	(2.447)	(3.430)	(4.984)	(-0.659)	(-0.198)	(0.166)	(0.379)
UNEMP	-0.120***	-0.115***	-0.111***	-0.107***	-0.007**	-0.007*	-0.006*	-0.004
	(-15.448)	(-13.183)	(-10.534)	(-9.711)	(-2.007)	(-1.957)	(-1.716)	(-1.125)
GDPG	0.015***	0.019***	0.022***	0.022***	-0.010***	-0.010***	-0.010***	-0.008***
	(3.284)	(3.734)	(3.833)	(3.677)	(-3.842)	(-4.336)	(-4.439)	(-3.843)
Constant	5.540***	5.271***	5.212***	4.993***	-0.808***	-0.976***	-1.165***	-1.326***
	(14.807)	(13.276)	(12.549)	(11.841)	(-4.019)	(-4.939)	(-5.780)	(-6.555)
Observations	23,255	22,503	21,769	21,052	23,259	22,507	21,771	21,053
R-squared	0.284	0.267	0.250	0.237	0.040	0.035	0.033	0.031

Table 5. Main regression outcomes (parameter estimates and two-way clustered robust t-statistics in parenthesis) of model (1) with dependent variable given by logLLR=log(LLR/LOANS) (Panel A) and logDR=log((UPL+NPL)/LOANS) (Panel B) at different predictive horizons h. Statistical significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

	Panel A: logLLR				Panel B: logDR			
Variables	$h = 1$	$h = 2$	$h = 3$	$h = 4$	$h = 1$	$h = 2$	$h = 3$	$h = 4$
LOGCPR	-0.001***	-0.001***	-0.001***	-0.002***	-0.001	-0.001*	-0.001**	-0.002***
	(-7.206)	(-8.285)	(-8.164)	(-7.824)	(-1.380)	(-1.955)	(-2.457)	(-2.588)
DLLP	0.470***	0.476***	0.442***	0.426***	-1.500***	-1.126***	-0.831***	-0.919***
	(6.346)	(7.199)	(6.798)	(5.909)	(-6.871)	(-5.031)	(-3.859)	(-3.979)
REEXP	0.001	0.001	0.002	0.002*	0.009**	0.011***	0.015***	0.018***
	(1.020)	(1.279)	(1.499)	(1.759)	(2.164)	(3.051)	(4.372)	(5.218)
ROA	-0.331***	-0.300***	-0.284***	-0.279***	-1.855***	-1.517***	-1.222***	-1.115***
	(-8.350)	(-8.267)	(-8.064)	(-7.759)	(-13.029)	(-11.175)	(-9.314)	(-8.346)
RETURN	0.000	0.000	-0.000	-0.001	-0.004**	-0.006***	-0.007**	-0.010**
	(0.865)	(0.547)	(-0.584)	(-1.018)	(-2.555)	(-2.933)	(-1.988)	(-2.531)
IV	0.046***	0.065***	0.090***	0.111***	0.331***	0.416***	0.486***	0.535***
	(4.624)	(7.035)	(10.495)	(9.895)	(9.314)	(10.062)	(9.279)	(9.252)
IS	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000
	(-0.664)	(-0.666)	(-0.747)	(-0.201)	(-1.130)	(-1.528)	(-1.480)	(-0.801)
SIZE	-0.002***	-0.001***	-0.001***	-0.001***	0.003***	0.003***	0.004***	0.004***
	(-17.726)	(-13.271)	(-9.182)	(-6.104)	(5.889)	(5.644)	(5.393)	(4.991)
BM	0.001***	0.002***	0.002***	0.002***	0.005***	0.006***	0.006***	0.005***
	(13.560)	(14.137)	(12.746)	(11.270)	(11.816)	(11.734)	(10.025)	(8.049)
TIER1	0.003	0.001	-0.002	-0.004	0.004	-0.002	-0.008	-0.012
	(1.170)	(0.333)	(-0.660)	(-1.510)	(0.656)	(-0.384)	(-1.112)	(-1.640)
TIER2CM	-0.002***	-0.002***	-0.002***	-0.001***	-0.002***	-0.001***	-0.000	0.000
	(-14.337)	(-13.239)	(-10.370)	(-7.975)	(-5.222)	(-3.113)	(-0.989)	(0.520)
CONTAGION	0.000	0.000**	0.000*	0.000*	0.000***	0.000**	0.000	0.000**
	(1.459)	(1.992)	(1.726)	(1.821)	(3.287)	(2.558)	(1.269)	(2.533)
STWSF	-0.005***	-0.001	0.002*	0.005***	-0.010***	0.001	0.013***	0.023***
	(-5.113)	(-1.440)	(1.737)	(3.383)	(-3.230)	(0.334)	(2.738)	(4.321)
YIELDSPREAD	0.000	0.000	0.000	-0.000	-0.000*	-0.001*	-0.001**	-0.002***
	(0.736)	(0.913)	(0.249)	(-0.613)	(-1.841)	(-1.906)	(-2.216)	(-3.032)
UNEMP	0.001***	0.001***	0.001***	0.001***	0.004***	0.004***	0.003***	0.003***
	(14.367)	(16.034)	(16.124)	(13.694)	(14.648)	(14.181)	(11.112)	(8.724)
GDPG	0.000	-0.000	-0.000	-0.000**	-0.000	-0.000***	-0.001***	-0.001***
	(1.096)	(-0.064)	(-1.375)	(-2.480)	(-1.511)	(-2.614)	(-3.880)	(-4.320)
Constant	0.028***	0.025***	0.021***	0.019***	-0.060***	-0.068***	-0.077***	-0.081***
	(14.964)	(11.539)	(8.473)	(6.110)	(-6.108)	(-6.256)	(-6.148)	(-5.725)
Observations	23,259	22,507	21,771	21,053	23,259	22,507	21,771	21,053
R-squared	0.532	0.541	0.537	0.518	0.595	0.581	0.544	0.499

Table 6. Descriptive statistics (mean, quartiles and standard deviation) at the bank-quarter level of the dependent variables in model (3).

Variables	Mean	Q1	Median	Q3	Std.Dev.
LOSSES	0.371	0	0	0.693	0.637
σ(ROA)	0.001	3.43E-04	0.001	0.001	0.002
σ(ROE)	0.019	0.004	0.006	0.015	0.034
σ(RET)	0.139	0.086	0.116	0.169	0.080
σ(DLLP)	0.001	2.01E-04	3.78E-04	0.001	0.001
Z-score	4.839	4.201	5.079	5.653	1.169
ΔLOAN	0.021	0.005	0.019	0.036	0.030

Table 7. Main regression outcomes (parameter estimates and Driscoll-Kraay's robust t-statistics in parenthesis) of model (3) with LLRU proxied by logRC (Panel A) or CLUE (Panel B). By columns, the dependent variable in each regression measured over the subsequent 3-year rolling window. Statistical significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

	Panel A: logRC							Panel B: CLUE						
Variables	LOSSES	$\sigma(ROA)$	$\sigma(ROE)$	$\sigma(RET)$	$\sigma(DLLP)$	Z-score	$\Delta LOANS$	LOSSES	$\sigma(ROA)$	$\sigma(ROE)$	$\sigma(RET)$	$\sigma(DLLP)$	Z-score	$\Delta LOANS$
LLRU	-0.080**	-0.000***	-0.004**	-0.007*	-0.000***	0.069	0.007***	2.794***	0.010***	0.170***	0.362***	0.007***	-4.535***	-0.353***
	(-2.635)	(-2.903)	(-2.369)	(-1.870)	(-3.052)	(1.388)	(4.069)	(2.928)	(4.027)	(3.969)	(3.923)	(5.560)	(-3.404)	(-10.757)
LOGCPR	-0.071	0.000	0.000	0.002	-0.000	-0.066	0.006***	-0.067	0.000	0.001	0.003	-0.000	-0.083	0.006**
	(-1.611)	(0.296)	(0.146)	(0.384)	(-0.784)	(-0.776)	(2.954)	(-1.545)	(0.420)	(0.267)	(0.519)	(-0.616)	(-0.920)	(2.558)
REEXP	0.712**	0.002**	0.028**	0.119***	0.001***	-1.076***	-0.025**	0.695**	0.002**	0.026**	0.113**	0.001**	-0.978***	-0.020*
	(2.248)	(2.629)	(2.522)	(2.859)	(2.897)	(-3.228)	(-2.153)	(2.086)	(2.320)	(2.148)	(2.646)	(2.505)	(-2.746)	(-1.740)
RETURN	-0.386***	-0.001***	-0.013***	-0.047***	-0.000***	0.496***	0.006***	-0.397***	-0.001***	-0.014***	-0.048***	-0.001***	0.511***	0.007***
	(-4.326)	(-4.633)	(-3.683)	(-4.030)	(-5.142)	(3.966)	(3.124)	(-4.204)	(-4.902)	(-3.866)	(-4.028)	(-5.415)	(4.385)	(3.442)
IV	7.811***	0.020***	0.350***	1.282***	0.014***	-14.551***	-0.267***	7.770***	0.020***	0.347***	1.263***	0.013***	-14.390***	-0.236***
	(5.233)	(4.593)	(3.991)	(6.696)	(6.388)	(-6.728)	(-13.094)	(5.957)	(5.594)	(4.941)	(6.664)	(6.639)	(-7.793)	(-5.612)
BM	0.009	0.000*	0.006***	0.015**	0.000	-0.071*	-0.008***	-0.001	0.000	0.005***	0.013**	0.000	-0.047	-0.007***
	(0.238)	(1.851)	(4.953)	(2.590)	(1.360)	(-1.713)	(-3.513)	(-0.026)	(1.510)	(5.145)	(2.391)	(0.612)	(-1.410)	(-2.993)
TIER1	-0.631	-0.003**	-0.077***	-0.316***	-0.002**	2.652***	0.205***	-0.517	-0.003*	-0.074***	-0.312***	-0.002***	2.673***	0.198***
	(-1.500)	(-2.066)	(-5.116)	(-3.345)	(-2.630)	(3.741)	(7.432)	(-1.298)	(-1.980)	(-5.576)	(-3.442)	(-2.719)	(3.881)	(7.542)
TIER2CM	0.071*	0.000	0.002*	0.006	0.000	-0.035	0.003**	0.075*	0.000	0.002*	0.006	0.000	-0.038	0.003*
	(1.897)	(1.129)	(1.683)	(1.240)	(1.080)	(-1.021)	(2.086)	(1.967)	(1.231)	(1.966)	(1.328)	(1.220)	(-1.125)	(1.793)
STWSF	1.770***	0.003***	0.045***	0.135***	0.002***	-2.197***	-0.024*	1.834***	0.003***	0.048***	0.141***	0.003***	-2.263***	-0.031*
	(4.424)	(4.401)	(4.406)	(3.206)	(4.725)	(-4.857)	(-1.692)	(4.257)	(4.269)	(4.323)	(3.234)	(4.311)	(-4.828)	(-1.868)
YIELDSPREAD	-0.156***	-0.001***	-0.008***	-0.022***	-0.000***	0.397***	0.003***	-0.158***	-0.001***	-0.008***	-0.022***	-0.000***	0.402***	0.004***
	(-3.806)	(-4.937)	(-5.416)	(-2.998)	(-4.056)	(9.636)	(3.042)	(-3.887)	(-4.959)	(-5.492)	(-3.067)	(-4.176)	(9.750)	(3.368)
GDPG	-0.010**	-0.000	-0.000	-0.002*	-0.000***	0.024*	0.001**	-0.010*	-0.000	-0.000	-0.002	-0.000**	0.022	0.001**
	(-2.010)	(-1.334)	(-1.165)	(-1.708)	(-2.672)	(1.731)	(2.556)	(-1.728)	(-1.197)	(-0.983)	(-1.513)	(-2.265)	(1.493)	(2.592)
Constant	-0.066	0.001	0.010	0.094***	0.000	4.871***	0.024**	-0.069	0.001	0.011	0.098***	0.000	4.789***	0.021**
	(-0.306)	(1.340)	(1.410)	(4.136)	(0.657)	(23.501)	(2.373)	(-0.308)	(1.297)	(1.408)	(4.311)	(0.793)	(20.438)	(2.013)
Observations	23,597	22,163	22,163	22,268	22,141	15,695	23,597	23,601	22,167	22,167	22,272	22,145	15,699	23,601
Number of groups	759	732	732	733	732	573	759	759	732	732	733	732	573	759
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R2	0.223	0.207	0.235	0.319	0.278	0.308	0.214	0.220	0.205	0.235	0.321	0.278	0.310	0.220