Why Do Bank Managers Understate Loan Loss Reserves?*

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Abstract

We investigate why bank managers use accounting discretion to leave credit-risk exposures from delinquent loans without adequate reserve-funded coverage. Because the discretion to delay credit loss recognition is a real option, we posit that this managerial activity is driven by factors that characterize the degree of corporate risk aversion, low income, and adverse economic conditions. We address this hypothesis by examining listed U.S. banks between 2001 and 2019. Consistent with our hypothesis, we find that the propensity of bank managers to underprovision loan loss reserves is greater for banks which (1) are prone to risk-taking and gambling; (2) face recent poor performance or distress conditions; (3) exhibit systemic characteristics; and (4) have greater managerial discretion. The evidence in this paper offers novel insights on bank incentives behind loan loss reserve underprovisioning and late credit loss recognition.

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

JEL: 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 a substantial volume of delinquent 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 U.S. history.

In this paper, we examine some of the reasons underlying bank managers' decisions to delay credit loss recognition and understate LLR relative to the size of the loan portfolio at risk, a practice we henceforth refer to as loan loss reserves underprovisioning (LLRU). 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 this corporate strategy at the bank level is less clear. We build on insights from the literature on corporate real options, self-insurance and operational risk management to offer a novel perspective and empirical evidence on the role played by managerial risk preferences and related adverse economic conditions in bank LLRU decisions.

The central motivation for our paper is as follows. Bank managers confront a dilemma regarding the timing for recognizing expected but not yet realized credit losses on their loan portfolios. If LLR are fully provisioned in expectation of such losses (i.e., if expected losses are timely "recognized"), the bank writes them off from current earnings and reduces the corresponding book value of loans. The economic repercussions of provisioning for

[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).

credit losses are not necessarily limited to earning cuts. Since loans are opaque assets (Morgan, 2002), investors, depositors and other outsiders face considerable informational asymmetry. In this context, unanticipated changes in earnings, even when meant to offset credit risk, might be interpreted as an adverse signal about asset quality, potentially leading to negative announcement effects, deposit withdrawals and tighter regulatory monitoring; see, among others, Lancaster et al. (1993). Bank managers thus have incentives to delay LLR recognition to avoid such costly negative outcomes, particularly so in adverse economic conditions when earnings are low and asymmetric information is high. Bank managers can thus take advantage of informational asymmetries exerting discretion to defer expected credit loss recognition because loan loss provisions (LLP henceforth) are highly judgmental and "inevitably imprecise" (Federal Reserve System, 2017, Section 2065.3). Such "wait-and-see" approach may help avoid the potentially negative effects of timely recognition, buying time and giving bank managers a speculative chance to conceal bad prospects as long as credit default does not materialize in the meantime.[2] A drawback of deferring credit losses, however, is that it increases the likelihood of corporate failure as the bank will more likely be exposed to exacerbated future losses, particularly if late recognition takes place during an economic recession (Laeven and Majnoni, 2003; Beatty and Liao, 2011; Bushman and Williams, 2012, 2015).

From a complementary perspective, timely recognition of credit losses by setting aside adequate LLR can be seen as an operational hedging or self-insurance strategy meant to mitigate the expected consequences of credit risk and reduce earnings volatility; see Smith and Stulz (1985) and Van Mieghem (2011).[3] This offers a different perspective to understand why setting aside LLR is costly (Beaver et al., 1989; Ahmed et al., 1999; Kanagaretnam et al., 2005), since this activity is analogous to purchasing insurance against credit default (i.e., buying a put option written on the assets of the bank), which makes LLR

[2]The wait-and-see incentive behind delayed expected credit loss recognition has been explicitly recognized by regulators and motivated specific regulation in the European Union; see, for instance, European Commission (2018).

[3]Operational hedging refers to any corporate action taken to mitigate a particular risk exposure using operational instruments and/or managerial flexibility. For example, investing in reserves is a core risk mitigation strategy; see Van Mieghem (2011) for an overview.

more costly in more adverse economic conditions.[4] Further, the opportunity for managers to defer business decisions in the face of uncertainty is a form of operational flexibility known as the real option to wait (McDonald and Siegel, 1986; Trigeorgis, 1996). This real option held by managers is analogous to a financial call option and represents an important risk containment tool used by firms to manage operational uncertainty.

Therefore, choosing the right timing for recognizing expected credit losses can be framed within a cost-benefit optimization analysis involving the value of the real option to defer (i.e., a call option held by managers) and the cost of self-insurance (i.e, the value of a put option). In circumstances where bank managers perceive the option to defer LLR recognition as valuable or the cost of self-insurance as too high, they will rationally opt to engage in LLRU. Whereas undertaking such risk may be acceptable from the perspective of shareholders owing to limited liability and/or the existence of public guarantees, it may pose a systemic threat to the stability of the financial system. Under adverse economic conditions, bank managers may have incentives to understate LLR stemming from moral hazard, increasing not only the likelihood of bank failures but also of the entire banking system.

Managerial preferences for LLRU are likely driven by factors that characterize the degree of corporate risk aversion. In this regard, the theories of decision-making under uncertainty (Pratt, 1994; Arrow, 1971) and real options and operational risk hedging (Trigeorgis, 1996) allow us to make predictions involving risk preferences underlying LLRU. In particular, we hypothesize that the propensity of bank managers to understate LLR and delay credit loss recognition is driven by (1) their willingness to assume greater corporate risk-taking, (2) the firm's economic conditions, including uncertainty, that determine the value of the real option to defer and the cost of self insurance or put option premium, and (3) a bank's systemic characteristics underlying expectations of public support. Additionally, since the choice to defer LLR recognition under-insuring the credit loan portfolio involves managerial discretion, we posit that (4) banks whose managers can exert greater accounting discretion

[4] Merton (1977) uses a similar argument to price deposit guarantees, noting that these are equivalent to a financial put option issued by a deposit guarantor.

(i.e., with lower accounting transparency and facing greater asymmetric information and operational risk) will engage more actively in LLRU. These predictions are discussed in greater detail in Section 3.

To test these hypotheses, we examine a broad sample of 748 publicly traded U.S. banks in the period 2001-2019, involving 23,258 quarter-firm observations. We analyze the main drivers of LLRU by means of panel-data regressions at horizons ranging from one quarter to one year. To estimate LLRU we rely on accounting measures that, on the basis of observable information, measure the mismatch between the bank's credit portfolio at risk (underperforming and nonperforming loans) and provisioned LLR. The predictive variables in our analysis include bank-specific variables associated with corporate risk-taking, accounting quality, bank performance, solvency, and systemic importance, among others, as well as market-wide economic indicators.

Our findings lend support to the prediction that bank managers use managerial discretion and take speculative risks with the timing of credit loss recognition. Banks with greater proclivity for risk taking, especially these facing more adverse economic conditions and lower accounting transparency, are more prone to understate LLR relative to troubled loans. The most significant predictors include idiosyncratic volatility, high managerial discretion in LLP, and poor recent bank performance. Indicators of economic distress, such as low or negative real GDP growth and high state unemployment rates, are also significant predictors of LLRU. The role of moral hazard and systemic effects is also evident via bank size and short-term wholesale liquidity over-reliance.

We carry out a number of supplementary analyses. We document greater proclivity for LLRU in geographic areas with greater tolerance to risk taking and gambling, proxied by variation in religious composition at the county level. Previous liteture has used this ratio to proxy corporate risk culture; see, for instance, Kumar (2009). We address potential concerns involving endogeneity and causality in two main ways. First, we re-estimate the predictive panel-data regressions using the Generalized Method of Moments (GMM). The evidence from this analysis largely agrees with that based on our fixed-effect models. Additionally, we use the natural disaster setting of hurricane Katrina that differentially affected various U.S. states in 2005 as an identification strategy to perform a pseudo-experimental difference-in-difference regression analysis examining if banks with more risk-taking behavior underprovision LLR more aggressively. Our evidence shows that banks with greater exposure to idiosyncratic shocks had a significantly greater proportion of impaired loans not covered with loan loss reserves.

The remainder of the paper is organized as follows. Section 2 develops the arguments for the option-like, insurance and gambling-type nature of LLRU, reviews the related literature and develops our main hypotheses. Section 3 describes our data and main variables used in the predictive regression analysis. Section 4 details our methodological approach and discusses our main empirical results. Section 5 discusses supplementary analyses. Section 6 shows robustness results from GMM estimation and discusses our quasi-experimental endogeneity test. The last section concludes and offers policy implications.

2. Literature and hypothesis development

2.1. Background and related literature

LLR represent, in the assessment of bank managers, the size of expected losses from uncollectible loans. 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 current earnings are the most direct consequence of LLR, provisioning for credit losses can also have further economic implications. 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 increases in LLP may also induce negative announcement effects if market investors interpret them as a negative revision of the bank's expectations (Docking et al., 1997; Blose, 2001). Stock price may decline in the context of deteriorating bank performance, while asymmetric information may raise concerns over bank failure, leading to tighter monitoring, higher FDIC insurance cost premia and potential bank runs (Akins et al., 2017). Consequently, the total economic costs associated with timely recognition of LLR depends on firm-specific as well as market-wide conditions and may well exceed any direct charges against earnings.

As the costs of building up LLR increase, bank managers have stronger incentives to conceal private expectations. Given that loans are opaque assets, banks can readily hide expected losses (Morgan, 2002). Leaving troubled loans without adequate reserve coverage can, however, have dire long-term consequences because hidden expected credit losses will likely have to be recognized in the future under possibly more adverse economic conditions. Consequently, understating LLR in the present not only erodes accounting credibility and increases informational asymmetry (overstating the bank's asset quality and earnings potential) but it also creates severe loss overhangs that may impair the bank's ability to withstand unexpected future losses. 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 certainly aware of these severe long-term risks, understating LLR amounts to a speculative managerial strategy to save on the costs associated with timely credit loss recognition at the risk of exposing the bank to much higher future losses from delayed recognition. The effectiveness of this strategy depends on the likelihood of credit default and its timing. LLRU can thus be seen as a managerial bet against default. Even though late recognition and eventual default are likely outcomes, LLRU also embeds a gambling-like benefit, namely, that default and related loan losses will not eventually occur. Essentially, this managerial practice buys time in the hope that a seemingly likely default will not materialize. This "wait-and-see" incentive behind 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 take out full self-insurance against a hazardous event.

As a result, LLRU involves aspects commonly associated with risk-taking, under-insuring and gambling behavior. Thus, bank managers are more likely to engage in this speculative activity when they have strong preferences for risk taking and especially when the bank faces more dire economic circumstances, which also raise the cost of insurance and make building up LLR coverage more costly. Public bailout guarantees, which provide implicit insurance by the government, may further encourage LLRU, even when the expected cost from delayed LLR recognition exceeds the benefits due to risk shifting and moral hazard. We elaborate further 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) and Beatty and Liao (2014) for a discussion. Understating LLR with the aim of reducing the volatility of reported earnings (i.e., earnings smoothing) is another form of LLRU. More evidently, when banks are close to failure, bank managers have even stronger 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 theoretical angle from an option and insurance perspective and 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 directly observable accounting measures of LLRU. 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 with higher concentration of Catholics-to-Protestants and in areas experiencing large economic shocks dealing to greater uncertainty are more likely to understate LLR.

2.2. Main hypotheses

The main hypothesis in this paper is that bank managers choose the timing of expected credit loss recognition according to a cost-benefit analysis in which the risk preferences as well as the value of the option to delay recognition and the cost of self insurance play a fundamental role. The value of LLRU is partly driven by the degree of managerial risk aversion, which depends on risk attitudes and current wealth conditions. Consistent with this premise, we develop three interrelated hypotheses:

$\mathbf{H}_1$: (**Risk preferences**) *Banks with stronger tolerance for risk taking will, all else being equal, engage in greater LLRU, i.e., hold a greater proportion of troubled loans not covered with LLR.*

Managers of banks with a corporate culture characterized by a greater risk tolerance will rationally make decisions that involve greater risk taking conforming with the expectations of their job (March and Shapira, 1987). These risk preferences manifest themselves in investments and operational decisions with substantial repercussions on earnings (Gormley and Matsa, 2016). Consequently, we expect a stronger propensity to understate LLR in banks with greater tolerance for risk.

H_1 is generally well-rooted in the Arrow-Pratt theory of risk aversion (Pratt, 1994; Arrow, 1971) and further supported by two related arguments involving operational hedging. Stulz (1984) and Smith and Stulz (1985) show the relevance of managerial risk preferences in operational hedging decisions. Provisioning for LLR is an operational hedging decision meant to mitigate the adverse consequences of credit risk. Banks with stronger preferences for risk taking will be more prone to LLRU, assuming a greater exposure to the adverse consequences of credit risk rather than incurring in extra insurance-like costs arising from timely recognition. Further, the opportunity for bank managers to delay credit loss recognition is a real option providing operational hedging similar to the wait option in investments (Trigeorgis, 1996). Hence, banks with greater propensity to risk taking will be more prone to delay credit loss recognition, seeking to obtain some speculative benefit rather than currently incurring the cost of recognizing expected but not-yet-realized losses.

H_1 is further supported by theoretical arguments relating risk-aversion to the demand for self-insurance, as discussed among others in Ehrlich and Becker (1972), Dionne and Eeckhoudt (1985), Briys and Schlesinger (1990), Konrad and Skaperdas (1993), and Machina (2013). Building on such arguments, we show in an online appendix that a manager making decisions in accordance with more aggressive risk preferences will optimally decide to hold lower LLR.

Because risk preferences underlying bank decisions are not directly observable, we proxy for them at the bank-quarter level with measures associated with greater risk taking and risk exposure. In particular, we rely on estimates of idiosyncratic volatility (IV henceforth) and idiosyncratic skewness (IS henceforth) of stock returns. Return volatility is a statistical measure of uncertainty widely used to appraise risk taking in extant literature.[5] We use IV rather than total volatility as a more relevant driver of the firms real option to delay or as a driver of the cost of self insurance (as a put option). Return idiosyncratic skewness is related to the propensity of returns to exhibit extreme tails. This characteristic of the

[5] Whereas market-wide measures of risk appetite based on return volatility (e.g., CBOE VIX index) capture total variability, IV focuses on the idiosyncratic component of return variability. As such, it is expected to track bank-specific risk taking more closely. The evidence provided in the main section is not sensitive to the use of IV or total volatility. Similar results arise if total variability of returns (rather than the idiosyncratic component) are used.

distribution of stock returns has also been associated with the presence of real options and represents a more extreme manifestation of risk taking; see, for instance, Del Viva et al. (2017). Both high IV and IS have also been used to proxy for gambling preferences; see, for instance, Kumar (2009). According to H_1, banks more prone to risk taking, as manifested in exposures that give rise to greater IV and IS in stock returns, are expected to have greater LLRU and delay expected credit loss recognition.

H_2: (**Adverse economic conditions**) *LLRU is influenced positively by adverse economic conditions which also determine the value of the real option to defer credit loss recognition and the cost of self-insurance (put option). The greater the firm-specific uncertainty, all else being equal, the greater the intrinsic value of these options and LLRU.*

Two main arguments support H_2. First, considerable evidence suggests that individuals and firms become more prone to risk taking when they face adverse economic conditions (Bowman, 1980; Laughhunn et al., 1980), as poverty, losses and financial distress increase their risk appetite; see, among others, Kumar (2009) and Kumar et al. (2011). In the Arrow-Pratt theory of risk aversion, risk-averse individuals facing poor economic conditions characterized by low income obtain greater marginal utility from increments in wealth, which reduces their degree of absolute risk aversion.[6] Thus, in conjunction with H_1 above, banks facing distressed economic conditions characterized by low income, economic losses, and high uncertainty will have greater incentives to take on more risk, and hence will have greater LLRU. Low economic states are also associated with higher uncertainty.

Second, higher uncertainty increases the intrinsic value of the option to defer (McDonald and Siegel, 1986; Dixit et al., 1994; Trigeorgis, 1996) and, similarly, the cost of self-insurance or operational hedging against credit risk. The option to defer credit-loss recognition, analogous to a call option, is more valuable when uncertainty is greater. Equivalently, the decision to increase LLR provides self-insurance benefits analogous to taking a long position

[6]The Arrow-Pratt measure of absolute risk aversion is defined as $-U''(w)/U'(w)$, with $U(w)$ denoting the agent's utility function on current wealth w. Given risk-averse preferences, marginal utility is higher when w is low, thereby decreasing the coefficient of absolute risk aversion.

in a put option, whose cost increases with uncertainty.[7] These arguments lend additional support to the suitability of using IV as a predictor of LLRU in H_1, because greater bank-specific uncertainty in current market conditions, reflected in higher idiosyncratic volatility, increases the value of the option to delay and simultaneously makes self-insurance against credit risk more costly.

To test H_2, we rely on bank-specific market and accounting measures of firm performance, namely financial stock returns and return on assets (ROA), as well as macroeconomic indicators that capture a bank's sensitivity to local economic conditions such as state unemployment and real GDP growth rates in the state in which the bank is headquartered.

H_3: (**Moral hazard incentives**) *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.*

A large mismatch between LLR and troubled loans may partly reflect managerial "optimism" about future bank conditions, which would lead to a conservative appraisal of the probability of default or the size of credit losses borne by shareholders. While several factors may underlie such views, in close connection to H_1, bailout assistance programs and government guarantees, which create incentives for risk shifting (Demirgüç-Kunt and Detragiache, 1997; Gropp et al., 2014), are also likely to exacerbate the bank's propensity to take on operational risks and understate LLR owing to moral hazard. Specifically, banks that are "too big to fail" have a higher expectation of benefiting from public guarantees (Farhi and Tirole, 2012). Therefore, these banks may have greater incentives for delaying credit loss recognition as they may shift negative consequences onto outsiders. H_3 is directly supported by the literature on moral hazard and risk-shifting (Jensen and Meckling, 1976). We test H_3 using systemic indicators of size and financial interconnectedness.

[7] Ehrlich and Becker (1972) show that a risk averse expected utility maximizer will always accept a self-insurance strategy. 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.

Finally, a necessary condition for concealing expected credit losses via LLRU is the conjunction of asymmetric information and managerial accounting discretion. Accordingly, we state the following hypothesis:

H$_4$: (**Managerial discretion**) *Banks with lower accounting quality allowing managers greater accounting discretion, all else being equal, will more actively engage in LLRU.*

H$_4$ seems a priori a logical restriction only. If bank managers cannot exert high accounting discretion in a context of asymmetric information (e.g., owing to enhanced market discipline or tighter supervisory monitoring), the option to delay credit loss recognition will be practically infeasible and have little managerial value. Notably, H$_4$ can also be related to risk preferences and risk-shifting incentives. Consistent with H$_1$, banks with a risk culture prone to risk-taking are more likely to tolerate greater operational risk involving less strict risk controls and adequate supervisory mechanisms. Christensen et al. (2018) show that firms headquartered in geographic areas characterized by a local culture more tolerant to risk taking and gambling are more prone to intentional accounting misreporting. Further, since lower accounting quality and greater asymmetric information are also associated with greater idiosyncratic volatility, a positive association between IV and LLRU can be taken as supportive evidence of H$_4$. Similarly, Bushman and Williams (2012) argue that accounting discretion and moral hazard are interconnected, showing that banks with a greater propensity to delay expected loss recognition exhibit greater risk-shifting behavior.

In accounting, LLP result from adding a discretionary component, chosen by managers, to a non-discretionary charge to earnings determined according to the situation of loans in terms of credit risk. The discretionary component of LLP (denoted as DLLP henceforth) has been associated with lower reporting quality (Dechow et al., 2010) and more asymmetric information (Wahlen, 1994). To test H$_4$, we measure DLLP cross-sectionally using a non-discretionary accrual model; see Section 3 for details.

3. Data

Our primary data source is the Bank Regulatory Database of the Federal Reserve Bank of Chicago. This comprises quarterly data obtained from required 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 their balance sheets and income statements. The sample period is dictated by data availability, since data on underperforming loans, Tier 2 Capital and excess allowances for loan and lease losses are not available before 2001.[8] 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 the FRED database at the Federal Reserve Bank of St. Louis. In a supplementary analysis, we use geographic variation in religious composition of Catholic-to-Protestant ratio (CPR) across U.S. counties to capture differences in local preferences for risk and gambling. These data, compiled by the Glenmary Research Center, are available from the American Religion Data Archive (ARDA).

A. Loan Loss Reserve Underprovisioning

The "true" size of expected uncollectible loans is unobservable to outsiders, who must rely on available accounting data for their appraisal. The reserve coverage (RC henceforth), defined as the ratio of LLR to nonperforming loans, is one of the most important variables used in financial analysis and accounting reporting.[9] Higher values of this ratio have been associated with a better ability to absorb future loan losses and less delay in credit loss recognition; see, e.g., Beatty and Liao (2011) and Akins et al. (2017).

[8]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.

[9]The RC ratio has been the subject of specific regulation in the European Union, requiring a common minimum loss coverage level for nonperforming loans; see European Commission (2018).

Building on the inverse (or negative) of RC ratio in logs, we propose a simple refinement that, besides nonperforming loans, uses additional information on underperforming loans from the balance sheet. For the i-th bank at quarter t, we define the *log-reserve undercoverage* (logRU) ratio as:

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

where NPL and UPL denote nonperforming and underperforming loans, respectively, and LLR is the allowance for loans and lease losses reserves.[10] We consider both NPL and UPL because unserviced loans, even at an early stage of delinquency, may contribute to understating LLR. A larger proportion of impaired loans not covered by LLR, leading to greater values of logRU, is more likely to indicate that provisions expensing is insufficient and that credit losses may be realized in the future. The logRU ratio is thus our primary measure of LLRU in the analysis of hypotheses H_1 to H_4. Robustness to alternative measures of LLRU based on observable accounting information is addressed in Section 5.1.

[**Insert Figure 1 around here: logRU dynamics**]

Figure 1 shows the time-series dynamics of the 10th, 50th and 90th percentiles of the quarterly cross-sectional distribution of the logRU ratio over the sample period. On average, impaired loans not covered with LLR represent a small portion of outstanding loans. The mean value of logRU over the sample period is 0.159, but this ratio displays substantial cross-sectional dispersion and pro-cyclical variability. Before the 2007-2009 financial crisis (shaded area), banks appear to follow a prudent accounting policy holding LLR that exceeds the size of their loan portfolio at risk. About 53% of observations during this period correspond with banks having LLR in excess of impaired loans. The sample average of logRU over this period is 0.224. However, this changes radically during the 2007-2009

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

crisis. Over this period, delinquent loans not covered with LLR represent a sizable 1.81% of total loans. Furthermore, the propensity to keep an excess of LLR over impaired loans decreases dramatically: Figure 1 reveals that the large increase in the size of the credit portfolio at risk is not matched with LLR. As a result, about 93% of quarterly observations correspond with values of LLR below the size of impaired loans. The mean value of logRU during the 2007:Q3-2009:Q2 period increases significantly up to 0.765. 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 LLRU. 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 observed strong cross-sectional dispersion suggests that a number of firm-specific factors beyond common regulatory drivers may have intervened in the decision to leave troubled loans uncovered.

B. Bank risk-taking

To test H_1, we proxy for managerial risk attitudes with variables commonly associated with corporate risk taking. Most papers in related literature consider either accounting or market measures of volatility in this regard. We use market data to compute idiosyncratic volatility (IV) as the sample standard deviation of the residuals from the Fama-French 3-factor (FF3F) model estimated for each bank stock i on a quarterly basis with the daily data available in that particular quarter, namely: $IV_{it} = \left(\sum_{s_t=1}^{n_t} \widehat{\varepsilon}_{i,s_t}^{\,2}/n_t\right)^{1/2}$, from

$$\widehat{\varepsilon}_{i,s_t} = \tilde{r}_{i,s_t} - \widehat{\alpha}_{i,t} - \widehat{\beta}_{i1,t}\tilde{r}_{M,s_t} - \widehat{\beta}_{i2,t}SMB_{s_t} - \widehat{\beta}_{i3,t}HML_{s_t}$$

where $\widehat{\varepsilon}_{i,s_t}$ denotes the estimate of the s-th daily idiosyncratic return in the t-th quarter for firm i; n_t is the number of daily observations; $\tilde{r}_{i,s_t}$ and $\tilde{r}_{M,s_t}$ are the excess returns of the bank stock and the market portfolio over the risk-free rate, respectively; SMB and HML are the size and value factors, and $\widehat{\alpha}_{i,t}, \ldots, \widehat{\beta}_{i3,t}$ are rolling-window OLS estimates of the regression parameters that characterize the FF3F model.

We further capture the effects of tail-risk exposure by means of idiosyncratic skewness (IS), estimated as the sample skewness of the FF3F residuals, namely, $IS_{it} =$

$n_t^{-1} \sum_{s_t=1}^{n_t} \left(\frac{\widehat{\varepsilon}_{i,t_s} - \widehat{\mu}_{i,t}}{\widehat{\sigma}_{i,t}} \right)^3$, with $\widehat{\mu}_{i,t}$ and $\widehat{\sigma}_{i,t}$ denoting the sample mean and standard deviation of daily idiosyncratic returns in the t-th quarter for bank i.

In supplementary analysis in Section 5, we also consider the interaction between IV and the logarithm of the Catholic-to-Protestant ratio at the county level, a variable used in previous literature to proxy for risk and gambling attitudes in the geographic area in which a firm is headquartered.[11] A higher CPR has been associated with stronger preferences for risk; see, among others, Kumar (2009), Kumar et al. (2011), SShu et al. (2012), and Christensen et al. (2018).[12] The rationale for this is that the incentives to engage in LLRU may be more pronounced in geographic areas in which local risk culture and religious beliefs are more permissive with regard to risk taking and gambling.

C. Economic conditions

To address H_2, we consider bank-specific and local performance variables capturing economic distress and economic uncertainty. At the bank level, we rely on market and accounting measures of bank profitability and management quality, measured by quarterly stock return (RETURN) and return on assets (ROA). At the local level, we consider time-varying macroeconomic conditions at the state level that are common for all banks in the same geographic area. In particular, we collect data on unemployment (UNEM) and the real GDP growth (GDPg) rate in the state in which the bank is headquartered.

D. Systemic importance

To address the risk-shifting and moral hazard incentives underlying H_4, we consider bank systemic characteristics that underlie expectations of benefiting from government

[11]We construct this variable considering the number of adherents to the Catholic Church relative to adherents to Anglican and Mainline Protestant Churches in the county in which each bank is headquartered using data from ARDA. Data 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).

[12]The extant literature provides two main reasons why local risk attitudes shape corporate risk culture. First, 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. Second, 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.

bailout guarantees. Building on regulatory considerations and previous studies, we consider bank size, measured by the natural logarithm of total assets (SIZE), and interconnectedness, captured by the ratio of short-term wholesale funding to total assets (STWF). Both variables are major drivers of systemic importance; see, among others, 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 (DDLP) at the bank-quarter level as the residuals from the following cross-sectional regression:

$$LLPTA_{it} = \alpha + \beta_1 NPL_{it} + \beta_2 UPL_{it} + \beta_3 \Delta NPL_{it} + \beta_4 \Delta UPL_{it} + LTA_{it} + LLRT_{it-1} + u_{it}$$

where LLPTA is LLP deflated by total assets; ΔNPL and ΔUPL denote changes in NPL and UPL, respectively; LTA is the ratio of loans to total assets, and LLRT_{it-1} is the lagged ratio of LLR to delinquent loans (NPL and UPL). This regression is run in a rolling-window framework using exclusively data available up to a specific quarter to ensure our results are not driven by forward-looking bias.

F. Control variables

Our regression analysis includes several firm-specific and market-wide control variables: (1) the bank's book to market (BM) ratio, partially associated with growth opportunities; (2) Tier 1 capital (TIER1), (3) Tier II capital management (TIER2CM) as per Ng and Roychowdhury (2014), defined as a dummy variable indicating if LLR are below 1.25% of gross risk-weighted assets to capture capital-related incentives;[13] (4) risk exposure in the real estate lending market (REXP), measured as the ratio of real estate loans to total loans; (5) local contagion or distress conditions (CONTAGION), measured by the sum of absolute-valued losses from all bank failures in a state in a given quarter based on data from FDIC failures file; and (6) yield spread (YIELDSP), measured as the spread between

[13]It is zero for those banks above this threshold; for banks using internal ratings as the limit of gross risk-weighted assets it does not apply.

the U.S. Treasury benchmark 10-year bond and the U.S. 3-month T-bill, a market-wide indicator associated with distress and banks' risk appetite.

4. Baseline regression analysis: main results

To test hypotheses H_1 to H_4, we estimate the predictive panel-data regression model:

$$\begin{aligned} LLRU_{it+h} &= \alpha + \delta_i + \beta_1 IV_{it} + \beta_2 IS_{it} + \beta_3 RETURN_{it} \beta_4 ROA_{it} + \\ &\quad \beta_5 UNEMP_{it} + \beta_6 GDPg_{it} + \beta_7 SIZE_{it} + \beta_8 STWSF_{it} + \\ &\quad \beta_9 DLLP_{it} + Controls_{it} + \varepsilon_{it+h} \end{aligned} \tag{1}$$

at horizons of $h = 1, 2, 3, 4$ quarters ahead, with $LLRU_{it+h}$ proxied by $logRU_{it+h}$. The right-hand side predictive variables are as described in Section 3; $Controls$ denotes the control variables described in Section 3.F; δ_i represents individual bank fixed effects, and ε_{it} denote a prediction error term obeying standard assumptions. All variables are winsorized at the top and bottom 0.5% to reduce the influence of extreme values. Table 1 reports descriptive statistics on these variables. Model (1) is estimated using predictive panel-data regressions with fixed effects at the bank level and two-way cluster-robust standard errors accounting for bank and quarter. The main results from this analysis are reported in Table 2.

[Insert Tables 1 and 2 around here]

First, consistent with the arguments supporting H_1 and H_2, IV is a strongly significant predictor of logRU at all horizons, suggesting that banks subject to greater exposure to idiosyncratic risk have a greater propensity for LLRU. This is consistent with underlying risk preferences having little temporal variability leading to persistent LLR policies over time. Idiosyncratic skewness, reflecting a greater propensity of stock returns to exhibit asymmetric tail values, is negatively related to LLR imbalances at horizons of one and two quarters. The negative coefficient suggests that banks whose idiosyncratic characteristics make them more prone to larger negative (positive) shocks to stock prices will delay loss recognition more (less) actively. At horizons of $h = 3$ and $h = 4$ quarters ahead, the estimated coefficients on IS are negative but not significant. Because tail risk is often caused by unpredictable events that lead to large, short-lived shocks to returns, such events may be followed by short-term adjustments in LLR.

Second, as posited in H_2, bank managers are more likely to understate LLR relative to impaired loans under economic distress conditions when insurance costs associated with building up LLR rise and when the option to delay credit loss recognition is more valuable. Bank-specific conditions associated with distress, reflected in lower stock returns (RETURN) and accounting performance (ROA), are strong predictors of LLRU at all horizons. Similarly, recessionary economic conditions in the state the bank is headquartered, reflected in high state unemployment and negative GDP growth, anticipate larger LLRU at all horizons. Further, YIELDSPREAD is negatively related to LLRU, suggesting that banks are more reluctant to build up LLR when long-term interest rates drop in relation to short-term yields, an often indicator of market distress.

Third, large-scale banks (SIZE) and those more interconnected in the interbank market as indicated by greater short-term wholesale funding (STWSF) engage in LLRU more actively, consistent with moral hazard hypothesis in H_3. Accordingly, the presence of public guarantees gives managers of banks with systemic characteristics more incentives for delaying credit loss recognition owing to risk-shifting behavior.

Fourth, the discretionary component of loan loss provisions (DLLP) is negatively associated with LLRU, as posited in H_4. Accordingly, banks with lower accounting quality and greater reporting opacity, enabling managers to exploit asymmetric information more easily, will understate LLP more actively.

Concerning our control variables, the coefficient estimates on TIER1 and TIER2CM are significantly positive. Consistent with evidence reported in Ahmed et al. (1999), Laeven and Majnoni (2003), and Bikker and Metzemakers (2005), this result suggests that bank managers use LLP to manage total capital. Greater risk exposure in the real estate sector (REEXP) is also positively associated with logRU, though our evidence suggests a more long term effect (at $h = 3$ and $h = 4$ quarters). CONTAGION also seems to have a long-term effect, whereas Book-to-Market (BM) appears insignificant.

5. Supplementary analyses

In this section, we report results from supplementary analyses addressing two additional questions. In Subsection 5.1 we check the robustness of our results using alternative accounting measures of LLRU. In Subsection 5.2 we delve deeper into the role played by managerial preferences for risk and gambling, analyzing geographical effects associated with local risk culture and religious characteristics.

5.1. Alternative LLRU measure

To address the robustness of our results to the definition of LLRU, we alternatively define *credit loss uncovered exposure* (CLUE) as:

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

where LOANS is the size of total outstanding loans. The ratio CLUE measures the difference (positive or negative) between total impaired loans (NPL and UPL) and LLR scaled by the total portfolio of loans. Like logRU, larger values of CLUE indicate higher LLRU.

[Insert Table 3 around here: Predictive regressions: CLUE]

We again estimate (1) at horizons $h = 1, ..., 4$ but this time using the CLUE ratio as the dependent variable. Table 3 reports the main results from this analysis. The overall picture that emerges largely agrees with the evidence reported previously in Table 2. The variables IV, RETURN, ROA, UNEMP, GDPg, SIZE and DLLP are strong significant predictors of both logRU and CLUE (at all horizons analyzed), as predicted from H_1-H_4. The variable YIELDSPREAD is also strongly significant.[14]

[14]There are some differences that seem to relate to idiosyncratic differences between logRU and CLUE, but which do not qualitatively affect our main conclusions. For example, IS loses its significant predictive power (the coefficients are negative but no longer significant) and BM is now significantly positively associated with CLUE. A plausible explanation is that large falls in stock price may lead to large negative skewness in returns and an increase in the BM ratio. Whereas the redundancy between these two variables is resolved in favor of IS in the regression of logRU, BM seems to convey greater incremental information in predicting CLUE. The bottom-line message is the same: consistent with H_1 and H_2, managers of

5.2. Local risk culture and exacerbated incentives for LLRU

A main premise of this paper is that the propensity of bank managers to engage in LLRU and delay expected credit losses recognition is greater in banks with greater risk tolerance and gambling attitudes. Naturally, corporate risk attitudes are influenced by local risk culture, namely the prevailing social, cultural and religious views about risk. Social, cultural and religious norms influence bank managers' decisions, manifested in corporate outcomes in line with these social norms.

In some contexts, local risk culture has been proxied by religiosity and heterogeneity in religious composition; see, among others, Hilary and Hui (2009), Kumar (2009), Kumar et al. (2011), Shu et al. (2012), Chen et al. (2014), Adhikari and Agrawal (2016), and Christensen et al. (2018). To measure (excessive) risk taking and gambling preferences, these studies use the ratio of Catholics to Protestants in U.S. counties, since the Catholic church has more tolerant views on gambling. Building on this literature, we analyze if the idiosyncratic propensity to understate LLR is exacerbated by local views on gambling, extending model (1) by adding the interaction of IV and the logarithm of the Catholic-to-Protestant ratio (logCPR), namely:

$$LLRU_{it+h} = \alpha + \delta_i + \gamma \ (IV_{it} \times logCPR_{it}) + \beta' X_{it} + Controls_{it} + \varepsilon_{it+h} \tag{2}$$

with X_{it} denoting a vector containing the right-hand side variables IV,IS,...,DLLP enumerated in (1), and $\beta = (\beta_1, ..., \beta_9)'$ denoting a conformable vector of unknown parameters. This interaction term reflects exacerbated incentives for risk taking and gambling associated with bank-specific idiosyncratic characteristics and local culture common to all banks in the geographic area. According to H_1, this interaction term should

banks with stock prices which are more sensitive to extreme returns tend to misstate LLR more actively. There also exists some substitutability between SIZE and STWSF as big banks are typically complex lending institutions highly interconnected in the interbank market. Whereas SIZE is strongly significant in predicting logRU and CLUE and STWSF is a significant predictor of logRU, STWSF yields somewhat mixed results in predicting CLUE. Nevertheless, the relevance of systemic characteristics is evident by the strong significance of SIZE.

predict a greater propensity to engage in LLRU, predicting a significant positive regression coefficient γ.

The results from this supplementary analysis, reported in Table 4, show positive and highly significant estimates of γ at all horizons. Accordingly, managers of banks headquartered in geographic areas with more social tolerance to 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 more actively delay credit risk recognition. The first two rows in Table 4 indicate that LLRU activity is most pronounced for banks characterized by greater idiosyncratic volatility and headquartered in geographic areas characterized by a local risk culture more permissive to risk-taking and gambling. This result in in line with the evidence in Christensen et al. (2018) but from a different perspective. A similar picture arises if we use CLUE instead of logRU (results not reported but available from the authors upon request).

[**Insert Table 4 around here: Gambling incentives**]

6. Endogeneity

In this section, we address concerns related to endogeneity and causality. Section 6.1 reports the results from GMM estimation. Section 6.2 conducts a difference-in-difference analysis in the natural disaster setting of hurricane Katrina to facilitate causal interpretations of the association greater risk taking and LLRU.

6.1. GMM estimation

In this section, we rely on GMM estimation to address endogeneity concerns involving two econometric considerations. First, banks can recognize expected credit losses gradually seeking to smooth earnings volatility; see, for example, Bouvatier and Lepetit (2008), Laeven and Majnoni (2003) and Fonseca and Gonzalez (2008). Although (1) is a static model, neglected dynamics are not a major concern because double-clustered standard errors allow for robust inference against residual autocorrelation. Nevertheless, accommodating dynamic adjustments in logRU can increase efficiency in estimation and offer a more complete picture in our analysis. More importantly, since bank-specific accounting ratios are not strictly exogenous variables, a potential source of greater concern in the regression analysis is the possibility of endogenous biases.

We handle both issues concurrently using two-step System GMM estimation (Arellano and Bover, 1995; Blundell and Bond, 1998) in a dynamic panel data model. This approach not only generates robust estimates against heteroskedasticity and autocorrelation but also controls for potential endogeneity of a large number of variables by using lags of the variables as instruments. This procedure is particularly indicated for panels characterized by a large number of cross-sectional observations but a small time-series dimension.

Specifically, we accommodate dynamic adjustments in LLRU by augmenting (1) with four lags of the dependent variable. Owing to the quarterly nature of the data, this seems a plausible choice. Results based on a higher-order augmentation including up to six lags do not lead to different qualitative conclusions. We instrument all variables with 2-3 lags of own variables when predicting at horizons $h = 1, 2$, and with 3-4 lags when predicting at $h = 3, 4$. GMM estimation is carried out using forward orthogonal differences, since this method delivers more efficient estimates in unbalanced panels. The validity of the instruments is verified using Hansen's J test statistic. The results from the GMM estimation of the dynamic model are reported in Table 5.

[Insert Table 5 around here: GMM dynamic model]

In Table 5, persistence in LLRU is accommodated by stationary autoregressive coefficients that decay quickly to zero. In particular, at $h = 1$ the estimate of the first-order autoregressive coefficient is 0.664, while the fourth-order autoregressive lag is 0.063, both statistically significant. Consistent with H_1 and the evidence reported in Section 4, the estimated coefficients on IV are positive and significant at all predictive horizons. Similarly, the estimated coefficients on IS are negative and statistical significant at horizons of $h = 1$ and $h = 2$, in line with the evidence reported previously in Section 4; see Table 2 for details. Consistent with H_2, RETURN is significantly negatively associated with LLRU at all horizons. The variable ROA does not seem to add incremental predictive power after accounting for dynamic adjustments. Similarly, UNEMP is positively and significantly associated with LLRU at all horizons, in line with the evidence reported in Section 4. The estimates on GDPg are still negative but this variable only adds incremental predictive power at horizons of $h = 3$ and $h = 4$. H_3 is mainly supported by positive and significant estimates on SIZE at horizons of up to three quarters ahead. STWSF again offers mixed evidence. Finally, DLLP is negative and significant at horizons of $h = 1$ and $h = 2$ quarters ahead, lending support to H_4. While the inclusion of dynamics and the use of instrumental estimation leads to small qualitative differences, the overall picture that emerges agrees with the main results reported in Section 4.

6.2. Quasi-experimental analysis: Hurricane Katrina

Hurricane Katrina, the largest natural disaster in U.S. history, hit the Gulf Coast of the U.S. in August 29, 2005, killing 1,833 people and causing an estimated $108 billion (in 2005 dollars) in property damages (Knabb et al. 2005). The damage was relatively concentrated in 179 counties in four U.S. states (all counties in Louisiana and Mississippi, 22 counties in Alabama and 11 in Florida).[15] We use this natural disaster, exogenous to any bank managerial decision, as a quasi-experiment in a Difference-in-Difference (D-i-D) research design aiming to shed light on a causal interpretation between banks' risk-taking and LLRU. To this end, we estimate the following panel data regression model:

$$\begin{aligned} LLRU_{it+h} \;=\;& \alpha + \beta' X_{it} + Controls_{it} + \gamma_1 T_t + \gamma_2 B_i + \gamma_3 \left(T_t \times B_i\right) + \\ & \gamma_4 \left(T_t \times IV_{it}\right) + \gamma_5 \left(B_i \times IV_{it}\right) + \gamma_6 \left(T_t \times B_i \times IV_{it}\right) + \\ & \gamma_7 \left(T_t \times IS_{it}\right) + \gamma_8 \left(B_i \times IS_{it}\right) + \gamma_9 \left(T_t \times B_i \times IS_{it}\right) + \varepsilon_{i,t+h} \end{aligned} \tag{3}$$

at horizons $h = 1, 2$. T_t is a time dummy variable taking value one if the t-th quarter is either 2005-Q3 or 2005-Q4 and zero otherwise (post-treatment period); B_i is a bank dummy taking value one if the i-th bank was headquartered in any of the U.S. counties

[15]The list of specific counties affected is available from the Federal Emergency Management Agency (FEMA) of the Department of Homeland Security. We select the counties designed by FEMA as "Individual assistance areas".

affected by the hurricane (intervention group). All other variables have been introduced previously.

The "treated" group consists of banks headquartered in the areas affected by hurricane Katrina. The remaining observations in the sample form the "control" group. The post-treatment period is limited to the two immediate quarters following the natural disaster in order to capture abnormal changes in loan-loss provisioning as a direct consequence of the natural disaster. Our main interest here is on the coefficients associated with the difference-in-difference interactions, $T_t \times B_i \times IV$ and $T_t \times B_i \times IS$, capturing the incremental response of LLRU (as proxied by logRU) to the exogenous shock given bank corporate risk preferences reflected in IV and IS, respectively.

[**Insert Table 6 around here: Difference-in-Difference analysis**]

The results are summarized in Table 6. Model (3) is alternatively estimated using pooled regression (Panel A) and fixed effects (Panel B), with double-clustered robust standard errors. The coefficient of the bank dummy variable B_i is not identified in the fixed-effects estimation since this variable is time invariant. Because the parameter estimates of the variables in X_{it} and $Controls$ are similar to those reported in Section 4, Table 6 reports only the estimates associated with the D-i-D analysis (complete results are available upon request).

The coefficient on the unconditional interaction effect $T_t \times B_i$ is negative and significant, indicating that affected banks increase LLR as a response to the natural disaster, thus reducing LLRU. This result is consistent with Dal Maso et al. (2022), indicating that banks in areas affected by natural disasters recognize (unconditionally) higher LLP. The estimates of the coefficient on the interaction effect $T_t \times B_i \times IV$, capturing incremental effects given IV, reveal significant adjustments conditional on this variable. Consistent with H_1, these estimates are positive and strongly significant, indicating that banks with greater exposure to idiosyncratic risk tend to leave a greater proportion of impaired loans without reserve coverage, all else equal. The size of the estimated coefficients is both statistically and economically significant, showing sizable adjustments. Similarly, the estimates on the

$T_t \times B_i \times IS$ interaction are negative and significant at $h = 2$, suggesting the presence of conditional adjustment effects associated with tail risk.

7. Conclusions and policy implications

The main goal of this study is to shed further 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-based models, the main focus of this paper is on economic factors that affect the behavior of bank managers at the firm level. To this end, we have adopted a risk-based perspective viewing the discretion to delay LLR recognition as a real option, leveraging on an analogy between understating LLR and not taking adequate insurance against a hazard event.

Our findings are consistent with the premise that LLR underprovisioning is akin to a speculative strategy that aims to avoid the insurance-type costs associated with early credit loss recognition at the risk of exposing the bank to potentially much higher future losses and related long-term consequences. The speculative activity after this managerial behavior is more pronounced in banks with a corporate risk culture prone to taking on excessive risks and in circumstances that manifest adverse economic or distress conditions. Both features are related to the fundamental drivers of risk-taking and the demand for operational hedging and self-insurance. Moreover, large banks with systemic characteristics are more likely to understate LLR due to a moral hazard problem.

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

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Figures and Tables

Figure 1. Quarterly fluctuation in the cross-sectional percentiles of logRU over the period 2002:Q2 through 2019:Q4. 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. The overlayed shaded recession band corresponds to NBER economic recession (2007:Q4-2009:Q2).

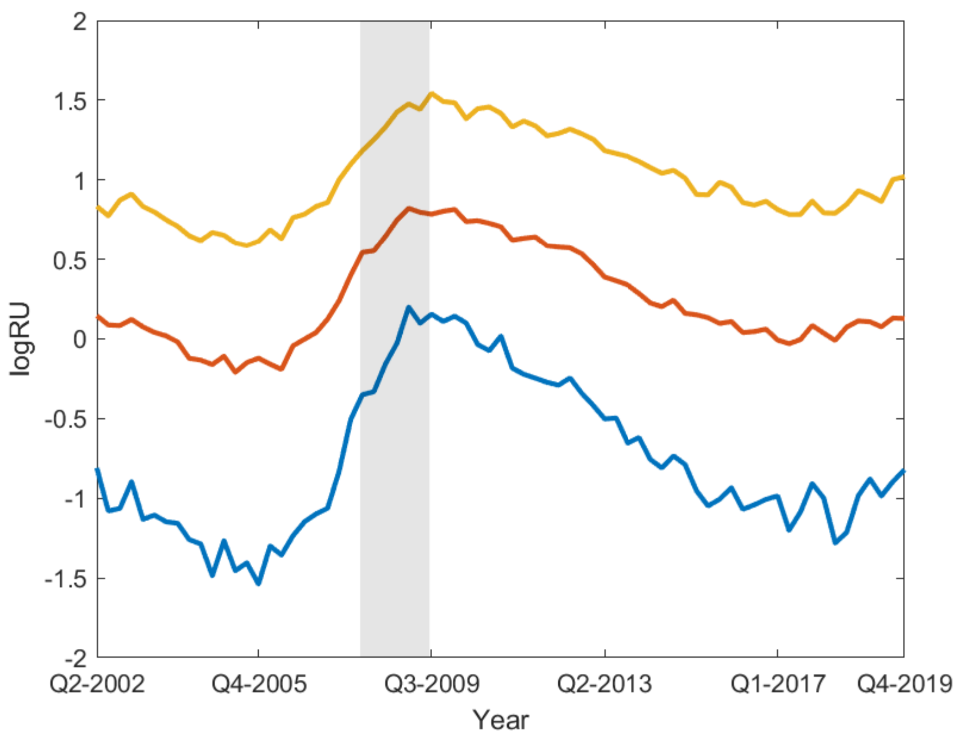

Table 1. Descriptive statistics (mean, median, bottom and top quartiles, and standard deviation) at the bank-quarter level.

Variables	Mean	Median	Q1	Q3	Std.Dev.
logRU	0.159	0.891	-0.275	0.237	0.693
IV	0.018	0.013	0.010	0.020	0.015
IS	0.229	0.152	-0.207	0.555	0.936
RETURN	0.022	0.019	-0.050	0.095	0.159
ROA	0.002	0.002	0.001	0.003	0.003
UNEMP	0.061	0.056	0.047	0.070	0.020
GDPg	0.016	0.018	0.006	0.027	0.021
SIZE	14.906	14.545	13.735	15.693	1.653
STWF	0.070	0.055	0.026	0.099	0.062
DLLP	1.38E-05	-9.08E-05	-4.09E-04	2.10E-04	0.001
BM	0.952	0.721	0.523	0.988	0.892
TIER1	0.130	0.121	0.106	0.143	0.042
TIER2CM	0.138	0	0	0	0.345
REEXP	0.728	0.766	0.654	0.851	0.179
CONTAGION	0.620	0	0	0	2.607
YIELDSPREAD	0.019	0.021	0.012	0.027	0.011

Table 2. Main regression outcomes (parameter estimates and two-way clustered robust t-statistics in parenthesis) from the estimation of predictive regression model (1) at the h-quarter ahead horizon with LLRU proxied by logRU. The description of the predictive variables are detailed in Section 3. Statistical significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Dependent: logRU	Predictive horizon			
	$h = 1$	$h = 2$	$h = 3$	$h = 4$
IV	9.411***	10.833***	11.344***	11.483***
	(8.033)	(7.152)	(6.494)	(6.778)
IS	-0.015**	-0.015**	-0.013	-0.007
	(-2.362)	(-2.048)	(-1.590)	(-0.825)
RETURN	-0.240***	-0.281***	-0.305**	-0.377***
	(-2.783)	(-2.739)	(-2.504)	(-3.087)
ROA	-20.388***	-16.749***	-14.542***	-12.983***
	(-6.003)	(-4.705)	(-4.401)	(-3.892)
UNEMP	0.117***	0.112***	0.108***	0.104***
	(15.145)	(12.955)	(10.279)	(9.446)
GDPg	-0.016***	-0.021***	-0.023***	-0.023***
	(-3.471)	(-3.982)	(-4.076)	(-3.907)
SIZE	0.301***	0.285***	0.280***	0.267***
	(14.018)	(12.155)	(11.182)	(10.221)
STWSF	0.366**	0.444***	0.636***	0.786***
	(2.289)	(2.679)	(3.518)	(4.559)
DLLP	-56.077***	-46.375***	-43.061***	-44.606***
	(-12.120)	(-10.013)	(-9.826)	(-11.108)
BM	0.007	-0.002	-0.009	-0.017
	(0.486)	(-0.123)	(-0.633)	(-1.350)
TIER1	1.337***	1.138***	1.017***	0.833***
	(6.019)	(4.907)	(4.236)	(3.720)
TIER2CM	0.106***	0.121***	0.127***	0.136***
	(5.271)	(6.326)	(6.042)	(6.513)
REEXP	0.140	0.198	0.317***	0.429***
	(1.192)	(1.638)	(2.613)	(3.563)
CONTAGION	0.004	0.002	0.001	0.005**
	(1.492)	(0.682)	(0.425)	(2.274)
YIELDSPREAD	-0.019	-0.045**	-0.073***	-0.108***
	(-1.156)	(-2.356)	(-3.354)	(-4.921)
Constant	-5.434***	-5.152***	-5.084***	-4.870***
	(-14.636)	(-13.099)	(-12.321)	(-11.582)
Observations	23,255	22,503	21,769	21,052
R-squared	0.279	0.262	0.245	0.232

Table 3. Main regression outcomes (parameter estimates and two-way clustered robust t-statistics in parenthesis) from the estimation of predictive regression model (1) at the h-quarter ahead horizon with LLRU proxied by CLUE. The description of the predictive variables are detailed in Section 3. Statistical significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Dependent: CLUE	Predictive horizon			
	$h = 1$	$h = 2$	$h = 3$	$h = 4$
IV	0.285***	0.350***	0.396***	0.424***
	(9.775)	(9.973)	(8.561)	(8.780)
IS	-0.000	-0.000	-0.000	-0.000
	(-1.096)	(-1.570)	(-1.549)	(-0.938)
RETURN	-0.004***	-0.006***	-0.006**	-0.009***
	(-3.527)	(-3.478)	(-2.293)	(-2.914)
ROA	-1.522***	-1.216***	-0.936***	-0.834***
	(-12.558)	(-10.315)	(-8.727)	(-7.591)
UNEMP	0.003***	0.002***	0.002***	0.002***
	(13.827)	(12.362)	(9.024)	(7.000)
GDPg	-0.000***	-0.000***	-0.001***	-0.001***
	(-2.684)	(-3.514)	(-4.442)	(-4.459)
SIZE	0.005***	0.005***	0.005***	0.005***
	(10.319)	(9.422)	(8.390)	(7.570)
STWSF	-0.004*	0.003	0.011***	0.018***
	(-1.694)	(0.872)	(2.887)	(4.515)
DLLP	-1.968***	-1.600***	-1.267***	-1.349***
	(-11.371)	(-8.412)	(-7.020)	(-7.414)
BM	0.004***	0.004***	0.004***	0.003***
	(9.820)	(9.749)	(8.219)	(6.587)
TIER1	0.001	-0.003	-0.007	-0.008
	(0.201)	(-0.621)	(-1.052)	(-1.292)
TIER2CM	0.000	0.001*	0.001**	0.001***
	(0.686)	(1.931)	(2.548)	(3.398)
REEXP	0.008**	0.010***	0.013***	0.016***
	(2.368)	(3.436)	(5.272)	(6.382)
CONTAGION	0.000***	0.000**	0.000	0.000**
	(3.738)	(2.536)	(1.050)	(2.563)
YIELDSPREAD	-0.001**	-0.001**	-0.001***	-0.002***
	(-2.343)	(-2.364)	(-2.623)	(-3.553)
Constant	-0.088***	-0.092***	-0.099***	-0.100***
	(-10.490)	(-10.352)	(-9.548)	(-8.729)
Observations	23,259	22,507	21,788	21,070
R-squared	0.501	0.483	0.443	0.400

Table 4. Main regression outcomes (parameter estimates and two-way clustered robust t-statistics in parenthesis) from the estimation of predictive regression model (2) at the h-quarter ahead horizon with LLRU proxied by logRU. The description of the predictive variables are detailed in Section 3. Statistical significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Dependent: logRU	Predictive horizon			
	$h = 1$	$h = 2$	$h = 3$	$h = 4$
IV	11.147***	12.748***	13.333***	13.352***
	(9.651)	(8.549)	(7.464)	(7.560)
IV × logCPR	2.207***	2.397***	2.452***	2.313***
	(9.710)	(12.146)	(12.409)	(8.987)
IS	-0.016**	-0.016**	-0.013	-0.006
	(-2.543)	(-2.165)	(-1.638)	(-0.797)
RETURN	-0.240***	-0.281***	-0.305**	-0.377***
	(-2.876)	(-2.834)	(-2.574)	(-3.175)
ROA	-20.141***	-16.650***	-14.500***	-12.971***
	(-5.949)	(-4.681)	(-4.411)	(-3.908)
UNEMP	0.120***	0.115***	0.111***	0.107***
	(15.491)	(13.297)	(10.644)	(9.805)
GDPg	-0.015***	-0.019***	-0.022***	-0.022***
	(-3.291)	(-3.738)	(-3.835)	(-3.680)
SIZE	0.306***	0.291***	0.287***	0.274***
	(14.208)	(12.388)	(11.442)	(10.494)
STWSF	0.282*	0.359**	0.557***	0.720***
	(1.816)	(2.264)	(3.244)	(4.376)
DLLP	-56.158***	-46.514***	-43.200***	-44.906***
	(-12.210)	(-10.248)	(-9.991)	(-11.205)
BM	0.007	-0.003	-0.011	-0.018
	(0.497)	(-0.187)	(-0.752)	(-1.462)
TIER1	1.293***	1.084***	0.964***	0.783***
	(5.859)	(4.698)	(4.046)	(3.551)
TIER2CM	0.104***	0.118***	0.124***	0.133***
	(5.207)	(6.288)	(5.963)	(6.383)
REEXP	0.166	0.223*	0.339***	0.447***
	(1.419)	(1.850)	(2.795)	(3.714)
CONTAGION	0.003	0.001	0.000	0.004*
	(1.108)	(0.329)	(0.038)	(1.894)
YIELDSPREAD	-0.021	-0.047**	-0.075***	-0.110***
	(-1.245)	(-2.445)	(-3.438)	(-4.999)
Constant	-5.537***	-5.268***	-5.210***	-4.991***
	(-14.793)	(-13.271)	(-12.524)	(-11.806)
Observations	23,255	22,503	21,769	21,052
R-squared	0.284	0.267	0.250	0.237

Table 5. Main regression outcomes (parameter estimates and robust standard errors in parenthesis) from two-step System GMM estimation of model (1) augmented with four lags of the dependent variable given the h-quarter predictive horizon. LLRU is proxied by logRU. All variables are treated as endogenous. Rows AR(1) and AR(2) show the p-values of the Arellano-Bond tests for zero autocorrelation in first-differenced errors at orders 1 and 2, respectively. The last row shows the p-value of Hansen's J test for validity of instruments. Statistical significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Dependent: logRU	Predictive horizon			
	$h = 1$	$h = 2$	$h = 3$	$h = 4$
logRU(-1)	0.664***	0.724***	0.759***	0.771***
	(0.045)	(0.053)	(0.060)	(0.050)
logRU(-2)	0.101***	0.054	0.020	-0.015
	(0.033)	(0.036)	(0.070)	(0.079)
logRU(-3)	0.054***	0.065***	0.077**	0.070*
	(0.015)	(0.016)	(0.033)	(0.039)
logRU(-4)	0.063***	0.077***	0.067***	0.064**
	(0.017)	(0.018)	(0.019)	(0.025)
IV	7.119***	5.750***	3.030***	3.151***
	(0.689)	(0.782)	(0.695)	(0.841)
IS	-0.009***	-0.007*	-0.004	0.002
	(0.003)	(0.004)	(0.003)	(0.004)
RETURN	-0.136***	-0.100***	-0.074***	-0.120***
	(0.019)	(0.020)	(0.027)	(0.018)
ROA	-4.880	0.823	1.297	1.278
	(4.787)	(3.501)	(3.535)	(3.532)
UNEMP	0.016***	0.016***	0.012***	0.011***
	(0.005)	(0.004)	(0.003)	(0.004)
GDPg	-0.002	-0.002	-0.003**	-0.002*
	(0.002)	(0.001)	(0.001)	(0.001)
SIZE	0.048**	0.033**	0.030**	0.022
	(0.019)	(0.014)	(0.014)	(0.015)
STWSF	0.039	-0.147*	0.033	0.176**
	(0.095)	(0.087)	(0.084)	(0.078)
DLLP	-47.645**	-28.178**	-15.817	-10.362
	(18.693)	(13.630)	(13.773)	(11.709)
BM	-0.061***	-0.049***	-0.029***	-0.024**
	(0.008)	(0.009)	(0.009)	(0.011)
TIER1	-1.042	-2.224***	-1.678***	-0.509
	(0.697)	(0.603)	(0.609)	(0.572)
TIER2CM	0.014	0.029***	0.022*	0.023**
	(0.012)	(0.011)	(0.012)	(0.011)
REEXP	0.154**	0.157**	0.199***	0.205***
	(0.062)	(0.063)	(0.058)	(0.054)
CONTAGION	0.001	-0.002	-0.001	0.003***
	(0.001)	(0.001)	(0.001)	(0.001)
YIELDSPREAD	-0.038***	-0.044***	-0.045***	-0.054***
	(0.004)	(0.004)	(0.004)	(0.004)
Observations	20,505	19,829	19,159	18,508
AR(1) p-value	0.000	0.000	0.000	0.000
AR(2) p-value	0.746	0.660	0.317	0.226
Hansen p-value	0.370	0.328	0.276	0.263

Table 6. Main regression outcomes (parameter estimates and robust t-statistics in parenthesis) from difference-in-difference analysis of model (3) estimated with pooled regression (Panel A) and fixed effects (Panel B) at horizons of $h = 1$ and $h = 2$ quarters ahead. The coefficient on the bank-related dummy variable B_i is not identified in the fixed effect model and it is therefore omitted. Statistical significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

	Panel A: Pooled regression		Panel B: Fixed effects	
	$h = 1$	$h = 2$	$h = 1$	$h = 2$
Risk-related D-i-D interactions				
$T_t \times B_i \times IV$	70.410***	63.590***	46.826***	41.900***
	(11.511)	(9.164)	(8.374)	(8.063)
$T_t \times B_i \times IS$	0.058	-0.107***	0.054	-0.100***
	(0.527)	(-3.392)	(0.411)	(-3.062)
$T_t \times IV$	-10.460**	-15.630**	-11.313***	-18.033***
	(-2.346)	(-2.279)	(-4.883)	(-4.643)
$B_i \times IV$	-2.725	-2.903	-5.632***	-5.700***
	(-1.071)	(-1.163)	(-4.258)	(-3.751)
$T_t \times IS$	-0.005	-0.009	0.019	-0.008
	(-0.157)	(-0.212)	(0.481)	(-0.136)
$B_i \times IS$	0.063**	0.063**	0.024	0.028
	(2.199)	(2.265)	(0.988)	(1.151)
T_t	-0.094	-0.095	-0.044	-0.029
	(-1.577)	(-0.998)	(-1.188)	(-0.450)
$T_t \times B_i$	-0.981***	-0.814***	-0.872***	-0.722***
	(-6.709)	(-7.043)	(-7.403)	(-9.337)
B_i	0.400***	0.406***	-	-
	(6.938)	(7.011)	-	-
IV	7.231***	8.815***	9.638***	11.000***
	(5.592)	(5.295)	(8.243)	(7.194)
IS	-0.025***	-0.022***	-0.016**	-0.015**
	(-3.744)	(-2.786)	(-2.370)	(-2.010)
Constant	-2.080***	-1.990***	-5.334***	-5.023***
	(-11.074)	(-9.869)	(-13.601)	(-12.353)
Observations	22,958	22,212	22,958	22,212
Controls	Yes	Yes	Yes	Yes
Fixed effects	No	No	Yes	Yes
Robust s.e.	Yes	Yes	Yes	Yes
R-squared	0.222	0.216	0.285	0.270