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What Drives Loss Given Default? Evidence From Commercial Real Estate Loans at Failed Banks *

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Abstract

This paper extends what we know about loss given default (LGD) by examining a newly available dataset on commercial real estate (CRE) loan losses. These data come from 295 failed banks resolved by the FDIC using loss-share agreements between 2008 and 2013. We examine over 14,000 distressed CRE loans to study the relationship between LGD and loan size, workout period, loan seasoning, asset price changes over the life of the loan, and other factors related to losses. We also examine the relationship between LGD and certain bank characteristics. The results inform commercial lenders and regulators about the factors that influence losses on defaulted loans during periods of distress.

Keywords: loss given default; recovery rates; credit risk; commercial real estate
JEL Classification Codes: G21, G32

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1 Introduction

Commercial real estate (CRE) lending is a major source of income—and losses—at commercial banks. It is also a major contributor to bank failure: over 70 percent of U.S. bank failures during 2008–2011 were CRE lending specialists.[1] Therefore, a good understanding of CRE credit risk is essential for both bankers and bank regulators.

Yet large gaps remain in the accumulated knowledge. In his review on loss given default (LGD), Schuermann (2004) states: "[M]ost of the published research treats recoveries of bonds rather than loans for the simple reason that that's where the data is."[2] In addition, most of the LGD literature has focused on general commercial lending rather than CRE. The research that is available on CRE loans relies on data from life insurers, securities or large loans that trade on secondary markets.[3] A few studies are based on the commercial loan portfolios of very large banks.[4] But how relevant are these results to the portfolios and performance of smaller CRE loans at smaller banks?

This paper begins to fill that gap by exploiting a newly available dataset on CRE loans held by 295 banks that failed in the recent crisis and were resolved using loss-sharing arrangements between the FDIC and acquiring institutions. Of course, these banks can hardly be characterized as typical. The banks failed during the worst downturn in 60 years, and the results cover only this distress period. Even so, an analysis of a wide variety of CRE loans held by small and mid-sized banks provides important insights. This is the first available study that focuses on LGD for smaller CRE loans that were originated and held by small and mid-sized banks. Because the sample includes loans from so many banks, it also enables us for the first time to analyze the effects of certain bank characteristics on LGD.

LGD is a key component for expected loss, which is central to credit risk management. The expected loss (EL) to a portfolio is defined as:

$$EL = \sum_i PD_i \times LGD_i \times EAD_i \tag{1}$$

[1]Source: FDIC calculations. The definitions for lending specialty follow FDIC (2012).

[2]Schuermann (2004), 259.

[3]For example, see Ciochetti (1997), Gupton, Gates and Carty (2000), Acharya, Bharath and Srinivasan (2003), and Altman et al. (2005).

[4]Asarnow and Edwards (1995) examine loans from Citibank. Araten, Jacobs and Varshney (2004) examine loans from JPMorgan Chase. Both studies include a mix of commercial loan types, including CRE.

where PD is the probability of default from obligor i; LGD is the loss given default, expressed as a proportion of the total exposure that is lost if default occurs; and EAD is the value in dollars of that exposure at the time of default. LGD is also directly tied to the recovery rate (RR) on a defaulted loan. The recovery rate is the proportion of bad debt that may be recovered in the event of default: $RR=1\text{-}LGD$.

LGD affects several areas of bank operations. It influences the economic capital required to support the loans, as well as the regulatory capital requirement (at least for large banks that are required to undertake advanced measurement techniques). It affects the management of portfolio risks, including the development of risk metrics, stress testing, and the estimation of loan-loss reserves on bank financial statements. Many smaller banks struggle with these calculations because it is difficult to quantify LGD when the bank does not have many defaulted loans—especially if there are also difficulties in measuring historical LGD for those loans. The results of this study provide useful insights and benchmarks for these banks and their regulators.

Theoretically, CRE loans default when two conditions are met: 1) the net operating income of the property falls below the cost of servicing the debt, and 2) the value of the property falls below the outstanding loan balance.[5] In addition, CRE loans might default if the loan has a balloon payment at maturity and the borrower is unable to obtain new financing, even if one or both of the above conditions are not met. The subsequent losses are (or may be) influenced by four primary factors: origination quality, servicing quality, changes in property prices and market conditions, and seasoning of the loan at the time of default.

Origination Quality

Origination quality includes a combination of tangible and intangible items. The loan-to-value ratio (LTV) and the debt-service coverage ratio (DSCR) are probably the most important; others include the property type, the quality of the borrower, the extent of the relationship between the borrower and lender, and the usage of covenants or guarantees to enhance loan quality. Seniority of creditor status and collateral type have consistently been found to be major determinants of LGD.[6] However, authors who focus solely on CRE loans or structured securities generally omit lien

[5] See Moody's (2011b) and Kim (2013) for additional discussion. Brown, Ciochetti and Riddiough (2006) present a more nuanced model. Construction and development loans have additional risks.

[6] Examples include Acharya, Bharath and Srinivasan (2003), Altman et al. (2005), Schuermann (2004), Araten,

status.[7] In addition, results of CRE studies can sometimes be inconsistent. For example, Pendergast and Jenkins (2003) and Fitch (2012) stratify commercial mortgage-backed securities (CMBS) recovery rates by property type: Pendergast and Jenkins (2003) find that the retail sector is among those with the lowest loss severity (31.2%) whereas Fitch (2012) finds retail properties to have the highest loss severity (56.9%).[8]

Servicing Quality

Servicing quality is difficult to measure, but practitioners have often emphasized its importance.[9] Proactive identification and management of problem credits can have a major impact on LGD. Several authors have found that LGD increases with the length of the workout period.[10] However, when interpreting results, it can be difficult to separate servicing effects from the quality of the underwriting on the loan.

Market Conditions

Numerous studies have focused on the effects of changing market conditions on asset prices. The authors have found a strong relationship between LGD and industry-wide default rates. For example, Altman et al. (2005) find that supply and demand factors play a large role in this result. Acharya, Bharath and Srinivasan (2003) find that distress of the borrower industry dominates over general macroeconomic conditions. Brown, Ciochetti and Riddiough (2006) explore the effects of market conditions on the interaction between lender and borrower and related decisions to foreclose or restructure. They demonstrate why foreclosures and long workout periods occur more often when markets are weak and illiquid.

Loan Seasoning

Loan seasoning matters for LGD because poorly underwritten or poorly managed projects tend

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Jacobs and Varshney (2004), and Moody's (2000). Senior tranches have much lower LGDs. The best collateral type is marketable securities.

[7] For example, Ciochetti (1997), Hu and Cantor (2004) and Fitch (2012). No reason for the omission is stated. Junior liens may be rare for large loans.

[8] Pendergast and Jenkins (2003), 31, and Fitch (2012), 7. Pendergast and Jenkins (2003) report on liquidations that occurred from 1998 through 2002; Fitch (2012) reports on losses that occurred in 2010.

[9] See Bohn (2009), and Cermele, Donato and Mignanelli (2002).

[10] See Acharya, Bharath and Srinivasan (2003) and Esaki, L'Heureax and Snyderman (1999).

to default shortly after origination, and because market rents and asset prices generally rise over time (thus current LTV improves). If a loan defaults near its maturity date, the property's net income is likely high enough to support the debt payments, making the LGD relatively modest.

Our empirical methodology in this paper is largely driven by the bimodal nature of the LGD data: we observe a high frequency of defaulted loans that fully recover, with the remainder of those loans dispersed across a broad range of losses. To address this characteristic, we use a two-stage estimation approach that allows the factors that influence cure rates to differ from the factors that influence loss severity. First, we ask what influences the probability of a loan experiencing zero versus non-zero losses. Second, conditional on experiencing non-zero losses, we ask what influences the loss severity. We then combine these two stages to estimate the overall marginal impact on expected LGD. The two-stage approach provides a better understanding of these factor relationships with LGD.

We see several contributions of this study to the literature: 1) We examine the behavior of LGD for CRE loans at small and mid-sized banks—the existing literature on LGD has focused on very large loans or bonds, and it is not known how applicable those results are for typical loans at typical banks. 2) Because our sample is comprised of defaulted loans at numerous failed banks, we are able to look at certain bank-level characteristics and their influence on LGD. To our knowledge, no other papers have examined bank factors affecting LGD. 3) Our two-stage methodology reveals additional insights that distinguish influences on the probability of zero versus non-zero losses and on loss severity. 4) We show new evidence suggesting a relationship between loan seasoning and LGD. (Existing literature has focused on loan seasoning and probability of default (PD).) 5) We are the first to empirically explore the relationship between judicial foreclosure and out-of-territory lending and LGD. 6) We also find a new potential channel that increases losses to the FDIC if regulators delay the closing of troubled banks.

The rest of this paper is organized as follows: Section 2 describes the LGD data; Section 3 outlines our methodology; Section 4 presents the results of our analysis; and Section 5 concludes.

2 Data

In this section, we describe the FDIC loss-share program (our primary data source) and our definition of LGD. We also discuss relevant characteristics of the data.

2.1 FDIC loss-share program

From 2008 through 2013, the FDIC closed 304 banks under its loss-share program. These banks held $68 billion in CRE loans at failure.[11] Under loss share, the acquiring institution purchases loans from a failed bank and the FDIC indemnifies in part the subsequent credit losses for those assets. The FDIC uses a database to manage its associated risk exposure and support program administration. Our definition of LGD flows from the provisions of the loss share program and related data availability, and our sample covers losses reported from IV/2008 through II/2014.

Under the program, the FDIC covers the following types of losses:

- Chargeoffs (net of recoveries)
- Loss on sale of asset (loan or owned real estate (ORE))
- Expenses paid to third parties related to the asset, except servicing fees (legal fees, foreclosure expenses, appraisals, property maintenance costs, etc.)
- Up to 90 days of accrued interest

If the asset goes into foreclosure, the FDIC is entitled to share in any income earned from the collateral. The full indemnification period is five years. For an additional three years, the acquirer is required to continue reporting all losses and recoveries, and continues to share recoveries (net of certain collection expenses) with the FDIC.

Although the FDIC's share of losses varies by agreement, most of the agreements provide the acquirers with 80% indemnification for most assets. The FDIC loss coverage may weaken the incentives of acquirers to work assets effectively. However, the FDIC has taken several actions to mitigate the potential effects.[12] Based on comparisons of these data to other studies, discussions

[11] Excluding construction and development loans. The FDIC also entered into a loss-sharing agreement with Citibank in 2008. This analysis excludes this agreement.

[12] Requirements include: a) acquirers must manage the covered assets in the same way that they manage their own assets; b) acquirers must provide regular standardized reporting, adequate workpapers and evidence that the loans

with loss share monitoring staff and program evaluations, we conclude that the mitigation is largely effective.

Another important provision is that the acquirers only receive FDIC loss-share coverage on bulk loan sales if the FDIC concurs. Bulk sales of loss share assets have not occurred often because they generally result in higher LGDs than more active workout strategies. Therefore, for banks that rely heavily on bulk loan sales to dispose of their problem loans, the results in this paper may not be very relevant.

2.2 LGD assumptions and details

A loan is assumed to be in default if any of the following events occurred:

- The loan became 90 days or more delinquent
- The loan was placed in non-accrual status
- The loan was classified as being in foreclosure or bankruptcy
- A charge-off was taken on the loan, or any claim was made under the loss-share program

Except as described below, the sample includes all defaulted loans, regardless of whether the acquiring bank filed a claim under the loss-share program.

We calculate the LGD of a defaulted loan as follows:

$$LGD = 1 - \{\frac{\frac{EAD - \sum_{t=1}^{T}(CO_t - REC_t + LOSALE_t)}{(1+r)^T} - \sum_{t=1}^{T}(\frac{EXP_t}{(1+r)^t} + \frac{AI_t}{(1+r)^t})}{EAD}\} \tag{2}$$

The denominator (EAD) is defined as the exposure at default. The numerator is defined as the discounted net principal recovery minus expenses. Acquirers do not report all cash inflows under the loss-share program, but they report principal losses and expenses. Therefore, we estimate principal recovery as the exposure at default minus principal losses (defined as chargeoffs (CO_t) net of recoveries (REC_t) plus the loss on sale ($LOSALE_t$)). We also assume that the entire net

are being worked effectively; and c) the FDIC performs regular reviews of loss claims and on-site compliance reviews at least once a year. If the FDIC identifies a problem, the agency may demand program improvements, reverse loss claims or, in the case of a serious contract breach, abrogate the loss share coverage altogether. Acquirers have the right to contest any FDIC actions. For an example agreement, see `https://www.fdic.gov/bank/individual/failed/oldecypress_p_and_a.pdf`.

principal recovery occurs when the asset is extinguished.[13] Expenses (EXP_t) consist of legal fees, foreclosure expenses, appraisal fees, property preservation costs, property taxes, etc., and AI_t is the unpaid accrued interest on the loan.[14] The loan's interest rate r_t is used as the discount rate.[15] Loans with LGDs that exceed 100 percent occur relatively often: for example, they occur any time that a loan is fully charged off (as a result of unpaid accrued interest plus any collection expenses). A cap at 100 percent appears reasonable but might understate true losses in light of the uncertainties and costs involved with a problem loan portfolio. After examining the distribution of LGDs in our sample, we cap LGD at 130 percent of exposure at default.[16] If the loan defaults but no claims are made, we assume a full recovery.

Our definition differs somewhat from the definition of economic loss that is set forth in the guidance on LGD for the Basel II Advanced Approach models. In addition to the items in our definition, the Basel II definition includes servicing costs and unpaid fees at the time of default. Because unpaid fees are usually small, the main difference between our definition and the Basel II definition for economic loss is the exclusion of servicing costs. Servicing costs can be material yet are inherently difficult to measure.[17]

All of the loans in our sample were originated prior to the originating bank's failure, existed when the bank failed, and were extinguished after the bank failed. Unlike other studies, most of the loans in our analysis likely underwent a change in the servicing regime over the life of the loan.[18]

[13] An asset is extinguished when it is paid off in full, written off in full, sold, or when it is foreclosed and the collateral is sold.

[14] Details on the expenses and offsetting income covered by loss share can be found at `www.fdic.gov`. An example agreement can be found at `www.fdic.gov/bank/individual/failed/oldecypress_p_and_a.pdf` We use the accrued interest claim as our estimate for accrued interest costs. In cases where the loan was placed in nonaccrual status prior to bank failure, the acquirer cannot make such a claim, and unpaid accrued interest has probably been capitalized into the loan by the failed bank. Our definition excludes capital gains. The loss-share program sets a number of restrictions on fees imposed on defaulted loans.

[15] In a few cases, the interest rate is not available. For these loans, we estimate the interest rate as the rate charged by the bank for similar loans or, for banks with small portfolios, the average rate charged by all banks for similar loans. Because we lack a full payment history, we assume that borrowers paid no interest after default if the loan did not cure, and that borrowers repaid all interest due if the loan cured. Cured loans are defined as loans that defaulted but were extinguished with no loss claims.

[16] LGDs exceed 130 percent before adjustment for 0.9 percent of the loans in the sample. We are not the first authors to report LGDs above 100 percent. See Araten, Jacobs and Varshney (2004).

[17] The Congressional Oversight Panel noted that special servicers that handle problem loans "typically earn a management fee of 25 to 50 basis points on the outstanding principal balance of a loan in default as well as 75 basis points to one percent of the new recovery of funds." See Congressional Oversight Panel (2010), 44. They were discussing servicing arrangements under Commercial Mortgage Backed Securities, or CMBS. Banks frequently do not hire special servicers to handle their problem loans, and bank loans are much smaller. Therefore, servicing costs for bank loans might differ substantially from CMBS loans.

[18] A few loans may not have been funded until after the bank failed. A few acquirers may not have made significant changes to the servicing for some parts of the portfolio.

Because many private sector banks retain and service the CRE loans that they originate, servicing regime changes are less likely at other banks. Because all of the originating banks failed in our sample, the quality of the loan servicing during the early period of the loan might be weaker than average. In addition, the originating banks in our sample might have been slow to recognize losses or aggressively work out their troubled loans to avoid the associated harm to earnings and capital. On the other hand, the acquiring bank had good reason to recognize losses and work out troubled loans promptly so that losses could be realized before the FDIC's loss share coverage expired.

We exclude from the sample foreign loans and very small loans (under $100 exposure at default). We also exclude loans with meaningful data quality problems for the dependent or independent variables, and loans where independent variables are missing. The largest number of exclusions are made for loans that have not yet been extinguished (right-censored).[19] LGDs on loans that are right-censored are difficult to predict because the loans are active assets with unknown future losses. Unlike most other LGD studies, our dataset is left-censored as well. This occurs because loans that defaulted and either cured, modified or were extinguished prior to bank failure are not reported in the loss share data. Therefore, not all loans that defaulted shortly after origination are present in the sample. These loans are likely to have had relatively low LGDs. Loans that defaulted well before failure are also excluded. The net effect of left- and right-censoring on LGD in the dataset is unclear.[20]

Our final sample for this study includes 14,225 loans from 295 failed banks.[21] The data are not highly concentrated by bank: the top five banks by number of loans hold less than 20 percent of the sample. The geographic concentrations are much stronger: 19 percent of the loans are from Georgia, and 65 percent are located in the top five states by number of loans.[22] Mean LGD is 44 percent, and the median is slightly lower at 41 percent. Table 1 presents further details. Like previous authors,[23] we find a strong bimodal distribution for LGD, depicted in Figure 1. About 30

[19]A total number of 18,035 exclusions (56 percent) were made from a starting sample of 32,460 defaulted loan observations. Of these 18,035 exclusions, 13,592 (75 percent) were made for censoring (most of these were assets that were still active). Another 2,691 (15 percent) of the exclusions lacked data for explanatory variables. Other reasons included foreign assets (4 percent), loan size below $100 (4 percent) and data errors (2 percent).

[20]The nature of this censoring has both dependent and independent variable observations missing. These are not missing relative to any particular threshold values. They are simply outside the snapshot of losses captured at the time of loss share reporting. Censored or truncated regression modeling would not be suitable for these data.

[21]Five banks participated in the loss-share program but had no CRE loans.

[22]The top five states are Florida, Georgia, Illinois, California and Washington.

[23]See Asarnow and Edwards (1995), Araten, Jacobs, and Varshney (2004), and Schuermann (2004).

percent of the loans cured, and 10 percent had LGDs that exceeded 100 percent.

Because our sample is drawn from banks that failed during a severe recession, the results should be interpreted with care.[24] Banks rarely fail unless their portfolios have unusually high default rates. Moreover, bank failures during the recent crisis were concentrated in geographic regions that experienced higher-than-average economic distress. Of the 353 banks headquartered in Georgia at year-end 2007, 87 (25 percent) failed by the end of 2013. None of the banks in North Dakota failed.[25] Despite the sample characteristics, our analysis supports the view that the LGDs are generally comparable to other CRE bank loans during high-stress periods.[26]

3 Methodology

The approach we take is motivated largely by the empirical distribution of the LGD data. In Figure 1 we observe a large spike in the LGD distribution for defaulted loans with zero losses, after which the frequency drops off dramatically. The abrupt spike on the far left tail suggests that the loans with zero losses may behave differently from the rest of the defaulted loans. In his survey of the LGD literature, Schuermann (2004) makes a similar observation: "Defaults resulting in 100 percent recovery (0 percent LGD) are probably somewhat special and should be modeled separately. Put differently, it is likely that there may be different factors driving this process, or that the factors should be weighted differently."[27]

With this in mind, we use a two-stage approach in our analysis. In the first stage we ask: What factors influence the probability of a defaulted loan incurring losses? We assign LGD observations into binary categories: loans having zero losses are set equal to 0; and loans that incur losses are set equal to 1. Then we perform a logit regression on the probability of incurring a loss. In the second stage we ask: Conditional on a defaulted loan incurring losses, what influences the loss severity? We isolate the sub-sample of defaulted loans that experience losses and perform a linear regression using their continuous LGD values. We then combine results from the two stages to examine the marginal impact on expected LGD. Modeling the combination of loss probability and loss severity in this way allows us to distinguish between drivers of LGD for defaulted loans that experience full

[24] Eighty-two percent of the loans in the sample were held by banks that failed in 2009 and 2010.
[25] Source: FDIC.
[26] See Shibut and Singer (2014) for additional discussion.
[27] Schuermann (2004), 270.

recoveries and those that do not.

The expected value of LGD in our model is not a simple mean, but is weighted by the probability of falling into either loss category:

$$E(LGD) = \sum_{i=1}^{n} LGD_i \times \pi_i + 0 \times (1 - \pi_i) \tag{3}$$

where n is the number of defaulted loan observations, LGD_i is the estimate of loss given default, π_i is the probability of loan i incurring a loss, and $(1 - \pi_i)$ is the probability of loan i incurring no loss. The probability π_i of incurring a loss on the defaulted loan is computed from the logit model, and the loss severity LGD_i is computed from the linear regression model.[28]

Stage 1: Logistic regression with full sample

In the first stage, we examine what influences the probability of a defaulted loan in our sample incurring zero versus non-zero losses. We separate the defaulted loans into two categories: those with losses and those without losses. We have for outcome variable y_i:

$$y_i = \begin{cases} 1 & \text{if defaulted loan } i \text{ incurs a loss} \\ 0 & \text{if defaulted loan } i \text{ has no loss} \end{cases}$$

Then for $y_i = \{0, 1\}$, the probability of observing realization y_i from random variable Y_i is:

$$\Pr\{Y_i = y_i\} = \pi_i^{y_i} (1 - \pi_i)^{1 - y_i} \tag{4}$$

where π_i is the probability that y_i takes a value of 1 and $(1 - y_i)$ is the probability that it takes a value of 0. The logit function takes the underlying probabilities for realization $\{y_1, \cdots, y_n\}$ and

[28] Leow and Mues (2012) use a similar approach to model LGD for residential mortgage loans. They have a probability of repossession model to capture the likelihood of an account undergoing repossession given that it has gone into default, and a haircut model to estimate the discount on the sale price of the repossessed property. The former is estimated with a logistic regression; the latter uses Ordinary Least Squares, or OLS.

links them to the linear predictor variables:

$$\text{logit}(\pi_i) = \log(\frac{\pi_i}{1-\pi_i}) = \mathbf{x}_i'\beta \tag{5}$$

where $\mathbf{x}_i$ is the vector of covariates and β is the vector of regression coefficients. Solving for the underlying probability π_i of realization y_i gives:

$$\pi_i = \frac{\exp\{\mathbf{x}_i'\beta\}}{1+\exp\{\mathbf{x}_i'\beta\}} \tag{6}$$

The coefficients can be solved for via maximum likelihood.

Stage 2: Linear regression with loss sub-sample

In the second stage, we take the LGD loss sample and perform a linear regression. Conditional on incurring losses, the LGD associated with defaulted loan i takes the form:

$$LGD_i = \beta_0 + \mathbf{x}_i'\beta + \epsilon_i \tag{7}$$

where $\mathbf{x}_i$ is again the vector of covariates and β is the vector of regression coefficients. This allows us to examine the relationship between explanatory covariates and the severity of losses on these loans.

To control for bank-level fixed effects in our analysis, we use cluster-robust standard errors in estimation.

4 Analysis

In this section, we describe the explanatory variables in our regressions and discuss our results.

4.1 Explanatory variables and expected effects

4.1.1 Loan characteristics

The defaulted loans in our sample are far smaller in asset size than those examined elsewhere in the LGD literature. Our sample has a mean loan balance of $929,599 and a median loan balance of $306,797 at the time of default. For comparison, Esaki et al. (1999) report a mean asset size of $4 million in their sample of CRE loans held by life insurers.[29] The smallest loan reported by Gupton et al. (2000) in their study of U.S. syndicated loans was $60 million.[30] Ghent and Valkanov (2014) report a mean size of $58 million for CMBS loans.[31] Because certain collection costs are fixed or semi-fixed, there is reason to expect that smaller loans would have higher LGDs. We therefore include *ln_loan_bal*, or the log of the asset size at default, in our analysis.

We include several variables related to the seasoning of the loan at the time of default. First, we include the age of the loan at default, *age*, to capture the observed tendency for worse quality loans to default sooner. About 10 percent of the defaulted loans in our sample did so in the first year, and 43 percent defaulted within the first three years.[32] We include the squared term *sq_age* to allow nonlinear effects of age on LGD. In addition, we include *pct_remain*, the percentage of the original loan balance remaining unpaid at default. We expect loans that default early, with a high percentage of the original balance remaining, to have higher LGDs. We also include a dummy for loans already in default when the bank failed: *default_at_failure*. We expect a positive relationship with LGD because we anticipate that the servicing quality is generally lower at failed banks than at the acquiring banks and may result in worse recoveries.

A key way that banks differentiate loan quality at origination is through the interest rate offered to the borrower.[33] Because our sample includes loans originated in a variety of interest-rate environments, we use the difference between the loan's interest rate and the analogous Treasury

[29] Esaki et al. (1999), 80.

[30] Their primary source is Moody's, and their analysis covers commercial loans from 1989 through 2000. In the appendix, they provide loan level information for defaults that occurred in 1999 and 2000; the $60 million is the smallest figure reported there.

[31] They also report a mean size of $23 million for bank CRE loans, but their bank loan sample is not comparable to the sample in this paper because it excludes loans below $2.5 million.

[32] To check for the possibility that loan age is really capturing effects of loan vintage, we included dummies for year of loan origination. We found that these were insignificant when added to the regression equation and did not change the impact of loan age on LGD. It appears that our inclusion of the change in the commercial property price index (CPPI), between origination and extinction, *cppi_change*, appears to effectively control for loan vintage effects.

[33] In fact, Morgan and Ashcraft (2003) find that interest rates align with asset quality more closely than with bank risk metrics calculated at origination.

rate at origination.[34] The mean interest-rate premium *rate_prem* on these loans is 3.32 percent. We expect LGD to increase as the interest-rate premium increases.

The workout period is an important indicator of both servicing quality (good servicers stay of top of the assets and move promptly as needed) and origination quality (foreclosure takes time and occurs more frequently for weaker credits). We include variables for the workout period (*wkout*), the squared workout period (*sq_wkout*), and a foreclosure dummy (*foreclose*). The mean workout period is 6.12 quarters, and 29 percent of the loans in the sample were foreclosed.

In recognition of the additional costs associated with judicial foreclosure, we include a dummy indicator for loans where the collateral is located in states that require judicial foreclosures (*judicial*).[35] We expect that judicial foreclosure will increase LGD, both for foreclosed loans (because of increased expenses) and other loans with losses (because of stronger bargaining power for distressed borrowers). As a result of potential complications in both the origination and servicing of loans that are collateralized by assets outside of the bank's geographic footprint, we include a dummy indicator for out-of-territory loans (*out_territory*). The definition follows that of the Community Reinvestment Act, except that we base the designation on the collateral location rather than the borrower location. We believe our paper is the first paper that provides empirical evidence on the effect of judicial foreclosure and out-of-territory status on LGD.

We exclude lien status from the core regression on account of missing data for about 3,000 observations. However, we separately report the estimated effect of lien status on LGD in our results section below. About 10 percent of the remaining loans had junior liens.

We lack data for several relevant items that are related to the origination process and have been found in prior research to influence LGD. We do not have the original LTV, and thus we cannot estimate the current LTV. We do not have net operating income for the collateral, and thus cannot calculate the DSCR. We do not know the type of property (for example, multi-family or office building); neither do we know the borrower's industry. We also do not know about the extent of the relationship between lender and borrower—that is, whether a bank made multiple loans or provided other services to the borrower.

[34] For adjustable rate loans, the interest-rate premium is calculated as the loan interest rate at bank failure minus the 1-year Treasury bill rate at bank failure. For fixed-rate loans, the premium is calculated as the loan interest rate minus the Treasury rate at origination for the Treasury note or bond with a term closest to the loan term.

[35] For observations where the collateral location is unknown but the borrower location is known, we assume that the borrower and the collateral are co-located. We follow the same treatment for all geographic areas.

4.1.2 Bank characteristics

Because banks of different sizes may differ in their resources for the origination and servicing of loans, we include a variable for the log bank size, *ln_bank_size*. The mean failed bank size in our sample is $805 million, and the median is $281 million. In addition, strong asset growth prior to the demise of a failed bank could harm the origination and servicing capabilities of the bank. To test for these effects, we include the average annual loan growth rate of the failed bank for the three-year period leading up to the peak size of the failed bank: *peak_growth*.[36] We base this window on regulator evidence concerning the life cycle of bank failures.[37] We expect that both smaller banks and banks that grew quickly before failure would face challenges in origination and servicing, and thus would have higher LGDs. We also include the number of quarters that the bank had a CAMELS rating of 4 or 5 during the period leading up to failure: *delay_close*. Because failed banks that experience serious distress for a long time are likely to face more serious resource constraints than those that fail quickly, and because serious resource constraints might harm servicing quality, we expect a positive coefficient.

We examined several other bank-level variables that were dropped because of insignificance. The bank's coverage ratio and its default rate at failure were expected to serve as further indicators of bank origination and servicing quality. However, we did not find either of these to be significant in our regressions. Dummy indicators for year of bank failure were also tested but were not significant. We looked at business lines for the failed banks; however, most of the banks were classified as CRE lending specialists and exhibited very little variation. We also examined de novo status, which we found to be highly correlated with bank size and growth rates.

4.1.3 Market conditions

To gauge the overall market condition, we include the year-over-year change in the industry-wide noncurrent rate for CRE loans at the time of default: *industry_nc*.[38] We also capture asset price changes in commercial real estate from the Commercial Property Price Index (CPPI) published by

[36]For banks that shrank for a long period prior to failure, we use the growth rate leading up to failure. For very high-growth banks, we cap the growth rate at 1000 percent; 21 banks exceeded the cap. Almost all of them were de novo banks.

[37]FDIC (1997). The three-year period was the shorter range observed for the bank failure life cycle; we also tried the longer range of five years and found similar results.

[38]Source: FDIC calculations.

CoStar at the regional level. For this variable, we calculate the log change in the regional CPPI (based on collateral location) between origination and the date when the asset was extinguished: *cppi_change*. The mean reduction in asset prices between origination and disposition is 20 percent, and the median is even higher at 25 percent. Many of these properties suffered from very serious asset price declines.

We examined several alternative macro-level variables that were not included in the final regression. We looked at quarterly GDP, unemployment and personal income at the state level, and regional dummy indicators. We examined other variables to capture real estate market conditions, including the Real Estate Investment Trust (REIT) Equity Index, CMBS delinquency rates, and the quarterly volume and average price of commercial property repeat sales provided by Real Capital Analytics. Most of these were eventually left out of the regression equation because of multi-collinearity, but a few (personal income and regional indicators) were dropped because they lacked statistical significance.

Table 2 presents our explanatory variables in context of the primary factors (origination quality, servicing quality, changes in property prices and market conditions, and seasoning) described in the introduction. Table 3 provides their summary details.[39]

4.2 Regression analysis

Table 4 summarizes our regression findings. Column (1) shows the coefficient estimates from a simple linear regression using the full LGD sample for comparison. We next categorize LGD as a binary "loss" variable, where *loss=0* for defaulted loans with zero losses and *loss=1* for defaulted loans with losses. We run a logit regression, with the coefficients shown in column (2) and their marginal effects in column (3).[40] In the second stage of the analysis we use a linear regression for the sub-sample where *loss=1*. Column (4) shows these coefficients for loss severity. The last column shows the predicted marginal impact at the mean for a one-unit change in each of the regression variables. These are calculated by combining results from both logit and linear regression stages via equation (3). To improve the interpretation of various nonlinear relationships, Figures 2 and

[39]Variable correlations and variance inflation factors were also considered in determining the final regression specification.

[40]We also estimate probit and complementary log-log functions as possible alternative linking formulations and found that the results were not significantly changed.

3 provide predictive margins and confidence intervals for selected variables and combinations of variables. Our findings from the two-stage analysis are largely consistent with the initial linear regression. However, the two-stage methodology enables a deeper understanding of the covariate impacts on LGD.

We find that a larger loan size at default is associated with lower losses, aligning with our intuition regarding the probable effects of fixed or semi-fixed collection costs on smaller loans. Other explanations for this phenomenon could be that the banks are more actively working the largest of their defaulted loans for recoveries, or that the larger loans are made to higher-quality borrowers with better chances for recovery. Other authors have found mixed results regarding asset size.[41] If fixed costs or resource allocation underlie the results, it is logical that the effect would be stronger for our sample than for other studies that are based on larger assets. Loan size matters in both the full and loss sample linear regressions, but it is not statistically significant in the logit regression. This gives us a more nuanced interpretation of loan size effects with respect to LGD. It does not appear to affect the probability of incurring losses. However, conditional on *loss=1*, smaller loans are associated with a higher LGD. The effects are material, especially for smaller loans: an increase in loan size from $100,000 to $200,000 is associated with a 311 basis point reduction in LGD; a similar $100,000 increase from $1 million to $1.1 million is associated with a 42 basis point reduction in LGD.

Consistent with the literature on effects of loan seasoning on the probability of default (PD), we find evidence that loan seasoning relates to LGD. Loans defaulting soon after origination and with higher proportions of unpaid balances remaining may be riskier or lower quality credits. This influences both the likelihood of incurring losses as well as the loss severity. While the relationship between loan seasoning and PD has been explored elsewhere, to our knowledge ours is the first paper to show evidence for a relationship between loan seasoning and LGD. At the mean age of just over four years, a one-quarter increase in the age of the loan at default is associated with a 47 basis point reduction in LGD. The effects are stronger early in the life of the loan: a one-quarter increase at 1 year of age is associated with a 62 basis point reduction in LGD. The true marginal effect might be lower than our measurement to the extent that loan seasoning is serving as a proxy

[41] Acharya, Bharath and Srinivasan (2003) find that size is generally not significant at emergence from bankruptcy, but is often significant for market prices at default. Schuermann (2004) concludes that asset size probably doesn't matter. Pendergast and Jenkins (2003) find that size matters for CMBS loans.

for origination or servicing quality effects. Loans with lower origination quality are likely to default sooner. In addition, loans that defaulted before the originating bank failed also have higher losses, suggesting that the servicing quality for those early defaults may have been weaker.

We also find that a higher percentage of the original loan balance remaining at default is associated with a higher LGD. This may indicate that amortizing loans provide lenders a little more safety than comparable balloon loans. The coefficient is significant in the logit regression but is insignificant in the linear regression for the *loss=1* sub-sample. It appears that the relationship between high loan balances and LGD is driven more by the increased probability of incurring losses than by the severity of the loss.

We considered—but rejected—the possibility that the loan seasoning variables might be serving in some way as a channel of the relationship between default rates and LGD. We include the change in the industry noncurrent ratio (*industry_nc*) was to try to control for these effects.[42] We therefore think that the relationship between LGD and loan seasoning may indeed matter.

The interest rate premium is insignificant in the linear regression for loss severity, but the logit regression suggests that a higher interest rate premium is associated with a lower probability of incurring losses. This may reflect more prudent underwriting standards on some of these loans. However, the effect of the interest rate premium on the probability of incurring a loss is small.

Workout period appears to matter a great deal: longer workout periods are related to higher losses, indicating that the servicing quality is an important factor for LGD. Origination quality may be relevant to this result as well, because inherently weaker credits are less likely to cure quickly and more likely to be foreclosed. The non-linear workout term indicates that increases in the length of the workout period probably matter most early in the workout process. This implies that early efforts in the workout process for defaulted loans may be important for reducing losses. The workout period is highly significant in both the logit regression and the loss sample regression, affecting both the probability of incurring loss and the severity of loss. At a mean of 6.2 quarters, a one-quarter increase in the workout period is associated with a 295 basis point increase in LGD. The marginal effects are considerably stronger for workout periods of less than two years than for longer workout periods, perhaps because cures generally occur shortly after default. The marginal effects are weaker for loans in foreclosure. (See Figure 2.)

[42] We also tried the industry noncurrent ratio in levels and found results to be similar.

As expected, materially higher losses occur with foreclosures. The estimated marginal effect under the two-stage model is a full 20 percentage points. These loans may be associated with weaker underwriting, higher expenses, weaker markets and longer time lines.

The judicial foreclosure indicator is insignificant in the logit regression, but it is highly significant for the loss sample. Having collateral in a judicial foreclosure state does not appear to affect the probability of a full-recovery on the loan. Intuitively, the additional costs associated with foreclosure would have no effect on loans that are strong enough to avoid losses. However, these additional costs are associated with a substantially higher loss severity conditional on *loss=1*. The estimated effect is an increase of 550 basis points in severity for loans incurring losses, and 392 basis points for expected LGD when combined with the logit effects of an increased probability of incurring losses.

One might expect that judicial foreclosure influences LGD for loans where the collateral is foreclosed but not for other troubled loans. To test this hypothesis, we try interacting the judicial foreclosure indicator with foreclosure status to see whether foreclosed loans in judicial foreclosure states have higher losses. We find that the coefficient on this interaction term is insignificant. Borrowers may be able to seek more concessions from lenders in these locations because both parties are aware of the additional cost and delay associated with judicial foreclosure. This in turn would increase LGD regardless of whether foreclosure is undertaken.[43]

Consistent with what we think, loans made out-of-territory are associated with a higher LGD. This may reflect a greater degree of asymmetric information with out-of-territory lending during the origination or the servicing process (or both). This effect may also reflect a higher cost of servicing these loans. The estimated marginal impact on expected LGD for out-of-territory loans is 312 basis points.

The coefficient for bank size is significant in the logit regression but is insignificant in the loss sample regression. Bank size is associated with the probability of loss, with smaller banks appearing to have lower full-recovery rates. This lower rate could be explained in part by better resources at larger banks for identifying and working problem credits. It may also that some of these smaller banks accepted more credit risk at origination or lent outside of their core specialization areas in the lead-up to the crisis. Bank size does not appear to affect the severity of losses, however. Taking both the logit and linear regression results into account, we estimate that a $100 million marginal

[43] Judicial foreclosure (or location in a judicial foreclosure state) may also extend the workout period.

increase in bank size (at a median bank size of $281 million) is associated with a 51 basis point reduction in LGD.

The bank's asset growth prior to its demise is insignificant in our regression. However, there is some collinearity of asset growth rates with bank size—smaller banks in our sample tend to have higher growth rates. We also find that the significance of strong asset growth is affected by the age of the loan as well as the inclusion of default-at-failure and out-of-territory dummy variables. In other words, banks with higher growth rates appear more likely to have bad loans that defaulted early, and they are more likely to have higher out-of-territory lending rates. Thus, the effect of asset growth rates on LGD may already be captured through other aspects of the regression.

The length of time between being downgraded to a 4 or 5 CAMELS rating and bank failure is not associated with whether losses occur in the logit regression. However, the time element does have a positive relationship with loss severity for loans with *loss=1*. The relationship may indicate a diminished capacity to manage seriously troubled assets, perhaps compounded by a desire to delay the recognition of loan losses. This result also identifies a potential channel for increased losses when regulators delay closure of problem banks. We estimate that a one-quarter lengthening of the failed bank's distress period at the mean of 4.82 quarters is associated with a 110 basis point increase in LGD.

The change in the industry noncurrent rate is significant in both the logit and the loss sample regressions, but their effects move in different directions. An increase in the industry noncurrent rate is associated with a lower probability of incurring losses, but higher LGDs if losses occur. We think that this may be a supply-side story—when the supply of defaulted loans is high, the market may lower its valuation of the underlying collateral and thus greater losses may occur (hence the positive effect in the loss sample). However, despite the higher incidence of noncurrent loans, many of the better-quality borrowers may eventually be making good on their loans, resulting in a lower probability of losses (hence the negative effect in the logit regression).

A decline in the CPPI between origination and the end of the workout period is associated with higher LGDs. This provides evidence that losses are affected by changes in asset prices relative to origination. The coefficient is negative and statistically significant in both logit and loss sub-sample regressions, affecting both the probability of incurring loss and loss severity. The marginal effect is smaller than one might expect: the predicted marginal effect of a 1 percentage point drop in CPPI on LGD at the mean is 16 basis points.

Previous literature has found seniority status to be important for corporate bonds and larger bank loans.[44] When we include a dummy indicator for junior lien status, we see a significant and positive relationship to LGD. The logit regression suggests that lien status does not influence the probability of incurring losses, but the linear regression suggests that it is an important factor for loss severity: it increases the marginal expected losses by over 800 basis points.

4.3 Robustness considerations

Since we differ from others in the literature by capping LGD at 130 percent rather than at 100 percent, we explore how this might affect our results. Around 10 percent of our sample of defaulted loans exceeds 100 percent. For comparison, we run the same regressions by imposing a cap of 100 percent and find that our results change very little. It does somewhat lower the impact for some of the explanatory variables—but not in a statistically significant manner. The mean LGDs only change by around 1.5 percentage points.

We try dropping our largest failed bank from the sample. We find that the bank size effect disappears from the full-sample linear regression, but remains significant in the logit regression. This supports our two-stage conclusion that larger banks have a lower probability of incurring losses, but do not necessarily appear to differ in the severity of the losses.

Another consideration is loan size. The majority of the loans in our sample are small, with 77 percent below $1 million and 87 percent below $5 million. However, there is a very long right tail that extends to just over $45 million. Dropping the largest loans in the tail of the loan distribution produces no significant change in the loan size effects on loss severity. For the logit model, we observe that loan size is significant in influencing the probability of loss for loans below $1 million, but is insignificant when loans up to $5 million and above are included. This suggests that loan size categories or thresholds may have some bearing on LGD behaviors.

We try creating a category for the very smallest loans in our sample. Many of the higher LGDs come from smaller loans, so we allow for the possibility that these small loans may be driving the loan size effects on LGD. We include a dummy variable for loans having a balance of $100,000 or less at default (about 20 percent of the sample). We find this dummy coefficient to be significant,

[44] See Acharya, Bharath and Srinivasan (2003) and Schuermann (2004), for example.

but the coefficient on loan size still matters. We therefore believe that the loan size effect on loss severity is not being driven solely by high loss percentages on the smallest of the loans.

To test for the influence of regional factors on LGD, we try including regional dummies and find that the coefficients on regional dummies are insignificant. Despite seeing geographic concentrations in the data, there is not much unexplained regional variation in the results. The regional CPPI index variable appears to have adequately captured the regional effects. Alternately, this result may be partly explained by the broad reach of the recession during this time period, or because all of the loans came from failed banks.

In addition, around 5.5 percent of our sample are loans from de novo banks. We include a dummy indicator variable for de novo status, with the hypothesis that it is likely to be associated with higher LGDs. The dummy is insignificant, but we do find that de novo status is correlated with bank size and peak growth rates. Dropping these reveals a significant and positive influence for de novo status in the logit regression. De novo status thus appears to matter for the probability of incurring loss, but is otherwise captured through bank size and peak growth rate characteristics in the regression.

5 Conclusion

In this paper we analyze a new dataset of over 14,000 defaulted CRE loans at 295 failed banks during the recent financial crisis. We see several contributions of this study to the literature: 1) We examine LGD for loans at small to mid-sized banks. Since the existing literature on LGD has focused on large loans or bonds, and it is not known how applicable those results are to typical loans at typical banks. 2) We provide new evidence suggesting a meaningful relationship between loan seasoning and LGD. (Existing literature has focused on loan seasoning and probability of default (PD).) 3) We identify certain bank-level characteristics that influence LGD. To our knowledge, no other papers have examined bank factors affecting LGD. 4) Our two-stage approach reveals insights that distinguish influences on the probability of loss and loss severity for LGD. 5) We find, as far as we know for the first time in published research, empirical evidence of a relationship between LGD and judicial foreclosure and out-of-territory lending. 6) We find a new potential channel that could increase losses to the FDIC if regulators delay the closing of troubled banks.

We find evidence that the key factors that other authors have found to influence LGD for large CRE loans tend to have similar effects on smaller CRE loans at failed banks. The length of the workout period has a significant relationship with LGD, as does foreclosure. Lien status has a strong effect, and changes in commercial property prices are important. Loan size has a stronger relationship to LGD in our study than other authors—a characteristic possibly related to the effects of fixed costs on a sample of loans that are much smaller than studied elsewhere. We estimate that an increase in loan size from $100,000 to $200,000 is associated with a 311 basis point reduction in LGD, and a $100,000 increase from $1 million to $1.1 million is associated with a 42 basis point reduction in LGD. The channel appears to be a smaller severity of losses for loans that do not fully recover (rather than the cure rate).

Although it is well known that loan seasoning influences default rates, the effect of loan seasoning on LGD for commercial loans has largely been unexplored to date. We find evidence that loan seasoning has a substantial effect on both the full-recovery rate and the loss severity for uncured loans. At the mean, a one-quarter increase in the age of the loan at default is associated with a 47 basis point reduction in LGD. The effects appear to be somewhat larger for loans that default shortly after origination. In addition, the share of the original loan balance that remains outstanding at default is positively related to loss severity and negatively related to the odds of a full recovery. We believe that risk measurement and stress testing at banks can be improved by incorporating loan seasoning into LGD estimation. Supervisors should be aware that loan seasoning influences LGD as well as PD when considering policies and procedures associated with high loan growth.

We find that CRE loans at small banks tend to have higher LGDs because they experience lower full-recovery rates than larger banks. At the median, a $100 million increase in bank size is associated with a 51 basis point reduction in LGD. It is unclear whether this effect relates to differences in the underwriting or the servicing quality at these banks. It may be that larger banks are better able to identify problem credits promptly, or small banks face difficulties in maintaining a high-quality workout staff. This bank size effect could be explained in part by some of these smaller banks lending beyond their core specializations in the lead-up to the crisis, or by a large share of small banks being de novo banks with an immature infrastructure.

We are able to isolate the relationship of out-of-territory lending to LGD, and find that out-of-territory loans tend to have moderately higher LGDs, probably because they present challenges in both the origination and servicing functions. In addition, we find that judicial foreclosure regimes do not influence the odds of experiencing losses, but are associated with a material increase in LGD for loans that do experience a loss, regardless of whether foreclosure occurs. It appears that judicial foreclosure may improve the distressed borrower's position in negotiating with the lender.

For CRE loans with non-zero losses, we find that loss severity is positively related to the length of time that banks remain in trouble prior to failure. The effects are material: a one-quarter delay in bank closure at the mean is associated with a 110 basis point increase in LGD. The result points toward a previously unexplored channel for increasing losses to the FDIC if the closing of troubled banks is delayed. Troubled banks might experience increasing difficulties in maintaining servicing quality as their problems persist. This finding supports prompt corrective action provisions for troubled banks.

All of our results are based on a censored sample of loans from small and mid-sized banks that failed in the midst of a major recession. Moreover, the loans are geographically concentrated, and most of them defaulted in the middle of the recession. Therefore, our results should be interpreted with care.

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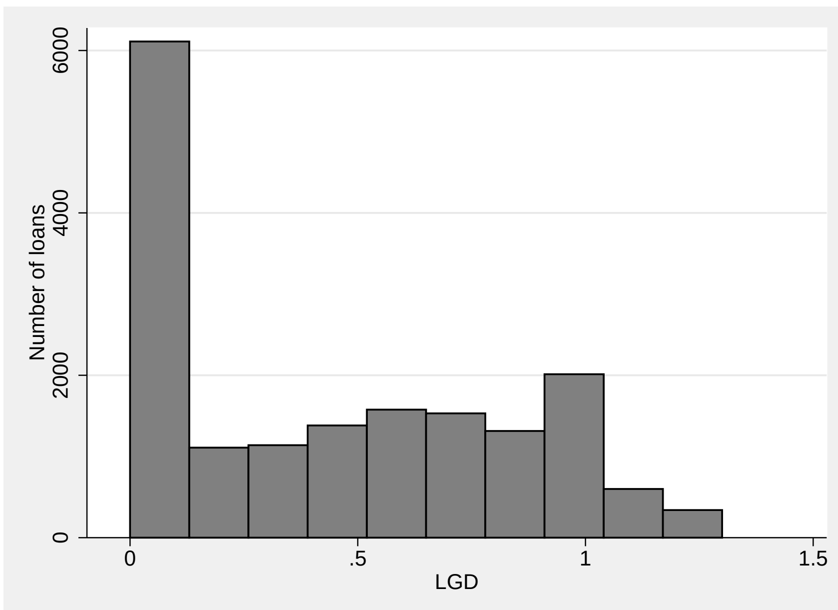

Figure 1: Distribution of LGD observations in sample.

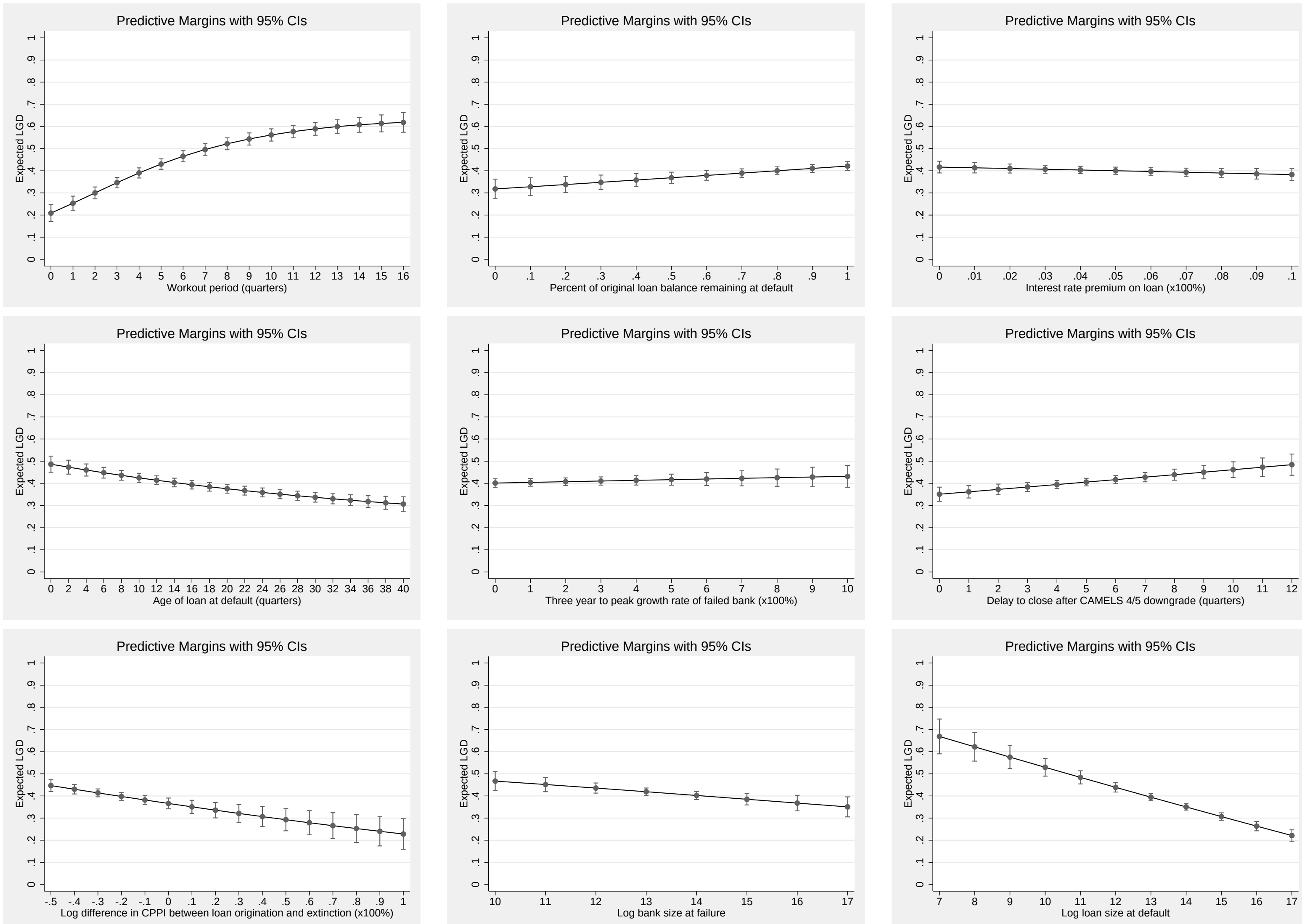

Figure 2: Plots of the predicted marginal effects on expected LGD for one-unit changes in continuous variables. Calculated by combining logit and linear effects from both regression stages in equation (3).

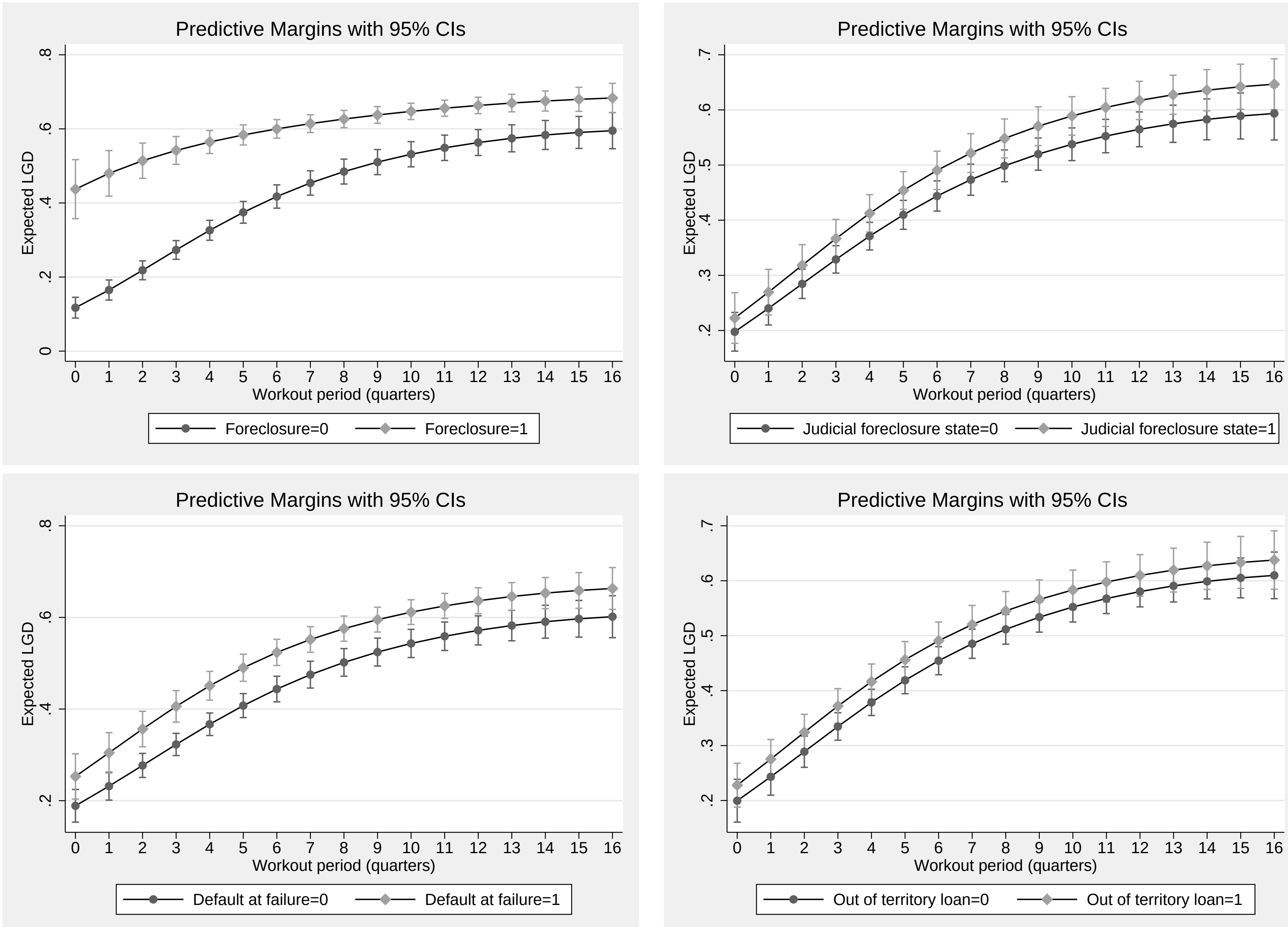

Figure 3: Plots of the predicted marginal effects on expected LGD for a change for dummy variable status $x_i = 0$ to $x_i = 1$. Calculated by combining logit and linear effects from both regression stages in equation (3). Presented relative to workout period as a baseline trajectory.

Mean LGD	43.78%
Median LGD	41.06%
Standard deviation of LGD	39.48%
Number of loans	17,116
Aggregate loan balance at failure (in millions)	$15,911
Total number of failed banks	295
Distribution of loan balances at failure	
25th percentile	$114,534
Median	$306,797
75th percentile	$869,104
Mean	$929,599
Concentration by bank (based on asset counts)	
% from largest bank	6%
% from five largest banks	17%
Concentration by bank (based on asset balances)	
% from largest bank	7%
% from five largest banks	25%
Concentration by location	
% from state with most failures (GA)	19%
% from 5 states with most failures (GA,CA,FL,IL,WA)	65%

Table 1: Summary statistics.

	Origination quality	Servicing quality	Property prices & market conditions	Loan seasoning
Loan characteristics				
Size of loan at default	X	X		
Age of loan at default	X			X
Percent remaining balance at default	X	X		X
Loan in default at time of failure	X	X		X
Interest rate premium	X			
Workout period	X	X	X	
Property foreclosed	X	X	X	
Collateral in judicial foreclosure state		X		X
Out-of-territory loan	X	X		
Bank characteristics				
Size of bank at failure	X	X		
Three-year to peak asset growth rate	X	X		
Ratings downgrading to failure		X		
Market conditions				
Change in industry noncurrent rate			X	
Change in CPPI			X	
Unemployment rate			X	

Table 2: Explanatory variable factors influencing LGD within general classification framework.

	Mean	Median	Std.	Min	Max
Loan characteristics					
Size of loan at default	$952,070	$314,055	$2,261,593	$103	$46,100,000
Age of loan at default (in quarters)	16.29	14.18	11.48	0.011	126.91
Percent remaining balance at default	0.867	0.954	0.215	0.0001	1.000
Loan in default at time of bank failure (dummy)	0.267	0	0.443	0	1
Interest rate premium	0.033	0.031	0.247	0	0.232
Workout period (in quarters)	6.12	5.22	5.05	0	30.08
Property foreclosed (dummy)	0.290	0	0.499	0	1
Collateral in judicial foreclosure state (dummy)	0.473	0	0.499	0	1
Out-of-territory loan (dummy)	0.316	0	0.465	0	1
Bank characteristics*					
Size of bank at failure (in thousands)	$3,232,931	$896,864	$6,047,738	$18,155	$25,000,000
Three-year to peak asset growth rate	1.17	0.657	1.84	-0.635	10.00
Rating downgrade to failure (in quarters)	4.82	4.70	2.81	0	19.88
Market conditions					
Pctg. pt. change in industry noncurrent rate at default	0.846	0.997	1.29	-1.19	2.57
Change in CPPI, loan origination to extinction	-0.236	-0.287	0.188	-0.558	0.953
Unemployment rate at time of default	0.097	0.100	0.017	0.032	0.142

Table 3: Explanatory variable summary statistics. *Calculated across loans in the sample, not across banks.

LGD	Coefficients				Predicted margin
	OLS-full	Logit	Logit-mfx	OLS-loss	(in percentage points)
	(1)	(2)	(3)	(4)	(5)
ln_loan_size	−0.039***	−0.031	−0.004	−0.064***	−4.42
age	−0.007***	−0.042***	−0.006***	−0.005***	−0.47
sq_age	0.001***	0.001**	0.001**	0.001	
pct_remain	0.157***	1.18***	0.170***	0.041	0.11
default_at_failure	0.069***	0.549***	0.073***	0.049***	7.05
rate_prem	−0.260	−6.46 ***	−0.936***	0.134	−0.34
wkout	0.064***	0.485***	0.070***	0.017***	2.95
sq_wkout	−0.002***	−0.014***	−0.002***	−0.001	
foreclose	0.137***	2.98***	0.305***	0.046***	20.41
judicial	0.023	0.042	0.006	0.055***	3.92
out_territory	0.027**	0.255**	0.036**	0.022*	3.12
ln_bank_size	−0.015***	−0.247***	−0.036***	−0.001	−1.68
peak_growth	0.004	0.044	0.001	0.01	
delay_close	0.006**	−0.012	0.002	0.016***	1.10
industry_nc	0.005	−0.162***	−0.023***	0.038***	0.01
cppi_change	−0.189***	−1.55 ***	−0.225***	−0.089**	−0.16
intercept	0.657***	1.55		1.17***	
No. observations	14425	14425		10030	
R-square	.3679			.2282	
Pseudo R-square		.3995			
Root MSE	.3124			.2934	

Table 4: Estimation results from (1) full sample linear regression, (2) logit regression estimating probability of nonzero losses, (3) logit regression marginal effects, (4) linear regression for loss severity conditional on nonzero losses and (5) combined marginal effect on expected LGD from two-stage logit and conditional loss regressions. Marginal impacts for dummies calculated as a change from 0 to 1; all others calculated as a 1 unit change at the mean. For each margin calculation, the remaining variables are held constant at their mean values. Separate squared-term marginal effects not shown as these are combined within the linear term marginal calculations.