Commercial real estate loan performance at failed US banks

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Introduction

Exposure to commercial real estate (CRE) loans at regional and small banks and thrifts has soared over the last two decades.[2] As banks' balance sheets become more concentrated in these types of loans, banks have become more sensitive to swings in CRE fundamentals. The concentration in CRE loans peaked in 2007, just as commercial real estate prices started a historic free fall, declining more than 30 per cent in just two years.[3] Over this same time CRE concentration has been a significant factor in recent bank failures.

Default and loss models of CRE mortgages have previously been estimated using loan data from large, income-generating properties financed by insurance companies and the commercial real estate mortgage (CMBS) market. Early research used data from insurance companies (Synderman (1991), Esaki et al (1999), Vandell et al (1993), Ciochetti et al (2003)), while more recently researchers have used data from the CMBS market (Ambrose and Sanders (2003), Archer et al (2002), Deng et al (2004), Seslen and Wheaton (2010), An et al (2009)). Black et al (2010) found that loans in CMBS pools that had been originated by portfolio lenders, such as insurance companies or commercial banks, were of a higher quality and outperformed loans originated by conduit lenders or investment banks.

The CMBS and insurance company loans used in these studies differ in structure and underlying collateral from the loans backed by bank CRE loans. Roughly a third of bank CRE loans are backed by owner-occupied CRE and another 20 to 30 per cent by land and construction loans.[4] The owner-occupied properties, which lack an external and explicit rental stream, are usually not candidates for securitisation. The loans in bank portfolios backed by land acquisition, development, and construction (ADC) projects are even less similar to those in CMBS and in insurance company portfolios. Land and construction loans are short term and the collateral is the raw land or the partially completed construction project. Finally, the loans on banks' books backed by existing income-generating commercial properties are likely to be different from those found in CMBS pools or in insurance company portfolios. Regional and small banks also make much smaller loans than those usually seen in CMBS pools or in insurance company portfolios. Clearly, each of these types of loans has performed differently during this recent financial crisis, yet we are still dependent on default and loss models estimated using data from only one type of loan.

Ours is the first paper to estimate CRE default and loss models using a loan-level dataset drawn from bank portfolios. We develop a unique dataset consisting of loan-level information on CRE portfolios for a sample of banks entering FDIC receivership over the past several years. We use this dataset to estimate a series of default and loss models. We estimate

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1 Federal Reserve Board.

2 Throughout the paper we mean for the term "bank" to include both commercial banks and savings institutions ("thrifts").

3 Call Report data.

4 Call Report data.

these models on the loans backed by existing CRE properties and compare the results with those from other papers that estimate CRE default using data from the CMBS and insurance companies. We then extend our analysis to the performance of land and construction loans, providing the first loan-level analysis of the performance of such loans.

Data

Our data are collected from a sample of banks that have failed and entered FDIC receivership over the past several years. The FDIC starts collecting data from a bank that is expected to fail several weeks before its failure date. These data are used by the FDIC to estimate the value of the bank's portfolio as it starts to market the bank to potential acquirers. The data are an output from the Automated Loan Examination Review Tool (ALERT), which every bank is required to carry out as part of the examination process.

Because the ALERT file system is used for all loan categories, it only includes variables that are populated for every loan, such as origination date, outstanding balance, maturity and interest rate. It does not include variables specific to commercial real estate, such as loan-to-value or debt service coverage ratios. It also does not include the location of the collateral. But it does include the address of the borrower, which we use as a proxy for the approximate location of the collateral. This allows us to identify "out-of-footprint" loans to borrowers outside the state the bank is headquartered in.

The dataset also does not have a consistently defined field for the type of collateral. But it does include information about how the loan is categorised in the bank's own accounting systems (the "G/L code"). These tend to be fairly descriptive (for example "vacant land", "office building", "warehouse", "convenience store"). We created a set of standard definitions of collateral type using the bank-specific data.

After a bank fails, the FDIC often engages in a "loss-sharing" transaction with the acquiring bank.[5] This is a type of guarantee in which the FDIC will reimburse the acquirer for a percentage of losses on the portfolio, usually after losses exceed a certain threshold based on the estimated losses on the portfolio. Because the FDIC has continuing exposure to these assets, it requires the banks to quarterly submit the status (paying as agreed, delinquent, charged off, or in the "other real estate owned" portfolio) of every loan to the agency. This provides us with information on the resolution of a sample of failed CRE loans that we use to estimate our loss models.

Our sample has 84,839 observations from 196 banks. There are significant differences in data quality in and between different banks. We apply a series of filters, excluding loans with missing data (interest rate, origination date, term, balance, original loan amount, state, collateral type). Data quality varies significantly across the banks. For a quarter of our banks, we have the interest rate for less than 8 per cent of their loans, while for another quarter of our banks, all the loans have an interest rate. This raises some significant doubt about the data that were recorded at some of the banks with exceptionally sparse data. We apply a final filter that exclude the data from all banks where less than 50 per cent of that bank's loans can pass our other filters. This leaves us with a final sample of 20,827 observations from 61 different banks. Of these observations, 11,890 are loans on existing CRE properties, with the remainder are land and construction loans.

[5] See, eg, http://www.fdic.gov/bank/individual/failed/lossshare for more information about loss-share agreements.

We compare the loan characteristics in our sample with loan-level data from an independent sample of large healthy banks and a sample drawn from CMBS pools. We use a new internal database produced jointly by the Federal Reserve System (FRS), the Office of the Comptroller of the Currency (OCC), and the Federal Deposit Insurance Corporation (FDIC). These data consist of an ongoing quarterly survey of the CRE portfolios at 15 banks. The database contained just over 35,000 loans in 2010 Q4 release. Although the database contains much information not available in our database of loans from failed banks, it also lacks some data that are present in our failed bank database, namely the ability to differentiate between land and construction loans. The CMBS data are drawn from a database provided by Realpoint and are based on a sample of loans that were current in December 2009. Table 1 reports the differences across these three datasets.

Table 1

Differences in CRE loans at large healthy banks, small failed banks and in CMBS pools

	Small failed Banks		**Large healthy Banks**		**CMBS**
	Existing CRE	Construction and land	Existing CRE	Construction and land	
Original loan amount	$888,886	$1,450,099	$10,623,051	$12,863,457	$11,398,795
	(1,646,691)	(3,467,959)	(28,196,742)	(26,159,376)	(46,463,5766)
Interest rate	6.4%	6.6%	6.2%	3.9%	6.5%
	(1.9)	(2.2)	(1.7)	(1.5)	(1.3)
Original term (in years)	16.4	5.0	5.8	3.4	5.2
	(10.7)	(5.5)	(4.0)	(3.5)	(4.7)

Note: Standard deviations shown in parentheses. Data on small failed banks from FDIC. Data on large healthy banks from FRS/OCC/FDIC survey. Data on CMBS from Realpoint.

The most obvious, and entirely expected, difference is that loans at large healthy banks and in CMBS are much larger than those at smaller banks. Interest rates on loans on existing properties are similar between the large healthy and the small failed banks, while interest rates on construction and land loans are significantly higher at the small failed banks than at the larger healthy banks. The most significant difference between the large and the small banks is the difference in the terms of the loans. At the small failed banks, the average term on existing property loans is 16 years, while it is 6 years at the large banks and 5 years in CMBS. Construction and land loans also have longer terms at the small failed banks.

Model

We estimate the probability that a loan was in our "default" status at the time of the bank's failure. We include all loans that are 30+ days delinquent, on nonaccrual status, or in foreclosure as "defaulted" in our model. Besides the probability of default (PD) model results, we also estimate a loss given default (LGD) model. The terms of the loss-share agreements stipulate that the bank must submit a list of loans and the associated loss on each to be reimbursed for covered losses. The ability to track the individual loans through the loss-share process enables us to see when a loss occurs and for how much. We are consequently able to calculate the LGD for the loans in our sample.

We have a subsample of 91 loans backed by existing CRE properties. The average LGD in our sample is 19.1 per cent. To gauge the impact of not having the balance at time of default, we also calculated LGD as a percentage of the originally observed balance and any undrawn lines. This version of LGD is also 19.1 per cent. As they are very similar, we consider this a good sign that our version of LGD is a good proxy for the more accurate number that we would have computed had we known the remainder at the time of the loan's default. We also have a subsample of 412 land and construction loans where we observe losses. The average LGD in our sample is 24.9 per cent and the version of LGD, calculated as a percentage of the maximum possible balance, is 22.2 per cent.

Column (1) of Table 2 reports the results of the PD model for loans on existing CRE properties. The results are largely consistent with our priors and the related literature. We expect lenders to charge riskier borrowers higher interest rates. Consistent with Black et al (2010) and Vandell et al (1993), we indeed see a significant and positive coefficient on the interest rate. We also expect that larger loans are significantly more likely to default, as Black et al (2010) found. We do find that out-of-footprint loans were more likely to default. The signs on the original term are as expected, suggesting that loans with longer terms are less likely to default. Loans within six months of their maturity date were significantly more likely to be in default at the time of bank failure. This finding is consistent with the significant impact of term defaults. If borrowers have little chance to get financing at maturity, to either refinance their balloon payment or to obtain takeout financing for their construction loan, they are less likely to keep up with the payments on their current loan. We find, similar to Vandell et al (1993), that hotels have a higher propensity to default. We also find that multi-family properties also have a higher propensity to default. The estimated probability of bank failure, based on a logistic bank failure model estimated with bank-level regulatory data as of 2007, was insignificant.

The results of the LGD model for loans on existing CRE properties, shown in the second column of Table 2, do not show as many statistically significant variables as in the PD model. The most statistically and economically significant variable, after the intercept term, is the size of the loan – larger loans have lower LGDs. This is in contrast to our PD results. While larger loans are more likely to default, their losses are smaller. The term of the mortgage is also negatively correlated with loss, as loans with shorter terms had higher loss rates. The out-of-footprint variable is insignificant.

Column (3) of Table 2 reports the results of our default model for the land and construction loans and Column (4) the LGD model. Rather than the property-type controls we used for the models for CRE loans on existing properties, we used dummies for land and single-family construction loans, holding multi-family construction as the reference case. The results are largely consistent with those in the models for CRE loans on existing properties, with the interest rate, loan size, proximity to maturity, and being out of footprint all positively correlated with default, while the original term is negatively correlated with default. Single-family loans are significant and positively correlated with default. Unlike in the existing land model, the bank quality variable is negative and significant, ie, the banks with a higher probability of failure tend to have lower default rates on their ADC loans. Unlike the loss models for CRE loans on existing properties, neither the interest rate nor the original term is significant. The original loan size, however, is significant. Land loans also had significantly higher loss rates.

This impact of the bank quality proxy is surprising and worth some added discussion. Our prior was that bad banks, ie, banks that had higher probabilities of failure, made worse loans. Our finding seems to show the opposite. Because the concentration in land and construction loans is a significant driver in the bank failure model; this proxy variable may be instead picking up the impact of bank specialisation. A bank specialising in land and construction lending may, on a loan-by-loan basis, underwrite better loans than a bank with a more diversified loan portfolio. But the concentration in land and construction loans leaves them more exposed to systemic shocks, such as a sudden drop in demand for residential construction. We intend to explore this avenue more fully in a subsequent draft of the paper.

Table 2

PD and LGD model results

	Existing CRE		Land and construction loans	
	PD model	**LGD model**	**PD model**	**LGD model**
Intercept	–5.706***	1.779***	–2.648***	0.674***
	(0.408)	(0.476)	(0.327)	(0.143)
Interest rate	0.309***	–0.0215	0.126***	0.00427
	(0.017)	(0.0177)	(0.016)	(0.00689)
Original term	–0.046***	–0.0167***	–0.199***	0.00180
	(0.005)	(0.00625)	(0.011)	(0.00304)
Within 6 months of maturity date	2.170***	–0.00189	0.418***	0.00228
	(0.136)	(0.100)	(0.070)	(0.0322)
Log (original loan amount)	0.217***	–0.104***	0.187***	–0.0325***
	(0.025)	(0.0213)	(0.017)	(0.00876)
Out of footprint	–0.347***	0.152	0.434***	0.00757
	(0.113)	(0.285)	(0.091)	(0.05411)
Retail	0.105	0.125		
	(0.124)	(0.172)		
Industrial	0.200			
	(0.147)			
Multi-family	0.705***	0.0571		
	(0.120)	(0.157)		
Hotel	0.620***			
	(0.202)			
Land			–0.113	0.477*
			(0.086)	(0.245)
Single-family			0.178**	–0.0365
			(0.070)	(0.0300)
Probability of bank failure	0.1150		–1.693***	
	(0.555)		(0.615)	

Note: Standard deviations shown in parentheses. State fixed effects are limited to states and banks with large numbers of loans. The omitted property type variable for the existing CRE loan models is "office", and for the land and construction loan models, it is "multi-family". *** indicates significant at 1% level. ** indicates significant at 5% level. * indicates significant at 10% level.

Conclusion

This is one of the first papers to analyse loan-level commercial real estate data from a variety of banks. The study of land, construction, and development loans is challenging, since these loans rarely exist outside bank portfolios and little academic research exists on their performance characteristics. Previous research has depended on loans in CMBS pools and in insurance company portfolios.

The results of our analysis of the performance of CRE loans backed by existing properties are largely consistent with those in the existing research. We also find that loans approaching the scheduled maturity date are much more likely to default. Our proxy for bank quality is not significant in our default model of CRE loans on existing properties.

Land and construction loans present an entirely different risk profile, with significantly higher default and loss rates. Among land and construction loans, single-family construction loans had a higher default risk, but land loans had a higher loss rate. The risks associated with out-of-footprint lending were also higher for land and construction loans than for loans backed by existing CRE properties. Interestingly, our proxy for bank quality is significant and negative in our land and construction loan model.

The significance of loan characteristics, collateral and property type, and location in the default and loss models all show the need for more granularity in supervisory data. Recent identification of single-family construction loans in the Call Report was a step in the right direction, but the inability to identify land loans, geographical concentrations, or other loan characteristics can hinder the regulators' ability to correctly identify potential risk to institutions and the banking industry as a whole.

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