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Determinants of Losses on Construction Loans: Bad Loans, Bad Banks, or Bad Markets?

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Abstract

Construction loan portfolios have experienced notoriously high loss rates during economic downturns and are a key factor in many bank failures. Yet there has been little research on what drives losses on construction loans and how to mitigate those losses, due to a lack of data. Using proprietary loan-level data from more than 15,000 defaulted construction loans at over 275 banks that failed between 2008 and 2013, we explore the extent to which observed losses during a severe downturn are driven by the characteristics of the loans, the originating banks, and the local markets. We find close ties between loss rates and certain loan characteristics as well as market conditions both at and after origination, while institution-level differences across banks appear less important. We find that the risk of higher losses on construction loans is influenced not only by the originating bank's behavior but also by the behavior of other local lenders in the market. This finding has important implications for how lenders and regulators manage risk through the real estate cycle. We also find support for existing regulatory guidance regarding higher capital requirements for construction loans, specifically for land and lot development loans.

JEL Classification Codes: R31, R33, G21
Keywords: ADC, Construction Loan, LGD, CRE.

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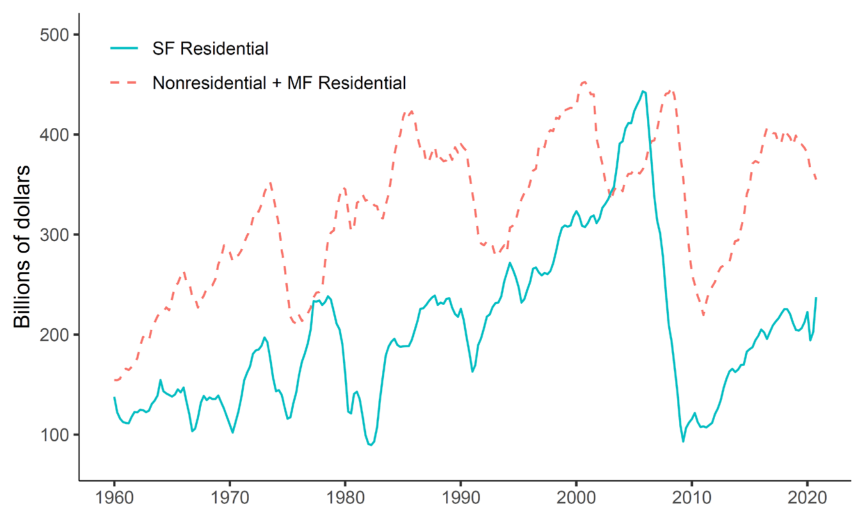
1. Introduction

The construction sector of the economy is inherently cyclical. Figure 1 presents residential and nonresidential construction investment in the United States from 1960 to 2020 and reveals a series of large swings for both types of collateral. The bust was especially strong in the Great Recession, with a peak-to-trough decline of 79 percent for residential investment and 51 percent for nonresidential and multifamily investment.[4] An important contributor to this high degree of cyclicality in the construction sector is the stickiness of construction spending, caused by the time required to plan, finance, and construct a project. Many commercial projects take three or more years to complete, making it difficult to quickly adjust the level of investment in response to demand shocks.[5]

Figure 1: Level of Investment in Construction from 1960 to 2020



Note: Nonresidential investment excludes drilling, mining, and power.
Source: U.S. Bureau of Economic Analysis.

It is not surprising, then, that construction loans have often played a significant role in weakening bank balance sheets and contributing to bank failures during periods of financial distress.[6] Noncurrent loan rates for acquisition, development, and construction (ADC) loans at U.S. banks were more than double the noncurrent rates of other types of mortgages during both

[4] Residential investment peak is 2005Q4 and trough is 2009Q2, while for nonresidential investment the peak is 2008Q2 and the trough is 2011Q1.
[5] For example, see Grenadier (1995) and Wheaton (2014).
[6] We include in our analysis not only loans for the construction of the actual buildings but also loans to acquire the land itself and loans to develop the lots before the actual building construction (i.e., putting in curbs and pipes, etc.) For the remainder of the paper, construction loans refer to the subset of loans that finance the construction of the actual buildings.

the Great Recession and the 1980 to 1994 banking crisis.[7] Researchers have also found that banks with heavy exposures to ADC loans were more likely to fail during both crises.[8] More broadly, periods of real estate speculation have frequently contributed to financial crises around the world.[9] Thus bankers need to approach ADC loans with appropriate caution and expertise, and banking regulators need to set policies and procedures that suitably address the risk.

Unfortunately, there is much less information in the literature about what triggers losses for ADC loans than for retail loans, corporate loans, or mortgages on existing residential and commercial properties. Other types of loans often use nonbank financing, such as public debt markets or securitization, that provide publicly available loan performance data for empirical studies.[10] ADC loans instead have, until recently, been limited to bank financing. As a result, data availability has severely restricted research on ADC loan performance. In fact, we are unaware of any empirical research that focuses on loss given default (LGD) for ADC loans, despite its critical importance to the losses of this high-risk asset class.

This paper fills this hole in the literature by using a unique and proprietary set of loan-level data. The goal of this paper is to learn about the factors that drive distressed LGD for ADC loans and to explore the implications for lenders and regulators. We decompose LGD on ADC loans into components that can inform bankers, investors, and regulators about risk exposures in actionable ways. We then group the explanatory variables into loan, bank, and market characteristics, and we examine the sensitivity of LGD to each group. Losses due to poor underwriting or poor bank management can be mitigated through changes in lending policies and supervisory oversight. Other factors that are not under direct control of the lender, such as losses tied to changes in market conditions post-origination, are best addressed by loss reserves or capital requirements.

We analyze LGD for a sample of more than 15,000 loans from over 275 failed banks that were resolved by the FDIC from 2008 to 2013. Most of these loans were originated during the boom period in the mid-2000s, defaulted during the Great Recession, and were worked out during and after the Great Recession. We acknowledge that this sample is hardly random: clearly we are oversampling bad loans at bad banks during a very bad time.[11] However, we feel that this is

[7] Author calculations using Call Report data. From 2008 through 2013, the noncurrent rate for ADC loans peaked at 16.8 percent, single-family peaked at 8.1 percent, and the others (C&I, multifamily, and other CRE) peaked below 5 percent. From 1991 to 1994, ADC loans peaked at 14.1, and the next highest loan type (other CRE) peaked at 5.5 percent. Data are not available for most loan types before 1991.
[8] See GAO (2013) and Friend, Glenos, and Nichols (2013) for analysis of the Great Recession. See Fenn and Cole (2008) and Collier, Forbush, and Nuxoll (2003) for analysis of the 1980 to 1994 crisis.
[9] Both Kindleberger (2000) and Reinhart and Rogoff (2011) cite speculation in various forms of construction and real estate as an underlying cause for many historical financial crises.
[10] See, for example, Altman, Resti, and Sironi (2004) and Downs and Xu (2015).
[11] We perform a benchmarking exercise in Appendix B, comparing our data against losses on construction loans from a separate and independent supervisory data collection for large banks. We find differences between the two samples, but we also find credible explanations for these difference that relate to the composition of the sample

precisely the sample one would want to work with to explore the drivers of ADC loan risk. It is losses on bad loans during bad times that account for the majority of ADC losses at banks and are the most damaging to the banking industry. And it is the drivers of distressed LGDs that is what is interesting, as aggregate losses on construction loans during benign periods have historically been negligible.

One of our key findings is that banks exert no direct control over some factors that heavily influence distressed LGD. More specifically, we find two factors related to local markets at the time of default: the share of noncurrent ADC loans held by local lenders when the loan defaults, and the change in the local ratio of ADC loans to total loans between origination and default. Higher local noncurrent rates for ADC loans at the time of default are an indication of markets that are experiencing distress. At the same time, an increase in local ADC lending between origination and default shows the extent to which other lenders are leaning into the market. If a local area has both strongly increasing ADC lending and relatively high local noncurrent rates at the same time, the local market may be unstable or overheating. We would expect to observe higher losses on loans defaulting in these markets. We believe that the sensitivity of losses for ADC loans to changes in these local market factors post-origination provides a strong argument supporting the use of higher capital requirements and lower loan-to-value (LTV) limits than for less cyclically sensitive loans.[12]

We document the importance of market conditions at loan origination as well. The bank's decisions regarding when and where to make ADC loans are not exogenous: they reflect a bank's ability to properly assess and manage risk based on information available when the lending decision is made. We find that loans originated in markets with higher proportions of ADC loans to total loans are associated with higher losses, and loans originated in markets with higher ADC lending growth in the period leading up to origination also have higher losses. Local markets with outsized ADC lending exposure and faster ADC loan growth at origination may contribute to higher losses through multiple channels, such as less experienced lending officers and builders, weaker loan covenants, and less focus on risk exposures. In highly competitive markets, lenders are well aware that they can originate loans only if their loan terms and covenants are competitive. They may pay insufficient attention to increases in the supply of homes and buildings (including the extent of new inventory that will or may soon arrive), optimistic construction budgets or real estate appraisals, or environmental or other construction risks. Given the time delay required to complete construction and the inability to adjust investment quickly, a risk of oversupply under such conditions may be heightened.

(such as size and geography) and variable definitions, increasing our confidence in the representativeness of the FDIC loan data.

[12] The noncurrent rate for ADC loans, as reported in the Call Report, soared from 0.8 percent as of year-end 2006 to 16.8 percent as of March 31, 2010. The peak rate for ADC loans was more than double the peak rate for other loan types.

We find that loan characteristics also explain a large share of the variation in LGD. Loans for projects earlier in the development cycle, specifically those to purchase land and develop lots, had significantly higher losses than loans for the actual construction of either single-family or commercial buildings ("vertical" construction). This supports tighter capital and LTV guidance for these loans. We find that smaller loans in our sample also have higher loss rates. The location of the project matters, with loans outside of the originating bank's footprint or in a judicial foreclosure state[13] having higher losses as well. We do not observe a significant difference in LGD between single-family and commercial construction loans.

We examine several loan-level characteristics based on the observed performance of the mortgages post-origination. This includes the timing of the default (specifically the age of the loan at default) and whether the loan defaulted at the expected maturity of the loan (a "maturity default"). We also include the share of the committed balance that has been drawn at the time of default and whether the bank allowed the borrower to draw more than what was originally committed (an "overage"). These loan-level variables at default reflect a combination of borrower/builder performance and the monitoring function of the lender. From a collateral perspective, these variables may reflect the extent of progress made in creating collateral value through construction.

In contrast to market and loan characteristics, bank-level factors seem to explain much less of the variation in LGD. These include broad measures that are readily comparable across banks, such as asset size or portfolio growth, which may, for example, reflect institutional differences in specialization or in how loans are originated or monitored. We find that larger banks tend to suffer lower losses in default. We also observe that LGD is higher when the bank had high ADC loan growth leading up to origination and when it spent a longer time in distress before failure. But overall, the impact of bank-level characteristics on LGD appears much smaller than loan-level or market-level characteristics.

Our results have important implications to both bankers and regulators. When the demand (or speculative demand) for new homes and buildings triggers a sustained strong increase in ADC lending, the conditions for overbuilding—followed by high ADC defaults and high LGD on defaulted loans—strengthen. Banks would be well served by astute credit risk functions that are well informed about the risks that ADC loans pose during periods of distress, and how those risks are exacerbated when the local market experiences a sustained period of new construction and high levels of competition. While good underwriting and loan monitoring processes within the originating bank will mitigate losses during periods of distress, the actions of other local lenders and builders may contribute to oversupply in the market. Bank examiners should look for evidence that banks understand these risks, have the appropriate levels of loss reserves, actively

[13] That is, a state where a court order is required for foreclosures.

monitor for potential overbuilding, and do—or stand ready to—pull back their lending or promptly take other actions to reduce their exposures as risks increase.

The rest of the paper is organized as follows. Because lending related to construction has unique traits that influence LGD, Section 2 provides institutional background information that informs our analysis. Section 3 discusses the FDIC Loss Share Administration program and the data used for our analysis. Section 4 lays out the methodology, Section 5 provides the results, and Section 6 discusses the implications of those results. Section 7 concludes.

2. Institutional Background

Several unique aspects of ADC loans set them apart from other mortgages. The most significant difference from the perspective of modeling losses is that a large share of the collateral that backs ADC loans is created during the loan term. There is no cash flow from rents available to service the debt. There is no rental history upon which to base a valuation, merely a speculative estimate of value based on market conditions as of the expected completion date. This is a foundational difference that influences the loan origination and servicing processes, the loan terms, and the lender's risk exposure. Section 2.1 begins by explaining the processes involved in originating and managing these loans and the loan terms. Section 2.2 discusses the lender's risks from ADC loans and how they relate to the nature of the collateral, the loan administration processes, and the loan terms. In both sections, ADC loans are compared with other, more familiar, types of real estate loans,[14] and relevant academic literature is discussed.

2.1 Loan Processes and Terms

This section begins with a discussion of the typical loan origination process and loan terms, followed by sections on the collateral valuation at origination, the monitoring process, default, and the loan workout process.[15]

2.1.1 Loan Origination and Loan Terms

Investors frequently form a Limited Liability Corporation (LLC) for each specific project. The LLC acts as the official borrower, who hires a builder to do the construction; sometimes the builder is the investor. The investor normally purchases the property and places it in the LLC (if any), designs the construction project, hires the builders, and completes the entitlement process[16] before origination.

The term to maturity for ADC loans is relatively short, and larger projects usually involve multiple loans. For example, for a single-family housing development, the borrower might obtain a land development loan to put in curbs, underground pipes, and electrical service and a separate

[14] Specifically, to a typical first lien for a single-family home or commercial real estate loan (CRE) loan.
[15] This section is based on anecdotal information from discussions with bankers, examiners, and other experts.
[16] That is, the process of obtaining the zoning changes and other regulatory approvals that are required before construction begins.

construction loan to build the houses. Even single construction loans are often structured in tranches, with the next segment of the committed balance being issued to the borrower only if certain thresholds are met. For larger office/retail complexes, there may be separate loans or loan tranches for each phase of development. Many ADC loans include a "permanent" (that is, long-term) financing phase once construction is complete and other thresholds are met.[17] A large share of the profits come from fees at origination. The loan structures for other types of mortgages are more permanent and less complex, with interest income comprising a larger share of the lender's profit.

ADC projects rarely produce income for the borrower until construction is complete and the property is either leased to tenants or sold. Therefore, the loans are normally structured with an interest reserve with no payments due directly from the borrower until maturity (or, in the case of single-family developments, as homes are sold). With an interest reserve, the total amount of the loan includes funds disbursed to the borrower and undisbursed funds that are used to cover interest expenses during the loan term. This structure contrasts with other types of mortgages, where regular payments are due throughout the loan term (and which serve as a key measure in determining default).

The payment stream to the borrower also differs markedly from other mortgages. For single-family residential (SFR) and commercial real estate (CRE) mortgages, the full loan amount is normally disbursed at origination. For ADC loans, the loan documents set forth a pre-defined schedule, where new disbursements are made as various phases of construction (or in some cases sales or leases) are completed. The requirements for each tranche of the loan to be disbursed are spelled out in the loan covenants. Disbursements are often relatively modest during the early part of the loan term.

One other significant difference between ADC loans and other mortgages is the prevalence of recourse. Lenders frequently require borrowers to provide personal guarantees to back ADC loans. These guarantees, or recourse, provide some "skin-in-the-game" on the part of the borrower, if the value of the raw land or partially built project that is pledged as collateral is not sufficient. Recourse is less frequently used for other types of mortgages, where the equity share of the existing property pledged as collateral provides the "skin-in-the-game." Glancy, et al. (2021) find that recourse in transitional loans (defined as construction and redevelopment loans) is correlated with unobserved risks, as transitional loans with recourse have higher spreads at origination and worse performance during the COVID pandemic, however they are looking at the impact of recourse on default and not recovery rates.

[17] For example, for a multifamily loan, a specified share of the apartments might have to be leased.

2.1.2 Valuation at Origination

Banks must decide whether to originate an ADC loan based on the potential value of the project, which is by definition unobserved. Third-party certified appraisers are hired during the loan approval process and must adhere to well-developed standards that govern estimation methods and the products they produce.[18] Loan commitments often occur before the appraisal is complete—and are often conditional on the appraised value—but loan originations always occur after the appraisal. Appraisals for construction projects are by their nature more speculative than for existing buildings, where historical rental cash flows are available.

Banks normally request both an "as is" appraised value and one or more "as will be" appraised value(s). There are two standard "as will be" measures of value. The first, known as "as stabilized" value, represents the value for the finished project when the appraiser assumes that the property is already built and leases have stabilized or finished lots or homes have been sold as of the appraisal date. The second, known as the bulk value, represents a value based on a discounted cash flow approach when the appraiser develops assumptions about the time needed for building, the time needed for lease stabilization or asset sale(s), the future value of the finished project, and then discounted the estimated future value to the appraisal date. Finished product values are invariably higher, and banks used them more often—and relied on them more heavily—during boom periods. We expect that, especially when markets are shifting, the appraisals are significantly less reliable for construction projects than for other real estate.

2.1.3 Loan Monitoring

The monitoring process for ADC loans is much more labor intensive than for other mortgages and often requires detailed knowledge of construction, the local regulatory approval process, the loan contract details, the local market, and the title insurance process. Over the term of the loan, the lender monitors the progress of the construction, including items such as the receipt of materials, payments to suppliers, progress on the building(s), and associated regulatory approvals. Based on the status of the construction and the loan covenants, the lender determines when draws can be made, the size of the allowed draws, whether and how the loan terms should be adjusted (if construction problems arise or markets shift), and when payments are due. Adjustments are commonplace as the construction progresses and may arise because of issues such as changing prices for labor or materials, delays in receiving materials, subcontractor availability, environmental problems, poor quality construction, or changes in local demand.

2.1.4 Loan Default

The timing of loan default falls into two categories: term defaults and maturity defaults. Maturity defaults occur when the borrower is unable to sell the collateral at an adequate price, or, for commercial properties, when the borrower cannot obtain sufficient permanent financing to pay

[18] See Appraisal Standards Board (2017) for details.

off the ADC loan in full.[19] Because the borrower does not make regular payments, term defaults[20] are almost always determined by the lender (or in some cases bank examiners); they are frequently based on an evaluation of the local market conditions and anticipated demand, or on the borrower being unable to meet performance covenants. This contrasts sharply with other types of mortgages, where borrowers make regular payments and default is simply determined by payment delinquency.[21] Because loan default involves judgment on the part of the bank, the timing may be less consistent across banks for ADC loans.[22]

2.1.5 Loan Workout

The workout process for ADC loans is more complex and the lender's negotiating position is weaker than in the other types of mortgages, for two reasons. First, the investor's equity position is more likely to be deeply negative, especially during a severe crisis.[23] Thus investors may be unwilling or unable to bring additional capital to the project or monitor the building process. Second, and more importantly, the builder has considerable scope to influence the outcome and incentives that rarely align with those of the lender. The construction industry is highly cyclical, and during distress periods builders are retrenching and desperate for cash to pay staff and fund operations. With no new construction projects available, builders aggressively seek additional draws from existing loans to survive. They rarely have any reason to cut back on existing projects, regardless of whether demand exists for the finished project. All the loan participants are well aware of the high cost of changing builders in the middle of a project and the significant discount to market value for an incomplete building, and builders and investors can use that knowledge at the lender's expense during negotiations.

2.2 Risks

We now link some of the institutional aspects of ADC lending to specific risks that can help drive losses. We divide these risks into four separate, but often interrelated, topics: construction risks, the opacity of ADC loans, the option value of land, and sensitivity to real estate cycles. Both construction risks and opacity contribute to the higher level of idiosyncratic risk of construction loans, while the option value of land and the sensitivity to real estate cycles contribute to the higher level of cyclical risks for ADC loans. We provide a summary of risks in Appendix A.

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[19] In some cases, this takes the form of being unable to meet the lender's requirements for a conversion to permanent financing (that is a conversion to a CRE loan).

[20] Term defaults occur before the maturity of the loan. We define maturity defaults as defaults that occur within 90 days of maturity or after maturity. All other defaults are term defaults.

[21] In some cases, lenders may place CRE loans into nonaccrual status even when payments are current, because the value of the collateral has dropped and the lender no longer expects full repayment of the loan at maturity. This is common in the commercial mortgage-backed securities (CMBS) market, where the master servicer will transfer such a loan to the special servicer to begin the loan workout process even if the loan is still current.

[22] However, banks have some scope to restructure other types of troubled loans in ways that minimize reported defaults, known as "evergreening." This type of restructuring is less likely to occur for single-family mortgages because most of them have standard terms.

[23] In some cases, solvency may be uncertain or positive but the investor is illiquid.

2.2.1 Construction Risks

Cost overruns for construction projects are commonplace. Problems often begin with the budget itself, which may suffer from optimism bias, inadequate feasibility analysis, omissions of required items, or simplistic assumptions that do not adequately consider risks or entrepreneurial profit. Other problems can include bad weather; delays in the availability of subcontractors, staff, materials, or government inspectors; design changes and scope creep; cost increases for labor or materials; unexpected underground conditions and other environmental problems; inexperienced builders; or foul play and corruption.[24] The potential for these challenges to arise results in the need for ongoing, and costly, monitoring of ADC loans by the lender.

2.2.2 Opacity

As discussed in Section 2.1, the lending function for ADC loans involves more complicated terms and conditions than for other types of mortgages. The loan monitoring process is more complex, and determining whether the loan is in default is more ambiguous. The loan workout process is more likely to depend on stakeholders with incentives that differ markedly from the lender. Loan guarantees are used more frequently, and the value of these guarantees are not readily discernable. The appraisal process requires more estimation that introduces more opportunities for error, and the construction process involves numerous potential pitfalls that are not immediately obvious. Taken as a whole, these characteristics support a conclusion that ADC loans are more opaque than other mortgage types. This opacity explains why there is no standardized underwriting process and why banks usually retain ADC loans in their portfolios. It also may magnify the scope for lender myopia or overconfidence.

2.2.3 Option Value of Land

A wide range of research exists on the option value of land, from Quigg (1993) to Munneke and Womack (2020). The underlying theory is that all land, both developed and undeveloped, is valued based on its highest and best use. Geltner et al. (2014) documented how the highest and best use may change over time in response to changes in the local market and demand for space. Property whose highest and best use was as a farm may instead now have a highest and best use as single-family residences. Once the option value of developing the land (or redeveloping it to change the property type) reaches a certain threshold, the project becomes viable and can acquire investment and financing.

One aspect of the option value of land that is relevant to thinking about potential loss on construction loans is the limited reversibility of investment. When the project starts, the highest and best use might be single-family residential. However, once the project reaches completion, the highest and best use may have shifted due to market developments and is now retail. The

[24] See Ahiaga-Dagbui and Smith (2014) for additional discussion.

physical aspects of the project are difficult to reverse: for example, the street plan for a housing development would not serve an office park.

But zoning restrictions can often be even more difficult to reverse. Before loan origination, builders must obtain local approvals to construct the building(s) and, for single-family developments, break the property into separate lots for future sale, which is often time-consuming and politically challenging. This process can add substantial value to the project: on a per-acre basis, the value of timberland or farmland is often a fraction of the value of the same acreage (in the same condition and location) that has been approved for homes or a retail shopping center. But it also represents a stickiness in terms of optimal land use. For example, if agricultural land had been re-zoned as residential, it could be costly—or politically impossible—to transition it to another higher best use. The option value of the land is "spent" once the project has begun. A shift in demand during a project's lifetime could lead to higher losses on the ADC loan.

2.2.4 Sensitivity to Real Estate Cycles

LGD for ADC loans is far more sensitive to real estate price changes than other types of mortgages, for several reasons. First, substantial time elapses between the date the lender commits to the loan and completion of the construction. This lag is caused by the time to build, which is often longer than the original estimate because of time lost to address supply problems and subcontractor schedules, longer-than expected regulatory approvals (such as demolition, environmental impact, various stages of construction, and sometimes zoning), and investor and lender decisions associated with change requests, and lender inspections and approvals for draws. Major market shifts can occur between the loan commitment date and the completion of construction.[25] The potential for losses relating to the time delay between origination and completion is compounded by two additional factors: (a) strong incentives for builders to continue building during periods of distress regardless of the declining value of the finished product, and (b) potential weaknesses in appraisals, such as reliance on "as stabilized" valuations.

Second, most construction projects end with empty buildings, and the borrower's ability to repay the loan is generally contingent on finding buyers or tenants for the finished product.[26] Relocation costs, and the transaction costs for purchasing real estate, are substantial and may hinder sales or leases. Relatively few ADC loans are backed by owner-occupied buildings or projects with significant levels of pre-leasing or pre-sale contracts in place at the time of loan commitment. During periods of serious distress, pre-leasing and pre-sale agreements can fall

[25] See Grenadier (1995) and Wheaton (1999) for additional discussion. Both authors cite this time lapse as a contributing factor to real estate cycles.

[26] Or, for horizontal construction, approval of a new loan for the next phase of construction.

through. On the other hand, many commercial leases are long-term. These phenomena mitigate losses for other types of residential and commercial mortgages but amplify the sensitivity to business cycles for ADC loans.[27]

Third, while all loan types are affected by heightened competition during boom periods, ADC loans tend to be more strongly affected. ADC loan growth was much stronger than other loan types during the boom before the Great Recession: from year-end 2003 to year-end 2007, ADC loans held by banks increased 131 percent, but other types of mortgages held by banks increased 45 percent.[28] Lenders with a stronger appetite for growth—and thus a higher willingness to take on risk—gravitated to ADC loans, most likely because it was easier for them to gain market share.[29] For example, as of year-end 2007, the median ratio of ADC loans to total loans held by de novo banks was 17 percent; the ratio was only 5 percent for banks that were ten years old or older and had the strongest CAMELS composite rating.[30] During boom periods, lenders may feel pressure to grow quickly, and the benefits of monitoring (including tight loan covenants) diminish while the costs remain constant.[31] In addition, the average experience levels of lending officers and builders declines. New builders are more likely to make mistakes, both in the cost estimation process and the construction itself. New lending officers have less knowledge of and skill in all aspects of the loan origination process, and they lack memories of the high costs associated with real estate downturns. Lusht and Leidenberger (1979) found empirical evidence that both builder and lending officer experience reduced the probability of default for construction loans; there is good reason to expect the same for LGD.[32]

3. Data

This section introduces the FDIC Loss Share Administration data that are the primary data used in the paper. We then discuss the construction of our LGD measure, including a decomposition of the loss into different components. The decomposition supports the comparison of our LGDs with those from other sources that may contain different components. We then provide a range of

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[27] See Grenadier (1995) for additional discussion.

[28] Percentages derived from bank Call Reports. See Rajan (1994) for additional discussion and evidence that heightened competition results in looser bank lending policies (such as relaxed underwriting criteria and less stringent monitoring).

[29] According to bank Call Reports, as of year-end 2006 (at the height of the boom), de novo banks, banks with high loan growth rates, and banks that relied heavily on brokered deposits all had higher concentrations of ADC loans and higher ADC loan growth rates than other banks. Yom (2005) discusses the incentives for de novo banks to grow quickly.

[30] Data from bank Call Reports and examinations. De novo is defined as eight years old or younger. For the second group, only banks with a CAMELS composite rating of 1 are included in the calculation. CAMELS ratings are supervisory designations of bank condition and range from 1 (very strong) to 5 (very weak).

[31] At least as long as the boom continues. See Rajan (1994) and Levitin and Wachter (2013) for evidence and discussion on pressure for earnings and asset growth during boom times. See Ruckes (2004) for an analysis of the net benefit of loan monitoring across the cycle.

[32] There is substantial evidence of the same phenomenon for lending more generally. See, for example, Berger and Udell (2003) and Rötheli (2012).

descriptive statistics about our loss data, both overall and across different regions and property types.[33] We end with a brief discussion of potential concerns about our data.

3.1 FDIC Loss Share Administration Data

In this study, we use LGD data from banks that failed and were resolved by the FDIC in the aftermath of the 2008 financial crisis. Loan portfolios held by failed banks oversample the upper end of the credit loss distribution of ADC loans, and they should incur higher default rates than portfolios at healthy banks. The nature of this sample selection works to our benefit. A significant driver of losses to a bank will depend on the performance of the worst-performing loans in their portfolio. A lending institution's solvency is not dependent on the performance of the median loan, but by the performance and losses in the upper tail of the credit loss distribution.[34]

The FDIC has a loss share program to help dispose of assets from failed banks. From 2008 through 2013, the FDIC sold $39 billion in ADC loans from 289 failed banks to 144 bank acquirers with loss share coverage. Most of the FDIC loss share agreements provided the acquirers with 80 percent indemnification from credit losses for five years for assets covered under the agreement (thus acquirers would absorb just 20 percent of the losses).[35] To manage its risk exposure and support program administration, the FDIC collected information from the failed banks as of the sale date (that is, the date the bank failed) and through detailed quarterly reporting requirements from the acquiring banks after the sale date. Note that when we refer to bank characteristics in this paper, we are referring to the characteristics of the failed bank that originated the loan and not the acquiring bank that serviced the loan. The dataset contains data from the inception of the program in 2008 through year-end 2015.[36]

One of the unique aspects of the loss share program data is its detail on the components of the losses. As we discuss further in Section 3.2, most existing LGD data in the literature do not have this level of detail. Loss share LGD components include

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

[33] Given that the loan level data we use are by definition drawn from failed banks, Appendix B provides a benchmarking exercise with a separate and independent set of data on defaulted construction loans from the Federal Reserve's FR Y-14Q Schedule H.2.
[34] Compared with surviving banks, failed banks had higher ratios of ADC loan exposure to capital and higher loan default rates during the Great Recession. This does not necessarily mean that they had higher LGDs. We tested whether the individual bank's loan default rate influenced LGD for our sample, and we found that the relationship between LGD and the bank's default rate was insignificant in most specifications.
[35] For an additional three years, the acquirer was required to continue reporting all losses and recoveries, and to continue to share recoveries (net of certain collection expenses) with the FDIC. However, most of the loss share transactions were terminated shortly before or after the full indemnification period ended.
[36] As of year-end 2015, either the loss share agreements had been terminated or the loss-sharing period had expired for 243 of the 289 agreements. Only $860 million (2 percent) of the ADC loan portfolio was still active.

For loans foreclosed under the loss share program, the FDIC was entitled to share in any income earned from the collateral. Losses from bulk loan sales were covered by the FDIC, but only if the acquirer could demonstrate that a bulk loan sale was more cost-effective than loan-level (or borrower-level) workout strategies. Therefore, bulk loan sales were rare.

The loans in our sample were originated by banks that failed. When the originating bank failed, the loan underwent an ownership change during the loan term or workout period. This is not a random sample of all defaulted ADC loans in the United States during the relevant time horizon. To address concerns that our sample may not be representative of defaulted ADC loans at privately held banks, we note that almost all of these loans were originated when the originating banks were healthy and when there was substantial industry-wide growth in ADC loans. In addition, Shibut and Singer (2015) compared LGD using similar data for commercial real estate (CRE) loans backed by completed buildings from the FDIC's loss share program to LGDs reported in studies that relied on public sources (i.e., not failed banks). After presenting results from multiple studies, they concluded that "the LGDs in this sample are generally consistent with other studies that focus on periods of distress."[37] We also compare our sample to a group of distressed ADC loans at large banks and conclude that the FDIC data seem consistent with the Y-14 data in several ways (see Appendix B).

We considered the possibility that the FDIC indemnification under the loss share program might weaken the incentives of acquirers to work out assets effectively when compared with assets that lack indemnification coverage. The FDIC took several actions to mitigate the potential effects. First, it required that acquirers work out covered assets in the same way that they work out their own assets. Second, it required regular standardized reporting, adequate workpapers, and evidence that the loans were worked out effectively. Third, it reviewed loss claims and performed on-site compliance reviews at least once a year. The FDIC had the right to demand program improvements, reverse loss claims or, in the case of a serious contract breach, abrogate the loss share coverage altogether.[38] These factors help mitigate any bias due to the incentive created by the loss sharing agreement.

We drop loans from the sample for several reasons. Loans are dropped if the asset had not yet been extinguished (that is, the asset is sold, paid off, or written off in full) when the loss share

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[37] Shibut and Singer (2015), p. 11, with additional discussion on p. 10. The authors note that close comparisons are not available, but they include LGDs calculated from defaulted commercial mortgage-backed securities and CRE loans held by life insurance companies.

[38] These are just some of the FDIC's options to manage its exposure. Acquirers have the right to contest any FDIC action. For more details about the loss share program, see www.fdic.gov. All agreements are posted in the failed bank section. See also FDIC (2010) for details about the data collected from acquirers and FDIC Office of Inspector General (2013) for additional discussion about the FDIC's monitoring program and its effectiveness.

agreement was terminated or at the end of sample period (right-censoring),[39] or because of data problems associated with loans that defaulted before the bank failed. Loans that defaulted well before failure are omitted from the sample.[40] Loans are also dropped if they are from a U.S. territory (primarily Puerto Rico) or a foreign country, if they had very small outstanding loan balances at default ($100 or less), or because of other missing data.[41]

3.2 Key Definitions

Our definition of LGD is based on a combination of the guidance on LGD for the Basel 2 Advanced Approach models and data availability. The definition is as follows:

$$LGD = (EAD - REC + EXP)/EAD$$

EAD is the exposure at default, defined as the total drawn and undrawn balance committed on the loan at the time of default; *REC* is the discounted net principal recovery on the loan; *EXP* are the discounted expenses consisting of legal fees, foreclosure expenses, appraisal fees, property preservation costs, property taxes, and so on, plus up to 90 days of accrued interest at the time of default. Acquirers do not report all the cash inflows under the loss share program, but they report principal losses and expenses. Therefore, we back out the discounted principal recovery *REC* as the exposure at default EAD minus charge-offs CO (net of recoveries) and any loss on sale of the asset $LOSALE$, all discounted as of the default date at the interest rate on the loan: $REC = EAD - CO - LOSALE$.[42] Like many studies, our definition excludes two items that are included in the definition in the Basel 2 framework: servicing costs[43] and unpaid fee income. To guard

[39] The notion of "resolution bias" suggests defaulted loans that are extinguished quickly tend to have lower losses, so an exclusion of longer workouts outside our sample period would tend to bias LGD downward. However, failed bank acquirers had strong incentives to complete the workout for defaulted loans before the loss share coverage terminated, particularly for defaults with larger anticipated losses. We therefore do not believe that resolution bias is likely to be an issue in our sample.

[40] Some banks retain data on charge-offs in their loan servicing system for only a year after charge-offs are taken. Thus, loans that defaulted more than a year before failure are omitted because we are uncertain that the historical charge-off information is complete.

[41] Specifically, observations were also dropped if (a) the asset type was uncertain, (b) there were math errors in the acquirer's loss submissions or the FDIC's corrections of those submissions, (c) the ADC loan was combined with other types of loans during the workout process, or; (d) data for explanatory variables (or data needed to calculate explanatory variables, such as location of the collateral) were missing or incoherent. Also, note that some items were estimated, notably the type of collateral and stage of development (which were estimated using heuristic methods applied to relevant text data fields).

[42] The Basel 2 framework requires discounting to the default date using a market rate. There is no strong consensus on the appropriate interest rate, but the loan rate is frequently used. See Maclachlan (2004) for additional discussion and a survey of discounting methods used in academic research on loan losses.

[43] The Financial Crisis Inquiry Commission noted that a special servicer that handles problem loans "typically earns 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 Financial Crisis Inquiry Commission (2010), p 44. The Commission discussed servicing arrangements for loans that collateralize CMBSs. Servicing costs for construction loans might be different.

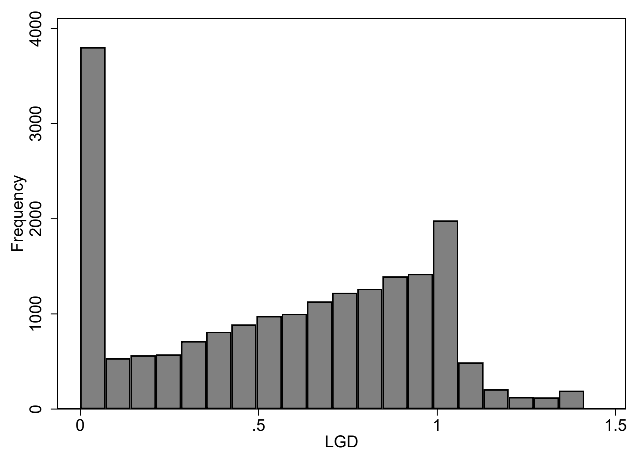
against potential reporting errors, we winsorize observed LGD in our sample at the 99th percentile.

A key aspect of any LGD definition is how defaults are measured. In our study, we define default as occurring the first time that we observe any of the following:

- 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, or
- A charge-off was taken on the loan, or any claim was made under the loss share program.

Figure 2 shows our sample distribution of LGD. Only 16 percent of the defaulted loans avoid losses altogether, and 15 percent have losses of 100 percent or more. Had we constrained LGD to be no higher than 100 percent, Figure 2 would look similar to the "U" shape seen in many studies of realized losses.[44] We observe in our sample many loans with losses exceeding 100 percent. LDGs above 100 percent typically occur when expenses are significant and principal recoveries are small. Such loans tend to be small (median EAD of $87,000, versus $260,000 for the others), are more likely to be foreclosed (56 percent, versus 44 percent for the others), and have longer workout periods (median of 11 quarters, versus 7 quarters for the others).

Figure 2: Sample Distribution of LGD

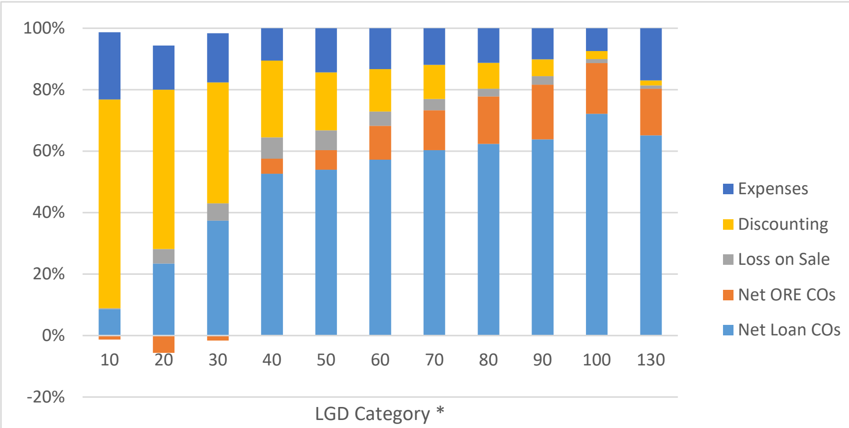


One contribution of our paper is that it uses a detailed measure of LGD that captures nearly the full range of costs a lender would incur in resolving a defaulted ADC loan. Many studies of losses on CRE mortgages are limited in their data on the composition of losses, and are limited to comparing market price reactions to default announcements for CMBS securities or the subsequent sales price of the property to loan exposure at default. We show in Figure 3 the decomposition of LGD across different buckets of LGD losses. This breakdown shows how expenses, the top (dark blue) segment in each column, account for a significant share of total losses across the loss distribution. For loans with very small positive LGDs, expenses comprise

[44] See Araten et al. (2004) and Asarnow and Edwards (1995) for examples of realized loss distributions.

more than 20 percent of losses. Charge-offs (COs) occasionally reflect the impact of successful downstream recoveries. In some cases, they even offset some of the losses from expenses and discounting, which is noticeable in the negative values for owned real estate charge-offs (ORE COs) in the first three bars of Figure 3. For the segment with losses greater than 100 percent, the share of expenses is approximately 17 percent of the total losses, highlighting the importance of using loss measures that include expenses. The share of losses associated with charge-offs after the bank has assumed ownership of the property—the ORE COs—increases as losses approach and exceed 100 percent. ORE COs represents another 15 percent of the total losses for high LGD loans in our sample, indicating that a significant portion of the total loss is being recognized later in the workout process. LGD estimates that do not consider expenses related to assets in default, or subsequent charge-offs for ORE assets, later in the workout are likely to underestimate the extent of true losses incurred.

Figure 3: Decomposition of Net Losses by LGD Category



* 10 includes 1% < LGD =< 10%, 20 includes 10% < LGD =< 20%, etc. CO stands for charge-offs, net of recoveries.
Source: FDIC loss share and failed bank data.

3.3 Descriptive Statistics

This section begins with basic descriptive statistics across the full sample. We then provide additional detail on key variables and a breakdown of the sample based on geography and type of collateral.

3.3.1 Full sample characteristics

As shown in Figure 4a, most of our loan originations occurred between 2005 and 2010, with 25 percent occurring in 2007 and 63 percent occurring between 2006 and 2008.[45] One interesting aspect of the origination dates is that it includes a non-trivial share of construction loans originated during the financial crisis, when overall construction lending dropped significantly. Most defaults occurred between 2009 and 2011, with 33 percent in 2009, 29 percent in 2010, and 15 percent in 2011. This is clearly a sample of loans that defaulted during a period of severe

[45] Observations where either the origination date or the default date are missing are excluded.

distress, which is exactly when losses on construction loans are of greatest concern for lenders and the broader economy.

Figure 4b shows the distribution of the term to maturity at origination. The mean term to maturity is 4 years, and the mean age at default is 3.2 years.[46] In addition, 60 percent of the loans are maturity defaults.[47] Assuming the project has progressed as expected, a default occurring at maturity would suggest that a bank would have a complete or nearly complete project to seize as collateral, instead of a partially complete project with greatly reduced value.

Figure 4a: Distribution of Origination and Default Date

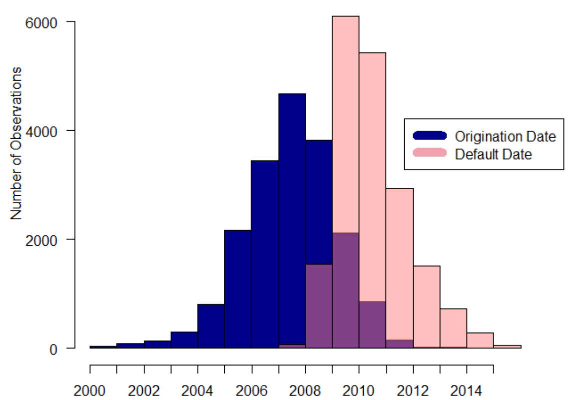


Figure 4b: Distribution of Term to Maturity

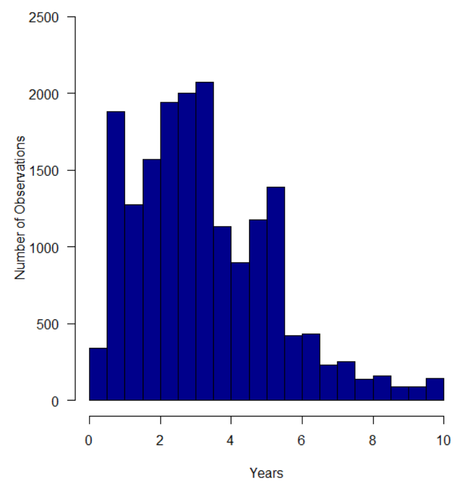


Figure 5 reports the distribution by asset size. The distribution is strongly skewed, with a large number of smaller assets that relate to construction of individual single-family properties, and is not dominated by large construction loans for single-family developments or large commercial projects. This is due in part to the nature of the crisis itself, which was strongly associated with a boom-bust cycle in single-family lending. It is also due in part to the nature of failed banks, many of which were smaller institutions specializing in smaller single-family and commercial construction projects rather than larger residential or commercial developments. It is possible, for example, that the experience of builders or the structure of financing for those large-scale projects could differ in certain ways from most of the defaulted loans in our sample. Our results from this crisis should be interpreted with this in mind.

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[46] The average length of the loan is significantly longer than the time it takes to complete a single residential unit, which is 7.8 months. The difference between the loan term and typical construction period reflects the additional time built into the loan for preparation before vertical construction, the construction of multiple buildings financed by the same loan, the construction of buildings with more than a single unit (where the average time to build is 17.4 months), and time required to sell the completed properties.

[47] A maturity default is defined as a default that occurs within 90 days of the scheduled maturity or after maturity.

Figure 5: Sample Distribution of Asset Size

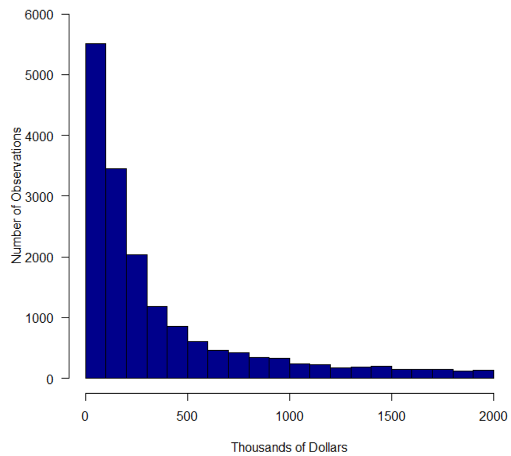

Table 1 reports descriptive statistics for the full sample. The first section of the table provides data on the characteristics of the loans. The mean LGD is 56.7 percent, and the median is 62.4 percent. Defaulted loans with a positive loss for the lender make up 84.4 percent of the sample, while 15.6 percent of the defaults resolve with no loss. As shown in Figure 5, the distribution of the size of the loans is heavily skewed: although the mean exposure at default is $1.06 million, the median is only $230,000. The median interest rate is 6 percent. And as mentioned previously, the mean term to maturity at origination is four years, and the median is three years. The mean age of the loan at default is about three years, and 60 percent are maturity defaults. About 37 percent of the sample was already in default when the originating bank failed, and 46 percent of the loans were foreclosed during the workout period. The mean workout period is 25 months, and it varies substantially across the sample. The legal process for foreclosure influences the ability of lenders to seize assets and may be relevant to explain loan loss, so we look at whether loans are in judicial foreclosure states (41 percent).[48] Construction lending is also an informationally intensive business, where knowledge of local market conditions are important, so we track whether loans are made outside of Core-Based Statistical Areas (CBSAs) in which the originating bank has a branch presence ("out-of-territory"). About 25 percent of the loans were made based on collateral located outside of the lender's CBSA footprint; these are not distributed evenly across regions or banks. For 9 percent of the loans, the outstanding loan balance exceeded the initial loan amount at some point during the loss share period (thus indicating that the acquiring bank authorized additional funds to minimize losses).

[48] In judicial foreclosure states, foreclosure requires a court order.

Table 1: Descriptive Statistics for the Sample

Variable	No. of Obs	10th Percentile	Median	90th Percentile	Mean	Standard Deviation
Basel LGD based on discounted loss share cash flows	19,427	0	0.624	1.015	0.567	0.383
1 if basel LGD has a nonzero loss	19,427	0	1	1	0.844	0.363
Loan Characteristics						
Outstanding balance at default ($1,000)	19,427	31	230	2,658	1,056	2,598
Interest Rate	19,427	4.0	6.0	8.5	6.3	2.3
Term to maturity (years)	18,658	1.0	3.0	7.0	4.0	3.84
Age at default (years)	18,780	0.93	2.82	5.69	3.17	2.12
Maturity default*	18,661	0	1	1	0.60	0.49
In default when the bank failed	18,639	0	0	1	0.37	0.48
Foreclosed	19,427	0	0	1	0.46	0.50
Workout period (months)	19,427	3.5	23.5	50.4	25.3	17.9
Ratio of balance drawn to total exposure **	19,427	1	1	1	0.95	0.14
Land development loan	9,286	0	1	1	0.89	0.32
Judicial foreclosure state	18,493	0	0	1	0.42	0.49
Out of territory loan (CBSA)	17,775	0	0	1	0.25	0.43
Overage (Asset bal > init exposure at any time)	19,427	0	0	0	0.09	0.29
Bank Characteristics						
Bank 3-yr ADC loan growth rate at loan origination	19,427	0	1.25	4.00	1.67	1.42
CAMELS rating at origination	18,549	2	2	4	2.49	1.05
Asset size of failed bank at loan origination ($ millions) +	18,714				3,389	6,574
Failed bank time spent in distress (years)	19,427	0.45	1.18	2.10	1.27	0.66
Market Characteristics						
Local ratio of ADC to total lending at origination	18,487	0.063	0.117	0.190	0.123	0.051
Local NC rate for ADC loans at origination	18,481	0.002	0.013	0.153	0.048	0.064
Local 3-yr change in ADC to total lending at origination	18,481	-0.026	0.025	0.075	0.024	0.042
Local 3-yr change in brokered to total deposits at orig	18,481	-0.020	0.022	0.058	0.020	0.041
One year pct point chg in SFR permits/total stock at orig	18,472	-0.004	-0.002	0.001	-0.002	0.002
Local average vacancy rate for CRE at orig	18,449	0.056	0.081	0.106	0.081	0.020
Local change in ADC to total lending (orig to def)	16,287	-0.090	-0.032	0.004	-0.037	0.038
Local NC rate for ADC loans at default	18,501	0.084	0.168	0.223	0.162	0.057
Change in local ratio of NC ADC to total loans	18,481	0.012	0.119	0.205	0.114	0.076

* Default was within 90 days of scheduled maturity or after maturity

** Capped at 100%

+ Percentile items omitted for privacy reasons

NC stands for noncurrent (including nonaccrual). SFR stands for single family residential.

The next section of the table looks at the characteristics of the banks in our sample. Growth in the originating banks' ADC portfolios was strong during the period leading up to origination: on average, it was 36 percent in the previous year and 167 percent in the previous three years. The mean CAMELS rating at origination is 2.49, and the median is 2. The mean size of the failed banks at origination is $3.4 billion, and the median is somewhat less than $1 billion. We also track the time the originating bank spends in distress (defined as having a CAMELS composite rating of 4 or 5). If a bank is closed shortly after it begins to experience distress, then the loans are more quickly transferred to a healthier institution, which may result in lower losses. In our sample, the average time spent by the originating bank in distress is just over 1.5 years.

A key focus of our paper is the degree to which local market characteristics can explain ADC loan loss rates. The last section of Table 1 reports several market-level measures calculated from the balance sheets of all banks with branches located in the CBSA where the loan's collateral resides. These measures are meant to reflect the general climate of ADC lending with respect to other local lenders competing in that market space. Geographic allocations for loans from local banks are based on CBSA-level branch shares as reported in the FDIC Summary of Deposits (SOD).

Our sample is heavily weighted toward markets that experienced significant construction lending growth. The average local ratio of ADC loans to total loans at origination is 12 percent, and the average percentage point increase in this ratio over the three years before loan origination was 2 percent.[49] Interestingly, a significant share of the loans—22 percent— was originated when the three-year change in the ratio of ADC loans to total loans was declining.[50] These loans also were originated in areas where banks were aggressively seeking new sources of deposits, with the ratio of brokered to total deposits increasing 2 percentage points, on average, during the three years before loan origination. We interpret these local lending measures as a proxy for how aggressive the competition may be from other local banks in the market and as a reflection of local supply conditions.

We look at other measures of market conditions that relate new ADC lending to existing stock. We use the one-year regional change in single-family permits to total stock at origination, which averages -0.2 percent. A negative value is a forward-looking indication that growth in single-family stock is slowing, while a positive value is a forward-looking indication that single-family stock is increasing. A higher positive value at origination reflects markets in which the supply of single-family housing is increasing more dramatically. The slower adjustment of construction sector investment (arising from the time required to build) could exacerbate the mismatch between demand and supply if demand decreases sharply post-origination, contributing to higher losses in default. We also include the local vacancy rate by commercial property type at origination, which averages 8.1 percent.[51] These rates show how much supply exists in the market relative to demand for finished commercial properties when the loan is made. ADC loan originations where vacancy rates are already high may be a sign of lenders originating into markets with a lower capacity for future absorption when construction is complete, increasing the losses in default should there be a negative shock to demand.

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[49] For context, contrast levels and changes of ADC lending for the Atlanta and Boston CBSAs during the period leading up to the crisis. In Atlanta, the peak ratio of ADC loans to total loans was 19.3 percent; in Boston, it was 4.9 percent. In Atlanta, the average three-year percentage point increase in that ratio exceeded 3 percentage points from March 2005 to September 2008, with a maximum of nine percentage points in March 2007; in Boston, it never reached two percentage points.

[50] About 40 percent of the loans were originated when the one-year percentage point change in ADC loans to total loans was negative.

[51] State-level data were used for loans outside a CBSA designation.

We also look at what happens in the local market between origination of the loan and default. These variables relate to the risk ADC lenders face that local market conditions may change after originating the loan and before construction is complete. The average change in the ratio of ADC loans to total loans from origination to default is -3.7 percentage points. A decline in this ratio indicates that lenders may be reducing exposures because they recognize markets are shifting and they are adapting their lending volume to that risk. On the other hand, when this ratio is increasing dramatically between the time of loan origination and default, there is a greater chance that default is occurring in an overzealous or glutted market, and recoveries may suffer as a result. Therefore, we expect higher losses in our sample if this measure is increasing between origination and default. This variable differs from our inclusion of the local three-year change in ADC lending to total lending in the lead up to origination in terms of when the information is available to lenders. The three-year percentage point change in ADC lending before origination could be considered part of the lender's available information set when the loan is made. However, the change in ADC lending between origination and default is a measure of the change in ADC lending after loan origination, and would not be observable to lenders at origination. While the former variable is tied to the extent to which lenders are managing their risk exposure from excessive market growth, the latter highlights the risk faced by lenders in fast-growing markets after origination, before the property may be completed and sold. We also look at the ratio of noncurrent ADC loans to total loans at the time of default to get a sense of distress in the local market. If a large share of local projects are in distress when the loan defaults, we expect that the value of the collateral for a defaulted loan will be lower and the losses will be higher.

3.3.2 Segmented sample characteristics

We take a deeper dive into the data by looking at the sample segmented across different regions and property types. Figure 6 provides a map of loan location counts by state, and Table 2 provides a breakdown of the sample by collateral type and location.[52] The sample is not highly concentrated by bank. The largest bank (in terms of sample size) held 10.8 percent of the loans; the top five held 24.7 percent.

[52] We also report separately loans where, due to data quality issues, we could not identify the type of project.

Figure 6: Sample Location by State

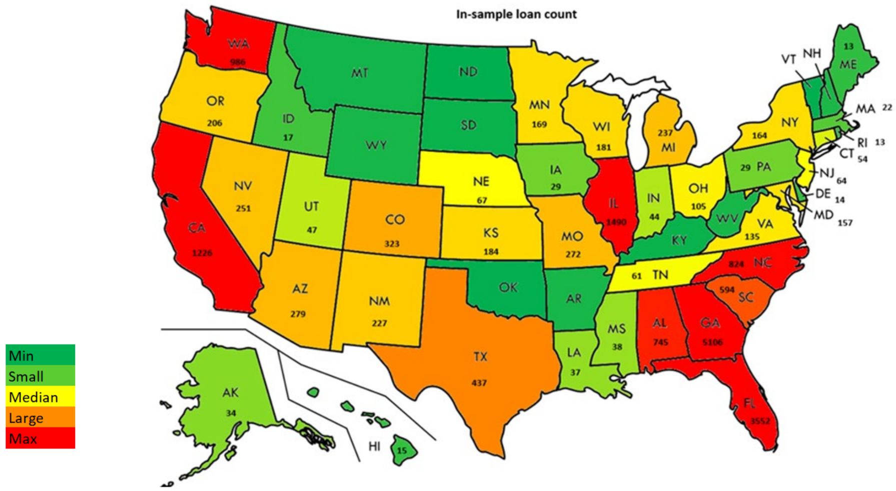

Table 2: Sample Breakout by Collateral Location and Type

	Full Sample		Collateral Type									
			Single Family				Commercial				Unknown	
	No. of Obs	Pct of Total Sample	No. of Obs			Pct of Total for Location	No. of Obs			Pct of Total for Location	No. of Obs	Pct of Total for Location
			Land/Dev	Home	Unknown		Multi-family	Retail	Other/ Unknown			
By State												
Georgia	5,106	27.6%	1,704	463	1,263	67%	30	55	386	9%	1,205	24%
Florida	3,552	19.2%	1,911	54	529	70%	52	37	237	9%	732	21%
Illinois	1,490	8.1%	183	55	194	29%	353	31	276	44%	398	27%
California	1,226	6.6%	229	78	344	53%	140	45	84	22%	306	25%
Washington	986	5.3%	418	68	99	59%	63	33	51	15%	254	26%
All Other	6,140	33.2%	2,041	306	1,600	64%	137	180	473	13%	1,403	23%
By Region*												
Northeast and Midwest	3,603	19.5%	691	155	722	44%	435	166	511	31%	923	26%
South	11,273	60.9%	4,568	611	2,585	69%	116	105	807	9%	2,481	22%
West	3,624	19.6%	1,227	258	722	61%	224	110	189	14%	894	25%
Total	18,500	100.0%	6,486	1,024	4,029	62%	775	381	1,507	14%	4,298	23%
Pct of Total			35%	6%	22%		4%	2%	8%		23%	

* The Northeast region is made up of Connecticut, Delaware, Massachusetts, Maine, New Hampshire, New Jersey, New York, Pennsylvania, Rhode Island, and Vermont; the Midwest region is made up of Iowa, North Dakota, South Dakota, Illinois, Indiana, Michigan, Minnesota, Missouri, Nebraska, Ohio, Wisconsin, Kansas, Oklahoma, and Texas; the South Region is made up of Alabama, Arkansas, Florida, Georgia, Kentucky, Louisiana, Maryland, Mississippi, North Carolina, South Carolina, Tennessee, Virginia, District of Columbia, and West Virginia; the West region is made up of Arizona, California, Colorado, Idaho, Montana, New Mexico, Nevada, Oregon, Utah, Washington, Wyoming, Alaska, and Hawaii. Northeast and Midwest regions are combined for privacy reasons.

The sample is heavily concentrated both in the South and in loans collateralized by single-family properties. Loans from the South comprise 61 percent of the sample, whereas those from the Northeast comprise a mere 2 percent. At 28 percent of the sample, Georgia is the most heavily represented, even though it accounted for only 3 percent of the U.S. population in 2007.[53] Several factors contribute to this feature of the sample. First, at the onset of the crisis, FDIC-insured banks headquartered in the South were more heavily invested in ADC loans: as of year-end 2007, institutions headquartered in the South held 40 percent of the total balance of ADC

[53] FDIC loss share data and Census data.

loans but only 28 percent of industry assets.[54] Second, institutions from the South and the West failed and were resolved using the loss share program more often (South, 6.6 percent; West, 6.8 percent), whereas only 1.9 percent of banks in the Midwest and 0.9 percent of banks in the Northeast failed and were placed into the loss share program.[55] In total, 47 percent of the banks placed under the FDIC's loss share program were headquartered in the South, 28 percent in the Midwest, 22 percent in the West, and 3 percent in the Northeast. Moreover, the failed banks in the Northeast had lower concentrations of ADC loans than those in other regions, and those in the South had the highest concentrations.[56]

Table 3 reports loan, bank, and market characteristics by region. Mean LGD is highest in the South: 61 percent, versus 48 percent to 50 percent for the other regions. Loan sizes are much smaller in the South, with a median value ($177,000) less than half that of loans in other regions ($326,000 to $500,000). The difference in loan size may reflect the higher share of loans in the South that are collateralized by single-family properties. In most regions, maturity defaults account for roughly 60 percent of all defaults, but in the Northeast they account for only 47 percent. However, the average draw rates suggest most of these projects drew almost all of their committed balances even if they defaulted before maturity. Median interest rates on the loans are slightly higher in the Midwest and West. Few states in the West are judicial foreclosure states, while most states in the Northeast are. The share of loans where the asset balance at some point exceeded the original committed balance is fairly consistent across regions, with a slightly higher frequency observed in the South and the West.

There are strong regional patterns associated with out-of-territory lending by banks in our sample. Loans collateralized by properties in the Midwest were the least likely to be out-of-territory (13 percent), where there were a significant number of local bank failures but no boom preceding the crisis. A strikingly large share of the loans in the Northeast were out-of-territory (77 percent). There could be several reasons for this difference. First, there was no significant real estate boom or bust there in the Northeast, and few local ADC lenders from that region failed; thus, in our sample, lenders with loans in the Northeast tended to have higher shares of out-of-territory loans than average. Second, construction may be more heavily constrained in the Northeast because of zoning or less availability of suitable land for new development.

The originating failed banks in all four regions of our sample had high ADC loan growth at origination, especially in the Northeast and West. When the sample loans were originated, the

[54] Call Report data.

[55] FDIC failure and Call Report data. Failure rates are calculated as total failures placed under the loss share program from 2008 through 2013 divided by total number of institutions as of year-end 2007. Puerto Rico banks had even higher failure rates than what is reported for any of the regions reported here, but Puerto Rico is omitted because loans from Puerto Rico are excluded from the sample.

[56] Call Reports as of the quarter immediately before failure. The mean ADC concentrations were 13.2 percent for the Northeast, 18.1 percent for the Midwest, 21.2 percent for the West, and 23.2 percent for the South.

Table 3: Sample Breakout by Region

Variable	South Mean	South Median	South Std	Midwest Mean	Midwest Median	Midwest Std	West Mean	West Median	West Std	Northeast Mean	Northeast Median	Northeast Std
Basel LGD based on discounted loss share cash flows	0.61	0.69	0.38	0.48	0.48	0.40	0.48	0.51	0.36	0.50	0.53	0.41
1 if basel LGD has a nonzero loss	0.87	1	0.34	0.75	1	0.43	0.83	1	0.37	0.75	1	0.44
Loan Characteristics												
Outstanding Balance at Default ($1,000)	757	177	1889	1155	326	2527	1897	500	3897	1678	345	3615
Interest Rate	6.18	6.00	2.17	6.40	6.50	2.14	6.82	6.50	2.65	6.63	6.25	2.05
Term to maturity (years)	3.53	2.96	3.04	5.94	3.85	6.04	3.76	3.02	2.93	4.68	3.47	3.44
Age at Default (years)	2.98	2.66	2.03	3.78	3.25	2.62	3.24	2.88	1.88	3.04	2.64	1.66
Maturity Default *	0.60	1	0.49	0.55	1	0.50	0.64	1	0.48	0.47	0	0.50
In default when the bank failed	0.37	0	0.48	0.33	0	0.47	0.42	0	0.49	0.48	0	0.50
Foreclosed	0.51	1	0.50	0.33	0	0.47	0.38	0	0.49	0.21	0	0.41
Workout period (months)	26.6	25.5	17.5	25.1	22.0	19.7	23.8	22.2	17.0	24.2	19.7	20.6
Ratio of balance drawn to total exposure **	0.94	1	0.15	0.95	1	0.13	0.95	1	0.13	0.93	1	0.17
Land development loan	0.90	1	0.30	0.84	1	0.37	0.85	1	0.35	0.98	1	0.15
Judicial foreclosure state	0.44	0	0.50	0.65	1	0.48	0.07	0	0.25	0.85	1	0.35
Out of territory loan (CBSA)	0.25	0	0.43	0.13	0	0.33	0.28	0	0.45	0.77	1	0.42
Overage (Asset bal > init exposure at any time)	0.10	0	0.30	0.08	0	0.27	0.10	0	0.30	0.07	0	0.25
Bank Characteristics												
Bank 3-yr ADC loan growth rate at loan origination	1.46	0.91	1.38	1.65	1.25	1.41	1.90	1.63	1.23	1.94	1.50	1.48
CAMELS rating at origination	2.65	2	1.12	2.30	2	1.01	2.18	2	0.74	2.32	2	0.72
Asset size of failed bank at loan orig ($ millions) +	3,855		7,435	2,727		5,188	2,775		4,825	2,332		4,814
Failed bank time spent in distress (years)	1.28	1.20	0.63	1.42	1.31	0.77	1.09	1.15	0.61	1.24	1.14	0.77
Market Characteristics												
Local ratio of ADC to total lending at origination	0.143	0.140	0.046	0.090	0.087	0.030	0.099	0.086	0.050	0.037	0.030	0.020
Local NC rate for ADC loans at origination	0.057	0.017	0.069	0.039	0.013	0.054	0.029	0.009	0.049	0.022	0.016	0.025
Local 3-yr change in ADC to total lending at orig	0.025	0.034	0.048	0.017	0.019	0.025	0.028	0.024	0.033	0.013	0.012	0.011
Local 3-yr change in brokered to total deposits at orig	0.024	0.027	0.034	0.015	0.016	0.038	0.017	0.017	0.058	-0.022	-0.003	0.052
One year pct pt chg in SFR permits/total stock at orig	-0.002	-0.003	0.002	-0.001	-0.001	0.001	-0.003	-0.004	0.003	-0.001	-0.001	0.001
Local average vacancy rate for CRE at orig	0.084	0.087	0.019	0.086	0.089	0.017	0.067	0.063	0.017	0.061	0.057	0.010
Local change in ADC to total lending (orig to def)	-0.045	-0.041	0.041	-0.026	-0.024	0.027	-0.028	-0.024	0.032	-0.004	-0.001	0.014
Local ratio of NC ADC to total loans at default	0.165	0.173	0.051	0.152	0.153	0.061	0.168	0.170	0.066	0.111	0.113	0.046
Change in local ratio of NC ADC to total loans	0.107	0.112	0.074	0.113	0.119	0.078	0.139	0.149	0.079	0.090	0.090	0.046

* Default was within 90 days of scheduled maturity or after maturity

** Capped at 100%

\+ Median omitted for privacy reasons

NC stands for noncurrent (including nonaccrual). SFR stands for single family residential.

lenders' mean three-year ADC loan growth rate ranges from 146 percent in the South to 194 percent in the Northeast. All these rates exceed total industry growth: the industry's peak three-year growth rate for ADC loans during this period was 108 percent.[57]

Banks that originated loans in the South were larger than in the other regions, with average assets of $3.8 billion compared with $2.3 billion in the Northeast and $2.7 billion in the West and Midwest. Banks that originated loans in the West spent the shortest average time in distress, just over a year on average, while banks in the Midwest were in distress for 1.4 years on average.

The geographical pattern of loans in our sample reflects the conventional wisdom that construction lending was the most aggressively competitive in the South and probably the least competitive in the Northeast. This pattern can be seen in the greater increase in de novo lenders in the South and the aggregate increase in concentration in construction loans in the South. The estimated mean share of ADC to total loans at local competing banks at origination was 14 percent in the South, 10 percent in the West, 9 percent in the Midwest, and only 4 percent in the

[57] Call Report data. The industry's peak growth period ran from year-end 2003 to year-end 2006. The industry's quarterly growth rate peaked in June 2005 at 8.3 percent, started to decline in June 2006, and turned negative in June 2008.

Northeast. Banks in the South were also more aggressive in acquiring funds, with larger growth in brokered deposits. The South exhibited a larger average decline in local ADC lending between loan origination and default, suggesting a more dramatic correction in construction lending supply during this period. The estimated increase in local ADC noncurrent rates was strong in all regions, ranging from 9 percent in the Northeast to 14 percent in the West. However, the noncurrent rates were lower at origination in the Northeast. At default, the estimated local noncurrent rate for ADC loans exceeded 16 percent for the South and the West, 15 percent for the Midwest, and 11 percent for the Northeast.

Table 4 repeats our analysis, breaking out the sample by project type instead of region. The commercial ADC loans tend to be larger in size and with longer terms than single-family. They also have a somewhat lower incidence of maturity defaults and out-of-territory originations. We saw high growth in ADC loans at originating banks in the period leading up to loan origination across all collateral types. For local ADC lending ratios, the average three-year change appears somewhat higher in local areas for single-family collateral. In addition, brokered deposits grew more in local areas in our sample where single-family loans were originated. Other measures of local market conditions are largely consistent across collateral types.

Table 4: Sample Breakout by Project Type

	SFR land			SFR homes			SFR (stage unknown)			Commercial			Unknown		
Variable	Mean	Median	Std	Mean	Median	Std	Mean	Median	Std	Mean	Median	Std	Mean	Median	Std
Basel LGD based on discounted cash flows	0.58	0.66	0.39	0.51	0.48	0.35	0.56	0.59	0.37	0.52	0.55	0.38	0.59	0.67	0.38
1 if basel LGD has a nonzero loss	0.83	1.00	0.38	0.87	1.00	0.34	0.86	1.00	0.34	0.81	1.00	0.40	0.84	1.00	0.37
Loan Characteristics															
Outstanding Balance at Default ($1,000)	857	175	2,264	848	248	1,817	677	193	1,701	1,795	499	3,673	1,355	315	2,960
Interest Rate	6.48	6.25	2.21	6.26	6.00	2.58	6.03	6.00	1.91	6.25	6.25	2.15	6.57	6.23	2.63
Term to Maturity (years)	4.26	3.56	3.17	2.80	2.45	2.33	3.15	2.75	2.76	5.65	3.50	5.93	3.74	2.92	3.89
Age at Default (years)	3.64	3.33	2.12	2.55	2.30	1.51	2.60	2.30	1.67	3.62	3.02	2.64	2.90	2.50	2.09
Maturity Default *	0.60	1	0.49	0.69	1	0.46	0.61	1	0.49	0.53	1	0.50	0.60	1	0.49
In default when the bank failed	0.29	0	0.46	0.50	1	0.50	0.43	0	0.50	0.36	0	0.48	0.42	0	0.49
Foreclosed	0.42	0	0.49	0.52	1	0.50	0.50	0	0.50	0.37	0	0.48	0.49	0	0.50
Workout period (months)	26.8	25.5	18.1	24.3	23.0	16.2	24.2	22.3	17.3	26.3	25.3	18.3	25.7	23.8	18.2
Ratio of balance drawn to total exposure **	0.95	1	0.13	0.93	1	0.17	0.93	1	0.19	0.96	1	0.10	0.95	1	0.13
Judicial foreclosure state	0.47	0	0.50	0.19	0	0.39	0.35	0	0.48	0.48	0	0.50	0.41	0	0.49
Out of territory loan (CBSA)	0.26	0	0.44	0.23	0	0.42	0.24	0	0.43	0.21	0	0.41	0.25	0	0.43
Overage (Asset bal > init exposure at any time)	0.08	0	0.26	0.09	0	0.29	0.09	0	0.28	0.10	0	0.30	0.13	0	0.33
Bank Characteristics															
Bank 3-yr ADC loan growth rate at loan orig	1.44	1.10	1.28	1.56	1.24	1.27	1.53	0.93	1.42	1.84	1.49	1.46	1.71	1.27	1.39
CAMELS rating at origination	2.48	2	1.04	2.54	2	1.08	2.59	2	1.11	2.39	2	1.02	2.48	2	1.03
Asset size of failed bank at loan orig ($ millions) +	3,285		6,400	1,296		921	4,531		7,822	1,920		3,857	3,998		7,451
Failed bank time spent in distress (years)	1.38	1.31	0.70	1.23	1.26	0.70	1.19	1.18	0.70	1.35	1.30	0.63	1.13	1.18	0.54
Market Characteristics															
Local ratio of ADC to total lending at origination	0.128	0.122	0.049	0.131	0.133	0.049	0.124	0.123	0.052	0.104	0.092	0.047	0.123	0.116	0.053
Local NC rate for ADC loans at origination	0.046	0.010	0.064	0.056	0.021	0.063	0.053	0.016	0.068	0.048	0.014	0.064	0.044	0.014	0.058
Local 3-yr change in ADC to total lending at orig	0.025	0.029	0.043	0.029	0.035	0.043	0.021	0.024	0.046	0.019	0.020	0.036	0.027	0.025	0.036
Local 3-yr change in broker to tot deposits at orig	0.023	0.024	0.043	0.023	0.026	0.038	0.018	0.022	0.045	0.013	0.016	0.035	0.023	0.024	0.039
One yr pct pt chg in SFR permits/tot stock at orig	-0.002	-0.002	0.002	-0.002	-0.003	0.002	-0.002	-0.003	0.002	-0.002	-0.002	0.002	-0.002	-0.003	0.002
Local average vacancy rate for CRE at orig	0.080	0.078	0.020	0.085	0.091	0.021	0.082	0.084	0.020	0.083	0.086	0.019	0.079	0.079	0.020
Local change in ADC to total lending (orig to def)	-0.046	-0.041	0.040	-0.041	-0.037	0.037	-0.032	-0.026	0.036	-0.035	-0.031	0.034	-0.030	-0.025	0.036
Local ratio of NC ADC to total loans at default	0.163	0.169	0.057	0.171	0.184	0.052	0.154	0.160	0.057	0.171	0.180	0.053	0.160	0.166	0.058
Change in local ratio of NC ADC to total loans	0.117	0.126	0.080	0.115	0.121	0.076	0.101	0.104	0.072	0.123	0.134	0.076	0.116	0.115	0.073

* Default was within 90 days of scheduled maturity or after maturity
** Capped at 100%
\+ Medians omitted for privacy reasons
NC stands for noncurrent (including nonaccrual). SFR stands for single family residential.

Our sample is composed of loans originated (for the most part) during one real estate boom, and defaulted and resolved during one period of distress. While similarities exist across real estate and banking crises, certain characteristics are unique to each crisis. This period saw significant expansion in the supply of single-family housing before the crisis, but less of an expansion for commercial properties. The next real estate crisis will probably play out differently.

4. Methodology

We implement a two-step estimation approach in our analysis to accommodate the bimodal nature of the LGD data. As shown in Figure 2, the observed distribution is a mixture of discrete and continuous outcomes, with a discrete spike at zero representing defaulted loans that experience no loss and a continuous portion above zero representing the severity conditional upon incurring a loss.[58] The two-step model distinguishes between discrete and continuous portions of the LGD distribution, and it allows the underlying process to differ between them. This helps disentangle the two channels of loss probability and loss severity in the different modes of the LGD distribution. As observed in Schuermann (2004), "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," (p. 270). Versions of the two-step approach have been used elsewhere in the existing LGD literature; examples include Matuszyk (2010), Bellotti and Crook (2012), Leow and Mues (2012), Loterman et al. (2012), Leow et al. (2014), Hwang et al. (2016), Tanoue et al. (2017), Do et al. (2018), and Do et al. (2019).

In the first step of the model, we estimate the probability of falling into either mode of the LGD distribution: $\Pr(y = 0|x)$ and $\Pr(y > 0|x)$, where y represents observed values of LGD and x is the vector of covariates. In the second step, we estimate the loss severity conditional upon falling into the loss mode of the distribution, where we assume that y follows a log-normal distribution for observations where $y > 0$. If we generalize $\Pr(y > 0|x) = F(x\delta)$ as the cumulative distribution function (typically chosen from either a probit or logit distribution), and $g(x\gamma)$ as the appropriate density for $y|y > 0$, then the log-likelihood contribution for observation i is written as

$$ln[L_i(\theta)] = 1[y_i = 0]ln[1 - F(x\delta)] + 1[y_i > 0]ln[F(x\delta)g(x\gamma)]$$

where x is the vector of covariates, and δ and γ are the estimated parameters of their respective functions. The MLE of δ for the binary loss outcome can be a probit or logit estimator. The MLE of γ for loss severity is the OLS estimator, which we specify as a regression of $ln(y)$ on x, conditional on $y > 0$. The two steps can be estimated separately since the parameters are additively separable in the log-likelihood function; see Belotti et al. (2015).

[58] While the spike at zero may resemble a censored distribution, these are actual observed zero losses conditional on default rather than the product of a censoring constraint. As the entire distribution of LGD is observable, no correction for selection bias is needed. See Leung and Yu (1996) and Belotti et al. (2015) for further detail on the two-step approach; Wooldridge (2010) provides useful discussion as well; see Chapter 17, pp. 690-692.

The results from the two estimation steps may then be combined to attain the overall marginal impact of the covariates on LGD. The expected value for LGD then is not a simple mean, but is weighted by the probability of incurring loss

$$E(y|x) = Pr(y > 0|x)E(y|x, y > 0)$$

where $Pr(y > 0|x) = exp(x'\delta)/[1 + exp(x'\delta)]$ is from the first-step logit regression and $E(y|x, y > 0) = exp(x'\gamma + \sigma^2/2)$ is from the second-step log-linear regression.

Coefficients are reported for the first-step logit and second-step linear regressions, as well as for the combined marginal effects on LGD. For all regressions, standard errors are clustered at the level of the originating bank. Because we expect that LGD will behave differently for loans collateralized by single-family and commercial projects, we run separate sets of regressions for each collateral type.

As detailed in Section 3.3, we observe variation in our sample at the level of the individual loans in default, the failed banks originating the loans, and the local markets in which the loan collateral is located. Loan-level characteristics include basic information on the individual loans that may be known at origination (such as the amount of committed exposure and whether the collateral is out-of-territory), but also certain later indications (like cost overruns) suggesting that the construction process may have run into trouble. Characteristics of the failed bank (such as growth rates at origination or time spent in distress before failure) could reflect shared qualities on loans related to origination practices or management troubles at the originating institution. Finally, conditions in the local markets—both at origination and at default—may inform about factors like local loan supply or default trends that could affect the value of recoveries in default. To highlight the relative importance of these categories, we estimate our regressions using the following general format: *LGD=f(Loan characteristics, Originating bank characteristics, Market characteristics).*

5. Results

We present the results from our analysis by discussing the impact of the loan characteristics in Section 5.1, the bank characteristics in Section 5.2, and the market characteristics in Section 5.3. Section 5.4 presents an analysis of counterfactuals to shed additional light on the core results, and Section 5.5 discusses robustness testing.

Our primary results are shown in Table 5. Columns 1–3 provide single-family results and columns 4–6 provide commercial collateral results. For each collateral type, the logit model is shown first (columns 1 and 4), then the GLM results for assets with positive losses (columns 2 and 5), and then marginal effects that combine the logit and GLM results (columns 3 and 6).

Table 5: Primary Regression Results

	Single- Family ADC Loans			Commercial ADC Loans		
	(1)	(2)	(3)	(4)	(5)	(6)
	Logit	GLM	Margin	Logit	GLM	Margin
Loan level variables						
Land development loan	-0.039	0.250***	0.137***			
	(-0.229)	(4.712)	(4.239)			
Exposure at default (log)	0.183***	-0.070***	-0.026***	0.329***	-0.067***	-0.007
	(4.841)	(-7.810)	(-4.143)	(5.576)	(-5.944)	(-0.903)
Judicial foreclosure state	0.307**	0.080**	0.067***	-0.041	0.148***	0.071***
	(1.982)	(2.228)	(2.996)	(-0.228)	(4.707)	(3.337)
Out of territory loan (CBSA)	0.321**	0.031	0.041**	-0.034	-0.006	-0.006
	(2.078)	(1.146)	(2.142)	(-0.164)	(-0.169)	(-0.236)
Balance drawn / total exposure	-1.709	-1.136**	-0.760***	1.859	-3.239***	-1.483**
	(-1.092)	(-2.401)	(-2.622)	(0.622)	(-3.035)	(-2.471)
Balance drawn / total exposure, Squared	2.498**	0.792**	0.627***	0.284	2.136***	1.103***
	(2.048)	(2.382)	(3.011)	(0.131)	(2.837)	(2.605)
Overage	0.553**	0.111***	0.103***	1.213***	0.090***	0.146***
	(2.305)	(4.900)	(4.814)	(3.344)	(2.8138	(4.236)
Loan age at default (quarters)	-0.042***	-0.016***	-0.012***	-0.041***	-0.011***	-0.009***
	(-3.302)	(-7.582)	(-8.052)	(-5.479)	(-5.180)	(-7.259)
Maturity default	-0.633***	-0.049***	-0.074***	-0.023	-0.006	-0.005
	(-5.823)	(-3.225)	(-6.316)	(-0.131)	(-0.250)	(-0.263)
Bank level variables						
3-year growth ADC to total lending at origination	0.115*	0.026***	0.023***	0.184***	0.014	0.022***
	(1.856)	(2.718)	(3.237)	(3.143)	(1.246)	(3.179)
Asset size (log)	-0.152***	-0.019**	-0.022***	-0.128*	-0.014	-0.018**
	(-3.169)	(-2.033)	(-3.546)	(-1.752)	(-1.189)	(-2.144)
Time in distress (quarters)	-0.023	0.009**	0.003	-0.016	0.027***	0.013***
	(-0.748)	(2.093)	(0.983)	(-0.376)	(4.510)	(2.691)
Market level variables						
Local ADC to total loans at Origination	5.595*	0.266	0.562*	14.774***	0.987**	1.725***
	(1.906)	(0.597)	(1.692)	(4.332)	(2.030)	(4.665)
Local 3-yr growth ADC to total loans at origination	9.504***	2.319***	1.998***	-0.417	2.349***	1.153***
	(3.509)	(5.031)	(6.118)	(-0.155)	(4.339)	(3.249)
Local 3-yr change brokered to total deposits at origination	0.841	0.585**	0.389	2.097	0.515	0.434*
	(0.312)	(2.554)	(1.642)	(1.045)	(1.266)	(1.646)
1-yr change SFR permits to total housing stock at orig	19.555	22.139***	13.804***	94.538**	10.625	13.220**
	(0.549)	(4.308)	(3.497)	(2.125)	(1.198)	(2.292)
Local CRE vacancy rates by property type at origination	7.512**	1.311**	1.288***	3.402	3.415***	2.009***
	(2.251)	(2.003)	(2.879)	(0.735)	(4.419)	(3.720)
Change in local ADC to total loans (origination to default)	8.595***	2.179***	1.852***	13.363***	3.774***	3.017***
	(2.761)	(4.193)	(5.054)	(3.456)	(6.015)	(6.842)
Local noncurrent to total ADC loans at default	1.220	0.670***	0.464**	-1.314	0.970***	0.381*
	(0.674)	(2.602)	(2.356)	(-0.690)	(3.571)	(1.787)
Constant	0.494	0.777***		-3.580**	1.178***	
	(0.357)	(3.410)		(-2.474)	(2.774)	
Observations	6,414	5,351	6,414	2,399	1,934	2,399
Pseudo R-square	0.138	0.360	0.216	0.143	0.365	0.214

T-statistics are shown in parentheses under the parameter estimates. Standard errors are clustered at the level of the originating bank.[59]

5.1 Loan Characteristics

For single-family collateral, we find that land and land/lot development loans have consistently higher LGDs.[60] These loans experience a marginal increase of 13.7 percentage points for LGD relative to loans backed by completed homes. The result is consistent with other authors' findings that pricing is more volatile for projects in less complete stages; see Nichols, Oliner, and Mulhall (2013), for example.

We find consistent evidence that loan size matters for both collateral types, with smaller loans resulting in higher LGDs. Studies of LGD for CRE loans have found mixed evidence regarding loan size;[61] however, most other studies examine loans much larger than those in our sample, and thus may not be comparable in this respect. The median size of the loans in our sample is small ($230,000), and as noted in Section 2.1, the loan administration processes for ADC loans is more complicated than for other loan types. Therefore, fixed costs of the workout process probably explain some of these differences. For both collateral types, smaller loans in default are less likely to have positive losses, but the positive loss rates are higher when they occur. It may be that a larger share of the small loans is owner-occupied. Borrowers that occupy the property probably have information advantages over other borrowers, and they may be more highly motivated to address problems effectively so that they can retain control of the property. Thus, the weakened incentives associated with borrowers with negative equity positions may be less important for owner-occupied projects. Another factor could be the prioritization for lenders themselves, who may more intensely focus their recovery efforts and limited resources on larger loans to minimize the total amount of losses in their portfolios.

Likewise, loans in judicial foreclosure states consistently have higher LGDs for both collateral types. Judicial foreclosure laws require lenders to go through the courts to foreclose on a property, adding both time and cost to the foreclosure process. In addition, borrowers may well be able to leverage their knowledge of these additional costs when negotiating with lenders.[62] The majority of previous analyses on the impact of judicial foreclosure has been focused on how

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[59] We also estimated a Tobit specification of our model, with results that were consistent with the two-step specification. We believe that the two-stage approach reported here provides a better way to parse the bimodal variation in losses that we observe and also provides a better statistical fit of the data.

[60] We are unable to test for the significance of land/lot development loans for the commercial sample because this detail was not collected for commercial ADC loans in the Loss Share Administration data. We believe there are likely to be fewer land/lot development loans in the commercial ADC loan sample than in the single-family sample. We are told by industry experts that many of the commercial loans tended to be closer to the city center on established rather than new lots.

[61] Schuermann (2004) surveys the literature for CRE loans and concludes that asset size probably does not matter; Pendergast and Jenkins (2003) and Asarnow and Edwards (1995) find lower LGDs for larger loans.

[62] Shibut and Singer (2015) found that LGD, workout periods, and expenses were all higher for judicial foreclosure states, regardless of whether the loan was foreclosed. See Table 5 in that paper.

they change the incentives for lenders and borrowers, resulting in lower loan originations in Pence (2006) or more strategic defaults in Ghent and Kudlyak (2011). The impact of judicial foreclosure laws on loans to homebuilders may differ from those on homeowners. An et al. (2013) look at the impact of judicial foreclosure on CMBS loans. Kyle and Binder (2019), using bank loan data, find little correlation between the use of recourse on CRE loans and the presence of judicial foreclosure laws.

Single-family ADC loans made out-of-territory for the originating bank had higher losses. However, we do not see a similarly significant effect for commercial ADC loans that were out-of-territory. More than two-thirds of the out-of-territory single-family loans in our sample were made in the South, compared with slightly more than half for commercial collateral. The South experienced significantly higher proportions of ADC lending to total lending at origination, higher growth in brokered deposits at origination, and a more dramatic pullback in lending between origination and default, suggesting greater volatility in local markets. It is possible that out-of-territory lenders would have had greater difficulty monitoring loan performance and managing downside risks under those conditions.

While the preceding loan-level variables are set at the time of loan origination, the next several variables in our model relate to the performance of the borrower/builder after origination, the monitoring function of the lender, and the creation of collateral value for ADC loans over the loan term. Our model includes the age of the loan at default (to identify loans that got into trouble early on), the draw rate and squared draw rate at default (to measure progress via funds disbursed relative to total amount committed), a maturity default indicator (for construction that may be complete or near complete), and an overage indicator (for additional funding increasing the lender's exposure in an effort to minimize losses). These variables capture developments in the construction process after the loan is originated, highlighting the critical nature of loan-level risks for ADC loans after origination. In addition, these variables relate to risk with respect to collateral creation over the life of the ADC loan, with the idea that projects defaulting sooner and in a less complete state may tend to have lower collateral recovery values relative to completed collateral.

Loans backed by single-family or commercial projects that do not default until a large share of the balance is drawn—usually indicating most of the construction is complete—tend to have lower LGDs. This can be seen by the negative coefficient on the ratio of balance drawn to total exposure, or the draw rate. As builders are permitted successive draws on the loan, and as the collateral construction progresses further, the collateral property itself may have greater recovery potential for the lender. The positive coefficient on the squared term suggests that this effect is strongest in the early stages of construction and diminishes as the draw rate increases. Loans with overages tend to have higher losses, seen in the positive and significant coefficient on the overage variable, but will also tend to have a higher balance drawn at default than other loans at a similar stage of construction. Overages probably signal problems with either the initial estimate of construction costs, the construction process, or both, which would partially counter the observed negative effect on LGD for higher draws. In addition, there may be more noise in terms of construction progress and costs incurred when observing later stages of construction with higher draw rates on the loan. Hence, we see a nonlinear negative relationship between balance drawn and LGD that diminishes for higher draws. Further, there is a difficult tradeoff in uncertain outcomes for lenders, between the higher value of a project closer to completion and higher losses on poorly managed projects that were not cut off when they should have been. The ability of lenders to monitor projects effectively and make good decisions with respect to this tradeoff appears to be an important consideration in managing losses on ADC portfolios.

The age of the loan, or the time between loan origination and default, also shows consistent patterns across collateral types. Our results indicate that loans defaulting later in the life of the loan tend to incur smaller losses. This is different from our inclusion of the draw rate, which is meant to reflect the state of progress on the loan and the creation of collateral value. Rather, the age of the loan is meant to capture loans that get into trouble quickly, reflecting severe problems in the origination or construction processes that become evident fairly soon after origination.[63] We considered defining this variable as a ratio of the age of the loan at default to the term of the loan, due to relative differences in term lengths across loans. However, our intent here was not so much to reflect relative progress on the loan, particularly since we already include the draw rate at default, which we believe better captures the progression on the loan. Rather, we expect that early defaults would generally be weaker projects, and hence incur greater losses.

We find that maturity defaults tend to have lower LGDs for single-family projects, with a marginal decrease of 7.4 percentage points; the relationship is insignificant for commercial projects. Maturity defaults are somewhat more common for single-family (61 percent, versus 54 percent for commercial). However, the term defaults appear to perform more poorly for single-family than for commercial collateral, both in the incidence of non-zero losses (88 percent versus 79 percent) and the severity of non-zero losses (73 percent versus 67 percent). It could be that banks use simpler measures to determine default for single-family projects (which tend to be smaller), and thus only the worst single-family loans become term defaults. Commercial projects are larger and thus could merit more substantial monitoring, resulting in defaults being identified more promptly when minor problems arise. In addition, the construction process for single-

[63] The age of the loan at default and the draw rate are not highly correlated; in fact, the correlation within our sample is slightly negative (ρ=-0.09). Loans with shorter terms by nature would not reach the higher age at default that longer-term loans might sometimes attain; they might also tend to be further along in a relative sense in their rate of draws within the shorter window of term. Even defining the age at default as a ratio relative to the term of the loan, age is not highly correlated with the draw (ρ=-0.03). For example, in the event of a construction delay, the age of the loan would still advance, while the draw rate would not. In addition, cost overruns and overages may be reflected in the draw but not necessarily the age at default relative to loan term. This is consistent with our interpretation of different information reflected in the draw and the age variables for the regressions.

family projects may be simpler, so it may be less likely that covenant violations trigger default before maturity for single-family loans.

In summary, a strong relationship exists between loan characteristics and LGD. ADC loans are not monolithic: bank choices about the types of ADC loans that they originate and their monitoring practices have a big effect on distressed LGD. Further, the variables in our model concerning post-origination performance highlight the risk in ADC lending throughout the life of the loan and with respect to collateral value creation over the loan term. They also point to the importance of bank monitoring efforts, given the inherent construction and collateral risks involved for individual ADC loans.

We were unable to test certain loan attributes because of a lack of data. These attributes include the experience of the lending officer and the builder, which Lusht and Leidenberger (1979) find to be important for default, and details on the origination process, such as the type of capital contribution (cash or real estate) and the type of appraisal used for valuation.[64] In addition, we lack direct measures of the quality of loan monitoring, which may matter for LGD as well.

5.2 Originating Bank Measures

We find that three items related to the lender at origination inform LGD. First, we find that the lender's three-year growth rate for ADC loans to total loans during the period leading up to origination is positive and statistically significant. Lenders who have rapidly expanded in ADC lending—and thus have high growth rates—may have less experience managing the unique risks associated with ADC lending that a bank who has a more mature ADC lending operation. We control for the local three-year growth rate for ADC loans to total loans to ensure that we are capturing differences in bank behavior and not merely differences in local lending conditions.

We find that the size of the lender at origination matters, but the relationship is relatively modest. At the mean, an increase in bank size by 50 percent at origination is associated with a 1.1 percentage point decrease in LGD for single-family collateral and a 0.09 percentage point decrease for commercial collateral. Small banks are more likely to experience positive losses, and they tend to experience a higher loss severity for loans funding single-family development. This result may relate to the bank's resources and capacity to manage a troubled loan portfolio. We examine whether the effect could be driven by the de novo banks in our sample, which are significantly smaller (averaging just over $200 million in assets, compared to over $3 billion for other banks). However, we find that including a control for de novo banks does not change the significance of bank size for LGD. We also find that performing separate regressions for de novo

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[64] Some loan characteristics are important to LGD for other loan types but are not very relevant for ADC loans. This includes the seniority of the debt level (almost all ADC loans are first liens) and, for commercial and CRE loans, industry type and the financial condition of the borrower's industry. Almost all of these loans have the same industry type (construction), and many of the commercial properties are either multifamily (thus have no industry) or could meet the needs of tenants from multiple industries.

banks and non de novo banks reveals a bank size effect for both populations. It is possible that small banks, regardless of age, may feel pressure to grow in certain markets when competition is high. This may affect the lending decisions, the resources available to monitor and work out a distressed loan portfolio, and the losses incurred when markets turn.

In addition, the time that the lender spent in distress before its failure also has a modest effect. For loans secured by single-family collateral, time in distress is associated with loss severity only for loans with positive losses. For loans secured by commercial collateral, the overall marginal effect is positive and strongly significant. This measure probably relates to the bank's ability to service loans effectively, especially the larger, more complex loans used to finance commercial projects. Many troubled banks may face staffing disruptions and constraints that prevent them from effectively managing their loan portfolios.

We test measures of bank health at origination and found them to be insignificant. Although all of these banks failed, they were generally healthy at origination. The median equity ratio of these banks at origination was 8.5 percent, the median composite CAMELS rating was 2, and the median percentage of ADC loans that were noncurrent was 1.6 percent.

5.3 Local Market Measures

We find compelling evidence that local markets—both at origination and default—play an important role in LGD. We discuss measures as of the time of origination and then measures related to default.

5.3.1 Factors at Origination

For both collateral types, we find relationships between LGD and the local ratio of ADC loans to total loans at origination, as well as the local three-year change in ADC loans to total loans at origination. For loans secured by single-family collateral, the local share of ADC loans to total loans is associated with only the probability of positive losses and is significant only at the 10 percent level. For commercial collateral, the relationship is much stronger, both in the size of the effect and the statistical significance.[65] The local three-year change in the ratio of ADC loans to total loans has very strong marginal effects: a one standard deviation increase in the ratio is associated with an 8.4 percentage point increase in LGD for loans backed by single-family collateral and a 4.8 percentage point increase for loans backed by commercial collateral. Both of these factors relate to the strength of local market competition when the loan is originated, which can increase risk exposure through multiple channels, including weaker loan underwriting, less experienced lending staff, and higher potential for overbuilding.

As another measure of the state of local markets at origination, we include the three-year change in the ratio of brokered deposits to total deposits in the originating bank's local footprint. Our

[65] A one percentage point increase in the ratio results in a 1.9 percentage point increase in LGD.

regressions provide some evidence that the local share of brokered deposits can be associated with higher losses. We interpret a large inflow of brokered deposits into local banks as an indication of demand for ADC loans outpacing local core deposit availability, and where markets may be more likely to show signs of overheating. We also test brokered deposit ratios and growth rates at the originating bank to see if these measures point to riskier behaviors and higher losses, but we did not find significant results. Thus, it does not appear that banks with a higher level of brokered deposits necessarily had worse LGD outcomes, but rather loans that were made in areas with more brokered deposits rushing in had worse LGD outcomes.

The change in single-family permits to total housing stock focuses on expected increases in new buildings compared to the existing housing stock, a forward-looking measure of new construction that will be coming onto the market. We find a significant and positive association with LGD. ADC projects that are originated when this measure is increasing strongly may be coming online at completion in markets that are much more saturated than when the loans were originated. The risk of oversupply in these markets may be greater, with higher losses on loans in default.

We also include CBSA-level vacancy rates by commercial property type at origination.[66] This measure reflects the condition of the local CRE market at origination and how well the existing supply may be accommodating the demand for real estate. We anticipate that a higher vacancy rate at origination may indicate supply outpacing demand, and for higher losses to occur in default. Like the single-family permits, its marginal effect is large and strongly significant in both collateral types for loss severity. A one percentage point increase in the vacancy rate at origination is associated with a 1.3 percentage point increase in LGD for single-family collateral and a two percentage point increase for commercial collateral. Substituting commercial vacancy rates at default instead of at origination also matters for LGD, but we found a stronger association with LGD for vacancy rates at origination; a high correlation between the two precludes us from including both in the regression specification. Our interpretation would differ somewhat between them; we interpret the vacancy rate at origination as reflecting the information set for banks when the lending decision is made, and may inform forward-looking expectations of where the market for new completions may be headed. The vacancy rate at default, on the other hand, reflects the state of the market when the loan defaults, with implications for collateral valuation when the recovery efforts are beginning.

Looking across local market measures at origination, we find multiple factors related to the local environment at origination that are strongly related to LGD—losses that are realized later. No single item encompasses all aspects of the local market at origination, but the overall strength of these measures confirm that local market conditions at origination matter a great deal for LGD.

[66]CoStar. For loans in our sample where the property type was unknown, we used an average of the local CBSA-level vacancy rates for retail, office, and multifamily.

5.3.2 Factors at Default

Our model includes two items related to local market conditions associated with default: the change in the share of ADC loans to total loans for local banks between origination and default, and the noncurrent rate for local banks at default. The change in the local share of ADC loans to total loans is very strong for both collateral types. For loans backed by single-family projects, a one percentage point increase in the ratio is associated with a 1.9 percentage point increase in LGD; for commercial collateral, three percentage points. As discussed previously, there are multiple channels through which oversupply issues might increase LGD. Glutted markets are likely to trigger fire sales or lengthy and expensive delays in the sale as lenders wait for markets to recover. The oversupply is likely to exacerbate the divergence of incentives between the bank, the builder, and the investor, resulting in increased losses for the bank. Potential tenants may prefer not to move into new buildings because they can negotiate lower rates from existing landlords and avoid the cost of moving, or they may only be coaxed into moving with highly advantageous rents that reduce the value of the collateral.[67]

Our second measure, the estimated local ADC noncurrent rate at default, is also significant for LGD, but to a lesser degree and with less statistical significance than the change in local ADC lending between origination and default (95 percent for loans backed by single-family projects; 90 percent for commercial). A one percentage point increase in the local noncurrent rate is associated with a 46 basis point increase in LGD (single-family) and a 38 basis point increase (commercial). Note that the local ADC noncurrent rate at default varies considerably across the sample: the standard deviation is 5.7 percentage points, so a one standard deviation change is associated with a LGD change of 2.7 for single-family collateral and 2.2 percentage points for commercial collateral.

We consider but reject items measured as of the end of the workout period[68] or over time periods that end when the loan cures or the asset is extinguished. We believe that the length of the workout period is endogenous for the model, so its use would bias our results.

5.4 Counterfactual Analysis

In this section, we use two methods to study the sensitivity of LGD to loan-level, bank-level, and local market-level variables. In the first analysis, we determine whether high or low values of each regressor tend to reduce LGD (designated as "good") or increase LGD ("bad"). To determine the effects of the loan variables, we apply the marginal effects at the "good" and "bad" percentiles (25^{th} and 75^{th} as appropriate) for only the loan-level variables; we assume the median value for the remaining variables. We follow the same procedure for the bank-level and market-level variables. We also break down the market variables into those at origination and after

[67] The same basic idea also applies to potential buyers.

[68] The workout period is defined as the period between default and the cure date or the date the asset is extinguished.

origination, because the implications differ for these subgroups. We do this separately for single-family and commercial ADC loans, and we compare the relative dispersions in estimated LGD. Table 6 provides results.

Table 6: LGD Effects by Collateral Type

	Good	Bad	Difference
Single Family			
Loan Characteristics	43.6%	77.1%	33.5%
Bank Characteristics	51.8%	60.2%	8.4%
Market Characteristics			
at Origination	48.0%	67.0%	19.0%
after Origination	49.9%	62.7%	12.8%
Total	42.4%	74.6%	32.2%
Commercial			
Loan Characteristics	43.2%	62.6%	19.4%
Bank Characteristics	44.3%	57.8%	13.5%
Market Characteristics			
at Origination	40.8%	61.2%	20.4%
after Origination	43.9%	60.3%	16.4%
Total	34.4%	71.7%	37.3%

The difference in expected LGD between loans with "good" and "bad" loan-level characteristics is large: 33.5 percentage points for single-family collateral and 19.4 percentage points for commercial collateral. Likewise, the effects of markets are very strong, with swings of 32.2 percent for SFR and 37.3 percent for commercial. The effects for individual bank-level characteristics are smaller (respectively 8.4 percent and 13.5 percent). We also find that the effects of markets, both at and after origination, contribute significantly to LGD.

The originating banks themselves exert indirect control over the loan characteristics to some extent. Some loan characteristics, such as those tied to the location of loan, are static and known at origination. They cannot be changed by the bank but can enter into the bank's decision to originate the loan in the first place. Other loan characteristics can change over the life of the loan and are at least partly dependent on the ability of the bank's monitoring function to flag potential issues. Given the importance of the monitoring function in construction lending, we break the loan characteristics into those that are static and known at origination, and those that may be influenced in part by the loan monitoring function. Static loan characteristics in our model that are known at origination include the size of the loan, location in a judicial foreclosure state, out-of-territory status, and whether it is a land/lot development loan. Characteristics that are partly influenced by the monitoring function include the age of the loan at default, the ratio of the amount drawn to amount committed, term versus maturity default status, and whether an overage was granted to the borrower.

To explore the extent to which these non-static loan variables may be picking up on bank-level policies and behaviors, we repeat the above analysis using bank-level fixed effects instead of bank characteristic variables. Bank fixed effects will not inform us about specific relationships between bank characteristics and loan losses, but the intent here is to absorb as much of the bank-level explanatory power as possible via these fixed effects. This gives us a closer approximation for how much these non-static covariates on the loan should be interpreted as individual borrower/builder-driven versus bank-driven.[69] Since banks may target ADC lending of a particular type (i.e., single-family or commercial), we again examine the subgroups separately by collateral type in Table 7. Market-level variables are included in these specifications, as in the prior analysis, but are not reported the Table in order to focus more concisely on loan characteristics.

Table 7: LGD Effects by Collateral Type, with Bank Fixed Effects

	Good	Bad	Difference
Single Family with Bank FE			
Loan Characteristics			
Fixed at Origination	52.0%	64.4%	12.4%
Bank Monitoring Influence	47.3%	65.8%	18.5%
Total	44.2%	76.0%	31.8%
Commercial with Bank FE			
Loan Characteristics			
Fixed at Origination	48.1%	48.5%	0.4%
Bank Monitoring Influence	43.9%	54.5%	10.7%
Total	44.3%	55.1%	10.8%

Table 7 shows that bank-level fixed effects only slightly decrease the sensitivity of LGD to loan characteristics. We estimate a difference of 31.8 percentage points in LGD between "good" and "bad" loan-level specifications for single-family collateral, relative to 33.5 percentage points incorporating bank variables but not bank fixed effects in Table 6. We therefore interpret the variation in loan-level characteristics for single-family collateral as largely reflecting individual borrower/builder performance rather than bank monitoring practice. For the commercial sample, we find that bank-level fixed effects decrease the sensitivity of LGD to loan-level characteristics somewhat. We estimate a difference of 10.8 percentage points between "good" and "bad" specifications relative to 19.4 percentage points without bank fixed effects in Table 6. Much of the decline from bank-level fixed effects can be attributed to their absorbing the loan-level impact of judicial foreclosure location on LGD, which is highly correlated with the location of the bank itself. We therefore interpret the non-static loan level variables as largely reflecting

[69] It is also possible that some degree of variation is being driven within the bank by differences in monitoring skill and expertise across lending officers. We expect that the bank-level fixed effects would only cover the extent to which management policies and practices lead to a shared uniformity in the loan monitoring function at the bank.

individual loan performance rather than bank-level monitoring practices for commercial ADC loans as well.[70]

Our prior analysis examines the sensitivity of LGD to "good" and "bad" scenarios for the various explanatory covariate categories. To further confirm our results regarding the relative importance of loan, originating bank, and local market characteristics, we next examine them from a perspective of explanatory power for observed LGD. We run a series of regressions with different sets of explanatory variables and fixed effects. Instead of explanatory variables related to the bank characteristics, we use bank fixed effects. Instead of explanatory variables related to the local market, we cross CBSA and default year-quarter fixed effects. We first run the full model and then successively exclude either the loan variables, the bank fixed effects, or the local market fixed effects on the same sample of loans. We next measure the difference in the pseudo R-square compared to the full model, reflecting the relative explanatory power of the category left out. Results are shown in Table 8.

Table 8: Fixed Effects Analysis

Description of Regression	Pseudo R-square	Difference from Full Reg Pseudo R-square
Full regression with loan variables and bank and market fixed effects	.3828	
Regression with no loan explanatory variables	.3219	.0610
Regression with no bank fixed effects	.2778	.1050
Regression with no market fixed effects	.2282	.1546

These results indicate that market effects explain more of the variation in LGD than bank effects in our downturn sample of construction loan defaults. The comparison of the relative explanatory power from the bank and market fixed effects to the loan explanatory variables is less clear. As mentioned before, we lack certain measures of underwriting that would be useful in explaining loan level variation in LGD. It is actually impressive that the loan-level variables explain more than half of the total variation picked up with bank fixed effects.

[70] The analysis for commercial ADC loans does not capture differences between land/lot development loans versus loans for later stages of development. The loss share data collected by the FDIC lacks an indicator for construction stage on commercial ADC loans. As discussed previously, other authors have found prices for land and early stage construction real estate to be more volatile than completed projects.

5.5 Robustness Testing

In this section, we discuss results using our full sample and testing of alternatives for explanatory variables.

Although we believe that separate regressions by collateral type is optimal, many factors are included in both sets of equations and influence LGD in similar ways for both collateral types. Our sample includes a large number of loans that are omitted from the primary regressions because we are unable to determine the underlying type of collateral. Thus a regression that includes both collateral types provides us the chance to see if our findings hold when using a larger sample size. Table 9 presents results for the full sample. We find that the results are generally consistent with the baseline regressions.

We test several other variables that are excluded from the results shown here.[71] We tested additional market characteristic variables, including the de novo bank share of local markets, the share of local markets held by high-growth banks, and various combinations of risk indicators, both for the local market and the originating bank. Many of the risk factors are highly correlated: for example, de novo banks are more likely to have high ADC loan growth rates and large amounts of brokered deposits. The regressions that are shown seem to best capture the dynamics at play. We also tried crossing some of the measures, but these were usually insignificant. Likewise, we tried some measures associated with the failed bank acquirer but they were insignificant. We also tried alternative forms of many of the explanatory variables and found similar results.

[71] We test traditional measures of local economic activity, such as the unemployment rate and personal income growth, but the results are weaker than those for the indicators in our primary regression.

Table 9: Regression Results for the Full Sample

VARIABLES	(1) logit	(2) glm	(3) marginal effects
Land development loan	0.124	0.101***	0.065***
	(1.080)	(3.279)	(3.438)
Exposure at default (log)	0.171***	-0.068***	-0.024***
	(5.966)	(-8.901)	(-4.822)
Judicial foreclosure state	0.069	0.098***	0.058***
	(0.478)	(3.353)	(3.053)
Out of territory loan (CBSA)	0.273**	0.023	0.033*
	(2.415)	(0.734)	(1.708)
Loan age at default (in quarters)	-0.043***	-0.009***	-0.008***
	(-6.081)	(-5.307)	(-7.887)
Ratio of balance drawn to total exposure	-2.109	-1.443***	-0.946***
	(-1.585)	(-4.244)	(-4.503)
(Ratio of balance drawn to total exposure)^2	2.670***	1.022***	0.758***
	(2.702)	(3.515)	(4.358)
Overage	0.784***	0.098***	0.112***
	(3.792)	(5.855)	(6.402)
Maturity default	-0.425***	-0.060***	-0.065***
	(-3.968)	(-4.116)	(-5.760)
Asset size of failed bank (log)	-0.141***	-0.011	-0.017***
	(-3.419)	(-1.227)	(-2.882)
Bank 3-yr C&D loan growth rate	0.123**	0.019*	0.020***
	(2.463)	(1.828)	(2.844)
Failed bank time spent in distress (in quarters)	-0.016	0.015***	0.007*
	(-0.530)	(2.961)	(1.956)
Local ratio of C&D to total lending at origination	9.590***	0.571	1.031***
	(3.999)	(1.394)	(3.584)
Local 3-yr change in C&D to total lending at origination	4.417**	1.288***	1.034***
	(2.067)	(2.987)	(3.637)
Local 3-yr change in brokered to total deposits at orig	1.581	0.345**	0.307**
	(1.047)	(1.970)	(2.083)
Change in C&D to total lending (orig to def)	10.767***	2.835***	2.355***
	(4.603)	(5.593)	(7.172)
Local ratio of NC C&D to total loans at default	-0.161	0.858***	0.456***
	(-0.101)	(3.867)	(2.669)
Constant	0.959	0.801***	
	(1.039)	(4.629)	
Observations	12,296	10,295	12,296

*** p<0.01, ** p<0.05, * p<0.1

The results are consistent with the primary regression results broken out by collateral type, providing a valuable robustness test to our findings.

6 Implications for Banks and Regulators

6.1 Discussion of Findings

Not surprisingly, bad loans, bad banks, and bad markets all influence distressed LGD for ADC loans. We find interesting variation in our analysis that has implications for banks and regulators. Loan and market characteristics appear to matter more than bank characteristics. Loans that back construction in earlier stages of development are riskier, as are loans that experience construction problems and those in judicial foreclosure states. This finding serves as a reminder to lenders (and examiners) to be mindful of the inherent risk associated with the types of ADC loans they originate. Banks with high ADC loan growth and weak servicing capacity are likely to have LGDs that are significantly higher than other banks that lend in the same markets. But our results indicate that good loan underwriting and servicing can only go so far in protecting lenders from major declines in local market conditions.[72]

There is ample evidence that real estate cycles are commonplace, and that the downside of those cycles can result in elevated credit risk for bank ADC loan portfolios. While the inherently speculative nature of ADC loans makes it challenging to predict future performance, this study indicates two factors related to market forces that have microprudential implications. First, we show that information on local market conditions available to banks and regulators may provide useful signals of potentially elevated risk in local markets. Second, we elaborate on previous studies[73] that document the high cost to banks when that risk is realized and a substantial downturn occurs. Our findings about the strong relationship between market forces and LGD, coupled with existing evidence on real estate cycles and construction lending, generally confirm several current regulatory approaches and may point to potential areas of improvement.

For banks, our results support a risk mitigation approach that includes the avoidance of excessive ADC loan exposures, a vigilant focus on local market dynamics that point to an increased risk of overbuilding or an impending market downturn, and a prompt reduction in ADC loan originations and tightening of underwriting criteria as the market risk increases beyond acceptable levels.[74] On a related note, our results confirm the importance of the CRE lending guidance related to ADC loan exposures published in 2006 and higher capital standards for

[72] This point was also made by the FDIC Office of the Inspector General (OIG) in its study of banks with high ADC loan concentrations that did not become problem banks during the Great Recession. Consistent traits of those banks included conservative lending practices and portfolios located in areas that had less severe real estate downturns. See FDIC OIG (2012).

[73] See, for example, Friend, Glenos and Nichols (2013) and GAO (2013).

[74] This is not a new observation. Bonaccorsi di Patti and Kashyap (2017) study differences between banks that do and do not survive large adverse shocks, and conclude that "recovering banks are tougher in extending credit to riskier borrowers than banks that do not recover" (p. 3).

certain high volatility commercial real estate (HVCRE) loans.[75] Our results also indicate that early stage construction loans are more likely to have high LGDs, which in turn support lower LTV limits for land and land/lot development loans in the Interagency Guidelines for Real Estate Lending Policies.[76] Our results do not provide evidence supporting differences in LTV limits between ADC loans collateralized by vertical construction for single-family and commercial projects.[77] However, every real estate downturn is different, so this relationship may not be consistent across time.

Examiners may benefit from readily available reports that focus on the risks associated with ADC loans, and especially on local real estate market conditions. Our analysis draws from multiple data sources, relies on multiple threads of research, and uses relatively complex calculations. When examiners consider ADC risk exposure at a bank exam, they may be reviewing individual loan files or risk management reports that provide incomplete or dated information, and they probably will not have enough time to assemble a full, up-to-date picture of local market conditions, especially for out-of-territory loans.

From a macroprudential standpoint, these results suggest potential benefits to the introduction of countercyclical capital buffers associated with ADC lending for large banks subject to Basel III capital requirements. They show the importance of forward-looking supervisory tools, such as stress testing and other ongoing monitoring, that consider the impact of various future developments (both in demand and supply) in local markets on loan performance. They do not, however, point toward a simple and readily available formula—or even a good summary of relevant local indicators—to support the monitoring function. Moreover, many of our indicators are reported quarterly, whereas more timely indicators would better serve a monitoring function, especially indicators of markets that are overheated or beginning to decline. Both lenders and bank supervisors would benefit from the exploration, development, and timely publication of such measures.[78]

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[75]See Federal Register (2006) for the notice on guidance related to CRE lending. The HVCRE requirements were introduced as part of a broader set of capital guidance for large banks and have changed over time. See Federal Register (2012) for the initial proposal and Federal Register (2019) for the most recent change (which focused solely on HVCRE). As of year-end 2020, 39 percent of FDIC-insured banks with assets below $10 billion had opted into the Community Bank Leverage Ratio (CBLR) framework for capital requirements. These banks are not subject to risk-based capital requirements because they have accepted high leverage ratio requirements. According to Call Report data, as of year-end 2020 banks opting into the CBLR framework held 24 percent of ADC loans held by banks with assets up to $10 billion and 9 percent of ADC loans held by FDIC-insured banks..

[76] See Appendix A to Subpart A of part 365 (Interagency Guidance for Real Estate Lending Policies), https://www.fdic.gov/regulations/laws/rules/2000-8700.html#fdic2000appendixatosubparta365. The guidance treats loans collateralized by single-family and commercial collateral differently.

[77] Ibid. The current LTV limits are 65 percent for land, 75 percent for land development, 80 percent for commercial, and 85 percent for single-family and improved properties. Our results are hindered by data limits: for most of our sample, we cannot reliably separate ADC loans backed by commercial loans into vertical and horizontal projects.

[78] In addition to data on certain loan characteristics, a few items that were unavailable but that would have been useful include information about local commercial building permits, the total number of housing units at a local or

Another area that merits additional study is the role of, and difficulties associated with, appraisals for ADC loans. Certified appraisers adhere to well-developed standards that govern estimation methods and the valuations that they produce,[79] and banks depend heavily on their expertise. However, it may be difficult for appraisers to collect and assimilate all of the relevant data for valuation (especially information on nearby planned building projects that may undermine asset values). In addition, behavioral economists have documented a "conservative bias," where investors are slow to change their viewpoints in light of new evidence,[80] and researchers have found evidence that is consistent with similar behavior in appraisals.[81] The speculative nature of appraisals for unbuilt structures may make appraisals that back ADC loans especially vulnerable to this phenomenon. The time lapse between appraisal and completion, coupled with the volatility of land prices and the incentives of borrowers and builders, may result in less accurate appraisals than those for existing properties.

The strong effects of loan characteristics on LGD highlight the benefits of a thoughtful and well-informed approach to the origination and monitoring of ADC loans. Lenders and regulators have long recognized that construction loans are more difficult to effectively manage than other real estate loans.[82] Our study confirms that not all ADC loans pose the same level of risk. Banks should take this into account when choosing ADC loans to originate. Our results also support the view that a strong loan monitoring function is extremely valuable to ADC lenders.

Finally, we find that common measures of loan losses may significantly understate the full cost of default. For loans in our sample with positive losses, the median share of loan charge-offs to total losses is only 66.5 percent. The rest of the losses come from asset sales, principal losses after foreclosure, losses associated with delays in receiving principal recoveries (that is, discounting), and expenses. The median share of expenses to total losses is 8.4 percent. Moreover, our analysis understates total expenses (and total losses) because it excludes servicing costs, which are inevitably higher for problem loans than for performing loans.[83] Under Generally Accepted Accounting Principles (GAAP), loss reserve calculations exclude expenses and, for the most part, principal losses on foreclosed real estate. But our analysis indicates that

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state level, and better information on zoning restrictions. Construction employment is a strong indicator that is reported monthly.

[79] See Appraisal Standards Board (2017) for details.

[80] See, for example, Barbaris, Shleifer, and Vishney (1998).

[81] See Hendershott and Kane (1995), Olasov and Conway (2012), and Cannon and Cole (2012). A backward-looking bias would influence valuations differently across the business cycle. Valuations would be too low during boom times and too high during periods of distress.

[82] See, for example, Tockarshewsky (1979).

[83] The relative importance of various loss components for portfolio losses as a whole are not the same as they are for the median loan. As shown in Figure 3, loan charge-offs comprise a very small share of losses for loans with a low LGD. They comprise a relatively small share of losses for loans with a high LGD, but loans with high LGD tend to be small. When we aggregate loan losses across the entire portfolio, we find that loan charge-offs comprise 71.3 percent of total losses, and expenses comprise 7.3 percent.

these costs are significant and should factor into risk mitigation decisions by bank risk managers and regulators.

6.2 Caveats

We explicitly acknowledge certain limits of our analysis as they relate to the implications for supervision. The differences between the relative LGD of commercial and SFR ADC loans may reflect the nature of the relative markets from which the sample was drawn, which included significant overbuilding of single-family properties but less of an increase in supply of multi-family and commercial properties. An analysis of LGD after a cycle with more overbuilding of commercial properties than single-family properties, such as the office market after the 2001 recession, is likely to have results that differ from ours. This highlights one of our main points: the importance of balance between supply and demand in the local market, in both originating and regulating construction loans. But it is also a reminder of the dangers of setting supervisory guidance based on "the last war."

We also acknowledge the very real concern that tighter supervision for construction loans may result in increased growth in lending from nonbanks. Basset and Marsh (2017) found that the 2006 CRE concentration guidance slowed both CRE and commercial and industrial loan growth while encouraging more household loan growth at banks with concentrations in excess of the thresholds. Kim, Plosser, and Santos (2018) found that the interagency guidance of leveraged loans triggered a migration of leveraged lending to nonbanks. They also highlighted that this may not have reduced the banking system's risk exposure, as many of these nonbanks making leveraged loans were in turn dependent on bank borrowing themselves. However, these potential concerns should not discourage regulators from setting reasonable capital levels and expectations for appropriate risk management for regulated institutions.

Finally, our analysis provides no information about the contributions of loan, bank, or market characteristics to the default rate for ADC loans. In addition, our information about loan characteristics is limited, and our study examines losses from only one crisis period. There are still many gaps in our knowledge of ADC loan losses for future research to address.

7 Conclusions

This paper provides the first detailed, empirically based exploration of losses on ADC loans—an asset class that has and no doubt will continue to play an important part in financial crises and individual bank failures. Our key research question is, what explains the variation in losses on ADC loans: bad loans, bad banks, or bad markets? The answer is important for prioritizing loss mitigation strategies within banks and the allocation of limited supervisory resources for monitoring banks. We find that the primary sources of variation in LGD for ADC loans are loan and market characteristics, with bank-level characteristics playing a less significant role.

Local market effects—both conditions at loan origination, and changes in conditions during the life of the loan—significantly influence ADC LGDs. In particular, we find that measures of supply, such as recent growth in construction lending in a local market, and demand, such as CRE vacancy rates, at loan origination significantly affect losses. ADC loans that default in markets where banks have been leaning into ADC lending relative to total loan growth, or with high levels of noncurrent ADC loans, also have significantly higher losses.

The effects of local market conditions suggest two key implications. First, the impact of factors such as local market demand that are not directly under a bank's control provides support for higher capital requirements for ADC loans. The cyclical nature of these markets also calls for forward-looking capital requirements, such as countercyclical buffers or stress testing. The second implication is that both banks and supervisors should invest in tools to monitor local measures of supply and demand, both to avoid originating loans in markets starting to overheat and to know when to pull back from markets that are showing signs of oversupply.

We also document in this paper the impact of specific loan characteristics on ADC losses. Loans for projects earlier in the development cycle, specifically those to purchase land and develop lots, had significantly higher losses than loans for the actual construction of either single-family or commercial buildings. This supports guidance recommending lower leverage for land and lot development loans.[84] We do not find evidence of significant differences in losses between ADC loans for commercial projects and those for single-family residential projects in this crisis.

[84] See Appendix A to Subpart A of part 365 (Interagency Guidance for Real Estate Lending Policies), https://www.fdic.gov/regulations/laws/rules/2000-8700.html#fdic2000appendixatosubparta365.

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Appendix A: ADC Loan Risk Summary Table

Risk	Summary
Construction	• Optimistic or poorly constructed cost estimates • Bad weather, environmental problems • Price changes for materials or labor • Problems with suppliers and subcontractors, inspectors, etc.
Opacity	• Difficulties in measuring construction quality, progress • Difficulties in gauging value of final project and loan guarantees • Lender myopia or overconfidence
Option value of land	Construction projects cannot readily adjust to shifts in "highest and best use" of land due to zoning and contract issues
Real estate cycle sensitivity	Time to build • Market shifts after origination • Builder incentive to build regardless of market shifts • High cost to change builders or building plans • Appraisal weaknesses
	Originations during boom periods • Pressure to grow, increase earnings, reduced value of monitoring • ADC loan growth varies more across real estate cycles • Do novo banks gravitate to ADC lending • High growth results in, on average, less experienced builders, lenders
	• Credit availability contributes to collateral value ("feedback effect") • Empty buildings require filling

Appendix B: Benchmarking to Defaulted Construction Loans at Large Banks

A potential downside of our sample dataset is whether analysis based on this sample is relevant for the broader range of construction loans. These are construction loans originated by banks that failed under loss share. We discussed earlier how we think the fact that this database oversamples distressed construction loans actually makes it ideal to study the drivers of construction loan losses, since losses at the lower tail of the loan quality distribution drive portfolio losses. We also documented how FDIC contract terms, policies, and procedures mitigated incentive concerns introduced by the loss sharing agreement.

In this appendix, we further address the concerns about the representativeness of our sample by benchmarking it to a sample of defaulted construction loans from a group of the largest bank-holding companies that did not fail and whose loans were not in our sample. The comparison time period is roughly similar.

We use construction loans reported in Schedule H.2 of the FR Y-14Q, which has also been used in a few recent papers.[85] These data are collected by the Federal Reserve as part of the Comprehensive Capital Analysis and Review (CCAR) for banks with more than $50 billion in assets.[86] The data include rich information on loans, including the interest rate, committed exposure, outstanding balance, dates of origination and maturity, purpose (e.g., for construction versus refinance), interest rate type (e.g., fixed versus floating), and characteristics of the property securing the loan (e.g., zip code, property type, and appraised value). Banks report this microdata for all credit facilities with a committed exposure above $1 million.[87] The collection officially began in 2012, but the database contains loans provided to the Federal Reserve and OCC starting in 2010 as the collection was being designed. We limit our sample to loans that defaulted over the collection period, resulting in just over 9,000 loans. We exclude loans that defaulted but are not yet resolved as of the latest collection period, second quarter 2020. The Y-14 data are one of the only available sets of loan-level construction data that can be used to benchmark the FDIC Loss Share data. In many ways, the Y-14 data overlap nicely with the FDIC data. Figure B1 shows the distribution of origination and start dates in the Y-14 data.

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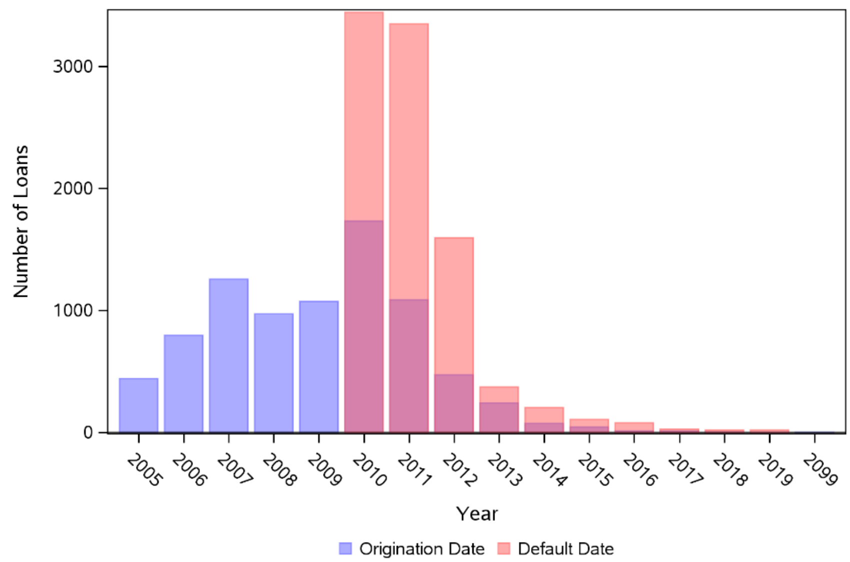
[85] See https://www.federalreserve.gov/apps/reportforms/reportdetail.aspx?sOoYJ+5BzDZGWnsSjRJKDwRxOb5Kb1hL for more information about these data. Example research using the data include Black et al. (2020) and Glancy and Kurtzman (2018).

[86] This cutoff was raised to $100 billion by the Economic Growth, Regulatory Relief, and Consumer Protection Act (S.2115) in 2018.

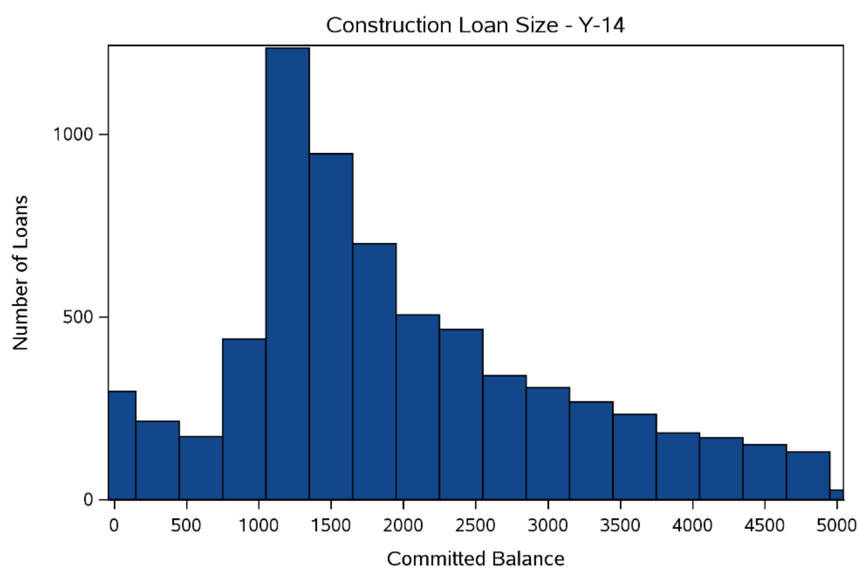
[87] Most credit facilities contain only a single loan, so we refer to the Y-14 data as loan level for the rest of the paper.

Figure B1: Distribution of Origination and Default Date for Y-14



Due to the cut-off in 2010, we naturally do not observe any defaults before that year; in contrast, 40 percent of the loss share sample is composed of loans that defaulted before 2010. As we saw in the FDIC data, we observe a non-trivial number of construction loans originated during the financial crisis. We also observe the rapid decline in loan defaults once the crisis has passed, with almost no construction loan defaults past 2014, the last period available in the FDIC dataset. The number of defaulted loans after this period, during a time of economic expansion, is miniscule. This highlights the cyclical nature of construction loan risk and why the concentration in the FDIC sample over the financial crisis period makes it optimal to study construction loan risk.

Figure B2



One aspect of the Y-14 data that has less of an overlap with the FDIC data is loan size. We documented above that the FDIC loan data include many loans under $1 million in committed balance; in fact, only 23 percent of the sample had total loan exposures over $1 million at default In the Y-14 data, $1 million is the minimum cut-off, as shown in Figure B2. The nature of the banks in the sample also no doubt contributes to the differences in the loan size distribution. The Y-14 collection is limited to the largest bank holding companies. These banks are more likely to provide financing for larger construction loans to home developers or for large commercial projects, and may be less likely to fund many of the stand-alone single-family residential projects in the FDIC data.

Another significant difference between the two datasets is the definition of loss given default. We use from the Y-14 data the cumulative net charge-off on the loan until it leaves the loan portfolio. If the loan is sold, we do not observe what happens as the loss mitigation continues. If the loan drops below the $1 million threshold, we no longer track it. If the loan is transferred to the ORE portfolio, we observe the losses only up until the transfer. To allow a more consistent comparison of LGD for our sample and the Y-14 data, Figure B3 provides LGD (defined as loan charge-offs) for the Y-14 data, and Figure B4 provides a distribution of loan charge-offs divided by EAD from the loss share data.

Figure B3

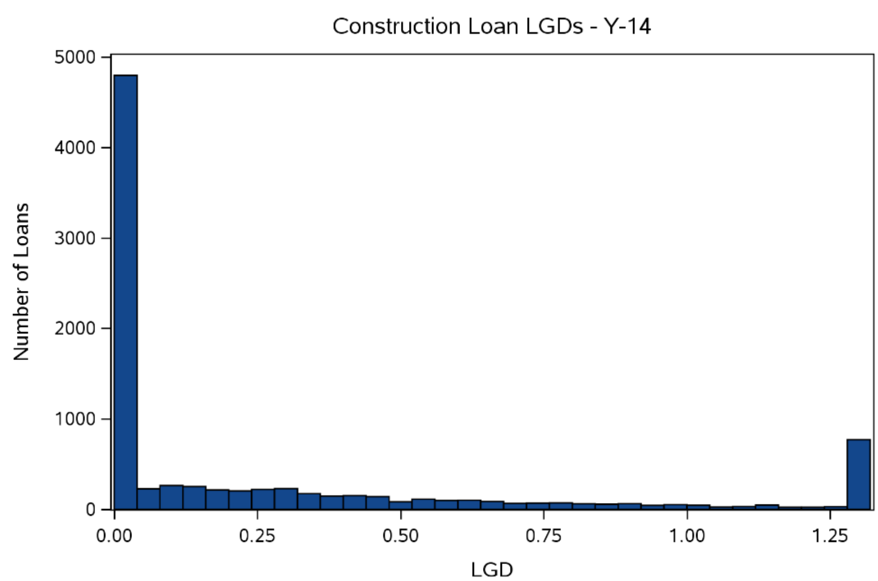
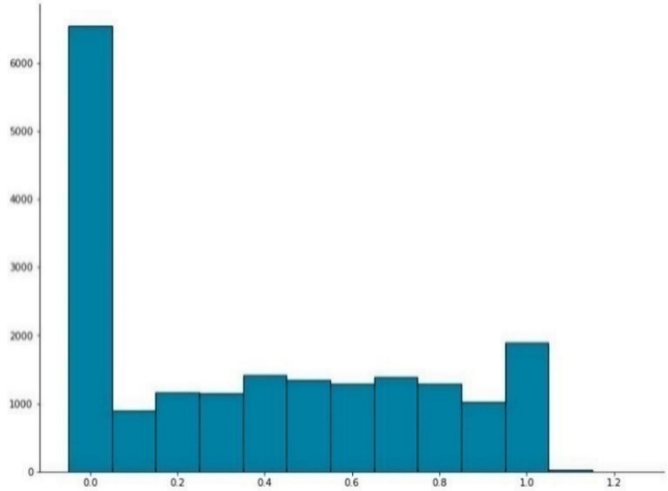


Figure B4: Loss Share Sample Distribution of Loan Charge-offs to EAD



For both samples, there is a heavy concentration of loans with zero LTV, although they comprise a smaller share of the full sample for the loss share data (36 percent did not have positive net loan charge-offs, versus 48 percent for the Y-14).

The subset of Y-14 banks that are subject to the Basel Advanced Approaches supervisory regime are also required to provide loss estimates under the Basel 2 framework for each loan. Figure B5 compares the distribution of these bank-provided estimates of the LGD under the Basel framework, which includes many of the components not captured using the realized LGDs calculated with just the net charge-offs. Only a few loans have zero Basel LGDs, but even fewer loans have Basel LGDs above 50 percent. This reflects the inclusion of the other components of LGD that we capture in the FDIC data, but it also may reflect a regulatory incentive for banks not to write down a 100 percent Basel LGD for a loan still in their portfolio.

Figure B5

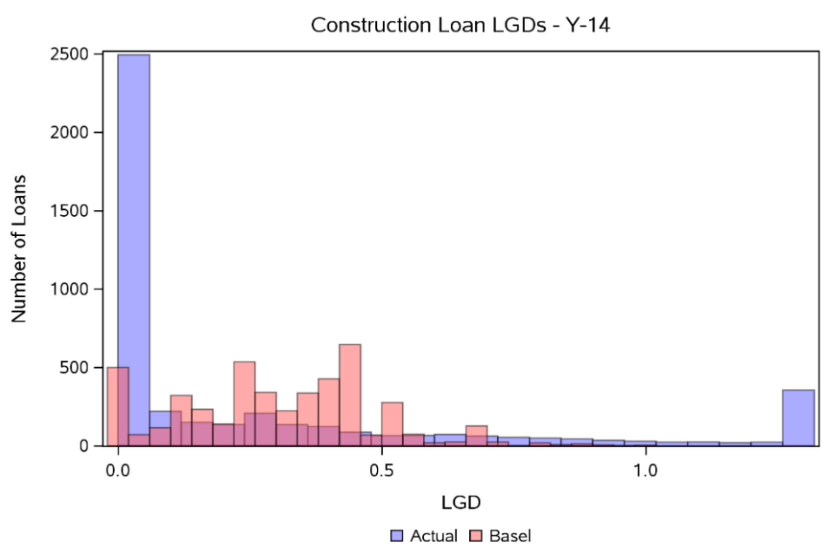


Table B1 provides some descriptive statistics available in the Y-14 data. As we have already seen, the average LGDs in the Y-14 data, both based on cumulative charge-offs and the reported Basel LGDs, are much lower than the FDIC data, at 28 and 30 percent, respectively. In our loss share sample, the mean ratio of loan charge-offs to EAD is 37 percent, which is much closer to the Y-14 sample. The Basel probability of default (PD) estimate provided by the advanced approaches banks at the time of loan default is 72 percent on average. The size of these loans is much higher than what we see in the FDIC data, but the interest rates on these loans and the share that are maturity defaults are very similar to the FDIC data. The average share of the total committed balance that was drawn at default was 70 percent.

Table B1: Descriptive Statistics for Y-14 Defaulted Construction Loans

Label	No. of Obs	Mean	Median	Standard Deviation
LGD based on Cummulative Charge Off	9,004	27.6%	0.0%	41.9%
PD, Advanced Approaches	3,403	72.0%	100.0%	40.0%
LGD, Advanced Approaches	4,553	29.9%	30.0%	18.4%
Share with no loss	9,221	51.8%	100.0%	50.0%
Outstanding Balance at Default ($1,000)	9,221	4,914	2,242	10,021
Remaining Term at Default (years)	9,221	0.9	0.0	1.9
Age at Default (years)	9,221	2.3	2.0	2.4
Maturity Default*	9,221	61.1%	100.0%	48.8%
Interest Rate	8,543	6.6%	4.5%	37.2%
Share Drawn at Default	9,221	70.2%	80.3%	30.8%

* Default was within 90 days of scheduled maturity.

Table B2 presents the distribution of the Y-14 sample by collateral location and type. The Y-14 defaulted construction loans are much less concentrated in the top five states than in the FDIC collection. In the Y-14 data, these states account for only 30 percent of the total sample compared with 70 percent in the FDIC data. This is not unexpected, as the Y-14 data include large national banks with more geographically diverse portfolios, whereas our sample comes from banks that are mostly located in areas of the country that had a stronger real estate boom or bust (or both) than other locations. The Y-14 sample is also much less concentrated in single-family projects, and among single-family projects are less concentrated in land loans. This may reflect a combination of the geographic differences and the $1 million cut-off in the Y-14 collection.

Table B2: Y-14 Sample Breakout by Collateral Location and Type

	Full Sample		Collateral Type									
			Single Family				Commecial				Unkown	
	No. of Obs	Pct of Total Sample	No. of Obs			Pct of Total for Location	No. of Obs			Pct of Total for Location	No. of Obs	Pct of Total Sample
			Land/Dev	Home	Unknown		Multi-family	Retail	Other/ Unknown			
By State												
Georgia	428	4.6%	15	60	39	26.6%	21	31	260	72.9%	2	0.5%
Florida	1,259	13.7%	64	156	76	23.5%	30	86	840	75.9%	7	0.6%
Illinois	280	3.0%	11	34	12	20.4%	15	31	177	79.6%	0	0.0%
California	657	7.1%	11	107	22	21.3%	36	69	408	78.1%	4	0.6%
Washington	117	1.3%	14	11	7	27.4%	9	11	65	72.6%	0	0.0%
All Other	6,480	70.3%	299	898	287	22.9%	245	437	3,912	70.9%	402	6.2%
By Region*												
Northeast	583	6.3%	28	89	26	24.5%	36	31	365	74.1%	8	1.4%
Midwest	1,145	12.4%	60	125	46	20.2%	71	130	713	79.8%	0	0.0%
South	4,278	46.4%	205	551	244	23.4%	125	275	2,852	76.0%	20	0.5%
West	1,479	16.0%	36	206	57	20.2%	90	156	927	79.3%	7	0.5%
Other	1,736	18.8%	85	295	70	25.9%	34	73	799	52.2%	380	21.9%
Total	9,221	100.0%	414	1,266	443	23.0%	356	665	5,656	72.4%	415	4.5%
Pct of Total			4.5%	13.7%	4.8%		3.9%	7.2%	61.3%		4.5%	

Our primary takeaway from this benchmarking analysis is that the FDIC data seem consistent with the Y-14 data. There are definitely differences in the data due to the nature of the banks in each sample and differences in the variable definitions and time horizons for data collection. Analysis of the FDIC data is far more relevant in exploring loss drivers for SFR land loans but might not be the best source to explain risks associated with large commercial projects. Given that banks that are most vulnerable to construction loan concentrations are smaller banks, these institutions will have loan portfolios more similar to those we observe in the FDIC data.