# Intermediary Segmentation in the Commercial Real Estate Market*

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**Abstract**

Banks, life insurers, and commercial mortgage-backed securities (CMBS) lenders originate the vast majority of U.S. commercial real estate (CRE) loans. While these lenders compete in the same market, they differ in how they are funded and regulated, and therefore specialize in loans with different characteristics. We harmonize loan-level data across the lenders and review how their CRE portfolios differ. We then exploit cross-sectional differences in loan portfolios to estimate a simple model of frictional substitution across lender types. The substitution patterns in the model match well the observed shift of borrowers away from CMBS when CMBS spreads rose in 2016.

**Keywords:** commercial real estate, life insurers, segmentation
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# 1 Introduction

Commercial real estate (CRE) lending in the United States is an important component of overall business lending, measuring at a little less than 14% of GDP as of 2018:Q3. Bank and nonbank lenders compete in the CRE market, with U.S. commercial banks holding almost 60% of the volume of commercial mortgage, and life insurance companies and issuers of asset-backed securities (CMBS) each holding about 15% of the market.[1] Even though CRE is a large asset class that is a key input into firm production (Ghent et al., 2018), there remain a number of open questions about the CRE market, as there has historically been limited quality, loan-level information for banks' and insurers' CRE portfolios. Along what dimensions do CRE loan originations differ by lender type? What are the sources of segmentation in the market? What are the implications of segmentation for how the market responds to a shock?

To address these questions, the first contribution of this paper is to harmonize loan-level sources to compare CRE originations across the three lender types. Our data include granular details on loan terms and property characteristics for the CRE loan portfolios of around 30 of the largest banks in the United States, all life insurers, and all loans in publicly issued, non-Agency CMBS deals. An examination of the loan-level data reveals a striking amount of segmentation in the CRE market: bank, life insurer, and CMBS lender originations differ substantially by interest rate, loan-to-value (LTV), size, property type, and time to maturity at origination.

A review of the institutional setting in which the lenders operate indicates a supply-side explanation for our findings. Lenders differ in regulation, funding structure, and other institutional characteristics affecting their incentives to originate particular types of loans, and these institutional differences can explain the segmentation in the data. For example, short-duration liabilities incentivize banks to make short-term, floating-rate loans, risk-sensitive capital requirements incentivize life insurers to make safer loans, and greater

[1] Data comes from the Flow of Funds. See Figure C.1 (in Appendix C) for more details. The government accounts for much of the rest of CRE debt. Therefore, banks, life insurers, and CMBS lenders account for the vast majority of private sector CRE financing.

diversification enables CMBS to make larger loans.

Guided by our review, we build a simple model with representative lender types that differ in how various loan characteristics affect required returns. Borrowers receive offers from the different lenders and choose the offer with the lowest interest rate, where rates reflect the lender-specific pricing of loan characteristics. We then estimate how lenders price loan characteristics by exploiting the cross-sectional variation in the terms on newly originated CRE loans. We use the estimated model to simulate the effects of supply shocks on the CRE market.

A key difficulty in validating our model is that while the interest rate on the originated loan is observable, the second-best offer—which determines the effect of a counterfactual supply shock—is not. Nonetheless, we are able to validate the substitution patterns in our model by exploiting a supply shock to CMBS lenders. Between 2015 and 2017, a large number of pre-crisis CMBS loans were maturing and needed to refinance.[2] In the middle of this "wall of maturities," stress in broader bond markets resulted in CMBS spreads rising over 50 basis points (bp). We study how this increase in spreads affected the propensity of borrowers previously financed by CMBS to transition to another lender type. We show that CMBS borrowers switch to other sources of finance at a rate in line with what is simulated in the model in response to a comparably sized supply shock.

The model also allows us to simulate how the market would respond to several counterfactual shocks. We estimate that the ability to switch to another lender offsets about a quarter of the effect of a 25bp shock to the pricing of CMBS loans.[3] Shocks to banks are more costly due to their larger market share and, on average, the lack of close substitutes. The estimated effects of supply shocks are also heterogeneous —those demanding loans unfavorable to other lenders are less likely to switch, and thus experience greater increases in spreads when their lender contracts supply. For example, CMBS supply shocks disproportionately

[2]CMBS lending was elevated between 2005 and 2007. Given that most CMBS loans have ten-year terms, significant prepayment restrictions, and minimal amortization, this resulted in high demand for refinance loans between 2015 and 2017.

[3]That properties can transition to other lender types when the market responds to a shock provides an additional insight into why deep capital markets are so valuable to the U.S. economy beyond the ability to fund early stage projects and expand the scale of operations (Feldstein, 2017).

affect borrowing costs for larger loans, as next-best offers on such loans are further away on average.

The extent of segmentation is also important in determining the effects of targeted regulation. We analyze a policy that raises the required rate of return on high-LTV bank loans. The estimated model suggests that since nonbank lenders make few loans with LTVs above 75%, few borrowers switch to other lenders. Such a policy therefore leads to higher interest rates than if the high-LTV segment of the market were less bank dominated.

### 1.1 Related Literature

Our paper ties into a large literature on financial contracting and how borrowers sort into different financing arrangements. Much of the work studies this question in the context of competition between banks and bonds for the provisioning of firm financing.[4] Chernenko et al. (2018) provide evidence that bank and nonbank lenders utilize different lending techniques and cater to different types of firms.

Most relevant to this paper, there is a literature studying the competition between banks and capital markets in the context of the CRE market. Downs and Xu (2015) find that banks are much quicker to resolve distressed loans than CMBS. Black et al. (2017, 2018) show that banks specialize in lending against risky properties where monitoring and renegotiation are important. Meanwhile, Ghent and Valkanov (2016) show that CMBS disproportionately hold loans against larger properties, consistent with a superior ability to diversify risk.[5]

We advance this literature along a number of dimensions. First, our data expands the coverage of the CRE market relative to these papers. Black et al. (2017, 2018) use the same data sources for CMBS and bank loan portfolios, but their analysis does not include life insurers. Downs and Xu (2015) and Ghent and Valkanov (2016) use data which includes insurers but does not come from regulatory filings, causing many fields pertaining to loan

[4] There is a large theoretical and empirical literature on this topic. Important examples include: Townsend (1979); Sharpe (1990); Diamond (1991); Rajan (1992); Hart and Moore (1998); Denis and Mihov (2003); Gande and Saunders (2012); Hale and Santos (2009); Becker and Ivashina (2014).

[5] Other work also studied differences within CMBS pools based on the type of lender. Conduit lenders have been shown to have a pricing advantage over portfolio lenders (An et al., 2011). Also, CMBS loans have been found to perform better when originated by life insurance companies (Black et al., 2012) or healthier originators (Titman and Tsyplakov, 2010).

terms to be poorly populated. Second, we differ in that our object of study is differences in the composition of loan portfolios more so than differences in outcomes. Instead of using matched samples or Heckman corrections to remove selection bias, we comprehensively investigate the nature of the differences in underwriting and assess institutional factors likely to drive the patterns in the data. Third, we build and estimate a quantitative model, which allows us to perform counterfactuals to assess how shocks and regulation affect the distribution and pricing of loans across the market.

The rest of the paper follows as such. In Section 2, we describe the data used in this paper and summarize how loan characteristics differ across lender types. We then outline the institutional differences across the lenders that could produce the observed differences in portfolios. Section 3 describes the model, its estimation and validation, and discusses counterfactuals. Section 4 concludes.

## 2 How and Why CRE Lending Differs by Intermediary Type

This section analyzes how and why loan characteristics vary across intermediary types. First, we describe the data sources. We then summarize how loan characteristics differ across the intermediaries. We conclude the section with a discussion of the institutional details pertinent to the observed differences in portfolios.

### 2.1 Data Description

For life insurers, we use data from the National Association of Insurance Commissioners (NAIC) regulatory filings. NAIC data has been used in other papers (Becker and Opp, 2013; Ellul et al., 2014, 2015; Chodorow-Reich et al., 2018), but, to our knowledge, our paper is the first to analyze the loan-level information on life insurer CRE portfolios. We study originations of commercial loans from the mortgage origination and acquisition schedule (Schedule B - Part 2), which has all originations and acquisitions for each insurer. For each loan, we have information on the geography (zip code), property type, interest rate, book value, appraised value of land and buildings, and dates of maturity and acquisition.[6]

[6]Some information is not available before 2014. However, for loans that were still in insurers' portfolios in 2014 (the majority due to their long maturities), we can backfill this information using data from year-end

For banks, we rely on quarterly, loan-level data from Schedule H.2 of the FR Y-14Q, which has also been used in a few recent papers (Black et al., 2017; Glancy and Kurtzman, 2018). This data is collected by the Federal Reserve as part of the Comprehensive Capital Analysis and Review (CCAR) for banks with more than $50 billion in assets when averaged over the previous four quarters.[7] The data includes rich information on loans, including the interest rate, committed exposure, outstanding balance, dates of origination and maturity, purpose (construction vs. income producing), interest rate variability (fixed vs. floating), and characteristics of the property securing the loan (zip code, property type, and appraised value). Banks report this microdata for all credit facilities with a committed exposure above $1 million.[8]

Our data on CMBS loans comes from Morningstar and is based on the information reported in the CRE Finance Council Investor Reporting Package.[9] This data is available from several vendors, including Morningstar, and has been widely used in the literature. The data cover all loans held within publicly issued, non-agency CMBS deals.[10] We have all the same fields as in the other two datasets for loans at origination.

Given that the data on each lender type comes from a different source, the fields available for one lender type do not always line up one-for-one with those for the other lenders. The finer details of how we harmonize these different data sets are covered in Appendix A. Here, we outline the three most important filters. First, we drop all loans under $1 million in size to maintain consistency with the reporting threshold for banks. Second, we drop bank construction loans, as CMBS lenders and life insurers lend almost exclusively against income producing properties, which tend to differ substantially in loan terms and risk characteristics.[11] Third, we restrict the sample to loans secured by retail, office,

portfolio holdings (Schedule B- Part 1). We provide more details on this backfilling procedure in Appendix A.

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

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

[9]See `http://www.crefc.org/irp` for details on the reporting package.

[10]CMBS loans are originated by many lender types, including banks who do the majority of such originations, as well as insurance companies, conduits, and other finance companies. We are focused on the incentives to hold a loan rather than originate a loan, so it is relevant to think of loans originated by banks or insurers as CMBS loans, as this CMBS lending is generally fee-driven lending.

[11]See Glancy and Kurtzman (2018) for a description banks' construction loan portfolios and Friend and

hotel, or industrial buildings. We exclude multifamily loans, as the government-sponsored enterprises account for a large share of the market. Other categories, for example health care, are dropped because of a lack of consistent reporting across the data sources.[12]

While this harmonized data set provides a detailed view of CRE loan portfolios, it does not track properties over time. As a supplement, we also use data on CRE transactions from Real Capital Analytics (RCA). RCA uses a combination of press releases, corporate filings, other public documents, and information from brokers to follow properties and who is financing them over time.[13] Although coverage of loan characteristics in RCA is less comprehensive than in our primary data, the ability to observe lenders changing over time is useful for examining substitution between lenders.[14] We use this data in Section 3 to study how supply conditions affect the propensity to switch lenders at refinancing.

## 2.2 Differences in Loan Characteristics Across Lenders

Table 1 reports summary statistics on the harmonized fields for the three different lender types.[15] The data include variables at the time of origination for loans originated between 2012 and 2017.[16]

One of the most pronounced differences is in time to maturity, with life insurers making long-term loans and banks making short-term loans. We show this graphically using a histogram in panel (a) of Figure 1. The figure shows that loans with over 10-years term are disproportionately originated by life insurers, whereas loans with under 10-year terms are disproportionately originated by banks. CMBS lenders, meanwhile, almost exclusively

Nichols (2013) for evidence that construction lending has historically been uniquely risky for banks.

[12]Health care is a property category in the CMBS and life insurance data, but not the bank data.

[13]The data cover transactions on properties in the U.S. CRE market above \$2.5 million dollars in size starting in 2001. See Ghent (2019) for a more detailed description of the data.

[14]For example, maturity date only exists for less than a quarter of loans originated by banks, but is reliably reported by CMBS. As the non-reporting is clearly non-random (reporting is better for larger properties and for CMBS), analysis of most loan characteristics in RCA is affected by selection bias.

[15]We leave a discussion of geographic differences to Appendix B. The most robust findings are that life insurers originate more loans in areas with lower unemployment rates, and CMBS lenders originate more loans in areas with higher vacancy rates. However, differences are not always consistent across the different geographic risk measures, and some findings are sensitive to how we control for time series or across-property type variation. Altogether, the differences in the geography of lending decisions across the lender types are not nearly as striking as the loan characteristics we summarize in this section.

[16]We show the 1st and 99th percentiles, rather than the min. and max. for confidentiality reasons related to the Y-14Q data. We start the data in 2012:Q1, as this is the quarter in which the Y-14Q data collection officially began.

Table 1
Summary Statistics for CRE Originations by Intermediary Type

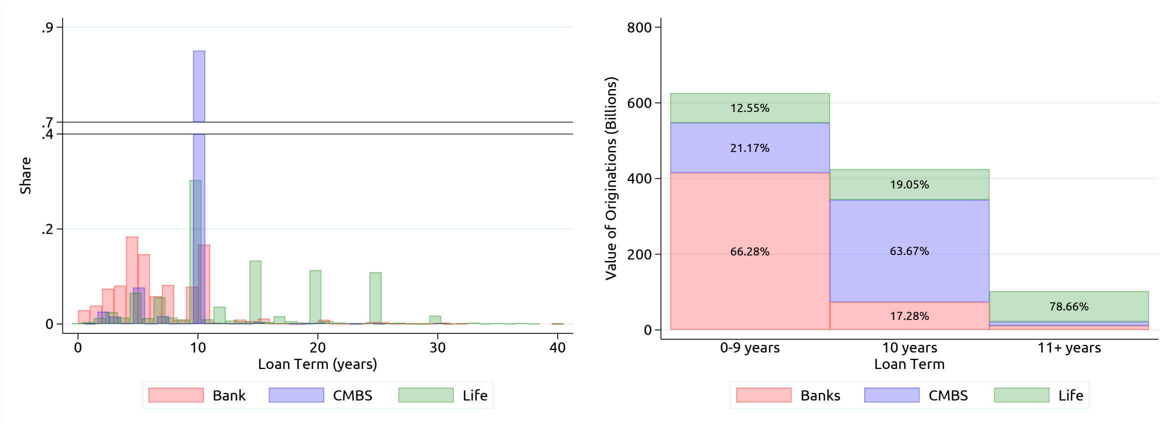
| | Bank Loans | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Mean | Std | p01 | p25 | p50 | p75 | p99 | N |
| Term (years) | 6.63 | 3.98 | 0.49 | 4.84 | 5.04 | 10.00 | 24.93 | 40,024 |
| Fixed-rate dummy | 0.34 | 0.47 | 0.00 | 0.00 | 0.00 | 1.00 | 1.00 | 40,024 |
| Property value (millions) | 33.09 | 513.16 | 1.40 | 3.35 | 7.19 | 20.95 | 369.62 | 40,024 |
| Loan balance (millions) | 12.48 | 28.88 | 1.00 | 1.73 | 3.49 | 10.09 | 127.13 | 40,024 |
| Loan-to-value ratio | 0.56 | 0.19 | 0.06 | 0.45 | 0.59 | 0.69 | 1.00 | 40,024 |
| Interest rate | 3.50 | 0.99 | 1.65 | 2.71 | 3.50 | 4.22 | 5.95 | 40,024 |
| Spread to swaps | 2.62 | 0.85 | 1.15 | 2.04 | 2.49 | 3.02 | 5.26 | 40,024 |
| | CMBS Loans | | | | | | | |
| | Mean | Std | p01 | p25 | p50 | p75 | p99 | N |
| Term (years) | 9.32 | 2.29 | 2.00 | 10.00 | 10.00 | 10.00 | 11.50 | 11,358 |
| Fixed-rate dummy | 0.96 | 0.20 | 0.00 | 1.00 | 1.00 | 1.00 | 1.00 | 11,358 |
| Property value (millions) | 75.11 | 272.88 | 2.73 | 9.00 | 15.90 | 36.33 | 1278.50 | 11,358 |
| Loan balance (millions) | 36.41 | 180.68 | 1.70 | 5.85 | 10.39 | 22.75 | 508.00 | 11,358 |
| Loan-to-value ratio | 0.65 | 0.09 | 0.35 | 0.60 | 0.66 | 0.71 | 0.77 | 11,358 |
| Interest rate | 4.72 | 0.64 | 2.84 | 4.39 | 4.70 | 5.02 | 6.50 | 11,358 |
| Spread to swaps | 2.64 | 0.80 | 1.39 | 2.15 | 2.49 | 2.97 | 5.85 | 11,358 |
| | Life Insurance Loans | | | | | | | |
| | Mean | Std | p01 | p25 | p50 | p75 | p99 | N |
| Term (years) | 13.59 | 7.01 | 1.92 | 10.00 | 10.08 | 20.01 | 30.08 | 19,144 |
| Fixed-rate dummy | 0.97 | 0.18 | 0.00 | 1.00 | 1.00 | 1.00 | 1.00 | 13,284 |
| Property value (millions) | 25.33 | 63.45 | 1.51 | 4.12 | 8.60 | 20.00 | 291.42 | 19,144 |
| Loan balance (millions) | 12.52 | 26.60 | 1.00 | 2.30 | 4.65 | 10.77 | 141.00 | 19,144 |
| Loan-to-value ratio | 0.57 | 0.15 | 0.13 | 0.50 | 0.59 | 0.67 | 0.83 | 19,144 |
| Interest rate | 4.31 | 0.81 | 2.31 | 3.86 | 4.25 | 4.65 | 7.00 | 19,144 |
| Spread to swaps | 2.18 | 0.94 | 0.66 | 1.63 | 2.05 | 2.51 | 5.92 | 13,284 |

Notes: This table presents summary statistics of various loan terms and characteristics by lender type. Interest rates are in percentage points. Interest rate variability is not reported in the life insurers' statutory filings, and is imputed based on whether the reported interest rate on a given loan changes over time. There is a smaller sample size for "Fixed-rate dummy" for life insurers, as some loans are only in the sample once—most of these observations are 2017 originations as this is the last year in our data. Interest rate spreads are with respect to 1-month dollar LIBOR for floating-rate loans, and maturity-matched swap rates for fixed-rate loans.

originate 10-year loans. The second panel shows the volume of lending for different lenders by term. Banks originate about two-thirds of loans with less than 10-year terms, while life insurers originate more than three-quarters of the loans with over 10-year terms.[17]

Table 1 also shows pronounced differences in the propensity to originate fixed-rate as

[17] Recall that our sample of bank loans does not cover banks with under $50 billion in assets. Therefore, the bank market shares in our sample are less than the bank shares of the actual market.




**(a)** Term (years) Histogram

**(b)** Total Lending by Term

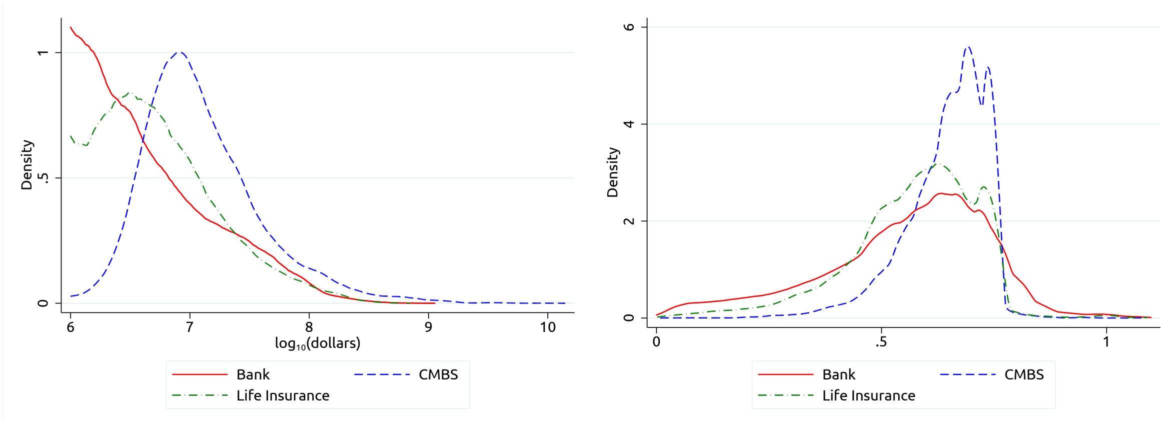
**Figure 1:** Time to Maturity by Intermediary Type

Notes: Panel (a) is a "broken" histogram of the time to maturity at origination for banks, CMBS, and life insurers, where the y-axis is not to scale between 0.4 and 0.7. Panel (b) shows the volume of originations by the different lender types with terms of less than 10 years, 10 years, or greater than 10 years. For panel (b), term is defined as the number of years between the date of origination and the original date of maturity, rounded to the nearest integer.

opposed to floating-rate loans. The typical bank loan is floating rate. Only about one-third of bank loans have fixed interest rates. Life insurers and CMBS lenders, however, almost exclusively make fixed-rate loans.

There are also notable differences in loan sizes, with CMBS loans on average being nearly three times as large as those made by the balance sheet lenders. The average balance on a CMBS loan in our sample is around \$36 million, compared with around \$12.5 million for banks and life insurers. This is likely an underestimate of the true difference since (1) we restrict the sample to loans over \$1 million, and (2) we do not include loans from small banks, which typically make smaller loans. Panel (a) of Figure 2 plots the probability density function of loan size for the different lender types. Most CMBS loans are over \$10 million, and CMBS loans are much more likely to be over \$100 million compared with balance sheet lenders. Meanwhile, banks have a probability density function which declines monotonically from where the data are censored, suggesting a large mass of loans are under \$1 million. Life insurers seem to operate in between these extremes.

CMBS loans also have somewhat higher LTV ratios, with an average LTV of 0.65 compared to a little more than 0.55 for the balance sheet lenders. However, the second




**(a)** Loan size

**(b)** Loan-to-value ratio

**Figure 2:** Loan Size and LTV Ratio by Intermediary Type

Notes: Panels (a) and (b) plot kernel density estimates of the distributions of loan size (the common logarithm of the original loan balance) and loan-to-value ratio by lender type, respectively. The distribution of size is estimated with the lower limit at 6, due the censoring at $1 million. Data includes new CRE originations between 2012-2017.

panel of Figure 3 highlights the substantial heterogeneity in LTVs by lender type. Banks are essentially the only lenders to make loans with LTVs above 0.75, yet banks are also the most likely to make loans with LTVs under 0.4. Life insurers and CMBS lenders offer a tighter range of LTVs, with life insurers generally requiring lower LTVs. The majority of life insurer CRE loans have an LTV between 0.50 and 0.67, while the majority of CMBS loans have LTVs between 0.60 and 0.71.

Not surprisingly, given the substantial differences in loan characteristics, the lender types differ in the interest rates they offer. Bank loans have the lowest interest rates at origination, largely due the high share of floating-rate loans and the upward-sloping yield curve during the sample period. When interest rates are measured as spreads to one-month dollar LIBOR for floating-rate loans, or spreads to comparable-maturity swaps for fixed-rate loans, life insurers have the lowest rates, with banks and CMBS offering similar spreads.

The lender types also differ in their origination shares by the type of properties securing loans. Table 3 tabulates the number of loan originations by lender and property type. The most apparent difference is with hotel loans, which constitute 24% of CMBS originations compared with only 4% for life insurers. Hotels are considered to be one of the riskier

Table 2
CRE Originations by Property Type and Lender Type

| | Lender type | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Bank | | CMBS | | Life | | Total | |
| | No. | Col % | No. | Col % | No. | Col % | No. | Col % |
| Hotel | 3,789 | 9 | 2,672 | 24 | 804 | 4 | 7,265 | 10 |
| Industrial | 7,566 | 19 | 816 | 7 | 5,416 | 28 | 13,798 | 20 |
| Office | 13,435 | 34 | 2,609 | 23 | 5,185 | 27 | 21,229 | 30 |
| Retail | 15,234 | 38 | 5,261 | 46 | 7,738 | 40 | 28,233 | 40 |
| **Total** | 40,024 | 100 | 11,358 | 100 | 19,143 | 100 | 70,525 | 100 |

Notes: This table presents information on the number and percent of loans secured by a given property type for a given lender type.

properties to lend against, so as with the findings for LTV, this points to life insurers being more risk averse. Life insurers, on the other hand, disproportionately make loans against industrial properties, with these loans accounting for 28% of life insurer originations, compared to 20% for the full sample. The composition of bank originations by property type is generally pretty close to the overall composition, although banks are a bit more oriented toward office buildings than the other lenders.

### 2.3 Summary of the Findings on Market Shares

To summarize the previous section, we highlight five findings regarding market shares by lender type.

- **Finding 1 (term):** Banks originate most loans under ten years, CMBS originate most loans that are 10 years, and life insurers originate most loans over ten years.

- **Finding 2 (fixed vs.floating):** Banks mostly originate floating-rate loans, while CMBS and life insurers almost exclusively originate fixed-rate loans.

- **Finding 3 (size):** CMBS loans are the largest, and bank loans the smallest on average.

- **Finding 4 (LTV):** CMBS loans have a higher average LTV, but banks make almost all loans with an LTV $> 0.75$.

- **Finding 5 (property type):** CMBS loans are disproportionately secured by hotels, while life insurers originate very few such loans.

## 2.4 Review of Relevant Institutional Differences

As noted in our literature review (Section 1.1), there is a large literature studying lender behavior across debt markets. In this subsection, we provide a brief review of the factors that are likely to contribute to the observed differences in loan characteristics across lenders. We provide an overview of the institutional environments faced by the different lenders, and discuss how those institutional details could affect incentives to originate particular types of loans. Here, we focus on the institutional details relevant to the differences discussed in Section 2.3. Further details on historical trends and regulatory differences are discussed in Appendix C.

### 2.4.1 Portfolio Lenders: Banks and Insurers

Banks and life insurers are similar in that they originate loans to hold in their portfolio. These lenders are therefore incentivized to carefully underwrite loans, as they would bear the brunt of any losses should the loan perform poorly. Portfolio lenders are also likely to be more flexible in terms of structuring loans upfront, or renegotiating them in the event of stress, as they are the sole holder of the debt, and thus do not have conflicts of interest across different investors complicating loan negotiations.

However, banks and life insurers differ in a couple of ways that influence their willingness to make particular types of loans. First, they differ significantly in how they are funded. Banks are predominantly funded by deposits, which frequently can be withdrawn on demand and thus need to reprice quickly with market rates. Life insurers, in contrast, are mostly funded by long duration liabilities (life insurance products or annuities) which often offer fixed rates or guaranteed minimum returns. If lenders want to minimize interest rate risk by matching the duration of assets and liabilities, banks should originate loans with short terms or floating rates and life insurers should originate loans with longer terms and fixed rates.

Second, banks and life insurers differ in their capital requirements. Although the two portfolio lenders both have risk-weighted capital requirements, these requirements tend to be more risk sensitive for life insurers, encouraging them to make safer loans. Until 2014, the risk weight on CRE loans for life insurers was proportional to a measure of the performance of the insurer's CRE portfolio relative to the rest of the industry (see Appendix C for more details). As delinquencies were rare for life insurers, a small number of loan restructurings, delinquencies, or foreclosures could result in a large increase in the risk weighting of the entire CRE book.[18] After 2014, capital requirements of life insurers changed so that risk weights depend on LTVs and debt service coverage ratios (DSCR). Although this change reduced the sensitivity of life insurers' capitalization to nonperforming loans, risk weights are still relatively sensitive: for most property types, if incomes decline such that DSCR fall below 1.5 or property values fall such that the current LTV rises above 85%, the risk weight on a loan will almost double. For hotel loans, the LTV and DSCR thresholds to avoid higher capital requirements are more restrictive.

### 2.4.2 Commercial Mortgage Backed Securities

Loans in CMBS are ultimately funded by capital markets. In a CMBS transaction, one or more lenders originate and then sell loans. The trust buying the mortgages funds the purchase by issuing a series of bonds, varying in payout priority and hence yield, duration, and risk. Buyers of these securities can therefore buy tranches tailored to their own risk tolerance and have an investment that is more liquid and more diversified than if the investor held a whole loan.

This diversification facilitates CMBS funding loans with higher idiosyncratic risk. By spreading the exposure to a particular loan across a large number of market participants, CMBS are able to finance large loans that would have created a prohibitively high level of concentration risk if funded by a single balance sheet lender.[19] Additionally, the ability to

[18]Differences in the performance of life insurance CRE loans across cycles supports the importance of risk-based capital requirements in disincentivizing risky lending. Life insurers and banks both experienced significant losses from CRE loans in the early 1990s, incentivizing the implementation of risk-weighted capital requirements. Delinquencies then remained near zero for life insurers during the financial crisis, while spiking for other lenders (see Appendix C, Figure C.2).

[19]CMBS may also have an advantage in funding large loans on top of the advantage in distributing the risk.

diversify risk across multiple loans may allow for higher LTVs than balance sheet lenders would allow, all else being equal, given that banks or insurers need to handle the full brunt of any loan losses.

While lending to distribute into CMBS allows for broader access to capital, this source of financing involves reduced flexibility for borrowers. As was evident from the summary statistics in Table 1, CMBS loans are fairly homogenous. The typical CMBS loan is a 10-year, non-recourse, fixed-rate loan on an income-producing property with prohibitive protections against prepayment. Borrowers wanting terms that deviate from standard CMBS characteristics likely need to turn to a balance sheet lender. The limited flexibility can also become problematic in the event that the loan requires modification. The special servicer, who is tasked with the responsibility of working out distressed loans, does not have all of the options for workouts that a balance sheet lender would have. For one, the trust holding the pool of commercial mortgages is typically structured as a Real Estate Mortgage Investment Conduit (REMIC) for tax purposes. As a REMIC must be a static pool of loans, significant loan modifications can threaten the favorable tax treatment. Additionally, special servicers are bound by rules in the CMBS's Pooling and Servicing Agreement, potentially further restricting the range of options for dealing with distressed CMBS loans.

## 3 Model and Estimation

Our examination of the incentives facing lenders described in Section 2 established that CRE lenders are likely to evaluate loans differently. Lenders differ in their capital requirements, funding structure, and degree of diversification. Consequently, a loan that is profitable at a given interest rate for one lender might not be profitable for another lender. In this section, we develop a simple model where lenders compete on interest rates, and loan characteristics are priced differently across lender types. We estimate the parameters of the model using the observed cross-sectional variation in loan characteristics. We validate the results by comparing the simulated substitution patterns in the model with the observed

Balance sheet lenders likely face frictions in raising capital, whereas the CMBS market accesses a deep pool of investor capital and can easily scale up bond issuance to fund a larger pool of loans.

substitution patterns during a period of stress in the CMBS market. We then conclude by analyzing the effects of various counterfactual supply shocks and regulatory changes through the lens of the model.

### 3.1 Model

Consider the following economic environment. Let a set of borrowers indexed by $i$ demand loans with a vector of characteristics $X_i$. Borrowers take out bids from a set of different lender types $J$ and choose the lender $j$ offering the lowest interest rate.[20]

Each lender type differs in either the expected cash flows from a given loan or how those cash flows are discounted. As a result, the net present value ($NPV$) of originating a loan at a given interest rate will vary across lender types. Let $R_{i,j}$ denote the minimum interest rate for which lender $j$ is willing to extend a loan with characteristics $X_i$. We assume $R_{i,j}$ is linear in characteristics with a loading $\beta_{j,n}$ on characteristic $n$, and has an idiosyncratic component, $\sigma\epsilon_{i,j}$, reflecting the match of the borrower with a given lender type.

The required rate of return on loan $i$ for lender $j$ is then:

$$R_{i,j} \equiv \min\{R|NPV_j(X_i, R) \geq 0\} = X_i'\beta_j - \sigma\epsilon_{i,j}. \tag{1}$$

Assuming zero profits for CRE lenders, the equilibrium interest rate for borrower $i$, denoted $R_i$, will be the lowest required rate of return across the lender types: $R_i = \min\limits_{j \in J}\{R_{i,j}\}$.

### 3.2 Estimation Strategy

We assume $\epsilon_{i,j}$ is distributed type-I extreme value, so the probability of lender $j$ originating a loan with characteristics $X_i$ is:

$$P_{i,j} = \frac{\exp(-\frac{1}{\sigma}X_i'\beta_j)}{\sum\limits_{j' \in J} \exp(-\frac{1}{\sigma}X_i'\beta_{j'})}.$$

With these assumptions, our model maps to the standard multinomial logit model.

[20] Assuming that loan characteristics are fixed simplifies the analysis, but it likely causes us to understate the ability of borrowers to switch to other lenders. While some characteristics such as property type and value are presumably immutable, others like LTV or term might be adjusted depending on how a lender prices loans.

Using loan characteristics to predict lender type will therefore provide estimates of how loan characteristics affect the required rate of return for different lender types. As always, the logit model does not identify the coefficient vector directly, instead it estimates $\beta_j$ relative to a reference group and up to a scale parameter—$\sigma$—reflecting the variance of the idiosyncratic component.[21] We estimate the multinomial logit using banks as the reference category, and thus produce estimates of:

$$\begin{aligned} \beta^{\text{Logit}}_{\text{CMBS}} &= \frac{1}{\sigma}(\beta_{\text{Bank}} - \beta_{\text{CMBS}}) \\ \beta^{\text{Logit}}_{\text{Life}} &= \frac{1}{\sigma}(\beta_{\text{Bank}} - \beta_{\text{Life}}). \end{aligned} \tag{2}$$

### 3.3 Estimation Results

In this subsection, we first present results from the multinomial logit described in the previous subsection, and then discuss our calibration of $\sigma$ and $\beta_{\text{Bank}}$. We provide further detail on our estimation procedure in Appendix D.

#### 3.3.1 Multinomial Logit Results

Table 3 presents the coefficient estimates from the multinomial logit model. Given that the reference group is banks, a positive coefficient on a particular loan term for a lender means that the lender prices loans with that term favorably relative to banks and is therefore more likely to make loans with that term.

The baseline specification in the first two columns includes loan term, ln(Property Value), LTV, a dummy variable for whether the LTV exceeds 75%, and a set property type dummies as explanatory variables. The findings are consistent with the patterns demonstrated in Section 2. Life insurers are more likely to lend long and banks short. CMBS lenders are the most likely to originate loans for large properties or with higher LTVs (up to a point), although banks are most likely to lend at LTVs over 75%. Regarding property types, CMBS lenders are most likely to lend against hotels and retail buildings (e.g., malls), while life

[21] Note that from (1), a proportional increase in the $\beta_j$ vectors and $\sigma$ would not change the equilibrium lender. Likewise, shifting each $\beta_j$ vector by the same amount would not affect the choice of lenders. This means the pricing terms are identified relative to a reference group, and relative to the dispersion in the match term.

Table 3
Multinomial Logit Results

| | Model 1 | | Model 2 | | Model 3 | |
|---|---|---|---|---|---|---|
| | CMBS | Life | CMBS | Life | CMBS | Life |
| Term (years) | 0.22** | 0.32** | 0.07* | 0.25** | 0.07** | 0.25** |
| | (0.04) | (0.04) | (0.03) | (0.03) | (0.03) | (0.03) |
| ln(Property Value) | 0.78** | 0.39** | 1.23** | 0.58** | 1.24** | 0.62** |
| | (0.09) | (0.10) | (0.15) | (0.15) | (0.14) | (0.15) |
| Loan-to-value ratio | 8.74** | 1.68** | 9.61** | 1.93** | 9.57** | 1.74** |
| | (0.51) | (0.51) | (0.61) | (0.64) | (0.60) | (0.65) |
| LTV $>$ 0.75 | -3.74** | -1.65** | -3.28** | -1.44** | -3.25** | -1.44** |
| | (0.34) | (0.22) | (0.31) | (0.21) | (0.31) | (0.21) |
| Hotel | 1.45** | -0.54* | 1.64** | -0.44 | 1.64** | -0.46+ |
| | (0.16) | (0.23) | (0.20) | (0.27) | (0.20) | (0.27) |
| Retail | 0.78** | 0.05 | 0.92** | 0.15 | 0.93** | 0.16 |
| | (0.06) | (0.10) | (0.08) | (0.11) | (0.08) | (0.11) |
| Industrial | -0.21* | 0.70** | -0.17 | 0.73** | -0.16 | 0.74** |
| | (0.10) | (0.14) | (0.14) | (0.18) | (0.14) | (0.18) |
| Fixed-rate dummy | | | 5.16** | 3.91** | 5.19** | 3.91** |
| | | | (0.35) | (0.45) | (0.34) | (0.44) |
| Obs. | 70526 | | 64666 | | 64666 | |
| Year Dummies | No | | No | | Yes | |

Notes: This table presents results from three specifications of the multinomial logit model outlined in Section 3.2. Relative to the baseline model (Model 1), Model 2 additionally includes a dummy variable for whether the loan is fixed rate as an independent variable. Relative to Model 2, Model 3 additionally includes year fixed effects. The reference group is banks. +,*,** indicate significance at the 10%, 5%, and 1% levels, respectively. Standard errors are clustered at the level of the entity holding the loan (the specific bank, the specific life insurer, or the CMBS deal).

insurers are most likely to lend against industrial properties.

The second model adds a dummy variable for whether the loan has a fixed interest rate, and the results do not qualitatively change. As expected, CMBS lenders and life insurers are much more likely to originate fixed-rate loans. We exclude this variable from the first model as borrowers are unlikely to have a very strong preference for fixed or floating rates given they have the ability to effectively switch their exposure through interest rate swaps. As borrowers are likely flexible, including it in the model could result in simulations overstating frictions from substituting between bank loans and nonbank loans. The third model additionally adds a set of origination year dummies, which do not change any of the coefficients notably. We work with the first model in the rest of our analysis.[22]

### 3.3.2 Required Rate of Return Estimation

As shown in (2), to simulate the effect of a given change in the required rate of return for a particular lender, we need to rescale the logit estimates by a factor of $\sigma$. Additionally, to know how lenders price a given term (as opposed to how they price the term relative to banks), we need to shift the estimates by $\beta_{\text{Bank}}$. In order to estimate the lender-specific elasticities, we choose $\sigma$ and $\beta_{\text{Bank}}$ in order to match observed elasticities of loan rates to loan characteristics to those from simulated data.

To simulate the pricing elasticities, we start by taking our initial dataset and creating 19 duplicates of each loan. This means we maintain the same distribution of borrower characteristics as in the actual data but limit the effects of sampling error when we draw error terms. For each of these observations, we generate an i.i.d. extreme value error term $\epsilon_{i,j}^{\text{Sim}}$ for each lender type $j \in J = \{\text{Life}, \text{Bank}, \text{CMBS}\}$. We then generate offer rates for each lender type (relative to the expected bank offer): $R_{i,j}^{\text{Sim}} = -X_i'\hat{\beta}_j^{\text{Logit}} - \epsilon_{i,j}^{\text{Sim}}$, and simulate the equilibrium interest rates as $R_i^{\text{Sim}} = \min_{j \in J}\{R_{i,j}^{\text{Sim}}\}$. Let $\hat{\beta}_j^{\text{OLS,Sim}}$ denote the vector of coefficients from a regression of $R_{i,j}^{\text{Sim}}$ on $X_i$ for the set of loans such that $j = \text{argmin}_{j' \in J}\{R_{i,j'}^{\text{Sim}}\}$.[23] Let $\hat{\beta}_j^{\text{OLS,Data}}$ be the coefficients from regressing actual loan spreads on characteristics for loans from lender type $j$. For each loan, we will then have a predicted offer rate based on both the data and model simulations.

Since $\sigma$, the scale parameter, affects the dispersion in the pricing of terms across lender types, we calibrate it such that the standard deviation in predicted interest rates across lender types from the model equals the standard deviation in predicted interest rates from the regression in the data. Specifically, we set $\hat{\sigma} = \text{E}_i(\text{sd}(X_i'\hat{\beta}_j^{OLS,Data})/\text{E}_i(\text{sd}(X_i'\hat{\beta}_j^{OLS,Sim})$, where $\text{E}_i()$ is the expectation over loans and sd() is the standard deviation of predicted offers

[22] We exclude interest rate variability, as it would likely overstate frictions in substitution. We exclude year dummies, as our counterfactual exercises study the effects of supply shocks, and we do not want these shocks to already be reflected in the coefficients on year dummies.

[23] These estimates systematically differ from $\hat{\beta}_j^{\text{Logit}}$ due to selection bias: lenders only originate loans for which their offer is lowest, which induces a correlation between $\epsilon_{i,j}^{\text{Sim}}$ and $X_i$ for loans originated by lender $j$. Appendix D.2 shows that the magnitude of this selection bias is likely to be economically significant. For this reason, we do not use pricing regressions to directly estimate differences in required returns.

Table 4
Estimates of How Lenders Price Different Terms

| | Logit Coefficients | | Lender-Specific Elasticities | | |
|---|---|---|---|---|---|
| | $\frac{1}{\sigma}(\beta_{\text{Bank}} - \beta_{\text{CMBS}})$ | $\frac{1}{\sigma}(\beta_{\text{Bank}} - \beta_{\text{Life}})$ | $\beta_{\text{Bank}}$ | $\beta_{\text{CMBS}}$ | $\beta_{\text{Life}}$ |
| Term | 0.22 | 0.32 | 0.02 | -0.06 | -0.10 |
| Size | 0.78 | 0.39 | -0.02 | -0.30 | -0.16 |
| LTV | 8.74 | 1.68 | 0.32 | -2.87 | -0.29 |
| LTV $>$ 0.75 | -3.74 | -1.65 | 0.06 | 1.43 | 0.67 |
| Hotel | 1.45 | -0.54 | 0.57 | 0.04 | 0.77 |
| Retail | 0.78 | 0.05 | 0.03 | -0.25 | 0.01 |
| Industrial | -0.21 | 0.70 | 0.04 | 0.12 | -0.21 |
| Constant | -21.46 | -11.06 | 2.40 | 10.25 | 6.45 |

Notes: This table shows the estimates from the multinomial logit in Table 3 and the implied estimate for the elasticity between loan spreads and the given characteristic for each lender type. The first two columns reproduce the multinomial logit coefficients from Model 1 in Table 3. The next 3 columns show the vectors of pricing factors for each lender type after rescaling by $\hat{\sigma}$ (calibrated from the dispersion in pricing factors from OLS regressions) and shifting by $\hat{\beta}_{\text{Bank}}$ (calibrated so that regressions on simulated data produce the same coefficient as regressions on actual data). See Subsection 3.3.2 for more details on the estimation of $\hat{\sigma}$ and $\hat{\beta}_{\text{Bank}}$.

for a given loan across lender types.

Since $\beta_{\text{Bank}}$ controls the level of the effect of a characteristic on loan rates, $\hat{\beta}_{\text{Bank}}$ is chosen so that the coefficients from regressing loan spreads on characteristics are the same in the actual data and the model generated data. Specifically, $\hat{\beta}_{\text{Bank}} = \hat{\beta}^{\text{OLS,Data}} - \hat{\sigma}\hat{\beta}^{\text{OLS,Sim}}$, where the lack of a subscript for $\hat{\beta}^{\text{OLS,Data}}$ and $\hat{\beta}^{\text{OLS,Sim}}$ indicate regression coefficients for the whole sample of loans instead of loans made (or simulated as being made) by a particular lender.

The results from transforming the logit coefficients in this way are reported in Table 4. The first two columns replicate the logit coefficients from the first model in Table 3. The last three columns present the estimates for $\beta_{\text{Bank}}$, $\beta_{\text{CMBS}}$, and $\beta_{\text{Life}}$, which come from rescaling the logit coefficients by $\hat{\sigma}$ and shifting by $\hat{\beta}_{\text{Bank}}$. Trivially, the qualitative findings from the logit all carry through, as the transformations do not shift the ordering of how lenders price different terms. The magnitudes of the estimates are generally reasonable. For example, larger loans have lower interest rates, with the preference for size being most pronounced for CMBS lenders. Hotel loans are riskier and thus require a premium, ranging from 4 basis points for CMBS lenders to 77 basis points for life insurers. Other property types are not found as having such significant premiums or discounts.

Only the required rate of return estimates around LTV seem hard to square with intuition. CMBS lenders are found to have lower loan spreads by about 29 basis points for loans with LTVs that are 10 percentage points higher. We believe this is due to the endogeneity of LTV. Although a higher LTV makes a loan riskier, all else equal, this may not be reflected in pricing regressions if lenders impose tighter LTV limits on loans with worse unobservable characteristics (Archer et al., 2002; Titman et al., 2005). If LTV is about unpriced on average, but CMBS originate higher LTV loans, we will estimate CMBS lenders have lower loan spreads for loans with higher LTVs.

### 3.4 Model Intuition and Implications

The key outputs of our model are estimates of how different lenders price loans on average (determined by $\beta_j$) and the dispersion of pricing around these averages (determined by $\sigma$). With these estimates, we can predict how supply shocks affect particular types of loans, or the CRE market overall. If a lender raises interest rates, the response of a prospective borrower depends on how close the second-best offer is to what the lender would have offered absent the shock. If another lender is willing to offer a similar rate, a shock will result in the borrower switching to that other lender; if there are no close substitutes, the shock will instead affect pricing.

More formally, denote $F_j(R)$ as the distribution of the pricing advantage for lender type $j$ relative to the next-best offer. The effect of a supply shock to lender $j$ in our model will be entirely determined by this distribution. If the required rate of return for lender $j$ increases by $\Delta$, the lender will raise offered interest rates by an equivalent amount. A portion $F_j(\Delta)$ of the loans which would have been originated by lender $j$ before now have a next-best offer close enough that a new lender will have the lowest offer following the supply shock.

The cost to lender $j$'s borrowers from the supply shock will be higher loan spreads. A portion $1 - F_j(\Delta)$ will remain with lender $j$ and see their rates rise by $\Delta$, as $j$ is still their lowest cost lender after the shock. A portion $F_j(\Delta)$ will switch and also see their rates rise, as their new lender charges a higher rate than lender $j$. In this case, their rate will rise by less than $\Delta$ (or they would have remained with lender $j$). The average increase in interest

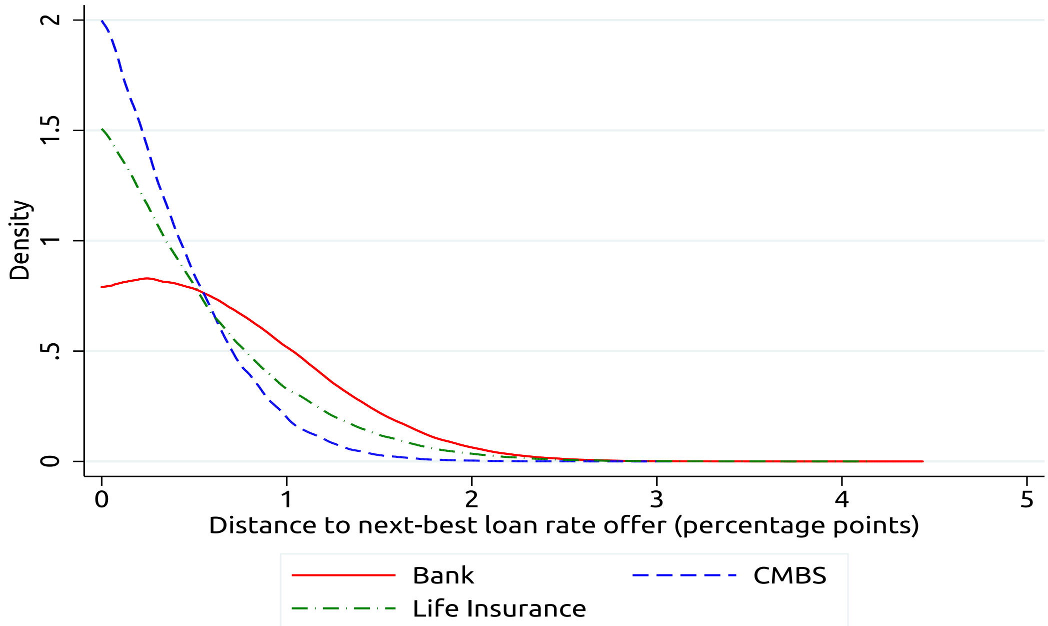



**Figure 3:** Distribution of Difference from Second-best Offer Rates

Note: This figure presents the simulated distribution of the pricing advantage for bank, CMBS, and life insurer CRE loans. Pricing advantage is defined as the difference between the interest rate offered by the lowest cost lender and second-best offer. Interest rate offers are simulated based on the pricing factors in Table 4 and i.i.d. extreme value error pulls.

rates is then $\int_0^{\Delta} r dF_j(r) + (1 - F_j(\Delta))\Delta$ for those who would have borrowed from lender $j$ in the absence of the shock.

The probability density function of the pricing advantage of each of the lender types based on the simulated loan offer rates is shown in Figure 3. For CMBS and life insurance, the PDF is highest near 0, and declines rapidly from there. This indicates that modest supply shocks to these lenders will result in fairly large changes in their market shares and, on average, fairly modest effects on borrowing costs. Banks, however, tend to have a larger distance between their offer and that of the next lender type, indicating that fewer borrowers will switch lenders in response to similarly sized shocks.

### 3.5 Model Validation: Loan Transitions in Response to a Supply Shock

A key difficulty in validating our model is that offer rates across the lender types are unobservable —we only observe the rate at which a loan is taken up by a single lender, and the lender who would have originated a loan absent a supply shock is unobservable. To overcome these difficulties, we use data from RCA, described in Section 2.1, to examine how the equilibrium lender changes when there is a supply shock to the CMBS market at the time when a CMBS loan needs to refinance. Between 2015-2017, a large number of pre-crisis CMBS loans became due, creating strong demand for refinance loans. In the middle of this episode, CMBS spreads rose notably, precipitated by stress in the broader bond market. We study how loans transitioned from CMBS to other lenders during this period of stress.

This episode is useful for two reasons. First, that the increase in CMBS spreads did not originate in the CMBS market increases confidence that the higher spreads actually reflect a change in supply, rather than a change in demand or loan composition. Second, while we cannot directly observe who would have lent absent the shock, we can observe that the borrower had taken out a CMBS loan earlier when conditions were more favorable. This provides a reasonable analogue to the lender who would have lent absent the shock that we observe in our model, allowing for a comparison of our model to the data.

First, we describe the supply shock, and then we compare how loans transition in the data to our model's predictions.

### 3.5.1 CMBS Supply Shock

Figure 4 shows that CMBS spreads rose notably around 2015 year-end and remained elevated throughout 2016. This increase in spreads coincided with general stress in the bond market, and thus was unlikely to reflect elevated demand for CMBS loans. As CMBS raise money in the capital market, lower demand for CMBS securities will result in an increase in required returns on newly originated CMBS loans.

Table 5 shows that changes in CMBS spreads do indeed pass through to loan rates, particularly for CMBS loans. Each column presents results of a regression of loan rate spreads on lender type dummies interacted with a metric for CMBS stress (either triple-A CMBS spreads or a dummy for whether the loan was originated in 2016). We can see that shocks to CMBS do not pass through equally to loan rates across the lender types as would be expected were CRE markets perfectly integrated. Instead, triple-A CMBS spreads pass through more than one-to-one into CMBS loan rates, while generally not affecting interest

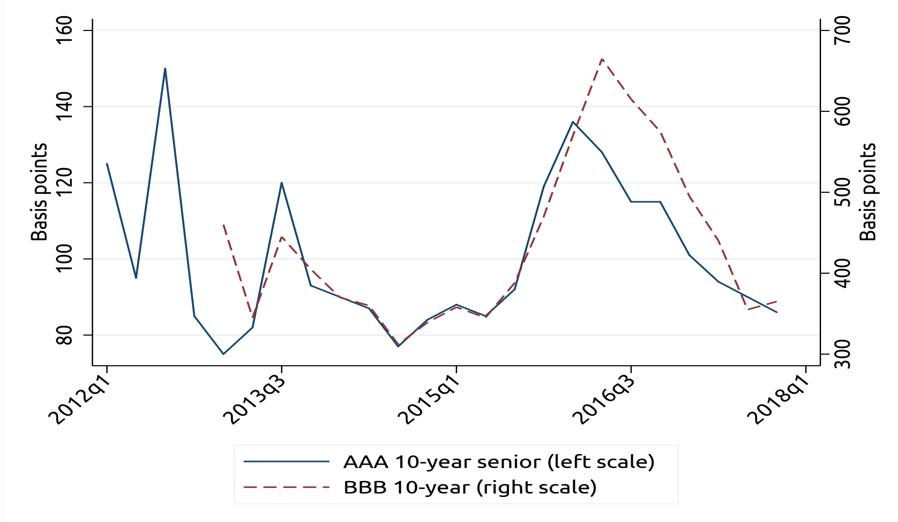



**Figure 4:** 10-year CMBS Spreads over Swaps

Notes: This figure shows a quarterly time series of AAA and BBB 10-year CMBS spreads over swaps. Data is averaged over the quarter.

rates for bank loans.[24] Life insurers are about half way in-between the other lenders in terms of pass-through. This makes sense given that CMBS yields do not directly affect life insurer funding costs. However, as large holders of private CMBS, these securities are likely seen as substitutes for direct lending for insurers.

The change in loan rates by lender type in 2016 matches what would be expected based on the findings in column 1. Loan spreads rose by 53bp for CMBS in 2016, while declining by 25bp for banks. Meanwhile, life insurers were in between, with an 18bp increase in spreads.

The next two columns restrict the sample to the years 2015 to 2017. During this period there was a sizable increase in the number of CMBS loans refinancing, due to the robust CMBS issuance between 2005 and 2007 and the convention that most CMBS loans have 10-year terms. This allows us to compare the increase in spreads in 2016 to years in which conditions were more similar, to make sure that the increase in interest rates observed is not just due to higher demand due to maturing loans with balloon payments. The results are generally similar to those estimated over the whole sample, with the exception that banks

[24] A 1 percentage point increase in yields higher up in the capital stack corresponds with a more than 1 percentage point increase lower in the stack, resulting in an increase in the required returns for the underlying loans of more than 1 percentage point.

Table 5
Pass Through of CMBS Spreads to Loan Rates

| | Full Sample | | Wall of Maturities (2015-2017) | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| AAA CMBS Spread x Bank | -0.11** | | 0.07** | |
| | (0.02) | | (0.03) | |
| x CMBS | 1.35** | | 1.42** | |
| | (0.04) | | (0.05) | |
| x Life | 0.56** | | 0.72** | |
| | (0.04) | | (0.05) | |
| 2016 x Bank | | -0.25** | | -0.06** |
| | | (0.01) | | (0.01) |
| x CMBS | | 0.53** | | 0.61** |
| | | (0.02) | | (0.02) |
| x Life | | 0.18** | | 0.34** |
| | | (0.02) | | (0.02) |
| CMBS | -1.01** | 0.27** | -0.79** | 0.39** |
| | (0.05) | (0.01) | (0.06) | (0.01) |
| Life | -0.71** | -0.12** | -0.62** | -0.07** |
| | (0.04) | (0.01) | (0.06) | (0.02) |

Notes: This table reports the estimates of OLS regressions of loan spreads on lender type dummies interacted with measures of CMBS stress. CMBS stress is measured by the spread of CMBS yields over swap rates in odd columns, and a dummy for the year 2016 in even columns. The first two columns present results for the full sample, while the last two restrict the sample to the period corresponding with the wall of maturities between 2015 and 2017. Loan rate spreads are with respect to comparable-maturity swap rates for fixed-rate loans and 1-month dollar LIBOR for floating-rate loans.

are found to keep rates mostly flat in 2016 instead of lowering rates.

### 3.5.2 Validation: How Did the Market Respond to the Shock in 2016?

There were a large number of CMBS loans originated between 2005 and 2007 which came due between 2015 and 2017. By restricting the sample to refinancing CMBS, we focus on borrowers who demanded CMBS loans at a time when the market was buoyant. However, the desire to borrow from CMBS might change when interest rates go up. Figure 5 indicates that this is indeed the case. The figure plots the share of refinancing CMBS loans which are originated by banks, CMBS, and life insurers by year. The gray bars show the number of CMBS loans refinancing in that year. We can see that CMBS typically retain refinancing

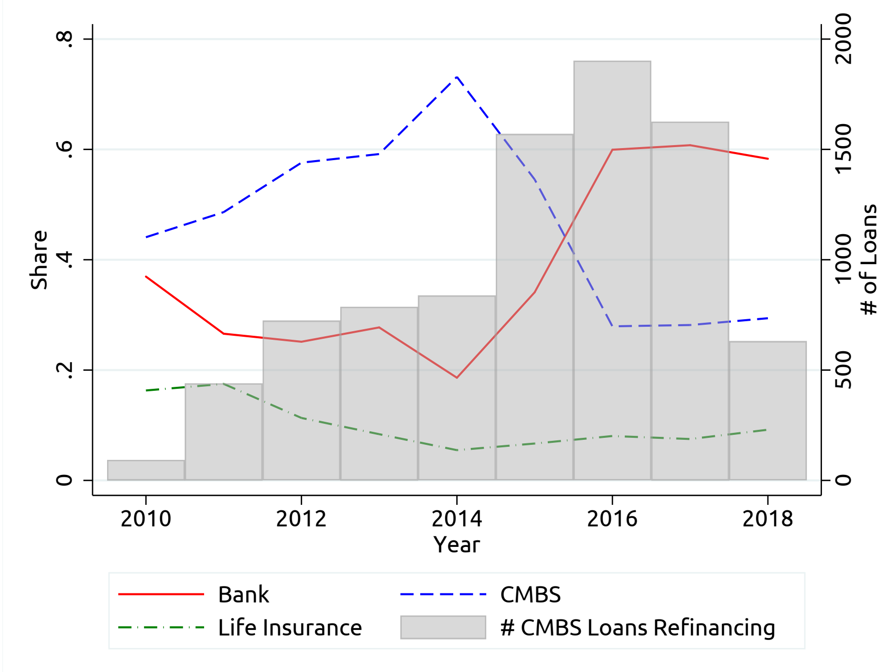



**Figure 5:** Market Shares for Refinancing CMBS Loans by Year

Notes: This figure plots the percentage of refinancing CMBS loans originated by banks, CMBS, and life insurers by year. The share of loans financed by each lender (left axis) is shown by the three lines. The total number of refinancing CMBS loans in that year (right axis) is shown by the grey bars. Data comes from Real Capital Analytics.

CMBS loans, originating around 60% of the loans most years. Banks perform most of the remaining refinances, originating about a quarter of the loans before 2016. However, when spreads rose in 2016, the market share of banks rose to about 50%. Life insurers' share also increased, but by very little in comparison with banks.

In Figure 6, we plot the share of loans that refinance into banks or insurance companies by the size of the property.[25] As would be expected given CMBS specialization in larger loans, balance sheet lenders take on smaller loans after a supply shock to CMBS, whereas CMBS are more likely to out-compete balance sheet lenders for larger loans, even at the higher rate. Among the smaller loans against $2.5 million properties, banks take on almost 80% of 2016 CMBS refinances, compared with only about a third of the largest $100 million properties. Life insurers are much less likely to take CMBS loans, with a market share that

[25] RCA data is at the property level instead of the loan level. To make the RCA data more comparable to the loan-level data, we aggregate the value of the properties in a given deal. The deal is considered to be a refinancing CMBS loan if the following holds: (1) the majority of the portfolio of properties is getting refinanced, and (2) the modal lender in the previous financing of the properties was a CMBS lender.

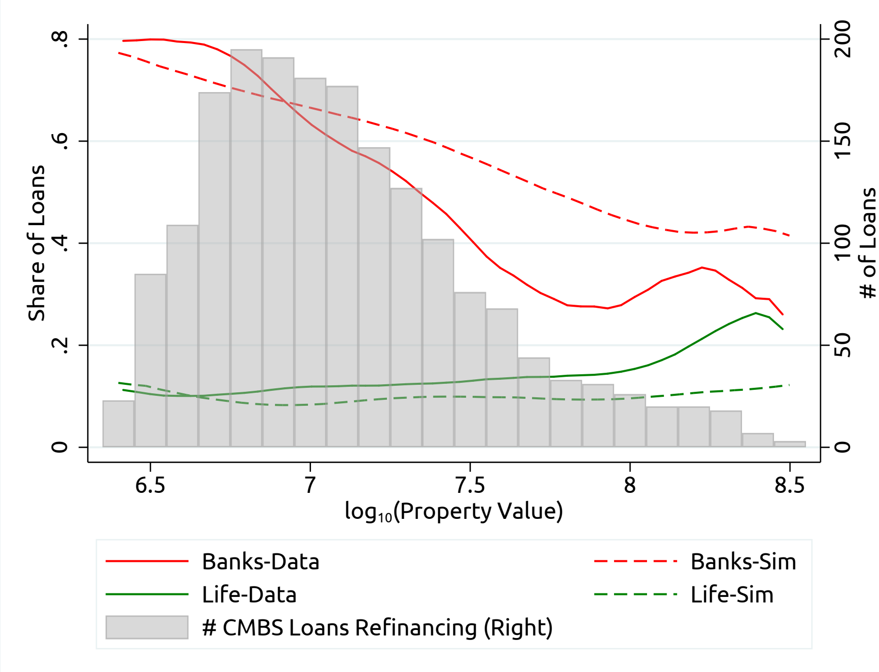



**Figure 6:** Market Shares for Refinancing CMBS Loans by Property Value in 2016

Notes: This figure plots the percentage of refinancing CMBS loans originated by banks and life insurers in 2016 by property size (the common logarithm of property value). The total number of refinancing CMBS loans in a given size range (right axis) is shown by the grey bars. The estimated share of loans originated by each lender (left axis) is shown by the four lines. In particular, each line plots the output of a local linear regression of lender type dummy variables on property size. Solid lines show the estimated share of refinancing CMBS loans being made by banks and life insurers using the actual data from RCA. Dashed lines show the estimated share of loans that switch from being financed by CMBS to other lenders as a result of an increase in CMBS spreads using simulated data.

is pretty steadily above 10%.

In Figure 6, we also present simulated shares using our estimated model. Specifically, we start with the set of 10-year maturity CMBS loans originated between 2005 and 2007 (the set of loans scheduled to mature during the wall of maturities) and simulate the interest rates that would be offered by banks, CMBS lenders, and life insurers given those loan characteristics and an idiosyncratic error term. We then simulate which of the loans that are assigned to CMBS lenders have offer rates such that the borrower would switch if CMBS interest rates rise by 67bp relative to bank rates and life insurance rates rise by 40bp relative to bank rates, as we observed in 2016. We can see that the patterns are broadly similar to what is observed in the actual data. Banks take on nearly 80% of the smaller refinancing loans, with this market share declining to a bit above 40% for larger properties. Life insurers take on a much smaller share, again around 10% across size categories.

### 3.6 Counterfactuals: How Does the Market Respond to a Shock?

Having validated that the substitution patterns in the model are consistent with the data (where observable), we simulate the effects of other supply shocks for which there is not a clear empirical analogue. Table 6 presents simulated market shares and average loan spreads for the three lender types in the event of a 25 basis point shock to each of the lender types. The baseline scenario, with no lender receiving a supply shock, is shown in column 1. The share of loans simulated as being originated by each lender matches the actual market shares in our data, and the average loan spreads are fairly close to those shown in Table 1.[26] Actual spreads range from about 2.2 for life insurers to 2.6 percentage points for banks and CMBS, while the simulated spreads range from about 2.3 for loans simulated as being originated by life insurers compared with 2.6 for banks and CMBS.

The three counterfactual scenarios are shown in columns 2 through 7, which simulate the effect of a 25 basis point increase in required rates of return for each lender type. Columns 2 and 3 show that a 25 basis point increase in the required rate of return for bank loans results in the market share of banks dropping by about 12 percentage points, with CMBS and life insurers increasing their market shares by about 5 and 7 percentage points, respectively. The average loan rate spread across lenders is predicted to rise by about 13 basis points, indicating that the ability to switch to other lenders offsets around 10% of the effect of a supply shock to banks.[27] The average loan rates for banks rise by about 21bp, less than the size of the shock, as some bank loans that are not as good a match, and thus carry higher rates, migrate to other lenders. Other lenders experience modest increases in interest rates as well, reflecting the fact that they are now originating some loans for which they are less well suited as a result of the shock.

The effects of a 25bp shock to CMBS (columns 4-5) or life insurers (column 6-7) are

[26]Matching market shares is essentially trivial, as the first-order condition for the alternative-specific constant matches the market shares in the data with the predicted market share in the model. Matching loan spreads is non-trivial as only the dispersion in pricing across lenders is targeted, not the alternative-specific levels.

[27]Banks start with a market share of 58%, so average loans rates would rise by 14.5bp as a result of 25bp shock to bank loan rates (0.58x25bp) if it were not for some marginal loans switching to other lenders. The increase in rates of 13.1bp is then 90% of what it would be absent switching (13.1/14.5).

Table 6
Counterfactual Estimates of how Market Shares and Spreads Respond to Supply Shocks to a Given Lender Type

| | | Response to a 25bp shock to lender type | | | | | |
|---|---|---|---|---|---|---|---|
| | | Banks | | CMBS | | Life | |
| | Baseline | Implied | Δ(bp) | Implied | Δ(bp) | Implied | Δ(bp) |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| Market Shares | | | | | | | |
| Banks | 0.58 | 0.46 | -11.8 | 0.62 | 3.7 | 0.64 | 5.9 |
| CMBS | 0.15 | 0.20 | 4.5 | 0.09 | -6.6 | 0.18 | 3.1 |
| Life insurers | 0.27 | 0.34 | 7.3 | 0.30 | 2.9 | 0.18 | -9.0 |
| Average Loan Spreads | | | | | | | |
| Overall | 2.51 | 2.64 | 13.1 | 2.54 | 2.9 | 2.57 | 5.5 |
| Bank | 2.59 | 2.80 | 20.5 | 2.61 | 1.8 | 2.62 | 2.3 |
| CMBS | 2.56 | 2.64 | 8.3 | 2.71 | 14.8 | 2.58 | 1.9 |
| Life Insurers | 2.31 | 2.44 | 12.1 | 2.35 | 3.8 | 2.39 | 7.1 |

| | | Response to a 50bp shock to lender type | | | | | |
|---|---|---|---|---|---|---|---|
| | | Banks | | CMBS | | Life | |
| | Baseline | Implied | Δ(bp) | Implied | Δ(bp) | Implied | Δ(bp) |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| Market Shares | | | | | | | |
| Banks | 0.58 | 0.35 | -23.5 | 0.64 | 6.0 | 0.68 | 9.9 |
| CMBS | 0.15 | 0.24 | 8.7 | 0.04 | -10.8 | 0.21 | 5.6 |
| Life insurers | 0.27 | 0.42 | 14.7 | 0.32 | 4.8 | 0.11 | -15.5 |
| Average Loan Spreads | | | | | | | |
| Overall | 2.51 | 2.74 | 23.2 | 2.56 | 4.5 | 2.60 | 9.1 |
| Bank | 2.59 | 3.00 | 41.0 | 2.62 | 3.1 | 2.63 | 4.2 |
| CMBS | 2.56 | 2.72 | 16.2 | 2.86 | 30.5 | 2.59 | 3.4 |
| Life Insurers | 2.31 | 2.54 | 23.0 | 2.38 | 6.6 | 2.44 | 12.6 |

Notes: This table presents simulated changes in market shares and borrowing costs resulting from supply shocks to different lender types. To simulate these effects, each loan in the data is duplicated 19 times and given a set of loan offers from the different lenders based on the pricing factors in Table 4 and i.i.d. type-I extreme value error terms. The first column shows baseline results before any supply shocks. A lender's market share is the percentage of loans such that the lender has the lowest offer rate, and the loan spread is the average spread for the set of loans that the lender type is simulated as originating. Columns 2, 4, and 6 list the new market shares and loan spreads after offer rates rise by 25bp (top panel) or 50bp (bottom panel) at banks, CMBS lenders, and life insurers, respectively. The associated changes in market shares and loan rates (in bp) are listed in columns 3, 5, and 7.

generally smaller. This partially reflects the fact that initial market shares are smaller, so fewer borrowers are affected. Additionally, a larger share of the increase in interest rates is offset by borrowers switching. Around 25% of the increase in rates due to a 25bp shock to CMBS is offset by switching, and a bit more than 15% of the effect of a shock to life insurers is offset by borrower switching. In other words, fewer borrowers are affected, and those that are affected are more able to switch to other lenders, mitigating more of the effect of a supply shock.

What happens when the shock is larger than 25bp, as we observed in 2016? In the bottom panel of Table 6, we repeat the analysis for a 50bp shock to the different lender types. The effects are qualitatively similar to the 25bp shock but larger. As before, banks preserve more of their market share when under stress compared with the other lenders, and the costs to borrowers are higher due to banks' larger initial market share and the greater pass-through to average spreads.

However, the magnitude of the effect does not scale linearly. While a 25bp shock to banks raises average loan spreads by about 13bp, a 50bp shock only raises spreads by about 23bp. This is due to the fact that the 25bp shock induces some borrowers to switch to other lenders, and therefore there is no marginal effect of a larger shock to these borrowers. As a result, the ability to switch offsets 20% of the effects of a 50bp shock to banks, compared with only 10% of a 25bp shock. Similarly, the ability to switch lenders offsets about 40% of the effect of a 50bp shock to CMBS and 33% of the effect of a 50bp shock to life insurers.

### 3.7 Counterfactuals: Heterogeneous Effects of a Shock

The effects of the pricing shocks studied in the previous section would not affect borrowers uniformly. If a prospective borrower from an affected lender does not have a close substitute available, a shock to their lender will pass through fully to their borrowing costs. On the other hand, if a borrower is on the margin between different lenders, a shock to their lender will not pass through fully, as they will just switch lenders. This means that supply shocks will disproportionately increase rates for those borrowers with characteristics more particular to their lender. For example, bank shocks will disproportionately affect those seeking an LTV above 75%, CMBS shocks will disproportionately affect those seeking large loans, and life insurer shocks will disproportionately affect those seeking long-term loans.

We demonstrate this point in Figure 7. We simulate how a 25bp shock to CMBS loan

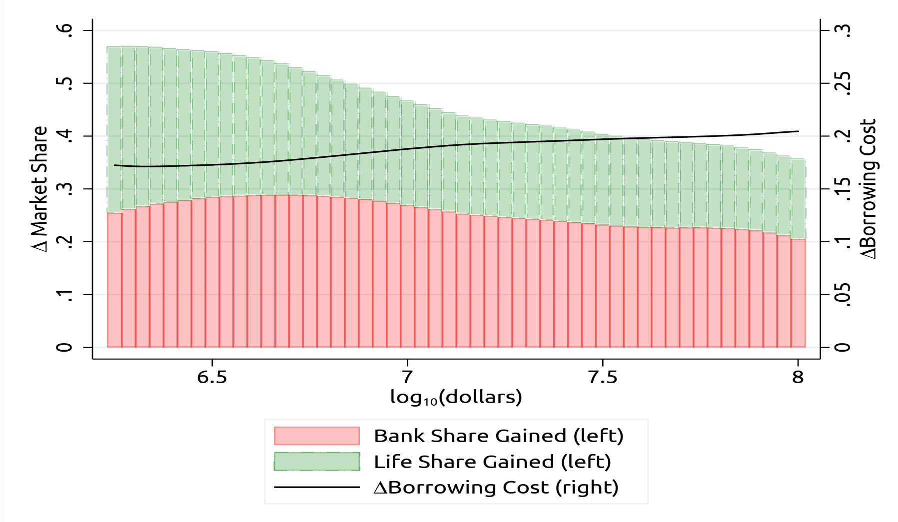



**Figure 7:** Effect of 25bp CMBS Shock by Property Value

Notes: This figure plots estimates for the share of CMBS loans that would switch to other lenders (left axis) and the change in interest rates for CMBS borrowers (right axis) resulting from a 25bp increase in CMBS loan rates. The height of the red and green bars show the share of CMBS loans of a particular size switching from CMBS to banks and life insurers, respectively. These estimates come from local linear regressions of borrower outcomes on the logarithm property values for the set of loans simulated as being made by CMBS before the supply shock. The dependent variables are indicators for whether CMBS loans switched to banks/life insurers due to the shock, and the change in borrowing costs due to the shock.

rates affects the propensity of loans to be financed by CMBS versus other lenders and how the shock passes through to aggregate borrowing costs. As was indicated in the analysis of the RCA data, when CMBS loans become more expensive, other lenders gain market share, particularly for smaller loans. We find that about 55% of the loans under $5 million that would have been financed by CMBS absent the 25bp shock are instead financed by banks or life insurers. These other lenders are less viable substitutes for larger loans, only originating about 35% of the $100 million loans that would have been originated by CMBS without the shock.

The availability of substitutes also determines how a supply shock affects aggregate borrowing costs. The total effect on rates is a function of those who remain with their lender type, who experience an increase of 25bp, and those who switch, who experience an increase between 0 and 25bp. Among the smaller loans that would have been originated by CMBS lenders absent the shock, the 25bp increase in CMBS offer rates causes borrowing costs to rise by 17bp on average.[28] The pass-through of the shock is more significant for

[28]The cost to those who originate their loan with another lender type is about 10bp. This can be derived from

loans backing larger properties, with average borrowing rates rising by around 20bp. As CMBS have a lower required rate of return for larger loans, balance sheet lenders are a less viable substitute. The lack of a close substitute results in more loans being made at the higher CMBS interest rate, rather than switching to another lender type.

### 3.8 Counterfactuals: The Effect of Targeted Regulation

Similarly of interest is how CRE markets would respond to regulation that changed the pricing of a particular characteristic at a specific lender type instead of flatly affecting all loans of a particular lender type. The substitution patterns resulting from such a change are more complex as there start to be multiple effects that may work in opposing directions. For example, a policy causing CMBS lenders to become more concerned about making large loans could have ambiguous effects. CMBS loans would become more expensive, on average, which has been shown to cause smaller loans to migrate to other lenders. However, the policy disproportionately affects pricing on larger loans, and could therefore cause larger outflows of such loans. Whether CMBS lose more loans from larger or smaller properties would depend on the relative strength of these substitution and pricing effects.

We focus on the effect of changing the pricing of LTV. This pricing change is perhaps most pertinent, as all three institutions have been subjected to some regulation in recent memory that could affect risk tolerance and loan pricing: bank capital became subject to stress tests in 2011, CMBS loans became subject to risk retention at the end of 2016, and life insurers had a significant change to CRE capital requirements in 2014. How could such rule changes affect borrowing costs and the allocation of lending across the different participants?

We simulate the effect of a policy that increases banks' required return on a loan by 1 basis point for every basis point increase in LTV above 0.6. The effect of this change in market shares and borrowing costs is shown in Figure 8. We can see that the effect of the shock nearly passes through completely into loans rates. At an LTV of 75%, the 15bp increase in borrowing costs results in only about 18% of loans switching to being funded by

the following: 17bp $\approx$ 55% $\times$ 25bp + 45% $\times$ $z_t$bp, where $z_t$ is the cost to those who switch to borrowing from another lender type. In this case, $z_t$ = 10.

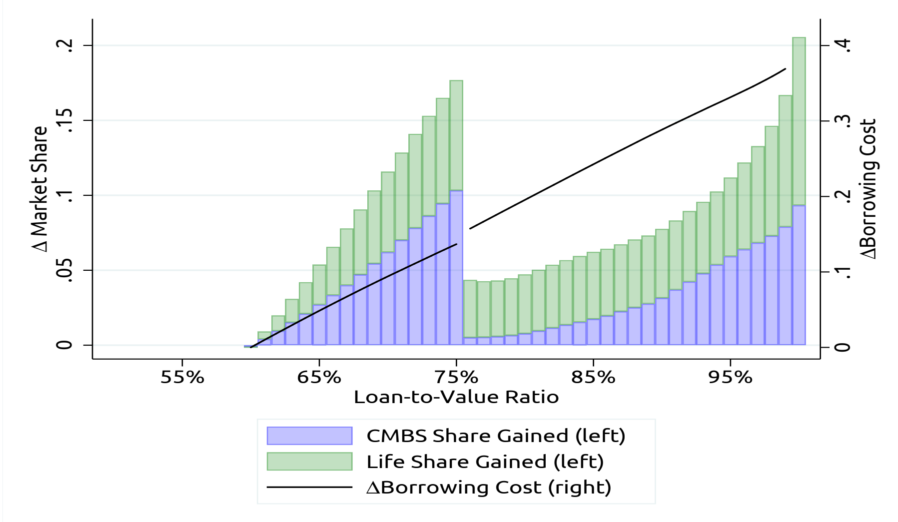



**Figure 8:** Effect of Banks Increasing Rates by $\max\{0, \text{LTV}_i - 0.6\}$

Notes: This figure plots estimates for the share of bank loans that would switch to other lenders (left axis) and the change in interest rates for bank borrowers (right axis) resulting from an increase in bank loan rates of $\max\{0, \text{LTV}_i - 0.6\}$. The height of the blue and green bars show the estimated share of bank loans at a particular LTV switching to CMBS and life insurers, respectively. These estimates come from local linear regressions of borrower outcomes on loan LTVs for the set of loans simulated as being made by banks before the supply shock. The dependent variables are indicators for whether bank loans switched to CMBS/life insurers due to the shock, and the change in borrowing costs due to the shock.

other lenders, and the average cost to borrowers is only slightly below 15bp.

Loans with an LTV above 0.75 are much less likely to switch over. Although the increase in the required rate of return for these high LTV loans is higher than those for lower LTVs, these loans are less likely to move away from banks because of the strict LTV limits at CMBS and life insurers. As a result, the pass-through of the policy to rates is marginally higher, and the share of loans leaving the banking sector is smaller. Although the regulation makes high LTV loan rates more costly, banks' dominance in this area means that bank lending falls less for high LTV loans than for intermediate LTV loans.[29]

Altogether, the response to targeted regulation parallels some of the earlier findings on how the market responds to a shock. If only one lender type dominates a subset of the market, shocks raise the cost of borrowing—at least in the short run.[30] If there are multiple

[29]While we show that banks likely would continue to dominate high LTV lending, this does not necessarily mean that borrowers will continue to take out high LTV loans at the given rate. If the higher interest rates induce a borrower to switch from an 80% LTV bank loan to a 70% LTV life insurance loan, this would indicate that the policy successfully reduced risk both overall and in the banking sector in particular. We would need a more complicated model to analyze such effects.

[30]In the longer run, if other lenders enter the market, then there will potentially be compositional changes in lending, as we find for small loans in response to shocks to CMBS. Understanding the conditions for lender

lenders that compete in that subset of the market, there can be nontrivial compositional changes in which lender takes-up new lending, and from the perspective of borrowers, the cost of targeted regulation can be significantly dampened.

## 4 Conclusion

Three intermediary types provision most CRE lending in the United States: banks, life insurers, and CMBS lenders. We harmonize comprehensive loan-level data sources across lender types, and identify key loan terms and property characteristics along which intermediaries segment themselves. We then build a simple model that is informed by the incentives facing the lender types, and estimate how various loan terms and property characteristics differentially affect the required return across the lender types.

The model allows us to put an estimate on the value to borrowers of having access to different types of lenders that vary in how they are regulated and funded. The ability to switch lenders offsets about one-quarter of a 25 basis point shock to CMBS interest rates in our preferred specification.

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# A Harmonized Originations Data - Further Details

This appendix provides more details on the construction of the harmonized dataset of loan originations described in Section 2. It is useful to first discuss a few further details on the cleaning of each dataset that were not described in the text.

The data on banks from the Y-14Q Schedule H.2 was downloaded from the Wholesale

Data Mart (WDM), which is maintained by staff at the Federal Reserve Bank of Chicago.[31] While the data are quarterly, we are interested in loan originations, so we keep the observation from the earliest date that a loan number (MDRM G063) appears. We keep observations where the line reported on the FR Y-9C (MDRM K449) is 5 or 6, so the loan is listed as either nonfarm nonresidential or owner occupied (and not construction, multifamily, or other). We only keep observations that have nonmissing maturity dates (MDRM 9914) and origination dates (MDRM 9912), and, from these variables, we construct loan time to maturity at origination. We only keep observations that have a property type (MDRM K451) equal to 1, 2, 3, or 7 (Retail, Industrial/Warehouse, Hotel/Hospitality/Gaming, or Office, respectively). Our loan-to-value (LTV) ratio measure is constructed by taking the ratio of the loan's committed exposure (the loan size) to the current value (MDRM M209). The other variables used in our analysis are the 5-digit zip code of the property (MDRM K453), interest rate variability category (MDRM K461), and the interest rate (MDRM 7889).

The Morningstar data are a monthly panel, but we take data from the earliest observation for each loan prospectus id within each CMBS deal. We only keep property types labeled as "Retail," "Office," "Hotel," or "Industrial." We also drop loans from pools where the deal id has a prefix of "FREM" or "FHLK" to drop agency loans. The main variables of interest are the dates of origination and maturity, the initial outstanding balance amount, the interest rate (gross coupon rate), the LTV at origination, the property type, and interest rate variability.

Identifying loans by deal id and loan prospectus id would result in some double counting as occasionally CMBS loans are split into several Pari Passu notes and distributed across multiple pools. For example, instead of one $60 million dollar loan against a $100 million property appearing in the data, two $30 million dollar loans would appear, each with a $100 million property value, 60% LTV, and identical terms. We aggregate these observations to a single loan, taking the total loan balance across the Pari Passu notes, the modal outcome for categorical variables (dates, zip codes, and property types), and the balance-weighted

[31]The instruction and reporting forms for the Y-14Q Schedule H.2 can be found here: `https://www.federalreserve.gov/apps/reportforms/reporthistory.aspx?sOoYJ+5BzDZGWnsSjRJKDwRxOb5Kb1hL`.

average for continuous variables (LTV, interest rates, and property value).[32] We treat CMBS deals identified as ”Single Property” that include multiple notes analogously.

We study originations of commercial loans from the mortgage origination/acquisition schedule (Schedule B - Part 2), which has all originations and acquisitions for each insurer. We include the data from both general and separate accounts, where each insurer is identified by its unique identifier, or "Cocode." For each loan, we have information on the zip code, property type, interest rate, book value, appraised value of land and buildings, and dates of maturity and acquisition. To backfill whether the loan is fixed or floating, we also obtain panel data on the year-end balances for the insurers from Schedule B - Part 1. Because loans are uniquely identified within an insurer, we can see if the loan's interest rate is constant over time. If the loan has the same interest rate in each year, we assume the loan is fixed. It is possible some of these loans are mixed rate, but anecdotal evidence suggests they are not.

We append the three datasets of originations by lender type and date. In the appended data, as noted in the text, we only keep loan originations between 2012 and 2017. We drop any observations from any source if the loan size is below $1 million or missing; the duration of the loan is reported as being negative, over 60 years, or missing; the interest rate on the loan is less than 0.5%, over 25%, or missing; or LTV is less than zero, greater than 1.5, or missing.

## B Geographic Differences across Lender Types

In addition to lenders differing on loan terms and building characteristics as discussed in Section 2.3, lenders also differ is in the geographic distribution of where they originate loans. This section studies the properties of markets in which the different lenders operate. Although 97% of the loans in our sample come from core-based statistical areas (CBSA) where all three lender types participate, we show there are some differences on the intensive margin.

Table B.1 presents summary statistics pertaining to various CBSA-level characteristics

[32] In almost all cases, these variables are the same across loans with a common Pari Passu id, with most of the exceptions involving missing data. Consequently, the means of aggregation for these loan terms is mostly irrelevant.

Table B.1
Geographic Differences in CRE Originations

| | Bank Loans | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Mean | Std | p01 | p25 | p50 | p75 | p99 | N |
| Vacancy rate (%) | 12.16 | 5.63 | 4.00 | 8.70 | 11.10 | 14.20 | 34.90 | 25,471 |
| Cap rate (%) | 5.42 | 0.97 | 3.70 | 4.78 | 5.27 | 5.85 | 8.39 | 25,471 |
| Std. dev. of NOI index | 6.50 | 5.79 | 0.95 | 2.82 | 5.02 | 7.87 | 35.33 | 25,454 |
| Unemployment rate (%) | 6.12 | 2.03 | 2.86 | 4.67 | 5.67 | 7.30 | 11.70 | 35,700 |
| Gateway City | 0.27 | 0.45 | 0.00 | 0.00 | 0.00 | 1.00 | 1.00 | 38,457 |
| | CMBS Loans | | | | | | | |
| | Mean | Std | p01 | p25 | p50 | p75 | p99 | N |
| Vacancy rate (%) | 14.55 | 7.41 | 5.40 | 9.70 | 12.60 | 15.90 | 39.70 | 7,203 |
| Cap rate (%) | 5.80 | 1.21 | 3.74 | 4.96 | 5.49 | 6.22 | 8.59 | 7,203 |
| Std. dev. of NOI index | 6.97 | 6.15 | 0.90 | 2.87 | 5.63 | 8.68 | 35.33 | 7,227 |
| Unemployment rate (%) | 5.90 | 1.89 | 2.87 | 4.65 | 5.54 | 6.83 | 11.10 | 9,623 |
| Gateway City | 0.21 | 0.41 | 0.00 | 0.00 | 0.00 | 0.00 | 1.00 | 10,353 |
| | Life Insurance Loans | | | | | | | |
| | Mean | Std | p01 | p25 | p50 | p75 | p99 | N |
| Vacancy rate (%) | 11.20 | 4.51 | 4.00 | 8.10 | 10.50 | 13.40 | 28.60 | 14,911 |
| Cap rate (%) | 5.39 | 0.86 | 3.74 | 4.80 | 5.31 | 5.84 | 8.21 | 14,911 |
| Std. dev. of NOI index | 6.35 | 5.42 | 0.95 | 2.75 | 5.27 | 8.14 | 35.33 | 14,818 |
| Unemployment rate (%) | 5.72 | 1.81 | 2.81 | 4.44 | 5.31 | 6.72 | 10.72 | 17,969 |
| Gateway City | 0.27 | 0.44 | 0.00 | 0.00 | 0.00 | 1.00 | 1.00 | 18,966 |

Notes: This table presents summary statistics for geographic risk measures by lender type. Vacancy rate and cap rate come from CBRE and are available at the property type-MSA-quarter level. NOI volatility is also from CBRE, and is at the property type-MSA level, with the standard deviation of NOI computed on data from 1983:Q4 to 2018:Q4. The unemployment rate is from the U.S. Bureau of Labor Statistics' Local Area Unemployment Statistics aggregated to the CBSA level. We define gateway cities as New York, Boston, Chicago, Los Angeles, San Francisco, and Washington, D.C.

for the markets in which the different intermediaries originate loans.[33] We look at how loans differ in the local vacancy rate, measuring the estimated percent of space for a given property type that is vacant in a given MSA-quarter, the cap rate, measuring the ratio of net operating income (NOI) to property value in an MSA-quarter, the volatility of NOI for a given property type in an MSA, the unemployment rate in a CBSA-quarter, and whether or not the loan is in a gateway city.

In general, life insurers seem to disproportionately lend in more stable markets (lower vacancy rates, less volatile NOI, and lower unemployment), while CMBS are more exposed

[33]Summary statistics exclude about 5,000 loans backed by properties in multiple zip codes.

to relatively volatile markets. The most prominent difference is in vacancy rate, where life insurers originate loans in property type-MSA-quarters where the vacancy rate is about 11% on average, compared to about 12% and 15% for banks and CMBS, respectively. Differences in NOI volatility are similar, with life insurers making loans where NOI is least volatile and CMBS where NOI is most volatile. Life insurers also make loans in CBSA-quarters with the lowest average unemployment rate. In contrast to the more CRE-specific risk measures, banks are found to make loans in areas with higher unemployment than CMBS. These differences seem to be reflected in the cap rates in the markets where the lenders operate. Lower risk for properties in a given area would make borrowers willing to accept a lower return on a property, resulting in lower cap rates. We indeed see that life insurers operate in markets with the lowest cap rates, although they are not too different from banks, while CMBS lend in markets with the highest cap rates. Some of these differences are potentially due to balance sheet lenders making more loans in gateway cities, where demand for properties is relatively more stable.

However, the unconditional averages are unlikely to entirely reflect geographic differences. Since many variables are defined by both property type and location, some of the differences could be due to the differences in property types shown in Table 2 instead of geographic differences. Likewise, some findings could reflect time series differences if some lenders did more lending soon after the crisis when unemployment was still elevated and others increased lending deeper into the recovery. Table B.2 presents results from regressing these geographic risk measures on lender type dummies using property type and year-quarter fixed effects to account for the non-geographic variation in these risk factors.

Once controls are included, differences across lenders are qualitatively similar, but mostly smaller. The higher vacancy rate for CMBS loans relative to banks is still statistically significant, but smaller. As hotels have the highest vacancy rates on average, the higher values for CMBS reflect not only geographic differences, but also differences in property types. Differences in NOI variability similarly drop by about a factor of four when controls are added. Additionally, we no longer find a higher unemployment rate for banks' markets relative to those of CMBS when controls are included. This indicates that the unconditional

Table B.2
Geographic Differences with Controls

| | Vacancy Rate | | NOI Volatility | | Unemployment Rate | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| CMBS | 2.40** | 0.67** | $0.47^{+}$ | 0.16 | -0.21* | -0.01 |
| | (0.38) | (0.22) | (0.28) | (0.26) | (0.09) | (0.04) |
| Life | -0.95* | 0.01 | -0.15 | 0.04 | -0.40** | -0.15** |
| | (0.37) | (0.22) | (0.31) | (0.28) | (0.07) | (0.04) |
| Hotel | | 11.73** | | 5.65** | | -0.01 |
| | | (0.38) | | (0.42) | | (0.05) |
| Retail | | -3.51** | | -4.38** | | 0.19** |
| | | (0.11) | | (0.31) | | (0.02) |
| Industrial | | -4.45** | | $0.36^{+}$ | | 0.21** |
| | | (0.21) | | (0.21) | | (0.04) |
| Constant | 12.16** | 13.48** | 6.50** | 7.65** | 6.12** | 5.90** |
| | (0.36) | (0.17) | (0.27) | (0.43) | (0.05) | (0.04) |
| Year-Qtr FE | | Yes | | Yes | | Yes |
| $R^2_a$ | 0.035 | 0.599 | 0.001 | 0.260 | 0.008 | 0.546 |
| Obs. | 47585 | 47585 | 47499 | 47499 | 63292 | 63292 |

Notes: This table reports results from OLS regressions of geographic risk factors on lender type and property type dummies, and year-quarter fixed effects. The dependent variable is the vacancy rate for the property type-MSA-year-quarter in the first two columns, the volatility of net operating income for a property type-MSA in the middle two columns, and the quarterly core-based statistical area unemployment rate in the last two columns. Odd columns only include lender type dummies as independent variables, while even columns additionally include property type and year-quarter fixed effects. Standard errors, in parentheses, are clustered at the level of the entity holding the loan (the bank, life insurer, or CMBS deal)

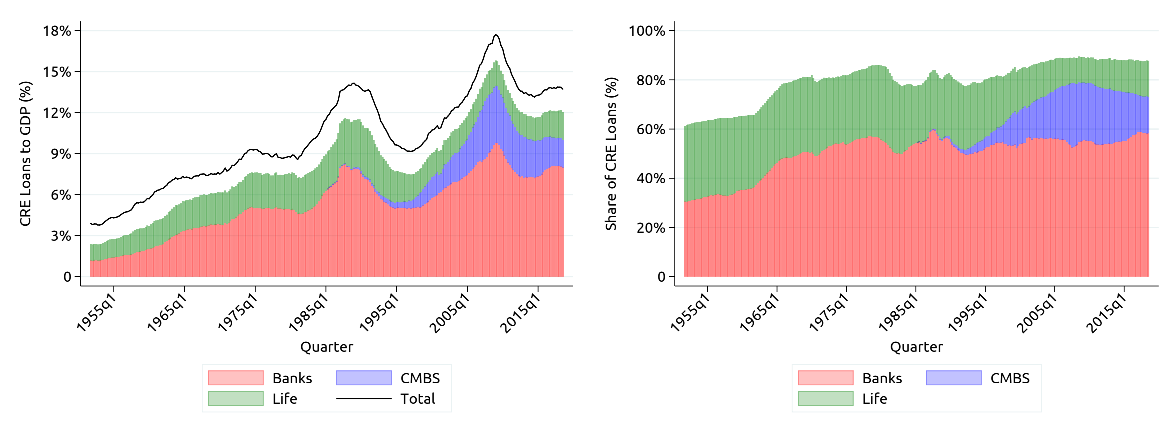
averages are driven by the slow recovery in CMBS lending after the crisis, which resulted in fewer loans in the early years when unemployment was still high.

Life insurers still seem to operate in the safest markets, but this finding is again weaker after accounting for controls. Life insurers are no longer found to operate in areas with lower vacancy rates or NOI compared with banks once controls are included. The unconditional difference from banks thus had more to do with life insurers being underweight in property types like hotels, which have higher vacancy rates and more volatile NOIs. Life insurers were still found to operate in areas with lower unemployment rates compared to the other lenders.

# C Further Details on the CRE Market

## History

The size of the commercial mortgage market has grown notably relative to the broader economy, rising from about 4% of GDP in 1951 to around 14% now (see Figure B.1). Banks account for a bit over half of this debt, with most of the remainder accounted for by commercial mortgage backed securities (CMBS) and life insurers. Life insurers used to play a larger role in the market, with commercial real estate (CRE) portfolios almost as large as banks, but they have ceded market share to CMBS since the 1980s savings and loan crisis.[34]




**(a)** As a percent of GDP

**(b)** As a percent of total CRE lending

**Figure C.1:** CRE Lending in the United States

Figure (a) is a stacked area chart of lending by banks (U.S.-chartered depository institutions - Flow of Funds Table L.220 - FL763065503.Q), life insurers (Life insurance companies - Flow of Funds Table L.220 - FL543065505.Q), and CMBS lenders (Issuers of asset-backed securities - Flow of Funds Table L.220 - FL673065505.Q), as a percent of U.S. nominal GDP. Figure (b) is a stacked area chart of lending by intermediary type as a percent of total CRE lending (Flow of Funds Table L.220 - FL893065505.Q). The data is quarterly and spans from 1951:Q4-2018:Q3.

Perhaps more eye-catching than any change in the composition of the lenders are the two boom-and-bust periods for the commercial mortgage market. The first such period occurred in the 1980s, in the period surrounding the savings and loan crisis, and the second occurred in the 2000s, in the period around the global financial crisis. Each downturn

[34]Life insurers are large holders of CMBS, so this decline in market share does not necessarily reflect a pull back from the CRE market. Reorienting investment from direct CRE loans to highly rated CMBS tranches may allow life insurers to maintain CRE exposure but hold assets with risk and liquidity characteristics they find more desirable.

resulted in the size of the commercial mortgage market dropping by almost 5% of GDP, financial institutions failing in large numbers, and eventually a regulatory overhaul for CRE lenders.

The first boom period occurred following the passage of the Economic Recovery Tax Act of 1981, which increased the demand for CRE by allowing for more rapid depreciation of assets, thus increasing discounted after-tax returns on CRE investments (Freund et al., 1997). Meanwhile, financial institutions were more than happy to meet this demand. The Depository Institutions Deregulation and Monetary Control Act of 1980 and the Garn-St Germain Depository Institutions Act of 1982 expanded allowances of savings and loans (S&Ls) to hold commercial mortgages and risky acquisition, development, and construction loans (Moysich, 1997). At the same time, commercial banks were incentivized to expand CRE lending to offset the loss of commercial clients to bond and commercial paper markets (Garner, 2008), while life insurers were increasing CRE exposure to maintain high returns to better compete for customer savings (Wright, 1991; Brewer III et al., 1993).[35]

Between the effects of earlier overbuilding and the removal of favorable tax treatment of CRE in the Tax Reform Act of 1986, the CRE market turned in the mid-1980s (Hendershott and Kane, 1992). Vacancy rates rose, prices fell, and loan delinquencies spiked. After S&L failures picked up in the second half of the decade, the Financial Institutions Reform, Recovery, and Enforcement Act of 1989 (FIRREA) was passed to deal with failing S&L's. It created the Resolution Trust Corporation (RTC) to close insolvent S&Ls while raising capital requirements and reimposing asset restrictions. The reinforcing relationship between loan losses and tightening credit along with the effects of the 1990-91 recession resulted in the CRE market continuing to decline into the mid-1990s.

A notable development coming out of this period was a swelling in CMBS volume. The RTC, when faced with the task of disposing of a large volume of CRE loans from failed S&Ls at a time when portfolio lenders were not looking to increase CRE exposure, turned

[35] Intense competition for consumer savings and for pension funds pressured insurers to develop interest rate sensitive products to compete. Over the course of the 1980s, life insurance companies shifted from predominately funding themselves through the sale of life insurance policies to funding themselves through the sales of annuities. Some insurers guaranteed excessively high interest rates and sought high risk investments such as junk bonds or real estate ventures to maintain returns.

to capital markets. The RTC used CMBS to sell loans in bulk in the early 1990s. Later in the decade, CMBS transitioned from being a means of selling seasoned loans from failed lenders to being a source of financing for new CRE originations, allowing property owners to access broader capital markets to finance themselves.

Partly buoyed by this expansion of the CMBS market, there was a second boom in CRE lending from the late 1990s to the mid-2000s. While the rapid expansion in the CRE market during this time is less emphasized than the concurrent expansion for residential mortgages, many similar factors were in play. Originators capitalized on strong demand for securitized products, resulting in eroding standards and accelerating CMBS issuance. While the adverse effects of an originate-to-distribute model were supposed to be offset by knowledgeable B-piece buyers maintaining a first-loss position in CMBS pools, these buyers were able sell these investments into collateralized debt obligations. As a result, many CMBS investments were made with informed investors having little skin in the game (Ashcraft et. al., forthcoming). However, securitization was not the only tailwind supporting the debt expansion. Banks also increased CRE lending for their own balance sheets, with the most dramatic expansion occurring for construction loans.

The size of the CRE market again sharply reverted during the financial crisis, with the CMBS market shutting down from late-2008 to 2009, and banks struggling with losses from delinquent loans. Since then, life insurers, who dodged the escalating CRE delinquencies faced by banks and CMBS, have regained some CRE market share and have been slowly increasing CRE concentration. Meanwhile, all major lenders received significant changes to how they are regulated. Banks have revised capital rules through Basel III, and their portfolios are now subject to stress tests. Life insurers have a new scheme for risk weighting their CRE portfolio. Finally, CMBS now are subject to risk retention rules.

### Capital requirements

The treatment of commercial real estate with regards to capital requirements has changed over time, as regulators have reacted to vulnerabilities that became apparent in the periods of stress discussed in our overview of the history of the market. Here, we discuss the design of capital requirements for banks and life insurers and how they have changed over time.

**Life insurers** The experience in the 1980s, with life insurers offering high guaranteed returns to attract customers and seeking risky investments in real estate ventures or junk bonds to maintain such returns, demonstrated the need for more risk-sensitive capital requirements for life insurers to curb risk taking (Webb and Lilly III, 1995). The National Association of Insurance Commissioners (NAIC) created a working group in 1990 to study the feasibility of risk-based capital (RBC) regulation. The RBC rule was then approved in December 1992 and went into effect in 1993.

The rule formed an RBC requirement reflecting a set of risk factors for insurers, and specified the regulatory actions to occur when a life insurer's ratio of total adjusted capital (TAC) to their RBC requirement fell below certain levels.[36] The factor for investment risk looks a lot like it does for banks. The investment risk factor is a linear combination of the value of different investment types with different weights for each investment reflecting the risk of the investment. However, unlike for banks, CRE capital requirements were historically highly sensitive to the risk of a given insurer's CRE portfolio.

Until 2014, mortgages in good standing were given a risk factor of 2.6% times a mortgage experience adjustment factor (MEAF), with a minimum of 0.5 and maximum of 3.5, reflecting the performance of a given life insurer's CRE portfolio relative to other life insurers over the previous two years. Life insurers for whom a larger percentage of their portfolio consists of loans that were restructured, delinquent, in the process of foreclosure, or foreclosed upon thus had higher risk weights on mortgages in the following couple of years. As a result, troubled loans affected capital requirements both by increasing the risk weight for a given

[36] The RBC requirement is a function of six risk factors: RBC requirement = $R_0 + \sqrt{\sum_{i=1}^{5} R_i^2}$. Each $R_i$ represents a particular risk factor: $R_0$:off-balance sheet/business risk; $R_1$:investment/interest rate risk (bonds and mortgages); $R_2$:equity risk; $R_3$: insurance risk (e.g., underpricing policies, mortality risk); $R_4$: health provider risk; $R_5$: business risk (health administrative expense risk).

Regulatory intervention depends on the ratio of total adjusted capital ($TAC$) to the risk-based capital requirement ($RBC$), where total adjusted capital = unassigned surplus + asset valuation reserve + .5 $*$ dividend liability.

The thresholds for intervention are as follows. No Action: $\frac{TAC}{RBC}>2$; Company Action level: $\frac{TAC}{RBC}<2$ (company submits plan to improve capital); Regulatory Action: $\frac{TAC}{RBC}<1.5$ (regulator specified corrective action); authorized control: $\frac{TAC}{RBC}<1$ (regulator may take control of LIC); mandatory control: $\frac{TAC}{RBC}<.7$ (regulator takes control of LIC). It is important to note that credit ratings or loan covenants may also depend on the RBC ratio, thus RBC may be a relevant constraint even for an insurer far from the company action level.

loan (9% weight for restructured mortgages, 18% for loans 90 days past due, and 23% for loans in foreclosure), and by increasing the MEAF, which increased the risk weight for the entire portfolio of loans still in good standing.[37]

This penalty for holding distressed loans encouraged life insurance companies to only make the safest loans. As a result, delinquencies for life insurers remained very low, even as delinquencies for other CRE lenders rose during the great recession. The low industry-wide holdings of distressed loans meant that even a modest rate of mortgage distress at a given company could result in significant swings in the performance of a given life insurer's portfolio relative to the industry average, and thus dramatic changes in capital requirements. For example, Conseco reported in their 2008 10-K filing that the foreclosure on two loans with a book value of $20 million increased their risk-based capital by $42 million, pushing the company close to an RBC ratio that would result in a covenant violation.

The risk weighting for CRE loans changed in 2014, so that the risk weight on one loan no longer depended on the performance of other loans. Although the new requirements reduced the penalties for having restructured or nonperforming loans, capital requirements remain highly sensitive to the risk of the loans in an insurer's portfolio. Capital requirements now depend on property type, LTV, and debt service coverage ratios (DSCR).[38] Maintaining the lowest risk factor (0.9%) typically requires a DSCR above 1.5 and an LTV under 85%. These bounds are tighter for hotel loans, which require a minimum DSCR of 1.85 and a maximum LTV of 60% to qualify for the minimum risk factor. If the net operating income or estimated value of a property falls, this can push the loan into another risk bucket and

[37]To give a sense of the magnitude of this effect, banks were required to have a ratio of total capital to risk-weighted assets of 8%, with CRE loans receiving a 100% risk weight, meaning that every $1 in CRE loans needed to be funded with at least 8 cents in equity. Life insurers need to hold capital against investment risks, with CRE loans given a risk factor of 2.6%. Life insurers are required to have a ratio of capital to risk-weighted capital of 2 to avoid supervisory action, meaning on average $1 in CRE loans needed to be funded with at least 5.6 cents in equity. However, this is multiplied by the MEAF reflecting recent loan performance for the insurer. This factor ranged from 0.5 to 3.5, meaning the amount of capital required to fund a loan ranged from 2.6% to 16.1%, depending on the performance of the CRE portfolio over the previous two years.

[38]LTV is the ratio of the outstanding balance on the loan to the contemporaneous value of the property, where the contemporaneous value is based on the last appraisal rescaled by the growth in the NCREIF price index since the appraisal. DSCR is the ratio of net operating income to the cost of debt service. Net operating income is measured as a rolling average from the past three years of financial statements, and debt service costs are the interest and principle payments given the loan's interest rate and balance, assuming a 300-month amortization period.

raise the risk factor up to a maximum of 7.5%.[39] Restructured mortgages no longer receive a higher risk factor, while loans which are delinquent and in the process of foreclosure continued to have risk factors of 18% and 23%.[40]

**Banks** Banks began facing risk-based capital requirements in the aftermath of the S&L crisis. The 1988 Basel Accord grouped banks' assets in broad categories by credit risk and set a minimum level of bank equity as a percentage of a bank's risk-weighted assets. Although these rules have been revised several times, the treatment of CRE loans has been fairly consistent, with CRE loans being given a 100% risk weight in each new iteration of Basel rules.[41] As of the end of 2018, banks have a minimum tier one capital to risk-weighted asset ratio of 6% and a capital conservation buffer of 2.5%. This means that banks with a tier 1 capital ratio under 8.5% are subject to restrictions on capital distributions and discretionary payments, and banks with a tier 1 ratio under 6% are deemed to be undercapitalized, triggering restrictions on expansion and requiring the bank to file a capital restoration plan. Given the 100% risk weight on CRE, banks need 8.5 cents in equity for every extra dollar of CRE lending to avoid facing such restrictions.

With a fixed risk weight for all CRE loans, banks would not need to use more capital to fund a particularly risky CRE loan than a particularly safe one. This stands in contrast to risk weights for life insurers who have capital requirements that are highly sensitive to the risk of the particular CRE loans in their portfolio.

Larger banks however are subject to other capital requirements in addition to the "standard approach" capital requirements already discussed. Basel II introduced an internal ratings-based approach for risk-based capital requirements for large banks whereby risk weights are a function of a loan's model-based estimates of loss likelihood and severity. Additionally, since the financial crisis, large banks are subject to the Comprehensive Capital Analysis and Review, which requires that a bank's equity is sufficient to still satisfy

[39] For most properties, this happens with a DSCR<0.95 or LTV>1.05; for hotels and specialty commercial the DSCR and LTV thresholds are 1.10 and 90% respectively.

[40] The final instructions for the revised CRE capital requirements are here: `https://www.naic.org/documents/committees_e_capad_lrbc_final_instructions.pdf`.

[41] An exception is the High Volatility Commercial Real Estate rule in Basel III, which increased capital requirements to 150% for high-leverage construction loans.

minimum capital requirements even after nine quarters of macroeconomic distress. These requirements are more sensitive to the underlying risk of a loan, as riskier loans have higher internal ratings based capital requirements, and result in larger projected losses under stress, resulting in lower post-stress capitalization.

**Effect on loan quality** The time series in loan delinquencies is consistent with differences in capital requirements affecting the riskiness of CRE loans across different lender types. Figure B.2 plots the delinquency rates of the three lender types over time using publicly available aggregate data from banks' Call Reports, Morningstar, and the American Council of Life Insurers.[42] We can see that the performance of bank and life insurer CRE loans were comparable in the aftermath of the 1990-91 recession, before the new life insurance risk based capital requirements went into effect. Both experienced significant delinquencies in the early 1990s, which slowly declined over the course of the decade.

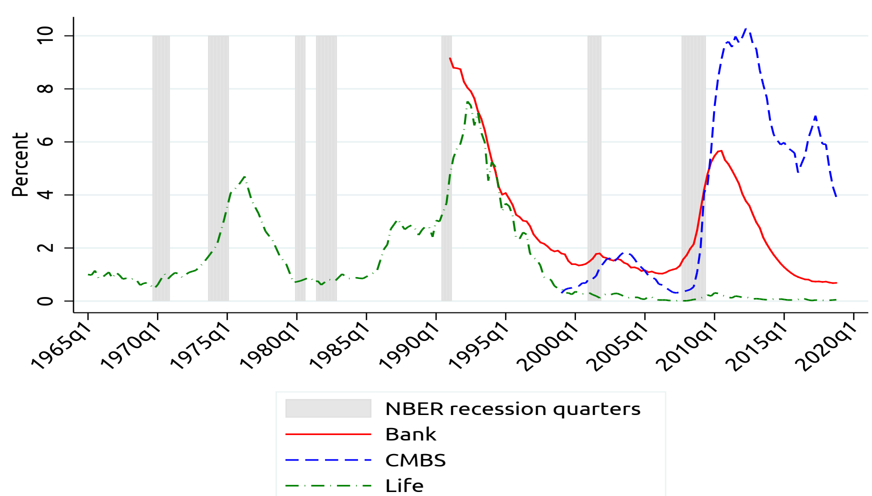



**Figure C.2:** Delinquency Rates by Lender Type

Notes: This figure shows measures of delinquency rates by lender type over time. Bank data starts in 1991:Q1, CMBS data starts in 1999:Q1, and life insurance data starts in 1965:Q1.

After the new risk-based capital requirements went into effect, the performance of life insurance loans and those of other lenders diverged. By 2000, the delinquency rate was negligible for life insurers. Their delinquency rate then remained near 0 thereafter, even

[42]The measures are imperfect, as the CMBS measure includes agency loans, while the bank measure includes construction lending.

as banks and CMBS faced modest increases in delinquencies after the dot-com crash and dramatic increases in delinquencies after the financial crisis.

# D Pricing Regressions

This section presents OLS estimates of how each lender type prices observable loan characteristics and presents results of such regressions on data simulated using the model in Section 3. This has two purposes. First, it provides more detail on how $\sigma$ and $\beta_{\text{Bank}}$ were calibrated. Second, it highlights the need for a structural model to estimate how intermediaries price loan characteristics. In particular, we show that direct pricing regressions are subject to selection bias.

## D.1 Parameter calibration

Recall that we are interested in estimating how lenders price particular loan terms. The multinomial logit specification described in Section 3, under the assumed data-generating process, can identify these lender specific pricing terms relative to a baseline group and up to a scale parameter. Namely, $\hat{\beta}_{\text{j}}^{\text{Logit}}$ provides an estimate of $\frac{1}{\sigma}(\beta_{\text{Bank}} - \beta_{\text{j}})$. To estimate the lender specific elasticities ($\beta_j$), we choose $\beta_{\text{Bank}}$ and $\sigma$ so that regressions on simulated data match those on the actual data.

Our simulation process is as follows:

(i) Take the original data set of N loans and create 19 duplicates of each loan. We do this to maintain the same distribution of loan characteristics as in the actual data but limit the effects of sampling error when we draw error terms.

(ii) Draw $N \times 20 \times 3$ i.i.d. error terms from a type-I extreme value distribution—one for each observation and lender type in the simulation data set. Denote the error for loan $i$ from lender $j$ as $\epsilon_{i,j}^{\text{Sim}}$.

(iii) Simulate the offer rate for each loan and lender using characteristics $X_i$, logit estimates for pricing factors $\hat{\beta}_j^{\text{Logit}}$, and the idiosyncratic match $\epsilon_{i,j}^{\text{Sim}}$. Denote the offer rate as

$R_{i,j}^{\text{Sim}} = -X_i'\hat{\beta}_j^{\text{Logit}} - \epsilon_{i,j}^{\text{Sim}}$. Note that $\hat{\beta}_{Bank}^{Logit}$ is a zero vector as the logit coefficients reflect pricing relative to banks.

(iv) Identify the equilibrium lender and loan rate given the set of offer rates.

$$\text{Lender}_i = \text{argmin}_{j' \in J}\{R_{i,j'}^{\text{Sim}}\},$$

where $R_i^{\text{Sim}} = \min_{j \in J}\{R_{i,j}^{\text{Sim}}\}$.

(v) Calculate OLS estimates of pricing factors from simulated data. Denote $\hat{\beta}_j^{\text{OLS,Sim}}$ as the vector of coefficients from regressing $R_{i,j}^{\text{Sim}}$ on $X_i$ for the set of loans such that $j = \text{argmin}_{j' \in J}\{R_{i,j'}^{\text{Sim}}\}$. And denote $\hat{\beta}^{\text{OLS,Sim}}$ as the coefficient from regressing $R_i^{\text{Sim}}$ on observable characteristics for the whole sample.

We also run equivalent regressions based on the actual lender types and interest rate. Denote $\hat{\beta}_j^{OLS,\text{Data}}$ as the coefficients from regressing interest rate spreads on characteristics for the set of loans from lender type $j$, and $\hat{\beta}^{OLS,\text{Data}}$ as the coefficient vector for the same regression over the full set of loans. The first four columns of Table D.1 present these coefficient estimates based on actual lender types and loan rate spreads, while the last four columns present the equivalent coefficients using the simulated interest spreads and lender types.

Since $\sigma$, the scale parameter, affects the dispersion in the pricing of terms across lender types, we calibrate it so as to match the dispersion in predicted interest rates across lender types. Specifically, we take the pricing coefficients in the first three columns, based on the regressions from the actual data, and calculate the predicted offer rates for each loan and lender type. We then compute the standard deviations in the predicted offer rate, $\text{sd}(X_i'\hat{\beta}_j^{OLS,\text{Data}})$, across the different lender types by loan. We analogously compute the dispersion in predicted offer rates using the simulated regression coefficients from columns (5)-(7). We thus can calibrate $\sigma$ as $\hat{\sigma} = \text{E}_i(\text{sd}(X_i'\beta_j^{OLS,\text{Data}})/\text{E}_i(\text{sd}(X_i'\beta_j^{OLS,\text{Sim}})$, where $\text{E}_i()$ is the expectation over loans.

Since $\beta_{\text{Bank}}$ controls the level of the effect of a characteristic on loan rates, $\hat{\beta}_{\text{Bank}}$ is

Table D.1
Pricing Regressions for Parameter Calibration

| | $\beta^{\text{OLS,Data}}_{\text{Bank}}$ | $\beta^{\text{OLS,Data}}_{\text{CMBS}}$ | $\beta^{\text{OLS,Data}}_{\text{Life}}$ | $\beta^{\text{OLS,Data}}$ | $\beta^{\text{OLS,Sim}}_{\text{Bank}}$ | $\beta^{\text{OLS,Sim}}_{\text{CMBS}}$ | $\beta^{\text{OLS,Sim}}_{\text{Life}}$ | $\beta^{\text{OLS,Sim}}$ |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Term (years) | -0.04** | -0.15** | -0.04** | -0.04** | -0.06** | -0.20** | -0.28** | -0.18** |
| | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) |
| ln(Value) | -0.12** | -0.12** | -0.12** | -0.10** | -0.11** | -0.64** | -0.40** | -0.22** |
| | (0.00) | (0.01) | (0.01) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) |
| Loan-to-value ratio | -0.33** | 0.57** | -0.07 | -0.10** | -0.80** | -6.89** | -2.11** | -1.15** |
| | (0.03) | (0.08) | (0.06) | (0.02) | (0.01) | (0.02) | (0.01) | (0.01) |
| LTV $>$ 0.75 | 0.24** | 0.54** | 0.27** | 0.21** | 0.41** | 3.05** | 1.70** | 0.40** |
| | (0.02) | (0.05) | (0.05) | (0.01) | (0.00) | (0.01) | (0.01) | (0.00) |
| Hotel | 0.47** | 0.30** | 0.60** | 0.49** | -0.08** | -1.03** | 0.29** | -0.22** |
| | (0.02) | (0.02) | (0.04) | (0.01) | (0.00) | (0.00) | (0.01) | (0.00) |
| Retail | -0.02* | -0.00 | -0.03 | -0.00 | -0.07** | -0.60** | -0.11** | -0.09** |
| | (0.01) | (0.02) | (0.02) | (0.01) | (0.00) | (0.00) | (0.00) | (0.00) |
| Industrial | -0.01 | 0.05* | -0.10** | -0.04** | -0.09** | 0.09** | -0.54** | -0.22** |
| | (0.01) | (0.03) | (0.02) | (0.01) | (0.00) | (0.01) | (0.00) | (0.00) |
| Constant | 4.87** | 5.59** | 4.80** | 4.49** | 2.79** | 17.33** | 10.62** | 5.70** |
| | (0.06) | (0.13) | (0.15) | (0.05) | (0.02) | (0.03) | (0.02) | (0.01) |
| $R^2_a$ | 0.073 | 0.260 | 0.115 | 0.121 | 0.076 | 0.705 | 0.837 | 0.505 |
| Obs. | 40024 | 11358 | 13284 | 64666 | 819095 | 213686 | 377739 | 1410520 |

Notes: This table presents the results of pricing regressions using both the loan spreads in the data (columns (1)-(4)), and the simulated loan spreads based on the logit pricing factors and idiosyncratic match pulls (columns (5)-(8)). The first four columns present results from regressing interest rate spreads on loan characteristics for (1) loans held by banks, (2) loans in CMBS pools, (3) loans held by life insurers, and (4) the full sample of loans. The last four columns present results from regressing simulated interest rate spreads on loan characteristics for loans simulated as going to (5) banks, (6) CMBS, (7) life insurers, and (8) the full sample of simulated loans.

chosen so that the coefficients from regressing loan spreads on loan characteristics for the overall sample are the same in the regressions on actual data and in the regressions on simulated data. Namely, we set $\hat{\beta}_{\text{Bank}}$ such that column (8) matches column (4) after rescaling the simulated pricing factors by $\hat{\sigma}$ and shifting by $\hat{\beta}_{\text{Bank}}$. This is accomplished by setting $\hat{\beta}_{\text{Bank}} = \hat{\beta}^{\text{OLS,Data}} - \hat{\sigma}\hat{\beta}^{\text{OLS,Sim}}$.

## D.2 Selection Bias in Pricing Regression

As we have interest rates in our data, one might wonder why we use a model to extrapolate differences in loan pricing based off a discrete choice model when such estimates can be achieved directly from a pricing regression such as in the first three columns of Table D.1.

We show that direct pricing regressions are subject to significant selection bias. If a given lender type makes a loan with observable characteristics that are unfavorable to it, this

Table D.2
Evidence of Selection Bias

| | True $\beta_j$ | | | OLS estimate of $\beta_j$ | | |
|---|---|---|---|---|---|---|
| | Bank | CMBS | Life | Bank | CMBS | Life |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Term | 0.02 | -0.06 | -0.10 | -0.00 | -0.05 | -0.08 |
| Size | -0.02 | -0.30 | -0.16 | -0.06 | -0.25 | -0.16 |
| LTV | 0.32 | -2.87 | -0.29 | 0.03 | -2.20 | -0.45 |
| LTV $>0.75$ | 0.06 | 1.43 | 0.67 | 0.21 | 1.18 | 0.68 |
| Hotel | 0.57 | 0.04 | 0.77 | 0.55 | 0.20 | 0.68 |
| Retail | 0.03 | -0.25 | 0.01 | 0.01 | -0.19 | -0.01 |
| Industrial | 0.04 | 0.12 | -0.21 | 0.01 | 0.07 | -0.16 |
| Constant | 2.40 | 10.25 | 6.45 | 3.42 | 8.74 | 6.29 |

Notes: This table simulates the effect selection bias has on direct pricing regressions. The first three columns show the pricing factors for each lender type and loan characteristic, after shifting and rescaling the logit estimates by $\hat{\beta}$ and $\hat{\sigma}$. The predicted pricing factors for banks are in column (1), for CMBS are in column (2), and for life insurers are in column (3). The last three columns show the OLS estimates of these factors coming from pricing regressions. Each column regresses loan spreads—coming from the pricing vector in the first three columns and an idiosyncratic match term—on loan characteristics for the set of loans simulated as going to a particular lender. The sample includes loans simulated as being made by banks in (4), by CMBS in (5), and by life insurers in (6).

means that unobservable characteristics for that loan must have been enough to compensate. For example, if life insurers are highly risk averse, they might only make high LTV loans to borrowers they know well and have reason to trust. This means that high LTV loans might not have higher interest rates for life insurers, because they all have favorable unobservable characteristics.

Our framework outlined in Section 3 allows us to simulate the likely effect of this bias. We simulate interest rates given logit coefficients and error terms as assumed under the data-generating process in the model. The assumed true betas (shifted and re-scaled) are listed in the first three columns of Table D.2. The coefficient generated by the OLS regression of simulated interest rates is shown in the last three columns.

We can see that the coefficients are biased toward the pricing of other lender types. Namely, OLS estimates preserve the relative ordering of how lenders price different characteristics, but understate the magnitude of the differences. For example, the simulated interest rates for hotel loans give a large pricing advantage to CMBS relative to life insurers, with CMBS requiring a 4bp premium on hotel loans, compared with 77bp for life insurers. The OLS estimates mute these differences, and generate pricing factors of 20bp and 68bp for CMBS and life insurers.[43] Intuitively, given that life insurers are usually reluctant to make hotel loans, when they do make such loans, they probably have a favorable idiosyncratic fit. This correlation between loan characteristics and error terms biases OLS estimates.[44] Similar patterns play out with the other variables as well, with the pricing coefficients of lenders at the extremes generally being biased toward the coefficient of the lender with the intermediate pricing sensitivity.

[43]Regressions using the actual lender type and loan spreads had CMBS requiring a 30bp premium and life insurers a 60bp premium, as shown in Table D.1.

[44]Were we able to observe offer rates for different loan types for the loans, this bias would go away. The problem comes from running the regression for the set of loans such that the lender type had the lowest offer.