Intermediary Segmentation in the Commercial Real Estate Market*

David Glancy†1, John Krainer‡1, Robert Kurtzman§1, and Joseph Nichols¶1

[1]Federal Reserve Board of Governors

June 14, 2021

Abstract

Banks, life insurers, and commercial mortgage-backed security (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 away from CMBS when spreads rose in late 2015 and early 2016. Counterfactuals suggest that the ability to substitute to other lenders offsets about 20% of the effect of a 25 basis point CMBS supply shock.

Keywords: commercial real estate, life insurers, segmentation
JEL Classification: G21, G22, G23, R33

*We thank Eva Steiner and Lara Loewenstein for their thoughtful discussions, Mike Batty and Eileen van Straelen for their helpful insights, and participants at the 2019 System Committee on Financial Institutions, Regulation, and Markets, 2020 American Real Estate and Urban Economics Association National Conference, and 2020 Northern Finance Association Annual Meeting for their helpful comments. The views expressed in this paper are solely the responsibility of the authors and should not be interpreted as reflecting the views of the Board of Governors of the Federal Reserve System or of anyone else associated with the Federal Reserve System.

†Email: david.p.glancy@frb.gov
‡Email: john.r.krainer@frb.gov
§Corresponding Author. Email: robert.j.kurtzman@frb.gov
¶Email: joseph.b.nichols@frb.gov

1 Introduction

Commercial real estate (CRE) lending in the United States is an important component of overall business lending, accounting for about 15% of total nonfinancial business credit as of 2019:Q4.[1] 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.[2] Though CRE is a large asset class and key input into firm production (Ghent et al., 2019), there remain a number of open questions about the CRE market: Along what dimensions do CRE loan originations differ by lender type? What are the underlying 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 nonfarm nonresidential CRE loan portfolios of around 30 of the largest U.S. banks, all U.S. 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 originations differ substantially by interest rate, loan-to-value (LTV), size, property type, and term.

A review of the institutional setting in which the lenders operate indicates a supply-side explanation for our findings. Due to differences in regulation, funding structure, and other institutional characteristics, lenders differ in their incentives to originate particular types of loans. 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 diversification enables CMBS to make larger loans.

[1]See Table 2 of the May 2019 Financial Stability Report of the Board of Governors of the Federal Reserve System: https://www.federalreserve.gov/publications/2020-may-financial-stability-report-borrowing.htm.

[2]Data comes from the Financial Accounts of the United States. See Figure D.1 (in Appendix D) 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.

Guided by our review, we build a simple model with representative lender types that compete on interest rates but differ in how loan characteristics affect required returns. In equilibrium, lenders have higher market shares for the loans for which they have a pricing advantage. We estimate the model using the cross-sectional variation in the characteristics of newly originated CRE loans.[3] The model allows us to estimate the impact of various supply shocks on loan spreads and lender market shares.

We test the validity of the substitution patterns in our model by exploiting a supply shock that occurred as a large number of pre-crisis CMBS loans were maturing and needed to refinance.[4] We show that CMBS borrowers switch to other sources of finance at a rate consistent with the predictions of the estimated model.

We then use the model to address the question we asked up front: What are the implications of segmentation for how the market responds to a shock? We estimate that the ability to switch to another lender offsets about 20% of the effect of a 25 basis point shock to the pricing of CMBS loans. 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: spreads rise most in response to supply shocks in the segments with the least competition. For example, CMBS supply shocks disproportionately affect borrowing costs for larger loans, given competing offers from banks and insurers are less competitive with CMBS in that segment of the market.

The extent of segmentation is also important in determining the effects of targeted regulation. We analyze a hypothetical policy that raises the required rate of return on high LTV bank loans. The estimated model suggests that nonbank lenders require a much higher premium than banks to originate loans with LTVs above 75%, given their low market

[3]Our estimation method follows in the spirit of the discrete-choice industrial organization literature (McFadden, 1973, 1984; Berry et al., 1995). Borrowers face a discrete-choice problem over lenders offering different loan contracts, and we estimate model parameters so as to match the observed selection of borrowers into particular lender types. Our approach differs in that loan rates in our model are bilateral agreements between borrowers and lenders (as opposed to posted prices), and borrowers minimize the cost of borrowing over a set of offered interest rates (as opposed to maximizing utility given known prices). Because of these differences, we are estimating supply functions rather than demand functions.

[4]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.

share for such loans. Since nonbanks are less competitive in this segment of the market, a regulation that raises the cost of high LTV bank loans mostly passes through into loan spreads rather than causing borrowers to switch to other lenders.

After we review the literature below, the roadmap for the paper follows as such: In Section 2, we describe the data, summarize how loan characteristics differ across lender types, and outline institutional differences across the lenders. Section 3 describes the model, discusses how it is estimated and validated, and presents the results of counterfactual supply shocks. Section 4 concludes.

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.[5] Chernenko et al. (2019) provide evidence that bank and nonbank lenders utilize different lending techniques and cater to different types of firms.

This paper is also closely related to a literature studying lender behavior in the context of the CRE market. Downs and Xu (2015) find that banks are quicker to resolve distressed loans than CMBS servicers. Black et al. (2017, 2020) 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.[6]

We contribute to 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, 2020) use the same data sources for CMBS and bank loan portfolios, but their analysis does not include life insurers. Moreover, their work does not take as comprehensive a look across loan and

[5] 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); and Becker and Ivashina (2014).

[6] Other work has 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). In addition, 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).

property characteristics. Downs and Xu (2015) and Ghent and Valkanov (2016) use data that include insurers but do not come from regulatory filings, resulting in less comprehensive data on loan characteristics. 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 supply shocks and regulatory changes affect loan pricing and lenders' market shares.

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 that could produce the observed differences in portfolios.

2.1 Data Description

We harmonize data for loans at origination from 2012-2017 across three data sources. 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., 2021), but, to our knowledge, our paper is the first to comprehensively analyze the loan-level information on life insurer CRE portfolios. We study originations of CRE 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.[7]

[7] Some information is not available before 2014. However, for loans that were still in insurers' portfolios in 2014, we can backfill this information using data from year-end portfolio holdings (Schedule B - Part 1). 5,428 of the 5,447 life insurance loans in 2012 and 2013, or 99.65%, are able to be backfilled. We provide more details on this backfilling procedure in Appendix A.

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.[8] The data includes rich information on loans, including the interest rate, committed exposure (the sum of the drawn and undrawn loan balance), 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.[9]

Our data on CMBS loans comes from Morningstar and is based on the information reported in the CRE Finance Council Investor Reporting Package.[10] 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.[11]

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. Third, we restrict the sample to loans secured by retail, office, hotel, or industrial buildings. We exclude multifamily loans, as the government-sponsored enterprises account for a large share of the market. We drop other categories because of a

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

[9]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.

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

[11]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, but funded by CMBS, as CMBS loans.

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 on a property changing over time is useful for examining substitution between lenders.[14] We use this data in Section 3.3 to study how supply conditions affect the propensity to switch lenders at refinancing.

2.2 Differences in Loan Characteristics Across Lenders

This subsection describes how loans differ across CRE lender types. We start by discussing summary statistics on the characteristics of newly originated loans by lender type. We then present results from various multinomial logit specifications where loan characteristics predict the type of lender.

2.2.1 Summary Statistics

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]

[12]For example, 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 (2021) 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.1. 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.

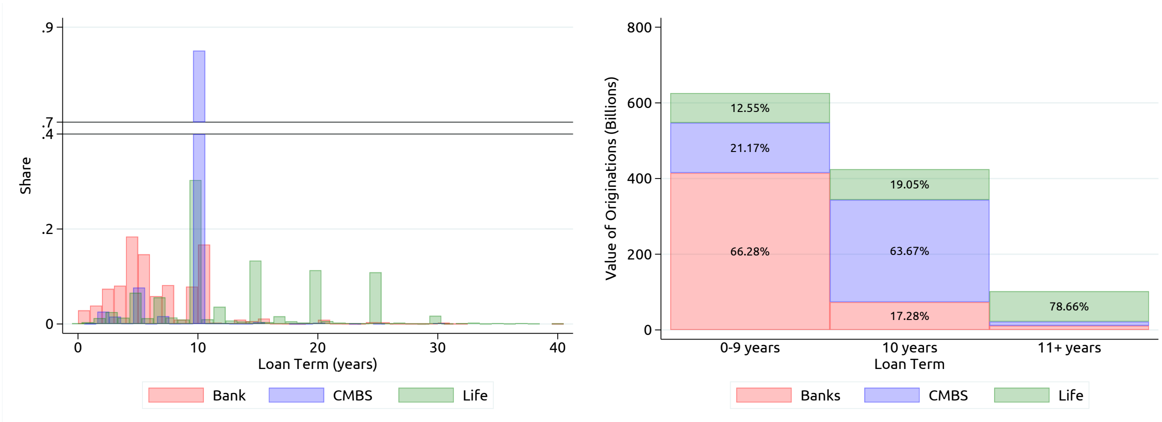
Table 1
Summary Statistics for CRE Originations by Intermediary Type

	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 property 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.

One of the most pronounced differences across lenders is in the 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 7.[17] The figure shows that loans with terms of greater than 10 years are disproportionately originated by life insurers, whereas

[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

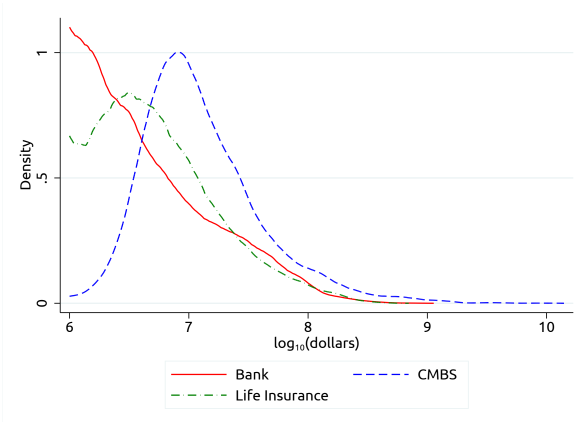
Notes: Panel (a) is a "broken" histogram of the time to maturity at origination for banks, CMBS, and life insurers, where the y-axis is not to scale between 0.4 and 0.7. Panel (b) shows the volume of originations by the different lender types with terms of less than 10 years, 10 years, or greater than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

loans with under 10-year terms are disproportionately originated by banks. CMBS lenders, meanwhile, almost exclusively 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. Notably, there are also significant differences in amortization schedules across lenders. In Appendix B.2, we show that longer-lived life insurance loans are typically fully amortizing, whereas CMBS loans typically have a 30-year amortization schedule, often preceded with a period in which borrowers only need to make interest payments.[18]

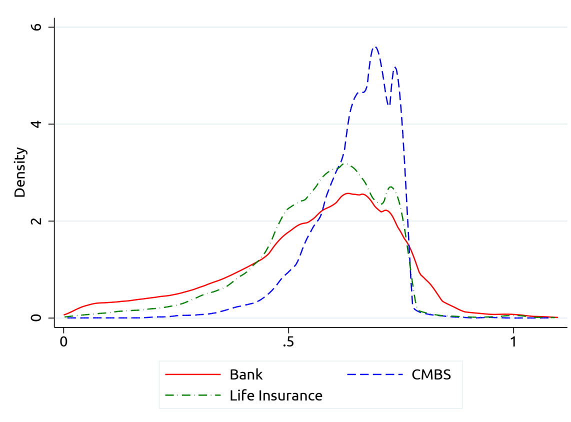
Table 1 also shows pronounced differences in the propensity to originate fixed-rate as opposed to floating-rate loans. Life insurers and CMBS lenders almost exclusively make fixed-rate loans, while only about one-third of bank loans have fixed rates.

We see 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 to around $12.5 million for banks

[18]Due to the lack of consistent reporting on amortization schedules across lender types, these statistics are backed out from data on changes in outstanding balances and interest rates. Since this process only works for fixed rate loans, and only identifies the amortization rate over a particular interval (rather than the life of a loan), we do not use this information in the model or present it in Table 1.



(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.

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 to balance sheet lenders. Meanwhile, banks have a probability density function over loan size that 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 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, panel (b) of Figure 2 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.

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.

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.

Lenders also differ in their propensity to originate loans secured by different property types. Table 2 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 to only 4% for life insurers. Hotels are considered to be one of the riskier properties to lend against, so, as with the findings for LTV, this points to life insurers being more risk averse. Life insurers instead 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 close to the overall composition, although banks are somewhat more oriented toward office buildings than the other lenders.

2.2.2 Multinomial Logit Results

We now examine the sorting of loans into the different lender types using a multinomial logit model. This analysis allows us to assess how loan characteristics relate to the probability that a particular lender originates a given loan while controlling for other characteristics.

Table 3 presents the results. We use banks as the reference group; therefore, a positive coefficient on a particular loan term for a given lender implies that lender is more likely to make loans with that term compared to banks. The baseline specification in the first two columns predicts lender type with loan term, ln(Property Value), LTV, and property type dummies as explanatory variables. The findings are consistent with the patterns demonstrated earlier in the section. Life insurers are more likely to lend for longer terms and banks shorter terms. CMBS lenders are the most likely to originate loans for large properties or with higher LTVs. Regarding property types, CMBS lenders are most likely to lend against hotels and retail buildings (e.g., malls), while life insurers are most likely to lend against industrial properties.

The second specification adds a dummy variable for whether the LTV exceeds 75% to the model. Consistent the findings presented in Figure 2 panel (b), CMBS and life are much less likely than banks to make loans above an LTV of 75%. The third specification adds price terms to the model. As expected, CMBS lenders and life insurers are much more likely to originate fixed-rate loans. Loans with higher spreads are more likely to be CMBS loans, while there is no significant difference in spreads between banks and life insurers. This finding indicates that the lower average spreads for life insurers compared to banks is a function of other observable characteristics (for example the lower LTVs or safer property types associated with life insurers' loans). The other findings pertaining to property characteristics or non-price loan terms are qualitatively similar when controlling for price terms. The third specification additionally adds a set of origination year dummies, the inclusion of which has little effect on the estimates.

Table 3
Multinomial Logit Results

	Specification 1		Specification 2		Specification 3		Specification 4	
	CMBS	Life	CMBS	Life	CMBS	Life	CMBS	Life
Term (years)	0.23**	0.33**	0.22**	0.32**	0.11**	0.26**	0.13**	0.26**
	(0.04)	(0.05)	(0.04)	(0.04)	(0.03)	(0.03)	(0.03)	(0.03)
ln(Property Value)	0.77**	0.40**	0.78**	0.39**	1.33**	0.60**	1.38**	0.64**
	(0.10)	(0.11)	(0.09)	(0.10)	(0.15)	(0.15)	(0.15)	(0.15)
Loan-to-value ratio	5.72**	0.78	8.74**	1.68**	9.59**	1.97**	9.54**	1.80**
	(0.40)	(0.48)	(0.51)	(0.51)	(0.61)	(0.64)	(0.59)	(0.65)
Hotel	1.44**	-0.52*	1.45**	-0.54*	1.32**	-0.55*	1.20**	-0.58*
	(0.16)	(0.22)	(0.16)	(0.23)	(0.19)	(0.26)	(0.19)	(0.26)
Retail	0.82**	0.07	0.78**	0.05	0.92**	0.16	0.95**	0.15
	(0.07)	(0.10)	(0.06)	(0.10)	(0.08)	(0.11)	(0.09)	(0.11)
Industrial	-0.24*	0.70**	-0.21*	0.70**	-0.13	0.74**	-0.09	0.75**
	(0.10)	(0.15)	(0.10)	(0.14)	(0.14)	(0.18)	(0.14)	(0.17)
LTV $>$ 0.75			-3.74**	-1.65**	-3.55**	-1.49**	-3.60**	-1.49**
			(0.34)	(0.22)	(0.30)	(0.20)	(0.31)	(0.20)
Fixed-rate dummy					5.42**	4.07**	5.72**	4.03**
					(0.36)	(0.45)	(0.35)	(0.43)
Spread to swaps					0.75**	0.20	1.04**	0.19
					(0.10)	(0.15)	(0.12)	(0.19)
Constant	-19.80**	-10.88**	-21.46**	-11.06**	-36.15**	-18.10**	-39.24**	-18.48**
	(1.78)	(1.99)	(1.80)	(1.97)	(2.99)	(2.82)	(3.06)	(2.93)
Obs.	70526		70526		64666		64666	
Year Dummies	No		No		No		Yes	

Notes: This table presents results from a multinomial logit model predicting lender type using loan-level data on loan terms and property characteristics. The independent variables in Specification 1 are the loan's term, the natural logarithm of property value, the loan's LTV, and a set of property type dummy variables. The second specification adds an indicator for whether the LTV exceeds 75%. The third specification adds pricing terms—specifically, the loan rate spread over swaps and an indicator for whether the loan has a fixed interest rate—to the second specification. The fourth specification adds a set of origination year dummy variables to the third specification. 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).

2.3 Summary of the Findings on Loan Characteristics

To summarize the empirical results, we highlight six findings regarding loan characteristics 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):** CMBS and life insurers almost exclusively originate fixed-rate loans. About two in three bank loans are floating, while about one in three are fixed.
- **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.
- **Finding 6 (Spreads):** Average loan rate spreads for life insurers are about 45 basis points below spreads for banks and CMBS, which have similar average levels of spreads.

2.4 Review of Relevant Institutional Differences

As noted in our review of the literature, there is a large body of work 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 in the CRE market. 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 summarized in Section 2.3. Further details on historical trends and regulatory differences are discussed in Appendix D.

2.4.1 Portfolio Lenders: Banks and Insurers

Banks and life insurers are similar in that they originate loans to hold in their portfolios. As the sole holders of the debt, they do not have conflicts of interest across different investors, which can complicate loan negotiations. Consequently, these lenders can be flexible regarding how they structure loans upfront or renegotiate them in the event of stress. However, portfolio lenders need to be cautious in managing risks, as they would bear the full brunt of any losses. Portfolio lenders are also subject to regulatory requirements and supervisory scrutiny that may affect their risk tolerance.[19]

Despite these similarities, banks and life insurers differ in a few key ways that influence their willingness to make particular types of loans. First, they differ 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 manage interest rate risk by matching the duration of assets and liabilities, then banks will on average originate loans with short terms or floating rates and life insurers will on average 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, in particular for CRE, encouraging them to make safer loans in this space. 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 D 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.[20] After 2014,

[19]Banks and insurers also invest in CMBS, which can have a more favorable capital treatment than whole loans. However, banks hold very little CMBS relative to their total CRE holdings, and insurers hold four times more CRE loans than CMBS. We provide further details on bank and insurer CMBS holdings in Appendix D.3.

[20]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

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, loan risk weights will almost double if either incomes decline such that the DSCR falls below 1.5 or property values fall such that the current LTV rises above 85%. The LTV and DSCR thresholds to avoid higher capital requirements are more restrictive for hotel loans.

In contrast to the risk-sensitive capital requirements for CRE loans at life insurers, non-construction CRE loans have a constant risk weight in banks' standard approach risk-based capital requirements. While other bank capital requirements (for example those from stress tests) are more risk sensitive, those risk-sensitive constraints are not necessarily binding relative to other capital requirements.[21] Thus, for many banks—even those subject to stress tests—a marginal increase in the risk of their CRE portfolio would have no effect on their required capital.

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 thus 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. Even when deals themselves are not diversified—as is the case with single asset single borrower deals which consist of a single large loan—the ability of investors to fund small portions of multiple deals enables diversification at the level of the CMBS investor.

This diversification facilitates CMBS investors funding loans with higher idiosyncratic

requirements. Delinquencies then remained near zero for life insurers during the financial crisis, while spiking for other lenders (see Appendix D, Figure C.2).

[21]For example, about half of large banks had a stress capital buffer at the minimum of 2.5% in 2020. Therefore, a marginal increase in expected stresses losses would not affect stress capital buffers in capital requirements. See: `https://www.federalreserve.gov/newsevents/pressreleases/bcreg20200810a.htm`.

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.[22] Additionally, the ability to 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 diversification may reduce some risks associated with CRE investing, there are still several checks on the allowable credit risk in CMBS pools. First, credit ratings agencies review the loans in a CMBS deal, compose presale reports for investors, and determine necessary credit enhancements for higher rated tranches. In addition, first-loss investors, whose returns are highly sensitive to the performance of the most risky portion of the loan pool, can re-underwrite and even kick-out problematic loans. Finally, CMBS issuers face potential reputational damage from issuing poorly performing deals. The incentives for issuers and first-loss investors to carefully review loans likely strengthened in late-2016 with the implementation of risk retention requirements.[23]

However, CMBS financing involves reduced flexibility for borrowers. As was evident from the summary statistics in Table 1, CMBS loans are fairly homogeneous. 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 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

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

[23] The risk retention rule requires a CMBS issuer to either retain 5 percent of the face value of each tranche in a deal or 5 percent of the fair value of the most subordinated classes (or a combination of the two). The subordinated classes can be sold to a qualified third-party investor. Investors in these risk-retention bonds are restricted from selling the bonds or hedging the exposure, incentivizing a careful review of the loans in a deal.

loan modifications can threaten the favorable tax treatment. Furthermore, special servicers are bound by rules in the CMBS Pooling and Servicing Agreement, potentially restricting the range of options for dealing with distressed CMBS loans.

3 Model, Estimation, and Quantitative Results

In Section 2, we documented stark heterogeneity in loan characteristics across lender types, and argued this heterogeneity is a function of differences in the lenders' institutional and regulatory environments. Yet, loan supply conditions vary over time as regulations change and other shocks hit the market. In this section, we are interested in the question of how the market would respond to such shocks given the significant segmentation we observe.

To obtain quantitative answers to this question, we build a simple model of competition in the CRE loan market that we can take to our rich microdata. In the first subsection, we present the model. In the second subsection, we describe our estimation strategy and results. In the third subsection, we perform a validation exercise comparing substitution patterns in the estimated model with those observed in the data during a period of CMBS market stress. In the remaining subsections, we then analyze the effects of various counterfactual supply shocks and regulatory changes through the lens of the model.

3.1 Model

Consider the following economic environment. On the demand side, 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.

On the supply side, 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, or the required rate of return used to discount the cash flows, 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. We assume $\epsilon_{i,j}$ is distributed type-I extreme value, as is common in the industrial organization literature (McFadden, 1973, 1984; Berry et al., 1995).

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:

$$R_i = \min_{j \in J}\{R_{i,j}\}. \tag{2}$$

Given our assumption that $\epsilon_{i,j}$ is distributed type-I extreme value, the probability that a particular lender offers the lowest interest rate is given by the standard multinomial logit formula. That is, the probability of lender j originating a loan with characteristics X_i is:

$$P_{i,j}(\beta) = \frac{\exp(-\frac{1}{\sigma}X_i'\beta_j)}{\sum\limits_{k \in J}\exp(-\frac{1}{\sigma}X_i'\beta_k)}. \tag{3}$$

Given β and σ, the model produces the distribution of offered interest rates from each lender for a given loan (β_j determines how each lender prices a loan on average and σ determines the dispersion around these averages). From this distribution of loan offers, we can calculate various outcomes of interest, including the effects of supply shocks on loan pricing or lender market shares.

3.2 Estimation Strategy and Results

In our model, we assume that lenders differ in how they value loans with different characteristics and that these valuations are reflected in the interest rates they offer to borrowers. Therefore, in equilibrium, lenders will be more likely to make loans they price favorably.

Our estimation procedure backs out lenders' pricing functions so as to match the sorting of loans into particular lenders observed in our rich microdata. This is done in two steps. In the first step, we use estimates from the multinomial logit results presented in Table 3 to identify differences in how intermediaries price different loan characteristics. Intuitively, this procedure estimates pricing factors so as to reproduce the differences in average loan characteristics documented in Section 2. In the second step, we estimate other parameters pertaining to the dispersion in the idiosyncratic match (σ) and the level of the pricing factors (as opposed to differences across lenders). These parameters are estimated so as to match moments in the data pertaining to regressions of interest rates on loan characteristics. A mathematical description of the model and estimation procedure, including all derivations, is in Appendix C.

Equation (3) shows that the probability a lender makes a particular loan is given by the multinomial logit formula. Consequently, the logit coefficients in Table 3 can be given a structural interpretation—each coefficient corresponds to an estimate of how a particular lender prices a loan characteristic relative to banks. Specifically, since banks were used as the reference category, the multinomial logit produces estimates of the following:[24]

$$\begin{aligned} \beta_{\text{CMBS}}^{\text{logit}} &\equiv \frac{1}{\sigma}(\beta_{\text{Bank}} - \beta_{\text{CMBS}}) \\ \beta_{\text{Life}}^{\text{logit}} &\equiv \frac{1}{\sigma}(\beta_{\text{Bank}} - \beta_{\text{Life}}). \end{aligned} \tag{4}$$

Functionally, these estimates provide the differences in pricing of loan characteristics needed to produce the differences in loan portfolios observed in the data.[25] For example, Table 1 shows that life insurance company loans have a term that is on average about 7 years longer than banks. As a result, the model estimates that life insurers offer more favorable pricing on long-term loans (relative to banks) so as to reproduce this selection of longer-term loans into life insurers.

[24]To see this, note that multiplying the numerator and denominator of (3) by $\exp(\frac{1}{\sigma}X_i'\beta_{\text{Bank}})$ implies $P_{i,j}(\beta) = \frac{\exp(X_i'\beta_j^{\text{logit}})}{\sum_{k\in J}\exp(X_i'\beta_k^{\text{logit}})}$. Thus, it is $\beta_j^{\text{logit}} \equiv \frac{1}{\sigma}(\beta_{\text{Bank}} - \beta_j)$ that is estimated by the multinomial logit.

[25]Appendix C.2.1 shows that the first order condition of the log-likelihood function equates average characteristics in the data to the average produced in the model.

We use the first specification in Table 3—which includes loan term, property size, LTV, and property type dummies—to identify how these loan and property characteristics are priced. We choose the specification that omits the high LTV and fixed rate indicators, as including these variables could result in us overstating frictions from substituting between bank loans and nonbank loans.[26] We choose a specification excluding the 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 the year dummies.

The next step is to estimate σ and β_{Bank}. We can see from Equation (4) that combining these estimates with the logit estimates allows us to solve for each pricing vector β_j. With these additional parameters, we can thus determine the expected pricing of a particular loan by a particular intermediary, determined by $X_i'\beta_j$, and the dispersion around the expectation, determined by $\sigma\epsilon_{i,j}$. We calibrate these remaining parameters so as to match key moments coming out of loan pricing regressions in the data.

Quantitatively, the more important of these parameters is σ, which affects the scale of how much lenders differ in pricing. For example, if σ were low, idiosyncratic differences in how lenders price loans would be small. In this case, we would interpret borrowers as being quite price-sensitive, as it would take only modest differences in loan pricing across intermediaries to produce the extent of segmentation observed in the data.

Since σ affects the dispersion in the pricing of terms across lender types, we calibrate it so as to match differences in predicted interest rates across lender types. Specifically, we run OLS regressions of interest rates on loan characteristics for each lender type and find the predicted values in both the actual data and the model. Since substitution patterns in the model largely depend on the difference between the lowest interest rate offered and the second-lowest offer, we target the median difference between the lowest and second lowest OLS-predicted interest rate.

[26] To provide more detail, the assumption that loan terms are exogenously chosen could be problematic for these indicator variables. Though nonbanks rarely originate loans with floating rates or LTVs above 75%, borrowers can choose a lower LTV or fixed-rate loan to accommodate those lender's preferences. Not allowing borrowers to make such adjustments can cause the model to overestimate switching costs. This is less of a concern for characteristics that are either immutable (such as property type or size) or enter continuously (such as term or LTV). For example, with a continuous specification, CMBS can seem like a viable substitute for 76% LTV loans or 9-year loans, despite rarely making loans with those exact terms.

The median loan in our data has an 8 basis point difference in predicted loan rates between the two lowest cost lenders. In the model, differences in the predicted interest rates produced by lender-specific pricing regressions are linear in σ (see Appendix C.2.2), and we match the moment in the data with a value of $\sigma = 0.37$.[27]

Our estimate of β_{Bank} controls the level of the effect of loan characteristics on loan rates. We thus estimate β_{Bank} so as to match the coefficients from an OLS pricing regression that pools loans across lender types. For example, when regressing observed loan rate spreads on the loan characteristics we use in the model, we get a coefficient of 0.49 on the hotel loan dummy. Our estimate of β_{Bank} has banks requiring 57bp a premium for hotel loans so as to reproduce this estimate. More generally, we show in Appendix C.2.2 that a change in the estimate of β_{Bank} produces a one-for-one change in the OLS-estimated pricing vector, implying we hit the targeted OLS results exactly. Note that changes in the estimate for β_{Bank} result in a parallel shift in pricing across all lenders, and thus does not alter which lender type a borrower chooses or how the borrower is affected by the counterfactual shocks we present.

To summarize, differences in how lenders price loan characteristics are estimated off of differences in the composition of loan portfolios. If a lender makes more of a particular type of loan, they are estimated as pricing that type of loan favorably so as to produce the observed differences in the data. The overall scale of these pricing differences is pinned down by differences in OLS-predicted rates across lenders. More variation in how different lenders appear to price loans in OLS regressions results in a proportionally higher estimate of the overall scale of how lenders differ in loan pricing. Finally, the level of how lenders price each characteristic is estimated to match the pricing regressions. If lenders appear to price a particular characteristic unfavorably overall, we set the overall pricing of that characteristic (as opposed to the difference from a reference group) to reproduce that pricing elasticity in the model.

Table 4 presents the estimated lender-specific pricing factors generated from this esti-

[27] As each $\epsilon_{i,j}$ has a standard deviation of $\frac{\pi}{\sqrt{6}}$, this value of σ means that the idiosyncratic match term has a standard deviation of 0.47.

Table 4
Estimates of How Lenders Price Different Terms

	Logit Coefficients		Lender-Specific Elasticities		
	$\frac{1}{\sigma}(\beta_{\text{Bank}} - \beta_{\text{CMBS}})$	$\frac{1}{\sigma}(\beta_{\text{Bank}} - \beta_{\text{Life}})$	β_{Bank}	β_{CMBS}	β_{Life}
Term (years)	-0.23	-0.33	0.02	-0.07	-0.10
ln(Property Value)	-0.77	-0.40	-0.01	-0.30	-0.16
Loan-to-value	-5.72	-0.78	0.37	-1.73	0.09
Hotel	-1.44	0.52	0.57	0.04	0.76
Retail	-0.82	-0.07	0.03	-0.27	0.00
Industrial	0.24	-0.70	0.04	0.13	-0.22
Constant	19.80	10.88	2.61	9.89	6.61

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 Specification 1 in Table 3. The next 3 columns show the vectors of pricing factors for each lender type after rescaling by $\hat{\sigma}$ (estimated off differences in OLS-predicted loan rates across lender types) and shifting by $\hat{\beta}_{\text{Bank}}$ (estimated so pricing regressions in the model produce the same coefficients as regressions on actual data).

mation strategy. The first two columns replicate the logit coefficients from the first model in Table 3. The last three columns present the estimates for β_{Bank}, β_{CMBS}, and β_{Life}, which come from rescaling the logit coefficients by $\sigma = 0.37$ and shifting by our estimate for β_{Bank}. 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 76 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 spreads that are about 17 basis points lower 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).

3.3 Model Validation: Loan Transitions in Response to a Supply Shock

To test the predictions from the model, 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 borrower demand to refinance. In the middle of this episode, CMBS spreads rose notably, due to some combination of broader bond market stress and the strong demand. While we cannot directly observe who would have supplied credit absent the CMBS shock, we can observe how frequently borrowers switch to other funding sources. The frequency of switching lenders at the time of refinancing provides an analogue in the data to the rate at which borrowers change lenders in response to a pricing shock in the model.

In the first two subsections, we describe the supply shock and measure its pass-through to loan rates. We then test whether borrowers' propensity to switch away from CMBS matches the predictions of the model.

3.3.1 CMBS Spreads and CMBS Refinance Market Shares

Higher CMBS spreads indicate a higher required return on CMBS securities and thus higher interest rates on newly originated CMBS loans. When CMBS financing becomes more expensive to borrowers relative to other sources, we would expect some borrowers to switch to other financing sources.

Figure 3 indicates that borrowers switch away from CMBS markets when spreads rise. The figure plots the share of previous CMBS loans refinancing into bank CRE loans against the average AAA CMBS spread for the quarter.[28] There is a positive relationship between CMBS spreads and banks' market shares of loans for properties previously financed by CMBS. That is, when CMBS financing becomes more expensive, borrowers who previously chose to finance properties in CMBS markets increasingly turn to banks.

We study the refinancing behavior of borrowers during the period when CMBS spreads spiked in 2015:Q4 and 2016:Q1. This period is useful to study for three reasons. First, the shock to CMBS spreads was large, with spreads rising to a peak of 150bp in 2016:Q1, compared to a normal range between 80 and 100bp. Consequently, this rise in spreads

[28]We stopped the analysis in 2016:Q2 as the first risk retention deals started to come to market in the following quarter. We observe changes in the relationships between CMBS spreads and loan pricing, and differences in the pass-through of CMBS spreads to loan rates after this point.

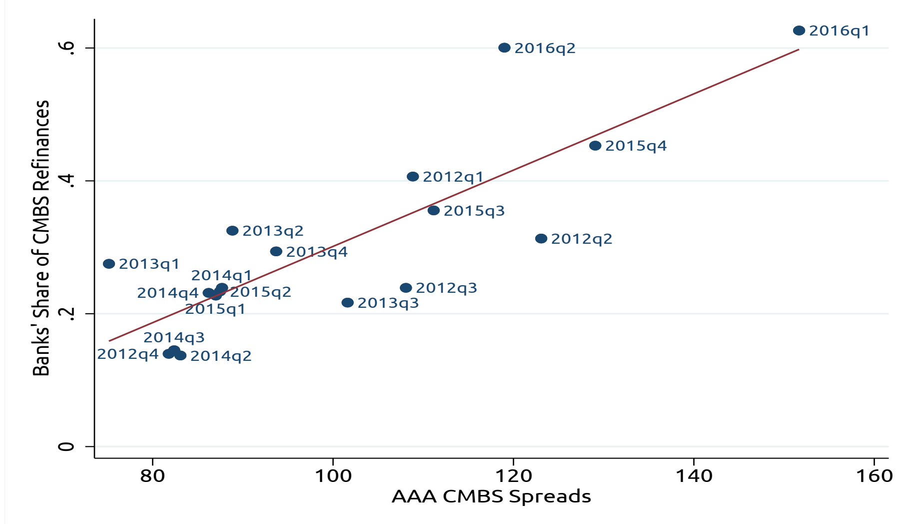


Figure 3: AAA CMBS Spreads and Banks' Share of CMBS Refinances

Notes: This figure shows a scatter plot of average quarterly AAA 10-year CMBS spreads over swaps and the share of refinancing CMBS loans that are financed by banks. Data runs from 2012:Q1 until 2016:Q2.

was likely the primary driver of changes in market shares for refinancing CMBS loans, dwarfing other possible developments in these quarters. Second, as shown in Figure 3, the relationship between spreads and bank market shares during these quarters was in line with the relationships between these variables for the post-crisis period more generally. This indicates the decline in market shares during this period is reflective of a more general relationship that holds in other time periods. Finally, the shock occurred at a time when a large number of CMBS loans were refinancing, giving us a sample size sufficient to study differences in which borrowers changed lenders due to the shock.

Figure 4 demonstrates this last point. The figure plots the share of refinancing CMBS loans that are originated by banks, CMBS, and life insurers by quarter. The gray bars show the number of CMBS loans refinancing in that year. The number of CMBS loans refinancing jumped to about 400 loans per quarter starting in 2015:Q2 after typically being under 200 loans per quarter before that time. During this period of elevated CMBS refinancing, CMBS spreads rose and banks started taking on a greater market share of refinancing CMBS loans. CMBS retained about two-thirds of refinancing CMBS loans in 2015:Q2, similar to what they had been retaining in the years before that; however, this share fell to under 30 percent by the time CMBS spreads peaked in 2016:Q1. Most of this decline in market share was due to

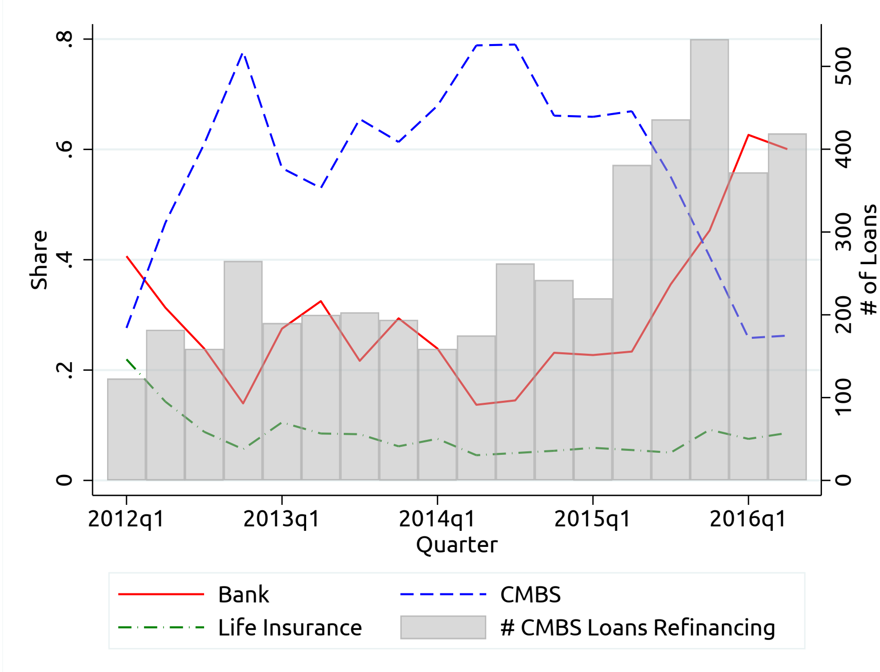


Figure 4: Market Shares for Refinancing CMBS Loans by Quarter

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 quarter (right axis) is shown by the grey bars. Data comes from Real Capital Analytics.

an increase in banks' market share, though life insurers' share also increased modestly.

3.3.2 CMBS Spreads and CRE Loan Rates

In order to quantitatively analyze how this increased propensity to refinance into bank loans compares with the predictions of the model, we need to determine how rising AAA CMBS spreads pass-through to loan spreads for each lender. 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 AAA CMBS spreads or a dummy for whether the loan was originated from 2015:Q4 to 2016:Q1). Note that these regressions also include as controls the independent variables in specification 1 of the multinomial logit presented in Table 3.

These regressions show that shocks to CMBS spreads do not pass through equally to loan rates across the lender types as would be expected if CRE markets were perfectly

Table 5
Pass-Through of CMBS Spreads to Loan Rates

	Full Sample		Wall of Maturities (2015-2016)	
	(1)	(2)	(3)	(4)
AAA CMBS Spread				
x Bank	0.11**		0.16**	
	(0.02)		(0.03)	
x CMBS	1.32**		1.52**	
	(0.04)		(0.06)	
x Life	0.48**		0.73**	
	(0.04)		(0.05)	
2015Q4-2016Q1				
x Bank		-0.12**		0.03*
		(0.01)		(0.02)
x CMBS		0.41**		0.49**
		(0.02)		(0.03)
x Life		0.04^{+}		0.13**
		(0.02)		(0.02)
CMBS	-1.05**	0.07**	-1.25**	0.07**
	(0.04)	(0.01)	(0.07)	(0.02)
Life	-0.49**	-0.14**	-0.77**	-0.15**
	(0.05)	(0.02)	(0.07)	(0.03)
Controls	Yes	Yes	Yes	Yes

Notes: This table reports results from OLS regressions of loan spreads on lender type dummies interacted with measures of CMBS stress. The sample includes CRE loans originated between 2012:Q1 and 2016:Q2. CMBS stress is measured by the spread of AAA CMBS yields over swap rates in odd columns, and a dummy for whether the loan was originated in 2015:Q4 or 2016:Q1 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 in 2015 and 2016. The controls are the independent variables from specification 1 of the multinomial logit presented in Table 3: the loan's term, the logarithm of property value, the loan's LTV, and a set of property type dummy variables. Loan rate spreads are with respect to comparable-maturity swap rates for fixed-rate loans and 1-month dollar LIBOR for floating-rate loans.

integrated. Instead, column 1 shows that AAA CMBS spreads pass through more than one-to-one into CMBS loan rates, while having little effect on interest rates for bank loans.[29] Life insurers are in between the other lenders in terms of pass-through. This makes sense;

[29] 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.

CMBS yields do not directly affect life insurer funding costs, but 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 late 2015 and early 2016, shown in column 2, roughly matches what would be expected based on the findings in column 1. Loan spreads rose by 41bp for CMBS in these quarters, while declining by 12bp for banks. Meanwhile, life insurers were in between, with a 4bp increase in spreads.

The next two columns restrict the sample to the years 2015 and 2016. During this period there was a sizable increase in the number of CMBS loans refinancing due to the large volume of pre-crisis CMBS loans maturing. This allows us to compare the increase in spreads during the period of interest to other quarters in which conditions were more similar (at least in terms of CMBS refinancing volumes). The results are generally similar to those estimated over the whole sample, with the exception that banks are found to keep rates mostly flat in late-2015 and early-2016 instead of modestly lowering rates.

In short, CMBS and life insurers' loan spreads rose about 53bp and 16bp, respectively, relative to banks during the period of 2015:Q4-2016:Q1. In the next section, we analyze the effect of this pricing shock on market shares in the model, and compare the results to what we observe in the data.

3.3.3 Validation: Effects of CMBS Shocks in the Model and Data

In Figure 5, we plot the shares of CMBS loans that refinance into banks or insurance companies by property value.[30] Solid lines present the shares of CMBS loans refinancing into banks or life insurers based on RCA data, while the dashed lines show the predictions from the model. Because CMBS specialize 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 with the higher loan rate spreads. Among the smaller loans against \$2.5 million properties, banks took on about three-quarters of CMBS refinances during the period of elevated CMBS spreads, compared with only about one-third

[30]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.

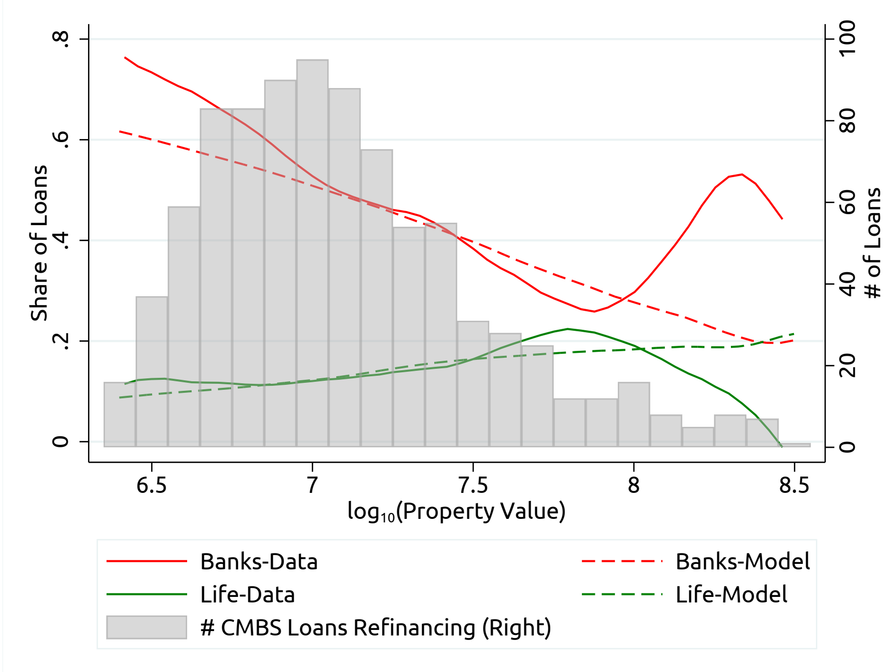


Figure 5: Market Shares for Refinancing CMBS Loans by Property Value

Notes: This figure plots the percentage of refinancing CMBS loans originated by banks and life insurers in 2015:Q4 and 2016:Q1 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 in the model that switch from being financed by CMBS to other lenders as a result of an increase in CMBS spreads during the period. The model estimates are based on a 53bp and 16bp increase in CMBS and life insurer loan rates, respectively, based on the results in Table 5.

of the largest $100 million properties. Life insurers are much less likely to refinance CMBS loans, with a market share typically between 10% and 20% depending on the property size.

To generate the model predictions, we start with data on 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 we compute the probability that CMBS borrowers with these attributes would alternatively borrow from banks or life insurers as a result of the increase in loan rates observed during 2015:Q4 and 2016:Q1.[31]

We can see that the patterns generated by the model are broadly similar to what is observed in the data. Banks take on over 60% of the smaller refinancing loans, with this market share declining to around 30% for larger properties. For properties around $10

[31]We show how we can analytically compute these switching probabilities in Appendix C.3.

million in value—the typical value for a refinancing CMBS loan during this period—banks average a market share slightly above 50% in both the data and the model. The model predictions are typically within 10 percentage points of the shares observed in the data. The fit is even closer for life insurers, with both the model and the data showing life insurer market shares rising from about 10% for \$2.5 million dollar properties to around 20% for \$100 million properties.

3.4 Counterfactuals: How Does the Market Respond to a Shock?

Having validated some of the substitution patterns in the model, we now address the question motivating this section: How does the market respond to supply shocks? Table 6 presents our first exercise, in which we simulate 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 modeled as being originated by each lender matches the actual market shares in our data, and the average loan spreads are reasonably close to those shown in Table 1. Observed loan spreads range from about 2.2 for life insurers to 2.6 percentage points for banks and CMBS, while the average spreads in the model range from about 2.3 for life insurers to 2.6 for banks. CMBS spreads are about 2.5 percentage points in the model, a bit lower than in the data. While market shares are a target moment when estimating the model, these lender-specific loan spreads are not. Thus, these baseline results provide further evidence of the external validity of the model.

Columns 2 through 7 present the estimated effects of a 25 basis point loan pricing shock to each lender type. For each of these shocks, there are two items of interest: (1) the degree to which market shares change in response to the shock and (2) the pass-through of the shock to loan rates. Columns 2 and 3 show that a 25 basis point increase in rates 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 for the entire CRE market is predicted to rise by about 13 basis points, indicating that the ability to switch to other lenders offsets slightly

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	0.57	0.45	-11.6	0.61	3.9	0.63	5.8
CMBS	0.16	0.21	4.7	0.10	-6.2	0.19	2.6
Life Insurers	0.27	0.34	6.9	0.29	2.4	0.19	-8.3
Average Loan Spreads							
Overall	2.51	2.64	12.7	2.54	3.2	2.57	5.7
Banks	2.63	2.81	17.8	2.65	2.5	2.66	2.8
CMBS	2.51	2.64	12.8	2.58	7.1	2.54	2.5
Life Insurers	2.27	2.42	14.9	2.31	3.7	2.31	4.0

		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	0.57	0.34	-23.1	0.63	6.4	0.67	9.8
CMBS	0.16	0.25	9.3	0.06	-10.4	0.21	4.8
Life Insurers	0.27	0.41	13.8	0.31	3.9	0.13	-14.6
Average Loan Spreads							
Overall	2.51	2.74	22.6	2.56	5.1	2.61	9.6
Banks	2.63	2.97	33.7	2.67	4.3	2.67	4.7
CMBS	2.51	2.75	23.4	2.64	12.5	2.55	4.1
Life Insurers	2.27	2.55	27.6	2.33	6.2	2.34	7.2

Notes: This table presents changes in market shares and borrowing costs resulting from supply shocks to different lender types. The first column shows baseline results before any supply shocks. 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 basis points) are listed in columns 3, 5, and 7.

more than 10% of the effect of a supply shock to banks.[32] The average loan rates for bank borrowers rises by about 18bp, 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

[32]Banks start with a market share of 57%, so average loans rates would rise by 14.25bp as a result of 25bp shock to bank loan rates (0.57x25bp) if it were not for some marginal loans switching to other lenders. The increase in rates of 12.7bp is 89% of what it would be absent switching (12.7/14.25).

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 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 20% of the increase in rates due to a 25bp shock to CMBS is offset by CMBS borrowers instead going to other lenders, and about 15% of the effect of a shock to life insurers is offset by borrowers switching lenders. In other words, fewer borrowers are affected, and those that are affected are more able to switch to other lenders, dampening the effects of supply shocks.

What happens when the shock is larger than 25bp, as we observed in 2015 and 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 effect of the shock does not scale linearly. While a 25bp shock to banks raises average loan spreads by about 13bp, a 50bp shock raises spreads by a bit less than 23bp. In percentage terms, the ability to switch offsets about 20% of the effects of a 50bp shock to banks, compared with about 10% of a 25bp shock. Similarly, the ability to switch lenders offsets more of the effect of a 50bp shock to CMBS or life insurers. Changes in borrowing costs are concave in pricing shocks because marginal increases in the pricing shock only affect borrowers that would not have already switched lenders.

3.5 Counterfactuals: Heterogeneous Effects of a Shock

The effects of the pricing shocks studied in the previous subsection do 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 the borrower will just switch lenders. This means that

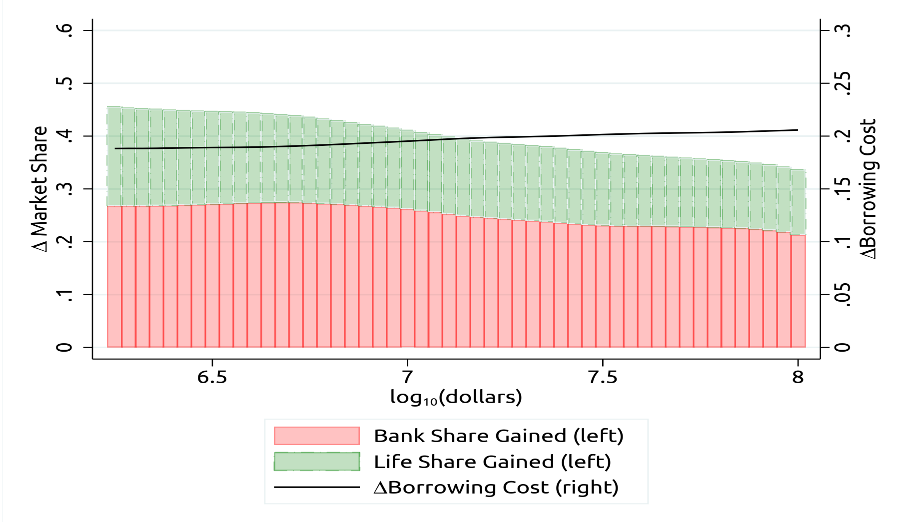


Figure 6: Effect of 25bp CMBS Shock by Property Value

Notes: This figure plots estimates of 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 shares 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 of property values for the set of loans that would have been 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.

supply shocks will disproportionately increase rates for those borrowers with characteristics more particular to their lender. For example, bank shocks will disproportionately affect small loans, CMBS shocks will disproportionately affect higher LTV loans, and life insurer shocks will disproportionately affect those seeking long-term loans.

We demonstrate this point in Figure 6. We estimate how a 25bp shock to CMBS loan 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 45% 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 one-third 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 change in borrowing costs depends on the share of borrowers that still borrow from CMBS markets (and have costs increase by 25bp), and the share that switch lenders (and have costs rise by less than 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 19bp on average.[33] The pass-through of the shock is more significant for loans backing larger properties, with average borrowing rates rising by around 21bp. 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.

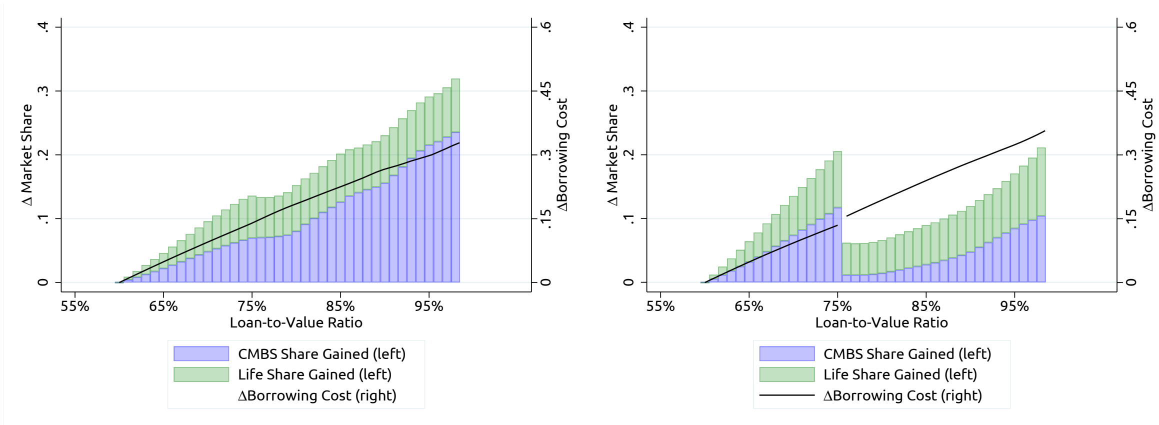
3.6 Counterfactuals: The Effect of Targeted Regulation

We now use our model to assess how the CRE market would respond to a regulation that changes how LTV is priced. This counterfactual policy is particularly relevant, as all three institutions have recently been subjected to regulations that could affect the pricing of LTV: banks' risk-weights on high LTV construction loans increased in 2015 due to the HVCRE rule, CMBS loans became subject to risk retention at the end of 2016, and life insurers' risk-weights on higher LTV loans rose with new requirements in 2014. The HVCRE rule and risk retention rule resulted in increased interest rates for affected loans (Glancy and Kurtzman, 2018; Furfine, 2020). Our model allows us to assess the equilibrium effect of such policies on borrowing costs and the allocation of lending across the different lender types.

Figure 7 presents the effect of a policy that increases the required return on bank loans by 1 basis point for every basis point increase in LTV above 0.6. We plot the implied change in market shares and borrowing costs under two different specifications for intermediaries' pricing functions. The results in panel (a) are based on specification 1 from Table 3, as in previous subsections. The results in panel (b) are based on specification 2, which adds an indicator for whether a loan's LTV exceeds 75% to specification 1.[34] As discussed in Section

[33] The average cost to those who switch to another lender is about 12bp. This can be derived from the following: 19bp $\approx$ 55% $\times$ 25bp + 45% $\times$ $z_t$bp, where z_t is the cost to those who switch to another lender and 55% is the share of borrowers remaining with CMBS. In this case, z_t = 12.

[34] To generate the results in panel (b), we reestimate the model based on the coefficients from specification 2 in Table 3. As part of this reestimation, we obtain a new value of 0.29 for σ. The results in Sections 3.3-3.5 are qualitatively similar using the model estimated based on this specification, although the fit of the validation



(a) Specification 1 **(b)** Specification 2

Figure 7: Effect of Banks Increasing Rates by $\max\{0, \text{LTV}_i - 0.6\}$

Notes: This figure plots 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 $\max\{0, \text{LTV}_i - 0.6\}$. Effects in panel (a) are based on specification 1 of the multinomial logit in Table 3 (as with the rest of the paper), while the effects in panel (b) come from specification 2, which additionally includes an indicator for whether a loan's LTV exceeds 75%. In both panels, the height of the blue and green bars show the estimated shares 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 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. The value of σ estimated using the first specification is 0.37 and the second specification is 0.29.

3.2, including the high LTV indicator can cause the model to overstate substitution frictions, since it does not allow borrowers to adjust loan sizes to satisfy LTV limits. However, as we are studying a policy change that specifically affects high LTV loans, and given there is a clear nonlinearity in the data in the propensity to lend at high LTVs, we find it useful to also examine substitution patterns when the extra term is included in the pricing function.

We can see that the effect of the shock mostly passes through into borrowing costs for LTVs of 75% or below. At an LTV of 75%, the 15bp increase in loan rates from banks results in only about 15% of loans switching to being funded by other lenders in panel (a) and 20% of loans switching in panel (b). The average cost to bank borrowers rises by about 13.5bp or 14bp—not far from the 90% pass-through rate of 25bp bank shocks found in Section 3.4.

The predicted effects of the shock differ more notably between the two panels for LTVs above 75%. Recall from Section 2 that very few CMBS or life insurer loans have LTVs above 75%. When this nonlinearity in the propensity to make high LTV loans is accounted for in

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exercise is somewhat worse compared to using specification 1.

panel (b), we find a discrete decline in the share of loans switching from banks for LTVs above 75%. Although the increase in the required rate of return for high LTV loans is greater than for those with lower LTVs, high LTV loans are less likely to transition away from banks due to banks' significant advantage in pricing such loans. As a result, the pass-through of the policy to borrowing costs is somewhat higher, and the share of loans leaving the banking sector is smaller.[35] Since the results in panel (a) do not account for the nonlinearity around 75% LTVs, the effects of the policy scale more linearly with the magnitude of the pricing shock.

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. If there are multiple lenders that compete in that subset of the market, there can be nontrivial changes in market shares, and the effect of the regulation on loan pricing can be dampened.

4 Conclusion

Three lender types account for the vast majority of 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 these 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 loan pricing.

The model allows us to estimate the costs of substituting between lenders, and thus study how the CRE market would respond to various supply shocks. The ability to switch lenders offsets about 20% of the effect of a 25 basis point shock to CMBS loans rates, with heterogeneous effects depending on how favorably other lenders price a particular borrower's loan terms.

[35]While we show that banks would likely 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 overall and in the banking sector in particular. We would need a more complicated model with endogenous selection of loan terms to analyze such effects.

References

An, X., Y. Deng, and S. Gabriel (2011). Asymmetric information, adverse selection, and the pricing of cmbs. *Journal of Financial Economics 100*, 304–325.

Archer, W. R., P. J. Elmer, D. M. Harrison, and D. C. Ling (2002). Determinants of multifamily mortgage default. *Real estate economics 30*(3), 445–473.

Ashcraft, A. B., K. Gooriah, and A. Kermani (2019). Does skin-in-the-game affect security performance? *Journal of Financial Economics 134*(2), 333–354.

Becker, B. and V. Ivashina (2014). Cyclicality of credit supply: Firm level evidence. *Journal of Monetary Economics 62*, 76–93.

Becker, B. and M. Opp (2013). Regulatory reform and risk-taking: Replacing ratings. *National Bureau of Economic Research Working Paper No. w19257*.

Berry, S. T., J. A. Levinsohn, and A. Pakes (1995). Automobile prices in market equilibrium. *Econometrica 63*(4), 841–890.

Black, L., C. Chu, A. Cohen, and J. Nichols (2012). Differences across originators in cmbs loan underwriting. *Journal of Financial Services Research 42*, 115–134.

Black, L., J. Krainer, and J. Nichols (2017). From origination to renegotiation: A comparison of portfolio and securitized commercial real estate loans. *The Journal of Real Estate Finance and Economics 55*(1), 1–31.

Black, L. K., J. R. Krainer, and J. B. Nichols (2020). Safe collateral, arm's-length credit: Evidence from the commercial real estate market. *The Review of Financial Studies 33*(11), 5173–5211.

Brewer III, E., T. S. Mondschean, and P. E. Strahan (1993). Why the life insurance industry did not face an s&l-type crisis. *Economic Perspectives 17, 4th.*(5).

Chernenko, S., I. Erel, and R. Prilmeier (2019). Why do firms borrow directly from nonbanks? *National Bureau of Economic Research Working Paper No. w26458*.

Chodorow-Reich, G., A. Ghent, and V. Haddad (2021). Asset insulators. *The Review of Financial Studies 34*(3), 1509–1539.

Denis, D. and V. Mihov (2003). The choice among bank debt, non-bank private debt, and public debt: evidence from new corporate borrowings. *Journal of Financial Economics 70*.

Diamond, D. W. (1991). Monitoring and reputation: The choice between bank loans and directly placed debt. *Journal of Political Economy 99*, 689–721.

Downs, D. H. and P. T. Xu (2015). Commercial real estate, distress and financial resolution: Portfolio lending versus securitization. *The Journal of Real Estate Finance and Economics 51*, 254–287.

Ellul, A., C. Jotikasthira, C. T. Lundblad, and Y. Wang (2014). Mark-to-market accounting and systemic risk: evidence from the insurance industry. *Economic Policy 29*(78), 297–341.

Ellul, A., C. Jotikasthira, C. T. Lundblad, and Y. Wang (2015). Is historical cost accounting a panacea? market stress, incentive distortions, and gains trading. *The Journal of Finance 70*(6), 2489–2538.

Freund, J., J. Curry, P. Hirsch, and T. Kelley (1997). Commercial real estate and the banking crises of the 1980s and early 1990s. In *History of the Eighties: Lessons for the Future. Vol. 1, An Examination of the Banking Crises of the 1980s and Early 1990s*, Chapter 3, pp. 138–165. Washington, D.C.: Federal Deposit Insurance Corportation.

Furfine, C. (2020). The impact of risk retention regulation on the underwriting of securitized mortgages. *Journal of Financial Services Research 58*(2), 91–114.

Gande, A. and A. Saunders (2012). Are banks still special when there is a secondary market for loans? *Journal of Finance 67(5)*, 1649–1684.

Garner, C. A. (2008). Is commercial real estate reliving the 1980s and early 1990s? *Federal Reserve Bank of Kansas City Economic Review 93*(Q3), 89–115.

Ghent, A. and R. Valkanov (2016). Comparing securitized and balance sheet loans: Size matters. *Management Science 62*, 2784–2803.

Ghent, A. C. (2021). What's wrong with pittsburgh? delegated investors and liquidity concentration. *Journal of Financial Economics 139*(2), 337–358.

Ghent, A. C., W. N. Torous, and R. I. Valkanov (2019). Commercial real estate as an asset class. *Annual Review of Financial Economics 11*, 153–171.

Glancy, D. and R. Kurtzman (2018). How do capital requirements affect loan rates? evidence from high volatility commercial real estate. *Finance and Economics Discussion Series 2018-079*.

Hale, G. and J. A. Santos (2009). Do banks price their informational monopoly? *Journal of Financial Economics 93*(2), 185–206.

Hart, O. and J. Moore (1998). Default and renegotiation: A dynamic model of debt. *The Quarterly Journal of Economics 113*, 1–41.

Hendershott, P. H. and E. J. Kane (1992). Causes and consequences of the 1980s commercial construction boom. *Journal of Applied Corporate Finance 5*(1).

McFadden, D. L. (1973). Conditional logit analysis of qualitative choice behavior. In P. Zarembka (Ed.), *Frontiers in Econometrics*, Chapter 4, pp. 105–142. New York: Academic Press.

McFadden, D. L. (1984). Chapter 24: Econometric analysis of qualitative response models. Volume 2 of *Handbook of Econometrics*, pp. 1395 – 1457.

Moysich, A. (1997). The savings and loan crisis and its relationship to banking. In *History of the Eighties: Lessons for the Future. Vol. 1, An Examination of the Banking Crises of the 1980s and Early 1990s*, Chapter 4, pp. 167–188. Washington, D.C.: Federal Deposit Insurance Corportation.

Rajan, R. (1992). Insiders and outsiders: The choice between informed and arm's-length debt. *Journal of Finance 47*, 1367–1400.

Sharpe, S. A. (1990). Asymmetric information, bank lending, and implicit contracts: A stylized model of customer relationships. *Journal of Finance 45*, 1069–1087.

Titman, S., S. Tompaidis, and S. Tsyplakov (2005). Determinants of credit spreads in commercial mortgages. *Real Estate Economics 33*(4), 711–738.

Titman, S. and S. Tsyplakov (2010). Originator performance, cmbs structures, and the risk of commercial mortgages. *Review of Financial Studies 23*, 3558–3594.

Townsend, R. M. (1979). Optimal contracts and competitive markets with costly state verification. *Journal of Economic Theory 21*, 265–293.

Webb, B. L. and C. C. Lilly III (1995). Raising the safety net: Risk-based capital for life insurance companies. Technical report, National Association of Insurance Companies.

Wright, K. M. (1991). The structure, conduct, and regulation of the life insurance industry. *Proceedings of The Federal Reserve Bank of Boston Conference Series on The Financial Condition and Regulation of Insurance Companies 35*, 73–116.

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.

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.[36] 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,

[36]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`.

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 average for continuous variables (LTV, interest rates, and property value).[37] We treat CMBS deals identified as "Single Property" that include multiple notes analogously.

We obtain data on life insurer loan originations from the NAIC mortgage origination/acquisition schedule (Schedule B - Part 2), which has all originations and acquisitions for each insurer. We include the data from the annual schedules for both the 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 exact dates of maturity and acquisition.

We additionally use panel data on the year-end portfolio holdings for the insurers from

[37] 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.

Schedule B - Part 1 to impute some additional fields. First, interest rate variability is not directly reported. To identify whether a loan is fixed or floating, we assess if the loan's interest rate is constant over time in the panel data. If the loan has the same interest rate each year, we consider it to have a fixed rate. Interest rate variability is missing when only one observation is available, a situation mostly limited to 2017 originations (the last year in the sample). In addition, property type, maturity date, and zipcode are not reported until 2014. We backfill this data for 2012 and 2013 originations data with later reported year-end portfolio data. Since life insurers mostly make long-term loans, most of these loans are still on the insurer's balance sheet when reporting expanded in 2014. To be precise, 5,428 of the 5,447 life insurance loans in 2012 and 2013, or 99.65%, are able to be backfilled.

We append the three datasets of originations by lender type. In the appended data, as noted in the text, we only keep loan originations between 2012 and 2017. We drop any observations where 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 Additional Loan and Property Characteristics across Lender Types

In addition to lenders differing on the loan terms and property characteristics discussed in Section 2.3, lenders can also differ in a number of other ways. In the first subsection, we explore the geographic distribution of where different lenders originate loans. In the second subsection, we discuss how amortization rates differ across lender types.

B.1 Geographic Differences across Lender Types

This section studies the characteristics 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

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.[38] 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

[38]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 lenders. 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 waited until deeper into the recovery to expand lending. 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

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)

relative to those of CMBS when controls are included. This indicates that the unconditional 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 variability (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 are still found to operate in areas with lower unemployment rates compared to the other lenders.

B.2 Information on Amortization across Lender Types

Data on the amortization of loans are not reported consistently across the different lender types. While these data are available for banks and CMBS, they are not provided for life insurers. However, we can impute some information on loan amortization for life insurers based on changes in outstanding balances over time.

Consider a fixed rate mortgage with a constant mortgage payment. The balance for this loan evolves according to: $B_t = B_{t-1}(1+r) - C \times B_0$, where B_t is the current balance at time t, r is the interest rate, B_0 is the balance at origination, and C is the mortgage constant (the required principal and interest payment as a fraction of the original loan balance). We can thus solve for the mortgage constant as a function of the decline in loan balances and the interest rate on the loan: $C = \frac{1}{B_0}(B_{t-1}(1+r) - B_t)$.

Given this mortgage constant, we can then solve for the amortization term, denoted T, using the annuity formula. Equating the loan balance to the discounted value of loan payments gives us that: $B_0 = C \times B_0 \times \frac{1}{r}(1 - (1+r)^{-T})$. Rearranging gives us that: $T = \ln(\frac{C}{C-r})/\ln(1+r)$.

Thus for fixed rate loans, we can use the available data to solve for the amortization term at a particular point in time.[39] Although we cannot determine the full amortization schedule for all lender types, we can at least characterize differences in early-life amortization schedules.

Estimates of amortization terms at origination across lenders are shown in Table B.3. Pct. I/O (%) gives the share of loans that are initially interest only (IO), and Amortization Term shows the 25th, 50th and 75th percentile of amortization terms for loans that are amortizing. These variables for life insurers are imputed as described above, while data on amortization for banks and CMBS are reported directly.[40]

Amortization schedules vary notably across lenders. CMBS loans have the longest

[39] Note that a loan may be interest only at the start of the term but then amortize later. In this situation, the amortization term will be undefined at the start ($C = r$), and then change when the loan starts amortizing.

[40] For banks, we use the amortization field (MDRM K457) from the Y-14Q. For CMBS, we use two fields from Morningstar: "OriginalInterestOnlyTerm" to identify whether a loan is IO or non-IO, and then "OriginalAmortizationTermMonths" to identify the amortization term. We clean the data following the procedures outlined in the rest of the paper. We also drop any observations that have missing or negative amortization terms, or those listed as having non-standard amortization schedules in the bank data.

Table B.3
Amortization Statistics across Lender Types

	#Observations	Pct. I/O (%)	Amortization Term		
			25th	50th	75th
Banks	13,582	7.90%	15.00	20.00	25.00
CMBS	10,907	43.10%	25.00	30.00	31.50
Life	5,950	0.32%	19.28	24.44	25.16
Life (15-year term)	893	0.0%	14.64	14.98	24.66
Life (20-year term)	788	0.0%	19.52	19.78	20.10
Life (25-year term)	637	0.0%	24.58	24.75	24.98
Life (30-year term)	637	0.0%	29.70	29.88	30.10

Notes: This table presents amortization statistics for fixed rate loans by lender type, as well as for life insurance loans with exactly 15-, 20-, 25-, and 30-year terms. The first column shows the number of observations. The second column (Pct. I/O) shows the percent of these loans that are initially interest-only. The third through sixth columns show summary statistics of the amortization properties of the non-I/O loans.

amortization terms. About 43% of CMBS loans are fully or partially IO (about 13% of CMBS loans are fully IO), and most amortizing CMBS loans have about a 30-year amortization schedule. Given the typical CMBS loan term is 10 years, these amortization schedules result in notable balloon payments at maturity. Bank loans have shorter amortization periods with a median of 20 years, and only about 8% of loans being initially IO. As bank loans typically have terms of 10 years or under, these results suggest that there are often balloon payments due at maturity.

Life insurance loans have amortization periods that are closest aligned with loan terms. The typical life insurance loan has a 20- or 25-year amortization term, and fewer than 1% of loans are IO. Most longer-term life insurance loans appear to be fully amortizing. When statistics for amortization are disaggregated by loan term, we find that the median amortization period for life insurer loans with terms of 15, 20, 25, and 30 years are 14.98, 19.78, 24.75, and 29.88 years, respectively.

C Mathematical Appendix

The first subsection establishes the notation used throughout the appendix. The second subsection explains how the parameters in the model are estimated. The third subsection presents the formulas used to evaluate the effects of counterfactual shocks. To keep the second and third subsections digestable, lengthy proofs and derivations are left to the fourth subsection.

C.1 Notation

Recall from Section 3.1 that lender j offers the rate $R_{i,j} = X_i'\beta_j - \sigma\epsilon_{i,j}$ to borrower i for a loan with a vector of characteristics X_i. $R_{i,j}$ is thus linear in characteristics with a loading $\beta_{j,n}$ on characteristic n, and has an idiosyncratic component $\sigma\epsilon_{i,j}$ The borrowers chooses the lowest interest rate offered among J lenders. $\epsilon_{i,j}$ is distributed type-I extreme value, meaning it has the CDF: $F(\epsilon) = \exp(-e^{-\epsilon})$.

Throughout the mathematical appendix, we use the following notation:

$$\begin{aligned}
y_{i,j} &= 1 \text{ if } i \text{ chooses } j\text{, 0 otherwise} \\
P_{i,j} &= \text{Probability}(i \text{ chooses } j) \\
N_j &= \sum_i P_{i,j} \\
\widetilde{R_{i,j}} &\equiv \frac{X_i'\beta_j}{\sigma} \\
\overline{R}_i &\equiv -\ln\left(\sum_{j\in J} \exp(-\widetilde{R_{i,j}})\right)
\end{aligned}$$

That is, $y_{i,j}$ is an indicator for whether j offers the lowest interest rate to a borrower with characteristics X_i. The variable $P_{i,j}$ is the probability that j lends to i. N_j is the mass of borrowers taking loans from lender j. $\widetilde{R_{i,j}}$ reflects the expected pricing of a loan to borrower i by lender j, normalized by the scale parameter σ. This term is important for determining the probability that j lends to i. Finally, $\overline{R}_i$ is an aggregation of the expected pricing of the different lenders. We will show that expected loan rates are proportional to $\overline{R}_i$, with scaling factor σ.

C.2 Parameter Estimation

The primary outcome variables of interest in the model are who makes a loan with a given set of characteristics, and at what interest rate is the loan made. Here we present the formulas pertaining to these model outcomes. In the remainder of this subsection of this appendix, we build on these formulas and show how we estimate the parameters with the microdata.

The probability that a borrower i chooses lender j and the expected interest rate of this loan are as follows:

$$P_{i,j} = \frac{e^{-\widetilde{R}_{i,j}}}{\sum_{j'} e^{-\widetilde{R}_{i,j}}} = \exp(\overline{R}_i - \widetilde{R}_{i,j}). \tag{5}$$

$$\mathbb{E}(R_i) = \sigma \overline{R}_i. \tag{6}$$

These formulas are derived in Appendix C.4.2 and C.4.3, respectively. Note that both of these expressions are functions of the model parameters β and σ and borrower characteristics X_i.

C.2.1 Estimating Pricing Factors Relative to Reference Group

As explained in Section 3.2, we use a multinomial logit to identify the pricing factors of life insurers and CMBS relative to banks. Given the probability of a particular lender lending defined in (5), we can write the likelihood of each borrower in the sample choosing their observed lender, $L(\beta)$, as:

$$L(\beta) = \prod_{i=1}^{N} \prod_{j} P_{i,j}^{y_{i,j}}.$$

We can estimate β by maximizing the log-likelihood function (LL):

$$\begin{aligned} LL(\beta) &= \sum_{i=1}^{N} \sum_{j} y_{i,j} \ln(P_{i,j}) \\ &= \sum_{i=1}^{N} \sum_{j} y_{i,j}(-X_i'\beta_j) - \sum_{i=1}^{N} \ln\left(\sum_{j' \in J} \exp(-\frac{X_i'\beta_{j'}}{\sigma})\right), \end{aligned}$$

where the second line comes from substituting equation (5) in for $P_{i,j}$ and simplifying.

What identifies the parameters in this estimation strategy? In order to provide clarity on this question, it is informative to look at the first order conditions of this log-likelihood function. Differentiating this equation with respect to $\beta_{k,n}$ (the pricing of term n by lender

k) gives:

$$\frac{\partial LL(\beta)}{\partial \beta_{k,n}} = -\sum_{i=1}^{N} y_{i,k} x_{i,n} - \sum_{i=1}^{N} \frac{\exp(-\frac{X_i' \beta_k}{\sigma})}{\sum_{j' \in J} \exp(-\frac{X_i' \beta_{j'}}{\sigma})} (-x_{i,n})$$
$$= \sum_{i=1}^{N} (P_{i,k} - y_{i,k}) x_{i,n}.$$

Setting this derivative equal to 0 and dividing by N_k, we can see that the first order condition implies that the average value for characteristic n in k's portfolio is equal in the data and in the model. In short, the pricing factors are estimated so that the the average loan characteristics by lender type in the data (as documented in Section 2) are matched in the model.

A second question is: What is identified? Due to the constraint that the probabilities add up to one, not all pricing factors are separately identified. Instead, the pricing factors are identified up to a scale parameter σ and reference group. Taking $j = 0$ to be the reference group, the lending probability can be written as:

$$P_{i,k} = \frac{\exp(-\frac{X_i' \beta_k}{\sigma})}{\sum_j \exp(-\frac{X_i' \beta_j}{\sigma})}$$
$$= \frac{\exp\left(X_i' (\frac{\beta_0 - \beta_k}{\sigma})\right)}{\sum_j \exp\left(X_i' (\frac{\beta_0 - \beta_j}{\sigma})\right)}.$$

We can thus see that it is the term $\beta_k^{\text{logit}} \equiv \frac{\beta_0 - \beta_k}{\sigma}$ that is identified by the multinomial logit. In the next subsection, we discuss how we estimate the other parameters—β_0 and σ—so as to estimate the pricing factors themselves.

C.2.2 Scale Parameter and Pricing of Reference Group

The scale parameter σ is important for identifying by how much a particular pricing shock affects the market in absolute terms. While the multinomial logit identifies the importance of the terms in X_i relative to one another, we need to estimate how much idiosyncratic variance there is across lender types. Intuitively, if σ is low (low idiosyncratic variance), then only small differences in the pricing of characteristics are needed to reproduce the difference in lender outcomes in the data. This means that any given pricing shock will have a larger effect on who lends.

The pricing factor for the reference group is less important for the model, as it does not affect substitution patterns. However, we still estimate these parameters to obtain estimates of how lenders price loans, rather than how they price loans compared to banks, even if the latter is sufficient for all of the counterfactual exercises we run.

We estimate σ and β_0 so that moments from pricing regressions in the data match moments from pricing regressions in the model. Note that from Equation (6), the expected interest rate of a loan with characteristics X_i, can be written as:

$$\begin{aligned}
\mathbb{E}(R_i) &= \sigma \overline{R}_i \\
&= -\sigma \ln\left(\sum_{j\in J} \exp(-\frac{X_i'\beta_j}{\sigma})\right) \\
&= X_i'\beta_0 - \sigma \ln\left(\sum_{j\in J} \exp(X_i'\beta_j^{\text{logit}})\right) \\
&= X_i'\beta_0 + \sigma \overline{R}_i^{\text{logit}},
\end{aligned} \tag{7}$$

where $\beta_k^{\text{logit}} \equiv \frac{\beta_0 - \beta_k}{\sigma}$ is the estimated coefficient from the multinomial logit, and $\overline{R}_i^{\text{logit}} \equiv -\ln\left(\sum_{j\in J} \exp(X_i'\beta_j^{\text{logit}})\right)$, the expected pricing of a loan (relative to the reference group), normalized by σ.

Calibration of β_0

We calibrate β_0 so that pricing regressions in the overall data (pooling all lender types) are equated in the model and the data. Denoting R^{data} and R^{model} as the vector of loan spreads observed in the data and the vector of predicted loan rates from the model, we thus set β_0 so that:

$$(X'X)^{-1}(X'R^{\text{data}}) = (X'X)^{-1}(X'R^{\text{model}})$$

$$\beta_{\text{data}}^{\text{OLS}} = \beta_0 + \sigma(X'X)^{-1}(X'\overline{R}^{\text{logit}}).$$

The second line comes from substituting in the vector of predicted rates from Equation (7). We can see that this equality holds when $\beta_0 = \beta^{\text{OLS}}_{\text{data}} - \sigma(X'X)^{-1}(X'\overline{R}^{\text{logit}})$, where $\beta^{\text{OLS}}_{\text{data}}$ is the vector of coefficients from an OLS regression of observed interest rates on loan characteristics.

When this equation holds, we have that for each loan characteristic n:

$$\sum_{i=1}^{N}(R_i^{\text{data}} - R_i^{\text{model}})x_{i,n}.$$

Therefore, similar to the identification of the pricing factors from the logit, this estimation strategy produces errors (pertaining to predicted interest rates rather than predicted lenders) that are orthogonal to loan characteristics.

Calibration of σ

Finally, we calibrate σ to match the results of lender-specific pricing regressions. Specifically, σ is chosen so that the median difference between the lowest and second lowest predicted rate across lenders is equalized.

Let $\widehat{R}^{\text{OLS}}_{j,\text{data}}$ denote the vector of predicted interest rates offered by lender j based on an OLS regression of interest rates on loan characteristics for loans made by j, and $\widehat{R}^{\text{OLS}}_{j,\text{model}}$ the equivalent predicted rate from the model. These vectors of OLS predicted rates are as follows:

$$\begin{aligned}
\widehat{R}^{\text{OLS}}_{j,\text{data}} &= X(X'Y_jX)^{-1}X'Y_jR_{\text{data}} \\
\widehat{R}^{\text{OLS}}_{j,\text{model}} &= X\left(B_0 + \sigma(X'P_jX)^{-1}X'P_j\overline{R}^{\text{logit}}\right),
\end{aligned}$$

where P_j and Y_j are diagonal matrices giving the probability of j lending from the model and the indicator for whether j lends in the data, respectively. That is, the predicted loan rates come from weighted-least squares estimates of interest rates, weighting by either the lender dummy or the probability a particular lender makes a given loan. Presented this way, we can see that Y_j is used as the empirical analogue of P_j, and R^{data} as the empirical analogue of R^{model}, as elsewhere in the estimation strategy.[41]

Differences in predicted interest rates across lenders scale linearly with σ. Therefore, we can calibrate σ so that differences in these predicted rates across lenders match in the data and model. Since the substitution patterns in the model depend predominantly on how close the pricing of the second-best offer is to the best offer, we use this as the measure of dispersion across lender types. In the data, borrowers have a median difference between the lowest OLS-predicted loan spread and second-lowest OLS-predicted loan spread of 8.6bp. In the model, the median difference is $\sigma \times 23.4$bp. Thus for $\sigma = 0.37$, the typical borrower in the model has a difference in OLS-predicted loan rates that exactly matches the data.

C.3 Effects of Shocks

This subsection shows how we use the estimated model to calculate the effects of various counterfactual shocks. The estimation procedure generates an estimate of β and σ, determining how lenders price loans on average, and how much rates differ around these averages. Here, we show how various outcomes in the market change if there were to be some shock producing a new pricing regime β'.

C.3.1 Probability of Switching Between Given Lender Types

In the validation exercise, the object of interest is the probability that a borrower switched from one lender to another particular lender due to a shock. Suppose that there is some shock that raises the offered loan rates by each lender j by $\sigma\Delta_j$. This would mean that $\widetilde{R'_{i,j}} = \widetilde{R_{i,j}} + \Delta_j$. We want to find the probability that a lender switches from $j = 0$ to $j = 1$. It is important to note that this indexing is used to denote the pre-shock lender and post-shock lender; $j = 0$ need not refer to the reference group.

In Appendix C.4.5, we show that the probability that a lender switches from $j = 0$ to

[41] The second equation uses the fact that $\mathbb{E}(R_i | Y_{i,j} = 1) = X_i'\beta_0 + \sigma\overline{R}_i^{\text{logit}}$. In other words, expected interest rates are independent of which intermediary lends. We prove this in Appendix C.4.4.

$j = 1$ can be calculated as:

$$\Pr(y_1' = 1|y_0 = 1) = \mathbb{1}[\min\{\Delta_0, \Delta_2\} > \Delta_1] \left(\frac{e^{-\widetilde{R_{i,1}}}(e^{\min\{\Delta_0,\Delta_2\}-\Delta_1} - 1)}{e^{-\widetilde{R_{i,0}}} + e^{-\widetilde{R_{i,2}}} + e^{-\widetilde{R_{i,1}}} e^{\min\{\Delta_0,\Delta_2\}-\Delta_1}} \right)$$
$$+ \mathbb{1}[\Delta_0 > \max\{\Delta_1, \Delta_2\}] \frac{P'_{i,0}}{P_{i,0}} \frac{e^{-\widetilde{R'_{i,1}}}}{e^{-\widetilde{R'_{i,1}}} + e^{-\widetilde{R'_{i,2}}}} \left(\frac{[e^{-\widetilde{R'_{i,1}}} + e^{-\widetilde{R'_{i,2}}}](1 - e^{\max\{\Delta_1,\Delta_2\}-\Delta_0})}{e^{-\widetilde{R'_{i,0}}} + [e^{-\widetilde{R'_{i,1}}} + e^{-\widetilde{R'_{i,2}}}] e^{\max\{\Delta_1,\Delta_2\}-\Delta_0}} \right).$$

C.3.2 Effects of 25bp and 50bp Shocks to Given Lender

The effects of the pricing shocks generated in Table 6 are straightforward given the formulas for market shares and interest rates as a function of β given in Equations (5) and (6). Noting that $P_{i,j}$ and $\overline{R}_i$ are functions of β (and explicitly writing them as such), we get the following formulas for changes in market shares or expected loan rates when the pricing factor changes to a new β'. For the counterfactuals in Table 6, β' is equal to β except for a 25bp or 50bp increase in the lender-specific constant for one lender.

- Change in average spreads: $\frac{1}{N} \sum_i \left(\overline{R}_i(\beta') - \overline{R}_i(\beta) \right)$.
- Change in average spreads for j's borrowers: $\frac{1}{N_j(\beta')} \sum_i P_{i,j}(\beta') \overline{R}_i(\beta') - \frac{1}{N_j(\beta)} \sum_i P_{i,j}(\beta) \overline{R}_i(\beta)$.
- Change in j's market share: $\frac{1}{N} \sum_i \left(P_{i,j}(\beta') - P_{i,j}(\beta) \right)$.

C.4 Derivations

C.4.1 Integrating over ϵ_i

All of the proofs in this section involve integrating over the idiosyncratic match terms in order to solve for either expected loan rates or the probabilities that particular lenders make particular loans. The idiosyncratic match is i.i.d. with the cumulative distribution function $F(\epsilon) = \exp(-e^{-\epsilon})$. A characteristic of this distribution is that:

$$\int \left(\prod_j F(C_{i,j} + \epsilon_{i,k}) \right) \exp(-\epsilon_{i,k}) d\epsilon_{i,k} = \frac{\exp(-e^{-\epsilon_{i,k}} \sum_j e^{-C_{i,j}})}{\sum_j e^{-C_{i,j}}} + C, \tag{8}$$

where $C_{i,j}$ is any borrower-lender level constant. In particular, this means that $\int_{-\infty}^{\infty} \left(\prod_j F(C_j + \epsilon_{i,k}) \right) e^{-\epsilon_{i,k}} d\epsilon_{i,k} = 1/\sum_j e^{-C_j}$. This expression occurs frequently, so we will prove this up-front and use equation (8) as a short cut through-out the proofs. The proof follows as such:

$$
\begin{aligned}
\int \left(\prod_j F(C_{i,j} + \epsilon_{i,k}) \right) \exp(-\epsilon_{i,k}) d\epsilon_{i,k} &= \int \left(\exp(-\sum_j e^{-(C_{i,j}+\epsilon_{i,k})}) \right) \exp(-\epsilon_{i,k}) d\epsilon_{i,k} \\
&= \int \left(\exp(-e^{-\epsilon_{i,k}} \sum_j e^{-C_{i,j}}) \right) \exp(-\epsilon_{i,k}) d\epsilon_{i,k} \\
&= \int \exp(t \sum_j e^{-C_{i,j}}) dt \quad (t = -e^{-\epsilon_{i,k}}) \\
&= \frac{\exp(t \sum_j e^{-C_{i,j}})}{\sum_j e^{-C_{i,j}}} + C \\
&= \frac{\exp(-e^{-\epsilon_{i,k}} \sum_j e^{-C_{i,j}})}{\sum_j e^{-C_{i,j}}} + C.
\end{aligned}
$$

C.4.2 Lending Probabilities

$P_{i,k}$ is the probability lender k lends to borrower i, meaning that k has the lowest offered interest rate. This can be derived as follows:

$$
\begin{aligned}
P_{i,k} &= \Pr(\widetilde{R}_{i,k} - \epsilon_{i,k} < \widetilde{R}_{i,j} - \epsilon_{i,j} \quad \forall j \neq k) \\
&= \Pr(\epsilon_{i,j} < \widetilde{R}_{i,j} - \widetilde{R}_{i,k} + \epsilon_{i,k} \quad \forall j \neq k) \\
&= \int_{-\infty}^{\infty} \left(\prod_{j \neq k} F(\widetilde{R}_{i,j} - \widetilde{R}_{i,k} + \epsilon_{i,k} \right) f(\epsilon_{i,k}) d\epsilon_{i,k} \\
&= \int_{-\infty}^{\infty} \left(\prod_{j} F(\widetilde{R}_{i,j} - \widetilde{R}_{i,k} + \epsilon_{i,k}) \right) e^{-\epsilon_{i,k}} d\epsilon_{i,k} \\
&= \frac{1}{\sum_j e^{\widetilde{R}_{i,k} - \widetilde{R}_{i,j}}} \\
&= \frac{e^{-\widetilde{R}_{i,k}}}{\sum_j e^{-\widetilde{R}_{i,j}}} = \exp(\overline{R}_i - \widetilde{R}_{i,k}).
\end{aligned}
$$

Getting to the fifth line from the fourth line uses equation (8).

C.4.3 Expected Interest Rate

We start by deriving the CDF for a borrower's loan rate. Note that a borrower's loan rate is less than r if it is not the case that all lenders have interest rate offers above r. Thus the CDF for $\frac{R_i}{\sigma}$ is:

$$\begin{aligned}
\Pr(\frac{R_i}{\sigma} \leq r) &= 1 - \Pr(\widetilde{R}_{i,j} - \epsilon_{i,j} > r \quad \forall j \in J) \\
&= 1 - \prod_j F(\widetilde{R}_{i,j} - r) \\
&= 1 - \exp(-\sum_j e^{r - \widetilde{R}_{i,j}})) \\
&= 1 - \exp(-e^r \sum_j e^{-\widetilde{R}_{i,j}})) \\
&= 1 - \exp(-e^r e^{-\overline{R}_i}) \\
&= 1 - \exp(-e^{r - \overline{R}_i}).
\end{aligned}$$

Note that this means that $\frac{R_i}{\sigma}$ has a PDF $\exp(-e^{r-\overline{R}_i})e^{r-\overline{R}_i}$ and $-\frac{R_i}{\sigma}$ has a PDF $\exp(-e^{-(r+\overline{R}_i)})e^{-(r+\overline{R}_i)}$. That is, $-\frac{R_i}{\sigma}$ is distributed type-I extreme value with mean $-\overline{R}_i$, giving us the following expected interest rate given X_i:[42]

$$\mathbb{E}(R_i|X_i, \beta) = \sigma\overline{R}_i = -\sigma \ln\left(\sum_{j \in J} \exp(-\frac{X_i'\beta_j}{\sigma})\right). \tag{9}$$

C.4.4 Expected Interest Rates Conditional on Lender

Here we show that Probability$(\frac{R_i}{\sigma} \leq r | y_{i,k} = 1) = 1 - \exp(-e^{r-\overline{R}_i})$. That is, loan rates have the same distribution when conditioning on a particular lender having the lowest interest rate. This means that the expected loan rates don't need to differ from that given in

[42] Technically, $\mathbb{E}(R_i|X_i)$ should be $\sigma(\overline{R}_i - \gamma)$, where γ is Euler's Constant, reflecting the non-zero mean of each idiosyncratic error term. To simplify notation, we redefine the lender-specific intercepts to include this constant.

Equation (6), when doing the lender-specific regressions used to calibrate σ.

$$\begin{aligned}
\Pr(\frac{R_i}{\sigma} \le r | y_{i,k} = 1) &= \Pr(\frac{R_i}{\sigma} \le r \cap y_{i,k} = 1)\Pr(y_{i,k} = 1)^{-1} \\
&= \int_{\widetilde{R}_{i,k}-r}^{\infty} \left(\prod_{j \neq k} F(\widetilde{R}_{i,j} - \widetilde{R}_{i,k} + \epsilon_{i,k}) \right) f(\epsilon_{i,k}) d\epsilon_{i,k} P_{i,k}^{-1} \\
&= \int_{\widetilde{R}_{i,k}-r}^{\infty} \left(\prod_{j} F(\widetilde{R}_{i,j} - \widetilde{R}_{i,k} + \epsilon_{i,k}) \right) e^{-\epsilon_{i,k}} d\epsilon_{i,k} e^{\widetilde{R_{i,k}} - \overline{R}_i} \\
&= \int_{\widetilde{R}_{i,k}-r}^{\infty} \left(\prod_{j} F(\widetilde{R}_{i,j} - \widetilde{R}_{i,k} + \epsilon_{i,k}) \right) e^{\widetilde{R_{i,k}} - \overline{R}_i - \epsilon_{i,k}} d\epsilon_{i,k} \\
&= \int_{\widetilde{R}_{i,k}-r}^{\infty} \left(\exp(-\sum_{j} e^{-(\widetilde{R}_{i,j} - \widetilde{R}_{i,k} + \epsilon_{i,k})} \right) e^{\widetilde{R_{i,j}} - \overline{R}_i - \epsilon_{i,k}} d\epsilon_{i,k} \\
&= \int_{\widetilde{R}_{i,k}-r}^{\infty} \exp(-e^{-(\overline{R}_i - \widetilde{R}_{i,k} + \epsilon_{i,k})}) e^{-(\overline{R}_i - \widetilde{R}_{i,k} + \epsilon_{i,k})} d\epsilon_{i,k} \\
&= \int_{\widetilde{R}_{i,k}-r}^{\infty} f(\overline{R}_i - \widetilde{R}_{i,k} + \epsilon_{i,k}) d\epsilon_{i,k} \\
&= 1 - F(\overline{R}_i - r) \\
&= 1 - \exp(-e^{r - \overline{R}_i}).
\end{aligned}$$

C.4.5 Switching Probabilities

Suppose that there is some change to the pricing vector causing $\widetilde{R}_{i,j}$ to increase to $\widetilde{R'}_{i,j} = \widetilde{R}_{i,j} + \Delta_j$. We want to find the probability that a particular borrower would switch from lender 0 to a different lender 1 as a result of the change.

We start by finding Probability($y_1' = 1 \cap y_0 = 1$). For 1 to lend after the shock, and 0 before the shock the following four conditions must hold:

$$\begin{aligned}
\epsilon_1 &< \widetilde{R_{i,1}} - \widetilde{R_{i,0}} + \epsilon_0 & \epsilon_2 &< \widetilde{R_{i,2}} - \widetilde{R_{i,0}} + \epsilon_0 \\
\epsilon_0 &< \widetilde{R'_{i,0}} - \widetilde{R'_{i,1}} + \epsilon_1 & \epsilon_2 &< \widetilde{R'_{i,2}} - \widetilde{R'_{i,1}} + \epsilon_1.
\end{aligned}$$

We can thus solve for Probability($y_1' = 1 \cap y_0 = 1$) as follows:

$$
\begin{aligned}
\Pr(y_1' = 1 \cap y_0 = 1)& \\
&= \int_{-\infty}^{\infty} \int_{\epsilon_0 - \widetilde{R'_{i,0}} + \widetilde{R'_{i,1}}}^{\widetilde{R_{i,1}} - \widetilde{R_{i,0}} + \epsilon_0} \int_{-\infty}^{\min\{\epsilon_0 + \widetilde{R_{i,2}} - \widetilde{R_{i,0}}, \widetilde{R'_{i,2}} - \widetilde{R'_{i,1}} + \epsilon_1\}} dF(\epsilon) \\
&= \mathbb{1}[A > 0] \int_{-\infty}^{\infty} \int_{\epsilon_0 + \widetilde{R_{i,1}} - \widetilde{R_{i,0}} - A}^{\widetilde{R_{i,1}} - \widetilde{R_{i,0}} + \epsilon_0} \int_{-\infty}^{\epsilon_0 + \widetilde{R_{i,2}} - \widetilde{R_{i,0}}} dF(\epsilon) \\
&+ \mathbb{1}[B > 0] \int_{-\infty}^{\infty} \int_{\epsilon_0 + \widetilde{R'_{i,1}} - \widetilde{R'_{i,0}}}^{\epsilon_0 + \widetilde{R'_{i,1}} - \widetilde{R'_{i,0}} + B} \int_{-\infty}^{\widetilde{R'_{i,2}} - \widetilde{R'_{i,1}} + \epsilon_1} dF(\epsilon) \\
&= \mathbb{1}[A > 0] \int_{-\infty}^{\infty} F(\epsilon_0 + \widetilde{R_{i,2}} - \widetilde{R_{i,0}})[F(\epsilon_0 + \widetilde{R_{i,1}} - \widetilde{R_{i,0}}) - F(\epsilon_0 + \widetilde{R_{i,1}} - \widetilde{R_{i,0}} - A)] f(\epsilon_0) d\epsilon_0 \\
&+ \mathbb{1}[B > 0] \int_{-\infty}^{\infty} \left[\int_{\epsilon_0 + \widetilde{R'_{i,1}} - \widetilde{R'_{i,0}}}^{\epsilon_0 + \widetilde{R'_{i,1}} - \widetilde{R'_{i,0}} + B} F(\epsilon_1) F(\widetilde{R'_{i,2}} - \widetilde{R'_{i,1}} + \epsilon_1) e^{-\epsilon_1} d\epsilon_1 \right] f(\epsilon_0) d\epsilon_0,
\end{aligned}
$$

where $A = \min\{\Delta_0 - \Delta_1, \Delta_2 - \Delta_1\}$ and $B = \min\{\Delta_0 - \Delta_1, \Delta_0 - \Delta_2\}$. The two expressions in the second equality correspond to the two possible constraints on the upper-bound for ϵ_2 in $\min\{\epsilon_0 + \widetilde{R_{i,2}} - \widetilde{R_{i,0}}, \widetilde{R'_{i,2}} - \widetilde{R'_{i,1}} + \epsilon_1\}$. Note that which of these terms is smaller also places and upper or lower bound on ϵ_1, which is reflected in the integration bounds in the second equality. Integrating these expressions gives us that:

$$
\begin{aligned}
&\Pr(y_1' = 1 \cap y_0 = 1)\\
&\quad = \mathbb{1}[A > 0]\left(\frac{1}{1 + e^{\widetilde{R_{i,0}} - \widetilde{R_{i,2}}} + e^{\widetilde{R_{i,0}} - \widetilde{R_{i,1}}}} - \frac{1}{1 + e^{\widetilde{R_{i,0}} - \widetilde{R_{i,2}}} + e^{-(\widetilde{R_{i,1}} - \widetilde{R_{i,0}} - A)}}\right)\\
&\quad + \mathbb{1}[B > 0]\frac{1}{1 + e^{\widetilde{R'_{i,1}} - \widetilde{R'_{i,2}}}}\left(\frac{1}{[1 + e^{\widetilde{R'_{i,1}} - \widetilde{R'_{i,2}}}]e^{-(\widetilde{R'_{i,1}} - \widetilde{R'_{i,0}} + B)} + 1} - \frac{1}{[1 + e^{\widetilde{R'_{i,1}} - \widetilde{R'_{i,2}}}]e^{\widetilde{R'_{i,0}} - \widetilde{R'_{i,1}}} + 1}\right)\\
&\quad = \mathbb{1}[A > 0]\left(P_{i,0} - \frac{e^{-\widetilde{R_{i,0}}}}{e^{-\widetilde{R_{i,0}}} + e^{-\widetilde{R_{i,2}}} + e^{-\widetilde{R_{i,1}}}e^{A}}\right)\\
&\quad + \mathbb{1}[B > 0]\frac{e^{-\widetilde{R'_{i,1}}}}{e^{-\widetilde{R'_{i,1}}} + e^{-\widetilde{R'_{i,2}}}}\left(\frac{e^{-\widetilde{R'_{i,0}}}}{e^{-\widetilde{R'_{i,0}}} + [e^{-\widetilde{R'_{i,1}}} + e^{-\widetilde{R'_{i,2}}}]e^{-B}} - P'_{i,0}\right)\\
&\quad = \mathbb{1}[\min\{\Delta_0, \Delta_2\} > \Delta_1]P_{i,0}\left(\frac{e^{-\widetilde{R_{i,1}}}(e^{\min\{\Delta_0,\Delta_2\} - \Delta_1} - 1)}{e^{-\widetilde{R_{i,0}}} + e^{-\widetilde{R_{i,2}}} + e^{-\widetilde{R_{i,1}}}e^{\min\{\Delta_0,\Delta_2\} - \Delta_1}}\right)\\
&\quad + \mathbb{1}[\Delta_0 > \max\{\Delta_1, \Delta_2\}]P'_{i,0}\frac{e^{-\widetilde{R'_{i,1}}}}{e^{-\widetilde{R'_{i,1}}} + e^{-\widetilde{R'_{i,2}}}}\left(\frac{[e^{-\widetilde{R'_{i,1}}} + e^{-\widetilde{R'_{i,2}}}](1 - e^{\max\{\Delta_1,\Delta_2\} - \Delta_0})}{e^{-\widetilde{R'_{i,0}}} + [e^{-\widetilde{R'_{i,1}}} + e^{-\widetilde{R'_{i,2}}}]e^{\max\{\Delta_1,\Delta_2\} - \Delta_0}}\right).
\end{aligned}
$$

To get the probability of transition: Probability$(y_1' = 1 | y_0 = 1)$ = Probability$(y_1' = 1 \cap y_0 = 1)P_{i,0}^{-1}$.

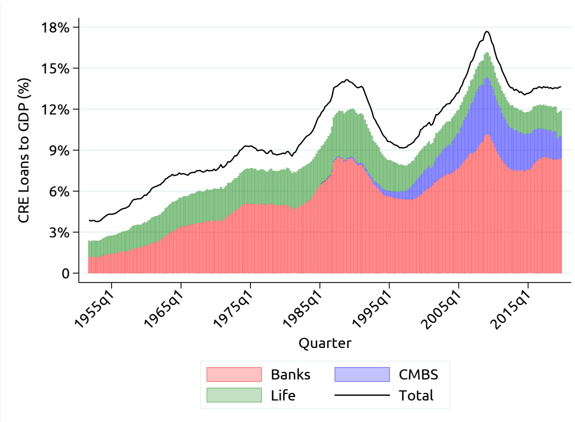
D Further Details on the CRE Market

D.1 History

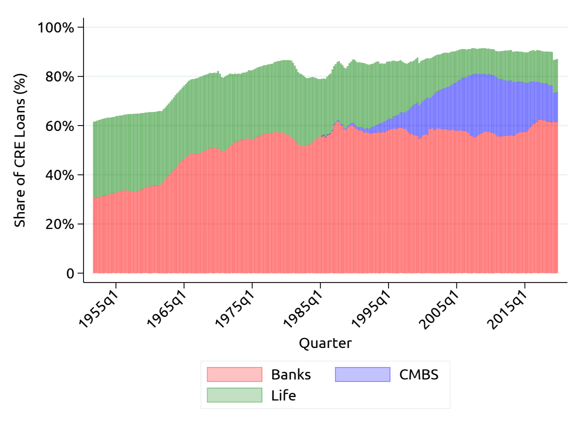
The size of the commercial mortgage market has grown notably relative to the broader economy, rising from about 4% of GDP in 1951 to around 14% as of 2020:Q3 (see Figure D.1). Banks account for about 60% of this debt, with most of the remainder accounted for by commercial mortgage backed securities (CMBS) 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.[43]

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

[43] 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.



(a) As a percent of GDP



(b) As a percent of total CRE lending

Figure D.1: CRE Lending in the United States

Notes: The data source is the Financial Accounts of the United States Z.1 Statistical Release. The data is quarterly and spans from 1951:Q4-2019:Q4. Panel (a) is a stacked area chart of commercial real estate loans at banks (red bars), life insurers (green bars), and CMBS lenders (blue bars), all as a percent of U.S. nominal GDP. The panel also shows total CRE lending as a percent of nominal GDP (the black line). Banks is U.S.-chartered depository institutions; commercial mortgages; asset (Table L.220 - FL763065503.Q) plus Foreign banking offices in the U.S.; commercial mortgages; asset (Table L.220 - FL753065503.Q) plus Banks in U.S.-affiliated areas; commercial mortgages; asset (Table L.220 - FL743065505.Q). Life insurers is Life insurance companies; commercial mortgages; asset (Table L.220 - FL543065505.Q). CMBS lenders is Issuers of asset-backed securities; commercial mortgages; asset (Table L.220 - FL673065505.Q) plus Mortgage real estate investment trusts; securitized commercial mortgages; asset (Table L.129 - FL643065543.Q). Total CRE lending is All sectors; commercial mortgages; asset (Table L.220 - FL893065505.Q). Panel (b) is a stacked area chart of lending for the same intermediary types as a percent of total CRE lending.

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 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).[44]

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&Ls. 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 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

[44]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.

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., 2019). 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 concentrations. 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 are now subject to risk retention rules.

D.2 Capital requirements

The treatment of commercial real estate with regard to capital requirements has changed over time as regulators have reacted to vulnerabilities revealed during times of stress. 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.[45] 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 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.[46]

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 Global Financial Crisis. The low

[45] 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.

[46] 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 5.2 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 18.2%, depending on the performance of the CRE portfolio over the previous two years.

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).[47] 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 raise the risk factor up to a maximum of 7.5%.[48] Restructured mortgages no longer receive a higher risk factor, while loans that are delinquent and in the process of foreclosure continue to have risk factors of 18% and 23%.[49]

Banks Banks began facing risk-based capital requirements in the aftermath of the S&L crisis. The 1988 Basel Accord grouped banks' assets into 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

[47] 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.

[48] 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.

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

consistent, with CRE loans being given a 100% risk weight in each new iteration of Basel rules.[50] 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 compared to 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.

Note that larger banks 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. In addition, 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 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.

Effect on loan quality Figure D.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.[51] 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

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

[51] The measures are imperfect, as the CMBS measure includes agency loans, while the bank measure includes construction lending. Additionally, there are some accounting differences across the lender types, for example when a loan is written off and no longer reported as delinquent.

new life insurance risk based capital requirements went into effect. Both banks and insurers experienced significant delinquencies in the early 1990s, which slowly declined over the course of the decade.

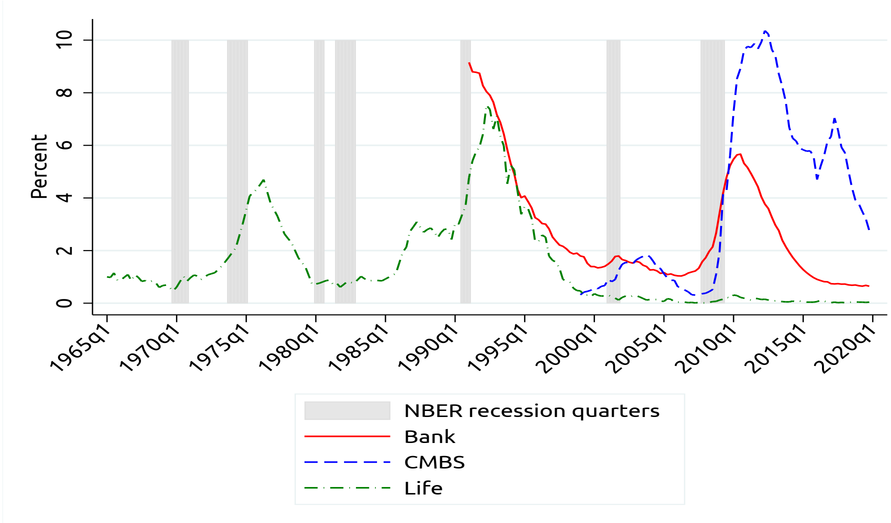


Figure D.2: Delinquency Rates by Lender Type

Notes: This figure shows measures of delinquency rates by lender type through 2019:Q4. 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 as banks and CMBS faced modest increases in delinquencies after the dot-com crash and dramatic increases in delinquencies after the financial crisis.

Altogether, the time series for loan delinquency rates by lender type suggests changes in capital requirements affect the riskiness of the CRE loans made by the different lender types.

D.3 Bank and Life Insurer CMBS Holdings

Although we have mostly discussed banks and insurers as portfolio lenders, it is important to note that they are also significant investors in securities. As a result, demand for CMBS securities—which ultimately determines how CMBS lenders will price loans—depends in part on how such securities are evaluated by banks and life insurers. If a portfolio lender is a large holder of CMBS, then it could result in supply shocks being correlated across lender types: deleveraging by an intermediary might result in a contraction in both direct lending and CMBS lending. While endogenizing the pricing factors to account for this interconnectedness is beyond the scope of this paper, here we present some information on bank and life insurer CMBS holdings to provide a sense of how important these intermediaries potentially are in influencing CMBS supply conditions.

Notably, bank and insurer CRE holdings are dominated by their portfolio loans: Direct CRE loans compose about 79% of life insurers' CRE investment exposure (CRE loans plus CMBS holdings) and about 98% of banks' CRE exposure. In terms of their CMBS holdings, life insurers are more prominent holders of CMBS than banks. As of 2019:Q4, life insurers held about a quarter of outstanding non-agency CMBS while banks held less than 10%.[52] Asset managers, such as commercial mortgage REITs, account for the majority of CMBS holdings.

[52]From the Financial Accounts of the United States, total non-Agency CMBS outstanding was about $511 as of 2019:Q4 (series FL673065403.Q and FL67306550.Q). Non-Agency CMBS holdings of banks and life insurers at this time were about $45 billion and $139, respectively, based on aggregations of Call Report data in the Financial Accounts (series LM763063653.Q and LM763063693.Q) and NAIC data provided by S&P Global. From S&P Global, banks and life insurers had about $1.8 trillion and $511 billion in commercial mortgages outstanding, respectively. Due to data limitations, all of these aggregations include both multifamily and nonresidential CRE loans.