Intermediary Segmentation in the Commercial Real Estate Market

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CRE loan market is about 14% of GDP

- Banks, CMBS, and life insurers hold nearly 90% of CRE loan market

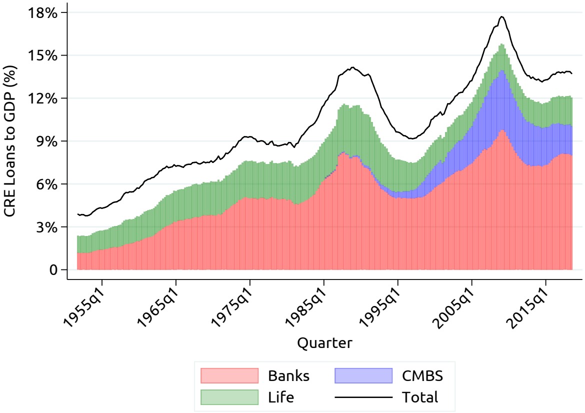

Figure: CRE lending as a percent of GDP in the United States

Source: Financial Accounts of the United States.

▸ Size Relative to Other Asset Classes ▸ CRE is 25% of Bank Loan Portfolios ▸ Delinquency Rates

This paper

Questions:

1. How do portfolios differ across CRE lenders?
2. How does segmentation affect the competitive landscape?

Contributions:

1. Document stark differences in loan terms across lenders
   - Harmonize loan-level data from banks, CMBS, and life insurers
2. Estimate model with heterogenous pricing across intermediaries
   - Validated by study of effects of CMBS supply shock
3. Simulate effects of supply shocks on borrowing costs and market shares

Harmonized datasets on originations

- Data Sources on CRE portfolios (2012-2017)
  - Banks: Y-14Q (banks over $50 billion, loans over $1 million)
  - CMBS: Morningstar (all loans in public CMBS deals)
  - Life insurers: NAIC Statutory Filings, Schedule B Parts 1 & 2 (full year-end balance sheet and new originations)
- Harmonized Data Items (for loans at origination)
  - Loan characteristics: Term, LTV, size, interest rate, fixed/floating
  - Property characteristics: Value, type, location
- Sample
  - Loans over $1 million for non-residential commercial properties

▸ Summary Statistics

Bank loans have shortest terms, life insurers longest

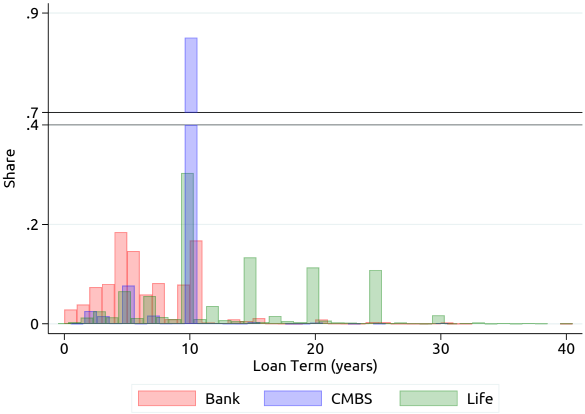

Figure: Loan Term Distribution by Lender Type

Explanation: Asset-liability matching (e.g. Chernenko, Erel, & Prilmeier, 2017)

- Banks (life insurers) have short (long) term liabilities

Banks loans mostly floating rate, others fixed

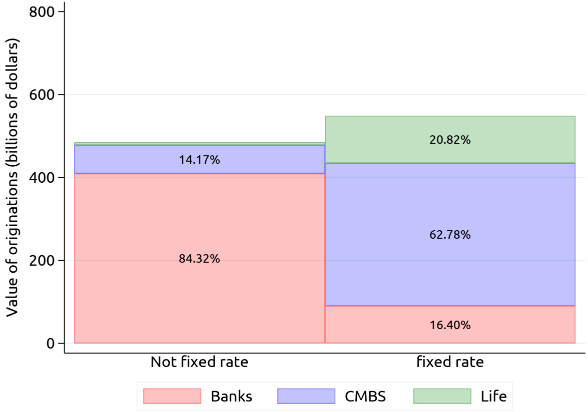

Figure: Total volume by rate type

Explanation: Asset-liability matching

- Bank deposits reprice quickly
- Life insurance products often offer fixed/minimum returns

Bank loans are smallest, CMBS largest

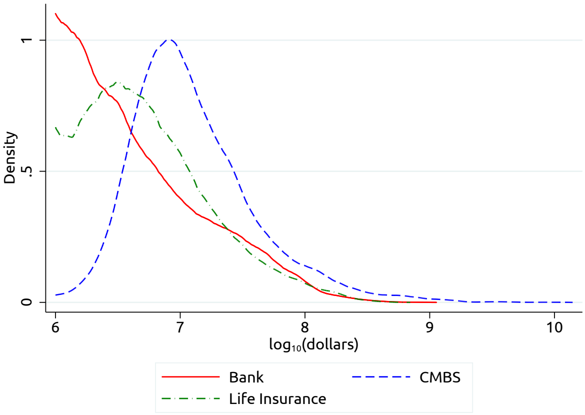

Figure: Loan size by lender type

Explanation: Diversification (e.g. Ghent & Valkanov, 2016)

- Dispersed CMBS investors reduce concentration risk

Life insurers have lowest LTVs, only banks allow LTVs > 0.75

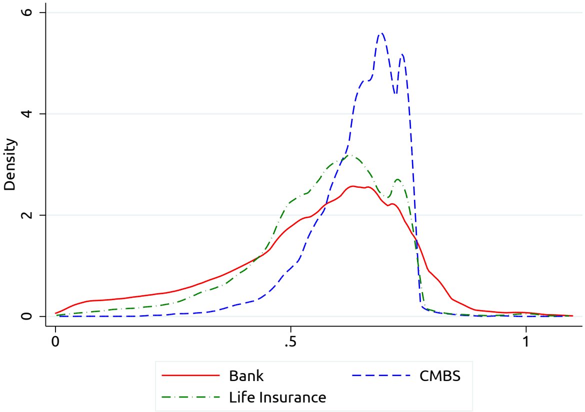

Figure: LTV by lender type

Explanations: Regulation/Risk Tolerance

- Life Insurance: Highly risk sensitive capital requirements
- Banks: Relationship lending (Black, Krainer, & Nichols, 2017)

Life insurers hold few hotel loans

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

Explanations: Regulation/Risk Tolerance

- Life insurers have stricter capital requirements for hotel loans

Discussion

Lenders originate loans that are favorable given their institutional environment.

Implications:

- Loan characteristics likely priced differently
- Frictional substitution across lender types

Next step: Model and estimation

- Estimate pricing functions off portfolio holdings
- Validate estimates by studying period of CMBS stress
- Simulate effects of supply shocks

Theoretical framework

- Characteristics differentially affect risks and expected returns, causing pricing to vary by lender type:

$$\text{Hurdle rate: } R_{i,j} \equiv \min\{R | NPV_j(X_i, R) \geq 0\} = X_i' \beta_j - \sigma \epsilon_{i,j}$$

  where:
  - X_i: Vector of loan characteristics
  - β_j: Lender j's pricing vector
  - $\epsilon_{i,j}$: Idiosyncratic Match

- Representative lender types, zero profits $\Longrightarrow$
  - Equilibrium rate: $R_i = \min_{j \in J}\{R_{i,j}\}$.
  - Equilibrium lender: $\text{argmin}_{j \in J}\{R_{i,j}\}$

Estimation of pricing factors

Assume idiosyncratic match ($\epsilon_{i,j}$) is distributed Type-I Extreme Value $\implies$ i chooses j w/ probability:

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

Multinomial Logit estimates β relative to scale parameter (σ) and reference group (β_{Bank})

$$\beta_{\text{CMBS}}^{\text{Logit}} = \frac{1}{\sigma}(\beta_{\text{Bank}} - \beta_{\text{CMBS}})$$
$$\beta_{\text{Life}}^{\text{Logit}} = \frac{1}{\sigma}(\beta_{\text{Bank}} - \beta_{\text{Life}})$$

We calibrate β_{Bank} and σ so that pricing regressions on simulated data match results of pricing regressions on actual data. ▸ Details

Estimates of pricing parameters

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	0.22	0.32	0.02	-0.06	-0.10
Size	0.78	0.39	-0.02	-0.30	-0.16
LTV	8.74	1.68	0.32	-2.87	-0.29
LTV > 0.75	-3.74	-1.65	0.06	1.43	0.67
Hotel	1.45	-0.54	0.57	0.04	0.77
Retail	0.78	0.05	0.03	-0.25	0.01
Industrial	-0.21	0.70	0.04	0.12	-0.21
Constant	-21.46	-11.06	2.40	10.25	6.45

*Every logit coefficient besides $\hat{\beta}^{\text{Logit}}_{\text{Life,Retail}}$ is significant at at least 5% level.

How much must rates rise for a borrower to switch lenders?

β_j and σ define distribution of offered rates.

- Estimates allow prediction of how supply shocks (change in β_j) affects lending spreads and market shares

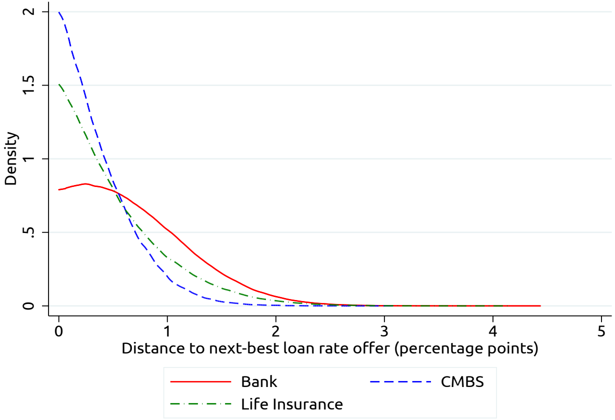

Figure: Distribution of distance to next-best offer

Does model imply reasonable substitution patterns?

Hard to validate model: substitution patterns depend on distribution of offers which is unobservable.

We study behavior of refinancing CMBS loans in 2016

- Large volume of 10-year pre-crisis CMBS loans refinancing
- CMBS spreads spiked due to general bond market stress CMBS Spreads

Question: Does substitution between CMBS and other lenders in model match propensity of CMBS loans to refinance into other lenders after supply shock?

RCA Data Description

Substitution in data similar to model

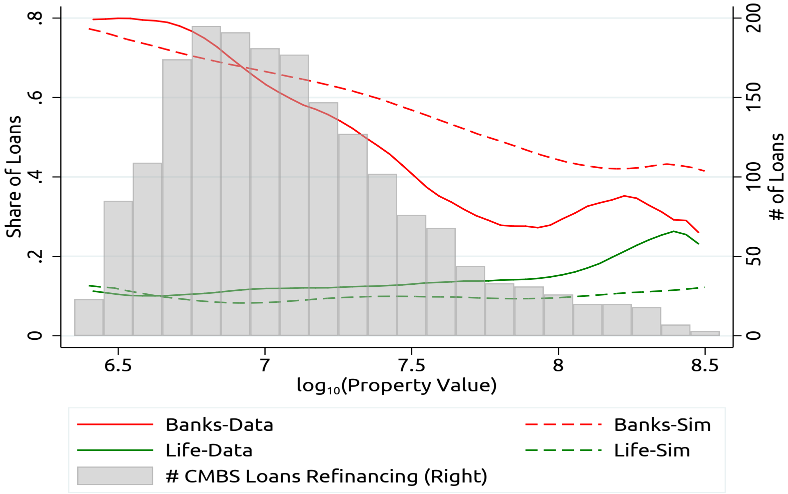

Figure: Substitution Away from CMBS After Shock

Counterfactual simulations

Simulated Response to 25bp Supply Shock

	Baseline	Change after 25bp shock to		
		Banks	CMBS	Life
Market Shares (changes in p.p.)				
Banks	58%	-11.8	3.7	5.9
CMBS	15%	4.5	-6.6	3.1
Life insurers	27%	7.3	2.9	-9.0
Avg. Spreads (changes in bp)				
Overall	2.51%	13.1	2.9	5.5
Bank	2.59%	20.5	1.8	2.3
CMBS	2.56%	8.3	14.8	1.9
Life Insurers	2.31%	12.1	3.8	7.1

25bp bank shock reduces market share by ≈12pp

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Avg. bank spread rise less than 25bp, as higher cost borrowers switch

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Rates rise at other lenders, as they originate comparably less favorable loans

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Overall increase in rates implies 90% pass-through of shock to borrowing costs

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CMBS/life insurance shocks less costly than bank shocks

Smaller effects driven by lower initial market shares & lower pass-through

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Counterfactual effect of discouraging higher LTV bank lending

Bank shocks almost fully pass through to loan rates, especially if LTV>75%

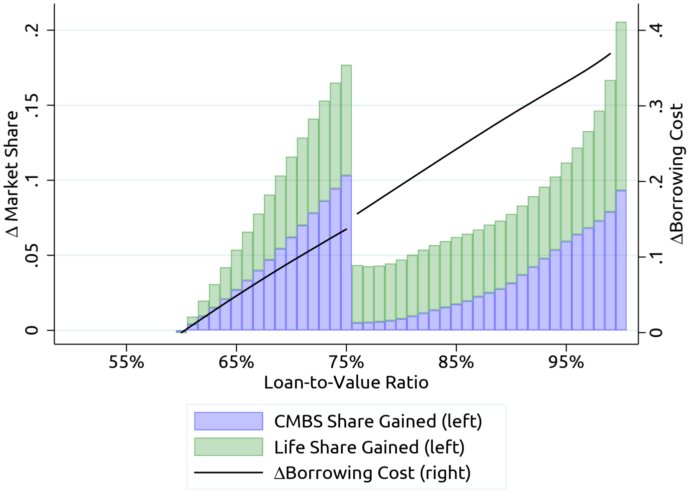


Figure: Effect of Banks Increasing Rates by $\max\{0, \text{LTV}_i - 0.6\}$

Conclusion

We document stark differences in CRE portfolios of banks, CMBS, and life insurers.

- Construct unique loan level dataset, harmonized across various sources

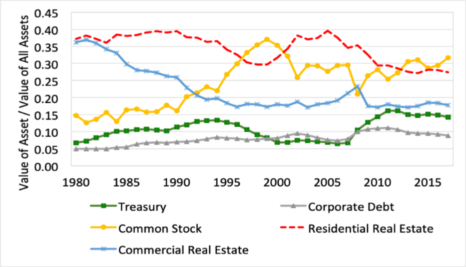
We use these differences in portfolios to estimate how intermediaries price different characteristics.

- Substitution patterns implied by estimates match observed migration from CMBS after 2016 supply shock

Estimates imply significant frictions in substituting between lender types.

- 75% pass-through of CMBS shock to borrowing costs (90% for banks)
- Pass-through depends on availability of substitutes for given loan

CRE is a large share of U.S. assets



(b) As Share of Assets

Notes: 1) CRE is measured as the sum of LM105035005.Q Nonfinancial corporate business real estate at market value and LM11035035.Q Nonfinancial noncorporate business real estate at market value both from Federal Reserve Flow of Funds. 2) US Treasuries is interest bearing marketable coupon debt including floating rate notes issued by the U.S. Treasury and is from SIFMA.org. 3) Common stock is the market capitalization of all U.S. domestically listed companies and is from the World Federation of Exchanges. 4) Corporate debt includes all non-convertible debt, MTNs, and Yankee bonds and is from SIFMA.org. 5) Residential real estate is Measured by LM155035005.Q Household and nonprofit organizations real estate at market value from Federal Reserve Flow of Funds. 6) US GDP is GDPA from the U.S. Bureau of Economic Analysis.

Figure: CRE as a Share of Assets from Ghent, Torous, and Valkanov (2018)

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CRE is over 25% of banks' loan portfolios

Share of Total Core Lending by Loan Category as of Jan 2, 2019

	All Banks	Large Banks	Other Banks	Foreign Banks
Consumer Share	18.1%	13.4%	4.7%	0.0%
RRE Share	27.0%	16.8%	10.2%	0.0%
C&I Share	28.3%	15.3%	8.1%	4.9%
CRE Share	26.5%	8.0%	17.5%	1.0%
NFNR Share	16.9%	5.0%	11.2%	0.8%
CLD Share	4.1%	1.2%	2.8%	0.2%
MF Share	4.3%	1.7%	2.5%	0.0%
Farmland Share	1.2%	0.1%	1.1%	0.0%
Total	100%	53.4%	40.6%	6.0%

Source: H.8 Reports on Assets and Liabilities of Commercial Banks, Federal Reserve Board.

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Loan performance differs across lender types

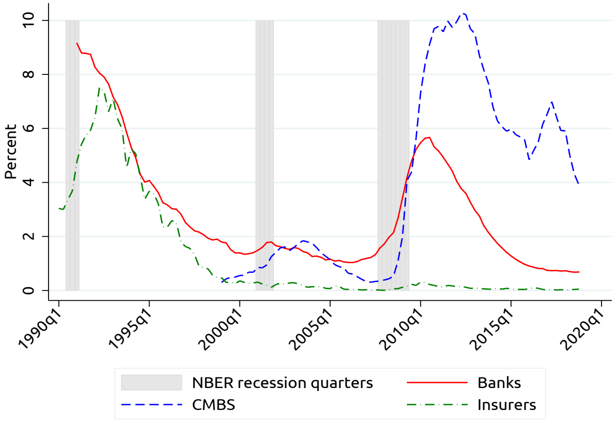

Figure: CRE delinquency rate by lender type

Sources: Call Reports, Morningstar, American Council of Life Insurers.

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Simulation methodology

1. Create 20 duplicates of each loan in data
   - Maintains X distribution, but reduces sampling error
2. Draw iid Extreme Value match term for each $i \times j$: $\epsilon_{i,j}^{\text{Sim}}$
3. Simulate interest rate offer: $R_{i,j}^{\text{Sim}} = -X_i' \hat{\beta}^{\text{Logit}} - \epsilon_{i,j}^{\text{Sim}}$
   - Simulated rate: $R_i^{\text{Sim}} = \min_{j \in J}\{R_{i,j}^{\text{Sim}}\}$.
   - Simulated lender: $argmin_{j \in J}\{R_{i,j}^{\text{Sim}}\}$
4. Estimate pricing regressions for both observed lender type/loan spread and simulated lender type/loan spread
5. Shift $\hat{\beta}^{\text{Logit}}$ by $\hat{\beta}_{\text{Bank}}$ and rescale by $\hat{\sigma}$
   - $\hat{\beta}_{\text{Bank}}$ set to match level of β in pricing regression
   - $\hat{\sigma}$ set to match dispersion in pricing across lenders

Produces estimated pricing vector for each lender. Combined with simulated idiosyncratic term, produces a set of interest rates offered for each lender type. Back

CMBS spreads rose in 2016

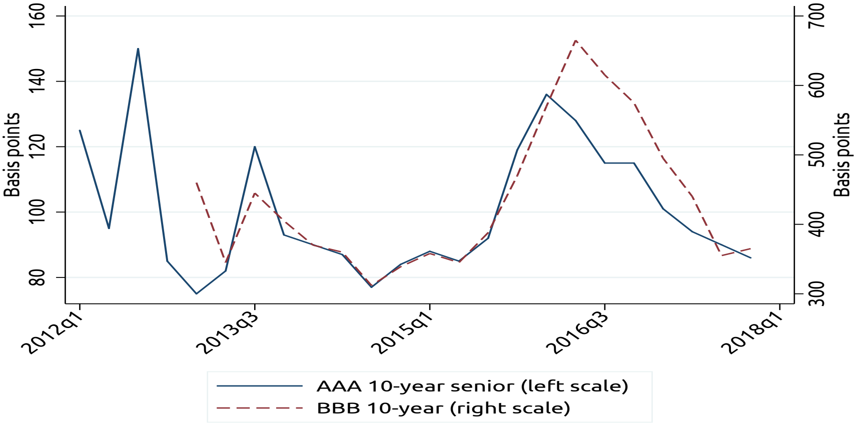

Figure: 10-year CMBS Spreads over Swaps

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RCA transactions data

- Almost the entire universe of CRE transactions for properties above $2.5 million in value.
- Borrowers and properties followed over time.
- Data reliably includes lender type, transaction size, and property type.
    - Worse coverage of loans terms (e.g. term, interest rate, LTV).
- We study properties refinancing in 2016 that were most recently financed by CMBS.

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Differences in average characteristics

Summary Statistics: CRE Originations by Intermediary Type

	Bank mean/sd	CMBS mean/sd	Life mean/sd
Term (years)	6.63	9.32	14.18
	(3.98)	(2.29)	(6.93)
Fixed-rate dummy	0.34	0.96	0.97
	(0.47)	(0.20)	(0.18)
Property value (millions)	33.09	75.11	18.00
	(513.16)	(272.88)	(44.29)
Loan balance (millions)	12.48	36.41	9.15
	(28.88)	(180.68)	(19.92)
Loan-to-value ratio	0.56	0.65	0.58
	(0.19)	(0.09)	(0.14)
Interest rate	3.50	4.72	4.33
	(0.99)	(0.64)	(0.76)
Spread to swaps	2.62	2.64	2.18
	(0.85)	(0.80)	(0.94)
Observations	40024	11358	13284

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