Market Power, Strategic Interaction, & Capital Market Dynamics

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MFS Lecture on Modeling, Measurement, & Estimation

May 2026

What This Talk Is About

Strategic competition and financial frictions jointly shape capital market dynamics

1. Customer Capital
   Dou_Ji (2021); Dou_Ji_Reibstein_Wu (2021); Dou_Ji_Reibstein_Tian (2026)
   - Customer capital shapes firm value, markups, risk, investment, & macro dynamics
   - Measure customer capital from demand-side perceptions and preferences, not only supply-side investments

2. Strategic Competitive Interactions
   Dou_Ji_Wu (2021, 2022); Chen_Dou_Guo_Ji (2024, 2026)
   - Market leaders sustain market power through strategic tactics, e.g., tacit collusion
   - Market power responds to financial shocks and amplifies them across industries

3. "The Cost of Intermediary Market Power for Distressed Borrowers"
   Dou_Wang_Wang (2026)

Outline

1. Customer Capital
Dou_Ji (2021); Dou_Ji_Reibstein_Wu (2021); Dou_Ji_Reibstein_Tian (2026)

2. Strategic Competitive Interactions
Dou_Ji_Wu (2021, 2022); Chen_Dou_Guo_Ji (2024, 2026)

3. Intermediary Market Power in Distressed Lending
Dou_Wang_Wang (2026)

What Is Customer Capital?

Customer capital is the stock of customer relationships, brand loyalty, and trust in quality that sustains future demand and market power

- It is a form of **intangible capital**: built slowly through customer acquisition, product quality, service, trust, and brand reputation/recognition
- It is **distinct from regulated franchise value** as a source of market power
  - Regulated franchise value comes from legally protected market access, scarce infrastructure, and regulated pricing rights
- It is **not explicitly on the balance sheet**, but it is increasingly viewed as a core intangible asset and a central source of firm value
  - e.g., Dou_Ji_Reibstein_Wu (2021); Belo_Gala_Salomao_Vitorino (2022)

Increasingly Central to Firm Value

The Three Largest US Firms in 1910

- Standard Oil
- US Steel
- Pennsylvania Railroad

Customer Capital ≈ <u>10%</u> Firm Value

Their market values were driven primarily by vertical integration, physical infrastructure, natural-resource control, & regulated franchises

Increasingly Central to Firm Value

The Three Largest US Firms in 1910

- Standard Oil
- US Steel
- Pennsylvania Railroad

The Three Largest US Firms in 2020

- Apple
- Microsoft
- Amazon

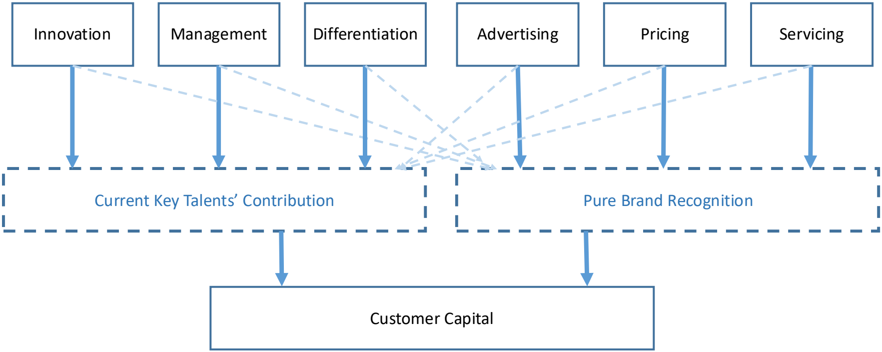
Customer Capital ≈ <u>10%</u> Firm Value

Their market values were driven primarily by vertical integration, physical infrastructure, natural-resource control, & regulated franchises

Customer Capital ≈ <u>60%</u> Firm Value

Their market power was **not** primarily driven by vertical integration, physical infrastructure, natural-resource control, & regulated franchises

How Do Firms Invest in Customer Capital?



Source: Dou_Ji_Reibstein_Wu (2021)

How Do We Measure Customer Capital in Data?

A perpetual-inventory method based on supply-side investment:

$$M_{i,t+1} = (1 - \delta_i) M_{i,t} + g_i(I_{i,t}), \text{ where } M_{i,t} \text{ is capital stock and}$$

- $I_{i,t}$ is firm i's observed investment expenditures in capital at time t
- δ_i is the depreciation rate, to be estimated
- $g_i(\cdot)$ maps $I_{i,t}$ into newly created capital, to be estimated

This method works well for estimating physical and organization capital

e.g., Hall (2001); Eisfeldt_Papanikolaou (2014)

- δ_i and $g_i(\cdot)$ are kind of homogeneous across firms (esp. within an industry)

For customer capital, a proxy uses sales and marketing expenses

e.g., Belo_Gala_Salomao_Vitorino (2022); He_Mostrom_Sufi (2025)

But this proxy has two important limitations:

- It mainly captures customer capital sustained by marketing and advertising
- δ_i and $g_i(\cdot)$ differ substantially across firms, even within industries

Proxy Based on Demand-Side Perceptions/Preferences

Structural IO methods are powerful but usually market- or segment-specific

BAV is one of the largest proprietary brand-perception databases
e.g., Larkin (2013); Dou_Ji_Reibstein_Wu (2021); Dou_Ji_Reibstein_Tian (2026)

- The survey is designed to be representative of U.S. consumers and contains more than **2.5 million respondents** on about **68,000 brands**

- **Measure customer capital with "brand stature"**

$$\text{Brand stature}_{i,t} = \text{Esteem}_{i,t} \times \text{Knowledge}_{i,t},$$

Esteem $\approx$ how highly consumers regard the brand

Knowledge $\approx$ consumers' familiarity with the brand

- **Measure talent-dependent customer capital with "brand strength"**

$$\text{Brand strengthen}_{i,t} = \text{Differentiation}_{i,t} \times \text{Relevance}_{i,t},$$

Energized differentiation $\approx$ how much consumers see the brand as innovative, unique, distinctive, different, & dynamic

Relevance $\approx$ how much consumers find the brand relevant to them

External Validation I

The talent-dependence of customer capital:

$$\text{ICC} \equiv \frac{\text{Brand strength}}{\text{Brand stature}}$$

	$\ln(\text{ICC})_t$				
	(1)	(2)	(3)	(4)	(5)
$\ln(\text{administrative expenses/sales})_{t-3:t-1}$	0.13^{***}				
	[2.97]				
$\ln(\text{R\&D/sales})_{t-3:t-1}$		0.26^{***}			
		[5.76]			
$\ln(\text{executive compensation/sales})_{t-3:t-1}$			0.25^{***}		
			[6.47]		
$\ln(\text{advertising expenditures/asset})_{t-3:t-1}$				-0.09^{**}	
				[-2.48]	
$\ln(\text{OC/asset})_{t-3:t-1}$					-0.04
					[-1.31]
Firm controls	Yes	Yes	Yes	Yes	Yes
Industry FEs & Year FEs	Yes	Yes	Yes	Yes	Yes
Observations	5,300	2,695	5,086	4,329	5,594
R^2	0.386	0.468	0.411	0.413	0.382

Source: Dou_Ji_Reibstein_Wu (2021)

External Validation II

1. High-ICC firms lose more customer capital after talent turnover
2. ICC declines after talent turnover

	Customer growth$_{t:t+2}$		Sales growth$_{t:t+2}$		Asset growth$_{t:t+2}$		ΔICC$_{t:t+2}$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\ln(\text{ICC})_{t-1}$	-0.04^{*}	-0.05^{**}	-0.04^{**}	-0.03^{*}	-0.07^{**}	-0.06^{**}		
$\times$Turnover$_t$	[-1.80]	[-1.98]	[-2.40]	[-1.79]	[-2.32]	[-2.30]		
Turnover$_t$	-0.01	-0.02	-0.07^{***}	-0.06^{***}	-0.11^{***}	-0.10^{***}	-0.18^{***}	-0.16^{**}
	[-0.63]	[-1.01]	[-3.65]	[-3.30]	[-4.51]	[-3.68]	[-2.70]	[-2.40]
$\ln(\text{ICC})_{t-1}$	0.14^{***}	0.15^{***}	0.07^{***}	0.03^{***}	0.07^{***}	0.03^{*}		
	[17.60]	[17.02]	[5.92]	[3.01]	[3.89]	[1.75]		
Firm controls	No	Yes	No	Yes	No	Yes	No	Yes
Industry FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,709	3,525	4,523	4,285	4,523	4,285	4,059	3,855
R^2	0.440	0.443	0.170	0.233	0.135	0.211	0.099	0.108

Source: Dou_Ji_Reibstein_Wu (2021)

Modeling Customer Capital: Demand Capacity

Traditional model without customer capital: demand is not a separate constraint, so sales ($S_{i,t}$) equal production ($Y_{i,t}$):

$$S_{i,t} = Y_{i,t}, \qquad Y_{i,t} = F(K_{i,t}, L_{i,t})$$

Customer capital is modeled as a stock of demand capacity
e.g., Gourio_Rudanko (2014); Dou_Ji_Reibstein_Wu (2021)

$$S_{i,t} = \min\{Y_{i,t}, M_{i,t}\}, \qquad Y_{i,t} = F(K_{i,t}, L_{i,t})$$

- $M_{i,t}$ is the firm's stock of customer capital
- It limits how much the firm can sell, even if production capacity is high
- Customer capital grows through costly customer acquisition:

$$M_{i,t+1} = (1-\delta)M_{i,t} + g(I_{i,t})$$

- $g(I_{i,t})$ builds customer relationships; δ captures depreciation

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Price Elasticity and Strategic Interaction

Demand capacity alone does not imply markups or market power

- Customer capital generates markups by shaping firm-level demand elasticity and strategic competitive interaction

Customer capital can be modeled as firm-specific demand persistence

e.g., Phelps_Winter (1970); Ravn_Schmitt-Grohé_Uribe (2006)

- Demand capacity constraint (Dou_Ji, 2021; Dou_Ji_Wu, 2021, 2022)

$$S_{i,t} = \min\{Y_{i,t}, C_{i,t}\}, \qquad Y_{i,t} = F(K_{i,t}, L_{i,t})$$

In CES demand, customer capital $M_{i,t}$ acts as a persistent demand weight

$$C_{i,t} = \frac{M_{i,t}}{M_t}\left(\frac{P_{i,t}}{P_t}\right)^{-\eta} C_t, \quad \text{with } P_t = \left[\sum_{j=1}^{I} \frac{M_{j,t}}{M_t} P_{j,t}^{1-\eta}\right]^{\frac{1}{1-\eta}} \text{ and } M_t = \sum_{i=1}^{I} M_{i,t}$$

Industry demand is downward sloping in the industry price index:

$$C_t = M_t P_t^{-\varepsilon}$$

Customer capital accumulation process of firm i:

$$M_{i,t} = \left[1 + \alpha(C_{i,t}/M_{i,t})^h - \delta\right] M_{i,t-1} + g(I_{i,t-1})$$

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Dou_Wang_Wang (2026)

Leaders Sustain Market Power via Strategic Interaction

Product markets are highly concentrated; so are some asset markets

- Product & asset market evidence: Gabaix (2011); Gutiérrez_Philippon (2017); Autor_Dorn_Katz_Patterson_Reenen (2020); Loecker_Eeckhout_Unger (2020); Dou_Ji_Wu (2021); Gabaix_Gopikrishnan_Plerou_Stanley (2006); Bryzgalova_Pavlova_Sikorskaya (2025); Dou_Wang_Wang (2026)

Market leadership is highly persistent

- Product & asset markets: Geroski_Toker (1996); Sutton (2007); Bronnenberg_Dhar_Dubé (2009); Bryzgalova_Pavlova_Sikorskaya (2025); Dou_Wang_Wang (2026)

$\Longrightarrow$ Strategic competitive interaction (tacit collusion) naturally emerges

Modern IO: strategic competitive interaction, such as tacit collusion, is an important source of market power

e.g., Harrington_Skrzypacz (2011); Miller_Weinberg (2017); Miravete_Seim_Thurk (2018)

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Incorporating Strategic Interactions into Macro-Finance

Traditional framework: non-collusive Nash equilibrium

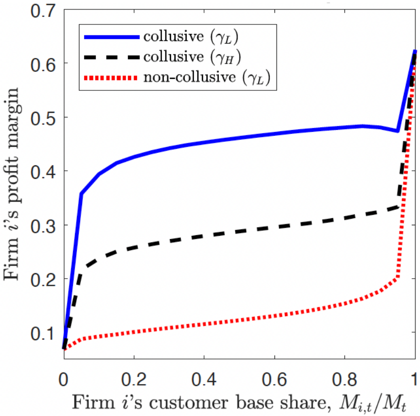
- Market leaders do not internalize the impact of their decisions on others
- Market power comes only from concentration and demand elasticity

Extension: tacit collusion in a collusive equilibrium

- Market leaders sustain supra-competitive profits in repeated interaction
- Each market leader has a short-run incentive to deviate
- Tacit collusion is sustained if deviation gains $\leq$ future punishment losses
- Grim-trigger punishment: Reversion to non-collusive competition
- It differs economically and legally from perfect cartel via explicit collusion

Insight: Lower discount rates strengthen tacit collusion and market power

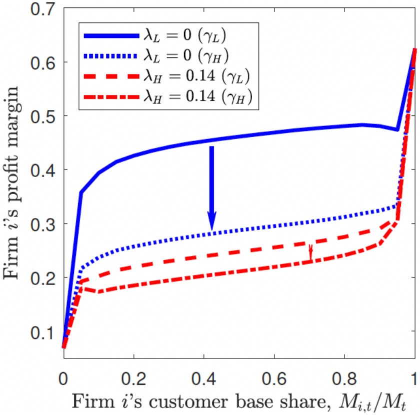
Impact of Discount Rates on Market Power



- Higher $M_{i,t}/M_t$ leads to greater market power (and higher margins)
- Tacit collusion further amplifies market power (and profit margins)
- A higher discount rate, $\gamma_L \to \gamma_H$, makes tacit collusion harder to sustain
- The discount rate has no direct effect on non-collusive market power

Source: Dou_Ji_Wu (2021)

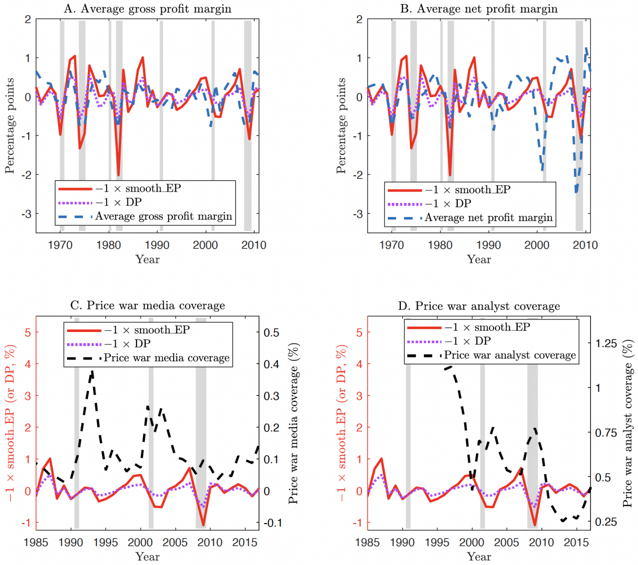
Stronger with Lower Leadership Turnover (More Persistent Leadership)



- More persistent leadership, $\lambda_H \to \lambda_L$, raises endogenous price-war risk

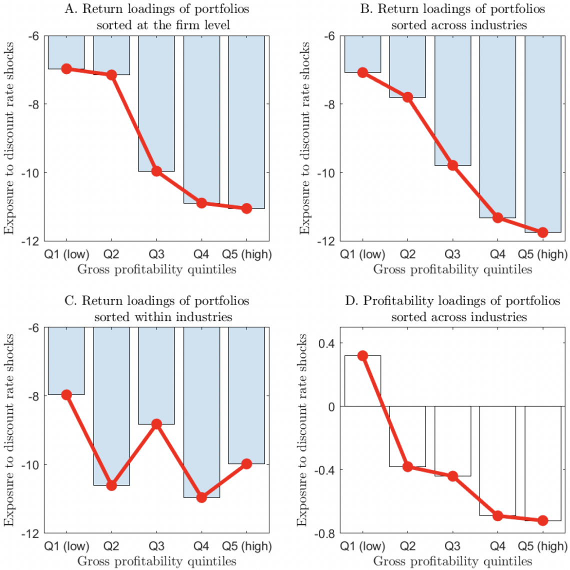
Source: Dou_Ji_Wu (2021)

Market Power and Discount Rates over Time



Source: Dou_Ji_Wu (2021)

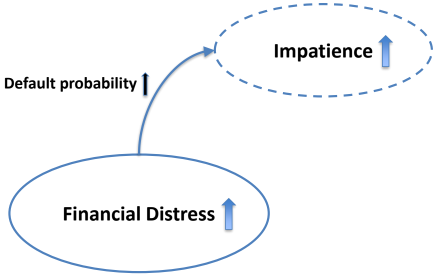
Gross Profitability Premium: Heterogeneous Discount-Rate Exposure



Source: Dou_Ji_Wu (2021)

Further Introducing Leverage and Financial Distress

The competition-distress feedback $\Longrightarrow$ A novel source of financial distress costs



Source: Chen_Dou_Guo_Ji (2024)

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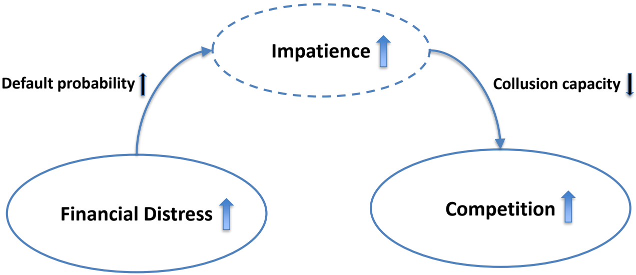

Impatience $\uparrow$ $\Longrightarrow$ **Collusion capacity** $\downarrow$

- Fudenberg-Maskin (1986)'s version of "folk theorem"

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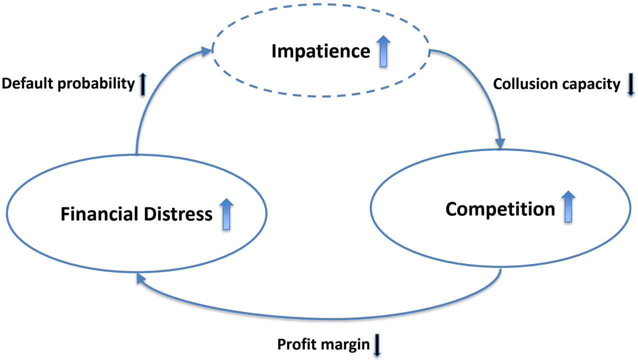

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Financial Distress Costs: From Firms to Lenders

Financial distress & bankruptcy costs have important macro implications

e.g., Jermann_Quadrini (2012), Arellano_Bai_Kehoe (2012), Khan_Thomas (2013), Gomes_Schmid (2021), Gilchrist_Sim_Zakrajšek (2014), Corbae_D'Erasmo (2021)

- Determining the ex-ante cost of financial distress for the corporate sector
    - ⇒ Shaping cost of capital and thus capital allocation efficiency
        - ⇒ Affecting industry dynamics, investments, and employment

Bankruptcy frictions: Value destruction due to stakeholder conflicts, asymmetric information, and judicial discretion or inexperience

e.g., Corbae_D'Erasmo (2021); Dou_Taylor_Wang_Wang (2021)

Liquidity in distress/bankruptcy: It buys restructuring time, accelerates resolution, preserves going-concern value, strengthens bargaining power, and prevents fire sales

e.g., Asquith_Gertner_Scharfstein (1994); Gilson (1997); Dahiya_John_Puri_Ramírez (2003)

This paper: High financing costs due to lender market power reduce survival-critical liquidity by 16–20%, worsening value destruction in distress and bankruptcy

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Research Objective & Challenges

Quantifying the risk-adjusted loan yield spread and dissecting it into:

Risk-adjusted loan yield spread

$=$ the private cost incurred by lenders in making loans,

(e.g., search, screening, monitoring, & information production costs)

$+$ the markup due to blocking power & concentration

$+$ the markup due to tacit collusion of specialized lenders

Empirical challenges:

(1) Lenders' loan-making costs are largely unobservable

(2) Latent confounders create endogeneity in estimating demand and supply

- Unobserved heterogeneity in distressed borrowers' demand curves
- Valid instruments are very difficult, if not impossible, to find

(3) Collusion capacity is unobservable and lacks reliable empirical proxies

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Method: Structural Model + Granular Data

A granular dataset of distressed loans, including detailed information on

- Loan yields, contractual terms, fees, loan sizes, lender participation, and bid-ask spreads in secondary loan markets
- CDS spreads for corporate bonds, industry-year bond and loan recovery rates

Embedding these data in a game-theoretic model, capturing both

- Strategic interactions of lenders' supply + latent heterogeneity in borrowers' demand
- Collusive and non-collusive equilibria coexist within a coherent unified framework

Closed-form solutions $\Rightarrow$ Bayesian MCMC estimation with latent variables

- Bayesian MCMC is well suited here because it treats latent demand heterogeneity as unobserved variables and jointly samples it with the structural parameters
  - It differs from the BLP with single-equation estimation + IVs
- Matlab code for teaching is available on the authors' websites

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Closed-form solutions $\Rightarrow$ Bayesian MCMC estimation with latent variables

- Bayesian MCMC is well suited here because it treats latent demand heterogeneity as unobserved variables and jointly samples it with the structural parameters
    - It differs from the BLP with single-equation estimation + IVs
- Matlab code for teaching is available on the authors' websites

Two Distressed Loan Markets

Two loan markets for distressed corporate borrowers:

- **Debtor-in-possession (DIP) loans:** Borrowers undergoing Chapter 11 bankruptcy
- **Highly-speculative loans:** S&P rating $\leq$ CCC+ or five-year CDS spread $\geq$ 10%

	Highly speculative loans	**DIP loans**
Definition	Loans to distressed firms (not in bankruptcy)	Loans to bankrupt firms (Chapter 11)
Use of proceeds	Working capital and capital investment	Working capital and legal expenses
Maturity (months)	49	11
Loan size/assets	0.130	0.107
Number of major lenders (syndication)	3.79	2.29
Risk-adjusted loan spread (bps)	308	711

Note: Highly speculative loans (2001 - 2017) and DIP loans (2002 - 2019)

Note: Load spreads are after removing the credit spread and liquidity premium components

Concentrated Markets

A. Names of specialized lenders

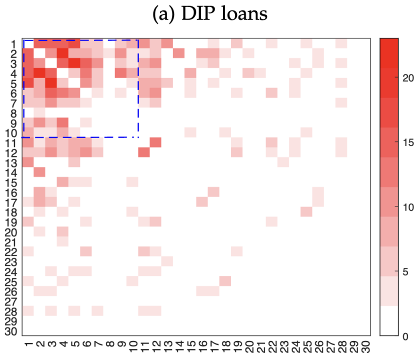
Rank	DIP loan market: Lender name	# of deals	Highly-speculative loan market: Lender name	# of deals
1	Wells Fargo	96	Bank of America	183
2	Bank of America	88	JP Morgan Chase	179
3	JP Morgan Chase	88	Wells Fargo	122
4	GE Capital	82	Citigroup	103
5	Citigroup	67	Credit Suisse	103
6	Deutsche Bank	41	Deutsche Bank	100
7	Credit Suisse	3	Goldman Sachs	60
8	Wachovia Bank	28	Wachovia Bank	28
9	Wilmington Trust	27	GE Capital	56
10	CIT Group	21	Wachovia Bank	53

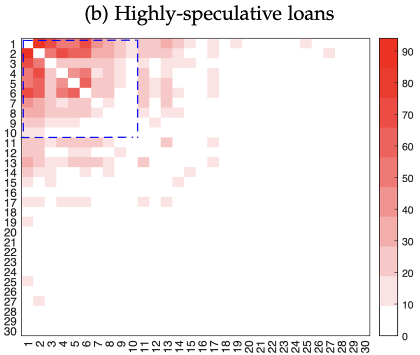
B. Three loan types

Lender type	DIP loans				Highly-speculative loans			
	# of deals	# frac.	$ of deals	$ frac.	# of deals	# frac.	$ of deals	$ frac.
Type 1: Existing creditor	56	12.80%	5	4.90%	50	11.49%	12	5.45%
Type 2: Specialized lender	334	76.60%	94	92.16%	332	76.32%	199	90.45%
Type 3: Lender of last resort	46	10.60%	3	2.94%	53	12.18%	9	4.10%
Total	436	100%	102	100%	435	100%	220	100%

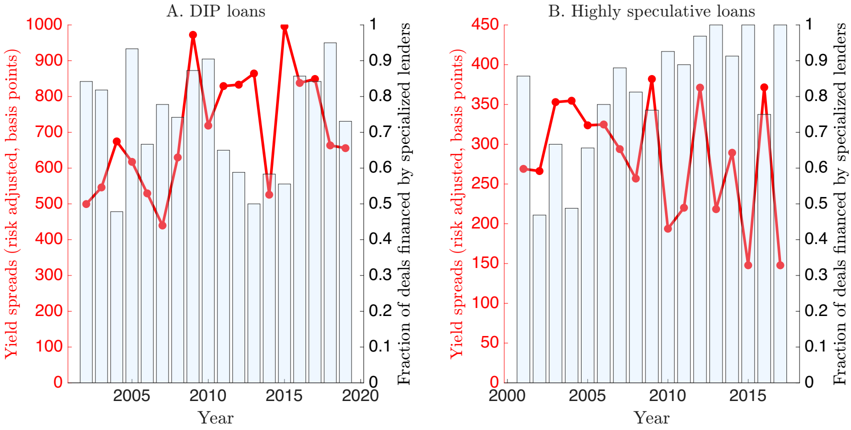
Note: The loan size are measured by constant 2019 dollars and presented in the unit of billion dollars
Note: Existing creditor loans are those with one major lender who is an existing but not specialized lender
Note: Lender-of-last-resort loans are those with over 50% of the major lenders as HFs and PEs

Syndication Interaction Intensity



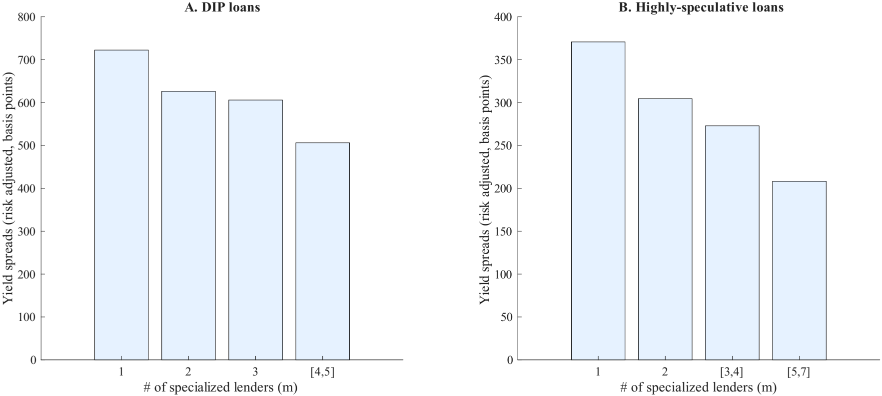


Ultra-High Risk-Adjusted Loan Spreads



Note: The curves represent the average risk-adjusted loan spread per year, and the bars represent the fraction of deals financed by the 10 specialized lenders per year

Lender Competition



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Demand for Loans

Demand side (distressed corporate borrowers)

– An iso-elastic demand curve for a borrower type $k \in \{1, \cdots, K\}$:

$$\ln(L/A) = \alpha_k - \varepsilon_k \ln(R) + \sigma z$$

- $L =$ loan size
- $A =$ asset size
- $R =$ risk-adjusted loan spread
- $\alpha_k =$ latent demand curve level
- $\varepsilon_k =$ latent elasticity
- $z =$ borrower-specific demand shock

– **A latent-variable model**

- Borrower type k is **latent** to econometricians
- More flexible than standard BLP parallel shifts

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Supply of Loans

Supply side (institutional lenders)

- There are 3 types of lenders: *existing, specialized, last-resort*

  (1) An existing creditor: Monopolistic lending with marginal costs $e^{\phi_1+\varsigma u}$

  (2) M specialized lenders: Cournot competition with potential tacit collusion and marginal costs $e^{\phi_2+\varsigma u}$

  - Specialized lender's dis-utility of participating syndication is w, which is private information and distributed as

$$w \sim \mu e^{-w/\mu}, \quad \text{where } \mu \text{ captures how difficult to participate}$$

  (3) A lender of last resort: Monopolistic lending with marginal costs $e^{\phi_3+\varsigma u}$

- Marginal costs: $u =$ deal-specific cost

- Nicely, the game should be played out in a sequential way

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- Marginal costs: $u =$ deal-specific cost
- Nicely, the game should be played out in a sequential way

Model Timeline

Distressed borrower demand for loans

Prob = $1 - \lambda_k$

Unsuccessful external financing block

Syndication of specialized lenders
with deterrence of large syndication
[w_i is the disutility from participation]
[$w_i \leq w^*$ for some specialized lender]

→ **Collusive lending by specialized lenders**
[specialized lenders syndicate]
[observe k, z, u]
[decide if deviate and pay $C_2 = e^{\phi_2 + \varsigma u}$]

No specialized lender participates
due to deterrence of large syndication
[w_i is the disutility from participation]
[$w_i > w^*$ for all specialized lenders]

→ **Monopoly lending by last-resort lenders**
[hedge funds and private equity funds]
[observe k, z, u]
[pay $C_3 = e^{\phi_3 + \varsigma u}$]

Prob = λ_k

Successful external financing block

→ **Monopoly lending by the existing creditor**
[observe k, z, u]
[pay $C_1 = e^{\phi_1 + \varsigma u}$]

Intuition for Tacit Collusion in Syndicated Loans

Suppose *m* specialized lenders endogenously choose to participate in the syndication (an endogenous outcome)

- Collusive equilibrium: small loan size $+$ high spread $\Rightarrow$ greater revenues
- Non-collusive equilibrium: large loan size $+$ low spread $\Rightarrow$ smaller revenues

Collusion is preferred by specialized lenders, subject to the IC constraints

- Collusion is sustained by punishment for deviation:

  Reversion to non-collusive Nash equilibrium with a probability ξ

  where ξ captures collusion capacity

- The IC constraint to prevent deviation is

  Short-run profits of deviation $\leq$ Long-run loss of cooperation value

Equilibrium path: The IC constraint is binding state by state

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Data Sample

DIP loan sample (2002-2019)

- Data sources: UCLA-LoPucki BRD, Bankruptcydata.com, PACER, and Dealscan
- Our sample: 436 loan facilities

Highly speculative loan sample (2001-2017)

- Data sources: IHS Markit, Compustat, Dealscan
- How to identify distressed loans?
  - *Step #1*: 5Y CDS Spread$>$1,000 bps or rating$\leq$ CCC+, whichever first, as the start of a distressed period
  - *Step #2*: 5Y CDS Spread$<$500 bps, rating$>$B-, default, or bankruptcy, whichever first, as the end of a distressed period
  - *Step #3*: Merge distressed periods with Dealscan
- Our sample: 435 loan facilities

LPC Loan Pricing Data

NYU-Salomon Center Default database + Moody's Default and Recovery database

Estimation

Latent variables to estimate:

- Clustering: identify the demand curve, labeled as k, each borrower belongs to

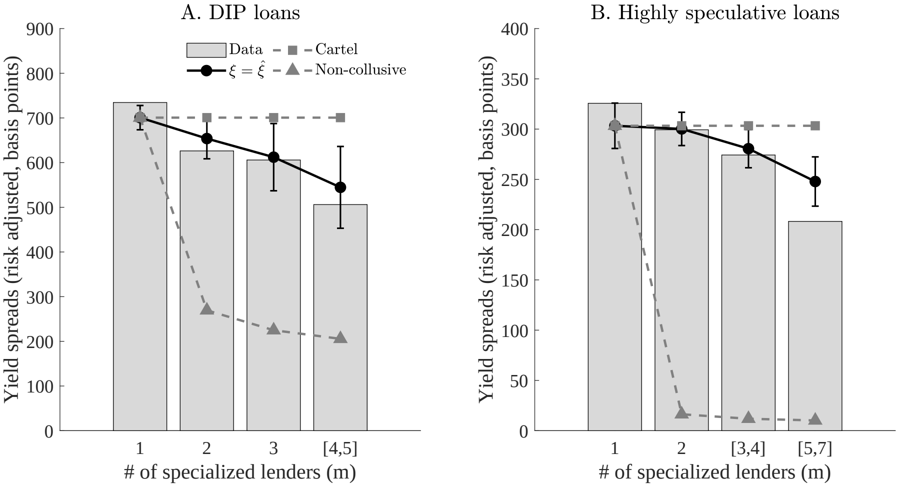
Model parameters to estimate:

- Heterogeneous demand curve: α_k and ε_k for $k \in \{1, \cdots, K\}$
- Punishment on deviation (collusion capacity): $\xi \in [0, 1]$
- Blocking external funding access (blocking power): λ_k for $k \in \{1, \cdots, K\}$
- Participation dis-utility (blocking power): μ
- Variable cost: ϕ_ℓ for $\ell \in \{1, 2, 3\}$

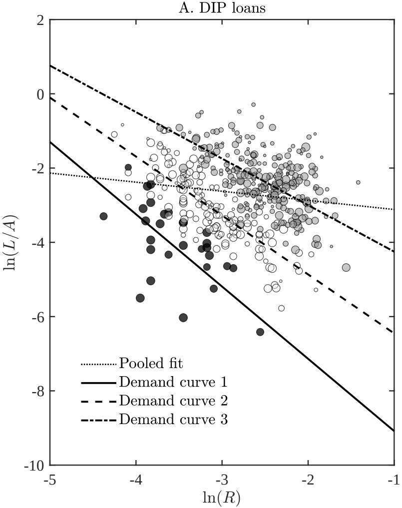
Bayesian MCMC estimation:

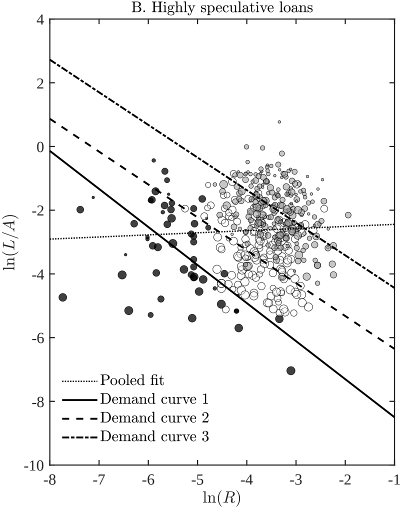
- Utilize the observables: lender type, lender number, loan size, loan prices
- Estimate the posterior of latent demand heterogeneity k and model parameters

Identification for ξ



Demand Curve Estimation



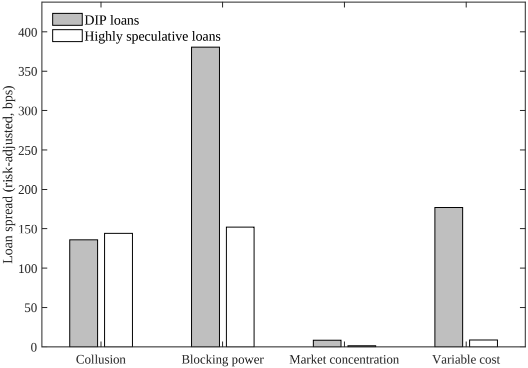


Parameter Estimates

	DIP loans				Highly speculative loans			
General parameters								
ξ	σ	ς	μ		ξ	σ	ς	μ
0.492	0.664	0.430	34.81		0.527	1.021	0.532	27.95
(0.094)	(0.046)	(0.020)	(4.67)		(0.031)	(0.035)	(0.016)	(2.48)
Lender-specific parameters								
	Existing creditor	Specialized lender	Last-resort lender			Existing creditor	Specialized lender	Last-resort lender
e^{ϕ_l}	0.0149	0.0158	0.0197		e^{ϕ_l}	0.0008	0.0007	0.0009
	(0.0035)	(0.0036)	(0.0045)			(0.0002)	(0.0001)	(0.0002)
Borrower-specific parameters								
	Demand curve 1	Demand curve 2	Demand curve 3			Demand curve 1	Demand curve 2	Demand curve 3
α_k	-11.031	-8.041	-5.505		α_k	-9.694	-7.386	-5.465
	(1.516)	(0.530)	(0.129)			(0.472)	(0.112)	(0.101)
ε_k	1.947	1.588	1.253		ε_k	1.195	1.032	1.024
	(0.287)	(0.108)	(0.040)			(0.076)	(0.008)	(0.006)
λ_k	0.036	0.150	0.119		λ_k	0.124	0.049	0.157
	(0.041)	(0.164)	(0.043)			(0.062)	(0.019)	(0.024)
γ_k		2.759	3.221		γ_k		0.607	1.633
		(1.502)	(1.114)				(0.577)	(0.209)
β_k		-1.011	-1.510		β_k		0.893	-0.403
		(0.508)	(0.298)				(0.330)	(0.171)

Note: Greater variable costs in the DIP market; Consistent with the intution: $\phi_1 \leq \phi_2 \leq \phi_3$

Counterfactual Analysis: Decomposition of Loan Spreads



Sources of Loan Spread:

Collusion ($\xi \to 0$);

Blocking power ($\mu \to 0$ and $\lambda_k \to 0$);

Market concentration ($M \to \infty$);

Variable costs ($\exp(\phi_i) \to 0$).

- Collusion contributes over 140 bps to the loan spreads as markups in both markets
- Existing creditors' blocking power is substantial, especially in the DIP loan market
- Market power remains large even when market concentration is low
- Much larger marginal costs of making loans in the DIP loan market
- Lender market power drains survival-critical liquidity by 20% in DIP and 16% in highly speculative loans

Conclusion

Endogenous market power from strategic competitive interactions

- Links discount rates to firms' cash-flow dynamics in capital markets
- Generates a crucial source of distress costs through competition–distress feedback

Market power of dominant investors in asset markets

- Distorts asset prices away from risk-based fundamentals
- Drains survival-critical liquidity from distressed firms, amplifying value destruction
- Creates a major source of distress costs through lender market power

Measuring customer capital and estimating demand

- **BAV** provides survey-based measures of customer capital
- **Bayesian MCMC** jointly learns latent demand heterogeneity and parameter values