NBER WORKING PAPER SERIES

THE COST OF INTERMEDIARY MARKET POWER FOR DISTRESSED BORROWERS

Winston Wei Dou
Wei Wang
Wenyu Wang

Working Paper 35206
http://www.nber.org/papers/w35206

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
May 2026

We thank our discussants Fernando Anjos, Samuel Antill, William Mann, Marcus Opp, Zhongzhi Song, Arthur Taburet, Alessandro Villa, Jonathan Wallen, Yufeng Wu, and Haotian Xiang, for their suggestions and comments. We are grateful for comments from Dean Corbae, Darrell Duffie, Brent Glover, Itay Goldstein, John Griffin, Zhiguo He, Edie Hotchkiss, Jean-François Houde, Ben Iverson, Lars-Alexander Kuehn, Karen Lewis, David Musto, Mitchell Petersen, Tom Sargent, Lukas Schmid, Amit Seru, Adi Sunderam, Chad Syverson, Luke Taylor, Toni Whited, Liyan Yang, conference participants at AFA, BI Norwegian Business School, BPI and Nova SBE Conference in Corporate Bankruptcy and Restructuring, CityU International Finance Conference, Econometric Society Summer School in Dynamic Structural Econometrics, Macro Finance Society Workshop, MFA, NFA, PHBS Finance Symposium, Stanford SITE, Summer Institute of Finance (SIF), Wisconsin (Economics), WFA, and seminar participants at Boston University, Carnegie Mellon University, Dauphine-PSL Paris, Indiana University, HKUST, Sargent Alumni Reading Group, Temple University, University of Georgia, and Wharton. We thank Edward I. Altman for kindly sharing the NYU-Salomon Center Default database. We acknowledge the funding support of the Social Sciences and Humanities Research Council of Canada (SSHRC). Winston Dou is grateful for the financial supports from the Golub Faculty Scholar Award at Wharton. Wenyu Wang gratefully acknowledges financial support from the Peter Chair in Investment Banking. The views expressed herein are those of the authors and do not necessarily reflect the views of the National Bureau of Economic Research.

The Cost of Intermediary Market Power for Distressed Borrowers
Winston Wei Dou, Wei Wang, and Wenyu Wang
NBER Working Paper No. 35206
May 2026
JEL No. C11, D43, G12, G18, G2, G21, G23, G28, K21, L13, L4

ABSTRACT

Distressed firms need urgent financing to preserve operations and avoid inefficient liquidation, but they borrow in concentrated markets shaped by existing-creditor blocking power and a small group of specialized lenders. We show that these borrowers pay exceptionally high loan spreads even after removing compensation for credit risk, liquidity risk, and non-risk loan-making costs. To quantify and decompose lender market power, we develop and estimate a dynamic game-theoretic model of distressed lending with latent demand heterogeneity, endogenous lender participation, creditor blocking power, and tacit collusion sustained by repeated syndication. Using granular facility-level data on debtor-in-possession (DIP) loans and highly speculative loans, we find that lender market power explains 533 bps of risk-adjusted spreads in the DIP loan market and 300 bps in the highly speculative loan market, including about 140 bps from tacit collusion in each market. Lender market power is therefore a major source of financial distress costs, reducing survival-critical liquidity by 16–20% and thereby worsening asset-value destruction.

Winston Wei Dou
University of Pennsylvania
The Wharton School
and NBER
wdou@wharton.upenn.edu

Wei Wang
Queens University
wwang@queensu.ca

Wenyu Wang
Indiana University
wenywang@iu.edu

An online appendix is available at http://www.nber.org/data-appendix/w35206
A SSRN Link is available at https://papers.ssrn.com/sol3/papers.cfm?abstract_id=4163319

1 Introduction

Financial distress and bankruptcy impose significant costs on corporate borrowers and, in turn, shape their ex ante cost of capital, resource allocation, industry dynamics, and aggregate investment and employment. Understanding the microfoundations of these costs is essential both for analyzing how they vary across macroeconomic conditions and for designing policies to mitigate their adverse effects.

A large literature emphasizes frictions inside the formal bankruptcy process, especially Chapter 11. Stakeholder conflicts, asymmetric information, and judicial discretion or inexperience can distort bankruptcy outcomes, leading to excessive liquidation, inefficient continuation, and delayed resolution (e.g., Corbae and D'Erasmo, 2021; Dou et al., 2021a).[1] These frictions can generate substantial losses for distressed and bankrupt firms.

This paper studies a different source of distress costs: the cost of obtaining survival-critical liquidity. Liquidity is especially valuable in distress, including bankruptcy, because it gives firms time to restructure, preserves going-concern value, improves bargaining power, accelerates resolution, and prevents fire sales (e.g., Asquith et al., 1994; Gilson, 1997; Dahiya et al., 2003). Yet firms in severe distress or bankruptcy must raise this liquidity in specialized lending markets where financing is exceptionally expensive even after adjusting for risk.

We show that lender market power is the primary driver of these high risk-adjusted financing costs. Quantitatively, this market power reduces survival-critical liquidity (operating cash flows available during distress) by 16–20%, substantially amplifying value destruction in financial distress and bankruptcy. To quantify this channel, we provide micro-level evidence on both the magnitude and sources of distressed financing costs. We conduct a structural estimation exercise using a granular dataset of distressed loans, that is, loans to borrowers in financial distress or bankruptcy, containing detailed information on loan yields, contractual terms, fees, loan sizes, lender participation, and bid-ask spreads in secondary loan markets, along with auxiliary data on credit default swap (CDS) spreads and loan and bond recovery rates. To our knowledge, this dataset is the most comprehensive of its kind and offers a unique lens for analyzing the financial burdens faced by distressed borrowers.

Specifically, we embed these data in a game-theoretic model that captures both strategic interactions among lenders and latent heterogeneity in borrowers' loan demand. The framework nests non-collusive competition, tacit collusion through loan syndication, and perfect cartel behavior, allowing us to estimate the costs of intermediary market power for distressed borrowers and decompose them into three key components: (i) the blocking power of existing creditors, (ii) market concentration among specialized lenders, and

[1] See Wang (2022) and Hotchkiss et al. (2023), among others, for recent surveys.

(iii) tacit collusion among these lenders in distressed lending markets.

A crucial step in understanding these financing costs is to recognize the structure of distressed loan markets. There are primarily two loan markets for distressed corporate borrowers: (i) the debtor-in-possession (DIP) loan market for firms undergoing Chapter 11 bankruptcy, and (ii) the highly speculative loan market for firms deeply in financial distress but not yet bankrupt. Much like intensive care units (ICUs) in the healthcare system, distressed loan markets, though not the largest in asset size, serve a vital function in the financial system by providing urgent funding to distressed firms at critical moments.

Importantly, the two lending markets for distressed corporate borrowers are both highly segmented and highly concentrated, with a small number of specialized lenders playing a dominant role. These lenders wield significant market power due to several factors. First, severe liquidity constraints and limited funding options weaken borrowers' bargaining power. Second, high entry costs from specialization and regulatory barriers create segmented, concentrated markets with limited competition (e.g., Eisfeldt et al., 2023). Third, by holding control rights over distressed borrowers' assets, existing creditors can exercise blocking power, restricting access to external funding and discouraging specialized lenders from joining syndications. Fourth, regulatory exemptions, such as the exclusion of syndicated loans from SEC registration and anti-fraud provisions, lower litigation risks and make anti-competitive behavior easier to sustain. Finally, dominant lenders frequently syndicate with one another, reinforcing cooperative ties and enhancing their market power.[2]

As a key contribution, this paper documents that a significant portion of loan yield spreads in these markets cannot be explained by credit and liquidity risk premia. Even after accounting for these risk components, a substantial unexplained yield spread remains, which we term the *risk-adjusted yield spread*. Over the past two decades, the average risk-adjusted yield spread has been 711 basis points for DIP loans and 308 basis points for highly speculative loans. Notably, these spreads do not follow clear cyclical patterns or strongly comove with macroeconomic conditions. This finding stands in sharp contrast to corporate bond markets and investment-grade loan markets, where credit and liquidity risks explain nearly all of the yield spread (e.g., Longstaff et al., 2005; Blanco et al., 2005). Cross-sectional evidence further shows that risk-adjusted yield spreads are higher for smaller borrowers and for borrowers facing fewer specialized lenders in the syndicate. These patterns suggest that lender market power may play an important role in distressed lending markets.

[2] These concerns have drawn increasing attention from regulators. Following the European Union (EU) report on competition in loan syndication (European Commission et al., 2019), authorities have begun scrutinizing potential explicit collusion among syndication lenders, particularly in the form of "club deals." The EU report examines leveraged buyouts (LBOs) and project/infrastructure finance across France, Germany, the Netherlands, Poland, Spain, and the UK.

Despite empirical evidence of concentrated lending markets and ultra-high risk-adjusted yield spreads, identifying lender market power and assessing its impact on the financing costs for distressed corporate borrowers remain challenging. First, high risk-adjusted loan spreads may not necessarily reflect lender market power. Instead, they may capture substantial private costs incurred by lenders in making loans, such as search, screening, monitoring, and information production costs, which are inherently unobservable to econometricians. Second, estimating borrower demand elasticity requires identifying both the demand system and the supply structure, but this is difficult because loan-making costs and some sources of demand heterogeneity are not directly observed, creating an omitted-variable problem. Third, potential collusion among lenders in these distressed lending markets is inherently implicit, making it difficult, if not impossible, to measure using empirical proxies. Finally, whether a distressed borrower ultimately secures a syndicated loan from specialized lenders or instead relies on alternative funding sources, such as hedge funds or private equity firms, is highly endogenous. A credible estimate of the value of these outside options is therefore essential for understanding the overall cost of borrowing.

To overcome these challenges, we develop and estimate a novel structural model that exploits the implications of lender market power for distressed borrowers. The model provides a unified characterization for both the DIP loan market and the highly speculative loan market. The model incorporates both the demand and supply sides of distressed lending markets. On the demand side, it characterizes the demand curves of distressed corporate borrowers by specifying the risk-adjusted yield spread they are willing to pay for a given loan amount. We provide micro-foundations for these demand curves in the spirit of Hendel (1999), taking into account how leverage affects the borrower's default risk. On the supply side, the model characterizes loan origination as a three-stage process. First, the distressed borrower negotiates with its existing creditors for financing. Second, if the existing creditors decline to lend, the borrower approaches a group of specialized lenders, who choose whether and how to participate in a syndicated loan. Third, if no specialized lender is willing to participate, the borrower turns to hedge funds and private equity firms, which serve as *lenders of last resort* and extract the entire surplus. Strategic interaction among specialized lenders is central to our analysis, and we model it within a repeated-game framework (e.g., Fudenberg and Maskin, 1986; Rotemberg and Saloner, 1986).[3] The model features imperfect competition among a clique of specialized lenders, who choose whether to participate in loan syndication and, conditional on participating, whether to lend cooperatively or non-cooperatively, taking into account how

[3]Relatively few studies examine the asset-pricing implications of strategic competition in repeated games. Recent exceptions include Opp et al. (2014), Dou et al. (2021c,d), Chen et al. (2021), Dou et al. (2022), and Bryzgalova et al. (2025).

current lending decisions affect expected future payoffs from syndication. This unified framework nests both collusive and non-collusive equilibria in a coherent way, ensuring that collusive capacity is determined endogenously and co-varies with other equilibrium outcomes, such as the number of specialized lenders and the size of the syndicated loan. More broadly, our paper makes an important methodological contribution by endogenizing the level of sustainable collusion in a repeated game and identifying it from the data.[4]

The model is analytically tractable, allowing us to derive a closed-form characterization of the joint distribution of exogenous characteristics and endogenous equilibrium outcomes on both the demand and supply sides, including borrower size, borrower type, lender type, syndicate composition, loan amount, and loan yield spread. This characterization makes likelihood-based estimation feasible. We estimate the model using Bayesian Markov Chain Monte Carlo (MCMC) methods and comprehensive datasets of 436 DIP loan facilities from 2002–2019 and 435 highly speculative loan facilities from 2001–2017, manually constructed from loan and court documents with detailed information on loan pricing and contract terms.

The Bayesian MCMC procedure recovers the posterior distribution of structural parameters and latent heterogeneity in borrower demand curves, conditional on the observed data. Bayesian MCMC is well suited to this setting. It treats latent utilities, demand shocks, and random coefficients as unobserved variables. It then samples them jointly with the structural parameters. This approach is widely used in structural industrial organization and quantitative marketing. Our estimation approach is closely related to Imai et al. (2009) and Norets (2009): all use Bayesian MCMC to jointly estimate structural parameters and latent demand heterogeneity. Their methods target dynamic discrete-choice models, combining model solution with posterior simulation; we apply a related Bayesian logic to estimate borrower demand curves with latent heterogeneity jointly with the supply-side pricing game, treating loan spreads as endogenous equilibrium outcomes. Furthermore, rather than estimating a standalone demand curve, our method jointly estimates loan demand and supply-side pricing, or a more general pricing equation, treats price (that is, the loan yield spread) as endogenous, and uses latent variables within the MCMC procedure to capture unobserved heterogeneity across distressed borrowers and loan demand shocks, similar to Yang et al. (2003), Jiang et al. (2009), and Li and Ansari (2014), among others.[5]

[4] For example, our approach differs from that of Nevo (2001), who studies a model with perfect collusion that may be infeasible under the estimated parameters. More recent work in empirical industrial organization (e.g., Ciliberto and Williams, 2014; Miller and Weinberg, 2017) modifies this approach by allowing departures from the non-collusive Nash equilibrium to depend exogenously on observed characteristics, such as the "multi-route contact" between carriers in Ciliberto and Williams (2014). Our paper goes one step further by endogenizing how departures from the non-collusive Nash equilibrium depend on structural parameters and borrower characteristics.

[5] Bayesian MCMC methods have seen rapid growth in finance research (Sorensen, 2007; Johannes and

Our method differs from the traditional instrumental-variable approach used in Berry (1994); Berry, Levinsohn, and Pakes (1995, hereafter BLP). The IV approach identifies demand from exogenous shifts in supply, whereas our approach uses the joint distribution of equilibrium observables to recover latent demand curves and structural parameters simultaneously.[6] Despite these different identifying assumptions, IV and full-information maximum likelihood estimators are equivalent when the instruments span all overidentifying restrictions implied by the model (e.g., Hausman, 1975).

Our estimation delivers several novel findings. First, lenders' tacit collusion accounts for a sizable component of risk-adjusted yield spreads, amounting to about 140 bps in both markets. Second, borrowers in the two markets exhibit similarly low price elasticities of demand. Taken together, these results imply that the higher excess spread in the DIP loan market cannot be explained by differences in collusive capacity or demand elasticity across the two markets. Instead, the key factors distinguishing the two markets are existing lenders' blocking power and variable lending costs. Existing lenders' blocking power accounts for 380 bps of the DIP loan spread, compared with 152 bps of the highly speculative loan spread, suggesting substantially stronger blocking power among existing creditors in the DIP loan market. We also find that DIP lenders incur significantly higher variable loan-making costs: the estimated variable cost is 180 bps in the DIP loan market, much higher than that in the highly speculative loan market, consistent with the greater complexity of DIP financing and reorganization bargaining.

Our decomposition of risk-adjusted yield spreads allows us to identify which borrowers are most exposed to lender market power. We partition borrowers into size quintiles and repeat the analysis for small borrowers in the bottom quintile and large borrowers in the top quintile. The results are striking: shutting down lender collusion reduces loan yield spreads by about 75 (121) bps for large borrowers and by 161 (166) bps for small borrowers in the DIP loan (highly speculative loan) market. Thus, small borrowers are especially vulnerable to institutional lender market power, mainly because they have lower loan-demand elasticity and give specialized lenders weaker incentives to deviate from coordination in loan syndication. These findings suggest that policies designed to support distressed firms during economic and financial crises should place particular emphasis on small firms, given their weaker bargaining positions and disadvantageous access to distressed loan markets.

Lastly, we use the estimated model as a laboratory to evaluate regulatory interventions. In particular, we consider a government special purpose vehicle that participates in the loan syndication process, and analyze lenders' strategic responses to this policy

Polson, 2010; Kortweg, 2010).

[6] Allen et al. (2018) is another exception that does not rely on IV to estimate demand. They exploit unique features of parallel multi-unit auctions to identify demand elasticities.

and its implications for borrower welfare.

Related literature. Our paper contributes to the literature on bankruptcy and financial distress costs. Bankruptcy costs are central to ex ante financial distress costs because firms and investors anticipate restructuring and liquidation losses before bankruptcy occurs (e.g., Bris et al., 2006; Bernstein et al., 2019; Pulvino, 1999; Corbae and D'Erasmo, 2021; Dou et al., 2021a; Antill, 2022; Graham et al., 2023; Ma et al., 2023; Antill and Hunter, 2024). Prior work shows that limited liquidity can destroy firm value by weakening consumer demand through concerns about future product quality (Hortaçsu et al., 2013), eroding customer capital as key talent leaves distressed firms (Dou et al., 2021b), and generating distress-competition feedback, in which tighter funding constraints and intensified product-market competition reinforce each other (Chen et al., 2024). Dahiya et al. (2003) and Eckbo et al. (2023) show that DIP financing provided to firms filing for bankruptcy is critical for addressing their liquidity issues yet carries high yield spread and fees. We identify a distinct liquidity-driven value-destruction channel: distressed firms must obtain survival-critical liquidity precisely when financing markets are most costly. Although liquidity preserves going-concern value, improves bargaining power, accelerates resolution, and prevents fire sales (e.g., Asquith et al., 1994; Gilson, 1997; Dahiya et al., 2003), distressed and bankrupt firms raise this liquidity in specialized lending markets where financing remains exceptionally expensive even after adjusting for risk. This paper shows that lender market power reduces survival-critical liquidity by 16–20%, substantially amplifying value destruction in financial distress and bankruptcy.

Our study contributes to the literature on strategic competitive interaction, especially tacit collusion. Classic repeated-game theories show how collusion can be sustained through future punishments and rewards (e.g., Green and Porter, 1984; Sannikov and Skrzypacz, 2007). Modern IO research shows how market leaders sustain market power through strategic competitive tactics, such as tacit collusion and implicit coordination, across various markets and settings (e.g., Harrington and Skrzypacz, 2011; Asker and Bar-Isaac, 2014; Miller and Weinberg, 2017; Miravete et al., 2018; Clark et al., 2024), with important macroeconomic implications (Syverson, 2019). Strategic interaction among major banks can also have real effects: Asker and Ljungqvist (2010) show that firms avoid sharing investment banks with product-market rivals because of information-leakage concerns, shaping bank competition, underwriting fees, and corporate investment, while Corbae and Gofman (2021) show how interbank lending can sustain collusion by allowing banks to share rents and commit not to compete in private lending. We complement this literature by focusing on distressed loan markets, where we show that lender market power and tacit collusion in loan syndications impose real costs on borrowers. We extend prior work by using granular loan-level data and a structural model of lender-borrower strategic interaction to quantify the dynamics and real consequences of financial-market collusion.

This paper also contributes to the burgeoning literature on how inelastic intermediary investment decisions distort asset prices away from risk-based fundamentals in macro-finance and capital markets (e.g., Koijen and Yogo, 2019; Gabaix and Koijen, 2023; Bretscher et al., 2026). We complement this literature by studying distressed loan markets and by microfounding intermediary inelasticity as an endogenous outcome of specialized lenders' market power, sustained by strategic competitive interactions, especially tacit collusion in repeated syndication.

2 Background and Motivating Evidence

2.1 Background

The loan markets for distressed corporate borrowers, while not the largest in terms of market value, are among the most important asset markets in the economy. Firms in financial distress often rely on these markets for critical financing to maintain working capital, support investment, and service liabilities. Without such financing, operations may be disrupted, potentially forcing inefficient liquidation. As a result, these markets materially affect the survival prospects of distressed firms and the efficiency of the bankruptcy process (Altman, Hotchkiss, and Wang, 2019). More broadly, they play a central role in determining the cost of financial distress for the corporate sector, even from an ex ante perspective.

There are two primary loan markets for distressed borrowers. The first is the DIP loan market, in which financing is extended to firms that have already filed for Chapter 11 bankruptcy. The second is the highly speculative loan market, in which loans are provided to firms that are severely distressed but have not yet entered bankruptcy, typically those with an S&P credit rating of CCC+ or lower. For most firms, these two markets operate in parallel rather than sequentially, because prepetition distressed lending and DIP financing are alternative funding channels tied to different legal regimes and restructuring choices, rather than consecutive stages of a single financing ladder. Our data are consistent with this parallel structure.[7]

We emphasize that the significance of an asset market is not always reflected by its size. Consider the Intensive Care Unit (ICU) analogy: although it constitutes less than 10% of hospital admissions and beds, it is critical for the entire healthcare system's functionality. Similarly, DIP loans and highly speculative loans may comprise only about

[7] A small number of firms in our data obtain prepetition rescue financing and later seek DIP financing after filing for Chapter 11, sometimes from the same lenders.

10% of the annual outstanding leveraged loans, yet they play an analogous role to the ICU in the financial system. Their importance becomes particularly evident during periods of stress. For example, their share rose to over 45% in 2009 during the Great Recession. Likewise, during the COVID-19 pandemic, an unprecedented number of large firms filed for bankruptcy, and many turned to distressed loan markets for liquidity DeMarzo et al. (2020). In essence, distressed loan markets play a role in the financial system analogous to that of ICUs in healthcare.

We construct a novel and comprehensive dataset on DIP loans from 2002 to 2019 and the highly speculative loans from 2001 to 2017. To the best of our knowledge, this is the first study to develop comprehensive facility-level panel datasets for both types of distressed loan markets. The construction of the loan samples is described in Sections 5.1 and 5.2. Summary statistics indicate that DIP loans and highly speculative loans have average maturities of 11 and 49 months, respectively, with syndicates comprising 2.29 and 3.78 major lenders. The average loan-to-asset ratios are approximately 10.7% for DIP loans and 13.5% for highly speculative loans. The average risk-adjusted yield spreads over LIBOR are about 711 and 308 basis points, respectively.

2.2 Motivating Evidence

We document stylized facts from the U.S. DIP loan market and the highly speculative loan market that together point to substantial market power of financial intermediaries over distressed borrowers.

Stylized Fact 1: Concentrated Markets Dominated by Specialized Lenders. We define *major lenders* as those holding key syndicate roles, such as lead arranger and agent bank, as identified from financing motions and master credit agreements, following Jiang et al. (2010). We then classify loans into three categories based on lender type: *existing-creditor loans*, *specialized-lender loans*, and *last-resort loans*. A *specialized lender* is a lender that ranks among the top 10 by the number of loans financed as a major lender in our sample, regardless of the number of major lenders in the syndicate. Specialized-lender loans are loans involving at least one specialized lender. Existing-creditor loans are those provided exclusively by a single lender that is an existing creditor but not classified as a specialized lender. Last-resort loans contain those where more than 50% of the major lenders are hedge funds and private equity funds.

Panel A of Table 1 lists the specialized lenders in each of the two markets. Panel B reports, for each loan type defined by lender type, its share of the total number of loans and total loan dollar volume. A few important points are worth mentioning. First, Panel A reveals that specialized lenders are generally large banks considered system-

Table 1: Specialized lenders and market concentration

A. Names of specialized lenders

Rank	DIP loan market Lender name	DIP loan market # of deals	Highly-speculative loan market Lender name	Highly-speculative loan market # 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	31	Goldman Sachs	60
8	Wachovia Bank	28	Wachovia Bank	28
9	Wilmington Trust	27	GE Capital	56
10	CIT Group	21	Wachovia Bank	53

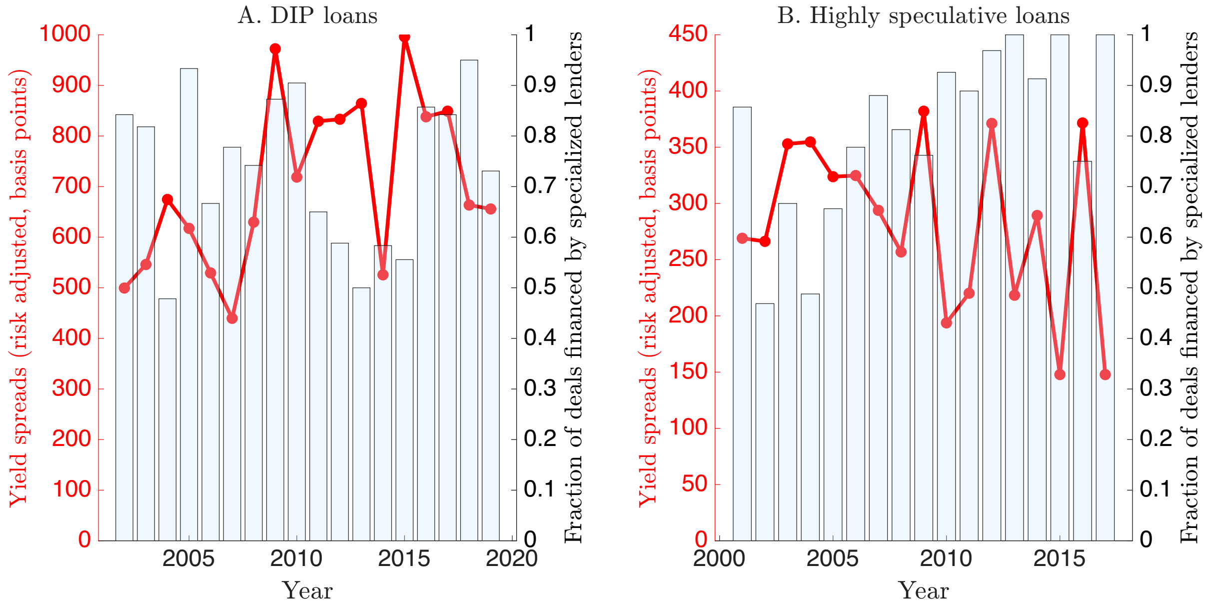
B. Three loan types

Loan type (defined by lender type)	DIP loans # of deals	DIP loans # frac.	DIP loans $ of deals	DIP loans $ frac.	Highly-speculative loans # of deals	Highly-speculative loans # frac.	Highly-speculative loans $ of deals	Highly-speculative loans $ 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 is measured by constant 2019 dollars and presented in the unit of billion dollars. The highly speculative loan sample includes only facilities after removing those with negative adjusted spreads. The first type includes loans provided exclusively by a single lender, who is an existing creditor but not categorized as a specialized lender. These are designated as *existing-creditor loans* and marked as *Type 1*. The second type comprises loans supplied by at least one specialized lender in scenarios involving multiple major lenders, as well as loans offered by a single specialized lender who is not an existing creditor. These are identified as *specialized-lender loans* and indicated by *Type 2*. The third type consists of loans where more than 50% of the major lenders are hedge funds and private equity funds, termed *last-resort loans* and denoted by *Type 3*.

ically important financial institutions. Second, Panel B demonstrates that specialized-lender loans account for 76.60% (92.16% in dollar terms) of the DIP loan market and 76.32% (90.45% in dollar terms) of the highly speculative loan market, respectively. In addition, Figure A1 in Appendix B shows that specialized lenders repeatedly syndicate with one another as joint major lenders within a small lending "club," rather than with other lenders. Finally, specialized lenders are largely overlapping (8 out of 10) between the DIP and highly speculative loan markets as specialized skills in distressed restructuring and bankruptcy are essential for becoming a major player in these markets. These facts indicate that the loan markets for distressed corporate borrowers are characterized by market segmentation, high concentration, significant barrier of entry, and the repeated syndication relation among a clique of specialized lenders.

Stylized Fact 2: Ultra-High Risk-Adjusted Yield Spreads. In addition to market concentration, we document a substantial markup component in the total cost borne by dis-



Note: The figure displays the average risk-adjusted yield spread and the fraction of deals financed by specialized lenders in both the highly speculative loan market and the DIP loan market, charted over several years. The curves depict the annual average risk-adjusted yield spread, while the bars show the yearly fraction of deals financed by the top 10 specialized lenders.

Figure 1: Risk-adjusted yield spreads and shares of specialized-lender loans

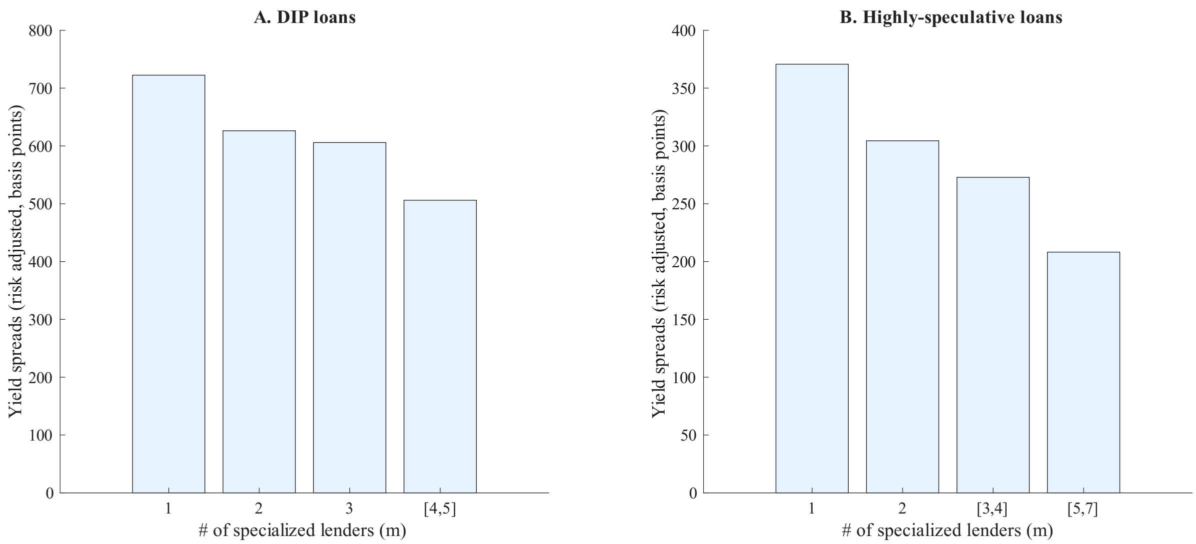
tressed borrowers. We measure the total cost to the borrower (TCB), in basis points, as the all-in borrowing cost per dollar drawn under the loan commitment. Specifically, TCB is defined as the interest rate spread over LIBOR plus fees paid to lenders, calculated as follows:

$$\begin{aligned}\text{TCB Spread} = {} & \text{Interest Rate Spread} + \text{Annual Fee} \\ & + \text{Upfront Fee/Risk Neutral Expected Loan Maturity in Years} \\ & + \text{Risk Neutral Expected Annualized Default Fee,} \end{aligned} \tag{1}$$

where we consider three main types of fees paid by the borrower, including upfront fee, annual fee (or facility fee), and state-contingent fee such as default interests. Our measure, which incorporates both interest spreads and fees paid to lenders, is consistent with the literature (e.g., Ivashina, 2009; Lim et al., 2014; Berg et al., 2016). As emphasized by Berg et al. (2016), lenders use a combination of spreads and fees, rather than any single component, to achieve target returns. Including fees is therefore essential, particularly in distressed settings where lenders with greater market power may extract rents through fees as well as interest rates.[8]

To understand how lender market power drives the cost to distressed borrowers, we remove the credit- and liquidity-premium components from TCB, because they are

[8]The details on the calculation of the risk-neutral expected loan maturity in years and the risk-neutral expected annualized default fee in Equation (1) is in Section 5.3 and Online Appendix OA.1.



Note: The figure displays the average risk-adjusted yield spread for distressed loans with different numbers of syndicators. Panel A is for DIP loans, while Panel B is for highly speculative loans. To make the number of observations in each group more comparable, we group together loans with different numbers of lenders when the syndicates are large (e.g., DIP loans with 4-5 lenders and highly speculative loans with 5-7 lenders), because such loans are fewer in the data.

Figure 2: Average risk-adjusted yield spreads and syndication concentration.

compensations for lenders taking the credit and liquidity risks of the loans. We focus on the remaining component of TCB, which we refer to as risk-adjusted spreads. The detailed estimation procedure for these risk components is described in Section 5.3.

Panel A of Figure 1 plots the annual average risk-adjusted yield spread of DIP loans together with the annual share financed by specialized lenders. Panel B reports the corresponding series for the highly speculative loan market. Several observations stand out. First, the share of loans financed by specialized lenders remains persistently high over time, with no obvious cyclical pattern or clear comovement with aggregate financial conditions. This suggests that the high concentration of distressed lending markets is not a temporary feature of particular periods, but a persistent feature of market structure. Second, the average risk-adjusted yield spread also remains persistently high, ranging from roughly 450 to 1000 basis points for DIP loans and 150 to 400 basis points for highly speculative loans, again with no obvious cyclical pattern or clear comovement with aggregate financial conditions.

Stylized Fact 3: Syndication Concentration and Risk-Adjusted Yield Spreads. We examine how the number of specialized lenders in a loan syndicate relates to the risk-adjusted yield spread. If ultra-high risk-adjusted spreads are mainly driven by limited competition, then more concentrated syndicates should be associated with higher spreads. Figure 2 confirms this prediction: the risk-adjusted yield spread declines monotonically with the number of specialized lenders in the syndicate. This pattern points to an important role for lender market power in shaping distressed borrowers' financing costs.

2.3 Sources of Market Power for Lenders in Distressed Loan Markets

In distressed loan markets, corporate borrowers typically rely on a clique of specialized lenders that provides a substantial share of financing. The novel evidence in Section 2.2 shows that, even after adjusting for credit and liquidity risk, loan yield spreads remain exceptionally high. This pattern suggests that these lenders possess substantial market power, for at least three main reasons.

(i) Sole Source of Urgent External Financing. Distressed borrowers have weak bargaining positions, and their demand for loans is likely to be highly inelastic. They face acute liquidity needs and require capital urgently to sustain operations. At the same time, they typically have few, if any, unencumbered assets that can be pledged as collateral for new secured borrowing. Unlike non-distressed firms, they have little access to alternative sources of external finance, such as equity issuance, bond financing, or unsecured credit lines. Moreover, distressed borrowers are often reluctant to approach many lenders or conduct an open auction to obtain better loan terms, because information leakage could harm their security prices, profit margins, customer base, and supply chains.

(ii) Tacit Collusion through Repeated Syndication among Specialized Lenders. High entry barriers result in segmented distressed lending markets in which a small clique of specialized lenders captures most market activity. These barriers are high not only because distressed lending is costly, but also because the required investments are fixed, specialized, and largely sunk. A lender must develop restructuring expertise, bankruptcy-law knowledge, collateral valuation capacity, monitoring infrastructure, and the ability to manage complex and fragile bargaining relationships with borrowers, existing creditors, advisors, and other syndicate members. These investments pay off only with long-term repeated deal flow. For occasional entrants, expected lending opportunities are too limited to justify the costly entry, leaving the market to established specialized lenders. Potential entrants may also be deterred by regulatory capital requirements. For example, under Basel III, loans to firms with higher default risk carry higher risk weights, requiring financial institutions to hold more regulatory capital. This "club" of specialized lenders may engage in tacit collusion in lending, facilitated by close and repeated syndication relationships (Cai et al., 2018; Hatfield et al., 2020). Such repeated interactions give these lenders both the incentives and the ability to sustain implicit coordination in loan provision.

(iii) Existing Creditors' Blocking Power over Outsiders. Existing creditors often discourage and restrain specialized lenders from participating in loan syndications for distressed borrowers, even when the borrowers prefer to invite more outsider lenders. Existing creditors have strong incentives to block outsider lenders because they are reluctant to share the investment opportunity and are concerned about ex-post coordination issues and creditor conflicts during bankruptcy processes (Gertner and Scharfstein, 1991; Morris and Shin, 2004; Brunner and Krahnen, 2008; Dou et al., 2021a). These creditors can exert substantial control over the distressed borrower to prevent the introduction of new lenders, for example, by threatening early liquidation at the interim date after key covenant violations. Consequently, competing outside lenders are likely to be shied away from the deals, allowing existing creditors to hold up borrowers for ultra-high risk-adjusted yield spreads (e.g., Sharpe, 1990; Schenone, 2010; Santos and Winton, 2008).

3 Environment

These empirical patterns motivate a game-theoretic model of imperfect competition in the DIP loan and highly speculative loan markets, two lending environments that share a common origination process. We introduce the model environment in this section and characterize the equilibrium in the next section.

3.1 Borrowers

Distressed Borrowers' Demand Curve for Loans. Our model features heterogeneous corporate borrowers. Each borrower is characterized by its size, A, and demand-curve type, $k \in 1, \ldots, K$. A distressed borrower of size A and type k faces the following downward-sloping demand curve:

$$\ln\left(\frac{L}{A}\right) = \alpha_k - \varepsilon_k \ln(R) + \sigma z, \tag{2}$$

where L denotes the loan amount borrowed by the distressed firm, and R is the risk-adjusted yield spread it pays for the loan. The intercept α_k captures the level of demand and the slope ε_k captures the elasticity of demand, both of which depend on the borrower's type k. The term σz represents the latent demand shock, in which σ controls the volatility of the shock and z is assumed to follow the standard normal distribution. Equation (2) is a standard iso-elastic demand curve. Consistent with the literature (e.g., Atkeson and Burstein, 2008), we assume that $\varepsilon_k > 1$.

The latent type k captures heterogeneity in borrowers' demand for financing at a given risk-adjusted yield spread. This type is observed by lenders but unobserved by the econometrician. The latent demand shock z captures additional borrower-specific demand shifts that are unobservable to lenders ex ante. This latent heterogeneity may reflect differences in underlying characteristics such as continuation value, internal liquidity, asset pledgeability, refinancing urgency, investment opportunities, bargaining position, outside options, and existing-loan covenant constraints, which may collectively shape expected new-loan covenant terms. We interpret k and z as reduced-form controls for latent demand heterogeneity, rather than as structural estimates of the effects of these underlying characteristics.

We provide a micro-foundation for the demand curve in Appendix A by deriving it from a standard optimization problem in which distressed borrowers choose the optimal loan amount to maximize their gains. In doing so, borrowers take into account borrowing costs determined not only by the risk-adjusted yield spread, R, but also by credit and liquidity risk premia, both of which increase with the loan-to-asset ratio, L/A. As shown in Appendix A, the sensitivity of these premia to L/A is fully captured by the coefficients α_k and ε_k.

Joint Distribution of Borrower Size A and Type k. We assume that borrowers are independently and identically distributed with respect to borrower size and demand curve type. Borrower size follows a distribution with discrete support $\mathbb{A} \equiv \{A_1, \cdots, A_J\}$, and k also follows a distribution with discrete support $\mathbb{K} \equiv \{1, \cdots, K\}$. To allow for a possible dependence between A and k, we specify the joint distribution of A and k as:

$$\Pr(A,\ k) = \frac{e^{a_k + b_k \ln(A)}}{1 + \sum_{k'=2}^{K} e^{a_{k'} + b_{k'} \ln(A)}} \times \Pr(A), \tag{3}$$

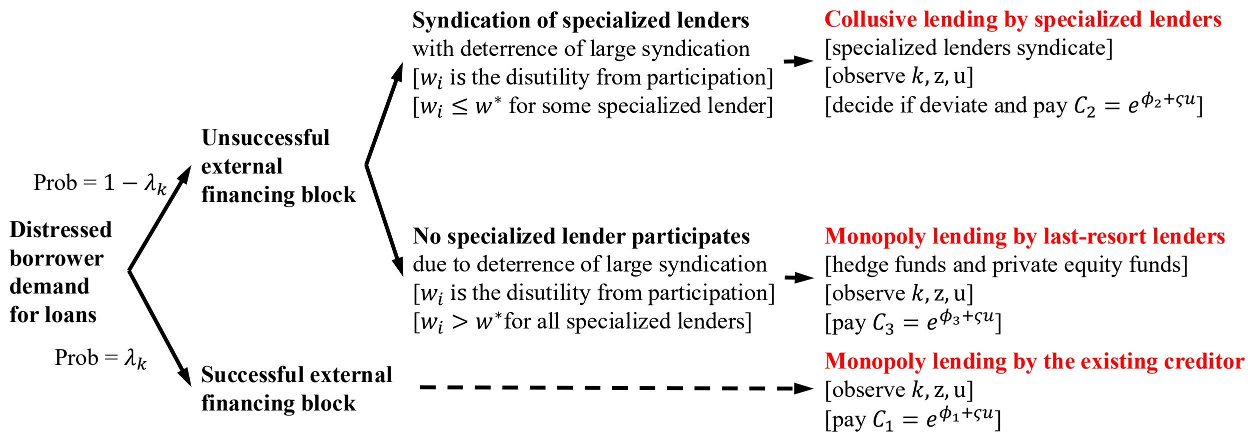
where $A \in \mathbb{A}$ and $k \in \mathbb{K}$ with normalization $a_1 = b_1 = 0$. The probability $\Pr(A)$ is given by the empirical distribution of A.

3.2 Lenders

Three Types of Lenders. There are three lender types, indexed by $l \in \{1, 2, 3\}$: the existing creditor ($l = 1$), the specialized oligopolistic lender ($l = 2$), and the non-specialized lender of last resort ($l = 3$), such as hedge funds and private equity firms.

Existing creditors ($l = 1$) possess substantial blocking power, which operates through two channels. First, they may block the borrower's access to outside lenders and thereby monopolize the origination of the new loan. Second, even when outside financing is permitted, they have both the incentive and the ability to limit participation by external lenders in the syndicate, as discussed in Section 2.3 (iii).

Specialized lenders ($l = 2$) decide whether to join the syndicate for the distressed



Note: This figure depicts the timeline of the model. In Stage 1, a distressed borrower arrives and negotiates with its existing creditor, who may exercise blocking power to monopolize the new loan with probability λ_k. In Stage 2, if the existing creditor fails to block external financing, the borrower seeks funding from specialized oligopolistic lenders, each of whom privately observes a participation cost and decides whether to join the syndicate; those with sufficiently low costs form the lending group and jointly determine the loan terms. In Stage 3, if no specialized lender chooses to participate, hedge funds and private equity firms serve as lenders of last resort, extending credit at substantially higher risk-adjusted yield spreads.

Figure 3: Model timeline

borrower. There is a stable group of $\overline{m}$ specialized oligopolistic lenders. Entry entails a lender-specific participation cost induced by deterrence from the existing creditor, so participation depends on this cost as well as on expected lending profits. Conditional on participation, we model competition among specialized lenders as Cournot, consistent with the literature on imperfect competition in credit markets (e.g., Corbae and Levine, 2024). Repeated syndication within a stable group of specialized lenders also creates scope for tacit collusion.

Lenders of last resort ($l = 3$), such as hedge funds and private equity firms, are the borrower's fallback source of financing. Borrowers turn to them only after existing creditors and specialized lenders decline to lend. These lenders face much higher required return and therefore charge higher yields, making them an unattractive option for distressed borrowers. Once borrowers turn to them, however, few alternative funding sources remain, so these lenders effectively extend credit monopolistically.

Model Timeline. Our model uses a sequential game to describe how distressed firms obtain loans, as illustrated in Figure 3. Distressed borrowers arrive in the market according to a Poisson process with arrival rate η. A distressed borrower of type k and size A must first negotiate with its existing creditor, $l = 1$, for the go-ahead to seek external funding, reflecting one dimension of the creditor's blocking power. With probability λ_k, the existing creditor successfully blocks external financing, and the borrower receives financing internally. With probability $1 - \lambda_k$, the existing creditor fails to block external financing, allowing the borrower to seek funding from specialized lenders. Each specialized lender i privately observes its own participation cost w_i, which differs across lenders, before making its participation decision. Specialized lenders with sufficiently low participation costs, $w_i \leq w^*$, where w^* is the endogenously determined equilibrium threshold, join the syndicate and jointly determine the loan size based on the downward-sloping demand curve in (2).

It is possible that no specialized lender chooses to participate in the syndicated loan; that is, all specialized lenders have $w_i > w^*$. In such cases, hedge funds and private equity firms serve as lenders of last resort ($l = 3$), extending credit at substantially higher risk-adjusted yield spreads because of their greater bargaining power and higher loan-making costs. As with existing creditors, the last-resort lender exercises monopoly power over the distressed borrower.

Loan Supply and Its Costs. When extending a loan, a lender faces a downward-sloping demand curve as specified in (2), and it chooses the its own loan supply L to maximize its lending profit, internalizing both the per-unit lending cost it bears, $C_l(u)$, and the effect of L on the risk-adjusted yield spread, $\mathcal{R}(L, A, k, z; L_{\text{other}})$, which is implied by (2). Here, L_{other} denotes the aggregate loan supply it perceives to be provided by other lenders in the syndicate, if any. The lender's profit is

$$\pi_l(L, A, k, x; L_{\text{other}}) \equiv [\mathcal{R}(L, A, k, z; L_{\text{other}}) - C_l(u)]\, L, \tag{4}$$

where $l \in \{1, 2, 3\}$ indicates the lender type, k represents the latent borrower type, z captures the latent demand shock, and u is the latent cost shock associated with loan supply. To simplify notation, let $x \equiv (z, u)$ denote the borrower-lender characteristics (i.e., demand- and supply-side shocks). The per-unit lending cost is specified as

$$\ln\left(C_l(u)\right) \equiv \phi_l + \varsigma u, \tag{5}$$

where ϕ_l is the expected lending cost for type-l lenders, and u is i.i.d. supply-side shock.

Specialized lenders incur a participation cost, w_i, to join loan syndication. We specify w_i to follow the cumulative distribution function

$$F(w; \mu) = 1 - e^{-w/\mu}, \tag{6}$$

which is common knowledge among all agents in the model. Similar to λ_k, which captures the existing creditor's ability to monopolize additional lending by blocking outside entry, the average cost parameter μ captures the creditor's ability to deter specialized lenders from entering the syndicate. A higher μ implies stronger deterrence.

4 Equilibrium

4.1 Existing Creditor's Problem

The existing creditor acts as a monopolistic lender to the borrower, and thus $L_{other} = 0$ in (4). Upon observing the latent borrower type k and borrower-lender characteristics $x = (z, u)$, the existing creditor chooses its loan supply L to maximize profits. Specifically, it first solves $\mathcal{R}(L, A, k, z; 0)$ as a function of L from the demand curve (2), which gives

$$\mathcal{R}(L, A, k, z; 0) \equiv \left(e^{\alpha_k + \sigma z} \frac{A}{L}\right)^{1/\varepsilon_k}, \tag{7}$$

It then substitutes (7) into (4) and takes F.O.C. w.r.t. L, which yields the optimal risk-adjusted yield spread and loan size:

$$R_1(k, x) = \frac{\varepsilon_k}{\varepsilon_k - 1} e^{\phi_1 + \varsigma u} \quad \text{and} \quad L_1(A, k, x) = \left(1 - \frac{1}{\varepsilon_k}\right)^{\varepsilon_k} h_1(k, x) A, \tag{8}$$

where $h_1(k, x)$ has the following expression for $l = 1$:

$$\ln\left(h_l(k, x)\right) \equiv \alpha_k - \varepsilon_k(\phi_l + \varsigma u) + \sigma z, \quad \text{for all lender types } l = 1, 2, 3. \tag{9}$$

Loan markup equals $\left[R_1(k, x) - e^{\phi_1 + \varsigma u}\right] / e^{\phi_1 + \varsigma u} = 1/(\varepsilon_k - 1)$, suggesting that the markup ratio decreases with the elasticity ε_k. When the elasticity ε_k is lower, the borrower's loan demand is effectively more urgent and pressing, leading to a higher markup.

Accordingly, the optimal *expected* profit, averaging over the vector of borrower-lender latent characteristics $x = (z, u)$, is

$$\Pi_1(A, k) = \frac{1}{\varepsilon_k}\left(1 - \frac{1}{\varepsilon_k}\right)^{\varepsilon_k - 1} \mathcal{H}_1(k) A, \tag{10}$$

where $\mathcal{H}_1(k)$ has the following expression when $l = 1$:

$$\ln\left(\mathcal{H}_l(k)\right) \equiv \alpha_k - (\varepsilon_k - 1)\phi_l + (\varepsilon_k - 1)^2 \varsigma^2/2 + \sigma^2/2, \quad \text{for all lender types } l = 1, 2, 3. \tag{11}$$

4.2 Specialized Lenders' Problem

We solve the specialized lenders' problem in three steps. We first describe the equilibrium of loan origination when syndication may be collusive. We then provide an analytical characterization of the equilibrium. Finally, we establish the existence of a collusive Nash equilibrium and show that, among all value-maximizing collusive Nash equilibria, the one closest to the perfect-cartel benchmark is unique.

4.2.1 Potential Collusive Lending among Specialized Lenders

Once the distressed borrower turns to specialized lenders, as illustrated in Figure 3, each specialized lender decides whether to join the syndicate by comparing its privately observed participation cost w with the expected profit from lending, integrating over the possible realizations of $x = (z, u)$ and taking into account the possible participation of other lenders. This decision follows a cutoff rule: only lenders with $w \leq w^*$ participate, where the cutoff w^* is determined by the indifference condition between participating and not participating.

Because expected lending profits depend on how specialized lenders strategically interact after entry, the cutoff w^* is itself equilibrium-dependent. To model this strategic interaction, we consider a general collusive Nash equilibrium that nests two polar benchmark cases: the perfect-cartel outcome and the non-collusive Nash equilibrium. This framework captures a central feature of distressed-loan markets discussed in part (ii) of Section 2.3: tacit collusion can naturally arise among a small and stable set of specialized lenders in repeated syndicated distressed lending.

This feature is also consistent with the data (see the stylized facts in Section 2.2). In practice, specialized lenders repeatedly meet in syndicates and form ongoing relationships. More broadly, an oligopolistic market structure combined with repeated interaction creates a natural environment for tacit collusion (e.g., Carrasco and Manso, 2006; Nocke and White, 2007; Hatfield et al., 2020).[9]

At one end of the collusive-Nash-equilibrium spectrum lies the perfect-cartel outcome, in which specialized lenders fully coordinate, lend as a unified monopolist, and then divide the total loan among themselves. The corresponding participation cutoff is denoted by w^*_M. This benchmark captures *explicit collusion*, which in practice can be sustained through binding agreements. Explicit collusion differs fundamentally from tacit collusion in both economic and legal terms. At the other end lies the non-collusive Nash equilibrium, in which specialized lenders compete independently and each maximizes current profit given the lending decisions of others, without regard to future interactions. The corresponding participation cutoff is denoted by w^*_N.[10]

Between these two polar benchmark cases, we consider collusive equilibria with varying degrees of collusive capacity, in which specialized lenders sustain intermediate competition through tacit collusion. This outcome is supported solely by the threat of rever-

[9] In credit markets dominated by a small number of large institutions, strategic interaction is common. For example, Knittel and Stango (2003) document tacit collusion under state-level interest-rate ceilings in the early-1980s credit-card market. In April 2019, the European Commission released a report on EU loan syndication that raised concerns about tacit collusion among syndicate lenders, warning that such coordination could distort competition by aligning interest rates and exchanging future cooperation for current restrictions on loan supply.

[10] Both benchmarks are described in detail in Online Appendix OA.3.

sion to non-collusion after a deviation, without any binding agreement. A lender deviates only if the short-run gain exceeds the expected cost of future punishment; otherwise, the collusive outcome is sustained by incentive-compatibility (IC) constraints alone. As a result, tacit collusion generates supra-competitive profits that lie between those of the two benchmark cases.

Break-Even Condition for the Participation Cutoff w^*. Each participation cutoff w_s^*, with $s \in \{C, N, M\}$, is determined by a break-even condition that makes a lender indifferent between participating in the syndicate and abstaining. A specialized lender participates if and only if its expected profit from syndication weakly exceeds its participation cost. Therefore, the cutoff w_s^* is given by

$$w_s^* = \mathbb{E}^{A',k'}\left[\mathbb{E}^{m'}\left[\Pi_2^s(A',k',m')|m' \geq 1\right]\right], \quad s \in \{C, N, M\} \tag{12}$$

where $\Pi_2^s(A,k,m)$ denotes the equilibrium expected lending profit under equilibrium $s \in \{C, N, M\}$, corresponding to the collusive, non-collusive, and cartel equilibrium; and m is the number of specialized lenders that choose to participate in the syndicate. In case $s \in \{C, M, N\}$, it holds that

$$m = \sum_{i=1}^{\overline{m}} \mathbf{1}_{\{w_i \leq w_s^*\}}. \tag{13}$$

Endogenous Distribution of the Number of Specialized Syndicators m. The break-even condition in (12) defines a fixed-point problem for w_s^*, because the right-hand side depends on w_s^* through the distribution of m. The participation cost w follows the exponential distribution with CDF given in (6). Therefore, for a given participation cutoff w^*, the probability that a specialized lender participates in the syndicate is $F(w^*;\mu)$. Since there are m specialized lenders in the market and each draws its own w independently, the number of specialized lenders participating in a syndicate, m, follows a binomial distribution:

$$q_s(m|w_s^*) = \binom{\overline{m}}{m} F(w_s^*;\mu)^m \left[1 - F(w_s^*;\mu)\right]^{\overline{m}-m}, \text{ with } s \in \{C, N, M\}. \tag{14}$$

Collusion Capacity ξ. We now introduce a parameter governing the sustainability of tacit collusion. A specialized lender may deviate from the collusive loan amount to raise current profit, taking the loan amounts of the other syndicate lenders as given. Such a deviation, however, triggers a breakdown of tacit collusion in future periods with probability $\xi \in [0, 1]$, thereby lowering the lender's continuation value. The parameter ξ therefore captures the strength and credibility of punishment. When ξ is close to zero, deviations are unlikely to be punished, so tacit collusion is difficult to sustain and the equilibrium approaches the non-collusive Nash outcome. When ξ is close to one, deviations are likely to be punished, which discourages deviation and shifts the equilibrium toward the perfect-cartel outcome.[11]

4.2.2 Characterizing the Equilibrium for Specialized Lenders

We first solve the optimal loan size L_2^s and risk-adjusted loan spread R_2^s for the cartel ($s = M$) and non-collusive equilibrium ($s = N$), two benchmark cases in our model. The solutions presented in Online Appendix OA.3 reveal an important homotheticity feature of the model: the equilibrium loan size L_2^M and L_2^N share the same functional form of

$$L_2^s(A,k,x,m) \equiv \mathcal{L}^s(A,k,m)\, h_2(k,x)\, A, \tag{15}$$

with the coefficient $\mathcal{L}^M(A,k,m) = \frac{1}{m}\left(1 - \frac{1}{\varepsilon_k}\right)^{\varepsilon_k}$ and $\mathcal{L}^N(A,k,m) = \frac{1}{m}\left(1 - \frac{1}{m\varepsilon_k}\right)^{\varepsilon_k}$ solved from the corresponding equilibrium, and $h_2(k,x)$ defined in (9) for $l = 2$.

Exploiting this functional form, we now solve the equilibrium loan amount L_2^C and risk-adjusted loan spread R_2^C for the collusive equilibrium. The solution critically depends on the collusion capacity ξ. Following the functional form, we express the equilibrium loan amount L_2^C as

$$L_2^C(A,k,x,m) \equiv \mathcal{L}^C(A,k,m)\, h_2(k,x)\, A, \tag{16}$$

where the coefficient $\mathcal{L}^C(A,k,m)$ is to be solved in the collusive equilibrium below.[12] The corresponding loan spread $R_2^C(A,k,x,m)$ is obtained by substituting (16) into the spread equation implied by the demand curve:

$$\mathcal{R}\left(L_2^C, A, k, z; (m-1)L_2^C\right) \equiv \left(e^{\alpha_k + \sigma z} \frac{A}{mL_2^C}\right)^{1/\varepsilon_k}, \tag{17}$$

Thus, the expected profit from collusive lending, denoted by $\Pi_2^C(A,k,m)$, averaged over the borrower-lender latent characteristics $x = (z,u)$, is given by

$$\Pi_2^C(A,k,m) = \left[\left(\frac{1}{m\mathcal{L}^C(A,k,m)}\right)^{1/\varepsilon_k} - 1\right] \mathcal{L}^C(A,k,m)\mathcal{H}_2(k)A, \tag{18}$$

[11] Even when $\xi = 1$, the collusive equilibrium need not coincide with the perfect-cartel outcome if the resulting loss in continuation value is still insufficient to deter deviation.

[12] Unlike $\mathcal{L}^M(A,k,m)$ and $\mathcal{L}^N(A,k,m)$, which are independent of borrower size A, $\mathcal{L}^C(A,k,m)$ may depend on borrower size A explicitly. The reason is that specialized lenders decide whether to deviate after observing A, so deviation incentives depend on borrower size. Intuitively, a larger A increases the short-run gain from deviation, making tacit collusion harder to sustain for a given punishment intensity.

where $\mathcal{H}_2(k)$ is defined in (11) with $l = 2$.

We now solve for the key coefficient $\mathcal{L}^C(A, k, m)$ in the collusive equilibrium by comparing the benefits and costs of deviating from collusion.

Profit Gain from Deviation. If a specialized lender deviates, it chooses L_2^D to maximize its lending profit this period, assuming that each of the other $m-1$ specialized lenders still supplies L_2^C in the syndicate:

$$\begin{aligned} L_2^D(A, k, x, m; \mathcal{L}^C) &= \operatorname*{argmax}_L \left[\mathcal{R}\left(L, A, k, z; (m-1)L_2^C\right) - e^{\phi_2 + \varsigma u} \right] L \\ &= \operatorname*{argmax}_L \left[\left(e^{\alpha_k + \sigma z} \frac{A}{(m-1)L_2^C + L} \right)^{1/\varepsilon_k} - e^{\phi_2 + \varsigma u} \right] L. \end{aligned} \tag{19}$$

This yields the following expression for the deviating loan amount:

$$L_2^D(A, k, x, m; \mathcal{L}^C) = \mathcal{L}^D(A, k, m; \mathcal{L}^C) h_2(k, x) A, \tag{20}$$

where $\mathcal{L}^D(A, k, m; \mathcal{L}^C)$ is determined from the first-order condition. The expected profit from deviation, denoted by $\Pi_2^D(A, k, m; \mathcal{L}^C)$, averaged over the borrower-lender latent characteristics $x = (z, u)$, is given by

$$\Pi_2^D(A, k, m; \mathcal{L}^C) = \left[\left(\frac{1}{\mathcal{L}^D(A, k, m; \mathcal{L}^C) + (m-1)\mathcal{L}^C} \right)^{1/\varepsilon_k} - 1 \right] \mathcal{L}^D(A, k, m; \mathcal{L}^C) \mathcal{H}_2(k) A.$$

The incentive to deviate is measured by

$$\Delta^D(A, k, m; \mathcal{L}^C) \equiv \Pi_2^D(A, k, m; \mathcal{L}^C) - \Pi_2^C(A, k, m). \tag{21}$$

A larger gap between $\Pi_2^D(A, k, m; \mathcal{L}^C)$ and $\Pi_2^C(A, k, m)$ implies a stronger incentive to deviate from the collusive loan amount.

Continuation Value Loss from Deviation. Along the collusive equilibrium path, a specialized lender that follows the prescribed collusive allocation in the current syndication preserves its ability to earn collusive profits in future syndications. Its continuation value is therefore

$$W^C = \frac{1}{1-\delta} \mathbb{E}^{A', k'} \left[(1 - \lambda_{k'}) \, \mathbb{E}^{w', m'} \left[\left(\Pi_2^C(A', k', m') - w' \right) \mathbf{1}_{\{w' \leq w_C^*\}} \right] \right]. \tag{22}$$

Here, $\delta \in (0, 1)$ denotes the effective discount factor. It incorporates η, the arrival rate of distressed borrowers, which captures the expected number of lending opportunities per unit of time in the distressed-loan market.[13] Equation (22) can be interpreted as follows. For any future borrower, specialized lenders have an opportunity to lend only if the existing creditor does not block access to external financing, which occurs with probability $1-\lambda_{k'}$. Conditional on such access, a specialized lender obtains a net gain from participating equal to its expected lending profit minus its participation cost, $\Pi_2^C(A',k',m')-w'$. This gain is realized only when the lender chooses to participate in the syndication, that is, when its participation cost w' is below the endogenous cutoff w_C^*, as captured by the indicator $\mathbf{1}_{\{w'\le w_C^*\}}$. Because both w' and the number of participating lenders m' are stochastic, expected net gains are taken over their joint distribution. In addition, future borrowers differ in size A' and type k', so we also integrate over their distribution. The continuation value W^C is then the present value of this stream of expected future gains, with the factor $\frac{1}{1-\delta}$ capitalizing perpetual payoffs.

By contrast, if a specialized lender deviates in the current loan syndication, it will be punished and pushed into the non-collusive equilibrium with a probability ξ. Its continuation value thus becomes

$$W^D=\xi W^N+(1-\xi)\,W^C, \tag{23}$$

where W^N denotes the continuation value under the non-collusive equilibrium:

$$W^N=\frac{1}{1-\delta}\mathbb{E}^{A',k'}\left[(1-\lambda_{k'})\,\mathbb{E}^{w',m'}\left[\left(\Pi_2^N(A',k',m')-w'\right)\mathbf{1}_{\{w'\le w_N^*\}}\right]\right]. \tag{24}$$

The difference between these continuation values,

$$W^C-W^D=\xi(W^C-W^N),$$

is the disciplining force that deters deviation and sustains tacit collusion. The term W^C-W^N captures the maximal continuation-value loss from deviation, while the parameter ξ determines what fraction of that loss is actually realized by governing the probability that tacit collusion breaks down and the syndicated loan deals reverts to the non-collusive equilibrium in future periods.

Incentive-Compatibility Conditions. Tacit collusion can be sustained only if the specialized lender's IC constraint holds. This constraint, together with the break-even cutoff condition, determines the collusive loan size $\mathcal{L}^C(A,k,m)$ defined in (16). For a given cutoff w_C^*, let $\mathbb{L}^C(w_C^*)$ denote the IC-feasible set consisting of all mappings $\mathcal{L}(A,k,m)$

[13] Under this parametrization, the actual discount factor per unit of time is $\delta_0=1-\eta(1-\delta)$.

from $\mathbb{A} \times \mathbb{K} \times \mathbb{M}$ to $\mathbb{R}$ such that the following three conditions hold:

$$\mathcal{L}^M(A,k,m) \leq \mathcal{L}(A,k,m) \leq \mathcal{L}^N(A,k,m), \tag{25}$$

$$\xi(W^C - W^N) \geq \Delta^D(A,k,m;\mathcal{L}), \tag{26}$$

$$w_C^* = \mathbb{E}^{A',k'}\left[\mathbb{E}^{m'}\left[\Pi_2^C(A',k',m') \mid m' \geq 1\right]\right]. \tag{27}$$

Condition (25) requires the collusive loan supply to lie between the perfect-cartel benchmark and the non-collusive outcome. Condition (26) is the incentive-compatibility condition ensuring that no lender wishes to deviate. Condition (27) is the break-even condition determining the equilibrium participation cutoff w_C^*. The feasible set $\mathbb{L}^C(w_C^*)$ depends on w_C^* because W^C in (26) depends on w_C^*, and the expectation over m' in (27) also depends on w_C^* through the endogenous distribution of syndicate size m.

4.2.3 Existence and Uniqueness.

We now establish the existence and uniqueness of the value-maximizing collusive Nash equilibrium. Consider a collusive syndicated-lending outcome characterized by a participation threshold w_C^* and an associated lending policy $\mathcal{L}^C(\cdot)$, satisfying the following conditions:

(i) the collusive lending outcome is incentive-compatible, that is, $\mathcal{L}^C(\cdot) \in \mathbb{L}^C(w_C^*)$; and

(ii) among all incentive-compatible lending outcomes, characterized by pairs $\left(w^*, \mathcal{L}(\cdot)\right)$, such that $\mathcal{L}^C(\cdot) \in \mathbb{L}^C(w_C^*)$, the pair $\left(w_C^*, \mathcal{L}^C(\cdot)\right)$ maximizes the specialized lenders' continuation value W^C.

The following proposition establishes the existence of a collusive Nash equilibrium and the uniqueness of the equilibrium that lies closest to the perfect-cartel benchmark among all value-maximizing collusive Nash equilibria. This result provides the theoretical foundation for identifying the structural model. The proof is given in Appendix C.

Proposition 4.1 *There exists at least one pair $\left(w_C^*, \mathcal{L}^C(\cdot)\right)$ that characterizes a collusive Nash equilibrium of the model. Among all collusive Nash equilibria, the maximal continuation value W^C is attained by at least one value-maximizing equilibrium. Furthermore, among all such value-maximizing collusive Nash equilibria, there exists a unique equilibrium that lies closest to the perfect-cartel benchmark, in the sense that its participation threshold w_C^* is closest to the perfect-cartel cutoff w_M^*.*

4.3 Last-Resort Lender's Problem

If no specialized lender is willing to lend, the borrower will turn to a lender of last resort, who acts as a monopolistic lender. It chooses the loan size that maximizes its lending profit given the latent borrower type k and the vector of borrower-lender latent characteristics $x = (z, u)$. Solving the lender's profit-maximization problem yields:

$$R_3(k, x) = \frac{\varepsilon_k}{\varepsilon_k - 1} e^{\phi_3 + \varsigma u} \quad \text{and} \quad L_3(A, k, x) = \left(1 - \frac{1}{\varepsilon_k}\right)^{\varepsilon_k} h_3(k, x) A, \tag{28}$$

where $h_3(k, x)$ is defined in (9) for $l = 3$. And the expected profit is

$$\Pi_3(A, k) = \frac{1}{\varepsilon_k} \left(1 - \frac{1}{\varepsilon_k}\right)^{\varepsilon_k - 1} \mathcal{H}_3(k) A, \tag{29}$$

where $\mathcal{H}_3(k)$ is defined in (11) for $l = 3$. The solutions are similar to those for existing creditors in (8) and (10), because they both act as monopolistic lenders, and differ only in the cost parameter ϕ_l.

5 Data Sample

We construct a comprehensive data sample that includes loans to both public firms already in Chapter 11 bankruptcy (i.e., DIP loans) from 2002 to 2019, and financially distressed but not yet bankrupt U.S. public firms (i.e., highly speculative loans) from 2001 to 2017. This section provides a detailed description of the data construction process and presents summary statistics of the two loan samples.

5.1 Debtor-in-Possession (DIP) Loans

A U.S. firm filing for Chapter 11 bankruptcy can obtain post-petition financing, commonly known as DIP financing, to support working capital and pay expenses in the bankruptcy process under Section 364 of the Bankruptcy Code. This law provision permits the bankrupt firm to arrange a DIP loan with super-priority status over all administrative expenses after notice and a court hearing. With existing lenders' court approval, a DIP loan can be secured by a senior or equal lien on a property that is already subject to a lien (i.e. the "priming lien" provision). These loan contracts are short term and typically contain extensive protective features such as restrictive covenants and milestones (Skeel, 2004; Ayotte and Elias, 2020; Eckbo et al., 2023). With such security and lender protection provision, the default risk of DIP loans are very low, comparable to that of high investment-grade loans (Eckbo et al., 2023).

Our initial sample, following Eckbo et al. (2023), includes all DIP loans to Chapter 11 filings by large U.S. public firms (with assets above $100 million in constant 1980 dollars) from 2002–2019, compiled from the UCLA-LoPucki Bankruptcy Research Database, Bankruptcydata.com, the Public Access to Court Electronic Record (PACER), and the Dealscan. We exclude DIP loans issued during the COVID-19 period and after, as government interventions such as emergency lending facilities and fiscal support programs materially affected credit supply and pricing, potentially confounding our analysis. We define three types of DIP loans based on the types of their major lenders: (i) existing-creditor loans (Type 1), (ii) specialized-lender loans (Type 2), and (iii) last-resort lender loans (Type 3). We remove DIP loans that cannot be classified into any of the above three types and keep a final sample of 436 DIP-loan facilities.[14] We retrieve firms' key financial information immediately before Chaper 11 filing from Compustat.

Table 2, Panel A, presents the summary statistics of our sample firms which obtained DIP-loan facilities. Firms in our sample are large, with average book assets of $3.7 billion and average of book liabilities of $3.5 billion respectively. The 436 loan facilities in our final sample have an average maturity of 10.6 months and amount to 10.7% of firms' book assets on average. Each facility has an average of 2.3 major lenders. Type-2 loan is the most dominant type, accounting for 76.6% of all DIP loans, while type-1 and type-3 loans account for 12.8% and 10.6%, respectively.

5.2 Highly Speculative Loans

We next assemble a dataset of loans to financially distressed firms that are not yet in bankruptcy. We rely on both credit default swap (CDS) prices and credit ratings to identify financially distressed firms. Using CDS prices is a market-based approach that is forward-looking and directly measures the cost for a firm to raise financing in the financial markets. With the rapid development and high trading liquidity in the credit derivative markets, several recent studies use CDS prices to assess the financial health of firms (e.g., Hortacsu et al., 2013; Brown and Matsa, 2016; Dou et al., 2024).

We retrieve monthly five-year CDS prices on senior unsecured bonds of U.S. public issuers from IHS Markit database and monthly S&P Long-Term Domestic Issuer Ratings of U.S. public firms from Compustat for the period from 2000–2017. Our sample ends in 2017 because Compustat stopped providing S&P ratings for U.S. public firms after that year. We use two criteria to identify the beginning of a firm's distressed period: (1) the five-year CDS price exceeds 1000 bps or (2) the firm's S&P credit rating drops to CCC+ or lower, whichever occurs first. We adopt the 1,000 basis point threshold for CDS spreads

[14] These loans include the case of General Motors as its DIP-loan, the largest size history ($33 billion), was provided by U.S. and Canadian governments with a large component of subsidy, and loans that are provided by potential acquirers that use the DIP loan to bridge takeover.

because prior studies classify bonds with yield spreads above the risk-free rate exceeding 1,000 basis points as distressed (Altman et al., 2019). We use CCC+ as the rating cutoff because loans issued by firms with ratings of CCC+ or below are generally no longer widely held by institutional investors such as collateralized loan obligations (CLOs), the primary investors in the leveraged loan market.[15] After identifying the initial starting month of a firm's distress period, we trace the firm's CDS spreads and credit ratings until the end of 2017. We use three criteria to identify the end of a firm's distress period: (1) the five-year CDS price falls below 500 bps, (2) the S&P credit rating rises to B- or higher, or (3) the firm defaults or files for bankruptcy, whichever occurs first. To determine bankruptcy status, we collect data on both Chapter 11 and Chapter 7 filings for all U.S. public firms from 2001 to 2019 from New Generation Research's Bankruptcydata.com.

Consolidating the distress periods identified using CDS spreads and ratings, removing duplicated time periods, and combining two consecutive periods that have an in-between time gap of less than a year, and removing distressed periods that are shorter than 6 months to avoid capturing transitory periods, we have 637 distressed periods of 520 firms from 2001–2017. We merge the distressed periods with the Dealscan database using the link file by Chava and Roberts (2008) to identify loan facilities that have a start date falling into the distress period. After removing facilities that have missing information on lender identities or loan spreads and annual fee, and loans that are unsecured or subordinated, we have a final sample of 520 loan facilities in 185 distressed periods. We record CDS prices at the end of the month immediately preceding the loan issuance date. We also collect Treasury Constant Maturity Rate of different maturities from the Federal Reserve at St. Louis and 3-month LIBOR rate from Bloomberg.

Similar to the classification of DIP loans, we categorize highly speculative loans into three types based on the identity of their major lenders, and exclude facilities that cannot be classified into any of these categories. We obtain firms' key financial information immediately before loan issuance from Compustat. Panel A of Table 2 presents the summary statistics of the highly speculative loan sample.

Distressed borrowers accessing this loan market are large, with mean book assets and liabilities approximately twice those of DIP-loan borrowers. These firms exhibit significant financial distress, with mean leverage ratios, ROA, and cash balances comparable to those of bankrupt firms. The average loan maturity is approximately four years, and these loan facilities represent 13.5% of book assets, on average. Among the 435 loan facilities, type-2 loans are the dominant category, accounting for 76.3% of highly speculative loans, while type-1 and type-3 loans account for 11.5% and 12.2%, respectively.

[15] This is primarily due to limits on the share of CCC-rated loans that can be included in the underlying collateral pool of CLOs (typically 7.5%). If any, CLOs are net sellers of CCC-rated loans.

Table 2: Summary Statistics

	N	Mean	Std	25%	Median	75%
Panel A: DIP Loans						
Assets	436	3,667	10,612	444	807	2,278
Liabilities	436	3,528	8,402	463	891	2,343
Leverage	413	1.096	0.493	0.834	0.999	1.236
EBITDA/assets	412	0.040	0.183	-0.001	0.059	0.104
PP&E/assets	414	0.410	0.258	0.193	0.385	0.621
Cash/assets	414	0.051	0.065	0.012	0.029	0.071
Loan maturity	436	10.587	6.273	6.000	9.000	12.000
Loan amount (L)	436	194.821	446.744	35.000	75.000	186.900
L/A	436	0.107	0.106	0.034	0.076	0.136
Risk-adjusted spread	436	711.437	377.551	413.233	651.806	950.733
Number of lenders	436	2.287	1.926	1	2	3
Loan type 1	436	0.128	0.335	0	0	0
Loan type 2	436	0.766	0.424	1	1	1
Loan type 3	436	0.106	0.308	0	0	0
Loan type 1 (# of lenders)	56	1	0	1	1	1
Loan type 2 (# of lenders)	334	2.557	2.083	1	2	3
Loan type 3 (# of lenders)	46	1.891	0.994	1	2	3
Number of specialized lenders	436	1.330	1.036	1	1	2
Panel B: Highly Speculative Loans						
Assets	435	7,731	11,700	535	2,533	10,292
Liabilities	435	7,739	13,181	544	2,473	9,951
Leverage	435	1.050	0.449	0.793	0.949	1.169
EBITDA/assets	435	0.066	0.133	0.037	0.074	0.114
PP&E/assets	435	0.380	0.227	0.172	0.355	0.536
Cash/assets	435	0.060	0.066	0.011	0.035	0.090
Loan maturity	435	48.611	20.838	35.000	48.000	60.000
Loan amount (L)	435	419.645	618.886	65.000	200.000	500.000
L/A	435	0.135	0.173	0.032	0.082	0.180
Risk-adjusted spread	435	307.679	203.993	163.692	262.423	408.355
Number of lenders	435	3.775	2.860	2	3	5
Loan type 1	435	0.115	0.319	0	0	0
Loan type 2	435	0.763	0.426	1	1	1
Loan type 3	435	0.122	0.327	0	0	0
Loan type 1 (# of lenders)	50	1	0	1	1	1
Loan type 2 (# of lenders)	332	4.277	2.711	2	4	5
Loan type 3 (# of lenders)	53	3.245	3.491	2	2	2
Number of specialized lenders	435	2.333	1.669	1	2	3

Note: This table presents the summary statistics of our sample firms. Our sample consists of 436 DIP loans (in Panel A) and 435 highly speculative loans (in Panel B) to U.S. public firms between 2001 and 2019. All financial variables are taken from the last fiscal year reported immediately prior to loan initiation, retrieved from Compustat. Assets and Liabilities are book assets and book liabilities, measured in millions of dollars, respectively. Leverage is the ratio of book liabilities to book assets. EBITDA/assets is EBITDA scaled by book assets. PP&E/assets is the ratio of net property, plant and equipment to book assets. Cash/assets is the ratio of cash and short-term securities to book assets. Loan maturity is the maturity in months. Loan amount (L) is in millions of dollars. L/A is the ratio of DIP amount to book assets. Risk-adjusted spread is the credit risk and liquidity risk adjusted loan spreads in basis points. Number of lenders is the number of unique institutions in a syndicate. Loan type 1, Loan type 2 and Loan type 3 are indicator variables for loans provided by an existing lender, specialist lenders, and lenders of last resort, respectively.

5.3 Measuring Risk-Adjusted Loan Yield Spreads

This section describes our measure of risk-adjusted loan yield spreads. Additional technical details are provided in Online Appendix OA.1 and OA.2

As discussed in Section 2.1, we measure the total cost to the borrower (TCB), in basis points, as the sum of the interest rate spread over LIBOR on the utilized portion of the facility, upfront fees, annual fees, and state-contingent default interest. We exclude commitment fees because they depend on ex post drawdown amounts, and distressed borrowers tend to use the full commitment amount in their secured credit lines (Nini and Smith, 2013). We also exclude other fees, such as utilization, cancellation, term-out, extension, and collateral monitoring fees, because they are not commonly used in syndicated loans (e.g., Berg et al., 2016).

Because the total cost to the borrower incorporates both credit and liquidity risk components, we first carefully quantify these risk premiums and net them out before estimating our model.

We estimate the credit risk component of yield spreads separately for DIP loans and highly speculative loans in our sample. For DIP loans, we assign a credit risk component of 20 basis points. DIP loans are typically short-term facilities with maturities below one year and are secured by first-priority, first-lien claims, making their effective credit risk close to risk-free in practice and no higher than that of high-grade short-term debt (Eckbo et al., 2023).

For highly speculative loans, we follow the parity relation between CDS spreads and bond credit spreads derived by Duffie (1999) to infer the implied risk-neutral default probability. CDS spreads provide a market-based measure of compensation for bearing default risk, which we combine with recovery-rate estimates for the underlying unsecured bonds to back out the firm's risk-neutral default probability. Importantly, we estimate recovery rates in a granular manner, allowing them to vary across industries and over time. This more granular approach contrasts with prior studies that impose constant recovery rates (e.g., Longstaff et al., 2005) or draw recovery rates randomly from empirical distributions (e.g., Schwert, 2020).

Specifically, for each distressed borrower in our sample, we identify its industry and loan issuance year, and assign the face-value-weighted average recovery rate of unsecured bonds in the same industry-year cell. Recovery data for unsecured bonds come from the NYU-Salomon Center Default Database.[16] We then combine the implied risk-neutral default probability with historical loan recovery rates from Badoer et al. (2019) to estimate the credit-risk component of loan spreads. These loan recovery rates are ul-

[16]The average recovery rate for U.S. unsecured bonds in the NYU-Salomon sample from 2000 to 2019 is 34.39%, consistent with Elton et al. (2001) and Dou et al. (2021a).

timate nominal recoveries from Moody's Default and Recovery Database, aggregated by Fama-French 12 industry. For each borrower, we assign a loan recovery rate based on its industry, adjusted for year and loan-type effects, namely revolving credit facilities versus term loans. Our estimates are robust to using the 25th percentile of the loan recovery rate distribution, which provides a conservative recovery-rate assumption and therefore overstates the credit-risk component. Using these inputs, we estimate the credit-risk component of each highly speculative loan in our sample. The average estimated credit-risk component is approximately 160 basis points.

We next estimate the liquidity risk component of yield spreads for DIP loans and highly speculative loans. To do so, we use bid and ask prices observed in the secondary market, obtained from the Loan Trading Database provided by LPC, commonly referred to as the "LSTA/LPS Mark-to-Market Pricing Data." This dataset is widely used in the leveraged loan literature and provides secondary-market price quotes for syndicated loans (e.g., Wittenberg-Moerman, 2008; Bushman et al., 2010; Beyhaghi and Ehsani, 2017).[17] Using borrower- and facility-level identifiers, we match these quotes to LSEG's LPC Dealscan database and Compustat to obtain additional loan and borrower characteristics. We exclude loans that are neither denominated in U.S. dollars nor issued within the U.S. Our focus narrows to only include "on-the-run" loan trades, which we define as trades occurring within two years following the loan's issuance.

Using bid and ask prices for revolving credit and term loans at the time of trading, we convert the bid-ask price spread into bid-ask yield spread based on the relation between loan price and yield to maturity, taking into account loan maturity, payment frequency, and any principal amortization (see Section OA.2 in Online Appendix for technical details). This procedure yields a time series of bid-ask yield spreads for each loan.

To estimate the liquidity component of DIP loans, we keep loans with yield spread lower than 150 bps (i.e., those loans that are investment-grade). We calculate the average liquidity premium across the entire sample, which amounts to 12.6 bps. Our analysis does not extend to calculating the liquidity premium for different industries, years, or loan types due to the negligible variation observed across these categories.[18]

[17] The database includes loan bid and ask price quotes reported to LPC by trading desks at institutions that make a market in loans. Prices are quoted as a percentage of par value. The database also provides information on borrower name, facility identifier, facility size, maturity date, and quote date, and covers more than 20 million observations from 1998 to 2019.

[18] Several factors contribute to this limited variation. First, DIP loans are short-term, typically with maturities of less than one year and are secured by first- or second-lien claims, and thus are not typically associated with significant liquidity concerns for investors. Second, existing evidence suggests that liquidity premia are modest even for relatively liquid debt instruments. For example, Chen et al. (2007) show that, for short-term bonds with maturities of one to seven years and ratings of AA− or higher, the liquidity premium accounts for only about 15% of the yield spread. Taken together, these considerations imply that the liquidity premium for DIP loans, already small relative to the credit risk component at 20 basis

For highly speculative loans, we use a three-step procedure. First, we restrict the loan-trading sample to loans with yield spreads above 150 basis points and compute the average bid-ask yield spread within each Fama-French 12 industry-year cell, separately for term loans and revolving credit facilities. This gives us an industry-year measure of the secondary-market liquidity premium for each loan type. We then assign to each highly speculative loan the corresponding liquidity premium based on its industry, issuance year, and loan type. We refer to this component as the liquidity-risk premium from the leveraged loan secondary market.

Second, we merge the LSTA/LPS Mark-to-Market Pricing Data with our sample of Chapter 11 filings from 2002–2019 and identify loan facilities that traded within 30 days after the filing date. We obtain bid-ask yield spreads for fewer than 300 unique loan facilities. The distribution of bid-ask yield spreads in this sample is highly skewed, with a mean of 26 basis points and the 75th and 90th percentiles at 108 and 255 basis points, respectively.[19] To avoid underestimating the liquidity premium of highly speculative loans, we use the 90th percentile, 255 basis points, as our measure of the liquidity-risk premium immediately after a leveraged loan enters bankruptcy.[20]

Finally, we estimate the ex-ante liquidity premium, allowing for wider bid-ask spreads in bankruptcy. We compute a weighted average of the liquidity premia for leveraged loans and post-bankruptcy loans, with weights based on the risk-neutral default probability of highly speculative loans derived from CDS prices, as described above. For example, consider a loan with an industry-year-loan type–matched liquidity premium of 20 basis points from the leveraged loan market and a risk-neutral default probability of 15%. The overall liquidity premium is then 55 basis points, calculated as 0.85×20 bps $+$ 0.15×255 bps.

Table 2 shows that after deducting the credit risk and liquidity risk components from the total cost to borrowers, the average risk-adjusted spread is 711 and 308 basis points for DIP loans and highly speculative loans, respectively.

6 Estimation

In this section, we bring the structural model to the data by estimating the key model parameters and jointly classifying loan deals into the latent demand curves to which they belong. We conduct the estimation separately for the DIP loan market and the

points, should exhibit little variation across industries, years, and loan types.

[19]For robustness checks, we also consider trading prices of loan facilities within 60 or 90 days after the Chapter 11 filing date and find that the distribution of bid-ask yield spreads is nearly identical to that based on trades within 30 days of filing.

[20]Loans traded after a Chapter 11 filing are substantially less liquid than DIP loans because DIP loans are newly issued (or on-the-run) and short term in nature.

highly speculative loan market, allowing the two markets to differ freely in their parameter values and empirical features. We impose no restriction on how similar or different these two distressed loan markets must be. Instead, through the lens of the same unified model framework, we let the data reveal the competitive structure of each market and the extent of potential collusion. Within each market, the key inputs into the estimator are the lender type l_i, the number of specialized lenders m_i, borrower size A_i, the loan amount normalized by borrower assets, $\ln(L_i/A_i)$, and the risk-adjusted loan yield spread, $\ln(R_i)$. In addition, each deal is associated with an unobserved demand-curve state $k_i \in \{1, \ldots, K\}$, which is treated as a latent variable in the estimation.

We estimate the model using a Bayesian MCMC procedure. The procedure treats latent demand heterogeneity as unobserved and jointly samples it with the structural parameters from their posterior distribution, which is determined by the likelihood function and prior distributions. It iterates between two steps. First, given the structural parameters, it updates and samples the posterior classification of each loan across latent demand curves. Second, given these demand-curve classifications, it updates and samples the posterior distribution of the structural parameters. Repeating these steps generates draws from the joint posterior distribution of the structural parameters and latent demand-curve classifications. Online Appendix OA.4 provides the prior specifications, likelihood functions, and details of the Bayesian MCMC procedure. We next discuss the identification mechanism that links the model parameters to observable data patterns.

6.1 Identification of Parameters

To clarify the identification logic, we discuss below which salient features of the data are most informative about the key mechanisms of the model and hence most useful for identifying the parameters. We then present the estimation results and empirical findings for the two distressed loan markets.

We begin with the demand-side parameters, namely the intercepts and slopes of the latent demand curves. A central identification challenge is that loans may come from different demand curves, but the data do not directly reveal which demand curve applies to each loan. This is a familiar problem in empirical IO, where observed prices and quantities may be generated by heterogeneous but unobserved demand curves. In our setting, we address this challenge with a full-likelihood approach that treats latent demand heterogeneity as unobserved and jointly samples it with the structural parameters from their posterior distribution.

Specifically, in each iteration of the Bayesian MCMC algorithm, the model assigns each loan to one of the latent demand curves based on the current parameter values and the full set of loan-level observables. These observables include not only price and quantity, measured by $\ln(R_i)$ and $\ln(L_i/A_i)$, but also lender type l_i, the number of specialized lenders m_i, and borrower size A_i. Through the model's equilibrium conditions, these variables are informative about the underlying demand and supply conditions.

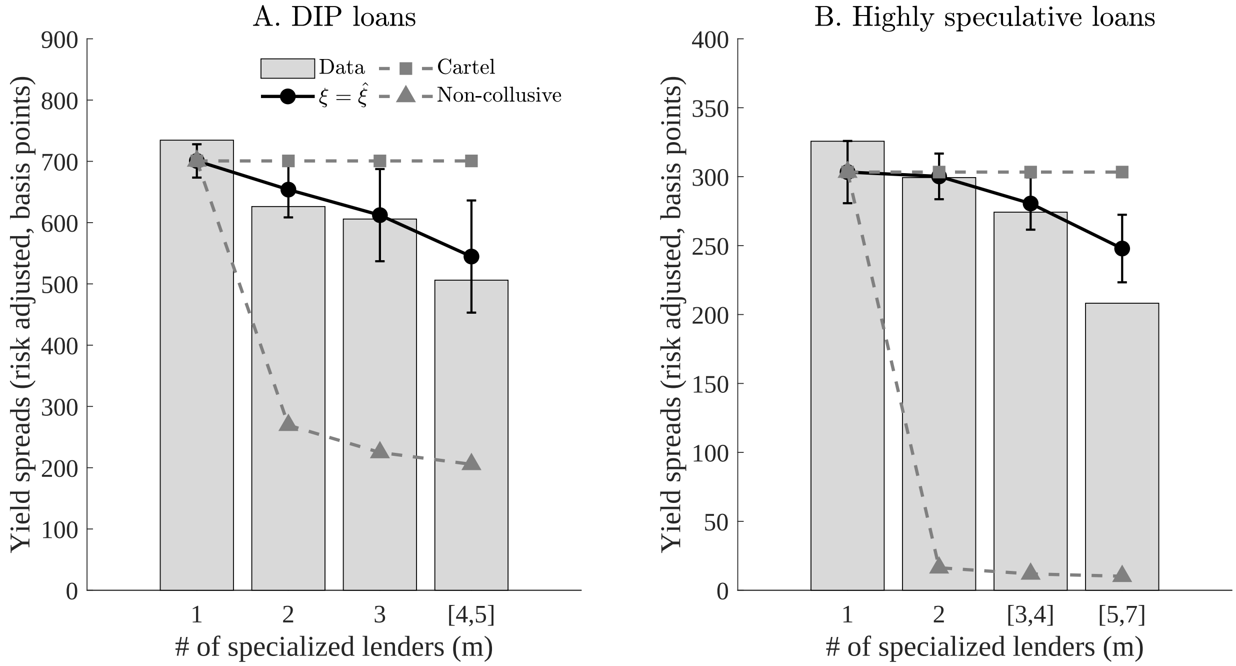
Thus, classification is not based on price-quantity pairs alone. Each loan is assigned to a demand curve with probability proportional to its full likelihood under that demand curve.[21] Conditional on these likelihood-based classifications, the joint variation in loan pricing and relative loan size within each latent group identifies the intercept and slope of the corresponding demand curve. The intercept identifies α_k, and the slope identifies ε_k, for $k = 1, \ldots, K$.

We next turn to ξ, which captures the intensity of collusion among specialized lenders and is central to our estimation. Our model nests the non-collusive benchmark when $\xi = 0$ and approaches cartel-like benchmark when $\xi = 1$.[22] The collusion intensity governs how loan prices, measured by the risk-adjusted spread $\ln(R_i)$, vary with the number of participating lenders in a loan syndication. Classical IO theory predicts that a high value of ξ pushes the market toward cartel-like behavior. In the extreme, the syndicate behaves like a single monopolistic lender regardless of how many lenders participate, so the loan price changes little with m. By contrast, as ξ approaches zero, collusion weakens and lenders within a syndicate compete more aggressively with one another, causing loan prices to decline more sharply as the number of lenders increases. Therefore, the way loan prices vary with syndicate size is the most informative "moment" for identifying the collusion intensity ξ: when ξ is high, loan prices are less sensitive to m, while when ξ is low, loan prices are highly sensitive to m.

To illustrate the identification argument above, we group loans by the number of participating lenders, for example $m = 1, 2, 3, \ldots$, and compute within each group both the average observed loan price in the data and the average model-implied loan price. Figure 4 presents the results, with the DIP loan market shown in the left panel and the highly speculative loan market shown in the right panel. The average loan price in the data is shown in bars, echoing the motivating evidence of possible collusion presented in Section 2.2, and we display three model-implied loan prices: the gray dash line with square markers represents the cartel; the gray dash line with triangle markers represents the non-collusive equilibrium; and the black solid line with circle markers represents ξ set to its estimated value, with the 95% confidence interval around the point estimates.

[21] Intuitively, given the parameter values from the previous iteration, the algorithm evaluates the probability that a loan belongs to each demand curve using the model-implied likelihood of all observables, and then samples a demand-curve assignment from this distribution.

[22] $\xi = 1$ implies that participating lenders impose the most stringent punishment on deviation, which facilitates collusion. This extreme case, however, does not guarantee a cartel outcome, because when the one-period payoff from deviation is sufficiently large, lenders may still deviate from cartel behavior, causing total lending quantity and price to differ from the monopoly outcome that a cartel would achieve.



Note: This figure illustrates the empirical patterns that help identify the parameter ξ governing collusion intensity. The left panel shows the DIP loan sample and the right panel shows the highly speculative loan sample. In both markets, we group together loans by the number of specialized lenders, $m = 1, 2, 3, \ldots$, and compute the average loan price (risk-adjusted spreads) within each group. The empirical values measured in the data are depicted by gray bars. We compare these moments with the model-implied loan prices under three scenarios: cartel equilibrium (gray dashed line with square markers), non-collusive equilibrium (gray dashed line with triangle markers), and ξ set to its estimated value (black solid line with circle markers), together with the 95% confidence interval around the point estimates.

Figure 4: Identification of collusion intensity ξ

As the figure shows, in a cartel equilibrium, loan prices would remain constant as the number of lenders m increases, reflecting perfect collusion behavior. In a non-collusive equilibrium, loan prices would decline sharply with m because of stronger competition among lenders. The data instead indicate that only an intermediate value of ξ, as recovered by our estimation, can match the empirical pattern.

Importantly, unlike moment-based approaches, the Bayesian MCMC procedure does not explicitly target this pattern as a moment. Hence, the close fit is not mechanically imposed by the estimation. The fact that the estimated model nevertheless matches this prominent empirical pattern provides validation that the model captures the underlying mechanism both qualitatively and quantitatively.

The remaining parameters are identified from additional features of the data. The parameter μ governs the average participation cost that specialized lenders incur when joining a syndicate, capturing one dimension of existing creditors' blocking power. Intuitively, when μ is low, more specialized lenders find it profitable to participate, so syndicates tend to include more specialized lenders. Conversely, when μ is high, participation becomes less attractive, and syndicate size declines. Thus, the average syndicate size among loans funded by specialized lenders is the key empirical feature that identifies μ.

The parameter λ_k is identified by the fraction of loans financed by existing creditors within each latent demand curve. In the model, λ_k is the probability that the existing creditor has the exclusive right to provide financing and can therefore prevent the firm from borrowing from outside lenders, capturing another dimension of existing creditors' blocking power. A higher λ_k implies that loans assigned to demand curve k are more likely to be financed by the existing creditor. Thus, the prevalence of existing-creditor financing in the data identifies λ_k for each demand curve.

Finally, the parameters ϕ_l capture differences in variable loan-making costs across lender types: existing creditors ($l = 1$), specialized lenders ($l = 2$), and lenders of last resort ($l = 3$). These cost parameters are identified from the portion of risk-adjusted spreads that remains after accounting for borrower demand elasticity, lender concentration, and strategic supply behavior. Thus, conditional on demand-curve type and the number of participating lenders, systematic differences in risk-adjusted spreads across lender types identify ϕ_l.

6.2 Estimation Results

We first present the posterior classification of loans across latent demand curves. For each loan i, the Bayesian MCMC procedure produces, at iteration g, a vector of posterior assignment probabilities $z_i^{(g)} = (z_{i1}^{(g)}, \ldots, z_{iK}^{(g)})$, where $z_{ik}^{(g)}$ denotes the conditional posterior probability that loan i belongs to demand curve k, given the current draws of the structural parameters and the observed data. For descriptive purposes, in each iteration g, we classify loan i into the demand curve with the highest posterior assignment probability in $z_i^{(g)}$. Based on the classification results, Figure 5 depicts the demand curves for the DIP loan sample (left panel) and the highly speculative loan sample (right panel). Each point in the figure represents an observation of a loan, and the size of the points indicates the borrower's size A_i. Points of the same color belong to the same estimated demand curve, and the straight lines show the estimated demand curves.

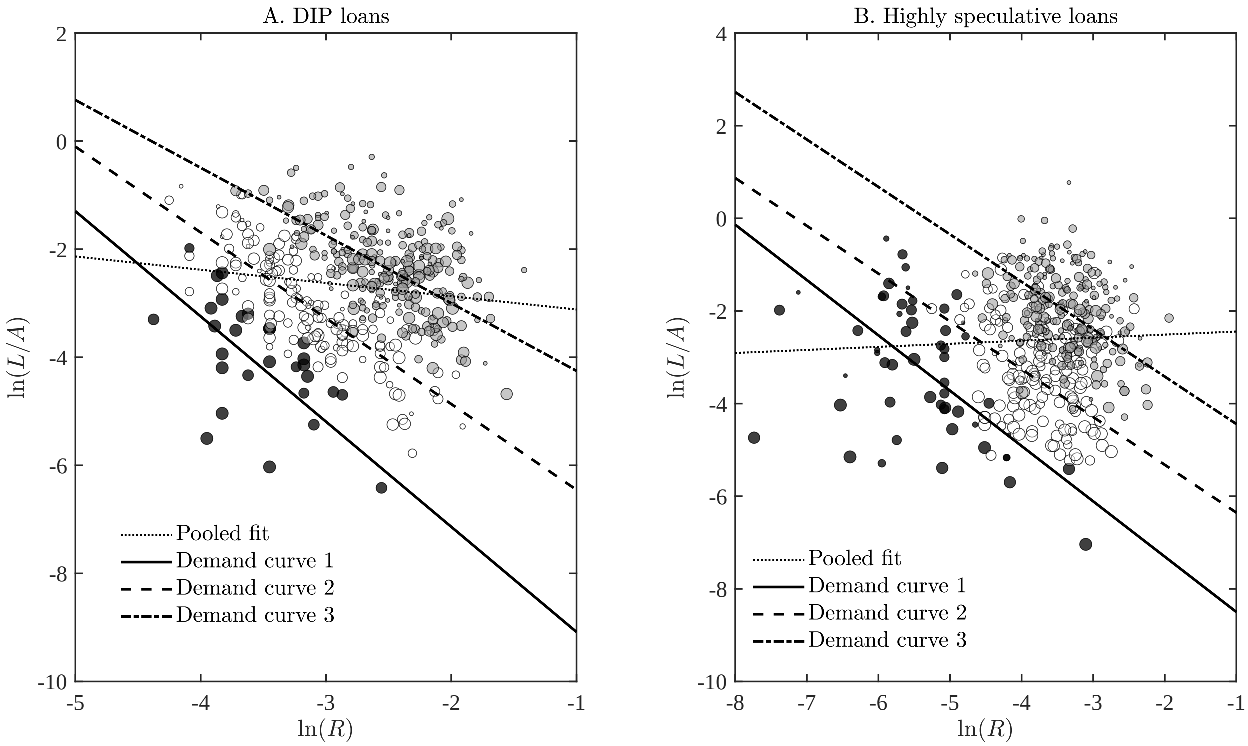
Two points are worth noting. First, each point in the figure represents the realized log loan amount and log yield spread, whereas the demand curves represent the expected relationship between these two variables. The distance between a point and its assigned demand curve reflects the ex post realizations of demand and supply shocks, $x = (z, u)$. Second, as discussed above, classification is based on the full likelihood of the model equilibrium. It therefore differs from a simple classification based only on the observed log relative loan amount, $\ln(L/A)$, and log yield spread, $\ln(R)$. These two forces explain why some points in the figure are not assigned to the nearest demand curve. For example, some points located near the lowest demand curve are instead assigned to the middle demand curve. Beyond realized demand and supply shocks, some of these loans have a large m, which is informative about a higher expected loan demand at a given yield spread in equilibrium.[23] Although m is not plotted in the figure, it shifts the likelihood-based classification of these points toward the middle demand curve, which has higher expected demand than the bottom curve. Their distance from the middle demand curve reflects a negative realization of z, which lowers the realized loan quantity.

To illustrate the importance of accounting for latent demand heterogeneity through Bayesian MCMC classification, we also estimate a pooled OLS regression that imposes a single common demand curve on all observations. The dotted line in Figure 5 shows the fitted line from this single-demand-curve OLS regression. The OLS slope is economically small and statistically indistinguishable from zero, in sharp contrast to our baseline estimates, where loan assignments to heterogeneous demand curves and demand-curve coefficients are jointly estimated. In both loan markets, borrowers assigned to the bottom demand curve have a lower intercept of loan size. They also exhibit a higher price elasticity of loan demand in the DIP market and a similar elasticity in the highly speculative loan market, relative to borrowers assigned to the middle and top demand curves. This indicates that bottom-curve borrowers have lower loan demand relative to size and, in the DIP market, are more sensitive to loan prices. Empirically, these borrowers are, on average, larger and have higher total revenues, suggesting stronger bargaining power, which helps explain the differences in their estimated demand curves.

In addition to estimating the latent demand curves, the Bayesian MCMC procedure produces draws from the joint posterior distribution of the structural parameters. These posterior draws summarize both parameter uncertainty and the uncertainty associated with the latent classification of loans across demand curves. Table 3 reports posterior point estimates and posterior standard deviations for each parameter, separately for the DIP loan and highly speculative loan samples. The point estimates summarize the center of the posterior distribution, while the posterior standard deviations measure estimation uncertainty based on the dispersion of the MCMC draws (i.e., standard errors of the parameters).

The punishment probability upon deviation, ξ, is estimated to be 0.492 for DIP loans. This implies that if a specialized lender deviates from the perceived collusive equilibrium, the syndication among specialized lenders transitions to the non-collusive equilibrium with approximately 50% probability. This parameter governs the capacity of tacit collusion in the model, and an estimate of 0.492 indicates a substantial degree of implicit coordination among specialized lenders. The estimated punishment probability is quantitatively similar for highly speculative loans, with ξ estimated at 0.527. Importantly, ξ is

[23] Specialized lenders make participation decisions based on the demand curve they observe. A higher level of demand raises expected lending profits and induces more specialized lenders to join the syndicate. Thus, a larger m is associated with higher expected demand.



Note: This figure shows the estimated demand curves and the classification of borrowers to these demand curves. Each point in the figure represents an observation in our sample, with points of the same color classified to the same demand curve. The straight lines are the estimated demand curves. The intercept and slope of the demand curves represent the constant term and the elasticity of the demand. We choose the optimal number of demand curves to estimate following the Lo-Mendell-Rubin tests, and our estimates suggest that there are three statistically distinct demand curves in both markets. The dotted line depicts the line of best-fit from an OLS regression that pool together all observations on only one hypothetical demand curve. The left panel depicts the classification in the DIP loan market and the right panel depicts the classification in the highly speculative loan market.

Figure 5: Demand Curves by Clusters

estimated with small standard errors in both samples, suggesting that the data strongly reject the no-collusion benchmark, $\xi = 0$. As discussed in Figure 4, ξ is identified in part by how loan prices vary with syndicate size. Intuitively, a higher collusion capacity implies that loan prices decline only moderately as the number of specialized lenders, m, increases, which matches a prominent pattern in the data.

The estimates of ς and σ indicate that unobserved heterogeneity, captured by borrower- and lender-side shocks $x = (z, u)$, is important for generating cross-sectional variation in loan size and spreads. A simple variance decomposition shows that the estimated model mechanism is able to explain 57% of the variation in $\ln(L/A)$ and 60% of the variation in $\ln(R)$ in the DIP loan sample, while the unobserved heterogeneity explains the rest of it. The corresponding shares are 40% and 32% for the highly speculative loan sample.

It is also worth noting that the lenders' participation cost, μ, is estimated to be higher in the DIP market. A key determinant of this cost is the blocking power of existing lenders. If an existing lender can strongly restrict the borrower's access to outside lenders, even when it does not provide the loan itself, this blocking power appears in

Table 3: 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: This table reports the estimated model parameters together with the standard errors obtained from MCMC. The top panel shows the general model parameters, including the likelihood of punishing deviation ξ, the demand and supply shocks σ and ς, and the average participation cost μ. The mid panel shows the lender-specific parameter e^{ϕ_l} that captures the lending costs for each type of lender, including existing creditors, specialized lenders, and lenders of last resort. The bottom panel shows the borrower-specific parameters, including the demand-curve intercept α_k, slope ε_k, and the likelihood λ_k that the existing lender finances the loan, together with γ_k and β_k, which govern how borrower size is related to latent demand-curve assignment.

the model as a higher participation cost borne by specialized lenders. In other words, stronger blocking power makes it more difficult for specialized lenders to enter the syndicate.

The middle panel of Table 3 reports lender-specific variable costs, which capture non-risk costs associated with lending to distressed firms. These variable loan-making costs measure the lender's marginal cost of supplying distressed credit, excluding funding costs and compensation for default, liquidity, or other priced risks. They include costs related to due diligence, screening, monitoring, information production, legal and restructuring work, and active participation in the bankruptcy or workout process.

For DIP loans, these variable costs are particularly high. DIP lenders must closely monitor the borrower's operations, assess cash collateral and collateral values, negotiate with creditors, interact with the bankruptcy court, evaluate priority claims, and participate in restructuring decisions. These activities make DIP lending operationally and legally more complex than highly speculative lending. Consistent with this intuition, we estimate variable costs of about 150 to 200 basis points in the DIP loan market, compared with only about 10 basis points in the highly speculative loan market.

Within DIP loans, estimated variable costs are approximately 150–160 bps for existing creditors and specialized lenders, but about 200 bps for lenders of last resort, most of which are hedge funds and private equity firms. This gap reflects well-understood institutional features of DIP lending. Existing creditors enter negotiations with borrower-specific information from their pre-petition relationship, while specialized lenders benefit from established underwriting procedures, legal expertise, and syndication networks built through repeated participation in distressed lending. Both advantages lower the marginal cost of evaluating, originating, and monitoring a DIP facility. Lenders of last resort, by contrast, enter primarily when other financing is unavailable; most appear only once or twice in our sample, indicating they are not regular DIP originators. They therefore incur higher costs to acquire borrower information, value collateral, and navigate the complex covenant and priority negotiations that Chapter 11 demands. The cost premium is further amplified by hedge funds' and private equity firms' active post-financing involvement, including board representation, managerial influence, and loan-to-own strategies (Jiang et al., 2012; Li and Wang, 2016; Ayotte and Elias, 2020), which requires resources well beyond the mechanical provision of credit.

The bottom panel of Table 3 reports the parameters governing the latent demand curves: the log demand level, α_κ, and the price elasticity of demand, ε_κ. Within each market, these estimates correspond to the demand curves shown in Figure 5. Across the two markets, DIP borrowers and highly speculative loan borrowers exhibit similarly low demand elasticities. Thus, the much higher spreads on DIP loans, relative to highly speculative loans, cannot be explained by demand elasticity alone. In both markets, borrower size appears an important determinant of demand-curve classification. Larger borrowers tend to have higher demand elasticities and borrow less relative to their size.

Although our Bayesian MCMC estimation is likelihood-based and does not explicitly target particular moments for point estimation, Table 4 shows that the estimated model matches key features of the data well. For DIP loans, the model predicts an average risk-adjusted spread of 702 bps, compared with 711 bps in the data. In both the model and the data, risk-adjusted spreads exhibit substantial variation of about 400 bps, indicating that the model captures the rich heterogeneity observed in the cross section. The average loan size is 0.110 in the model and 0.107 in the data, suggesting that DIP borrowers on average take up DIP loans about 11% of their pre-default book assets. The average number of lenders is 1.3 in the model and in the data, implying that syndication size is small in DIP loans. Breaking down the DIP loan sample by lender type, we find that 11.3% (12.8%) of these loans are made by existing lenders in the model (data), 71.7% (76.6%) by specialized lenders, and 17.1% (10.6%) by lenders of last resort. Among the

Table 4: Model Fits

Variable	DIP Loans			Highly Speculative Loans		
	Model	Data	S.E.	Model	Data	S.E.
Full Sample						
Avg. risk adjusted spreads in bps ($E[R]$)	702	711	18	306	308	10
Stdev. risk adjusted spreads in bps ($Std(R)$)	426	378	13	227	204	7
Avg. loan size relative to asset ($E[L/A]$)	0.110	0.107	0.005	0.201	0.135	0.008
Stdev. loan size relative to asset ($Std(L/A)$)	0.132	0.106	0.004	0.427	0.173	0.006
Avg. number of lenders ($E[m]$)	1.300	1.330	0.050	2.128	2.333	0.080
Stdev. number of lenders ($Std(m)$)	1.118	1.036	0.035	1.435	1.669	0.057
Existing Lenders (Type 1)						
Fraction of loans	0.113	0.128	0.016	0.111	0.115	0.015
Avg. risk adjusted spreads in bps ($E[R]$)	618	717	42	365	354	40
Avg. loan size relative to asset ($E[L/A]$)	0.124	0.084	0.008	0.213	0.124	0.019
Specialized Lenders (Type 2)						
Fraction of loans	0.717	0.766	0.020	0.835	0.763	0.020
Avg. risk adjusted spreads in bps ($E[R]$)	680	681	21	296	283	10
Avg. loan size relative to asset ($E[L/A]$)	0.114	0.114	0.006	0.203	0.132	0.010
Lenders of Last Resort (Type 3)						
Fraction of loans	0.171	0.106	0.015	0.054	0.122	0.016
Avg. risk adjusted spreads in bps ($E[R]$)	852	925	52	351	421	28
Avg. loan size relative to asset ($E[L/A]$)	0.081	0.085	0.010	0.151	0.165	0.018

Note: This table shows the overall model fit. We report the model-implied moments, the data moments, and the standard errors of the data moments in corresponding columns. We report the average and standard deviation of the risk-adjusted loan spreads, loan size, and the number of participating lenders for the full sample. We also report the fraction of loans obtained from the existing lenders (type 1), specialized lenders (type 2), and lenders of last resort (type 3), as well as the average risk-adjusted spreads and size of these loans.

three lender types, lenders of last resort, such as hedge funds and private equity firms, charge the highest risk-adjusted spreads.

Our model fits the highly speculative loan sample similarly well, while also capturing the key differences between the two markets. Compared with DIP loans, highly speculative loans feature markedly lower risk-adjusted spreads (306 bps in the model vs. 308 bps in the data), larger loan sizes (0.201 in the model vs. 0.135 in the data), and a higher average number of lenders (2.1 in the model vs. 2.3 in the data), all of which the model reproduces closely. The distribution of lender types is broadly similar: 11.1% (11.5%) of loans are made by existing lenders in the model (data), 83.5% (76.3%) by specialized lenders, and 5.4% (12.2%) by lenders of last resort, with the existing lenders and the lenders of last resort charging the highest risk-adjusted spreads.

7 Decomposing Loan Yield Spreads

Using the estimated model as a laboratory, we quantify the lenders' market power in the two distressed loan markets, and decompose their market power arising from three components: (i) the potential collusion among specialized lenders, (ii) the existing lenders' blocking power, and (iii) the concentration of distressed loan market. Figure 6 summarizes our findings for the DIP loan market and the highly speculative loan market.

Starting from the baseline model with the estimated parameters, we first quantify the effect of lender collusion. To do so, we set the key parameter ξ to zero. In this counterfactual model, all specialized lenders deviate from collusion because no punishment is imposed, and as a result, a non-collusive equilibrium emerges. We keep other model parameters at their estimated values so that the non-collusive equilibrium still features the blocking power by existing lenders and an oligopolistic market structure. We examine how lender collusion affects the average risk-adjusted yield spread by comparing the output from the baseline model and this counterfactual. We find that the average risk-adjusted yield spread for specialized lenders declines by 136 bps (from 702 bps to 566 bps) for DIP loans as lender collusion is eliminated, representing a 19.4% decline. For highly speculative loans, the decline is 144 bps (from 306 bps in the baseline model to 162 bps in the non-collusive counterfactual), representing a 47% reduction in spreads.

Next, we examine the effect of existing lenders' blocking power. In our model, existing lenders' blocking power manifests through two channels: first, with a probability of λ_k, they are able to hold the borrower and act as the monopolistic lender to extract the rent (i.e., type 1 loans); second, even if existing lenders allow borrowers to approach external lenders, they can restrict participation of these external lenders, reflected in the participation cost parameter μ. We construct a counterfactual benchmark that eliminates existing lenders' blocking power by setting λ_k and μ to zero. In this counterfactual model, we keep $\xi = 0$ to measure the *incremental* effect of removing blocking power from the non-collusive model. The direct changes are that existing lenders now do not lend to the borrower directly and all specialized lenders now participate in loan syndication and thus the number of lenders reaches the full capacity of 10.

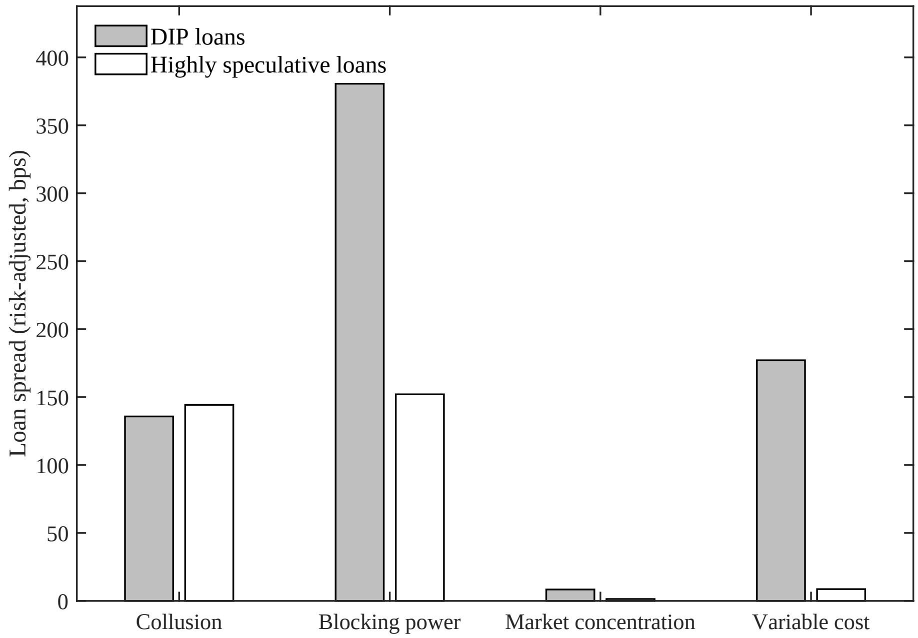
Figure 6 shows that the loan spread decreases by another 380 bps for DIP loans and 152 bps for highly speculative loans as a result of removing blocking power. The evidence suggests that existing lenders' blocking power has a much more pronounced effect in the DIP market than in highly speculative loan market. This is consistent with earlier studies that document that new DIP lenders cannot prime "liens" of existing lenders without their consent and thus "pre-petition" lenders possess a strong bargaining position in deciding who can participate in a DIP loan syndicate (Skeel, 2004; Ayotte and Morrison, 2009). Moreover, because borrowers tend to be selective in which lenders to approach before bankruptcy filing, it can be costly for some lenders to learn about the deal type (Eckbo et al., 2023). This is generally less of a case for highly speculative loans.

As the last step, we quantify the effect of market concentration. To turn an oligopolistic market into a fully competitive market, we increases the total number of specialized lenders from 10 to positive infinity. We build this counterfactual upon the non-collusive, zero blocking power model to capture the *incremental* effect. Figure 6 shows that the average risk-adjusted yield spread drops by a negligible amount in both markets. Interestingly, this finding shows that the oligopolistic structure is not the main cause of high risk-adjusted yield spread in either market, and the market would be competitive enough if all of the 10 specialized lenders actively participate.

Moving from the baseline model to the non-collusive, zero blocking power, competitive model, we find that the lenders' market power accounts for about 75% of the DIP loan's risk-adjusted yield spreads (i.e., $\frac{702-178}{702}$) and 97% of highly speculative loan's risk-adjusted yield spreads (i.e., $\frac{306-9}{306}$). A further decomposition of the market power suggests that lender collusion contributes to 26% of the market power for DIP loans (i.e., $\frac{702-566}{702-178}$) and 48% (i.e., $\frac{306-162}{306-9}$) of the market power for highly speculative loans, while existing lender blocking power contributes to 73% of the market power (i.e., $\frac{566-186}{702-178}$) for DIP loans and 51% of the market power (i.e., $\frac{162-10}{306-9}$) for highly speculative loans. Finally, the concentrated market structure alone contributes to the remaining negligible fraction of the market power to the two markets.

This figure reveals two main conclusions that are central to our paper. First, tacit collusion among specialized lenders is prevalent in both markets, which allows the lender group to extract sizeable rent from borrowers (around 140 bps). Second, the excess loan spread in DIP market, compared with that in the highly speculative loan market, is mainly explained by the existing lenders' strong power in blocking the borrowers from reaching out to alternative lenders and the high variable costs in DIP market.

With the decomposition results, we now evaluate how lender market power affects borrowers' survival-critical liquidity. In the DIP loan market, our estimates suggest that lender market power accounts for about 75% of risk-adjusted loan spreads. Equivalently, bankrupt borrowers overpay 533 basis points per year on DIP loans because of lender market power. Given an average facility-to-asset ratio of 11%, this excess spread implies an additional cost of 0.006 of total assets for each loan facility. When we aggregate facilities taken by the same borrower within a bankruptcy event, the cost rises to 0.008 of total assets. Since the average EBITDA-to-asset ratio for these bankrupt firms is 0.04 in our sample, the markup charged by DIP lenders absorbs roughly 20% of borrowers' survival-critical liquidity. The effect is similarly large for highly speculative loans. Distressed borrowers overpay about 300 basis points per year on these loans. Given an average facility-to-asset ratio of 13.5%, an EBITDA-to-asset ratio of 0.066, and the use of multiple facilities during distress episodes, lender market power drains about 16% of these borrowers' survival-critical liquidity. Moreover, because highly speculative loans have an average maturity of more than four years, this market-power-induced burden is not merely transitory. It imposes a substantial and lasting drag on distressed borrowers, slowing their recovery and weighing on their post-distress performance.



Note: This figure compares different components of risk-adjusted yield spreads in the DIP loan market and the highly speculative loan market. Collusion represents the component of risk-adjusted yield spreads that arises from the specialist lenders' tacit coordination in syndicated lending; Blocking power represents the component of risk-adjusted yield spreads that arises from exiting lenders blocking external lenders and restricting syndication size. Market concentration represents the component of risk-adjusted yield spreads due to the oligopolistic market structure with a few concentrated lenders; and variable costs represent the component of risk-adjusted yield spreads used to compensate the lenders for their lending costs (not include funding costs) such as monitoring costs.

Figure 6: Spread Decomposition

Among the different components that contribute to lender market power, lender tacit collusion often attracts most attention by regulators, and antitrust policies often target at breaking down such coordination. In the final part of the analysis, we examine which borrowers are more susceptible to lender market power by measuring the effect of lender tacit collusion on borrowers of different size. Specifically, we partition the borrowers into size quintiles and repeat our analyses of the baseline model and the non-collusive model performed above. We compare small borrowers (bottom size quintile) with large borrowers (top size quintile).

Table 5 reports the changes in the average risk-adjusted loan spread as we shut down tacit collusion among lenders. When collusion is eliminated, we find that small borrowers tend to benefit more. Specifically, DIP loan spread would drop 161 bps for small borrowers, representing a 21% decline, and 75 bps for large borrowers, a 13.7% decline. The highly speculative loan spread would drops by 166 bps for small borrowers and 121 bps for large borrowers. The evidence suggests that small borrowers in both markets are more susceptible to lender market power and the effect of collusion on smaller borrowers is much higher that for large borrowers. Our findings therefore imply that antitrust policies that deter lender collusion may benefit small lenders more, and in economic or financial crises, financial aids towards distressed companies should target at small firms.

Table 5: Heterogeneous Effects of Lender Collusion

		DIP Loans		Highly-speculative Loans	
	Borrower size	**Level (bps)**	**Pct. (%)**	**Level (bps)**	**Pct. (%)**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**
Avg. reduction in	Small	161	20.7%	166	46.2%
risk-adj. spreads (R)	Large	75	13.7%	121	46.1%

Note: This table examines the impact of lender tacit collusion on borrowers of different sizes. We report the change in level (in basis points) and in percentage that result from eliminating lender collusion.

The implication is consistent with a recent policy proposal by legal scholars to encourage the U.S. government to provide direct funding to small firms that filed for bankruptcy during the COVID-19 pandemic.[24]

8 Policy Analysis

The market power of a small group of specialized lenders, potentially sustained by tacit collusion through syndication, can lead to substantial mispricing and rent extraction. Because such implicit coordination is inherently difficult to detect, ex post enforcement is often of limited effectiveness. This creates a case for ex ante regulatory intervention, particularly during bankruptcy waves when such distortions can have broader effects on employment, investment, and aggregate economic activity. In practice, governments in the U.S. and other economies have responded by deploying special purpose vehicles (SPVs) to participate in syndicated lending to distressed or bankrupt firms and, in some cases, by imposing caps on the total financing costs that banks may charge such borrowers. For example, the Federal Reserve established the Main Street Lending Program to support lending to small and medium-sized for-profit businesses that were in sound financial condition prior to the onset of the COVID-19 pandemic. Relatedly, DeMarzo et al. (2020) and Conti-Brown and Skeel (2020) argue that the Federal Reserve should use its emergency authority to provide DIP lending facilities and discuss how such interventions could be implemented in practice. Owing to space constraints, we focus in the main text on the potential role of government lending facilities and defer the discussion of interest rate caps to Online Appendix.

Specifically, we use the estimated model as a laboratory for counterfactual policy analysis. After solving the model with government lending facilities,[25] we examine how these policies affect borrowing outcomes and borrower welfare. In particular, we focus

[24] See "Use of Chapter 11 and Federal Lending to Help Small Businesses," by Kathryn Judge and Jared A. Ellias, July 27, 2020, Letter to the Office of Senator Sherrod Brown, as Ranking Member of the Committee on Banking, Housing, and Urban Affairs.

[25] Details of the model solution are provided in Online Appendix OA.6.

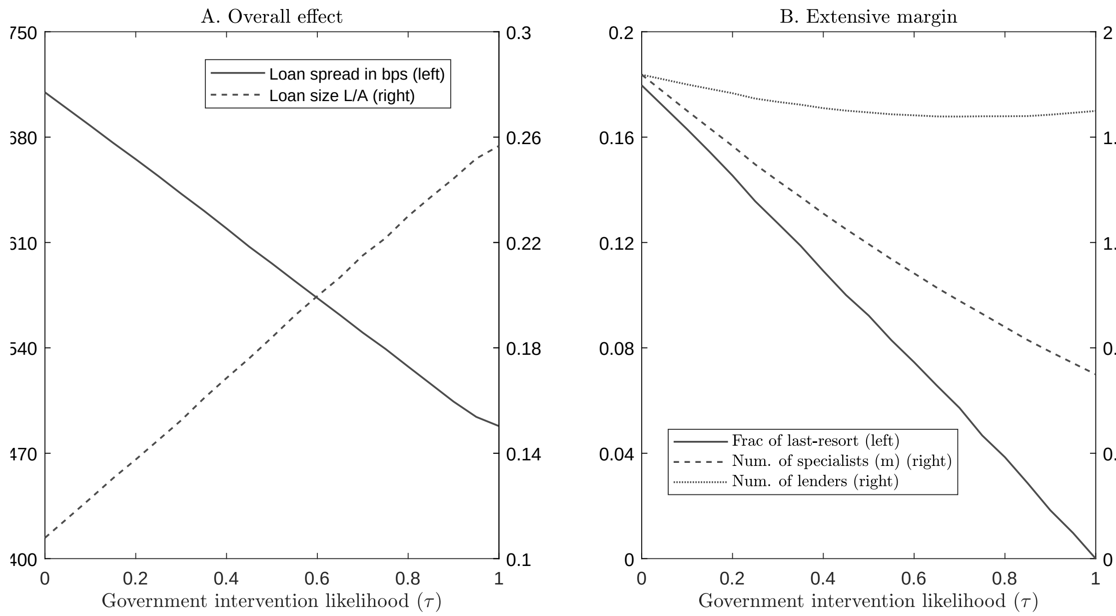
on two questions: (i) how government lending facilities affect the risk-adjusted yield spreads that borrowers pay and the amount of credit they obtain, and (ii) which types of borrowers are most affected by these policies. Because the qualitative policy implications are similar across the two markets, we present the results for the DIP loan market in the main text and defer the results for the highly speculative loan market to the Online Appendix.

Formulation of Policies in the Model for DIP Loans. Suppose the government sets up a SPV to participate in the loan syndicate for DIP borrowers. For each borrower, the government joins the syndicate with probability τ.[26] The parameter τ therefore captures the intensity of government intervention. The baseline model is nested as the special case $\tau \equiv 0$ within the extended model with government intervention. At the other extreme, when $\tau = 1$, the government SPV participates in the loan syndicate for every distressed borrower, in which case tacit collusion becomes unsustainable. Moreover, unlike in the counterfactual case of zero tacit-collusion capacity ($\xi = 0$), borrowers no longer rely on last-resort lenders, such as hedge funds and private equity funds, because the government SPV always participates in syndicated lending.

How Government Participation Affects Borrowing Costs and Credit Access? Government intervention affects borrowing costs and credit access through both direct and indirect channels. The direct effect captures how government participation changes the loan spread and loan size, conditional on the government participating in the current syndication. The indirect effect captures how the possibility of future government participation alters the loan spread and loan size in the current syndication by changing specialized lenders' incentives for tacit collusion. Clearly, the direct effect does not depend on τ, whereas the indirect effect increases with the intervention intensity $\tau \in [0, 1]$.

Specifically, our analysis of the DIP loan market, reported in Table 6, shows that the direct effect of government intervention reduces the average risk-adjusted yield spread on syndicated loans by specialized lenders (i.e., type-2 loans) by approximately 249 basis points for small borrowers and 129 basis points for large borrowers. At the same time, it increases the average loan-to-asset ratio by about 0.19 for small borrowers and 0.091 for large borrowers. As a result, borrower welfare rises by 17.5% for small borrowers and 12.6% for large borrowers, where these welfare gains are measured by integrating under the respective borrower demand curves. The direct effect is stronger for smaller borrowers because they are more exposed to the market power of specialized lenders, particularly through tacit collusion in syndication.

[26] Although the intervention intensity τ may in practice vary with borrower characteristics, for simplicity we restrict attention in this section to the case in which it is constant.



Note: This figure shows the intensive and extensive effects of the government lending facility for DIP loans. Panel A depicts the overall effect on the risk-adjusted yield spread, R, and the loan-to-asset ratio, L/A. Panel B shows the extensive-margin effect of the government lending facility on reducing the number of participating specialized lenders and decreasing the likelihood of borrowers' turning to lenders of last-resort. The total number of lenders, including the expected participation of the government, is also plotted.

Figure 7: The Overall Effect and Extensive Margin of the Government Lending Facility

Our analysis also shows that the indirect effect varies with the intensity of government intervention, τ, in a highly nonlinear, though monotonic, manner. Even at $\tau = 0.8$, the indirect effect remains limited, especially for small borrowers. Once $\tau = 1.0$, however, the indirect effect becomes substantial for both small and large borrowers. It reduces the average risk-adjusted yield spread on syndicated loans by specialized lenders (i.e., type-2 loans) by approximately 244 basis points for small borrowers and 125 basis points for large borrowers, broadly similar to the direct effect. At the same time, it increases the average loan-to-asset ratio by about 0.189 for small borrowers and 0.09 for large borrowers, again close to the direct-effect magnitudes. These changes raise borrower welfare by 17.2% for small borrowers and 12.1% for large borrowers. As with the direct effect, the indirect effect is stronger for smaller borrowers because they are more exposed to the market power of specialized lenders, particularly through tacit collusion in syndication.

What Are the Implications Along the Intensive and Extensive Margins? As shown in Panel A of Figure 7, a higher intensity of government intervention, τ, increases the overall benefits of government lending facilities for borrowers. This overall effect can be decomposed into intensive- and extensive-margin components. The intensive-margin effect captures how an increase in τ affects the risk-adjusted yield spread R and the loan-

Table 6: The Effect of Government Intervention: DIP Loans.

		Direct effect	Indirect effect	
			$\tau = 0.8$	$\tau = 1.0$
R (bps)	Small	−249	0	−244
	Large	−129	−69	−125
L/A	Small	0.190	0.000	0.189
	Large	0.091	0.039	0.090
Borrower	Small	0.175	0.000	0.172
Welfare	Large	0.126	0.075	0.121

Note: This table examines the impact of government lending facilities on borrowers of varying sizes. It focuses on type-2 loans, i.e., syndicated loans made by specialized lenders. We report the changes from the baseline model caused by the direct and indirect effects of government lending facilities.

to-asset ratio L/A, holding fixed the number of participants in type-2 syndicated lending at m. It is measured relative to the benchmark in which the same m participants collude in the syndicated loan at their estimated levels. Meanwhile, the extensive-margin effect captures how an increase in τ affects the risk-adjusted yield spread R and the loan-to-asset ratio L/A through changes in market participation: stronger government intervention (i) crowds out some specialized lenders, thereby reducing the number of participants m, and (ii) lowers the likelihood that borrowers are left without either specialized-lender or government participation in the syndicate, forcing them to rely on lending by private equity and hedge funds, as shown in Panel B of Figure 7.

On the one hand, a higher government intervention intensity, τ, unambiguously reduces the risk-adjusted yield spread R and increases the loan-to-asset ratio L/A along the intensive margin, because it weakens collusive capacity through both the direct and indirect channels discussed above, holding fixed the number of participants in type-2 syndicated lending at m. This is unambiguously improves the welfare of distressed borrowers. On the other hand, along the extensive margin, a higher τ has two countervailing effects on R and L/A, and thus on borrower welfare. On the positive side, it reduces the likelihood that borrowers are left without either specialized-lender or government participation in type-2 syndicated lending and therefore must rely on private equity and hedge fund lending; this lowers R and raises L/A, thereby benefiting distressed borrowers. On the negative side, it crowds out specialized lenders in type-2 syndicated lending; this increases R and lowers L/A, thereby hurting distressed borrowers. Our estimation suggests that this negative crowding-out effect is quantitatively limited, because the reduction in specialized-lender participation is, on average, almost fully offset by stronger participation by the government SPV, leaving the total number of lenders in the syndication almost unchanged, as reflected in dotted curves in Panel B of Figure 7. Taken together, the positive extensive-margin effect dominates the negative one.

9 Conclusions

This paper studies lender market power in the loan markets for distressed corporate borrowers, where a few specialized lenders finance a large fraction of loans. Even after removing credit- and liquidity-risk compensation, ultra-high risk-adjusted yield spreads persist, averaging 711 basis points for DIP loans and 308 basis points for highly speculative loans. We develop and estimate a dynamic game-theoretic model incorporating strategic competition, endogenous collusion capacity, endogenous market participation, and latent demand heterogeneity, estimated via Bayesian MCMC on 436 DIP and 435 highly speculative loan facilities.

Our estimation reveals that lender market power accounts for 75% of risk-adjusted spreads in the DIP market and 97% in the highly speculative loan market, including approximately 140 basis points from tacit collusion through syndication in each market. By reducing survival-critical liquidity by 16–20%, lender market power worsens asset-value destruction and amplifies financial distress costs, making it a quantitatively important source of deadweight losses from corporate financial distress, which was underappreciated in the literature. Smaller borrowers are particularly exposed, as their weaker bargaining positions and less elastic demand strengthen lenders' collusion incentives.

These findings carry nuanced policy implications. Blanket prohibitions on collusion are not straightforwardly welfare-improving: collusive rents support specialized lenders' entry, and eliminating them would shrink lender participation and push distressed borrowers toward expensive lenders of last resort. Our counterfactual analysis shows that government participation in distressed loan syndication reduces borrowing costs through both direct price effects and indirect effects on collusion incentives, with the largest welfare gains accruing to smaller borrowers most exposed to lender market power.

References

Allen, Jason, Jakub Kastl, and Milena Wittwer, 2018, Estimating demand systems with bidding data, Working paper.

Altman, Edward I., Edith Hotchkiss, and Wei Wang, 2019, *Corporate Financial Distress, Restructuring, and Bankruptcy* (Wiley).

Antill, Samuel, 2022, Do the right firms survive bankruptcy?, *Journal of Financial Economics* 144, 523–546.

Antill, Samuel, and Megan Hunter, 2024, Consumer choice and corporate bankruptcy, *Journal of Finance* forthcoming.

Asker, John, and Heski Bar-Isaac, 2014, Raising retailers' profits: On vertical practices and the exclusion of rivals, *American Economic Review* 104, 672–86.

Asker, John, and Alexander Ljungqvist, 2010, Competition and the structure of vertical relationships in capital markets, *Journal of Political Economy* 118, 599–647.

Asquith, Paul, Robert Gertner, and David Scharfstein, 1994, Anatomy of financial distress: An examination of junk-bond issuers*, *The Quarterly Journal of Economics* 109, 625–658.

Atkeson, Andrew, and Ariel Burstein, 2008, Pricing-to-market, trade costs, and international relative prices, *American Economic Review* 98, 1998–2031.

Ayotte, Kenneth M., and Jared A. Elias, 2020, Bankruptcy process for sale, Working paper, U.S. Berkeley School of Law.

Ayotte, Kenneth M., and Edward R. Morrison, 2009, Creditor control and conflict in chapter 11, *Journal of Legal Analysis* 1, 511–551.

Badoer, Dominique C, Evan Dudley, and Christopher M James, 2019, Priority Spreading of Corporate Debt, *The Review of Financial Studies* 33, 261–308.

Berg, Tobias, Anthony Saunders, and Sascha Steffen, 2016, The total cost of corporate borrowing in the loan market: Don't ignore the fees, *Journal of Finance* 71, 1357–1392.

Bernstein, Shai, Emanuele Colonnelli, and Benjamin Iverson, 2019, Asset reallocation in bankruptcy, *Journal of Finance* 74, 5–53.

Berry, Steven, James Levinsohn, and Ariel Pakes, 1995, Automobile prices in market equilibrium, *Econometrica* 63, 841–890.

Berry, Steven T., 1994, Estimating Discrete-Choice Models of Product Differentiation, *The RAND Journal of Economics* 25, 242–262.

Beyhaghi, Mehdi, and Sina Ehsani, 2017, The cross-section of expected returns in the secondary corporate loan market, *Review of Asset Pricing Studies* 7, 1121–1138.

Blanco, Roberto, Simon Brennan, and Ian W. Marsh, 2005, An empirical analysis of the dynamic relation between investment-grade bonds and credit default swaps, *The Journal of Finance* 60, 2255–2281.

Bretscher, Lorenzo, Lukas Schmid, Ishita Sen, and Varun Sharma, 2026, Institutional corporate bond pricing, *The Review of Financial Studies* 39, 605–660.

Bris, Arturo, Ivo Welch, and Ning Zhu, 2006, The costs of bankruptcy: Chapter 7 liquidation versus chapter 11 reorganization, *The Journal of Finance* 61, 1253–1303.

Brown, Jennifer, and David A. Matsa, 2016, Boarding a sinking ship? An investigation of job applicants to distressed firms, *Journal of Finance* 71, 507–549.

Brunner, Antje, and Jan Krahnen, 2008, Multiple lenders and corporate distress: Evidence on debt restructuring, *Review of Economic Studies* 75, 415–442.

Bryzgalova, Svetlana, Anna Pavlova, and Taisiya Sikorskaya, 2025, Strategic arbitrage in segmented markets, *Journal of Financial Economics* 166, 104008.

Bushman, Robert M., Abbie J. Smith, and Regina Wittenberg-Moerman, 2010, Price discovery and dissemination of private information by loan syndicate participants, *Journal of Accounting Research* 48, 921–972.

Cai, Jian, Frederik Eidam, Anthony Saunders, and Sascha Steffen, 2018, Loan syndication structure and price collusion, Working paper, Washington University at St. Louis.

Carrasco, Vinicius, and Gustavo Manso, 2006, Syndication and Robust Collusion in Financial Markets, Berkeley working papers, University of California at Berkeley.

Chava, Sudheer, and Michael R. Roberts, 2008, How does financing impact investment? the role of debt covenants, *Journal of Finance* 63, 2085–2121.

Chen, Hui, Winston Wei Dou, Hongye Guo, and Yan Ji, 2021, Feedback and contagion through distressed competition, Working paper.

Chen, Hui, Winston Wei Dou, Hongye Guo, and Yan Ji, 2024, Feedback and contagion through distressed competition, *The Journal of Finance* Forthcoming.

Chen, Long, David A. Lesmond, and Jason Wei, 2007, Corporate yield spreads and bond liquidity, *The Journal of Finance* 62, 119–149.

Cheng, Xu, Frank Schorfheide, and Peng Shao, 2023, Clustering for multi-dimensional heterogeneity with an application to production function estimation, Pier working paper archive, Penn Institute for Economic Research, Department of Economics, University of Pennsylvania.

Ciliberto, Federico, and Jonathan W. Williams, 2014, Does multimarket contact facilitate tacit collusion? Inference on conduct parameters in the airline industry, *The RAND Journal of Economics* 45, 764–791.

Clark, Robert, Ig Horstmann, and Hean-Francois Houde, 2024, Hub-and-spoke cartels: Theory and evidence from the grocery industry, *American Economic Review* 114, 783–814.

Conti-Brown, Peter, and David Skeel, 2020, Using the Federal Reserve's Discount Window for Debtor-in-Possession Financing During the COVID-19 Bankruptcy Crisis, Working paper, Economic StudiesProgram at The Brookings Institution.

Corbae, Dean, and Pablo D'Erasmo, 2021, Reorganization or liquidation: Bankruptcy choice and firm dynamics, *Review of Economic Studies* 88, 2239–2274.

Corbae, Dean, and Michael Gofman, 2021, Commit not to compete: Collusion versus liquidity sharing via interbank markets, Working paper, the university of wisconsin.

Corbae, Dean, and Ross Levine, 2024, Competition, stability, and efficiency in the banking industry, Working paper.

Dahiya, Sandeep, Kose John, Manju Puri, and Gabriel Ramirez, 2003, Debtor-in-possession financing and bankruptcy resolution: Empirical evidence, *Journal of Financial Economics* 69, 259–280.

DeMarzo, Peter M., Arvind Krishnamurthy, and Joshua D. Rauh, 2020, Debtor-in-Possession Financing Facility (DIPFF) Proposa, Working paper, Stanford University.

Dou, Winston, Lucian A. Taylor, Wei Wang, and Wenyu Wang, 2021a, Dissecting bankruptcy frictions, *Journal of Financial Economics* 142, 975–1000.

Dou, Winston Wei, Yan Ji, David Reibstein, and Wei Wu, 2021b, Inalienable customer capital, corporate liquidity, and stock returns, *The Journal of Finance* 76, 211–265.

Dou, Winston Wei, Yan Ji, and Wei Wu, 2021c, Competition, profitability, and discount rates, *Journal of Financial Economcis* 140, 582–620.

Dou, Winston Wei, Yan Ji, and Wei Wu, 2021d, The oligopoly lucas tree, *Review of Financial Studies* forthcoming.

Dou, Winston Wei, Shane Johnson, and Wei Wu, 2022, Compettition network: Distress spillovers and predictable industry returns, Working paper.

Dou, Winston Wei, Johnson Shane, and Wei Wu, 2024, Evidence on the Importance of Market Competition in Distress Propagation, Working papers, The Wharton School at University of Pennsulvania.

Duffie, Darrell, 1999, Credit swap valuation, *Financial Analysts Journal* 55, 73–87.

Eckbo, B Espen, Kai Li, and Wei Wang, 2023, Loans to chapter 11 firms: Contract design, repayment risk, and pricing, *Journal of Law and Economics* 66, 465–509.

Eisfeldt, Andrea L., Hanno Lustig, and Lei Zhang, 2023, Complex asset markets, *The Journal of Finance* 78, 2519–2562.

Elton, Edwin J., Martin J. Gruber, Deepak Agrawal, and Christopher Mann, 2001, Explaining the rate spread on corporate bonds, *Journal of Finance* 56, 247–277.

European Commission, Directorate-General for Competition, O Bretz, R Dawkins, M Leppard, H Bardell, and D Drury, 2019, *EU loan syndication and its impact on competition in credit markets : final report* (Publications Office).

Fudenberg, Drew, and Eric Maskin, 1986, The folk theorem in repeated games with discounting or with incomplete information, *Econometrica* 54, 533–54.

Gabaix, Xavier, and Ralph S. J Koijen, 2023, In search of the origins of financial fluctuations: The inelastic markets hypothesis, Working Paper 28967, National Bureau of Economic Research.

Gertner, Robert, and David Scharfstein, 1991, A theory of workouts and the effects of reorganization law, *The Journal of Finance* 46, 1189–1222.

Gilson, Stuart C, 1997, Transactions costs and capital structure choice: Evidence from financially distressed firms, *The Journal of Finance* 52, 161–196.

Graham, John, Hyunseob Kim, Si Li, and Jiaping Qiu, 2023, Employee costs of corporate bankruptcy, *The Journal of Finance* 78, 2087–2137.

Green, Edward J., and Robert H. Porter, 1984, Noncooperative collusion under imperfect price information, *Econometrica* 52, 87–100.

Harrington, Joseph E., and Andrzej Skrzypacz, 2011, Private monitoring and communication in cartels: Explaining recent collusive practices, *American Economic Review* 101, 2425–49.

Hatfield, John William, Scott Duke Kroiminer, Richard Lowery, and Jordan M. Barry, 2020, Collusion in markets with syndication, Working paper, Harvard University.

Hausman, Jerry A., 1975, An instrumental variable approach to full information estimators for linear and certain nonlinear econometric models, *Econometrica* 43, 727–738.

Hendel, Igal, 1999, Estimating multiple-discrete choice models: An application to computerization returns, *The Review of Economic Studies* 66, 423–446.

Hortaçsu, Ali, Gregor Matvos, Chad Syverson, and Sriram Venkataraman, 2013, Indirect costs of finanical distress in durable goods industries: The case of auto manufacturers, *Review of Financial Studies* 26, 1248–1290.

Hortacsu, Ali, Gregor Matvos, Chad Syverson, and Sriram Venkataraman, 2013, Indirect costs of financial distress in duratable goods industries: The case of auto manufacturers, *Review of Financial Studies* 26, 1249–1290.

Hotchkiss, Edith S., Karin S. Thorburn, and Wei Wang, 2023, The changing face of chapter 11 bankruptcy, *Annual Review of Financial Economics* 15, 351–367.

Imai, Susumu, Neelam Jain, and Andrew T Ching, 2009, Bayesian estimation of dynamic discrete choice models, *Econometrica* 77, 1885–1926.

Ivashina, Victoria, 2009, Asymmetric information effects on loan spreads, *Journal of Financial Economics* 92, 300–319.

Jiang, Renna, Puneet Manchanda, and Peter E. Rossi, 2009, Bayesian analysis of random coefficient logit models using aggregate data, *Journal of Econometrics* 149, 136–148.

Jiang, Wei, Kai Li, and Pei Shao, 2010, When shareholders are creditors: Effects of the simulataneous holding of equity and debt by non-commercial banking institutions, *Review of Financial Studies* 23, 3595–3637.

Jiang, Wei, Kai Li, and Wei Wang, 2012, Hedge funds and chapter 11, *Journal of Finance* 67, 513–560.

Johannes, Michael, and Nicholas Polson, 2010, Mcmc methods for continuous-time financial econometrics, *Handbook of Financial Econometrics: Applications* 1–72.

Kasahara, Hiroyuki, and Katsumi Shimotsu, 2009, Nonparametric identification of finite mixture models of dynamic discrete choices, *Econometrica* 77, 135–175.

Knittel, Christopher R., and Victor Stango, 2003, Price ceilings as focal points for tacit collusion: Evidence from credit cards, *The American Economic Review* 93, 1703–1729.

Koijen, Ralph S. J., and Motohiro Yogo, 2019, A demand system approach to asset pricing, *Journal of Political Economy* 127, 1475–1515.

Kortweg, Arthur, 2010, The net benefits to leverage, *Journal of Finance* 65, 2137–2170.

Li, Kai, and Wei Wang, 2016, Debtor-in-possession financing, loan-to-loan, and loan-to-own, *Journal of Corporate Finance* 39, 121–138.

Li, Yang, and Asim Ansari, 2014, A bayesian semiparametric approach for endogeneity and heterogeneity in choice models, *Management Science* 60, 1161–1179.

Lim, Jongha, Bernadette A. Minton, and Michael S. Weisbach, 2014, Syndicated loan spreads and the composition of the syndicate, *Journal of Financial Economics* 111, 45–69.

Longstaff, Francis A., Sanjay Mithal, and Eric Neis, 2005, Corporate yield spreads: Default risk or liquidity? new evidence from the credit default swap market, *The Journal of Finance* 60, 2213–2253.

Ma, Song, Joy Tianjiao, and Wei Wang, 2023, Bankrupt innovative firms, *Management Science* 68, 6971–6992.

Miller, Nathan H., and Matthew C. Weinberg, 2017, Understanding the price effects of the millercoors joint venture, *Econometrica* 85, 1763–1791.

Miravete, Eugenio J., Katja Seim, and Jeff Thurk, 2018, Market power and the laffer curve, *Econometrica* 86, 1651–1687.

Morris, Stephen, and Hyun Song Shin, 2004, Coordination risk and the price of debt, *European Economic Review* 48, 133–153.

Nevo, Aviv, 2001, Measuring market power in the ready-to-eat cereal industry, *Econometrica* 69, 307–342.

Nini, Greg, and David C Smith, 2013, Some facts and figures on secured lending, *Loan Market Chronicle* 79–82.

Nocke, Volker, and Lucy White, 2007, Do vertical mergers facilitate upstream collusion?, *The American Economic Review* 97, 1321–1339.

Norets, Andriy, 2009, Inference in dynamic discrete choice models with serially orrelated unobserved state variables, *Econometrica* 77, 1665–1682.

Opp, Marcus M., Christine A. Parlour, and Johan Walden, 2014, Markup cycles, dynamic misallocation, and amplification, *Journal of Economic Theory* 154, 126–161.

Pulvino, Todd C, 1999, Effects of bankruptcy court protection on asset sales, *Journal of Financial Economics* 52, 151–186.

Rotemberg, Julio J, and Garth Saloner, 1986, A supergame-theoretic model of price wars during booms, *American Economic Review* 76, 390–407.

Sannikov, Yuliy, and Andrzei Skrzypacz, 2007, Impossibility of collusion under imperfect monitoring with flexible production, *American Economic Review* 97, 1794–1823.

Santos, Joao A.C., and Andrew Winton, 2008, Bank loans, bonds, and information monopolies across the business cycle, *Journal of Finance* 63, 1315–1359.

Schenone, Carola, 2010, Lending relationships and information rents: Do banks exploit their information advantages?, *Review of Financial Studies* 23, 1149–1199.

Schwert, Michael, 2020, Does borrowing from banks cost more than borrowing from the market?, *Journal of Finance* 75, 905–947.

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

Skeel, David A., 2004, The past, present, and future of debtor-in-possession financing, *Cardozo Law Review* 25, 1905–1934.

Sorensen, Morten, 2007, How smart is smart money? A two-sided matching model of venture capital, *Journal of Finance* 62, 2725–2762.

Syverson, Chad, 2019, Macroeconomics and market power: Context, implications, and open questions, *Journal of Economic Perspectives* 33, 23–43.

Wang, Wei, 2022, The costs of bankruptcy restructuring, *Oxford Research Encyclopedia in Economics and Finance* August, 0.

Wittenberg-Moerman, Regina, 2008, The role of information asymmetry and financial reporting quality in debt trading: Evidence from the secondary loan market, *Journal of Accounting and Economics* 46, 240–260.

Yang, Sha, Yuxin Chen, and Greg M. Allenby, 2003, Bayesian analysis of simultaneous demand and supply, *Quantitative Marketing and Economics* 1, 251–275.

Appendix

A Microfoundations of Borrowers' Demand Curves

Given a distressed borrower of size A and type k, the borrower chooses the optimal loan amount L to maximize its gains from the loan:

$$\max_{L>0} \left\{ L^{\rho_k} S_k(A,z)^{1-\rho_k} - L\left[R + RP_k\left(\frac{L}{A}\right)\right]\right\}, \tag{A.1}$$

where $L^{\rho_k} S_k(A,z)^{1-\rho_k}$ captures the benefits derived from borrowing a loan of size L, $RP_k(L/A)$ captures the credit and liquidity risk premium, and R captures the risk-adjusted yield spread, including the important fees described in (1).

Specifically, the coefficient $\rho_k \in (0,1)$ captures the decreasing returns to scale for the borrower's business benefits with respect to the loan size, while $S_k(A,z)$ is the return shifter, a term that depends on latent firm characteristics (similar to Hendel, 1999). Here, type k reflects group-wise latent heterogeneity (e.g., Kasahara and Shimotsu, 2009; Cheng et al., 2023). The return shifter $S_k(A,z)$ is specified as follows:

$$S_k(A,z) \equiv Ae^{\nu_k+\sigma z}, \tag{A.2}$$

where ν_k represents latent group-wise heterogeneity, and z is a latent firm-specific demand shock.

The credit and liquidity risk premium $RP_k(L/A)$ is specified as follows:

$$RP_k\left(\frac{L}{A}\right) \equiv h_k\left(\frac{L}{A}\right)^{\gamma_k} \tag{A.3}$$

where $h_k > 0$ and $\gamma_k \in (0,1)$. Estimates in the literature suggest that γ_k is positive but small. Therefore, consistent with theoretical discussions and empirical studies, we assume that the credit and liquidity premium on corporate debt increases with the leverage ratio L/A, as the financial distress risk from the newly-issued distressed loan L depends on the borrower's size, A.

The first-order condition for L leads to a demand curve of loan size for a type-k borrower as follows:

$$\rho_k L^{\rho_k-1} S_k(A,z)^{1-\rho_k} = R\left[1+e^{\ln(h_k+\gamma_k)-\ln(R)+\gamma_k\ln(L/A)}\right] \tag{A.4}$$

Taking log on both sides leads to

$$\ln(\rho_k) + (\rho_k-1)\left[\ln(L/A) - \nu_k - \sigma z\right] \tag{A.5}$$

$$= \ln(R) + \ln\left[1+e^{\ln(h_k(1+\gamma_k))-\ln(R)+\gamma_k\ln(L/A)}\right] \tag{A.6}$$

The Campbell-Shiller log-linear approximation leads

$$\ln\left[1+e^{\ln(h_k(1+\gamma_k))-\ln(R)+\gamma_k\ln(L/A)}\right] \tag{A.7}$$

$$\approx a_{0,k} + a_{1,k}\left[\ln(h_k(1+\gamma_k)) - \ln(R) + \gamma_k\ln(L/A)\right], \tag{A.8}$$

where $a_{0,k} > 0$ and $a_{1,k} \in (0,1)$.

Thus, arranging terms in (A.8) leads to the following relationship:

$$\ln\left(\frac{L}{A}\right) \approx \alpha_k - \varepsilon_k\ln(R) + \sigma z, \tag{A.9}$$

where

$$\alpha_k \equiv \frac{\ln(\rho_k) + (1-\rho_k)\nu_k - a_{0,k} - a_{1,k}\ln(h_k(1+\gamma_k))}{1 + a_{1,k}\gamma_k - \rho_k}, \tag{A.10}$$

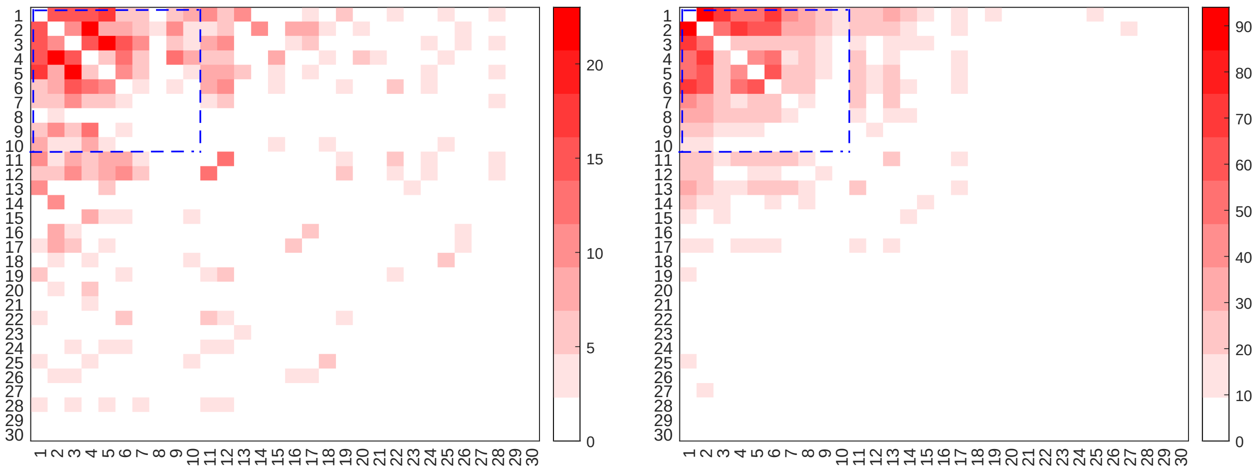
$$\varepsilon_k \equiv \frac{1-a_{1,k}}{1+a_{1,k}\gamma_k-\rho_k}. \tag{A.11}$$

A higher ε_k implies that the firm's loan demand L is more sensitive to increases in the risk-adjusted yield spread R set by lenders. This indicates greater elasticity in the borrower's demand for loans and, consequently, stronger bargaining power.

B Pairwise Syndication Interaction Intensity

Figure A1: Syndication interaction intensity in both markets

(a) DIP loans (b) Highly speculative loans



C Proof of Proposition 4.1

Exploiting the model's homotheticity property, we can first express $L_2^C(A,k,x,m)$ and $L_2^D(A,k,x,m;\mathcal{L})$ as follows:

$$L_2^C(A,k,x,m) \equiv \mathcal{L}^C(A,k,m)h_2(k,x)A \tag{A.12}$$

$$L_2^D(A,k,x,m;\mathcal{L}) \equiv \mathcal{L}^D(A,k,m;\mathcal{L})h_2(k,x)A. \tag{A.13}$$

We next derive the equilibrium conditions characterizing $\mathcal{L}^C(A,k,m)$ and $\mathcal{L}^D(A,k,m;\mathcal{L})$. Taking $\mathcal{L}^C(A,k,m)$ as given, the condition defining $\mathcal{L}^D(A,k,m;\mathcal{L})$ is

$$\mathcal{L}^D(A,k,x,m;\mathcal{L}^C) = \underset{\mathcal{L}}{\text{argmax}} \left[\left(\frac{1}{\mathcal{L}+(m-1)\mathcal{L}^C(A,k,m)} \right)^{1/\varepsilon_k} - 1 \right] \mathcal{L}. \tag{A.14}$$

The corresponding first-order condition is

$$1 - \frac{1}{\varepsilon_k} \frac{\mathcal{L}^D}{\mathcal{L}^D + (m-1)\mathcal{L}^C(A,k,m)} = \left[\mathcal{L}^D + (m-1)\mathcal{L}^C(A,k,m) \right]^{1/\varepsilon_k}. \tag{A.15}$$

It's clear that $\mathcal{L}^D(A,k,m;\mathcal{L}^C)$ is continuous in $\mathcal{L}^C(A,k,m)$. Thus, with the optimal deviation $\mathcal{L}^D(A,k,m)$ pinned down in (A.15), the optimal deviation profit is

$$\begin{aligned} &\Pi_2^D(A,k,m;\mathcal{L}^C) \\ &= \left[\left(\frac{1}{\mathcal{L}^D(A,k,m;\mathcal{L}^C)+(m-1)\mathcal{L}^C(A,k,m)} \right)^{1/\varepsilon_k} - 1 \right] \mathcal{L}^D(A,k,m;\mathcal{L}^C)\mathcal{H}_2(k)A, \end{aligned} \tag{A.16}$$

which is also continuous in $\mathcal{L}^C(A,k,m)$. Accordingly, by equation (18), the equilibrium profit under collusion, $\Pi_2^C(A,k,m)$, is also continuous in $\mathcal{L}^C(A,k,m)$. Taken together, we know that W^C, $\mathcal{L}^D(A,k,x,m;\mathcal{L}^C)$, $\Pi_2^D(A,k,m;\mathcal{L}^C)$, and $\Pi_2^C(A,k,m)$ are all continuous functions of $\mathcal{L}^C(\cdot) \in \mathbb{R}^G$, where $\mathbb{R}^G$ is a $G \equiv J \times K \times \overline{m}$-dimensional Euclidean space.

It follows that there exists a participation threshold w_C^* such that the incentive-compatible (IC) feasible set $\mathbb{L}^C(w_C^*)$ is nonempty. This holds because the non-collusive Nash equilibrium threshold w_N^* yields a nonempty IC feasible set $\mathbb{L}^C(w_N^*)$ that contains the non-collusive lending amount $\mathcal{L}^N$. Moreover, since W^C, $\mathcal{L}^D(A,k,x,m;\mathcal{L}^C)$, $\Pi_2^D(A,k,m;\mathcal{L}^C)$, and $\Pi_2^C(A,k,m)$ are all continuous functions of $\mathcal{L}^C(\cdot) \in \mathbb{R}^G$, the IC feasible set $\mathbb{L}^C(w_C^*)$ is a bounded and closed subset of $\mathbb{R}^G$ for any feasible cutoff w_C^* with nonempty IC feasible set $\mathbb{L}^C(w_C^*)$.

For any w_C^* that yields a nonempty IC feasible set $\mathbb{L}^C(w_C^*)$, the continuation value W^C is continuous and strictly concave in $\mathcal{L}^C(\cdot) \in \mathbb{R}^G$, as implied by equations (18) and (22). Consequently, there exists a unique maximizer $\mathcal{L}^C(\cdot) \in \mathbb{L}^C(w_C^*)$ of W^C, and we define

$$W^C(w_C^*) \equiv \max_{\mathcal{L}^C(\cdot) \in \mathbb{L}^C(w_C^*)} W^C. \tag{A.17}$$

The maximum continuation value $W^C(w_C^*)$ is continuous in w_C^* over the set of participation cutoffs that yield nonempty IC feasible sets. Let $\mathcal{M}^C$ denote this set. Because $\mathcal{M}^C$ is bounded and closed within $[w_N^*, w_M^*]$, the maximum is attained for some $w_C^* \in \mathcal{M}^C$. We focus on the largest such cutoff, which is unique by construction.