The Cost of Intermediary Market Power for Distressed Borrowers

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Abstract

In the loan markets for distressed corporate borrowers, a few specialized lenders finance a large fraction of loans. Ultra-high yield spreads prevail even after removing the credit- and liquidity-risk component. Borrowers are in desperate need of financing but face limited funding options, while specialized lenders have repeated syndication relations with restrained participation. We develop and estimate a dynamic game-theoretic model, accounting for strategic competition, endogenous collusion capacity, endogenous participation, and latent heterogeneity. Lender market power accounts for 74 - 92% of the risk-adjusted yield spreads, with a significant fraction attributable to collusion. Smaller borrowers are more susceptible to lender market power. Importantly, both specialized lenders and distressed borrowers would be worse off if collusion is completely prohibited, suggesting that vigorous antitrust policies can be efficiency retarding.

Keywords: Loan Pricing with Imperfect Competition, Collusion in Syndication, Bankruptcy and Distress, Bayesian MCMC, Antitrust Policy. (**JEL:** G12, G23, G30, L13)

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1 Introduction

Financial distress and bankruptcy impose significant costs on corporate borrowers, shaping their cost of capital, resource allocation, industry dynamics, and aggregate investment and employment. Understanding the micro-foundations of these costs is essential for analyzing their variation across macroeconomic conditions and for designing policies to mitigate their adverse effects.

Existing studies have primarily examined frictions in bankruptcy procedures, such as stakeholder conflicts, asymmetric information, and judicial discretion or inexperience. They often emphasize bankruptcy outcomes like excessive liquidation, inefficient continuation, and delayed resolutions, which impose significant losses on highly distressed or bankrupt firms (e.g., Corbae and D'Erasmo, 2021; Dou et al., 2021a).[1] However, these frictions are not the sole source of costs associated with financial distress and bankruptcy. Our paper highlights a critical yet understudied dimension — the excessively high risk-adjusted financing costs faced by highly distressed or bankrupt firms when raising external funding, driven by the market power of intermediary lenders in distressed loan markets.

To address this gap, we provide micro-level evidence on the magnitude and drivers of these financing costs. Using a granular dataset of distressed loans, including detailed information on loan yields, contractual terms, fees, loan sizes, lender participation, and bid-ask spreads in secondary markets, we conduct a structural estimation exercise. To our knowledge, this dataset is the most comprehensive of its kind, offering a unique lens to analyze the financial burdens faced by distressed borrowers.

Specifically, we integrate this data into a game-theoretical model that captures both strategic interactions among lenders and latent variations in borrowers' loan demand. This framework unifies non-collusive competition, tacit collusion in loan syndication, and perfect cartel behavior, enabling 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 (iii) tacit collusion among these lenders in distressed loan 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 highly-speculative loan market for firms deeply in financial distress but not yet bankrupt, and (ii) the debtor-in-possession (DIP) loan market for firms undergoing Chapter 11 bankruptcy. These markets operate in parallel rather than se-

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

quentially for two key reasons. First, firms in deep distress usually choose between two paths — taking on costly credit for a final attempt at survival (often leading to Chapter 7 if unsuccessful) or entering Chapter 11 for potential reorganization. Second, firms that secure significant funding through highly-speculative loans are unlikely to have the capacity or need to pursue DIP financing, even if they subsequently enter Chapter 11. Our data support this parallel structure. 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. Despite their importance, the data show that the two loan markets for distressed corporate borrowers exhibit significant segmentation and high concentration, with a few specialized lenders dominating. 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 337 basis points for highly speculative loans and 718 basis points for DIP 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 analysis further reveals that risk-adjusted yield spreads are higher for smaller borrowers and those with fewer specialized lenders in

[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.

the syndication. This pattern suggests that these elevated spreads are likely driven by lender market power in distressed loan markets, where a few dominant lenders finance most loans and compete imperfectly, potentially engaging in tacit collusion within their syndications.

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 monitoring, information generation, and funding costs, which are inherently unobservable to econometricians. Second, to assess the elasticity of demand among distressed borrowers, we need to estimate both the demand system and the supply structure. Without observing loan-making costs or shifts in the demand curve, obtaining a consistent estimate of the demand curve requires addressing the well-known omitted variable problem. Third, potential collusion among lenders is by nature implicit in these distressed loan markets and constructing empirical proxies can be very difficult if not completely impossible. Finally, it is highly endogenous whether the distressed borrower would end up getting the syndicated loan from specialized lenders or obtaining funding from alternative sources (e.g., borrow from hedge funds or PE firms as their outside options). Identifying and consistently estimating the size of the outside options is crucial to understand the overall costs of borrowing.

To overcome these challenges, we develop and estimate a new structural model that exploits the implications of lender market power on distressed borrowers. The model incorporates both the demand and the supply side of the distressed loan markets. The demand side of the model captures the demand curves of distressed corporate borrowers, which specifies the risk-adjusted yield spread that the distressed borrowers are willing to pay for a given amount of loan. We micro-found the demand curves in a similar vein to Hendel (1999), taking into account the effect of leverage on default likelihood. The supply side of the model characterizes the loan making process as a three-stage procedure: first, the distressed borrower negotiates with its existing lenders for a loan; second, if the existing lenders turn him down, the distressed borrowers approach a group of specialized lenders who choose whether and how to participate the syndicated loan; and third, if none of the specialized lenders is willing to make a loan, the distressed borrower turns to the lenders of last resort who extract all surplus. The strategic interaction among specialized lenders is central to our study, and we characterize it in a repeated game theoretical framework (e.g., Fudenberg and Maskin, 1986; Rotemberg and

Saloner, 1986).[3] It features imperfect competition among a clique of specialized lenders, in which they choose whether to participate in loan syndication, and if so, whether to lend cooperatively or not, taking into account how their current lending decision affects the expected payoffs from future syndication. This unified framework nests both collusive and non-collusive equilibriums and ensures that the collusion capacity is determined endogenously and co-varies coherently with other equilibrium outcomes such as the number of specialized lenders and the size of a syndicated loan. To this end, our paper also makes important methodological contributions to the literature by endogenizing the level of sustainable collusion in a repeat game and quantifying it from the data.[4] We use the model to decompose the risk-adjusted yield spreads into two components: the unilateral market power of lenders that arises from their non-coordinated conduct and the collusive market power of lenders, derived from their tacitly coordinated conduct. The model provides a unified characterization for both the highly-speculative loan market and the DIP loan market. The model is analytically tractable, which allows us to derive the closed-form solution that characterizes the joint distribution of equilibrium outcomes on both the demand and supply side, including the borrower's size, the lender's type, the number of lenders in syndication, loan amount, and loan spreads. It allows us to identify the latent demand system and the supply structure simultaneously using the likelihood-based estimation. Our method differs from the traditional instrumental variable approach (IVs) adopted by (Berry, 1994; Berry, Levinsohn, and Pakes, 1995, hereafter referred to as BLP): IV approach leverages exogenous shifts in the supply curve to identify the demand, while our approach utilizes the joint distribution of observables in equilibrium to back out the latent demand curves and the model parameters simultaneously.[5] Despite the different identifying assumptions, the IV estimator and the full information maximum likelihood estimator are equivalent if the instruments embody all the over-identifying model-implied restrictions (e.g., Hausman, 1975). We

[3]Not many studies have been developed on the asset pricing and corporate finance implications of strategic competition in repeated games; a few exceptions include the recent works by Opp et al. (2014), Dou et al. (2021c,d), Chen et al. (2021), and Dou et al. (2022).

[4]For example, our paper differs from the approach of Nevo (2001), who considers a model with perfect collusion that is possibly infeasible under the estimated parameters. In fact, there have been important efforts made lately in the empirical industrial organization literature (e.g., Ciliberto and Williams, 2014; Miller and Weinberg, 2017) to modify the approach of Nevo (2001) by modeling the departure from non-collusive Nash equilibria exogenously as a parametric function of certain observed characteristics, such as the "multi-route contact" between carriers in Ciliberto and Williams (2014). Our paper takes one step further by endogenizing the relation of the departure from non-collusive Nash equilibrium to the structural parameters and borrowers' characteristics.

[5]Allen et al. (2018) is another exception that does not rely on IV in estimating the demand system. They develop a structural framework to exploit unique features of parallel multi-unit auctions for identifying demand elasticities.

apply the Markov Chain Monte Carlo (MCMC) estimator to estimate the model using a comprehensive dataset that contains 441 distressed loan facilities from 2001—2017 and 436 DIP loan facilities from 2002—2019, manually constructed using loan and court documents that contain granular information on the pricing and contracting terms of those loans. The MCMC estimation methodology is a Bayesian approach and it computes the posterior distribution of the model parameters and latent demand conditioning on the observed quantities. The MCMC methodology has seen a quick growth in finance studies (Sorensen, 2007; Johannes and Polson, 2010; Kortweg, 2010). Our estimation delivers a few novel findings. First, we find that lenders' tacit collusion contributes to a sizable component of the risk-adjusted yield spread, amounting to about 210 bps, in both markets. Second, borrowers in both markets exhibit similar and low price elasticity of demand. Taken together, the excess spread present in the DIP loan market cannot be explained by the differentials in collusion capacity or those in price elasticity across the two markets. According to our estimates, the factors that set the two markets apart are the specialist lenders' participation cost and their variable cost of lending. Specifically, the participation cost accounts for 280 bps in the DIP loan spread but only 100 bps in the distressed loan spread. An important determinant of the participation cost is the existing lender's blocking power that prevents the borrowers borrowing from alternative lenders, and the other is the existing creditor's information advantage. Our results therefore suggest that existing lenders in the DIP-loan market have much stronger blocking power than those in the distressed loan market. Furthermore, we also find that lenders in the DIP loan market incur significantly higher variable cost of lending. The estimated variable cost is 180 bps in the DIP-loan market while only about 30 bps in the distressed loan market. This finding is quite intuitive since the DIP loan is expected to be more complex. Our decomposition of the risk-adjusted yield spread in both market allows us to further analyze which types of borrowers are particularly susceptible to the market power of institutional lenders. We partition the borrowers in our sample into size quintiles and repeat our analyses above on the small (bottom quintile) and large (top quintile) borrowers. Our findings are striking: shutting down lender collusion reduces the loan yield spread by about 156 (125) bps for large borrowers and by 240 (244) bps for small borrowers in the distressed loan (the DIP loan) market. Our analysis thus suggests that small borrowers are more vulnerable to the market power of institutional lenders mainly because small borrower usually have lower price elasticity of loan demand and give the specialized lenders smaller incentives to deviate from the coordination. As a result, policies aiming at helping distressed companies in economic and financial crises should target more at small firms given their weak bargaining power and disadvanta-

geous position in the distressed loan markets. Lastly, we use the estimated model as a laboratory to examine the effect of two widely debated regulatory intervention. First, we allow government to set up a special purpose vehicle to participate in the loan syndication process. Second, the regulators impose a cap on the specialist lenders' markup in lending and thus restrict the loan spread that can be charged by these lenders. We analyze the specialist lenders' strategic responses to these policies and the consequence on borrowers' welfare. Solving our model with the two types of government interventions yields a few intriguing implications. We show that government participation in the loan market has a direct effect on the loan spreads and loan size and an indirect effect on special lenders' incentives for tacit collusion. The direct effect of government participation leads to 75% and 26% increase in borrower welfare for small and large borrowers, respectively. The incentives for tacit collusion of specialized lenders are only impacted with very high intensity of government intervention. However, at the extreme, when government participates in every deal, the indirect effect of government lending facilities is large as it is equivalent to eliminating tacit collusion. Alternatively, as regulators impose caps on loan spreads, specialist lenders have less incentive to collude to a small loan size and thus they capture the residual profits by increasing the loan amount. Higher loan amount and lower spread improves the borrowers' welfare when they borrow from specialist lenders (i.e., a positive intensive margin). But meanwhile, rate-cap reduces the expected profits by specialist lenders and thus discourage their participation in the lending market. As a result, the likelihood for the borrowers to borrow from the lenders of last-resort rises. Since loans made by lenders of last-resort are much more expensive, rate-cap generates an unintended consequence of reducing the depth of specialist lenders' market (i.e., a negative extensive margin). Combining the two effects, we demonstrate that the effect of rate-cap on borrower welfare is hump-shaped and there exists an optimal level of rate-cap. The optimal spread averages about 100 bps for distressed loans and 400 bps for DIP loans, compared with 340 bps and 710 bps observed in the data.

Related literature. Our paper contributes to the literature on the costs of financial distress and bankruptcy. Several prior studies show that major economic frictions such as conflicts of interest between stakeholders, information asymmetry, and judicial inefficiencies result in significant costs to financially distressed firms. Such costs can be manifested in excess delay, excess continuation, inefficient liquidation, and inefficient resource reallocations. For example, Dou et al. (2021a) estimate a structure model that features bargaining frictions arising from creditor conflicts and asymmetric information to show that excess delay is one of the most important drivers for bankruptcy costs. Bris

et al. (2006), Bernstein et al. (2019), and Antill (2022) compare the costs and efficiency of liquidation and reorganization, and show that liquidation results in higher deadweight costs. Corbae and D'Erasmo (2021) show that the bankruptcy code has implications for firms' capital structure and investment behavior, which on aggregate, affects productivity and consumption. A few other studies such as Pulvino (1999); Graham et al. (2023); Ma et al. (2023) find significant costs associated with the reallocation of assets and labor in bankruptcy. Hortaçsu et al. (2013) show that durable goods manufacturers face substantial costs of financial distress as a result of decline in consumers' demand, even if they are not yet in bankruptcy. Antill and Hunter (2024) show that the indirect costs of corporate bankruptcy associated with loss of customers amount to 12%-15% of a firm's value. An important cost of financial distress that has not fully comprehensively examined by prior literature is the excessive costs of financing faced by distressed firms. Dahiya et al. (2003) and Eckbo et al. (2023) show that debtor-in-possession financing provided to firms filing for bankruptcy is critical for addressing their liquidity issues yet carries high yield spread and fees.

Our study builds on and contributes to the extensive literature on collusion. Green and Porter (1984) and Sannikov and Skrzypacz (2007) show that collusive behavior among firms relies on repeated interactions to enforce compliance. In financial markets, Corbae and Gofman (2021)illustrate that banks can engage in collusion by lending funds in the interbank market, thereby committing not to compete in the private loan market. Through interbank interest rates, banks are able to share the benefits of collusive arrangements. Empirical studies provide direct evidence of collusion in other industries. Clark et al. (2024) document hub-and-spoke collusion in Canadian grocery markets, with suppliers and retailers coordinating to raise bread prices by 50% over 15 years. Clark and Houde (2013, 2014) analyze gasoline cartels, showing how explicit communication sustained high margins and how larger firms allowed smaller ones to delay price increases. Deutschmann et al. (2014)examine collusion in sanitation services in Senegal, where a trade association inflated prices and restricted supply. In pharmaceuticals, Clark et al. (2022) find that collusion in the U.S. generic drug market raised prices by up to 166%, causing significant damages to Medicaid. Syverson (2019) contextualizes this body of micro-level evidence by arguing that increased market power may have broader macroeconomic consequences, including reduced investment, lower labor shares, and slower productivity growth. Our paper complements this literature by focusing on the financial distress loan market, where we show that lender market power and tacit collusion in distressed loan syndications impose real costs on borrowers. We extend these studies by leveraging granular loan data and modeling the strategic interactions between lenders

and borrowers to shed light on the dynamics of financial market collusion.

Intermediary market power plays a crucial role in shaping security prices and the cost of capital in financial markets. Allen and Wittwer (2023) highlight how intermediaries with capital constraints influence asset prices, leading to higher markups and reduced liquidity in exchange markets, and distorting prices in primary markets. Knittel and Stango (2003) demonstrate how nonbinding price ceilings in the credit card market served as focal points for tacit collusion, while Koijen and Yogo (2015) show how financial frictions and market power allowed life insurers to sell long-term policies at deep discounts during the financial crisis. These studies collectively underscore how intermediaries use market power and collusive strategies to shape outcomes, often resulting in inefficiencies.

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 vital asset markets in the economy. They are crucial in establishing the "financial distress cost" for the entire corporate sector, even ex ante. These markets significantly affect the survival prospects of financially distressed firms and the efficiency of bankruptcy procedures. Firms in financial distress commonly resort to these markets for critical financing to sustain working capital, fund investments, and manage debt repayments. Without this essential financing, their business operations could come to a halt, potentially leading to premature liquidation. 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, distressed loans, including highly-speculative and DIP loans, might only account for 10% of the annual outstanding leveraged loans, but they play an analogous role to the ICU in the financial system. Their proportion swelled to over 45% in 2009 due to the Great Recession.[6] In essence, distressed loan markets are to the financial system what ICUs are to the healthcare system.

We constructed a novel and comprehensive dataset on large public borrowers in the

[6]Financing distressed companies has captured significant attention from policymakers and practitioners, especially as the U.S. navigates a recession amid a global pandemic. In 2020, an unprecedented number of large companies went bankrupt. Notably, as DeMarzo et al. (2020) underscore, many of these firms underwent financial distress because of a temporary "pause" in their cash flows.

highly-speculative loan market from 2001 to 2017 and the DIP loan market from 2002 to 2019.[7] To the best of our knowledge, this study is the first to construct comprehensive facility-level loan panel datasets for both the highly-speculative and DIP loan markets, using diverse, authentic U.S. data sources, including loan trading prices in secondary markets, CDS prices, credit ratings, bankruptcy documents, court electronic records, and loan issuance details such as syndication participants and loan amounts.

In the highly-speculative loan market, loans are extended to firms that are highly distressed but not yet in bankruptcy, typically those whose S&P rating has fallen to CCC+ or lower. In the DIP loan market, loans are extended to firms that have already filed for Chapter 11 bankruptcy. On average, highly-speculative and DIP loans feature, respectively, maturities of 49 and 11 months, syndications involving 3.79 and 2.29 major lenders, and loan-to-asset ratios of about 13.0% and 10.7%. Based on total costs of borrowers, the average risk-adjusted yield spread over LIBOR for these loans is approximately 378 and 718 basis points, respectively.

2.2 Motivating Evidence

We present a set of observations regarding the U.S. highly-speculative loan market and the DIP market. These findings collectively suggest that intermediaries hold significant market power over distressed borrowers.

Stylized fact 1: Concentrated markets dominated by a few specialized lenders. We first determine whether a lender of a highly-speculative loan or a DIP loan is considered a "major lender" by following the methodology of Jiang et al. (2010), focusing on their titles from the financing motions and master credit agreements (e.g., agent bank and lead arrangers).

We then define a "specialized lender" in a specific loan market as one that ranks among the top 10 lenders by the number of loans financed as a major lender in our sample, irrespective of the count of major lenders in the loan syndicate. Utilizing this classification, we categorize loans in both the highly-speculative loan and DIP loan markets into three types: "existing-creditor loans," "specialized-lender loans," and "last-resort loans," details of which are provided in Table 1.

Panel A of Table 1 displays the names of the specialized lenders operating within the markets for highly-speculative loans and DIP loans. Panel B of Table 1 provides the breakdown of the number (and the total dollar value) of loans for each of the three

[7] The construction of the highly-speculative and DIP loan samples is detailed in Sections 5.1 and 5.2.

Table 1: Specialized lenders and market concentration

A. Names of specialized lenders

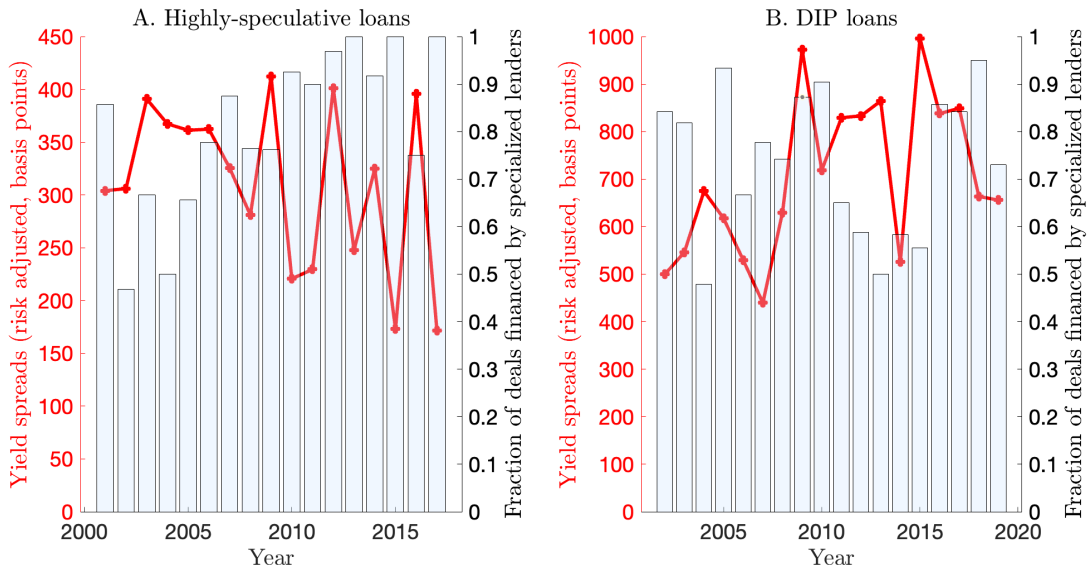
Rank	Highly-speculative loan market		DIP loan market	
	Lender name	# of deals	Lender name	# of deals
1	Bank of America	188	Wells Fargo	96
2	JP Morgan Chase	182	Bank of America	88
3	Wells Fargo	124	JP Morgan Chase	88
4	Citigroup	107	GE Capital	82
5	Credit Suisse	105	Citigroup	67
6	Deutsche Bank	102	Deutsche Bank	41
7	Goldman Sachs	60	Credit Suisse	31
8	GE Capital	58	Wachovia Bank	28
9	UBS	58	Wilmington Trust	27
10	Wachovia Bank	53	CIT Group	21

B. Three loan types

Lender type	Highly-speculative loans				DIP loans			
	# of deals	# frac.	$ of deals	$ frac.	# of deals	# frac.	$ of deals	$ frac.
Type 1: Existing creditor	52	11.80%	13	5.65%	56	12.80%	5	4.90%
Type 2: Specialized lender	336	76.20%	208	90.40%	334	76.60%	94	92.16%
Type 3: Lender of last resort	53	12.00%	9	3.91%	46	10.60%	3	2.94%
Total	441	100%	230	100%	436	100%	102	100%

Note: The loan size are 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."

types, illustrating their proportions as a fraction of the total number (and the total dollar value) of deals in our samples. There are several important points worth mentioning. First, Panel A reveals that specialized lenders are generally large banks considered "systemically important financial institutions." Second, Panel B demonstrates that specialized-lender loans account for 76.20% (90.40% in dollar terms) of the total highly-speculative loan market and 76.60% (92.16% in dollar terms) of the DIP loan market, respectively. Moreover, Figure A1 in Appendix D shows that specialized lenders predominantly collaborate with each other in loan syndication repeatedly, rather than with other non-specialized lenders in these markets. Finally, specialized lenders are largely overlapping (8 out of 10) between the highly-speculative and DIP loan markets for distressed corporate borrowers, supporting the hypothesis that specialized skills in distressed restructuring and bankruptcy are essential for becoming a major player in these markets.



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

These facts indicate that the loan markets for distressed corporate borrowers are characterized by market segmentation and high concentration, with a few specialized lenders dominating.

Stylized fact 2: Ultra-high risk-adjusted yield spreads. In addition to market concentration, we observe a significantly high markup component contributing to the total cost for distressed borrowers. We measure the total cost of borrowers (TCB) by incorporating relevant fees paid to lenders, consistent with the literature (e.g., Ivashina, 2009; Lim et al., 2014; Berg et al., 2016). As emphasized by Berg et al. (2016), lenders do not rely on a single measure such as an interest rate spread to ensure an appropriate expected return. Instead, they use combinations of fees and interest rate spreads. It is crucial to include the relevant fees for distressed borrowers in the calculation of a loan's yield spread, as lenders with greater market power may charge higher fees in addition to, or instead of, higher interest rates. Specifically, the TCB spread is measured in basis points and is defined as the interest rate spread of the loan facility over LIBOR for each dollar used under the loan commitment, plus any fees that the borrower must pay to the

lenders, calculated as follows:

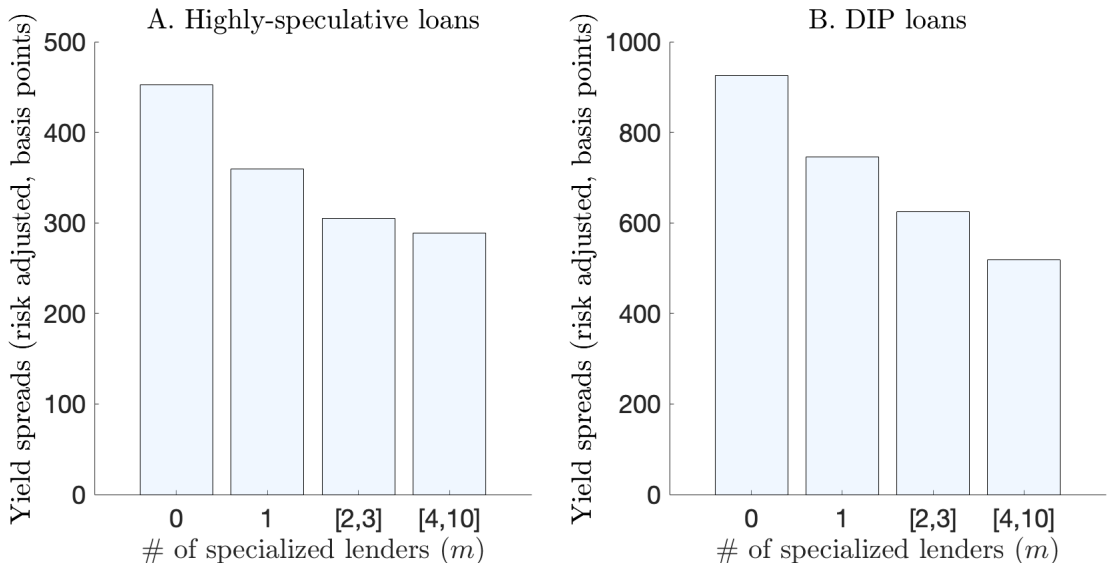
$$\begin{aligned}\text{TCB Spread} = {} & \text{Interest Rate Spread} + \text{Annual Fee} \\ & + \text{Upfront Fee/Risk Neutral Expected Loan Maturity in Years} \\ & + \text{Risk Neutral Expected Annualized Default Fee,} \end{aligned} \tag{1}$$

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.[8]

Our paper aims to analyze and break down the loan yield spread that cannot be attributed to compensation for credit and liquidity risk. We focus on the risk-adjusted yield spread, defined as the TCB spread minus the credit and liquidity risk components. The detailed estimation procedure for these risk components is described in Section 5.3. Panel A of Figure 1 shows the yearly average risk-adjusted yield spread of highly-speculative loans and the annual fraction financed by specialized lenders. Panel B depicts the same for the DIP loan market annually. Several key observations about Figure 1 merit attention. First, the fraction of loans financed by specialized lenders remains consistently high, showing no obvious cyclical patterns or clear comovement with financial conditions of the economy. These observations indicate that the high concentration in the loan markets for distressed corporate borrowers is not a temporary phenomenon tied to specific periods but a persistent characteristic of the industry structure. Second, the average risk-adjusted yield spread stays high over time, fluctuating between 150-400 bps for highly-speculative loans and 350-900 bps for DIP loans, without obvious cyclical patterns or clear comovement with financial conditions of the economy.

Stylized fact 3: Syndication concentration increasing risk-adjusted yield spreads. We explore the relationship between the number of specialized lenders in a loan syndication and the risk-adjusted loan yield spread. If the ultra-high risk-adjusted yield spreads are primarily driven by a lack of competition, we anticipate that as the concentration of syndication increases, the risk-adjusted yield spreads will also rise. Figure 2 demonstrates that the risk-adjusted loan spread decreases monotonically with the number of specialized lenders in a syndication. This pattern highlights the significant impact of lenders'

[8]Other types of fees include utilization fee (or usage fee), cancellation fee (or termination fee), term-out fee, extension fee, collateral monitoring fee, and commitment fee. We exclude those fees, except for the commitment fee, from our TCB measure because they are not commonly used in syndicated loans (e.g., Berg et al., 2016). The commitment fee is excluded because it is contingent on ex-post withdrawal amounts, and distressed, even bankrupt, corporate borrowers almost always use the entire commitment amount in their credit lines. The details on the calculation of the risk-neutral expected loan maturity in years and the risk-neutral expected annualized default fee in (1) can be found in Online Appendix 2.



Note: The figure displays the average risk-adjusted yield spread for distressed loans with different numbers of syndicators. Panel A is for highly speculative loans, while Panel B is for DIP loans. The bar labeled 0 represents the average risk-adjusted yield spread for distressed loans made by existing creditors. The bar labeled 1 represents the distressed loans made by one specialized lender in the syndication. The bars labeled $[2,3]$ and $[4,10]$ represent the average risk-adjusted yield spread for distressed loans with the number of syndicators ranging from 2 to 3 and 4 to 10, respectively.

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

market power on the total borrowing cost for distressed borrowers.

2.3 Sources of Market Power for Lenders in Distressed Loan Markets

In the markets for highly-speculative and DIP loans, distressed corporate borrowers typically engage with a clique of specialized lenders that finance a significant portion of the loans. In Section 2.2, we present novel evidence indicating that, even after adjusting for credit and liquidity risks, loan yield spreads remain exceptionally high. The evidence highlights the considerable market power wielded by these specialized institutional lenders, operating as a distinct clique of credit market leaders. Therefore, it is expected that such specialized lenders hold significant market power in financing distressed firms, attributable to at least three primary reasons.

(i) Sole source of urgent external financing. The bargaining position of distressed borrowers is weak, and their demand for loans exhibits low price elasticity. Distressed firms encounter severe liquidity crises and urgently need to secure capital to continue operations. Crucially, these firms typically have few, if any, "unencumbered" assets available

to offer as collateral for new secured loans. Unlike their non-distressed counterparts, they lack alternative external financing options, such as issuing equity, bonds, or obtaining unsecured lines of credit. Moreover, a distressed borrower is reluctant to approach a large number of lenders or to call for an open auction for securing the best-priced loan, due to concerns over information leakage that could adversely affect its security price, profit margin, customer base, and supply chain.

(ii) Tacit collusion through specialized lender syndication. High entry barriers result in segmented loan markets where a small clique of specialized lenders captures the majority of the market share. This clique may engage in tacit collusion in lending, facilitated by repeated syndication interactions. Lenders who lack expertise in restructuring distressed firms, or who are concerned about regulatory capital requirements, choose not to enter the market. For example, the Basel-III framework requires financial institutions to set aside larger quantity of capital for financing companies with higher default risk because of the higher regulatory risk-weighting of high risk loans. Moreover, because specialized lenders have tight and repeated syndication relationships, as documented by Cai et al. (2018) and Hatfield et al. (2020), they possess both the strong incentives and the capabilities needed for tacit collusion in the provision of loans.

(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., 2021b). 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. Consequently, competing outside lenders are likely to be shied away from the deals, and then, existing creditors are allowed to hold up borrowers for ultra-high risk-adjusted yield spreads (e.g., Sharpe, 1990; Schenone, 2010; Santos and Winton, 2008).

3 Environment

The above empirical facts motivate us to develop a game-theoretic model of imperfectly competitive distressed-loan markets to estimate lender markups and decompose them

into three components: (i) the blocking power of incumbent creditors, (ii) market concentration among a few specialized lenders, and (iii) tacit collusion among these specialized lenders.

In the model, each period, banks of different types, together with non-bank institutions such as hedge funds and private equity funds, extend credit to distressed corporate borrowers facing heterogeneous demand curves.

3.1 Borrowers

Distressed Borrowers' Demand Curve for Loans. Our model features heterogeneous corporate borrowers, and each borrower is characterized by its size, A, and its demand curve type, $k \in \{1, \cdots, K\}$. Given a distressed borrower of size A and type k, it faces a downward-sloping demand curve:

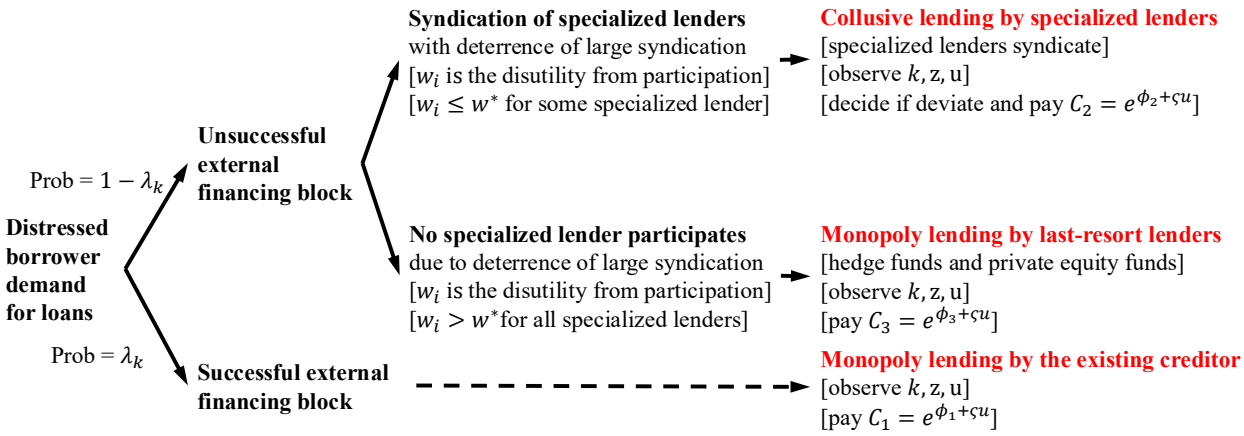
$$\ln\left(\frac{L}{A}\right) = \alpha_k - \varepsilon_k \ln(R) + \sigma z, \tag{2}$$

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 $\varepsilon_k > 1$.

In Appendix A, we provide a micro-foundation for the demand curve based on a standard optimization problem, in which distressed borrowers choose the optimal loan amount to maximize their gains while taking into account the borrowing costs driven not only by the risk-adjusted yield spread R, but also by the credit and liquidity risk premia, which in turn increase with L/A. As shown explicitly in Appendix A, the sensitivity of the credit and liquidity risk premia to the loan-to-asset ratio 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 possi-

Figure 3: Model timeline



ble 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 types of lenders, denoted by $l \in \{1, 2, 3\}$. The existing creditor is labeled as $l = 1$, the specialized lender as $l = 2$, and the last-resort non-specialized lender, such as hedge funds and private equity firms, as $l = 3$.

Existing creditors ($l = 1$) possess substantial blocking power that enables monopolistic lending, allowing them to prevent distressed firms from accessing external lenders or from forming syndications with a large number of specialized lenders, even when external financing would otherwise be allowed. As discussed in Section 2.3, this blocking power is strategically motivated and operates at two distinct stages of the distressed lending process. Beyond blocking external financing, existing creditors also have incentives to limit specialized lender participation in syndications to maintain control over the borrower, particularly during restructuring or liquidation. Excessive participation can heighten conflicts of interest, dilute monitoring incentives, and increase legal and coordination complexity, all of which erode the existing creditor's control and profitability.

There are several specialized lenders ($l = 2$) in the market, each deciding whether to participate in a syndicated loan to the distressed borrower. Participation in the syndication entails a lender-specific utility cost that arises from the existing creditor's deterrence. The strategic interaction among these specialized lenders is modeled as a Cournot competition, consistent with the literature on imperfect competition in credit markets (e.g., Corbae and Levine, 2024). Repeated syndication among a stable group of specialized lenders creates conditions conducive to tacit collusion.

Lenders of last resort, such as hedge funds and private equity firms, also extend credit monopolistically, but at substantially higher risk-adjusted yield spreads owing to their elevated funding costs.

Model Timeline. Our model uses a sequential game to describe the process through which distressed firms obtain loans, as illustrated in Figure 3. Distressed borrowers arrive in the market according to a Poisson process with arrival rate η. Borrowers are independently and identically distributed (i.i.d.), meaning the characteristics of one borrower are independent of others. A distressed borrower of type k and size A must first negotiate with its existing creditor, denoted as a lender of type $l = 1$, for go-ahead to seek external funding due to the creditor's blocking power. With probability λ_k, the existing creditor successfully blocks external financing, and the borrower receives the loan internally.

With probability $1 - \lambda_k$, the existing creditor fails to block external financing, allowing the borrower to seek funding from specialized lenders, denoted as lenders of type $l = 2$. There are $\overline{m}$ specialized lenders in the market, each deciding whether to participate in a syndicated loan to the distressed borrower. Participation in the syndication entails a lender-specific utility cost. 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, that is, those satisfying $w_i \leq w^*$, where w^* is the equilibrium threshold determined endogenously, form the syndicate and jointly determine the loan size based on the downward-sloping demand curve in (2).

It is possible that no specialized lender participates 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, denoted as lenders of type $l = 3$, extending credit at substantially higher risk-adjusted yield spreads due to their elevated funding costs. Similar to existing creditors, the last-resort lender exercises monopoly power over the distressed borrower.

Model Specifications on Credit Supply. Our model focuses on the competitive and strategic behavior of specialized lenders without imposing restrictive functional-form assumptions. We introduce two general specifications on the credit-supply side that capture the essential mechanisms while maintaining flexibility in functional form.

When extending a loan, the lender faces a downward-sloping demand curve as specified in (2) and chooses the loan size L to maximize profit, internalizing both the variable cost per unit of lending, $C_l(u)$, and the effect of L on the risk-adjusted yield spread, $\mathcal{R}l(L, A, k, z; L_{\text{other}})$, where L_{other} denotes the total loan amount provided by other specialized lenders. Here, $l \in \{1, 2, 3\}$ 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 origination. The lender's profit function is

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

where $x \equiv (z, u)$ denotes the vector of borrower-lender latent characteristics. The variable cost per unit of lending is specified as

$$C_l(u) \equiv e^{\phi_l + \varsigma u}, \tag{5}$$

where $u \sim N(0, 1)$ captures idiosyncratic latent cost shocks at the borrower-lender pair level.

The lender-specific utility cost of syndication participation, w_i, follows 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 reflects the existing creditor's ability to monopolize additional lending by blocking new entrants, the average cost parameter μ captures the creditor's capacity to limit the entry of specialized lenders into syndications. A higher μ corresponds to stronger deterrence.

4 Equilibrium

4.1 Existing Creditor's Problem

The existing creditor acts as a monopolistic lender to the borrower, choosing the loan size that maximizes its lending profit given the latent borrower type k and the vector of borrower-lender latent characteristics $x = (z, u)$. In this case with $l = 1$, the risk-adjusted

yield spread, $\mathcal{R}_1(L, A, k, z; 0)$, as in (4), is given by

$$\mathcal{R}_1(L, A, k, z; 0) \equiv \left(e^{\alpha_k + \sigma z} \frac{A}{L} \right)^{1/\varepsilon_k}, \tag{7}$$

which is obtained from the demand curve specified in equation (2).

Solving the lender's profit-maximization problem yields the following optimal outcomes:

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

where $h_l(k, x)$ has the following expression:

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

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 $\mathcal{H}_l(k)$ function has the following expression:

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

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.

4.2 Specialized Lender's Problem

Collusive Equilibrium and Collusion Capacity ξ. With probability $1 - \lambda_k$, the distressed borrower turns to specialized lenders, as illustrated in Figure 3. Each specialized lender then decides whether to participate in the syndicated loan by comparing its privately observed utility cost w of participation with the expected profit from lending before observing $x = (z, u)$, given the anticipated participation of other lenders. As shown below, the participation decision follows a threshold rule: only specialized lenders with utility costs below an endogenous cutoff w^* choose to join the syndicate.

Suppose that $m \in \{1, \ldots, \overline{m}\}$ specialized lenders join the syndicate. These m specialized lenders then engage in Cournot competition in loan origination. To capture their

strategic interaction, we consider a general collusive Nash equilibrium, which, in principle, nests two benchmark cases as special cases. The first is the perfect cartel benchmark, where specialized lenders fully coordinate, extend credit as a unified monopoly, and subsequently divide the total loan. This benchmark corresponds to explicit collusion, which can be sustained by binding agreements in practice. The second is the non-collusive Nash equilibrium, where specialized lenders compete independently, each maximizing its current profit given others' lending decisions, without considering future interactions.[9]

This collusive Nash equilibrium is both general and flexible and it captures a central structural feature of distressed loan markets discussed in (ii) of Section 2.3. Tacit collusion among a small set of specialized lenders arises naturally in distressed loan syndications. The data support this view (see the stylized facts in Section 2.2) as specialized lenders frequently meet in syndicates and form repeated relationships. An oligopolistic market structure combined with repeated interactions provides fertile ground for tacit collusion (e.g., Carrasco and Manso, 2006; Nocke and White, 2007; Hatfield et al., 2020).[10]

Within this environment, specialized lenders can sustain an intermediate competitive outcome through tacit collusion, supported solely by the threat of reversion to non-collusion as punishment for deviation, without any binding agreements. Intuitively, a specialized lender may increase its current profit by deviating from the collusive loan amount and decides whether to do so before observing $x = (z, u)$. However, the lender optimally refrains from deviation when the expected cost of future punishment exceeds the short-term benefit from deviation. Unlike explicit collusion, which relies on enforceable agreements and is subject to antitrust scrutiny, tacit collusion is sustained entirely by incentive-compatibility (IC) constraints. As a result, tacit collusion yields supra-competitive profits, higher than those under non-collusion but generally lower than those under explicit collusion, which corresponds to the perfect cartel outcome.

The sustainability of tacit collusion depends critically on the likelihood of punishment following deviation. A specialized lender can increase its current profit by deviating from the collusive loan amount L_2^C to a larger amount $L_2^D > L_2^C$, assuming all other $m-1$ lenders maintain L_2^C. However, such a deviation triggers a breakdown of collusion in the future with probability $\xi \in [0,1]$, reducing the lender's continuation value. The

[9] Both benchmarks are described in detail in Online Appendix 4.

[10] In credit markets dominated by a few large institutions, strategic competition 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 and warned that such coordination could distort competition by aligning interest rates, with lenders exchanging future cooperation for current restrictions on loan supply.

parameter ξ therefore captures the strength and credibility of punishment and, consequently, the degree of sustainability of tacit collusion. When ξ is close to zero, deviations are rarely punished, making deviation optimal and driving the equilibrium toward the non-collusive outcome, with L_2^C approaching the non-collusive Nash equilibrium loan amount L_2^N. Conversely, when ξ is close to one, deviations are almost surely punished, discouraging deviation behavior and shifting the equilibrium toward the perfect cartel outcome, with L_2^C approaching the perfect cartel loan amount L_2^M.[11]

Characterizing the Equilibrium. Formally, under the collusive loan amount L_2^C, each lender earns lending profit as defined in (4) with $l = 2$, with the risk-adjusted yield spread

$$\mathcal{R}_2(L_2^C, A, k, z; (m-1)L_2^C) \equiv \left(e^{\alpha_k + \sigma z} \frac{A}{m L_2^C} \right)^{1/\varepsilon_k}, \tag{12}$$

and the variable cost of $C_2(u) \equiv e^{\phi_2 + \varsigma u}$ per unit of loan supplied. This cost specification mirrors that of existing creditors, except that the average variable cost for specialized lenders, ϕ_2, may differ from that of existing creditors, ϕ_1. Such differences can arise from variations in expertise, borrower relationships, monitoring intensity, or other lender-specific characteristics.

We now characterize the equilibrium loan spread and loan amount, R_2^C and L_2^C, in the collusive equilibrium as functions of the punishment likelihood ξ and other structural parameters of the model. The first step is to derive the specialized lender's expected profits under collusion and deviation, averaged over the borrower-lender latent characteristics $x = (z, u)$. Exploiting the model's homotheticity property, we can express $L_2^C(A, k, x, m)$ as follows::

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

where $h_2(k, x)$ is defined in (9). The term $\mathcal{L}^C(A, k, m)$ is a function of borrower size A, borrower type k, and the number of specialized lenders in the syndicate m, to be determined in equilibrium.

Unlike the optimal loan amount, L_2^M, in the perfect-cartel benchmark or the equilibrium loan amount, L_2^N, in the non-collusive Nash equilibrium, L_2^C is not necessarily homogeneous of degree one in borrower size A, since specialized lenders decide whether

[11] Even when $\xi = 1$, the collusive equilibrium may not coincide with the perfect-cartel outcome if the continuation-value loss is insufficient to deter deviation. As lenders become perfectly patient and $\xi = 1$, the collusive outcome converges to the perfect cartel.

to deviate after observing A, and thus their deviation incentives depend on borrower size. Intuitively, when A is larger, the short-run gain from deviation becomes greater, making it more difficult to sustain tacit collusion at the same strength level.

Given the collusive loan supply of the syndicate characterized by (13), 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

$$\Pi_2^C(A,k,m)=\left[\left(\frac{1}{m\mathcal{L}^C(A,k,m)}\right)^{1/\varepsilon_k}-1\right]\mathcal{L}^C(A,k,m)\mathcal{H}_2(k)A, \tag{14}$$

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

If a specialized lender makes the decision to deviate, it will choose L_2^D to maximize its profit from the loan after observing $x=(z,u)$, taking as given that each of the other $m-1$ specialized lenders supplies L_2^C, characterized by (13). Formally, according to (4), it holds that

$$\begin{aligned}L_2^D(A,k,x,m;\mathcal{L}^C)&=\underset{L}{\operatorname{argmax}}\left[\mathcal{R}_2\left(L,A,k,z;(m-1)L_2^C\right)-e^{\phi_2+\varsigma u}\right]L\\&=\underset{L}{\operatorname{argmax}}\left[\left(e^{\alpha_k+\sigma z}\frac{A}{(m-1)L_2^C+L}\right)^{1/\varepsilon_k}-e^{\phi_2+\varsigma u}\right]L.\end{aligned} \tag{15}$$

This yields the solution for L_2^D as

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

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

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

The deviation incentive is captured by the difference $\Pi_2^D(A,k,m;\mathcal{L}^C)-\Pi_2^C(A,k,m)$. A higher value of $\Pi_2^D(A,k,m;\mathcal{L}^C)$ relative to $\Pi_2^C(A,k,m)$ indicates a stronger incentive to deviate from the collusive loan amount.

Next, we derive the continuation values under collusion and deviation. The difference between these continuation values provides the disciplining mechanism that deters specialized lenders from deviating and thereby sustains tacit collusion. Let A' denote

the size of a future borrower and k' its demand curve type. Along the collusive equilibrium path, a specialized lender that adheres to collusive lending in the current syndication expects to earn collusive profits from all future loans in which it participates. The corresponding continuation value is therefore

$$W^C = \frac{1}{1-\delta}\mathbb{E}^{A',k'}\left\{(1-\lambda_{k'})\,\mathbb{E}^{w',m'}\left[\left(\Pi_2^C(A',k',m') - w'\right)\mathbf{1}_{\{w'\leq w_C^*\}}\right]\right\}, \tag{17}$$

where $\delta \in (0,1)$ is the discount factor.

Equation (17) merits further explanation. First, for each future borrower, specialized lenders have the opportunity to lend only if the borrower's existing creditor fails to block its external financing access, which occurs with probability $1-\lambda_{k'}$. Second, a specialized lender's net gain from a loan equals its expected lending profit minus its participation cost, i.e., $\Pi_2^C(A',k',m') - w'$. Third, to realize this gain the lender must participate in the syndication, which happens only if its utility cost of participation, w', is below the endogenous cutoff w_C^*, itself determined in equilibrium. The indicator $\mathbf{1}_{\{w'\leq w_C^*\}}$ captures this condition. We treat w_C^* as given here and defer the explanation on how it is determined in the equilibrium to the end of the subsection. Fourth, because both the utility cost w' and the number of lenders in the future syndication m' are stochastic, the expected gain is computed over the joint distribution of w' and m'. Fifth, future borrowers are heterogeneous in size A' and demand curve type k', so we take expectations over their distribution as well.

In contrast, if a specialized lender deviates in the current loan syndication, its continuation value is

$$W^D = \xi W^N + (1-\xi)\,W^C, \tag{18}$$

where W^N is the continuation value in the non-collusive equilibrium, given by

$$W^N = \frac{1}{1-\delta}\mathbb{E}^{A',k'}\left\{(1-\lambda_{k'})\,\mathbb{E}^{w',m'}\left[\left(\Pi_2^N(A',k',m') - w'\right)\mathbf{1}_{\{w'\leq w_N^*\}}\right]\right\}. \tag{19}$$

The key difference between W^N and W^C is the anticipated profit from future distressed loans. If the punishment for deviation is triggered, specialized lenders supply their loans competitively in the non-collusive equilibrium and thus earn lower expected profits in all subsequent deals. To ensure that tacit collusion holds, the specialized lender's IC constraint below must hold, which in turn determines the collusive loan size $\mathcal{L}^C(A,k,m)$ defined in equation (13). Specifically, for a given cutoff point $\mathbb{L}^C(w_C^*)$, the IC feasible set $\mathbb{L}^C(w_C^*)$ consists of all the mappings $\mathcal{L}(A,k,m)$ from $\mathbb{A}\times\mathbb{K}\times\mathbb{M}\mapsto\mathbb{R}$ such that the

following three conditions are satisfied:

$$\mathcal{L}^M(A,k,m) \leq \mathcal{L}(A,k,m) \leq \mathcal{L}^N(A,k,m), \text{ and} \tag{20}$$

$$W^C - W^D \geq \Pi_2^D(A,k,m;\mathcal{L}) - \Pi_2^C(A,k,m), \text{ and} \tag{21}$$

$$w_C^* = \mathbb{E}^{A',k'}\left[\mathbb{E}^{m'}\left[\Pi_2^C(A',k',m')|m' \geq 1\right]\right]. \tag{22}$$

Condition (20) requires that the collusive loan supply lie between the perfect cartel benchmark and the non-collusive outcome in which specialized lenders behave competitively. Condition (21) enforces the incentive compatibility requirement, ensuring that no lender has an incentive to deviate. Condition (22) imposes the break-even condition that determines the equilibrium cutoff point w_C^*.

From relation (18), it follows that $W^C - W^D = \xi\left(W^C - W^N\right)$. Hence, the incentive compatibility condition (21) can be rewritten as

$$\xi\left(W^C - W^N\right) \geq \Pi_2^D(A,k,m;\mathcal{L}) - \Pi_2^C(A,k,m). \tag{23}$$

The IC feasible set $\mathbb{L}^C(w_C^*)$ depends on the cutoff w_C^* because W^C is a function of w_C^*.

The equilibrium collusive loan amount generally depends on borrower size A. In the IC constraint, the continuation value difference $\xi(W^C - W^N)$ is independent of A, whereas the profit difference $\Pi_2^D(A,k,m;\mathcal{L}^C) - \Pi_2^C(A,k,m)$ depends on A. Clearly, a larger value of ξ relaxes the IC constraint and thereby facilitates collusion, so $\mathcal{L}^C(A,k,m)$ is ultimately solved as a function of ξ and other primitive structural parameters.

Lastly, we characterize the specialized lender's syndication participation decision, determined by the endogenous threshold w_C^*. Analogously, w_N^* and w_M^* denote the participation thresholds in the non-collusive equilibrium and the perfect cartel benchmark, respectively. Each cutoff is endogenously determined by the break-even condition under which the lender is indifferent between participating and abstaining. A specialized lender participates if and only if its expected profit from syndication weakly exceeds its participation cost. Accordingly, the cutoff w_s^* satisfies

$$w_s^* = \mathbb{E}^{A',k'}\{\mathbb{E}^{m'}\left[\Pi_2^s(A',k',m')|m' \geq 1\right]\}, \quad s \in \{C,N,M\} \tag{24}$$

where $\Pi_2^s(A,k,m)$ denotes the equilibrium expected lending profit when the syndicate operates under equilibrium s, with $s = C$ for the collusive equilibrium, $s = N$ for the non-collusive equilibrium, and $s = M$ for the perfect cartel benchmark.

Since a specialized lender does not know the exact number of lenders in the syndica-

tion before it enters into the syndicate group, it has to take the expectation over the distribution of m. The utility cost, w, follows an exponential distribution with CDF defined in equation (6). Hence, for a participation threshold w^*, the likelihood for a given specialized lender to participate in a syndication is $F(w^*;\mu)$. Since there are $\overline{m}$ specialized lenders in the market and each makes i.i.d. draw of its own w, the number of specialized lenders in a syndicate group, m, follows a multinominal distribution:

$$q_s(m|w_s^*) = \binom{\overline{m}}{m} F(w_s^*;\mu)^m \left[1 - F(w_s^*;\mu)\right]^{\overline{m}-m}, \quad \text{with } s \in \{C, N, M\}. \tag{25}$$

By substituting the profits $\Pi_2^N(A,k,m)$ in (13) and the probabilities $q_s(m|w_s^*)$ in (25) for $s = N$ and all m into condition (24), we obtain the equilibrium cutoff w_N^* in the case of competitive syndication, that is, the non-collusive equilibrium. Given w_N^*, substituting (14) and (25) for $s = C$ and all m into condition (24) yields the equilibrium cutoff w_C^* and the corresponding optimal loan supply, characterized by $\mathcal{L}^C(A,k,m)$, in the collusive equilibrium. By substituting the profits $\Pi_2^M(A,k,m)$ in (11) and the probabilities $q_s(m|w_s^*)$ in (25) with $s = M$ and all m into condition (24), we obtain the equilibrium cutoff w_M^* corresponding to the perfect cartel benchmark.

Existence and Uniqueness of the Value-Maximizing Collusive Nash Equilibrium. We consider the collusive syndication lending outcome characterized by the syndication participation threshold w_C^* and the associated lending policy $\mathcal{L}^C(\cdot)$, which satisfy the following conditions:

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

(ii) among all incentive-compatible lending outcomes satisfying conditions (20), (22), and (23), w_C^* and $\mathcal{L}^C(\cdot)$ maximize the specialized lenders continuation value W^C.

The following proposition formally 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 the identification of the structural model. The proof is presented in Appendix B.

Proposition 4.1 *There exists at least one pair of $\mathcal{L}^C(\cdot)$ and w_C^* that characterizes a collusive Nash equilibrium of the model. Among all collusive Nash equilibria, the maximal continuation value W^C is attained at a 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 $x = (z, u)$. In this case with $l = 3$, the risk-adjusted yield spread, $\mathcal{R}_3(L, A, k, z; 0)$, as in (4), is given by

$$\mathcal{R}_3(L, A, k, z; 0) \equiv \left(e^{\alpha_k + \sigma z} \frac{A}{L} \right)^{1/\varepsilon_k}, \tag{26}$$

which is obtained from the demand curve specified in equation (2).

Solving the lender's profit-maximization problem yields the following optimal outcomes:

$$R_3(k, x) = \frac{\varepsilon_k}{\varepsilon_k - 1} e^{\phi_3 + \varsigma u} \quad \text{and} \quad L_3(A, k, x) = \left(1 - \frac{1}{\varepsilon_k} \right)^{\varepsilon_k} h_3(k, x) A, \tag{27}$$

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

$$\Pi_3(A, k) = \frac{1}{\varepsilon_k} \left(1 - \frac{1}{\varepsilon_k} \right)^{\varepsilon_k - 1} \mathcal{H}_3(k) A, \tag{28}$$

where $\mathcal{H}_3(k)$ is defined in (11). Although equations (27) and (28) resemble (8) and (10), they differ in the variable cost of lending, ϕ, and consequently in the constants h and $\mathcal{H}$.

5 Data Sample

Academics as well as practitioners commonly refer distressed loans as loans provided to firms that are either deeply distressed with the likely prospect of defaulting on its obligations or that are already bankrupt (Altman, Hotchkiss, and Wang, 2019). For our study, we construct a comprehensive data sample that includes bank loans to both financially distressed but not yet bankrupt U.S. public firms (i.e., highly-speculative loans) from 2001 to 2017, and public firms already in Chapter 11 bankruptcy (i.e., DIP loans) from 2002 to 2019.

5.1 Highly-Speculative Loans

We first assemble a data set of loans to financially distressed firms that are not yet in bankruptcy. The academic literature proposes several measures for identifying these firms. For our study, 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[12] or (2) the firm's S&P credit rating drops to CCC+ or lower,[13] whichever occurs first. 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,[14] whichever occurs first.

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 measured by the all-in spread drawn (AISD), which is the sum of LIBOR spread and annual fee, and loans that are unsecured or sub-

[12]Prior studies refer bonds whose yield spread above riskfree rate is over 1000 bps as distressed bonds (Altman et al., 2019)

[13]Loans that are issued by firms with CCC+ or lower ratings can no longer be widely held by institutional investors such as the Collateralized Loan Obligations (CLOs), the most important type of investors in the leveraged loan market, because there are limitations on the amount of CCC-rated loans that can be included in the underlying collateral pool of CLOs (typically 7.5% of the collateral pool). If any, CLOs are net sellers of CCC-rated loans.

[14]Bankruptcy filings, including both Chapter 11 and Chapter 7 filings, by all U.S. public firms from 2001 to 2019 are obtained from New Generation Research's Bankruptcydata.com.

ordinated, we have a final sample of 520 loan facilities (342 packages) in 185 distressed periods.

We consolidate all financial institutions to the parent company. For example, JP Morgan Securities would carry the same unique institution ID as JP Morgan & Co. Moreover, we consider institutions' M&As that occurred in our sample period and consolidate the target and the acquirer into one entity after the transaction. Moreover, we remove entities that are special purpose investment vehicles and structured products such as CLOs and CDOs, which have little direct involvement in the primary market of distressed loans.

Using historical loan issuance information in Dealscan, we are able to determine whether a major lender is an existing lender to a firm—that is, a lender of the distressed loan is also a lender in an earlier loan that has not yet matured. We also determine whether a lender is a private equity fund or hedge fund by searching the lender's website and industry publications (Jiang, Li, and Wang, 2012). Next, we identify the 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. Finally, we retrieve firms' key financial information immediately before loan issuance from Compustat.

We define three types of distressed loans: existing-creditor loans (type-1 loans), specialized-lender loans (type-2 loans), and last-resort loans (type-3 loans) (see Section 2.2). We remove 47 facilities that cannot be classified into any of the above three types. Among the 441 loan facilities in our sample before adjusting for credit- and liquidity-risk components from spreads and removing those with negative adjusted spreads, the type-2 loan is the most dominant type, accounting for 76.2% of the distressed loans, while the type-1 and type-3 loan account for 11.8% and 12.0%, respectively. Panel A of Table 3 presents the summary statistics of the sample of distressed loans.

5.2 Debtor-In-Possession (DIP) Loans

A U.S. firm filing for Chapter 11 bankruptcy can obtain post-petition financing, commonly known as debtor-in-possession (DIP) financing, to support working capital and pay expenses in bankruptcy 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

Table 2: Summary Statistics

This table presents the summary statistics of our sample firms. Our sample consists of 441 distressed loans (in Panel A) and 436 DIP 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, Liabilities and Sales are book assets, book liabilities, and revenue measured in millions of dollars, respectively. Leverage is the ratio of book liabilities to book assets. ROA 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 amount (L) is in millions of dollars. L/A is the ratio of DIP amount to book assets. AISD (R) is all-in-spread drawn 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.

	N	Mean	Std	25%	Median	75%
Panel A: Distressed Loans						
Assets	441	7,762	11,661	548	2,593	10,292
Liabilities	441	7,772	13,123	557	2,589	9,951
Leverage	441	1.053	0.446	0.797	0.950	1.172
ROA	441	0.067	0.133	0.037	0.075	0.114
PP&E/assets	441	0.378	0.225	0.172	0.355	0.528
Cash/assets	441	0.061	0.066	0.011	0.035	0.086
Loan maturity	441	48.846	20.951	35.000	48.000	60.000
Loan amount (L)	441	430.552	631.420	70.000	200.000	500.000
L/A	441	0.130	0.142	0.033	0.084	0.178
Risk-adjusted spread	441	337.450	207.120	201.6	292.1	447.2
Number of lenders	441	3.789	2.855	2	3	5
Loan type 1	441	0.118	0.323	0	0	0
Loan type 2	441	0.762	0.426	1	1	1
Loan type 3	441	0.120	0.326	0	0	0
Loan type 1 (# of lenders)	52	1	0	1	1	1
Loan type 2 (# of lenders)	336	4.307	2.700	2	4	5
Loan type 3 (# of lenders)	53	3.245	3.491	2	2	2
Number of specialized lenders	441	2.351	1.678	1	2	3
Panel B: 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
ROA	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	718.063	379.247	417.400	667.400	967.400
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

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 as shown by Eckbo et al. (2023).

Our initial study sample, similar to that used in 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.

Similar to highly-speculative loans, we define three types of DIP loans: existing-creditor loans (type-1 loans), specialized-lender loans (type-2 loans), and last-resort loans (type-3 loans). We remove 54 DIP loans that cannot be classified into any of the above three types.[15] Table 2, Panel B, presents the summary statistics of our sample firms which obtained DIP-loan packages. In the 436 loan facilities in our final sample, the 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. Table 2, Panel B, presents the summary statistics of our sample of DIP loans.

5.3 Measuring Risk-Adjusted Loan Yield Spreads

To measure the risk-adjusted yield spread, we estimate the credit and liquidity risk components based on various databases. To estimate the credit risk component in the yield spread of highly-speculative loans, we closely follow the parity relation between credit default swap (CDS) spreads and bond credit spreads derived by Duffie (1999).[16] We exert more caution in estimating the CDS recovery rate, accounting for heterogeneity more carefully than is typical in the literature (e.g., Longstaff et al., 2005). The historical information regarding the recovery rates of unsecured bonds is provided by the NYU-Salomon Center Default database.[17] The historical information on the loan recovery rates is obtained from Badoer et al. (2019), who use Moody's Default and Recovery Database to measure ultimate nominal recoveries at the completion of a debt restructuring to compile recovery statistics by industry and year. We estimate the credit risk component in the yield spread of DIP loans using Dealscan data. Following this, we estimate the

[15]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.

[16]Blanco et al. (2005) show that the parity relation derived by Duffie (1999) holds well among investment-grade bonds.

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

liquidity risk component in the yield spread of highly-speculative loans and DIP loans, utilizing data from the Loan Trading Database, often referred to as "LSTA/LPS Mark-to-Market Pricing Data." Details on the construction of the risk-adjusted yield spread are provided in the Online Appendix 1.1.

6 Estimation

6.1 Likelihood Function and Identification Strategy

Likelihood. Given a classification of all observations into different demand curves and size groups (i.e., give a realization of $\{k_i\}_{i=1}^N$), the observable variables include $y_i \equiv (m_i, l_i, \ln(L_i/A_i), \ln(R_i))$ for deals indexed by $i = 1, \cdots, N$. Here, l_i is the type of lenders in deal i, m_i is the number of specialized lenders, L_i/A_i is the loan amount normalized by the borrower's asset size, and R_i is the risk-adjusted loan yield spread. We denote by θ the parameter vector that contains all the model parameters $\{\alpha_k, \varepsilon_k, \lambda_k\}_{k=1}^K$, $\{\gamma_k, \beta_k\}_{k=2}^K$, σ, ς, ξ, μ, ϕ_1, ϕ_2, and ϕ_3.

Conditioning on a latent demand curve classification $\{k_i\}_{i=1}^N$, the model-implied log-likelihood of these observable variables can be factorized as follows:

$$P\left(\{y_i\}_{i=1}^N | \theta, \{k_i\}_{i=1}^N\right) = \prod_{i=1}^N P\left(y_i | \theta, k_i\right), \tag{29}$$

$$\begin{aligned} \text{where } \; P\left(y_i|\theta,k_i\right) &= P\left(l_i|\theta,k_i\right) \times P\left(m_i|\theta,l_i,k_i\right) \times P\left(\ln(L_i/A_i)|\theta,l_i,m_i,k_i\right) \\ &\quad \times P\left(\ln(R_i)|\theta,\ln(L_i/A_i),l_i,m_i,k_i\right). \end{aligned} \tag{30}$$

We summarize below the individual component of the likelihood function in Equation (30) for each observation. First, the likelihood of $\ln(R_i)$, conditioning on the parameters θ and the variables $\ln(L_i/A_i), l_i, m_i, k_i$, is a normal distribution with mean $\alpha_{k_i} - \varepsilon_{k_i} \ln(R_i)$ and variance σ^2. Thus, $P\left(\ln(R_i)|\theta, \ln(L_i/A_i), l_i, m_i, k_i\right)$ can be rewritten as $P\left(\ln(R_i)|\alpha_{k_i}, \varepsilon_{k_i}, \sigma, \ln(L_i/A_i), l_i, m_i, k_i\right)$, which identifies α_k and ε_k for $k \in \{1, \cdots, K\}$, as well as σ.

Second, the likelihood of $\ln(L_i/A_i)$, conditioning on the parameters θ and the variables l_i, m_i, k_i, is a normal distribution with mean $\ln \widehat{L}(k_i, m_i) + \alpha_{k_i} - \varepsilon_{k_i}\phi_{l_i}$ and variance ς^2. Thus, given that $\{\alpha_k, \varepsilon_k\}_{k=1}^K$ and σ, the conditional likelihood $P\left(\ln(L_i/A_i)|\theta, l_i, m_i, k_i\right)$ and its associated data identify ξ and $\{\phi_l\}_{l=1}^3$. Importantly, $\widehat{L}(k_i, m_i)$ is independent of the disutility of participating the syndication, w_i, given k_i and m_i, and thus, it doesn't depend on the parameter μ. Moreover, it is also worth noting that, ϕ_l does not show up in

$\widehat{L}(k_i, m_i)$ but only shows up in the scaling factor (i.e., the exponential term $e^{\alpha_k - \varepsilon_k \phi_l - \varepsilon_k \zeta u + \sigma z}$). That means, ϕ_l does not affect the ratio, $\frac{E[L/A_{m>1}]}{E[L/A_{m=1}]}$, where $E[L/A_{m>1}]$ and $E[L/A_{m=1}]$ are the average relative loan size of the cases with $m > 1$ and those $m = 1$, respectively. This ratio is powerful in identifying ξ, because as we take the ratio, ϕ_l drops out as the scaling factor cancels out, and the ratio decreases as the collusion capacity ξ increases. The rationale of identifying ξ using this ratio is further discussed in Figures 4 and 5 below.

Third, the likelihood of m_i, conditioning on the parameters θ and the variables l_i and k_i, is a multinomial distribution. Specifically, when $l_i = 1$ or $l_i = 3$, it holds that $P(m_i = 0|\theta, l_i, k_i) = 1$; when $l_i = 2$, it holds that $P(m_i|\theta, l_i, k_i) = \begin{pmatrix} M \\ m_i \end{pmatrix} F(w_C^*)^{m_i} \left[1 - F(w_C^*)\right]^{M - m_i}$. Conditioning on the parameters $\{\alpha_k, \varepsilon_k\}_{k=1}^K$, $\{\phi_l\}_{l=1}^3$, and ξ, which have already been identified using other conditional likelihoods, and the variables l_i and k_i, the equilibrium cutoff point w_C^* only depends on the parameter μ. Therefore, $P(m_i|\theta, l_i, k_i)$ identifies μ.

Lastly, we know that

$$
\begin{aligned}
P(l_i = 1|\theta, k_i) &= \lambda_{k_i}, \\
P(l_i = 2|\theta, k_i) &= (1 - \lambda_{k_i}) \left\{1 - [1 - F(w_C^*)]^M\right\}, \\
P(l_i = 3|\theta, k_i) &= (1 - \lambda_{k_i}) [1 - F(w_C^*)]^M.
\end{aligned}
$$

Thus, it is clear that $P(l_i|\theta, k_i)$ identifies $\{\lambda_k\}_{k=1}^K$.

Bayesian estimation. Using the Baysian approach, we estimate the posterior distribution for the variables of interest, $P\left(\{k_i\}_{i=1}^N, \theta|\{y_i\}_{i=1}^N\right)$. This posterior distribution describes the estimate of model parameters and the augmented latent cluster variable of each deal based on the observed variables. Based on Hammersley-Clifford Theorem (Besag, 1974), this posterior distribution is fully characterized by two conditional distributions $P\left(\theta|\{y_i\}_{i=1}^N, \{k_i\}_{i=1}^N\right)$ and $P\left(\{k_i\}_{i=1}^N|\theta, \{y_i\}_{i=1}^N\right)$, which in turn can be broken down into more lower dimensional conditional distributions.

Conditioning on $\{k_i\}_{i=1}^N$, the distribution $P\left(\theta|\{y_i\}_{i=1}^N, \{k_i\}_{i=1}^N\right)$ is determined by the distribution $P\left(\theta|\{k_i\}_{i=1}^N\right)$ and the likelihood function, $P\left(\{y_i\}_{i=1}^N|\theta, \{k_i\}_{i=1}^N\right)$, implied by the model solution. Specifically,

$$
P\left(\theta|\{y_i\}_{i=1}^N, \{k_i\}_{i=1}^N\right) \propto P\left(\theta|\{k_i\}_{i=1}^N\right) \times P\left(\{y_i\}_{i=1}^N|\theta, \{k_i\}_{i=1}^N\right) \tag{31}
$$

Meanwhile, conditioning on θ, the distribution $P\left(\{k_i\}_{i=1}^N|\theta, \{y_i\}_{i=1}^N\right)$ is determined by

$P\left(\{k_i\}_{i=1}^N|\theta\right)$ and the likelihood function $P\left(\{y_i\}_{i=1}^N|\theta,\{k_i\}_{i=1}^N\right)$:

$$P\left(\{k_i\}_{i=1}^N|\theta,\{y_i\}_{i=1}^N\right) \propto P\left(\{k_i\}_{i=1}^N|\theta\right) \times P\left(\{y_i\}_{i=1}^N|\theta,\{k_i\}_{i=1}^N\right) \tag{32}$$

6.2 MCMC Estimator

To implement MCMC estimator, for each loan i in the data, we define a vector π_i of dimension K (i.e., the number of possible demand curve) so that the kth element in the vector describes the probability of this deal belonging to demand curve k so that $\pi_{ik} \geq 0$ and $\sum_{k=1}^K \pi_{ik} = 1$. Then we apply the Metropolis-Hastings algorithm with the following procedure.

Step 1: In each iteration g, we first update $\pi_i^{(g)}$ for each deal i using the Bayes rule for classification based on outputs from the last iteration round $g-1$:

$$\pi_{ik}^{(g)} = \frac{\pi_{ik}^{(g-1)} P\left(y_i|\theta^{(g-1)}, k_i = k\right)}{\sum_{j=1}^K \pi_{ij}^{(g-1)} P\left(y_i|\theta^{(g-1)}, k_i = j\right)} \tag{33}$$

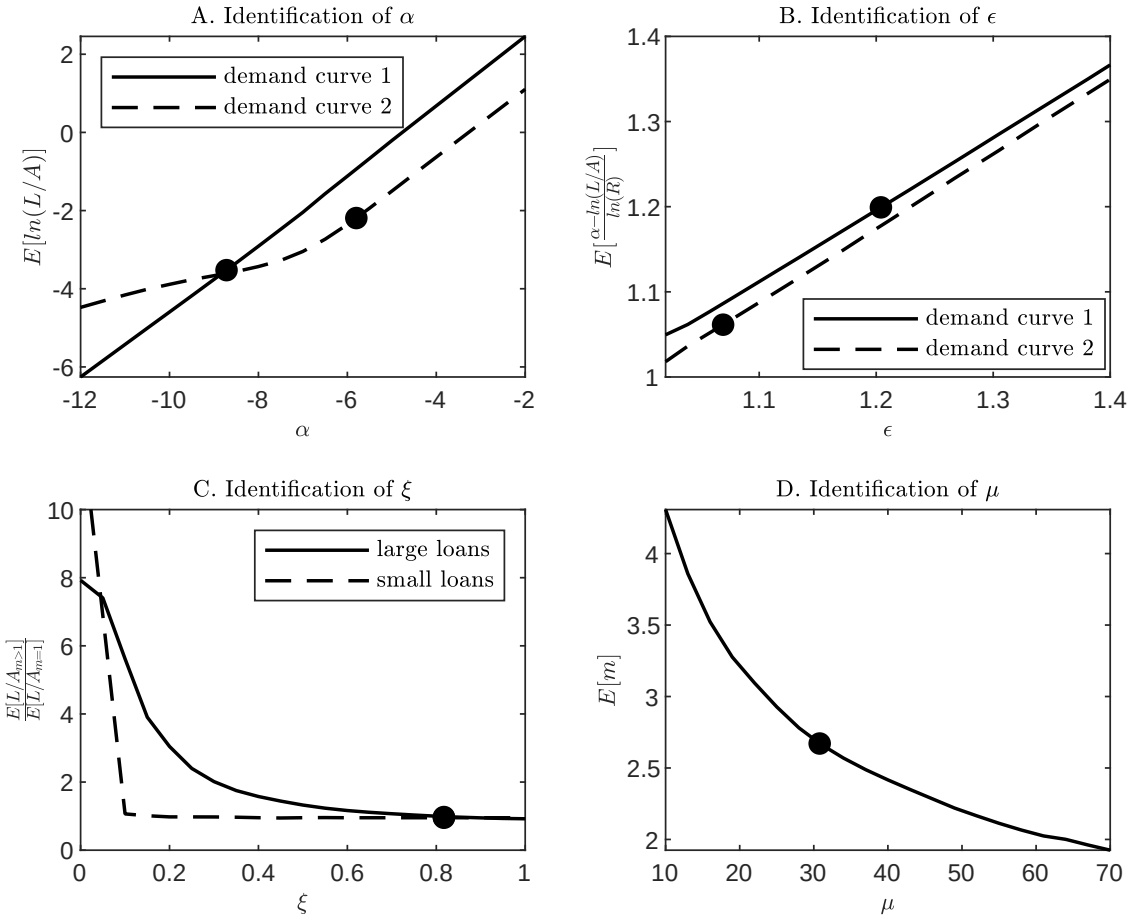
where $\pi_{ik}^{(g-1)}$ is the (posterior) probability of $k_i = k$, determined in the previous iteration (i.e., iteration $g-1$), and $P\left(y_i|\theta, k_i = k\right)$ is the likelihood function of observables evaluated at the parameter values simulated from the previous iteration (i.e., iteration $g-1$). We then follow the SEM algorithm (Celeux, 1985; Celeux and Diebolt, 1992) and draw the realization of $k_i^{(g)}$ from the multinomial distributions with weights in Equation (33). We throw out the draw and repeat this step if for any cluster k, the total number of deals assigned to this cluster is less than a cutoff (e.g., 3%).

Step 2: In the same iteration g, we then update other parameters in θ using the random walk Metropolis-Hastings algorithm based on the updated draws of $\{k_i^{(g)}\}_{i=1}^N$ from step 1. We compute the acceptance/rejection threshold:

$$\alpha\left(\theta^{(g)}, \theta^{(g-1)}\right) = min\left\{\frac{P\left(\theta^{(g)}|\{k_i^{(g)}\}_{i=1}^N\right)\prod_{i=1}^N P\left(y_i|\theta^{(g)}, k_i^{(g)} = k\right)}{P\left(\theta^{(g-1)}|\{k_i^{(g)}\}_{i=1}^N\right)\prod_{i=1}^N P\left(y_i|\theta^{(g)}, k_i^{(g)} = k\right)}, 1\right\}$$

where $\theta^{(g-1)}$ is the parameter vector from the last iteration, and $\theta^{(g)} = \theta^{(g-1)} + \Sigma\epsilon$ is the vector of proposed parameters.

Figure 4: Identification of parameters for the market of distressed loans



Step 3: In next iteration (i.e., iteration $g+1$), we repeat the procedure in step 1 and step 2 by simulating the classification realization $k_i^{(g+1)}$ according to the updated (posterior) probabilities $\pi_{ik}^{(g+1)}$ for all i, k and simulating the model parameters from the posterior distribution $P\left(\theta|\{y_i\}_{i=1}^N, \{k_i^{(g+1)}\}_{i=1}^N\right)$.

6.3 Identification of Parameters

In this section, we first discuss what empirical patterns in the data help the MCMC estimator to identify model parameters. We then present the estimation results and our empirical findings for the two distressed loan markets.

Figures 4 and 5 explain the identification results for the distressed loans and DIP loans, respectively. The parameter α_k for $k = 1, \cdots, K$ controls the intercept of the demand curve k, and thus the average loan size associated with each demand curve is

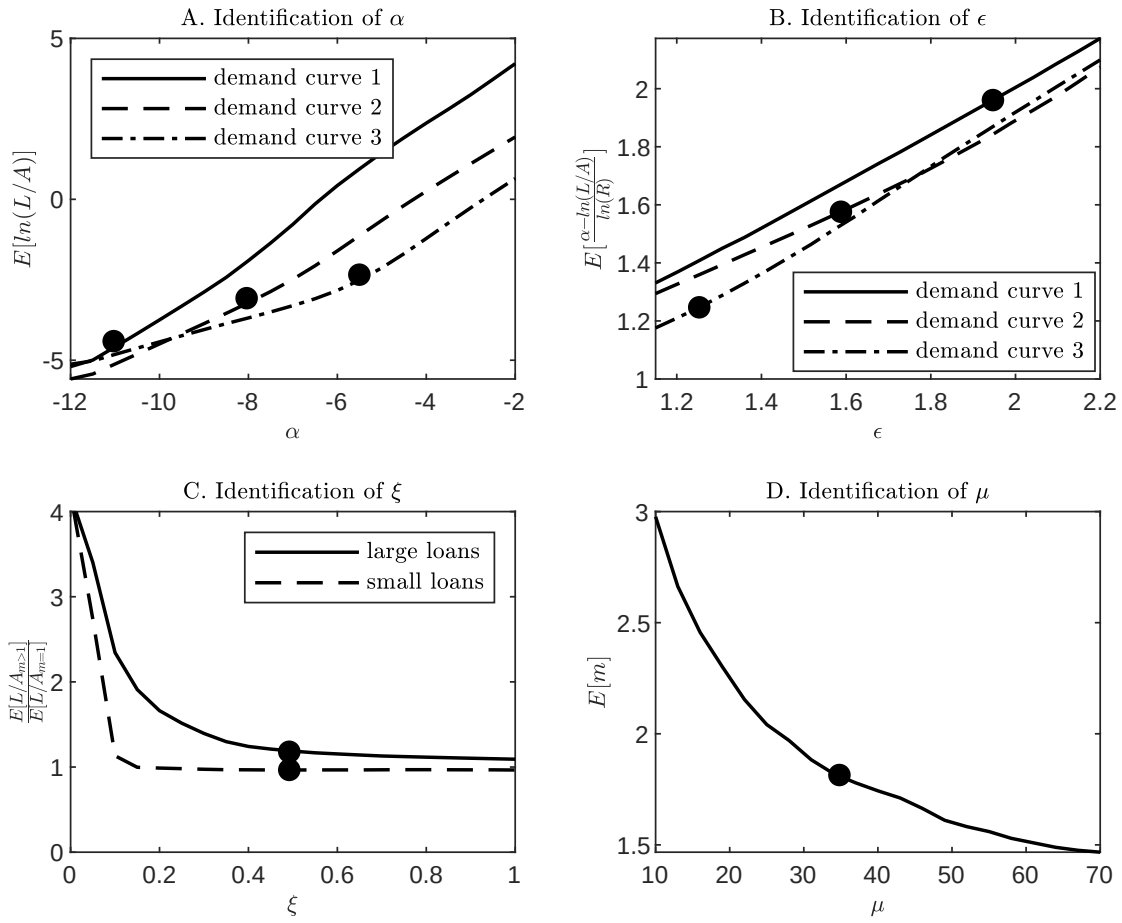
informative to identify this parameter. To illustrate this idea, we vary the value of α_k and solve the model for different values of α_k while keeping other model parameters at their baseline estimated values. We compute the model-implied average loan size, measured as the average logarithm of L/A, for each demand curve k, and examine how $\mathbb{E}[\ln(L/A)]$ varies with the value of α_k. Panel A of Figure 4 depicts the results for the distressed loan sample. For both demand curves, we observe that a higher α leads to a larger loan size, and the two dots represent the estimated value of α_k for $k \in \{1, \cdots, K\}$.

The parameter ε_k controls the elasticity of demand curve k, and the demand function specified in (2) suggests that this parameter is mainly identified by the slope of demand curve k. With the estimated intercept α_k, we compute the model-implied slope of demand curve k as $\mathbb{E}[\frac{\alpha_k - \ln(L/A)}{\ln(R)}]$, and we investigate how it varies as ε_k changes. Panel B of Figure 4 reveals that the model-implied demand curve slope monotonically increases with ε_k, showing that demand elasticity indeed rises as ε_k goes up.

A key parameter in our model, ξ, controls the tacit coordination among specialized lenders. In case of perfect collusion, lenders in a syndicate group coordinate as a cartel, and thus the total loan amount lent by the cartel equals the loan amount lent by a monopolistic lender. However, as collusion intensity falls, syndicated lenders lend more aggressively, leading to larger loan amount by the syndicate group than that by a monopolistic lender. As a result, the ratio of the average relative loan size made by a syndicate lender group with two or more specialized lenders to the average relative loan size made by a single monopolistic specialized lender, denoted by $\frac{\mathbb{E}[L/A_{m>1}]}{\mathbb{E}[L/A_{m=1}]}$, helps pin down ξ. Clearly, as ξ increases, this ratio declines. Two important things are worth noting here. First, when the profits from deviation are large enough, even the toughest punishment (i.e., $\xi = 1$) cannot fully restore perfect collusion, and therefore it is possible to observe the loan size ratio to remain above one even if $\xi = 1$. Second, collusion is harder to achieve in face of large borrowers, because profits from deviation increase as the demand grows. As a result, the model suggests that the loan size ratio is higher for large borrowers than for small borrowers given the level of ξ.

Panel C of Figure 4 illustrates how the loan size ratio varies with ξ for small borrowers by the dashed line and large borrowers by the solid line. With a ξ being around 0.2, the loan size ratio is already quite close to one, both in the model and in the data. We, however, observe that the loan size ratio is monotonically decreasing as ξ increases for loans made to large borrowers, and even with $\xi = 1$, the loan size ratio is still above one. The lines suggest that the parameter ξ is well identified in our estimation and the identification is mainly gained among larger borrowers. Since we estimate ξ using a likelihood-based approach, its estimated value is also affected by other observable vari-

Figure 5: Identification of parameters for the market of DIP loans



ables such as the loan size, the risk-adjusted yield spread, and the number of specialized lenders, and thus the loan size ratio is not the only factor that pins down ξ.

The parameter μ determines the average disutility of participating in the syndication by specialized lenders. Intuitively, when μ is low, more specialized lenders find it profitable to participate in forming the syndication and thus we expect to observe a larger syndicate group, m, in the data. Panel D of Figure 4 shows that the average number of specialized lenders in a syndication monotonically decreases as the average disutility of participation, μ, rises.

The fraction of loan deals financed by the existsing lender helps identify the parameter λ_κ. This linkage is established exogenously in the model by assuming that there is a probability λ_κ that the existing lender has the exclusive right to provide the financing and thus block the firm from borrowing from outside lenders.

Different type of lenders (i.e., existing creditors, specialized lenders, and lenders

of the last resort) may incur different variable costs. Part of the spread R is used to compensate for these variable costs. By comparing R across deals financed by different types of lenders, after controlling for the number of lenders involved, we can identify and estimate the parameter ϕ_l for existing creditors ($l = 1$), specialized lenders ($l = 2$), and lenders of the last resort ($l = 3$).

6.4 Estimation Results

MCMC estimator generates Markov chains for each model parameter and the augmented variables. We first present the estimation of demand curve classification. For each loan deal i in our sample, our estimator assigns it a vector $z_i^{(g)}$ that describes the likelihood of the deal belonging to each demand curve in the gth iteration on the MCMC chain, as specified in Equation (33). We take $z_i^{(g^*)}$ for the iteration g^* that generates the highest likelihood over the MCMC chain and classify loan i to the demand curve associated with the highest probability in the vector $z_i^{(g^*)}$. Based on the classification results, Figures 6 depicts the demand curves for the distressed loan sample and DIP loan sample, respectively. Each point in the figure represents an observation of loan, and the size of the points indicts the borrower's size. Points with the same color are classified as being on the same demand curve, and the straight lines depict the estimated demand curves. Our estimates suggest that, there are two statistically distinct demand curves in the distressed loan sample and three demand curves in the DIP loan sample. As we discussed above, the classification is performed based on the full likelihood of demand and supply in the model equilibrium and thus it differs from a simple classification based on the observed loan size $ln\left(\frac{L}{A}\right)$ and spread $ln\left(R\right)$. To illustrate this point, we also run an OLS regression by pooling together all observations on one demand curve. The dotted line plots the line of best-fit from the OLS regression. We find that the slope coefficient from OLS regression, which captures the elasticity of demand, is economically small and statistically insignificant from zero, which strongly contrasts the estimated elasticity of demand in our baseline results where classification of observations to different demand curves are jointly estimated with the demand curve coefficients. In both samples, borrowers on the demand curve 1 have a lower intercept of loan size but a similar (for distressed loans) or higher (for DIP loans) price elasticity of loan demand compared with those on demand curve 2 or 3. It indicates that borrowers on demand curve 1 have a lower level of overall demand for loan (relative to their size) and they are more sensitive to the loan price. Empirically, we find that borrowers on the bottom demand curve are also larger in size and have higher total revenues, which may explain partly the differ-

ence we identify in their demand curves.

Besides the classification of clusters and the associated demand curves, the MCMC estimator also delivers the posterior distribution of each model parameter. We report in Tables 3 the point estimate and the standard errors of each parameter for two samples respectively. The point estimate is taken as the parameter set that produces the highest likelihood along the chain, and the standard errors is computed as the standard deviation of the parameter draws along the chain.

The likelihood of punishment on deviation, ξ, is estimated to be 0.817 for distressed loans. It suggests that if a specialist lender deviates from the perceived cartel equilibrium, it will be pushed into a non-collusive equilibrium with 82% of chance. This parameter controls the collusion intensity in the model and a value of 0.817 implies a high level of tacit coordination among specialists. Our estimates show that the punishment on deviation is also sizeable for DIP loans with ξ estimated to be 0.492. ξ is estimated with relatively small standard errors in both samples, suggesting that the data pattern strongly rejects a model without tacit coordination among specialist lenders. As we discussed above, the ratio of loan size made by a syndicate group of lenders to the loan size made by a monopolistic lender disciplines the identification of tacit coordination among specialist lenders. Stronger coordination leads to a low loan size ratio, consistent with the data.

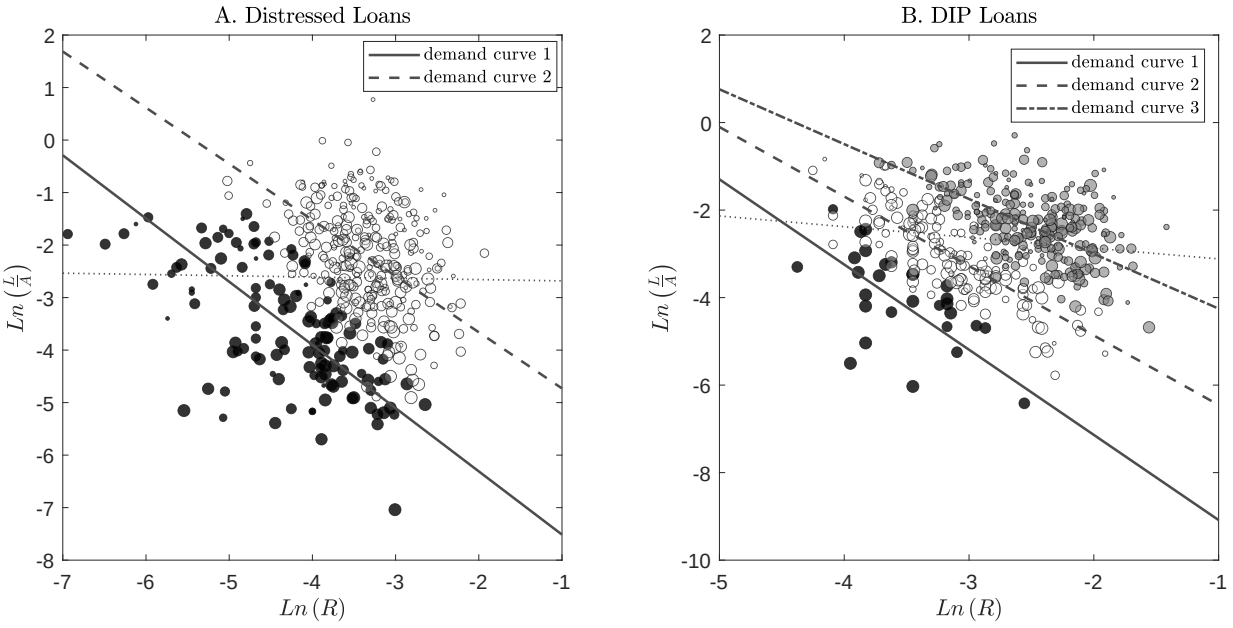
Our estimates of ς and σ show that unobservable heterogeneity, possibly driven by the lender-side and borrower-side shocks, is important in explaining the cross-sectional variation of the observed loan size and spread. A simple variance decomposition suggests that with the estimated unobservable heterogeneity, our model is able to explain 57% (40%) of variation in $ln(\frac{L}{A})$ and 40% (34%) of variation in $ln(R)$ for the DIP loan sample (distressed loan sample).

It is also interesting to note that the lenders' participation cost, μ, is estimated to be higher in the DIP market. A crucial determinant of the participation cost is the blocking power by existing lenders (Eckbo et al., 2023): if the existing lender has a strong power in blocking the borrower from reaching out to other lenders even when it does not make the loan to the borrower, then such blocking power can manifest as a large estimated participation cost born by specialist lenders (i.e., it is more difficult for specialist lenders to participate).

The mid panel of Tables 3 reports the lender-specific variable costs, which reflect the costs associated with lending to distressed firms. Monitoring cost and costs of lender participating in the restructuring process can be such variable costs. For example, as a distressed borrower approaches bankruptcy or is already in bankruptcy, lenders need

Figure 6: Demand Curves by Clusters

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, specified in Equation 2. We choose the optimal number of demand curves to estimate following the Lo-Mendell-Rubin tests, and our estimates suggest that there are two statistically distinct demand curves in the distressed loan sample and three demand curves in the DIP loan sample. The dotted line depicts the line of best-fit from an OLS regression that pool together all observations on only one demand curve. Panel (a) depicts the classification in the distressed loan market and panel (b) depicts the classification in the DIP market.



to pay close attention to the borrower's business operations and legal challenges in the court process. The fact that the estimated variable costs of DIP loans are much higher than those for distressed loans is consistent with more uncertainties faced by lenders in bankruptcy court.

An interesting evidence that stands out in the DIP loan sample is that the estimated variable costs are about 150-160 bps for existing lenders and specialist lenders but about 200 bps for lenders of last-resort (mostly hedge funds). Unlike the existing lenders who possess information advantage or the specialist lenders who have expertise in this market, hedge funds are rarely frequent players in this market. Most of them appear only

once or twice in our sample as the lenders of last-resort, and therefore it is plausible that they face higher variable costs. More importantly, hedge funds often play an active role in the governance of bankrupt firms such as seeking board representation and appointing managers in pursuing a "loan-to-own" strategy (Jiang et al., 2012; Li and Wang, 2016; Ayotte and Elias, 2020), which requires hedge funds' significant efforts and resources.

We report the parameters that govern the demand curves in the bottom panel of Tables 3. We estimate the level of demand, α_κ, and the price elasticity of demand, ε_κ. Within each market, the estimated intercept and elasticity just reiterate the demand curves shown in Figure 6. Across the two market, we find that DIP borrowers exhibit slightly higher elasticity of demand than distressed loan borrowers. Our estimates, therefore, suggest that the strikingly high spread of DIP loans, compared with that of distressed loans, cannot be explained by the price elasticity of demand. In both markets, borrower size seems an important determinant of demand curve classification: large borrowers on average exhibit higher elasticity of demand and borrow less relative to their own size.

7 Decomposing Loan Yield Spread

Using the estimated model as a laboratory, we quantify the lenders' market power in the two separate distressed loan markets and decompose their market power into three components: (i) the potential collusion among specialists, (ii) limited participation by these lenders, and (iii) the oligopolistic structure in this market.

Both markets exhibit a few unique and interesting features. First, there is a club of specialist lenders that intermediate a large fraction of loan deals. Indeed, 83% of distressed loans and 70% of DIP deals in our estimated model are financed by the top 10 specialist lenders. This lending market, therefore, resembles an oligopolistic structure. To illustrate the dominant position of top lenders in the two loan markets, Figure A1 shows the loan market network for distressed loans and DIP loans, respectively. It is clear that the top lenders in each market form a strong network with other top lenders in syndicating the loans. Second, most deals are syndicated by a small group of specialist lenders as shown in Table 2. It implies limited participation in lending by specialists, which further reduces lender competition. Third, the lender clique may give rise to possible collusion among specialists that is hard to be detected by outsiders. In this section, we employ the estimated model to perform a few counterfactual benchmarks and decompose the market power of specialist lenders.

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 coun-

terfactual model, all specialist 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 limited participation by specialist lenders and an oligopolistic market structure. We examine how lender collusion affects the average loan yield spread, loan size, and the number of participating lenders by comparing the outputs from the two models.

Table 4 shows the results. Columns (1) and (5) report the baseline model predictions for the distressed loan sample and DIP sample respectively, and columns (2) and (6) report the non-collusive model outputs for the two samples. Notably, the average loan yield spread for specialist lenders declines by 211 bps (from 343 bps in the baseline model to 132 bps in the non-collusive model) for distressed loans, representing a 62% reduction in spread if specialist lenders compete in a non-collusive equilibrium. DIP loan yield spread declines by 212 bps (from 680 bps to 468 bps) as lender collusion is eliminated, representing a 31% decline. Without collusion, specialists compete more aggressively and lend a larger amount in aggregation. The average loan amount, relative to the borrowers' size, rises from 0.177 to 1.31 for distressed loans and from 0.114 to 0.271 for DIP loans. Intense competition has a moderate deterrence effect on lender participation, evident by a drop in the average number of syndicated lenders.

Next, we examine the effect of limited participation by specialist lenders. In our model, each lender incurs a stochastic participation cost that is assumed to follow an exponential distribution with the mean parameter μ. We construct a counterfactual benchmark of full participation by setting μ to zero. In this counterfactual model, we still keep $\xi = 0$ to measure the incremental effect of removing limited participation from the non-collusive model. The results for this counterfactual model are reported in columns (3) and (7) of Tables 4 for the two samples. The direct change is that all specialist lenders now participate in loan syndication and thus the number of lenders reaches the full capacity of 10. Full participation increases competition among specialist lenders, and the loan spread decreases by another 103 bps for distressed loans and 282 bps for DIP loans. This result suggests that limited participation by specialist lenders has a much more pronounced effect in DIP market than in distressed loan market. Because participation costs in our model incorporate both the costs of learning about a loan deal and the existing lenders' power on blocking other lenders from participating, our estimates indicate that such costs are higher for lenders in the DIP-loan markets. This is consistent with earlier studies that document that new DIP lenders cannot prime "liens" of existing lenders without their consent and thus "prepetition" 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 distressed loans.

As the last step, we quantify the effect of an oligopolisitc market structure. To turn an oligopolistic market into a competitive market, we increases the total number of specialist lenders from 10 to positive infinity. We build this counterfactual upon the non-collusive, full participation model to capture the incremental effect. In columns (4) and (8) of Tables 4, we find that the average loan yield spread drops by a negligible amount for both distressed loans and DIP loans financed by specialist lenders. Interestingly, this finding shows that the oligopolistic structure is not the main cause of high loan yield spread in either market, and the market would be competitive enough if all of the 10 specialist lenders can participate.

Table 3: Parameter estimates.

Distressed Loans				DIP loans			
General parameters							
ξ	σ	ς	μ	ξ	σ	ς	μ
0.817	0.923	0.607	30.79	0.492	0.664	0.430	34.81
(0.058)	(0.125)	(0.072)	(10.13)	(0.093)	(0.046)	(0.020)	(4.61)
Lender-specific parameters							
	Existing creditor	Specialized lender	Last-resort lender		Existing creditor	Specialized lender	Last-resort lender
e^{ϕ_l}	0.0021	0.0022	0.0027	e^{ϕ_l}	0.0149	0.0158	0.0197
	(0.0010)	(0.0009)	(0.0012)		(0.0040)	(0.0040)	(0.0050)
Borrower-specific Parameters							
	Demand curve 1	Demand curve 2			Demand curve 1	Demand curve 2	Demand curve 3
α_k	-8.718	-5.799		α_k	-11.031	-8.041	-5.505
	(1.225)	(0.308)			(1.504)	(0.534)	(0.131)
ε_k	1.204	1.069		ε_k	1.947	1.588	1.253
	(0.184)	(0.022)			(0.286)	(0.111)	(0.040)
λ_k	0.113	0.140		λ_k	0.036	0.150	0.119
	(0.069)	(0.024)			(0.043)	(0.034)	(0.026)
γ_k		1.213		γ_k		2.760	3.221
		(0.637)				(1.488)	(1.099)
β_k		-0.631		β_k		-1.011	-1.510

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 punishment on deviation ξ, the demand and supply shock σ and ς, the parameters that control the correlation between borrower size and the demand curve, γ and β, as well as the average participation cost μ. The mid panel shows the lender-specific model parameter ϕ that captures the lending costs for each type of lenders (i.e., existing lenders, the specialist lenders, and lenders of the last resort). The bottom panel shows the borrower-specific parameters including the demand curve coefficient α and ε and the likelihood for the existing lender to finance the loan λ.

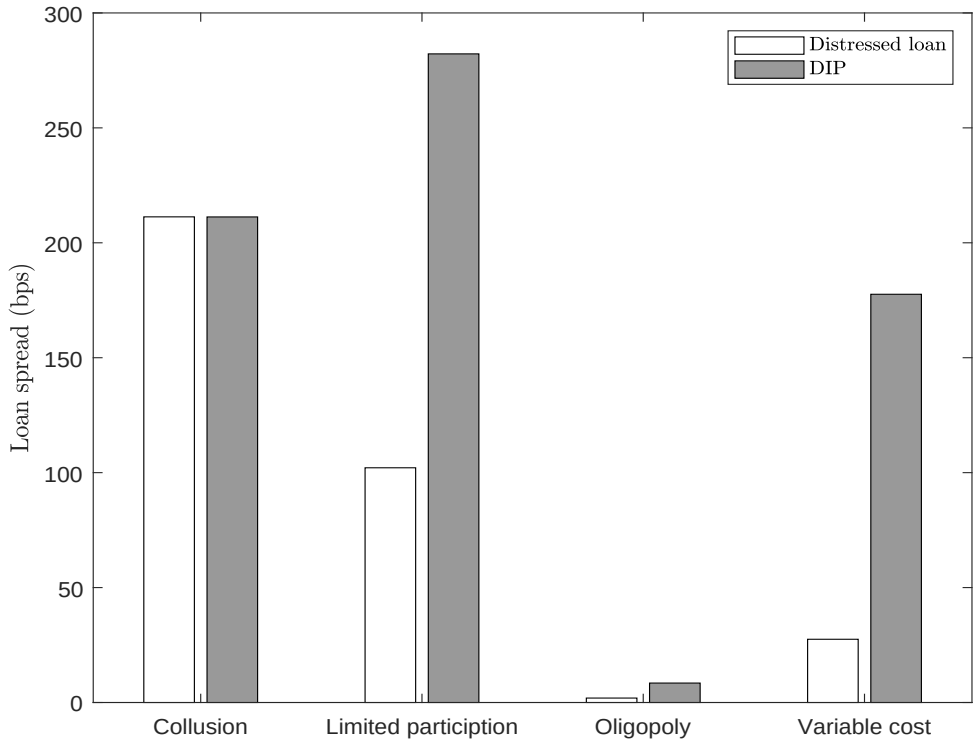
Table 4: Counterfactual Models and The Decomposition of Lender Market Power

This table reports the model implications for the estimated baseline model and a few counterfactual models. The Estimated model is the baseline model. In the non-collusive model, we shut down collusion by setting $\xi = 0$. In non-collusive, full participation model, we further zero out the participation cost for all specialist lenders and therefore all of them participate in a loan deal. In non-collusive, full participation, unlimited lenders model, we further increase the total number of specialist lenders to positive infinity so that it turns an oligopoly market to a competitive market.

	Distressed Loans				DIP Loans			
	Estimated Model	Non-collusive Model ($\xi = 0$)	Non-collusive, Full Participation ($\xi = 0, \mu = 0$)	Non-collusive, Full Participation, Unlimited Lenders ($\xi = 0, \mu = 0,$) ($M- > \text{inf}$)	Estimated Model	Non-collusive Model ($\xi = 0$)	Non-collusive, Full Participation ($\xi = 0, \mu = 0$)	Non-collusive, Full Participation, Unlimited Lenders ($\xi = 0, \mu = 0,$) ($M- > \text{inf}$)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Avg. Total Spread (bps)	344	182	68	68	702	566	235	228
Frac. Existing	0.128	0.128	0.128	0.128	0.113	0.113	0.113	0.113
Avg. Spread (bps)	334	334	334	334	618	618	618	618
Frac. Specialist	0.829	0.785	0.873	0.873	0.717	0.677	0.887	0.887
Avg. Spread (bps)	343	132	29	29	680	468	186	178
Frac. Last-Resort	0.044	0.088	0	0	0.171	0.211	0	0
Avg. Spread (bps)	391	407	NaN	NaN	852	853	NaN	NaN
Avg. m	2.67	2.22	10	Inf	1.81	1.72	10	Inf
Avg. L/A	0.177	1.310	2.764	2.972	0.114	0.271	0.677	0.722
Borrower Welfare	1.000	1.087	1.179	1.184	1.000	1.088	1.441	1.462

Figure 7: Spread Decomposition

This figure compares different components of risk-adjusted yield spreads in the distressed loan market and the DIP loan market. Collusion represents the component of risk-adjusted yield spreads that arises from the specialist lenders' tacit coordination in syndicated lending; Limited participation represents the component of risk-adjusted yield spreads that arises from the limited competition in small syndicated lending groups, which in turn is a consequence of high participation costs in the estimated model. Oligopoly 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.



Moving from the baseline model to the non-collusive, full participation, competitive model, we find that the lenders' market power accounts for about 92% of distressed loan's risk-adjusted yield spreads (i.e., $\frac{343-29}{343}$) and 74% of the DIP loan's risk-adjusted yield spreads (i.e., $\frac{680-178}{680}$). A further decomposition of the market power suggests that lender collusion contributes to 67% (i.e., $\frac{343-132}{343-29}$) of the market power for distressed loans and 42% of the market power for DIP loans (i.e., $\frac{680-468}{680-178}$), while limited participation contributes to 33% of the market power (i.e., $\frac{132-29}{343-29}$) for distressed loans and 56% of the market power (i.e., $\frac{468-186}{680-178}$) for DIP loans, Finally, the oligopolistic market structure contributes to the remaining negligible fraction of the market power to the two markets.

We summarize the decomposition of risk-adjusted yield spreads for the two markets in Figure 7. Specifically, we compare each component of the loan spread for distressed loans and DIP loans. This figure reveals two main conclusions that are central to our paper. First, tacit coordination among specialist lenders is prevalent in both markets, which allows the lender cartel to extract sizeable rent from borrowers (around 210 bps). Second, the excess loan spread in DIP market, compared with that in the distressed loan market, is mainly explained by the existing lenders' strong power in blocking the borrowers from reaching out to alternative lenders (i.e., high participation costs) and the high monitoring costs in DIP market (i.e., variable costs).

Among the different components that contribute to lender market power, lender tacit coordination often attracts most attention by regulators, and antitrust policies often target at breaking down such coordination. We then examine which borrowers are more susceptible to lender market power by measuring the effect of lender tacit coordination on borrowers of different size.

In the final part of the analysis, we partition the borrowers into size quintiles and repeat our analyses of the baseline model and the non-collusive model performed above. We report the changes in the average loan spread, loan size, and the number of participating specialist lenders as we shut down lender coordination in Table 5. We compare small borrowers (bottom size quintile) with large borrowers (top size quintile).

When lender coordination is eliminated, we find that small borrowers seem to benefit more. Specifically, the distressed loan spread drops by 260 bps (166 bps) for small (large) borrowers. DIP loan spread drops 255 bps (126 bps) for small (large) borrowers. The increase in loan size due to the elimination of collusion is also more pronounced for small borrowers than large borrowers in both markets. Overall, our analyses here suggest that small borrowers in both markets are more susceptible to lender market power and the effect of collusion on smaller borrowers almost doubles 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. 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.[18]

[18]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.

Table 5: Heterogeneous Effects of Lender Collusion

	(1)	(2)	(3)	(4)	(5)	(6)
	Borrower size	Baseline	Non-collusive	Government lending facility		
				Direct effect	Indirect effect	
		A. Distressed loans				
R (bps)	Small	396	−240	−249	0	−240
	Large	269	−156	−162	−102	−156
L/A	Small	0.195	1.359	1.380	0.000	1.359
	Large	0.131	0.748	0.762	0.274	0.748
Borrower	Small	1.000	0.117	0.120	0.000	0.117
Welfare	Large	1.000	0.118	0.122	0.078	0.118
		B. DIP loans				
R (bps)	Small	757	−244	−249	0	−244
	Large	518	−125	−129	−69	−125
L/A	Small	0.126	0.189	0.190	0.000	0.189
	Large	0.084	0.090	0.091	0.039	0.090
Borrower	Small	1.000	0.172	0.175	0.000	0.172
Welfare	Large	1.000	0.121	0.126	0.075	0.121

Note: This table examines the impact of lender tacit collusion and government lending facilities on borrowers of varying sizes, categorized into quintiles based on their book assets. For meaningful comparisons, this table focus on type-2 loans, i.e., syndicated loans made by specialized lenders.. To compare counterfactual outcomes between small borrowers (bottom quintile) and large borrowers (top quintile), we report the baseline model in column (2) and deviations between the results of alternative counterfactual scenarios and the baseline model in columns (3)–(6). The non-collusive model sets ξ to zero to eliminate lender collusion, as detailed in columns (4)–(6) which present the direct and indirect effects of government lending facilities, as studied in Section 8.1.

8 Policy Analysis

Our estimation and quantification results indicate that specialized lenders in the distressed and DIP loan markets extract rents from borrowers by charging excess risk-adjusted yield spreads above their marginal costs. The market power enjoyed by a few specialized lenders, particularly through tacit collusion in the form of syndication, enables a significant portion of these rents. Such implicit coordination is often hard to detect, making ex-post prosecution and enforcement challenging. Therefore, ex-ante regulatory intervention measures may be useful to mitigate the damage of inefficient bankruptcy, particularly during bankruptcy waves that affect the economy.[19] For instance, a government special purpose vehicle (SPV) can participate in the loan syndication process for distressed or bankrupt borrowers, while a cap on the total cost of dis-

[19] A recent bankruptcy wave took place when the cash-flow of almost all businesses took a pause as the result of the COVID-19 pandemic (e.g., DeMarzo et al., 2020; Conti-Brown and Skeel, 2020).

tressed or bankrupt borrowers charged by banks can be imposed.

To reduce the borrowing costs of distressed firms, including bankrupt ones, and facilitate credit accessibility, different government lending facilities have been proposed and implemented. For example, the Fed established the Main Street Lending Program to support lending to small and medium-sized for-profit businesses that were in sound financial condition before the onset of the COVID-19 pandemic. Additionally, DeMarzo et al. (2020) and Conti-Brown and Skeel (2020) recommend that the Fed should use its emergency authority to provide DIP lending facilities and provide useful discussions on how to implement the proposed intervention measures in practice.

Interest rate caps have historically and geographically been one of the most ubiquitous economic legislations, playing a vital role in economic activities across different economies (Blitz and Long, 1965). For example, in New York, corporations and limited liability companies (LLCs) cannot be charged more than 16% interest per annum for commercial loans whose amounts are above certain thresholds.

Below, we examine these two different intervention policies and compare their effects. We leverage the estimated model as a laboratory to perform counterfactual experiments. After we solve the model with government lending facilities or interest rate caps,[20] we investigate the effects of policies on borrowers' welfare. We focus on borrowers, because the specialized lenders are made unambiguously worse off by the policies. In particular, we are interested in the following two questions: (i) how the government lending facilities or interest rate cap policies influence the risk-adjusted yield spread that borrowers pay and the loan amount that they obtain, and (ii) which groups of borrowers are more affected by such policies. Since the effects of these policies are similar qualitatively in both markets, we present the results of the DIP loan market as an illustration, and leave these of the distressed loan market to Online Appendix.

8.1 Government Lending Facilities

Formulation of Polices in the Model. Suppose government sets up a special purpose vehicle (SPV) to participate the loan syndicate for distressed borrowers. For each borrower, there is a probability τ with which government will join the loan syndicate.[21] The probability τ captures the intervention intensity. The baseline model is a special case of the extended model with government intervention with $\tau \equiv 0$. Detailed derivations are available in Online Appendix 5.2.

[20] The details on the model solution are explained in Online Appendix 5

[21] While the intervention intensity τ may typically vary depending on borrowers' characteristics, for the sake of simplicity, we will limit our focus in this section to the case where it is constant.

Suppose $\tau = 1$, indicating that the government SPV participates in the loan syndicate for every distressed borrower. In this scenario, tacit collusion becomes unsustainable. Moreover, in contrast to the counterfactual scenario with zero tacit collusion capacity ($\xi = 0$), borrowers will not rely on last-resort lenders, such as hedge funds and private equity funds, because the government SPV always participates in the loan syndication. Specifically, in comparison to the baseline model, the risk-adjusted yield spread, R, declines from 344 bps to 155 bps for distressed loans, and from 702 bps to 488 bps for DIP loans. In comparison to the non-collusive scenario outlined in column (2) of Table 4, government intervention has an equivalent or even stronger effect than eliminating tacit collusion entirely by setting $\xi = 0$.

Direct and indirect effects of government participation. The total effect of government intervention is a result of both its direct and indirect effects. The direct effect measures how it alters the loan spread and loan size when the government participates in the current syndication. On the other hand, possible future government intervention can affect the specialized lenders' incentives for tacit collusion in the current syndication, which constitutes the indirect effect. We investigate how indirect effect varies with different levels of government intervention likelihood $\tau \in [0, 1]$.

To begin, we measure the direct effect of government intervention by comparing the loan spread, loan size, and borrower welfare in loan syndicates with and without government participation. We limit our analysis to type-2 loans, which are syndicated loans made by specialized lenders. By conditioning on the government SPV's participation in the current loan syndicate, we are able to isolate the direct effect of government intervention, independent of any potential future intervention.

Our analysis of the DIP loan, presented in Table 5, demonstrates that the average risk-adjusted yield spread is reduced by approximately 249 basis points and 129 basis points for small and large borrowers, respectively, due to the direct effect of government intervention. Additionally, the average loan-to-asset ratio increases by approximately 0.19 and 0.09 for small and large borrowers, respectively, as a direct result of government intervention. Finally, the direct effect of government intervention leads to a 75% and 26% increase in borrower welfare for small and large borrowers, respectively, with the effect being more significant for smaller borrowers, as anticipated.

Next, we examine the indirect effect of government intervention at different levels of intensity τ by comparing the loan spread, loan size, and borrower welfare in loan syndicates with and without government participation. When the government SPV is not part of the current loan syndicate, the expectations of specialized lenders about

future government intervention generate the indirect effect of government intervention. Our analysis, presented in columns (5) and (6) of Table 5, reveals a rather nonlinear relationship between the indirect effect and the intensity of government intervention. Even at an intensity of $\tau = 0.8$, the indirect effect is minimal, particularly for small borrowers. However, at an intensity of $\tau = 1.0$, the indirect effect becomes substantial for both small and large borrowers. In theory, as demonstrated in columns (3) and (6) of Table 5, when $\tau = 1.0$, the indirect effect of government lending facilities is equivalent to the effect of eliminating tacit collusion.

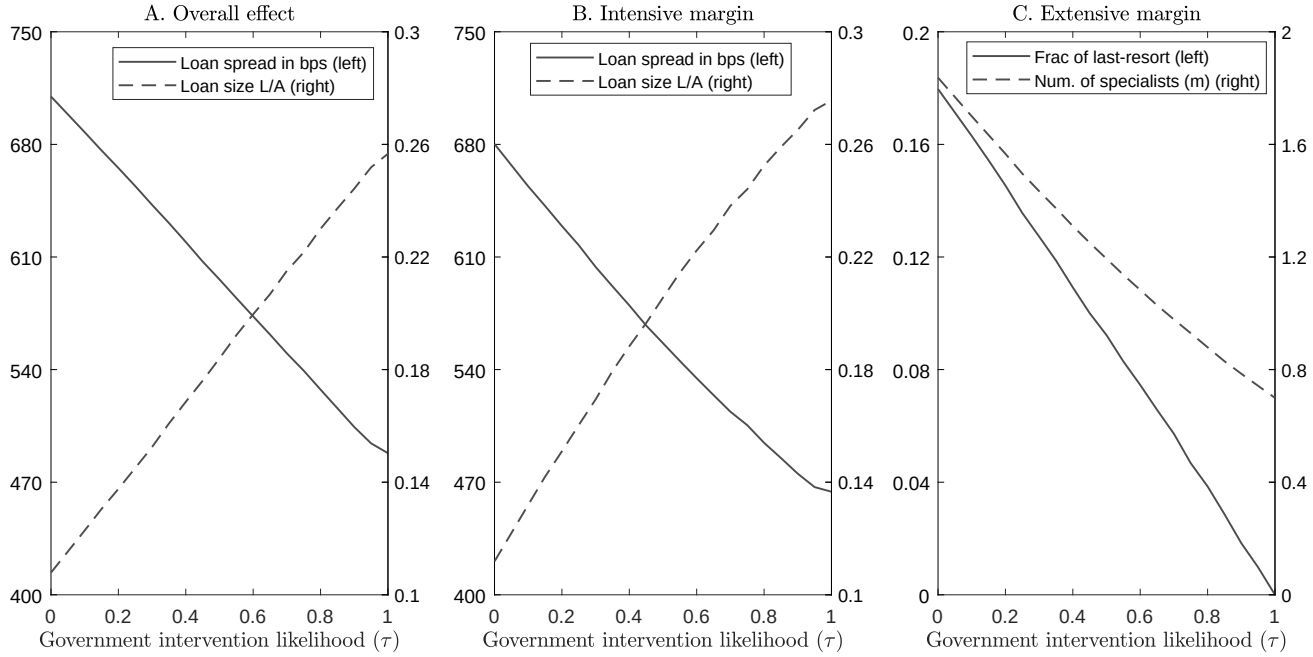
The Effects of Intensive and Extensive Margins. Increasing the intensity of government intervention τ leads to greater benefits for borrowers from government lending facilities, both at the extensive and intensive margins. Panel A of Figure 8 illustrates that as τ increases from 0 to 1, the overall effect of reducing the risk-adjusted yield spread R and increasing the loan-to-asset ratio L/A becomes stronger. This monotonic effect is in stark contrast to the U-shaped effect observed with the interest cap policy discussed in Section 8.2 (see Figure 9).

The overall effect of the government intervention facility results from both the intensive and extensive margin impact on how borrowers access credit. On the one hand, when borrowers obtain syndicated loans from specialized lenders (type-2 loans), higher τ leads to a greater reduction in the risk-adjusted yield spread R and a larger increase in the loan-to-asset ratio L/A. This is intuitive as higher τ induces a larger direct effect, making borrowers more likely to obtain syndicated loans with government intervention; additionally, a greater indirect effect occurs as it becomes more challenging for specialized lenders to sustain tacit collusion.

On the other hand, the extensive margin effect on borrowers' credit accessibility is mixed. Panel C of Figure 8 shows that while government intervention decreases the likelihood that borrowers obtain even more expensive funding from lenders of last resort, such as hedge funds and private equity funds, it also reduces the incentives of specialized lenders to participate in syndicated loans. This crowding out effect of government intervention arises as the participation of the government SPV eliminates tacit collusion in the syndication process, leading to lower potential profits for specialized lenders, and demoralizing them from participating in syndicated loans. Despite the crowding out effect, the beneficial effect dominates from the perspective of borrowers' credit accessibility. The government SPV fills the gap in the average number of syndicate participants, and thus its participation makes it more likely that borrowers receive financing.

Figure 8: The Intensive and Extensive Effects of the Government Lending Facility

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 depicts the intensive-margin effect of the government lending facility on reducing the risk-adjusted yield spread charged by specialized lenders, R, and increasing the corresponding loan size, L/A. Panel C 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.



8.2 Interest Rate Cap Policies

Formulation of Polices in the Model. The interest rate cap regulation can be implemented after conditioning on the characteristics of a borrower and adjusting the risk premium to better account for borrower risk heterogeneity and risk pricing. This can substantially improve the effectiveness of the interest rate cap policy because unsophisticated constant interest rate caps have severe limitations on balancing the tradeoff between borrower production and credit access (e.g., Cuesta and Sepúlveda, 2021). Assuming that the regulator can observe or estimate the marginal cost of providing distressed loans $e^{\phi+\varsigma u}$ and the risk premium of the loan, we can directly consider the interest rate cap that is imposed on the risk-adjusted spread R in the following form:

$$R_{max}(x) \equiv \mathcal{R}_{max} e^{\phi+\varsigma u}, \tag{34}$$

where $\mathcal{R}_{max}$ is a positive constant. A lower $\mathcal{R}_{max}$ reflects a stricter government intervention.

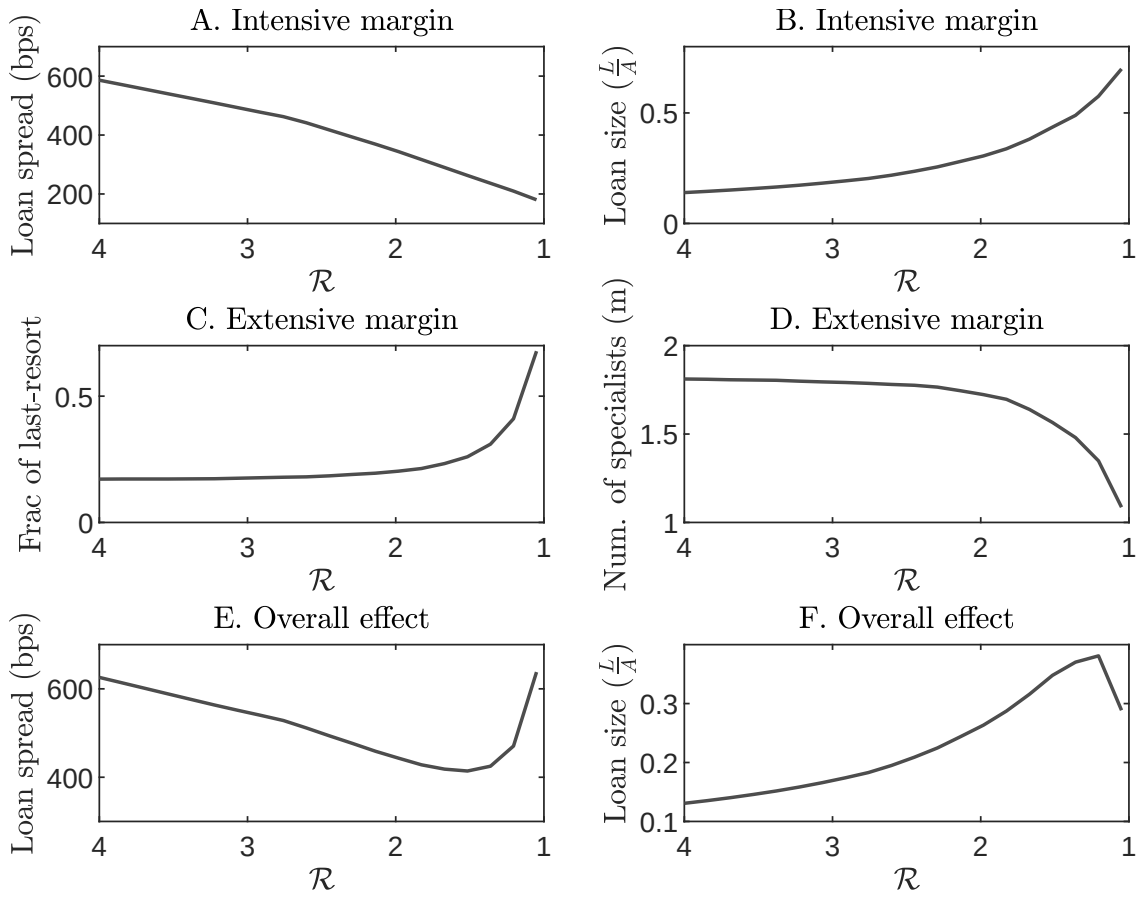
Similar to government lending facilities, the total effect of an interest rate cap is the result of both its direct and indirect effects. The direct effect measures how the cap alters the loan spread and loan size in the current syndication. Meanwhile, an interest rate cap imposed on future deals can influence specialized lenders' incentives for tacit collusion in the current syndication, which constitutes the indirect effect. Unlike the case of government lending facilities, both direct and indirect effects manifest simultaneously for each deal, and given the direct effect, the indirect effect of the interest rate cap is negligible.

The Effects of Intensive and Extensive Margins. We start with demonstrating the intended consequences of the interest rate cap policy. In panels A and B of Figure 9, we plot the risk-adjusted yield spread (left) and loan amount (right) as a function of the tightness of interest rate caps characterized by $\mathcal{R}_{max}$. As $\mathcal{R}_{max}$ decreases, the tightness of interest rate caps increases; as a result, the equilibrium risk-adjusted yield spread drops (see panel A) and the loan size increases (see panel B), for those borrowers who are able to receive loans from existing and specialized lenders. As expected, a tighter interest rate cap directly reduces the risk-adjusted yield spread. Moreover, because the loan spread for future deals is capped, the present value of future tacit coordination becomes lower, and thus the collusion capacity of specialized lenders is weakened. A lower cost faced by borrowers would boost the demand for loans, and meanwhile, a lower collusion capacity would incentivize specialized lenders to offer loans of larger size. Consequently, in panel B, we observe a sharp increase in the average equilibrium loan size for those borrowers who are able to receive loans from existing and specialized lenders as interest rate cap tightens. Both the decline in risk-adjusted yield spread and increase in loan size by specialized lenders benefit the borrowers if they can receive the loans from existing and specialized lenders.

Even though interest rate cap improves the welfare of borrowers who can obtain loans from the existing and specialized lenders, which is referred to as the intensive-margin effect, an adverse consequence of this policy is to discourage the participation of specialized lenders, thereby hindering the credit supply of specialized lenders to distressed borrowers. Such adverse effect of interest rate caps on the credit accessibility of distressed borrowers is referred to the extensive-margin effect. Intuitively, specialized lenders choose to participate the loan syndication only when their expected profits are higher than the participation costs. Interest rate cap reduces the expected profits earned by spe-

Figure 9: The Effects of Interest Rate Cap Policy

This figure shows the effects of the interest rate cap policy. Panels A and B depict the intensive-margin effect of interest rate cap policy on reducing the risk-adjusted yield spread charged by specialized lenders and increasing the corresponding loan size, respectively; panels C and D show the extensive-margin effect of interest rate cap policy on reducing the number of participating specialized lenders and increasing the likelihood of borrowers' turning to lenders of last-resort, respectively; and panels E and F illustrate the overall effect of interest rate cap policy on the average risk-adjusted yield spread and loan size, respectively.



cialized lenders and therefore excludes more specialist lenders from participating. If no specialized lenders are willing to participate in a specific deal, then the borrower is forced to borrow from the lenders of last-resort, such as private equity and hedge funds, which are not subject to the interest rate cap. Panels C and D confirm this model prediction. As $\mathcal{R}_{max}$ declines and the spread-cap tightens, the likelihood for the borrowers to borrow from lenders of the last-resort climbs sharply from about 15% to above 60%. Meanwhile, even if some borrowers can still borrow from specialized lenders, the average number of

participating lenders becomes significantly smaller. Lack of competition among the last-resort lenders and the high variable costs they bear make the loan very expensive.

Combining the positive effect of interest rate cap on the intensive margin and its negative effect on the extensive margin, Panel (e) and (f) illustrate the net effect. The net effect captures the likelihood of the borrowers borrowing from different types of lenders and the risk-adjusted yield spread charged by these lenders. We observe a U-shaped relation between the average risk-adjusted yield spread paid by borrowers and the tightness of rate cap and a hump-shaped relation between the average loan amount obtained by these borrowers and the tightness of rate cap. These findings suggest that there exists an optimal level of rate cap that maximizes the borrowers' welfare. Specifically, the optimal interest rate cap maps to an average risk-adjusted yield spread of about 400 bps across all types of lenders in the DIP loan market, compared with the observed spread of 700 bps in the data.

9 Conclusions

The lending market for distressed loans features an oligopolistic structure, with a few specialist lenders financing a large fraction of loans. It raises the question of how lender market power drives loan pricing in this market. We develop a dynamic game-theoretic model of strategic competition in distress loan markets with endogenous entry. Our entry and competing model provide several novel implications, including the "entry effect" of collusion capacity on the number of potential specialists and thus the likelihood of ex-post inefficient last-resort lending. Taking into account collusive lending by specialists and latent heterogeneity, we then use a comprehensive data sample that contains both distressed loans to bankrupt firms and those not yet in bankruptcy to estimate the structural model. We find that lender market power accounts for more than 90% of the risk-adjusted yield spread of distressed loans and for up to two-thirds of the risk-adjusted yield spreads of DIP loans. More than half of the lender market power is attributed to collusive lending in distressed loans and limited participation, likely due to lenders' blocking power, in DIP loans. Smaller borrowers are particularly susceptible to lender market power than larger borrowers, calling for more attention from policy makers towards small borrowers in difficult times. Without lender collusion, a large fraction of distressed borrowers would switch from lenders of last resort such as hedge funds to specialized lenders and benefit from a significantly larger loan amount and a much lower loan spread. Our policy analysis on interest rate cap suggests that such policy has a hump-shaped effect on the borrowers' welfare due to a positive intensive mar-

gin counteracting a negative extensive margin. Specifically, there exists an optimal level of rate-cap that can be imposed by regulators.

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:

$$\max_{L>0} \left\{ L^{\rho_k} S_k(A,z)^{1-\rho_k} - L \left[R + RP_k \left(\frac{L}{A} \right) \right] \right\}, \tag{35}$$

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:

$$S_k(A,z) \equiv A e^{\nu_k + \sigma z}, \tag{36}$$

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:

$$RP_k \left(\frac{L}{A} \right) \equiv h_k \left(\frac{L}{A} \right)^{\gamma_k} \tag{37}$$

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:

$$\rho_k L^{\rho_k - 1} S_k(A,z)^{1-\rho_k} = R \left[1 + e^{\ln(h_k + \gamma_k) - \ln(R) + \gamma_k \ln(L/A)} \right] \tag{38}$$

Taking log on both sides leads to

$$\ln(\rho_k) + (\rho_k - 1)\left[\ln(L/A) - \nu_k - \sigma z\right] \tag{39}$$

$$= \ln(R) + \ln\left[1 + e^{\ln(h_k(1+\gamma_k)) - \ln(R) + \gamma_k \ln(L/A)}\right] \tag{40}$$

The Campbell-Shiller log-linear approximation leads

$$\ln\left[1 + e^{\ln(h_k(1+\gamma_k)) - \ln(R) + \gamma_k \ln(L/A)}\right] \tag{41}$$

$$\approx a_{0,k} + a_{1,k}\left[\ln(h_k(1+\gamma_k)) - \ln(R) + \gamma_k \ln(L/A)\right], \tag{42}$$

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

Thus, arranging terms in (42) leads to the following relationship:

$$\ln\left(\frac{L}{A}\right) \approx \alpha_k - \varepsilon_k \ln(R) + \sigma z, \tag{43}$$

where

$$\alpha_k \equiv \frac{\ln(\rho_k) + (1-\rho_k)\nu_k - a_{0,k} - a_{1,k}\ln(h_k(1+\gamma_k))}{1 + a_{1,k}\gamma_k - \rho_k}, \tag{44}$$

$$\varepsilon_k \equiv \frac{1 - a_{1,k}}{1 + a_{1,k}\gamma_k - \rho_k}. \tag{45}$$

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 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:

$$L_2^C(A,k,x,m) \equiv \mathcal{L}^C(A,k,m)h_2(k,x)A \tag{46}$$

$$L_2^D(A,k,x,m;\mathcal{L}) \equiv \mathcal{L}^D(A,k,m;\mathcal{L})h_2(k,x)A. \tag{47}$$

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

$$\mathcal{L}^D(A,k,x,m;\mathcal{L}^C) = \underset{\mathcal{L}}{\operatorname{argmax}} \left[\left(\frac{1}{\mathcal{L} + (m-1)\mathcal{L}^C(A,k,m)} \right)^{1/\varepsilon_k} - 1 \right] \mathcal{L}. \tag{48}$$

The corresponding first-order condition is

$$1 - \frac{1}{\varepsilon_k} \frac{\mathcal{L}^D}{\mathcal{L}^D + (m-1)\mathcal{L}^C(A,k,m)} = \left[\mathcal{L}^D + (m-1)\mathcal{L}^C(A,k,m) \right]^{1/\varepsilon_k}. \tag{49}$$

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 (49), the optimal deviation profit is

$$\begin{aligned} &\Pi_2^D(A,k,m;\mathcal{L}^C) \\ &\quad = \left[\left(\frac{1}{\mathcal{L}^D(A,k,m;\mathcal{L}^C) + (m-1)\mathcal{L}^C(A,k,m)} \right)^{1/\varepsilon_k} - 1 \right] \mathcal{L}^D(A,k,m;\mathcal{L}^C)\mathcal{H}_2(k)A, \end{aligned} \tag{50}$$

which is also continuous in $\mathcal{L}^C(A,k,m)$. Accordingly, by equation (14), 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 (14) and (17). Consequently, there exists a unique maximizer $\mathcal{L}^C(\cdot) \in \mathbb{L}^C(w_C^*)$ of W^C, and we define

$$W^C(w_C^*) \equiv \max_{\mathcal{L}^C(\cdot) \in \mathbb{L}^C(w_C^*)} W^C. \tag{51}$$

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.

C Government intervention

Suppose government sets up a special purpose vehicle (SPV) to participate the loan syndicate for distressed borrowers. For each borrower, there is a probability $\tau(A)$ with which government will join the loan syndicate. The probability $\tau(A)$ captures the intervention intensity, and depends on the size of the borrower A. The baseline model is a special case of the extended model with government intervention with $\tau(A) \equiv 0$. Particularly, we can specify the intervention intensity $\tau(A)$ as a logistic function of A:

$$\tau(A) \equiv \exp(\tau_0 + \tau_1 A) / \left[1 + \exp(\tau_0 + \tau_1 A)\right]. \tag{52}$$

We set $g = 1$ if and only if government intervenes, and we set $g = 0$ otherwise.

Compared with the baseline model, the value functions $U^C(A, k, x, m; L^C)$, $U^N(A, k, x, m)$, and $U^D(A, k, x, m; L^C)$ have the same functional forms, with the only difference in their continuation values related to $W^C(L^C)$ and W^N. More specifically, the participation threshold with government intervention, denoted by w_G^*, is different from w_N^*. First, given the threshold w_G^*, the continuation value in a collusive Nash equilibrium is

$$W^C(L^C) = \mathbb{E}^{A',k'}\left\{\lambda_{k'}\frac{\Pi_1(A',k')}{M_0}\right\} \tag{53}$$

$$+ \mathbb{E}^{A',k'}\left\{(1-\lambda_{k'})\left[1-\tau(A')\right]\mathbb{E}^{w',m',x'}\left[\left(\Pi_2(A',k',x',m';L^C) - w'\right)\mathbf{1}_{\{w'\le w_C^*\}}|g=0\right]\right\} \tag{54}$$

$$+ \mathbb{E}^{A',k'}\left\{(1-\lambda_{k'})\,\tau(A')\mathbb{E}^{w',m',x'}\left[\left(\Pi_2(A',k',x',m'+1;L^N) - w'\right)\mathbf{1}_{\{w'\le w_G^*\}}|g=1\right]\right\} \tag{55}$$

and the continuation value in a non-collusive equilibrium is

$$W^N = \mathbb{E}^{A',k'}\left\{\lambda_{k'}\frac{\Pi_1(A',k')}{M_0}\right\} \tag{56}$$

$$+ \mathbb{E}^{A',k'}\left\{(1-\lambda_{k'})\left[1-\tau(A')\right]\mathbb{E}^{w',m',x'}\left[\left(\Pi_2(A',k',x',m';L^N) - w'\right)\mathbf{1}_{\{w'\le w_N^*\}}|g=0\right]\right\} \tag{57}$$

$$+ \mathbb{E}^{A',k'}\left\{(1-\lambda_{k'})\,\tau(A')\mathbb{E}^{w',m',x'}\left[\left(\Pi_2(A',k',x',m'+1;L^N) - w'\right)\mathbf{1}_{\{w'\le w_G^*\}}|g=1\right]\right\} \tag{58}$$

Here, conditioning on the government intervention, the expected profit from participating the syndication in the next period is

$$\mathbb{E}^{w',m',x'}\left[\left(\Pi_2(A',k',x',m'+1;L^N)-w'\right)\mathbf{1}_{\{w'\leq w_G^*\}}|g=1\right] \tag{59}$$
$$=\sum_{m'=1}^{M} q(m'|w'\leq w_G^*,w^*=w_G^*,g=1)\left[F(w_G^*)\mathbb{E}^{x'}\left[\Pi_2(A',k',x',m'+1;L^N)\right]-\int_{w'\leq w_G^*} w'dF(w')\right],$$

the profit of the syndicated lending with non-collusive loan size plan L^N is

$$\Pi_2(A',k',x',m'+1;L^N)\equiv\max_L\left[\left(e^{\alpha_{k'}+\sigma z'}\frac{A'}{L+m'L^N(A',k',m'+1)}\right)^{1/\varepsilon_{k'}}-e^{\phi_2+\varsigma u'}\right]L, \tag{60}$$

and the conditional probability $q(m'|w'\leq w_G^*,g=1)$ is

$$q(m'|w'\leq w_G^*,w^*=w_G^*,g=1)$$
$$=\frac{\mathbb{P}\left\{\text{This specialist and other } m'-1 \text{ specialists participate the lending}|w^*=w_G^*,g=1\right\}}{\mathbb{P}\left\{\text{This specialist participates the lending}|w^*=w_G^*,g=1\right\}} \tag{61}$$
$$=\binom{M-1}{m'-1}F(w_G^*)^{m'-1}\left[1-F(w_G^*)\right]^{M-m'}.$$

The following equality characterizes the cutoff w_G^*:

$$\sum_{m=1}^{M} q(m|w=w_G^*,w^*=w_G^*,g=1)\mathbb{E}^{A,k,x}\left[\Pi_2(A,k,x,m+1;L^N)\right]=w_G^*. \tag{62}$$

D Pairwise Syndication Interaction Intensity

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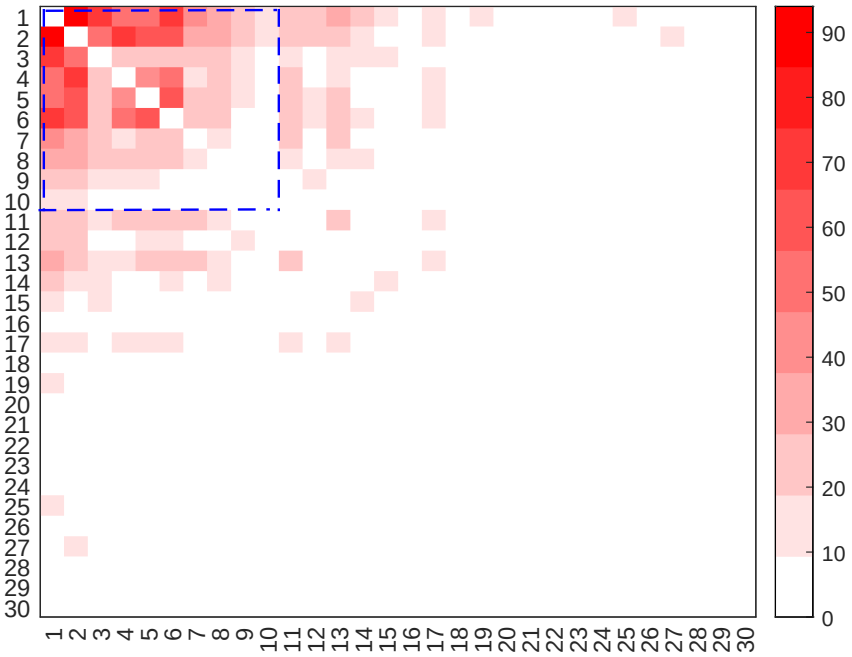
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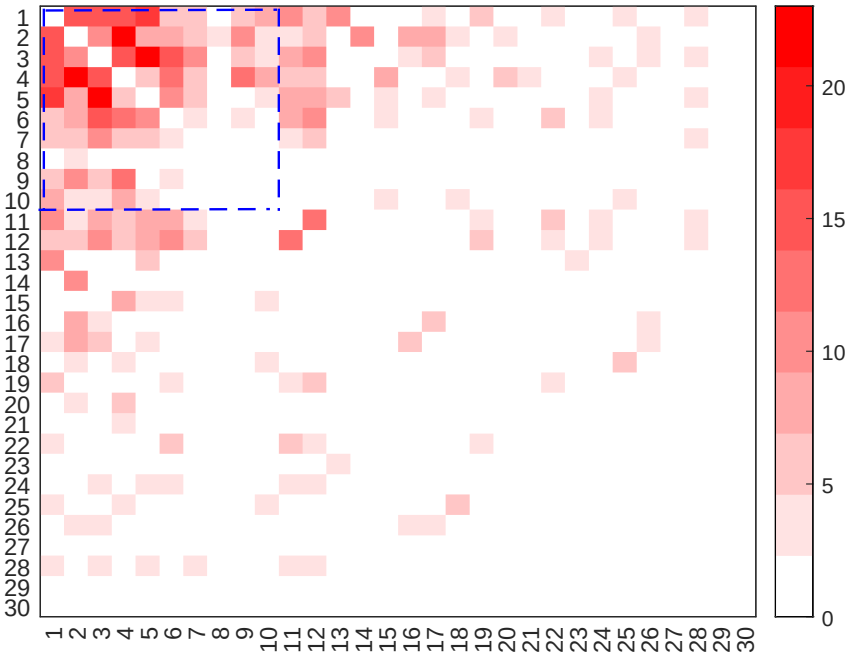
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Figure A1: Syndication interaction intensity in both markets

(a) Highly-speculative loans



(b) DIP loans



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