Feedback and Contagion through Distressed Competition

Hui Chen Winston Wei Dou Hongye Guo Yan Ji*

July 2, 2020

Abstract

Firms tend to compete aggressively when financially distressed; the intensified competition in turn reduces profit margins, pushing everyone further into distress. To study such feedback and contagion, we incorporate supergames of strategic competition into a dynamic model of long-term defaultable debt, featuring predation, self-defense, and collaboration. Due to the financial contagion, the credit risk of peer firms is interdependent. Industries with higher idiosyncratic-jump risk are more distressed, and they have lower aggregate-risk exposure due to the weaker competition-distress feedback. We provide empirical evidence and exploit exogenous variations in market structure – large tariff cuts – to test the core competition mechanism.

Keywords: Stock and Bond Returns, Predatory Price Wars, Collective Entry Prevention, Tacit Collusion, Financial Distress Anomaly. (**JEL**: G12, L13, O33, C73)

*Chen: MIT Sloan and NBER. Dou and Guo: University of Pennsylvania (Wharton). Ji: Hong Kong University of Science and Technology. We are grateful to Joao Gomes, Itay Goldstein, Rob Stambaugh, Neng Wang, and Wei Xiong for detailed discussions and comments. We also thank Andy Abel, Frederico Belo, Jess Benhabib, Utpal Bhattacharya, Alexandre Corhay, Sudipto Dasgupta, Lorenzo Garlappi, Vincent Glode, Vidhan Goyal, Zhiguo He, Zongbo Huang, Urban Jermann, Ron Kaniel, Don Keim, Richard Kihlstrom, Tim Landvoigt, Kai Li, Xuewen Liu, Zheng Liu, Jianjun Miao, Yoshio Nozawa, Krishna Ramaswamy, Mike Schwert, Ji Shen, Robert Townsend, Chaojun Wang, Pengfei Wang, Wei Wang, Colin Ward, Jialin Yu, Alminas Zaldokas, and participants at Conference on Systemic Risk and Financial Stability, McGill-HEC Winter Conference, CUHK-Shenzhen, HKUST and Jinan Macro Workshop, HKUST, PKU, PHBS Workshop on Macroeconomics and Finance, NFA, Wharton Micro Virtual Seminar, and University of Pennsylvania (Wharton) for comments.

1 Introduction

Product markets are often highly concentrated. Strategic competition among market leaders plays a vital role in determining industry profitability and dynamics (e.g. Grullon, Larkin and Michaely, 2018; Loecker and Eeckhout, 2019; Autor et al., 2019).[1] Moreover, such strategic competition is endogenously affected by firms' financial constraints (e.g., Frésard, 2010; Koijen and Yogo, 2015; Gilchrist et al., 2017; Cookson, 2017, for recent empirical works).

Motivated by the facts above, this paper studies the feedback and contagion effect generated by the dynamic interactions between strategic competition and financial distress. The competition-distress feedback and financial contagion effect arise because firms tend to compete more aggressively when they are in financial distress, and the intensified competition in turn reduces the profit margins for all firms in the industry, pushing everyone further into distress (see Figure 1). The competition-distress feedback effect further amplifies the negative response of firms' profit margins and equity returns to the aggregate discount-rate shocks through the endogenous competition channel studied by Dou, Ji and Wu (2020*a*), and importantly, more so in less financially distressed industries in the cross section. This is because the heterogeneity in financial distress in the cross section of industries stems mainly from the heterogenous amount of idiosyncratic jump risk born by these industries, and firms in the industries with higher idiosyncratic jump risk are effectively more impatient, rendering their cooperative incentives less responsive to the fluctuations in aggregate discount rates. This distressed competition mechanism helps rationalize the financial distress anomaly across industries, which otherwise seems puzzling under the canonical framework of Merton (1974) and Leland (1994). Moreover, the financial contagion effect, even across industries (see Figure 2), renders the financial distress of leading firms interdependent, thereby microfounding the key primitive assumption behind the information-based theories of credit market dynamics (e.g., Bebchuk and Goldstein, 2011). This economic mechanism also sheds important new light on how credit spreads depend on peer firms' financial conditions and industry structure.

We develop a novel theoretical framework that incorporates a supergame of strategic competition into a dynamic model of long-term defaultable debt (à la Leland, 1994) to study the dynamic interactions between strategic competition and financial distress systematically and quantitatively. In a nutshell, our model assumes that consumers' tastes toward firms' differentiated products are embodied in customer base, which fluctuates stochastically over time and is subject to large left-tail idiosyncratic jump shocks as in Seo and Wachter (2018).

[1] According to the U.S. Census data, the top four firms within each 4-digit SIC industry account for about 48% of the industry's total revenue (see Dou, Ji and Wu, 2020*a*, Online Appendix B). Similarly, Gutiérrez, Jones and Philippon (2019) and Corhay, Kung and Schmid (2020) investigate the forces behind the stylized fact that industry concentration (entry rate) has even been further increasing (decreasing) since 1980. Further, the strategic pricing competition is prevalent since the market leading position is highly persistent (e.g., Geroski and Toker, 1996; Matraves and Rondi, 2007; Sutton, 2007; Bronnenberg, Dhar and Dubé, 2009).

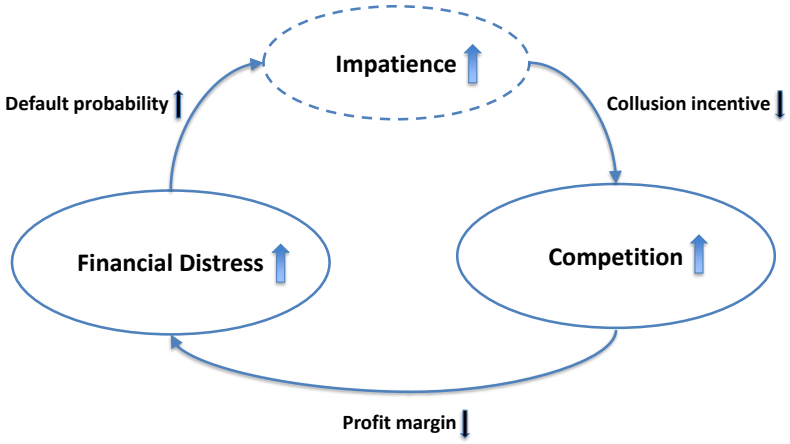


Figure 1: Feedback loop between financial distress and price competition.

Firms' cash flows are not only affected by their customer base but also their profit margins. The latter is endogenously determined by the repeated game of Bertrand competition on profit margins with differentiated products and tacit collusion (Tirole, 1988, Chapter 6). The key aggregate state of the economy is captured by the time-varying discount rate as emphasized by Cochrane (1991), which drives the dramatic fluctuations in competition intensity (e.g., Dou, Ji and Wu, 2020*a*).

More precisely, market leaders can tacitly collude with each other on setting high profit margins. Given that the competitor will honor the collusive profit-margin scheme, a firm can boost up its short-run revenue by undercutting profit margins to attract more customers; however, deviating from the collusive profit-margin scheme may reduce revenue in the long run if the profit-margin undercutting behavior is detected and punished by the competitor. Following the literature (e.g., Green and Porter, 1984; Brock and Scheinkman, 1985; Rotemberg and Saloner, 1986), we adopt the non-collusive Nash equilibrium as the incentive-compatible punishment for deviation. The collusive profit margins depend on firms' deviation incentives: a higher collusive profit margin can only be sustained by a lower deviation incentive, which is determined by firms' intertemporal tradeoff between short- and long-run cash flows. The intertemporal tradeoff is further shaped by the firm-specific financial condition and the aggregate discount rate. We study firms' behavior under tacit collusion or cooperation, because extensive empirical evidence shows that market leaders compete highly strategically through (tacit) collusion, and tacit collusion is prevalent across industries (e.g., Connor, 2016; He and Huang, 2017; Dasgupta and Zaldokas, 2018; González, Schmid and Yermack, 2019; Byrne and de Roos, 2019; Bourveau, She and Zaldokas, 2020).

Our model has the following main theoretical results. First, there exists a positive feedback loop between competition and financial distress. Intuitively, a firm's incentive to collude with its peers depends on how much it values the extra profit from cooperation in the future, following the idea of Fudenberg and Maskin (1986)'s "Folk theorem." As illustrated in

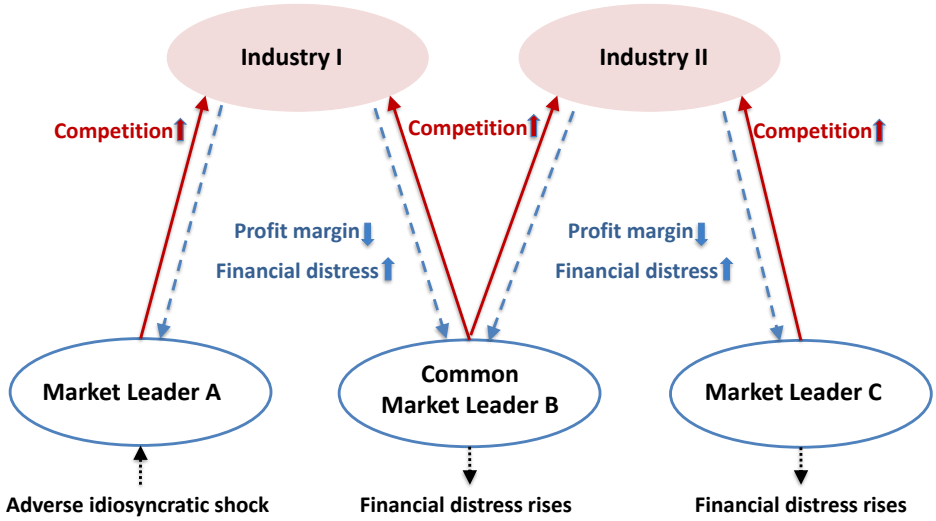


Figure 2: Financial contagion through endogenous competition in product markets.

Figure 1, when a firm becomes more financially distressed, it tends to compete more intensely, resulting in lower profit margins. This is because higher default risk makes the firm effectively more impatient, which renders the extra profit from cooperation in the future less valuable and the incentive for undercutting its competitors on profit margins stronger. Lower profit margins further elevate the level of financial distress and default risk.

Second, strategic competition in the product markets leads to financial contagion. This effect is straightforward to appreciate within an industry. When a leading firm is hit by a firm-specific shock and pushed into financial distress, competition tends to intensify within the industry (owing to the higher impatience explained above), which results in lower profits for all firms. Consequently, the financial conditions of the competitors in the same industry will also weaken. With multi-sector firms, the financial contagion can also spread across industries. For example, Figure 2 illustrates a setting with two industries and three firms, where firm B operates in both industries. When firm A in the first industry becomes financially distressed due to a firm-specific shock, the heightened competition raises the level of financial distress for firm B. Firm B responds by competing more aggressively in both industries, which eventually hurts the profitability of firm C in the second industry and pushes it deeper into financial distress.

Third, depending on the heterogeneity in market shares and financial conditions across firms in an industry as well as between incumbent firms and new entrants, firms can exhibit a rich variety of strategic interactions, including self-defense, predation (price war), and collaboration. Per the intuition of the "Folk theorem," the risk of exit can change the nature of strategic competition in several ways. As already discussed above, it can endogenously make a firm more impatient, which reduces its collusion incentive. In response to the profit-margin

undercutting by the weaker firm, the financially strong firm in the same industry might also cut profit margins to protect its market share. We refer to this as the self-defensive incentive. Next, when the threat of new entrant is sufficiently low (e.g., due to a high entry barrier) and the distressed firm is sufficiently close to bankruptcy, the strong firm might want to cut profit margins more aggressively, triggering the switch to a non-collusive equilibrium (a price war). In doing so, the strong firm could drive the weaker competitor out of the market sooner and enjoy the monopoly rent subsequently. This is the predatory incentive. However, if the failure of the weaker competitor results in the emergence of a powerful new entrant, the stronger firm's collaboration incentive might dominate: it might keep the level of its profit margin high in order to help the weaker firm remain solvent. Our model provides a quantitative evaluation and structural decomposition of the three types of incentives, which constitutes an important contribution to the industrial organization (IO) literature (e.g., Besanko, Doraszelski and Kryukov, 2014).[2]

The theoretical results above have several important implications for asset pricing. As the first set of asset pricing implications, our model shows that when analyzing firm-level credit risk, the market shares and financial conditions of the major competitors should also be taken into account. This crucial implication is missing in standard credit risk models (e.g., Merton, 1974; Leland, 1994, and many extensions), which explain firm-level credit risk primarily through firm-specific (e.g., leverage, earnings, and idiosyncratic volatility) and aggregate information (e.g., risk-free rate, risk premium, and uncertainty).

As the second set of asset pricing implications, our model provides a novel mechanism for explaining the distress anomaly at industry level. The joint patterns of stock returns, credit spreads, and financial distress are at odds with the canonical Leland models. We emphasize that in industries with higher left-tail idiosyncratic jump risk, firms face higher financial distress because they are more likely to default. This pattern is also robust in the data. Meanwhile, in such industries, firms find it more difficult to collude because the higher probability of exit makes the future punishment for deviation behavior less threatening. The lack of collusion incentives results in lower profit margins, which yet are more immune to fluctuations in discount rates, implying more stable competition intensity in these industries. Consequently, our model implies that shareholders are compensated with lower expected returns in industries with higher left-tail idiosyncratic jump risk because the competition intensity is endogenously more stable. Since the industries with higher left-tail idiosyncratic jump risk are associated with higher financial distress, our model explains the financial distress anomaly across industries. By contrast, the model implies higher credit spreads for the more

[2]Our structural decomposition is reminiscent of that of Besanko, Doraszelski and Kryukov (2014), and it corresponds to the common practice of antitrust authorities to question the intent behind a business strategy: Is the firm's aggressive pricing behavior primarily driven by the benefits of acquiring competitive advantage or by the benefits of overcoming competitive disadvantage caused by rivals' aggressive competition behaviors? The predatory motive maps into the first set of benefits and the self-defensive motive into the second set.

financially distressed industries because the higher left-tail idiosyncratic jump risk results in higher financial distress.

While our contribution is mainly theoretical, we quantitatively validate our model and empirically test the main predictions of our model by showing strong supporting evidence. We conduct our empirical analysis in four major steps as follows. First, we test the model's mechanism that rationalizes the financial distress anomaly across industries. We show that industries with higher financial distress or idiosyncratic jump risk have lower expected equity excess returns and higher credit spreads; and further, we show that these industries are less negatively exposed to discount-rate shocks. We then show that the idiosyncratic jump risk is significantly and positively associated with the financial distress in the cross section of industries, and the financial distress anomaly becomes insignificant after controlling for the idiosyncratic jump risk.

Second, we test the implications of the competition-distress feedback and financial contagion effect on firms' profit margins. We show that industry-level profit margins load negatively on discount rates, and the loadings are more negative in industries where firms are closer to their default boundaries. This empirical evidence is consistent with the theoretical prediction that the competition-distress feedback effect is stronger when the distance to default is smaller. Further, we show that adverse idiosyncratic shocks hitting one financially distressed market leader will motivate other market leaders within the same industry to cut their profit margins under common market structure. Specifically, by sorting the top firms within each industry into three groups based on their financial distress level, we find that adverse idiosyncratic shocks to the financially distressed group lead to lower profit margins of the financially healthy group, and that such within-industry spillover effect is more pronounced in the industries with higher entry costs or when the market shares of the two groups are more balanced. In addition, we provide evidence for the between-industry financial contagion effect for market leaders in two different industries which share common market leaders.

Third, we test the implications of the feedback and contagion effect on asset prices. We show that the difference in the exposure of equity excess returns to discount rates across industries with different gross profitability becomes larger when the distance to default is lower, supporting the theoretical prediction that the competition-distress feedback is stronger when firms in an industry are closer to the default boundary. Moreover, we show that the financial contagion effect among market leaders within the same industry is also reflected in firms' credit spreads. Specifically, by sorting the top firms within each industry into three groups based on their financial distress level, we find that adverse idiosyncratic shocks to the financially distressed group lead to higher credit spreads of the financially healthy group, and that such within-industry spillover effect on credit spreads is more pronounced when the market shares of the two groups are more balanced.

Finally, we directly test the core competition mechanism of the model. On the one hand, the core competition mechanism generates a differential sensitivity of profit margins to fluctuations in discount rates between industries with low and high distance to default (i.e., the feedback effect). On the other hand, the core competition mechanism generates an endogenous response of peer firms' competition intensity, as reflected in their profit margins, to idiosyncratic shocks of the financially distressed market leaders in the same industry (i.e., the financial contagion effect). According to the model, both the differential sensitivity and the financial contagion effect become weaker if the industries' market structure becomes more competitive (i.e., if the industry's price elasticity of demand ϵ or the number of market leaders n increases). Thus, a direct test of the core competition mechanism is to examine how the differential sensitivity and the financial contagion effect would change if the industry market structure shifts to a more competitive one.

We exploit a widely-used empirical setting to introduce variation in the competitiveness of industry market structure. In particular, we follow the literature (Frésard, 2010; Valta, 2012; Frésard and Valta, 2016) and use unexpected large cuts in import tariffs to identify exogenous variation in market structure.[3] Intuitively, large tariff cuts can lead to a more competitive market structure, because the reduction in trade barriers can increase (i) the industry's price elasticity of demand ϵ due to the similar products and services provided by foreign rivals and (ii) the number of market leaders n as foreign rivals enter and become major players in domestic markets. Consistent with the implications of the model, we find that when these industries' market structure becomes more competitive, the industries with high and low distance to default display less difference in their exposure to discount rates and the within-industry financial contagion effect becomes weaker.

Related Literature. Our paper contributes to the large and growing literature on the structural model of corporate debt, default, and equity returns (see Merton, 1974; Leland, 1994, for the seminal benchmark framework). Sundaresan (2013) provides a comprehensive review on this literature. Specifically, Hackbarth, Miao and Morellec (2006), Chen, Collin-Dufresne and Goldstein (2008), Bhamra, Kuehn and Strebulaev (2010*a*,*b*), Chen (2010), and Chen et al. (2018) focus on the impact of macroeconomic conditions on firms' financing policies, credit risk, and asset prices. Further, Anderson and Carverhill (2012) and Bolton, Wang and Yang (2019) focus on the impact of financial flexibility on firms' capital structure dynamics. Existing dynamic models of capital structure and credit risk typically assume that the product market offers exogenous cash flows unrelated to firms' debt-equity positions or corporate liquidity conditions. Our model differs from those in this literature by explicitly considering an

[3]Many other papers in the literature use tariff cuts as shocks to the competitiveness of industry market structure to address endogeneity concerns (e.g., Xu, 2012; Flammer, 2015; Huang, Jennings and Yu, 2017; Dasgupta, Li and Wang, 2018).

oligopoly industry in which firms' strategic competition generates endogenous cash flows. This allows us to jointly study firms' financial decisions in the financial market and their profit-margin-setting decisions in the product market, as well as their interactions. Like ours, Brander and Lewis (1986) and Corhay (2017) also develop models in which firms' cash flows are determined by strategic competition in the product market. Our paper is different in the following aspects: (i) the core mechanism is very different since we consider supergames and long-term debts, which allows us to investigate the competition-distress feedback effect; (ii) our model provides an explanation for the financial distress anomaly across industries; (iii) we emphasize the endogenous competition risk driven by variations in aggregate discount rates, whereas Corhay (2017) emphasizes the entry risk over business cycles; (iv) we also show the financial contagion effect on profit margins and financial distress through the distressed competition mechaism; and (v) we provide direct tests on the core competition mechanism in difference-in-differences designs by exploiting the unexpected large tariff cuts as instruments for exogenous shifts in the competitiveness of industries' market structure.

Our paper also contributes to the growing literature on the feedback effects between the capital market and the real economy. There are two major classes of channels for the feedback effects — the fundamental- and information-based channels. Seminal examples of the fundamental-based channel include Bernanke and Gertler (1989) and Kiyotaki and Moore (1997), who show that the price-dependent financing constraint can lead to an adverse feedback loop: when firms become more financially constrained, they are forced to reduce real investment and hiring, which in turn make them more financially constrained. Dou et al. (2020*b*) provide a recent survey for this class of macro-finance models. As emphasized by Bond, Edmans and Goldstein (2012), the fundamental-based channel is about primary financial markets, and the feedback effect between secondary financial markets and the real economy is also crucial yet mainly transmitted through the information-based channel (e.g., Chen, Goldstein and Jiang, 2006; Bakke and Whited, 2010; Edmans, Goldstein and Jiang, 2012). This paper introduces a novel fundamental-based feedback effect between imperfect capital markets and imperfect product markets as a result of strategic dynamic competition.

Like the feedback effect, financial contagion also takes place through two major classes of channels — the fundamental- and information-based channels (Goldstein, 2013). The fundamental-based channel is through real linkages between economic entities, such as common (levered) investors (e.g., Kyle and Xiong, 2001; Kodres and Pritsker, 2002; Kaminsky, Reinhart and Végh, 2003; Martin, 2013; Gârleanu, Panageas and Yu, 2015) and financial-network linkages (e.g., Allen and Gale, 2000; Acemoglu, Ozdaglar and Tahbaz-Salehi, 2015). Contagion can also work through the information-based channel such as self-fulfilling beliefs (e.g., Goldstein and Pauzner, 2004). This paper proposes a novel channel of strategic dynamic competition through which financial distress is contagious among product-market peers.

Our paper also contributes to the emerging literature on the impact of industry competition and customer market on financial decisions and valuations. Titman (1984) and Titman and Wessels (1988) provide the first piece of theoretical insight into and empirical evidence on the impact of product market characteristics on a firm's financial decisions. Specifically, Banerjee, Dasgupta and Kim (2008) and Hoberg, Phillips and Prabhala (2014), and D'Acunto et al. (2018) empirically investigate the effect of industry competition and customer base on firms' leverage decisions. Moreover, Dumas (1989), Kovenock and Phillips (1997), Grenadier (2002), Aguerrevere (2009), Back and Paulsen (2009), Hoberg and Phillips (2010), Hackbarth and Miao (2012), Gourio and Rudanko (2014), Hackbarth, Mathews and Robinson (2014), Bustamante (2015), Dou et al. (2019), and Dou and Ji (2019) investigate the implication of industry competition and customer base on various corporate policies such as investment, cash holdings, mergers and acquisitions, and entries and exits. Finally, a growing literature focuses on the implication of strategic industry competition and customer base on firms' valuation and equity returns (e.g., Aguerrevere, 2009; Belo, Lin and Vitorino, 2014; Opp, Parlour and Walden, 2014; Bustamante, 2015; Corhay, Kung and Schmid, 2017; Dou et al., 2019; Belo et al., 2019; Dou, Ji and Wu, 2020*a*,*b*). Our model highlights the dynamic interaction of endogenous competition and financial distress, generating competition-distress feedback effects and financial contagion effects, which are new to the literature.

Our paper is also related to the burgeoning literature on how financial characteristics influence firms' performance and decisions in the product market. In the early seminal works, Titman (1984) and Maksimovic and Titman (1991) study how capital structure affects a firm's choice of product quality and the viability of its products' warranties. Brander and Lewis (1986) focuses on the "limited liability" effect of short-term debt financing on product competition behavior. Bolton and Scharfstein (1990) show that financial constraints give rise to rational predation behavior. Jacob (1994) focuses on the role of long-term debt and shows that the accumulated profit is important in determining product market behavior. In Allen (2000), greater debt increases the probability of bankruptcy and liquidation which is costly, and thus, higher leverage will be associated with less aggressive product market behavior subsequently. Empirical advances on the product-market implications of financial frictions include Phillips (1995), Chevalier and Scharfstein (1996), Hoberg and Phillips (2016), Gilchrist et al. (2017), Hackbarth and Taub (2018), and Banerjee et al. (2019). Different from the existing works, our paper combines a dynamic Leland framework of long-term defaultable debt with dynamic strategic competition featuring collusive behavior.

2 The Model

We develop an industry-equilibrium model with dynamic games of n dominant firms, long-term bonds, and time-varying risk premia. Our model essentially extends the model of Leland (1994) by incorporating Bertrand competition with tacit collusion. For tractability, we assume that the industry has two dominant firms (i.e., $n = 2$), referred to as *market leaders*, and many followers of measure zero. Thus, the industry is effectively a duopoly. We label a generic market leader by i and its competitor by j when describing the model below.

2.1 Financial Distress

Financial Frictions. Financial frictions are modeled following Leland (1994). Firms are financed by debt and equity, and they issue long-term debt to take advantage of the tax shield but do not hold cash reserves. The corporate tax rate is $\tau > 0$. A levered firm first uses its cash flows to make interest payments, then pays taxes, and finally distributes the rest to shareholders as dividends. Firm managers make decisions and maximize the equity value of the firm. Shareholders have limited liability, and managers have the option to default on the debt: When internally generated cash flows cannot cover the interest expenses, the firm can issue equity to cover the shortfalls without paying any additional financing costs;[4] but, if shareholders are no longer willing to inject more capital, the firm goes bankrupt and exits. In other words, if the equity value falls to zero, managers will choose to file bankruptcy and exit. Upon exit, the firm is reorganized or liquidated, and its debtholders obtain a fraction ν of the abandonment value with $\nu \in (0, 1)$. The bankruptcy friction is the only financial friction in our model.[5]

Cash Flows. Firm i issues long-term debt modeled as a consol bond, which promises perpetual coupon payments at rate b_i. This is a standard assumption in the literature (Leland, 1994; Duffie and Lando, 2001), and it helps maintain a time-homogeneous setting. Thus, firm i's flow intensity of earnings after interest expenses and taxes over $[t, t + \mathrm{d}t]$ is

$$E_{i,t} = (1 - \tau) \left(\Pi_{i,t} M_{i,t} - b_i \right), \tag{1}$$

[4]The costless issuance of equity is a simplification assumption widely adopted in the credit risk models (e.g., Leland, 1994; Hackbarth, Miao and Morellec, 2006; Chen, 2010). Extending the model with costly equity issuance and endogenous cash holdings, as in Bolton, Chen and Wang (2011, 2013) and Dou et al. (2019), is interesting for future research.

[5]The bankruptcy loss incurred by the debtholders in the large cases is quite significant mainly due to the prolonged bankruptcy process (e.g., Dou et al., 2020*a*). In a recent paper, Antill (2020) also finds large bankruptcy loss for U.S. corporations. Further, Opler and Titman (1994), Pulvino (1998), Davydenko, Strebulaev and Zhao (2012), Glover (2016), Graham et al. (2019), and others also find evidence of significant indirect costs of bankruptcy and defaults.

where $M_{i,t}$ is the firm's customer base and $\Pi_{i,t}$ is the firm's endogenous profitability per unit of customer base, which is determined in the Nash equilibrium of competition games. We follow Leland (1994) and adopt a static capital structure framework: The coupon rate b_i is optimally chosen at the beginning to maximize firm value given the tradeoff between tax shield benefits and distress costs. The models with dynamic capital structure (e.g., Goldstein, Ju and Leland, 2001; Hackbarth, Miao and Morellec, 2006; Bhamra, Kuehn and Strebulaev, 2010*b*; Chen, 2010) allow firms to optimally issue more debt when current cash flows surpass a threshold, which helps generate stationary default rates under a general-equilibrium setup. We adopt a static capital structure since our partial equilibrium model does not focus on refinancing implications. Adopting the static capital structure framework makes the model more tractable given the complexity of the current setup, without changing the main insights or results of this paper.

More precisely, we assume that firm i's customer base $M_{i,t}$ evolves according to the following affine jump-diffusion process:

$$\frac{\mathrm{d}M_{i,t}}{M_{i,t}} = g\mathrm{d}t + \varsigma \mathrm{d}Z_t + \sigma_M \mathrm{d}W_{i,t} - \mathrm{d}J_{i,t}, \tag{2}$$

where the parameter g captures the growth rate of customer base, the standard Brownian motion Z_t captures economy-wide aggregate shocks, the standard Brownian motion $W_{i,t}$ captures idiosyncratic shocks to firm i's customer base, and the Poisson process $J_{i,t}$ with intensity λ captures left-tail idiosyncratic jump shocks to firm i's customer base. Upon the occurrence of a jump shock, firm i loses its entire customer base and exits the industry. The shocks Z_t, $W_{i,t}$, and $J_{i,t}$ are mutually independent. Our specification is close to Seo and Wachter (2018), who emphasize that the idiosyncratic jump risk is a crucial ingredient to understanding credit prices. Seo and Wachter (2018) calibrate a sector jump (in levels) of -76% on average as well as an average idiosyncratic jump of -95%. Similar to their calibration, these idiosyncratic jumps are infrequent and large enough that it makes exit virtually uncertain for simplicity as in our calibration.

The firm's financial distress is not only determined by the cash flow level $E_{i,t}$ but also crucially determined by the jump intensity λ. Intuitively, a higher jump intensity λ leads to a higher default frequency regardless of the current cash flow level $E_{i,t}$, leading to higher financial distress. Moreover, we show later that the jump intensity λ determines the endogenous profitability $\Pi_{i,t}$, thereby shaping firms' aggregate risk exposure, even though the left-tail idiosyncratic jump risk itself is not priced because of full diversification. As we show in the model and data, the time variation in financial distress of an industry is mainly driven by the fluctuation in the distance to default, while the cross-sectional variation in financial distress across industries is mainly due to the heterogeneous intensity of idiosyncratic jumps

λ. By focusing on the single ex-ante heterogeneity in λ across industries, our model is able to generate cross-industry variations in financial distress, profitability, and aggregate risk exposure.

Stochastic Discount Factor (SDF). Countercyclical risk premia are crucial for the Leland-type models to quantitatively reconcile the joint patterns of low leverage, high credit spreads, and low default frequency (e.g., Chen, Collin-Dufresne and Goldstein, 2008; Chen, 2010). Motivated by the previous studies, we directly specify the SDF Λ_t for tractability, which evolves according to

$$\frac{\mathrm{d}\Lambda_t}{\Lambda_t} = -r_f \mathrm{d}t - \gamma_t \mathrm{d}Z_t - \zeta \mathrm{d}Z_{\gamma,t}, \tag{3}$$

where Z_t and $Z_{\gamma,t}$ are independent standard Brown motions, r_f is the equilibrium risk-free rate, and γ_t is the time-varying market price of risk evolving as follows:

$$\mathrm{d}\gamma_t = -\varphi(\gamma_t - \overline{\gamma})\mathrm{d}t - \pi \mathrm{d}Z_{\gamma,t} \quad \text{with} \quad \varphi, \overline{\gamma}, \pi > 0. \tag{4}$$

Our specification of time-varying discount rate γ_t follows the literature on cross-sectional return predictability (e.g., Lettau and Wachter, 2007; Belo and Lin, 2012; Dou, Ji and Wu, 2020*a*). We assume $\zeta > 0$ to capture the well-documented countercyclical market price of risk. The primitive economic mechanism driving the countercyclical market price of risk could be, for example, time-varying risk aversion as in Campbell and Cochrane (1999). Therefore, our model is similar to Chen, Collin-Dufresne and Goldstein (2008), who show that the countercyclical market price of risk generated by the habit formation model (Campbell and Cochrane, 1999), combined with procyclical asset value and countercyclical default boundaries, can generate high credit spreads. Importantly, default boundaries are endogenous in our model, and moreover, the endogenous default boundaries are affected by the endogenous time-varying industry competition intensity driven by fluctuations in the discount rate γ_t.

Interpretation of the Shocks. The aggregate shock Z_t in equations (2) and (3) can be interpreted as the aggregate demand shock. The aggregate shock Z_t in equations (2) and (3) ensures that variation in the aggregate discount rate γ_t affects the valuation of firms' cash flows and can thus generate variation in industry competition intensity. In other words, the aggregate demand shock Z_t is needed for the discount-rate shock $Z_{\gamma,t}$ to have an impact on valuation and competition intensity. The discount rate γ_t is the only aggregate state variable. Economic downturns in our model are characterized by high γ_t.

The idiosyncratic shocks $W_{1,t}$ and $W_{2,t}$ can be interpreted as idiosyncratic demand (or taste) shocks. The idiosyncratic shocks are needed for the model to quantitatively match the default frequency and generate a non-degenerate cross-sectional distribution of customer base in the

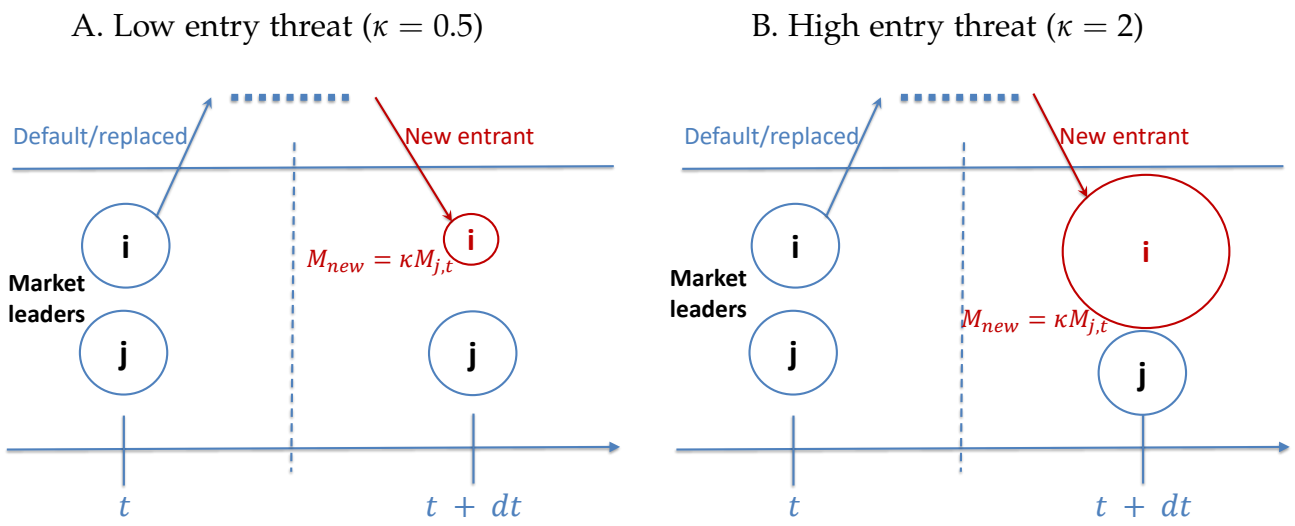


Figure 3: An illustration of "exit and reinjection" in our model.

stationary equilibrium.

The left-tail idiosyncratic jump shocks $J_{1,t}$ and $J_{2,t}$ play a crucial role in our theory and empirical results. Idiosyncratic jump risk has proven useful in explaining credit spreads and CDX spreads (e.g., Delianedis and Geske, 2001; Zhou, 2001; Collin-Dufresne, Goldstein and Yang, 2012; Seo and Wachter, 2018; Kelly, Manzo and Palhares, 2018). In this paper, we focus on the cross-industry heterogeneity in left-tail idiosyncratic jump intensity λ as a crucial and fundamental industry characteristic.

Exit and Entry. In our model, a market leader can exit the industry in two ways, either endogenously or exogenously. On the one hand, the market leader i can optimally choose to file bankruptcy and exit when its equity value drops to zero due to negative shocks to its customer base $M_{i,t}$. This force leading to exit is similar to that of the standard Leland models through the fluctuations in the distance to default. On the other hand, the market leader i may go bankrupt and exit due to the occurrence of the left-tail idiosyncratic jump shock (i.e., $\mathrm{d}J_{i,t} = 1$). This force leading to exit is similar to that of Seo and Wachter (2018) through the "disastrous" idiosyncratic jump risk. We refer to the first way of exiting as *endogenous default* and the second way of exiting as *exogenous replacement*.

To maintain tractability, we assume that a new firm enters the industry only after an incumbent firm exits so that the number of firms stays constant. This assumption is inspired by the "return process" of Luttmer (2007) and the "exit and reinjection" assumption in the models of Miao (2005) and Gabaix et al. (2016) for industry dynamics. The same assumption is also commonly adopted in the industrial organization literature on oligopolistic competition and predation (e.g., Besanko, Doraszelski and Kryukov, 2014) and is interpreted as the reorganization of the exiting firm. Essentially, the "exit and reinjection" assumption in our

model implies that we always focus on the rivalry between the two top market leaders in the industry.

In particular, upon an incumbent firm i's exiting, a new entrant firm with initial customer base $M_{new} = \kappa M_{j,t} > 0$ and coupon rate b_{new} enters the industry immediately, where b_{new} is optimally chosen to maximize firm value given the tradeoff between tax shield benefits and distress costs. The parameter $\kappa > 0$ captures the relative size of the new entrant firm and the non-exiting incumbent firm j (see Figure 3). A higher κ implies that the incumbent market leaders face greater entry threat. When an incumbent competitor exits and a new competitor enters, the dynamic game of Bertrand duopolistic competition described in Section 2.3 is "reset" to a new one between the non-exiting incumbent market leader and the new entrant competitor.

2.2 Product Market Competition

The setup in Section 2.1 almost follows the standard model of Leland (1994), except for the endogenous profitability $\Pi_{i,t}$. We now elaborate on the determination of $\Pi_{i,t}$ through strategic competition.

Demand System for Differentiated Products. We first introduce the demand system for differentiated products within an industry. To model strategic competition, we assume that consumers derive utility from a basket of differentiated goods, which are produced by firms. The industry-level consumption C_t is determined by a Dixit-Stiglitz constant-elasticity-of-substitution (CES) aggregation:

$$C_t = \left[\sum_{i=1}^{2} \left(\frac{M_{i,t}}{M_t}\right)^{\frac{1}{\eta}} C_{i,t}^{\frac{\eta-1}{\eta}}\right]^{\frac{\eta}{\eta-1}}, \text{ with } M_t = \sum_{i=1}^{2} M_{i,t}, \tag{5}$$

where $C_{i,t}$ is the amount of firm i's products purchased by consumers, and the parameter $\eta > 1$ captures the elasticity of substitution among goods produced by the two firms in the same industry. The weight $M_{i,t}/M_t$ captures consumers' relative taste for firm i's products.

Let $P_{i,t}$ denote the price of firm i's goods. Given the price system $P_{i,t}$ for $i = 1, 2$ and the industry-level consumption C_t, the demand for firm i's goods $C_{i,t}$ can be obtained by solving a standard expenditure minimization problem:

$$C_{i,t} = \frac{M_{i,t}}{M_t}\left(\frac{P_{i,t}}{P_t}\right)^{-\eta} C_t, \quad \text{with industry price index } P_t = \left[\sum_{j=1}^{2}\left(\frac{M_{i,t}}{M_t}\right) P_{i,t}^{1-\eta}\right]^{\frac{1}{1-\eta}}. \tag{6}$$

The demand for firm i's goods $C_{i,t}$ increases with $M_{i,t}$ in equilibrium, all else equal. From a firm's perspective, it is natural to think of consumers' taste $M_{i,t}$ as firm i's customer base (or

customer capital) and M_t as the industry's total customer base (e.g., Gourio and Rudanko, 2014; Dou et al., 2019). The share $M_{i,t}/M_t$ is the customer base share of firm i, and a larger $M_{i,t}/M_t$ implies that firm i has a greater influence on the price index P_t (see equation (6)).

To characterize how the industry demand C_t depends on the industry price index P_t, we postulate an isoelastic industry demand curve following the works on industry dynamics (e.g., Hopenhayn, 1992; Pindyck, 1993; Caballero and Pindyck, 1996):

$$C_t = M_t P_t^{-\epsilon}, \tag{7}$$

where the coefficient $\epsilon > 1$ captures the industry's price elasticity of demand. A micro-foundation for such an isoelastic industry demand curve is that a continuum of industries exist in the economy producing differentiated industry-level baskets of goods, with the elasticity of substitution across industries being ϵ and the preference weight for an industry's goods equal to its customer base M_t.[6] We assume that $\eta \geq \epsilon > 1$, meaning that products within the same industry are more substitutable. For example, the elasticity of substitution between the Apple iPhone and the Samsung Galaxy is much higher than that between a cell phone and a cup of coffee.[7]

The short-run price elasticity of demand for firm i's goods, taking into account the externality, is

$$-\frac{\partial \ln C_{i,t}}{\partial \ln P_{i,t}} = \underbrace{\mu_{i,t}\left[-\frac{\partial \ln C_t}{\partial \ln P_t}\right]}_{\text{cross-industry}} + \underbrace{(1-\mu_{i,t})\left[-\frac{\partial \ln (C_{i,t}/C_t)}{\partial \ln (P_{i,t}/P_t)}\right]}_{\text{within-industry}} = \mu_{i,t}\epsilon + (1-\mu_{i,t})\eta, \tag{8}$$

where $\mu_{i,t}$ is the (revenue) market share of firm i, defined as follows:

$$\mu_{i,t} = \frac{P_{i,t}C_{i,t}}{P_t C_t} = \left(\frac{P_{i,t}}{P_t}\right)^{1-\eta}\frac{M_{i,t}}{M_t}. \tag{9}$$

The short-run price elasticity of demand is given by the average of η and ϵ, weighted by the firm's market share $\mu_{i,t}$. On the one hand, when the market share $\mu_{i,t}$ shrinks, within-industry competition becomes more relevant for firm i, so its price elasticity of demand depends more on η. In the extreme case where $\mu_{i,t} = 0$, firm i becomes atomistic and takes the industry price index P_t as given. As a result, firm i's price elasticity of demand is exactly η. On the other hand, when $\mu_{i,t}$ grows, cross-industry competition becomes more relevant for firm i and thus its price elasticity of demand depends more on ϵ. In the extreme case with $\mu_{i,t} = 1$, firm i

[6] The CES utility function that embodies aggregate preference for diversity over differentiated products can be further micro-founded by the characteristics (or address) model and the discrete choice theory (e.g., Anderson, Palma and Thisse, 1989).

[7] This assumption is consistent with the literature (e.g., Atkeson and Burstein, 2008; Corhay, Kung and Schmid, 2017; Dou, Ji and Wu, 2020*a*).

monopolizes the industry, and its price elasticity of demand is exactly ϵ.

Endogenous Profitability and Externality. Now, we characterize the profitability function. Firms' shareholders choose production, set profit margins, and make default decisions optimally to maximize their equity value. The marginal cost for a firm to produce a flow of goods is a constant $\omega > 0$. That is, when firm i produces goods at rate $Y_{i,t}$, its total costs of production are $\omega Y_{i,t} \mathrm{d}t$ over $[t, t + \mathrm{d}t]$. In equilibrium, the firm finds it optimal to choose $P_{i,t} > \omega$ and produce goods to exactly meet the demand, i.e., $Y_{i,t} = C_{i,t}$, since the production is costly and the goods are immediately perishable. Firm i's operating profits per unit of customer base are

$$\begin{aligned} \Pi_{i,t} = \Pi_i(\theta_{i,t}, \theta_{j,t}) &\equiv (P_{i,t} - \omega)\, C_{i,t} / M_{i,t} \\ &= \omega^{1-\epsilon} \theta_{i,t} \left(1 - \theta_{i,t}\right)^{\eta - 1} \left(1 - \theta_t\right)^{\epsilon - \eta}, \end{aligned} \tag{10}$$

where $\theta_{i,t}$ and θ_t represent the firm-level and industry-level profit margins, given by

$$\theta_{i,t} \equiv \frac{P_{i,t} - \omega}{P_{i,t}} \quad \text{and} \quad \theta_t \equiv \frac{P_t - \omega}{P_t}. \tag{11}$$

It directly follows from equation (6) that the relation between $\theta_{i,t}$ and θ_t is

$$1 - \theta_t = \left[\sum_{j=1}^{2} \left(\frac{M_{i,t}}{M_t} \right) \left(1 - \theta_{i,t}\right)^{\eta - 1} \right]^{\frac{1}{\eta - 1}}. \tag{12}$$

Equation (10) shows that firm i's profitability $\Pi_i(\theta_{i,t}, \theta_{j,t})$ depends on its competitor j's profit margin $\theta_{j,t}$ through the industry's profit margin θ_t. This reflects the externality of firm j's profit margin decisions. For example, holding firm i's profit margin fixed, if firm j cuts its profit margin $\theta_{j,t}$, the industry's profit margin θ_t will drop, which will reduce the demand for firm i's goods $C_{i,t}$ (see equation (6)), and in turn firm i's profitability $\Pi_i(\theta_{i,t}, \theta_{j,t})$.

The earnings in equation (1) can be rewritten as

$$E_{i,t} = (1 - \tau) \left[\Pi_i(\theta_{i,t}, \theta_{j,t}) M_{i,t} - b_i \right], \tag{13}$$

which are determined by both firm i's profit margin $\theta_{i,t}$ and its competitor's profit margin $\theta_{j,t}$. The endogenous firm-level cash flows and externality of firms decisions are the key deviation of our model from the standard model of Leland (1994). Below we illustrate how firms optimally choose profit margins and default.

2.3 Nash Equilibrium

We solve the dynamic games with strategic profit margins and default decisions based on the SDF specified in equations (3) and (4).

Nash Equilibrium. The two firms in an industry play a supergame (Friedman, 1971), in which the stage games of setting profit margins are played continuously and repeated infinitely with exogenous and endogenous state variables varying over time. There exists a non-collusive equilibrium, which is the repetition of the one-shot Nash equilibrium and thus is Markov perfect. Meanwhile, multiple subgame perfect collusive equilibria also exist in which profit-margin strategies are sustained by conditional punishment strategies.[8]

Formally, a subgame perfect Nash equilibrium for the supergame consists of a collection of profit-margin strategies that constitute a Nash equilibrium for every history of the game. We do not consider all such equilibria; instead, we only focus on those which allow for collusive arrangements enforced by punishment schemes. All strategies are allowed to depend upon both "payoff-relevant" states $x_t = \{M_{1,t}, M_{2,t}, \gamma_t\}$ in state space $\mathcal{X}$, as in Maskin and Tirole (1988*a*,*b*), and a set of indicator functions that track whether any firm has previously deviated from a collusive profit-margin agreement, as in Fershtman and Pakes (2000, Page 212).[9]

Non-Collusive Equilibrium with Endogenous Default Boundaries. The non-collusive equilibrium is characterized by profit-margin scheme $\Theta^N(\cdot) = (\theta_1^N(\cdot), \theta_2^N(\cdot))$, which is a pair of functions defined in state space $\mathcal{X}$, such that each firm i ($i = 1, 2$) chooses profit margin $\theta_{i,t} \equiv \theta_i(x_t)$ to maximize equity value $V_i^N(x_t)$, under the assumption that its competitor j will set the one-shot Nash-equilibrium profit margin $\theta_{j,t}^N \equiv \theta_j^N(x_t)$. Following the recursive formulation in dynamic games for characterizing the Nash equilibrium,[10] optimization problems conditioning on no endogenous default at time t can be formulated by a pair of Hamilton-Jacobi-Bellman (HJB) equations with $i = 1, 2$:

$$\lambda V_i^N(x_t)\mathrm{d}t = \max_{\theta_{i,t}} \underbrace{(1-\tau)[\Pi_i(\theta_{i,t}, \theta_{j,t}^N)M_{i,t} - b_i]\mathrm{d}t}_{\text{earnings}} + \underbrace{\Lambda_t^{-1}\mathbb{E}_t\left[\mathrm{d}(\Lambda_t V_i^N(x_t))\right]}_{\text{value gain if no jump shock}}. \tag{14}$$

The left-hand side $\lambda V_i^N(x_t)\mathrm{d}t$ is the expected loss of equity value due to the left-tail idiosyncratic jump shock, which occurs with intensity λ. The right-hand side is the expected gain

[8] In the industrial organization and macroeconomics literature, this equilibrium is called the collusive equilibrium or collusion (e.g., Green and Porter, 1984; Rotemberg and Saloner, 1986). Game theorists generally call it the equilibrium of repeated game (see Fudenberg and Tirole, 1991) in order to distinguish it from the one-shot Nash equilibrium (i.e., our non-collusive equilibrium).

[9] For notational simplicity, we omit the indicator states of historical deviations.

[10] e.g., Pakes and McGuire (1994), Ericson and Pakes (1995), and Maskin and Tirole (2001).

of shareholders if the left-tail jump shock does not occur over $[t, t+\mathrm{d}t]$. The solutions to the coupled HJB equations give the non-collusive profit margin $\theta_{i,t}^N \equiv \theta_i^N(x_t)$ with $i = 1, 2$.

Denote by $\underline{M}_{i,t}^N \equiv \underline{M}_i^N(M_{j,t}, \gamma_t)$ firm i's endogenous default boundary in the non-collusive equilibrium. At the default boundary $\underline{M}_{i,t}^N$, the equity value of firm i is equal to zero (i.e., the value matching condition) and the boundary is optimal in terms of maximizing the equity value (i.e., the smooth pasting condition):

$$V_i^N(x_t)\Big|_{M_{i,t}=\underline{M}_{i,t}^N} = 0 \quad \text{and} \quad \frac{\partial}{\partial M_{i,t}} V_i^N(x_t)\Big|_{M_{i,t}=\underline{M}_{i,t}^N} = 0, \quad \text{respectively.} \tag{15}$$

The boundary condition at $M_{i,t} = +\infty$ is given in Online Appendix 1.4. Intuitively, firm i essentially becomes an industry monopoly with negligible default risk when $M_{i,t} = +\infty$, because its competitor j is negligible for any finite value of $M_{j,t}$.

Collusive Equilibrium with Endogenous Default Boundaries. In the collusive equilibrium, firms tacitly collude with each other in setting higher profit margins, with any deviation triggering a switch to the non-collusive equilibrium. The collusion is "tacit" in the sense that it can be enforced without relying on legal contracts. Each firm is deterred from breaking the collusion agreement because doing so could provoke fierce non-collusive competition.

Consider a generic collusive equilibrium in which the two firms follow a collusive profit-margin scheme. Both firms can costlessly observe the other's profit margin, so that deviation can be detected and punished. The assumption of perfect information follows the literature.[11] In particular, if one firm deviates from the collusive profit-margin scheme, then with probability $\xi \mathrm{d}t$ over $[t, t+\mathrm{d}t]$ the other firm will implement a punishment strategy in which it will forever set the non-collusive profit margin. Entering the non-collusive equilibrium is considered as a punishment for the deviating firm, because the non-collusive equilibrium features the lowest profit margin.[12] We use the idiosyncratic Poisson process $N_{i,t}$ to characterize whether a firm can successfully implement a punishment strategy. One interpretation of $N_{i,t}$ is that, with probability $1 - \xi \mathrm{d}t$ over $[t, t+\mathrm{d}t]$, the deviator can persuade its competitor not to enter the non-collusive Nash equilibrium over $[t, t+\mathrm{d}t]$.[13] Thus, the punishment intensity ξ can be viewed as a parameter governing the credibility of the punishment for deviation behavior. A

[11] A few examples include Rotemberg and Saloner (1986), Haltiwanger and Harrington (1991), Staiger and Wolak (1992), and Bagwell and Staiger (1997).

[12] We adopt the non-collusive equilibrium as the incentive-compatible punishment for deviation, which follows the literature (e.g., Green and Porter, 1984; Rotemberg and Saloner, 1986). We can extend the setup to allow for finite-period punishment. The quantitative implications are not altered significantly provided that the punishment lasts long enough.

[13] Ex-post renegotiations can occur because the non-collusive equilibrium is not renegotiation-proof or "immune to collective rethinking" (Farrell and Maskin, 1989). The strategy we consider is essentially a probabilistic punishment strategy. This "inertia assumption" also solves the technical issue of continuous-time dynamic games about indeterminacy of outcomes (e.g., Simon and Stinchcombe, 1989; Bergin and MacLeod, 1993).

higher ξ leads to a lower deviation incentive and higher profit margins.

Formally, the set of incentive-compatible collusion agreements, denoted by $\mathcal{C}$, consists of all continuous profit-margin schemes $\Theta^C(\cdot) \equiv (\theta_1^C(\cdot), \theta_2^C(\cdot))$, such that the following participation constraints (PC) and incentive compatibility (IC) constraints are satisfied:

$$V_i^N(x) \leq V_i^C(x), \quad \text{for all } x \in \mathcal{X} \text{ and } i = 1, 2; \qquad \text{(PC constraints)} \tag{16}$$

$$V_i^D(x) \leq V_i^C(x), \quad \text{for all } x \in \mathcal{X} \text{ and } i = 1, 2. \qquad \text{(IC constraints)} \tag{17}$$

Here, $V_i^N(x)$ is firm i's equity value in the non-collusive equilibrium, $V_i^D(x)$ is firm i's equity value if it chooses to deviate from the collusion, and $V_i^C(x)$ is firm i's equity value in the collusive equilibrium. Conditioning on no endogenous default at time t, $V_i^C(x)$ is pinned down recursively according to

$$\lambda V_i^C(x_t)\mathrm{d}t = \underbrace{(1-\tau)[\Pi_i(\theta_{i,t}^C, \theta_{j,t}^C)M_{i,t} - b_i]\mathrm{d}t}_{\text{earnings}} + \underbrace{\Lambda_t^{-1}\mathbb{E}_t\left[\mathrm{d}(\Lambda_t V_i^C(x_t))\right]}_{\text{value gain if no jump shock}}, \quad \text{for } i = 1, 2, \tag{18}$$

subject to the PC and IC constraints in equations (16) and (17), where $\theta_{i,t}^C \equiv \theta_i^C(x_t)$ with $i = 1, 2$ are the collusive profit margins. The left-hand side $\lambda V_i^C(x_t)\mathrm{d}t$ is the expected loss of equity value due to the left-tail idiosyncratic jump shock, while the right-hand side is the expected gain of shareholders if the left-tail jump shock does not occur over $[t, t + \mathrm{d}t]$. The non-default region is characterized by $M_{i,t} > \underline{M}_{i,t}^C \equiv \underline{M}_i^C(M_{j,t}, \gamma_t)$ where $\underline{M}_{i,t}^C$ is firm i's optimal default boundary in the collusive equilibrium, determined by the value matching and smooth pasting conditions:

$$V_i^C(x_t)\Big|_{M_{i,t}=\underline{M}_{i,t}^C} = 0 \quad \text{and} \quad \frac{\partial}{\partial M_{i,t}} V_i^C(x_t)\Big|_{M_{i,t}=\underline{M}_{i,t}^C} = 0, \text{ respectively.} \tag{19}$$

The boundary condition at $M_{i,t} = +\infty$ is identical to that in the non-collusive equilibrium, because when $M_{i,t} = +\infty$, firm i is essentially an industry monopoly and there is no benefit from colluding with firm j whose customer base share is zero.

Equilibrium Deviation Values. Let $V_i^D(x_t)$ be firm i's highest equity value if it deviates from implicit collusion. The highest deviation value evolves as follows:

$$\begin{aligned}\lambda V_i^D(x_t)\mathrm{d}t = \max_{\theta_{i,t}} & \underbrace{(1-\tau)[\Pi_i(\theta_{i,t}, \theta_{j,t}^C)M_{i,t} - b_i]\mathrm{d}t}_{\text{earnings}} \\ & - \underbrace{\xi\left[V_i^D(x_t) - V_i^N(x_t)\right]\mathrm{d}t}_{\text{if punished}} + \underbrace{\Lambda_t^{-1}\mathbb{E}_t\left[\mathrm{d}(\Lambda_t V_i^D(x_t))\right]}_{\text{value gain if no jump shock}}, \quad \text{for } i = 1, 2.\end{aligned} \tag{20}$$

The left-hand side $\lambda V_i^D(x_t)\mathrm{d}t$ is the expected loss of equity value due to the left-tail idiosyncratic jump shock, while the right-hand side is the expected gain of shareholders if the left-tail jump shock does not occur over $[t, t+\mathrm{d}t]$. The equilibrium recursive relation characterized by the coupled equations above only holds within the non-default region, characterized by $M_{i,t} > \underline{M}_{i,t}^D \equiv \underline{M}_i^D(M_{j,t}, \gamma_t)$ where $\underline{M}_{i,t}^D$ is firm i's default boundary if it chooses to deviate from collusion. The value matching and smooth pasting conditions for the optimal default boundary are

$$V_i^D(x_t)\Big|_{M_{i,t}=\underline{M}_{i,t}^D} = 0 \quad \text{and} \quad \frac{\partial}{\partial M_{i,t}} V_i^D(x_t)\Big|_{M_{i,t}=\underline{M}_{i,t}^D} = 0, \quad \text{respectively.} \tag{21}$$

The boundary condition at $M_{i,t} = +\infty$ is identical to that in the non-collusive equilibrium as discussed above.

More Discussions. Two points are worth more discussion. First, the equity value in the collusive equilibrium could be equal to that in the non-collusive equilibrium, i.e., the PC constraints (16) are binding. When one firm's PC constraint becomes binding, the two firms switch to the non-collusive equilibrium. The endogenous switch to the non-collusive equilibrium captures endogenous price wars, which we illustrate in Section 3.3. We assume that once the two firms switch to the non-collusive equilibrium, they will stay there forever.[14] The endogenous switching between the collusive and non-collusive equilibrium (i.e., predatory price war) due to financial distress is our model's key difference from the model of Dou, Ji and Wu (2020*a*), in which firms never suffer from financial distress because they are financed wholly by equity. In their model, the PC constraints for profit-margin collusion are never binding since higher profit margins always lead to higher equity values in the absence of default or exit.

Second, there exist infinitely many elements in $\mathcal{C}$ and hence infinitely many collusive equilibria. We focus on a subset of $\mathcal{C}$, denoted by $\overline{\mathcal{C}}$, consisting of all profit-margin schemes $\Theta_i^C(\cdot)$ such that the IC constraints (17) are binding state by state, i.e., $V_i^D(x_t) = V_i^C(x_t)$ for all $x_t \in \mathcal{X}$ and $i = 1, 2$.[15] It is obvious that the subset $\overline{\mathcal{C}}$ is nonempty since it contains the profit-margin scheme in the non-collusive Nash equilibrium. We further narrow our focus to the "Pareto-efficient frontier" of $\overline{\mathcal{C}}$, denoted by $\overline{\mathcal{C}}_p$, consisting of all pairs of $\Theta_i^C(\cdot)$ such that there does not exist another pair $\widetilde{\Theta}^C(\cdot) \in \overline{\mathcal{C}}$ with $\widetilde{\theta}_i(x_t) \geq \theta_i^C(x_t)$ for all $x_t \in \mathcal{X}$ and $i = 1, 2$, with strict inequality holding for some x_t and i.[16] Our numerical algorithm follows a

[14] The firm that proposes to switch to the non-collusive equilibrium is essentially deviating, and thus we assume they will not return to the collusive equilibrium to be consistent with our specification of punishment strategies.

[15] Such equilibrium refinement is in spirit similar to that of Abreu (1988), Alvarez and Jermann (2000, 2001), and Opp, Parlour and Walden (2014) in a general equilibrium framework.

[16] It can be shown that the "Pareto-efficient frontier" is nonempty based on the fundamental theorem of the

method similar to that of Abreu, Pearce and Stacchetti (1990).[17] Deviation never occurs on the equilibrium path. Using the one-shot deviation principle (Fudenberg and Tirole, 1991), it is clear that the collusive equilibrium characterized above is a subgame perfect Nash equilibrium.

Debt Value. Given the optimal default boundaries $M_i^C(x_t)$ characterized above in (19), we can directly calculate the value of corporate debt. Debt value equals the sum of the present value of the cash flows that accrue to debtholders until the endogenous default time or the occurrence of the idiosyncratic jump shock (i.e. the exogenous replacement), whichever is earlier, plus the recovery value upon the endogenous default or exogenous replacement.

The recovery value upon endogenous default is determined by the firm's abandonment value. We follow the literature on dynamic debt models (e.g., Mello and Parsons, 1992; Leland, 1994; Hackbarth, Miao and Morellec, 2006) and set the abandonment value to be a fraction ν of the firm's unlevered asset value. We assume that, when the idiosyncratic jump shock hits the firm i over $[t, t+\mathrm{d}t]$ (i.e., $\mathrm{d}J_{i,t}=1$), there are possible outcomes: first, with probability ϖ, the firm is wiped out with little debtholder recovery; and second, with probability $1-\varpi$, the firm is restructured by the new entrant firm, during which the old debt is retired at par value and a new debt will be optimally issued as in Leland (1998) and Goldstein, Ju and Leland (2001). In other words, upon $\mathrm{d}J_{i,t}=1$, the firm defaults on the debt with probability ϖ.

The unlevered asset value is the value of an all-equity firm. In the collusive equilibrium, the unlevered asset value $A_i^C(x_t)$ is determined similarly by equations (14) – (21) except for setting $b_i=0$ and removing the default boundary conditions (15), (19), and (21).

The value of debt in the non-default region (i.e., $M_{i,t} > \underline{M}_{i,t}^C$) of the collusive equilibrium, denoted by $D_i^C(x_t)$, can be characterized by the following coupled HJB equation:

$$\varpi\lambda D_i^C(x_t)\mathrm{d}t = \underbrace{b_i\mathrm{d}t}_{\text{coupons}} + \underbrace{\Lambda_t^{-1}\mathbb{E}_t\left[\mathrm{d}(\Lambda_t D_i^C(x_t))\right]}_{\text{value gain if no jump shock}}, \quad \text{for } i=1,2, \tag{22}$$

with boundary conditions:

$$D_i^C(x_t)\Big|_{M_{i,t}=\underline{M}_{i,t}^C} = \nu A_i^C(x_t)\Big|_{M_{i,t}=\underline{M}_{i,t}^C} \quad \text{and} \quad \lim_{M_{i,t}\to+\infty} D_i^C(x_t) = \frac{b_i}{r_f+\varpi\lambda}, \quad \text{for } i=1,2. \tag{23}$$

The left-hand side of equation (22) is the expected loss of debt due to the left-tail idiosyncratic jump shock, while the right-hand side is the expected gain of debtholders if the jump shock

existence of Pareto-efficient allocations (e.g., Mas-Colell, Whinston and Green, 1995), as $\overline{\mathcal{C}}$ is nonempty and compact, and the order we are considering is complete, transitive, and continuous.

[17] Alternative methods include Cronshaw and Luenberger (1994), Pakes and McGuire (1994), and Judd, Yeltekin and Conklin (2003), which contain similar ingredients to those of our solution method. Proving the uniqueness of the equilibrium under our selection criterion is beyond the scope of the paper. We use different initial points in our numerical algorithm and find robust convergence to the same equilibrium.

does not occur over $[t, t + \mathrm{d}t]$ or if it only results in restructuring with full debt recovery rather than defaulting on the debt. The first condition in equation (23) is the recovery value to debtholders at the default boundary, and the second condition in equation (23) captures the asymptotic behavior of debt value when customer base $M_{i,t}$ approaches infinity, which is basically the value of a consol bond with constant coupon rate b_i and default rate $\varpi\lambda$.

3 Main Theoretical Results

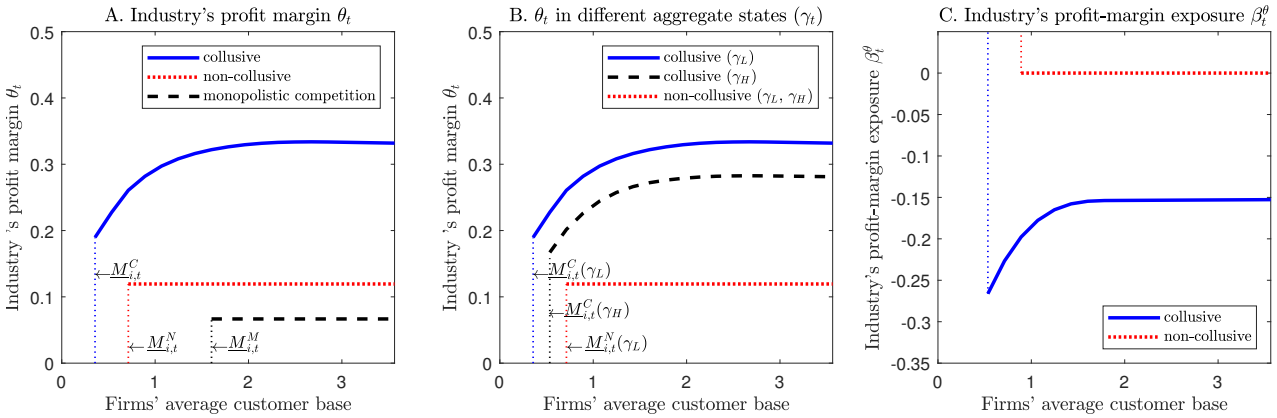
Our model has the following main theoretical results. First, there exists a positive feedback loop between competition and financial distress (see Section 3.1). When a firm becomes more financially distressed, it becomes more impatient and thus competes more aggressively. The intensified competition narrows profit margins for all firms, which in turn elevates the level of financial distress and default risk. The competition-distress feedback largely amplifies the industry's exposure to aggregate discount-rate shocks in γ_t.

Second, strategic competition of financially distressed firms in the product markets leads to financial contagion (see Section 3.2). For instance, negative idiosyncratic shocks hitting one leading firm may intensify competition of the industry, resulting in lower profit margins and higher default risk for other firms. Such financial contagion effects are more pronounced in industries with more balanced market shares.

Third, our model implies that in industries with low entry threat, predatory price war could emerge endogenously when one incumbent competitor falls into deep financial distress after adverse idiosyncratic shocks; by contrast, in industries with high entry threat, collaboration could take place to help the distressed incumbent competitor to survive and prevent powerful new competitors from entering (see Section 3.3), referred to as collective entry prevention in the literature.

Fourth, both the competition-distress feedback and financial contagion effect are dampened when industries' market structure becomes more competitive (see Section 3.4). This is a unique testable prediction for the core endogenous competition mechanism of our model.

Finally, the competition-distress feedback effect helps rationalize the financial distress anomaly (see Section 3.5). The competition-distress feedback is weaker in industries in which firms are more financially distressed in the cross section, because firms are more exposed to the idiosyncratic jump risk and have less incentive to collude. As a result, firms in such industries are less exposed to discount-rate shocks and pay lower expected excess returns to shareholders.



Note: We consider a duopoly industry with two identical firms (i.e., $M_{i,t} = M_{j,t}$). The blue solid and red dotted lines in panel A plot the duopoly industry's profit margin θ_t as a function of firms' average customer base. The black dashed line plots the profit margin of an industry of monopolistic competition where a continuum of firms exists (see Online Appendix 1.5 for its characterization). We set $\gamma_t = \overline{\gamma}$ in panel A. Panel B plots the same duopoly industry's profit margin θ_t for different aggregate states γ_t. The blue solid and black dashed lines represent a low $\gamma_t \equiv \gamma_L$ and a high $\gamma_t \equiv \gamma_H$ in the collusive equilibrium. The red dotted line represents the non-collusive equilibrium. We set $\gamma_L = \overline{\gamma}$ and $\gamma_H = \overline{\gamma} + 2\text{std}(\gamma_t)$ in panel B. Panel C plots the profit-margin beta to γ_t defined in equation (24). The blue solid and red-dotted lines represent collusive and non-collusive equilibria respectively. In all panels, the vertical dotted lines represent firms' default boundaries in corresponding cases. Other parameters are set according to our calibration in Section 4.2.

Figure 4: Positive feedback loop between competition and financial distress.

3.1 Feedback between Competition and Financial Distress

Our model implies that there exists competition-distress feedback at the industry level. Increased competition leads to more financial distress, which in turn intensifies competition.

Profit Margin and Distance to Default. To fix ideas, consider a duopoly industry with two identical firms for illustration. Panel A of Figure 4 plots the industry's profit margin as a function of firms' average customer base, as well as endogenous default boundaries. The industry has higher profit margins in the collusive equilibrium (the blue solid line) than in the non-collusive equilibrium (the red dotted line). Moreover, compared to an industry of monopolistic competition with a continuum of firms (the black dashed line), firms in the duopoly industry have higher profit margins.

On the one hand, as shown by the vertical lines in panel A, firms' default boundary in the collusive equilibrium is lower than that in the non-collusive equilibrium of the duopoly industry, which is lower than that in the industry of monopolistic competition (i.e., $\underline{M}_{i,t}^C < \underline{M}_{i,t}^N < \underline{M}_{i,t}^M$). Therefore, given the same average customer base of firms, the distance to default decreases when the market structure becomes more competitive. Moreover, focusing on the collusive equilibrium (i.e., the blue solid line), we learn that, as the competition intensifies (i.e., the profit margin narrows), the distance to default decreases; namely, higher competition intensity leads to more financial distress, because undercutting profit margins erodes firms' cash flows.

On the other hand, panel A of Figure 4 also shows that the profit margin in the collusive

equilibrium (the blue solid line) endogenously decreases as firms' distance to default decreases (i.e., the average customer base decreases with the coupon kept fixed). This indicates that financial distress intensifies competition and thus lowers equilibrium profit margins. Intuitively, the incentive to collude on higher profit margins depends on how much firms value future cash flows relative to their contemporaneous cash flows. By deviating from the collusive profit-margin-setting scheme, firms can obtain higher contemporaneous cash flows; however, firms run into the risk of losing future cash flows because once the deviation is punished by the other firm, the non-collusive equilibrium will be implemented, which features low profit margins. When firms are closer to the default boundary, they are more likely to exit the market in the near future due to the higher probability of default. As a result, firms become effectively more impatient and care less about the future cooperation. This motivates firms to undercut their competitors' profit margin. Thus, to ensure that deviation does not occur in the collusive equilibrium (i.e., the IC constraints (17) are satisfied), the mutually agreed profit margins must fall when firms are driven closer to the default boundary. Therefore, increased financial distress would result in lower profit margins and intensify competition.[18]

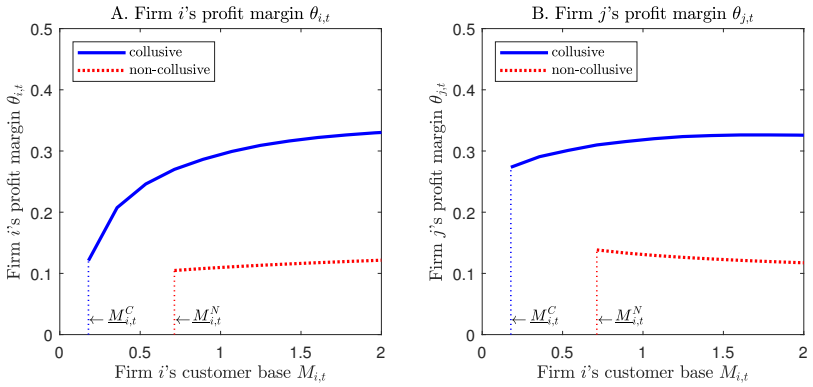
Taken together, panel A of Figure 4 shows a positive feedback loop between competition and financial distress. By contrast, there is no feedback loop in the non-collusive equilibrium (the red dotted line) or in the industry of monopolistic competition (the black dashed line), because the industry's profit margin is constant regardless of the average customer base of firms in these two cases. This is because in both cases, the intensity of competition is only determined by the constant price elasticity of demand when the market share is kept fixed, and the distance to default has no effect on competition intensity.

Exposure of Profit Margins to Discount-Rate Shocks. Our model implies that a higher discount rate leads to a higher industry competition intensity, especially when firms in the industry are closer to the default boundary due to the competition-distress feedback.

As an illustration, panel B of Figure 4 plots the duopoly industry's profit margin in the collusive equilibrium in the states with a low discount rate γ_L (the blue solid line) and a high discount rate γ_H (the black dashed line). It is shown that the industry's profit margin is lower when the discount rate is higher.[19] This is because a higher discount rate γ_H makes firms more impatient and focus more on short-term cash flows, thereby making firms care less about the future cooperation. As a result, future punishment becomes less threatening and higher profit

[18] Our model echoes and formalizes the generic insight of Maskin and Tirole (1988*a*) and Fershtman and Pakes (2000) in a quantitative framework: if firms are more likely to exit the market in the future, the incentive for collusive behavior becomes weaker.

[19] Kawakami and Yoshihiro (1997) and Wiseman (2017) show that in a market with exits but no entries, firms may have less incentive to collude with each other when the discount rate is lower, and instead they enter into a price war until only one firm in the industry is alive. This is not the case in our model because we allow new firms to enter the industry.



Note: Panels A and B plot the profit margins of firm i and j as a function of firm i's customer base $M_{i,t}$. The blue solid and red dotted lines represent the collusive equilibrium and the non-collusive equilibrium. The vertical dotted lines represent default boundaries of firm i in corresponding cases. We set $\gamma_t = \overline{\gamma}$ and $M_{j,t} = 2$. Other parameters are set according to our calibration in Section 4.2.

Figure 5: Financial contagion between the two firms in the same industry.

margins are more difficult to sustain. By contrast, in the non-collusive equilibrium, profit margins remain unchanged when the discount rate rises (see the red-dotted line) because competition intensity is only determined by the constant price elasticity of demand when the customer base share is kept fixed.

To illustrate how the exposure of profit margins to the discount rate varies with the distance to default, we calculate the profit-margin beta β^{θ}_t to the discount rate, defined as the ratio of the industry's profit margin between the two aggregate states:

$$\beta^{\theta}_t \equiv \theta^C_t(\gamma_H)/\theta^C_t(\gamma_L) - 1. \tag{24}$$

Importantly, the blue solid line in panel C of Figure 4 shows that in the collusive equilibrium, the profit-margin beta becomes more negative when the industry becomes more financially distressed. In particular, when the industry is close to the default boundary, the profit-margin beta is as large as -0.27, indicating that the industry's profit margin decreases by 27% in responding to a two standard deviation increase in the discount rate γ_t. This is because the endogenously intensified competition is further amplified by the feedback loop between competition and financial distress, dramatically increasing the industry's exposure to discount rates, especially when the industry is financially distressed.[20] By contrast, the profit-margin beta is zero in the non-collusive equilibrium (see the red dotted line).

3.2 Financial Contagion through Strategic Competition

We show that there exists financial contagion among firms within the same industry through the endogenous competition channel: negative idiosyncratic shocks hitting one firm may also

[20]We provide more discussion on equity's risk exposure in Online Appendix 1.1.

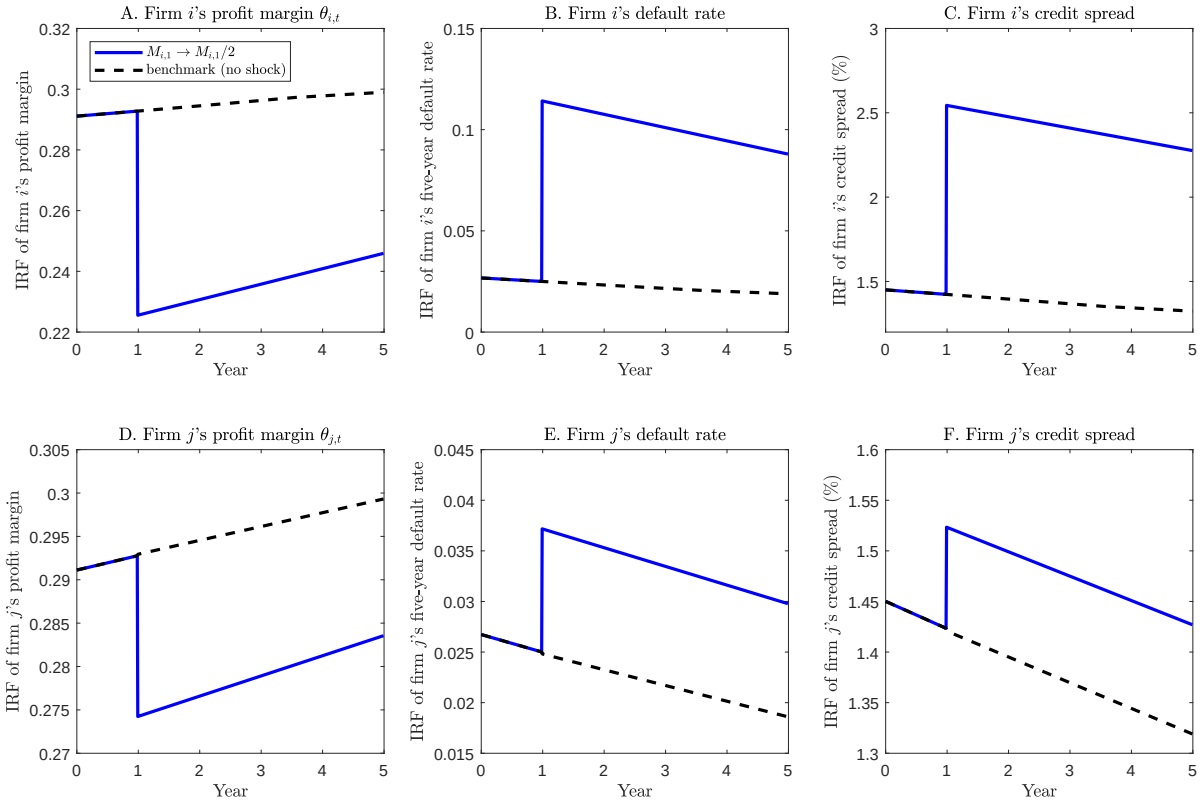
increase its competitor's default risk. To elaborate on the financial contagion effect, panels A and B of Figure 5 plot the firms i and j's profit margins as a function of firm i's customer base $M_{i,t}$, respectively, with firm j's customer base fixed at $M_{j,t} = 2$. The blue solid line in panel A shows that firm i reduces its profit margin when it becomes more financially distressed (i.e., lower distance to default as $M_{i,t}$ decreases). Moreover, its financially strong competitor, firm j, also lowers profit margin (the blue solid line in panel B) even though firm j's customer base $M_{j,t}$ remains unchanged.

The competitor firm j undercuts profit margin because it knows that the financially weak firm i will cut its profit margin to compete for customers (the blue solid line in panel A). Firm j's intention to set a lower profit margin is to prevent its financially weak competitor from stealing demand.[21] Specifically, if firm j were to keep its profit margin unchanged, its financially weak competitor, firm i, will deviate from the collusive equilibrium by significantly undercutting the profit margin. To prevent firm i from deviating and maintaining the tacit collusion, firm j has to cut its own profit margin, which itself is an optimal response to increased financial distress of firm i. Thus, firm j's profit-margin undercutting behavior mainly reflects its self-defensive incentives.[22]

To better illustrate the contagion effect, Figure 6 plots the two firms' impulse response functions (IRF) of profit margins, 5-year default rate, and credit spreads after a negative shock to firm i's customer base. In panels A, B, and C, the blue solid lines plot the IRF of firm i's profit margin, 5-year default rate, and credit spread, respectively, after its customer base is reduced unexpectedly by half at $t = 1$. The black dashed lines represent the benchmark case without the shock. Consistent with panel A of Figure 5, firm i's profit margin decreased dramatically after being hit by the idiosyncratic shock at $t = 1$ (panel A of Figure 6) due to the competition-distress feedback. The lower profit margin and customer base significantly increase firm i's default rate (panel B of Figure 6) and credit spread (panel C of Figure 6). In panels D, E, and F, the blue solid lines plot the IRF of firm j's profit margin, default rate, and credit spread, respectively, in response to the shock on firm i's customer base. Although firm j is not hit by any shocks, its profit margin also decreases when firm i is hit by the shock as discussed above. Importantly, firm j's default rate increases by 1.3% and credit spread increases by about 10 basis points when its competitor, firm i, becomes more financially

[21] By contrast, in the non-collusive equilibrium, firm i's profit margin increases with its own customer base $M_{i,t}$ (the red dotted line in panel A) and firm j's profit margin decreases with its competitor firm i's customer base $M_{i,t}$ (the red dotted line in panel B). In other words, both firms' non-collusive profit margins are increasing in their own customer base share. This is because non-collusive profit margins are one-shot Nash equilibrium outcomes, which simply reflect the short-run price elasticity of demand that firms face. As shown by equation (8), a firm's short-run price elasticity of demand decreases with its customer base share, and thus a larger customer base share leads to a lower elasticity and a higher non-collusive profit margin.

[22] Firm j's profit-margin undercutting behavior may also partly reflect its predatory incentives. In Online Appendix 1.3, we discuss how to structurally isolate the predatory incentives from self-defensive incentives in our model. Our isolation of predatory incentives provides a valuable complement to that of Besanko, Doraszelski and Kryukov (2014).



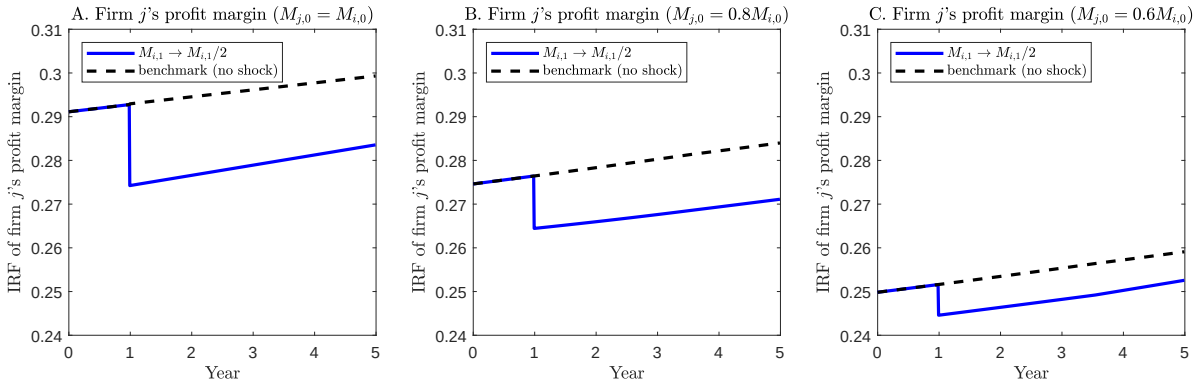
Note: Panels A – C illustrate the IRF of profit margins, 5-year default rates, and credit spreads of firm i after a negative idiosyncratic shock to firm i's customer base. Panels D – F illustrate the IRF of profit margins, 5-year default rates, and credit spreads of firm j after the same negative idiosyncratic shock to firm i's customer base. The black dashed lines plot the benchmark case without aggregate or idiosyncratic shocks for both firms. The blue solid lines plot the IRF when there is an unexpected idiosyncratic shock at $t = 1$, which reduces firm i's customer base by half, from $M_{i,1}$ to $M_{i,1}/2$. We set $M_{i,0} = M_{j,0} = 1$ and $\gamma_t = \overline{\gamma}$. The coupon rates b_i and b_j are optimally chosen at $t = 0$. Other parameters are set according to our calibration in Section 4.2.

Figure 6: Impulse response functions to illustrate the financial contagion effect.

distressed upon the impact of the shock at $t = 1$, indicating the existence of financial contagion within the industry.

In Figure 7, we further study how the relative size of the two firms in the industry affects the financial contagion effect. In particular, we consider industries with different initial distribution of customer base in panels A, B, and C. For the same shock to firm i's customer base at $t = 1$, the negative impact on firm j's profit margin is the largest when the two firms' customer base is comparable (panel A), and the impact becomes smaller when their customer base share becomes more imbalanced (panels B and C).

Intuitively, when the two firms have similar size of customer base (i.e., they have more balanced customer base share), both firms have large influence on the industry's price index through equation (6). This generates large externality and strong strategic concerns in profit-margin decisions as both firms know that the industry's price index is sensitive not only to their own profit margins but also to their competitor's profit margins. As a result, a change in



Note: This figure illustrates the IRF of firm j's profit margins after a negative idiosyncratic shock to firm i's customer base. We consider three industries with different initial customer base share, i.e., $M_{j,0} = M_{i,0}$ in panel A, $M_{j,0} = 0.8M_{i,0}$ in panel B, and $M_{j,0} = 0.6M_{i,0}$ in panel C. The black dashed lines in all panels plot the benchmark case without aggregate or idiosyncratic shocks for both firms. The blue solid lines in all panels plot the IRF when there is an unexpected idiosyncratic shock at $t = 1$, which reduces firm i's customer base by half, from $M_{i,1}$ to $M_{i,1}/2$. In all panels, we set $M_{i,0} = 1$ and $\gamma_t = \overline{\gamma}$. Other parameters are set according to our calibration in Section 4.2. In all cases, the coupon rates b_i and b_j are optimally chosen at $t = 0$.

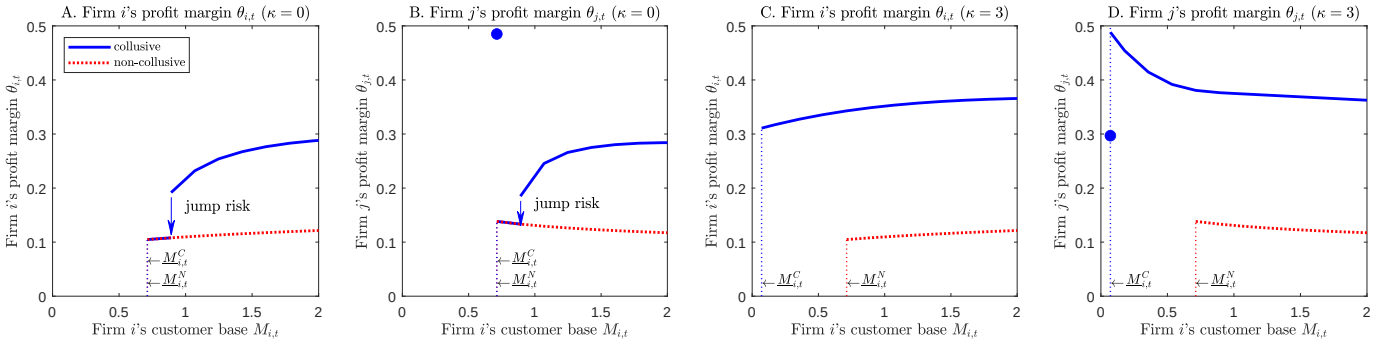
Figure 7: Financial contagion in industries with different distribution of customer base.

one firm's financial distress would generate a large impact on the other firm's profit margins. By contrast, when the two firms' customer base shares are very imbalanced, both firms would have little strategic concerns. Therefore, in industries with more imbalanced distribution of customer base, both the small and the big firms' profit margins reflect more about their own financial condition rather than their competitors' financial condition due to weaker strategic interactions. For instance, when the larger firm owns almost all the customer base, the larger firm sets monopolistic profit margin determined by ϵ, whereas the smaller firm sets monopolistically competitive profit margin determined by η. Changes in financial distress of either firm have little impact on its competitor's profit margin.

3.3 Self-defense, Predation, and Collaboration

Although our calibration suggests that the contagion effect is mainly due to the self-defensive incentive of peer firms, our model can also generate other types of strategic behavior depending on the size of potential new entrants relative to incumbent firms, which is captured by the parameter κ. Recall that when firm i exits, a new entrant with initial customer base $M_{new} = \kappa M_{j,t}$ immediately enters the market (Figure 3). A smaller value of κ implies that the industry has lower entry threat for incumbent market leaders. While our benchmark calibration focuses on average industries with $\kappa = 0.3$ (see Section 4.2 for our calibration), we illustrate two extreme industries with $\kappa = 0$ and $\kappa = 3$, representing two industries with extremely low and high entry threat for incumbent market leaders, respectively.

In the industry with $\kappa = 0$ (i.e. no entry threat), panels A and B of Figure 8 show that profit margins are lower compared to the baseline industry (panels A and B of Figure 5) as



Note: In panels A and B, we consider an industry with no entry threat ($\kappa = 0$) and plot the two firms' profit margins as a function of firm i's customer base $M_{i,t}$. In panels C and D, we consider an industry with high entry threat ($\kappa = 3$). In all panels, the blue solid and red dash-dotted lines represent the collusive equilibrium and the non-collusive equilibrium. The blue dots in panels B and D represent the profit margin that firm j would set immediately after firm i defaults and exits the market. We set $\gamma_t = \overline{\gamma}$ and $M_{j,t} = 2$. Other parameters are set according to our calibration in Section 4.2.

Figure 8: Illustration of endogenous predatory price wars and collaboration.

firms' collusion incentive is dampened. Intuitively, both firms know that by driving their competitors out of the market, they can monopolize the industry and enjoy much higher profit margins in the future. Thus, they have less incentive to collude with each other ex-ante.

In panels A and B of Figure 8, holding firm j's customer base fixed at $M_{j,t} = 2$, when firm i's customer base $M_{i,t}$ drops below 0.85, the financially strong firm j would enter a full-blown price war by jumping into the non-collusive strategies. The collusive profit margin suddenly jumps downward at $M_{i,t} = 0.85$, and it stays at the non-collusive profit margin level for $\underline{M}^C_{i,t} < M_{i,t} < 0.85$ with $\underline{M}^C_{i,t}$ being the endogenous default boundary of firm i.[23] Thus, our model implies that the within-industry contagion effect on profit margins is more dramatic in industries with lower entry threat.[24]

In the industry with $\kappa = 3$ (i.e., extremely high entry threat), panels C and D of Figure 8 show that firms collude on much higher profit margins compared to the baseline industry (see panels A and B of Figure 5). This is because both firms worry about losing market power to the large new entrants, and thus they collaborate with each other to reduce the default risk.

[23] In Online Appendix 1.2, we show that it is the financially strong firm, firm j in this example, that wants to drive its financially weak competitor, firm i, into default by waging the price war. The downward jump in firm j's profit margins reflects its high real predatory incentives.

[24] In fact, when the entry threat is lower, the contagion effect on credit spreads implied by the model could become stronger or weaker, even though the contagion effect on profit margin always becomes stronger. In other words, the relation between the contagion effect on credit spreads and entry threat is ambiguous in our model, depending on the calibration. Intuitively, when the entry threat is lower, the financially strong firm j reduces its profit margin more when its financially weak competitor i becomes more financially distressed due to increased predatory incentives (see panel B of Figure 8), which generates two countervailing effects on its credit risk. On the one hand, the lower profit margin implies lower contemporaneous cash flows for firm j, increasing its default rate and credit risk. On the other hand, the lower profit margin attracts more demand from the financially weak competitor i, which reduces firm i's cash flows and may quickly drive firm i into default. The higher default probability of firm i implies that the financially strong firm j is more likely to gain more market power (due to low entry threat) and set higher profit margins in the near future, leading to lower default rates and credit risk for firm j.

In particular, panel D shows that when firm i's customer base decreases, firm j is willing to sacrifice its demand by increasing its profit margin, with the intention of mitigating firm i's financial distress by boosting its cash flows.

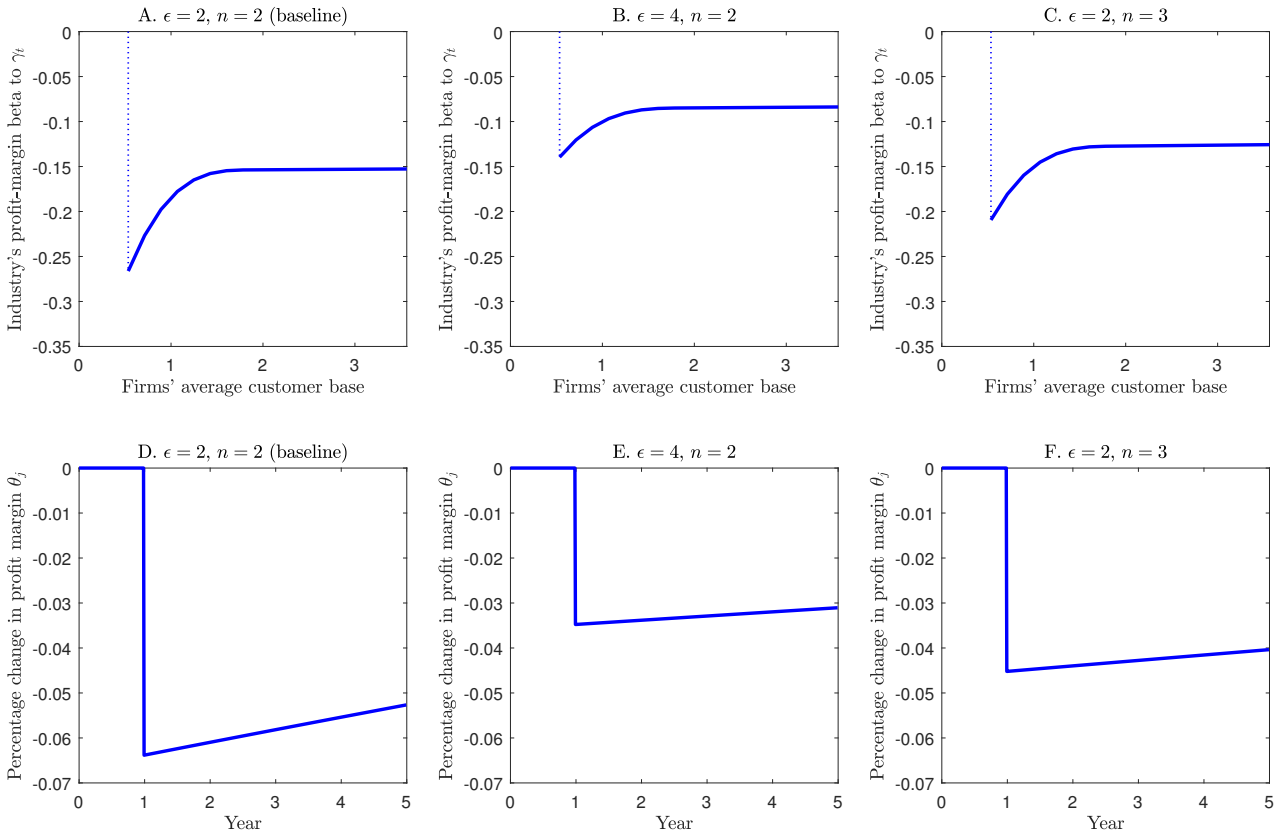
There is an extensive literature in industrial organization that attempts to rationalize predatory pricing as an equilibrium phenomenon by means of reputation effects (e.g., Kreps and Wilson, 1982), informational asymmetries (e.g., Fudenberg and Tirole, 1986), financial constraints (e.g., Bolton and Scharfstein, 1990), or learning-by-doing (e.g., Cabral and Riordan, 1994; Snider, 2008; Besanko, Doraszelski and Kryukov, 2014).[25] Our model complements these theories by establishing the connection between predatory pricing and financial distress. Our numerical illustration in panel B of Figure 8 nevertheless reveals the widespread existence of equilibria involving strategic behavior that resembles conventional notions of predatory pricing in the sense that aggressive pricing in the short run is associated with reduced competition in the long run. The full-blown predatory price war endogenously breaks out if the predatory incentive dominates, which is the case when the firms have very imbalanced financial condition and face very low entry threat.

3.4 Competition Mechanism under Different Market Structure

The endogenous competition mechanism generates both the competition-distress feedback and financial contagion effect. Here, we examine the feedback and contagion effect under various *market structures*. Like in many other studies in the literature, we characterize the competitiveness of a market structure by the cross-industry price elasticity of demand ϵ and the number of market leaders n in our model.

First, we analyze how industries' market structure influences the competition-distress feedback effect. Panel A of Figure 9 plots the profit-margin beta to the discount rate γ_t under our baseline calibration with the market structure of low cross-industry price elasticity of demand and duopoly (i.e., $\epsilon = 2$ and $n = 2$). Panels B and C consider a more competitive market structure by increasing the cross-industry price elasticity of demand to $\epsilon = 4$ or the number of market leaders to $n = 3$, respectively. Relative to the baseline calibration in panel A, the profit margin beta in panels B and C is less negative, especially when the industry is close to the default boundary (i.e., the blue solid lines in panels B and C are flatter than that in panel A). Intuitively, firms have less incentive to collude with each other when industries' market structure becomes more competitive. The dampened collusion incentive weakens the response of competition intensity to changes in the distance to default, and reduces the magnitude of the competition-distress feedback. The weakened competition-distress feedback in turn significantly lowers the sensitivity of profit margins to discount-rate fluctuations for

[25] Early papers also investigate the interaction between compensation contracting and oligopolistic competition (e.g., Fershtman and Judd, 1987; Aggarwal and Samwick, 1999).

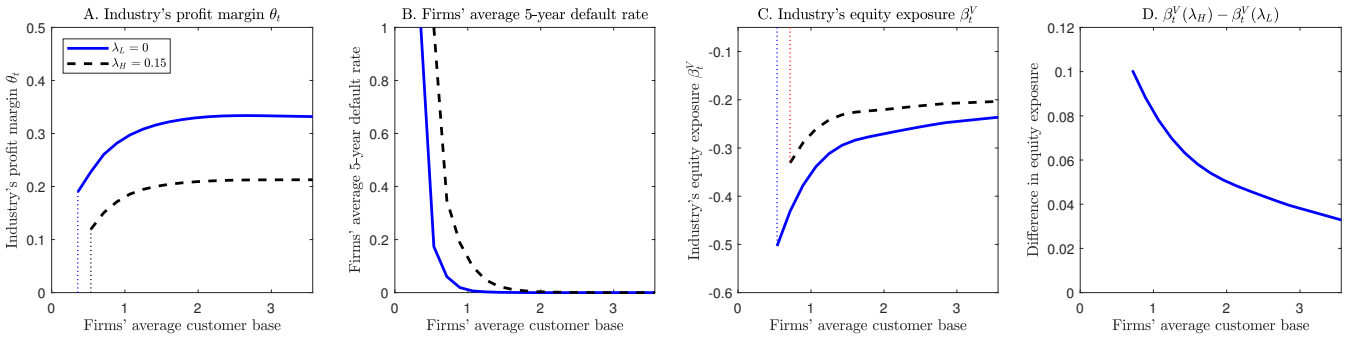


Note: Panels A – C illustrate the profit-margin beta (defined in equation (24)) under various market structure. In panel A, we consider the market structure with $\epsilon = 2$ and $n = 2$ according to our baseline calibration in Table 1. In panel B, we set $\epsilon = 4$ and $n = 2$; and in panel C, we set $\epsilon = 2$ and $n = 3$. In all panels, we focus on the industries within which firms have identical customer base for expository purposes. The vertical dotted lines represent firms' default boundaries in corresponding cases. We set $\gamma_L = \overline{\gamma}$ and $\gamma_H = \overline{\gamma} + 2\text{std}(\gamma_t)$. Panels D – F illustrate the contagion effect on profit margins under various market structure. To measure the contagion effect, we conduct an experiment similar to that of Figure 6. In particular, we compute the percentage deviation in firm j's profit margin in response to an unexpected idiosyncratic shock that reduces the customer base of its competitor, firm i, by half at $t = 1$. That is, the contagion effect in an industry is measured by calculating the percentage deviation of the blue solid line from the black dashed line in panel D of Figure 6. Other parameters are set according to our calibration in Section 4.2.

Figure 9: Feedback and contagion under various market structure.

industries with low distance to default.

Next, we show that the financial contagion effect is also weaker when industries' market structure becomes more competitive. We conduct impulse-response experiments similar to those in Figure 6. In particular, we measure the within-industry contagion effect on profit margins by computing the percentage deviation in firm j's profit margin (relative to the counterfactual without shocks, i.e., the black dashed line in panel D of Figure 6) in response to an unexpected idiosyncratic shock that reduces the customer base of firm i by half at $t = 1$. Panel D of Figure 9 plots this contagion effect under our baseline calibration. Panels E and F show that the contagion effect on profit margins becomes less significant as we increase the cross-industry price elasticity of demand ϵ or the number of market leaders n.



Note: We consider duopoly industries with two identical firms (i.e., $M_{i,t} = M_{j,t}$). Panel A plots the profit margin θ_t of industries with λ_L and λ_H as a function of firms' average customer base in the state of γ_L. The vertical dotted lines represent firms' default boundaries in corresponding industries. Panel B plots firms' average 5-year default rate in the two industries. Panel C plots the equity beta β_t^V (equation (25)) of the two industries. Panels D plots the difference in the equity beta between the two industries. We set $\lambda_L = 0$, $\lambda_H = 0.15$, $\gamma_L = \overline{\gamma}$ and $\gamma_H = \overline{\gamma} + 2\text{std}(\gamma_t)$. Other parameters are set according to our calibration in Section 4.2.

Figure 10: Industry exposure to discount-rate shocks in the cross section.

3.5 Financial Distress Anomaly across Industries

We now discuss the asset pricing implications of the competition-distress feedback in the cross section of industries with different intensity λ of left-tail idiosyncratic jump shocks. In Section 4.3, we evaluate the quantitative performance of our model in terms of its ability to match the cross-sectional asset pricing patterns in the data.

Our model implies that the feedback effect is weaker in industries with higher λ. Intuitively, firms in such industries are more financially distressed because of their higher exposure to left-tail idiosyncratic jump shocks (i.e., higher probability of exogenous replacement). The higher exit rate makes firms less concerned with the future cooperation, thereby dampening their incentives to collude. As the competition-distress feedback effect arises from endogenous collusion, the feedback effect naturally diminishes when firms have weaker collusion incentives. A weaker competition-distress feedback further implies that industries with higher λ are less exposed to aggregate discount-rate shocks, and thus investors demand lower expected excess returns for holding these industries' stocks.

Taken together, the model implies that industries with higher λ are less profitable and more financially distressed in the cross section, and meanwhile, these industries are less exposed to discount-rate shocks, leading to lower expected stock returns. Therefore, our model provides an explanation for the financial distress anomaly across industries.

As an illustration, we consider two industries with different left-tail idiosyncratic jump intensity, λ_L and λ_H, satisfying that $\lambda_L < \lambda_H$. We assume that the firms in the same industry have the same customer base. Panels A and B of Figure 10 show that the industry with λ_L has a higher profit margin and a lower 5-year default rate than the industry with λ_H. To show the difference in the exposure of equity between the two industries, we define the industry-level

equity beta (β_t^V) to the discount-rate shock as the value-weighted firm-level equity beta:

$$\beta_t^V = \sum_{i=1}^{2} w_{i,t}^V \beta_{i,t}^V, \text{ where } \beta_{i,t}^V = \frac{V_{i,t}^C(\gamma_H)}{V_{i,t}^C(\gamma_L)} - 1 \text{ and } w_{i,t}^V = \frac{V_{i,t}^C(\gamma_L)}{\sum_{j=1}^{2} V_{j,t}^C(\gamma_L)}, \tag{25}$$

for all $M_{i,t}, M_{j,t} > 0$. Panel C of Figure 10 compares the two industries' equity beta. For both industries, the equity beta is more negative when the industry is closer to the default boundary, reflecting the competition-distress feedback effect. Importantly, the equity beta is much less negative in the industry with λ_H (the black dashed line) because the competition-distress feedback effect is weaker owing to the weaker collusion incentive. Presumably the difference in the magnitude of the competition-distress feedback between the two industries should also be larger when industries are closer to the default boundary (i.e., when the distance to default is smaller), as this is the time when the economic mechanism of competition-distress feedback becomes more relevant. Panel D shows that the gap in the equity beta between the two industries is indeed wider when their distance to default is smaller.

4 Quantitative Analysis

In this section, we conduct quantitative analysis. In Subsection 4.1, we describe the data and the measures of financial distress, discount rates, and left-tail idiosyncratic jump risk. In Subsection 4.2, we present the parameter choice in our calibration analysis. In Subsection 4.3, we systematically study the model's implications on the stock returns and credit spreads of industry portfolios sorted on financial distress and left-tail idiosyncratic jump risk. Importantly, we show that the model can quantitatively rationalize the financial distress anomaly across industries. Finally, in Subsection 4.4, we examine the model mechanisms quantitatively by conducting counterfactual experiments.

4.1 Data and Empirical Measures

We obtain firm-level accounting data from Compustat and stock returns from CRSP. Industry-level profit margin is the average profit margin of firms in the same industry weighted by their sales. Industry-level stock returns are the average firm-level stock returns weighted by market capitalization. Same as Chen et al. (2017), our credit spread data combine the Mergent Fixed Income Securities Database (FISD) from 1973 to 2004 and the Trade Reporting and Compliance Engine (TRACE) Database from 2005 to 2018. We clean the Mergent FISD and TRACE data following Collin-Dufresne, Goldstein and Martin (2001) and Dick-Nielsen (2009). For each transaction, we calculate the credit spread by taking the difference between the bond yield and the treasury yield with corresponding maturity. The credit spread dataset spans from 1973

to 2018 and covers a cross section of 400 to 750 firms. Industry-level credit spreads are the average firm-level credit spreads weighted by the par value of bonds. We organize the cross section of accounting data by the calendar year in which the fiscal year ends. For instance, an observation with a fiscal year ending in March of 2002 is categorized with other observations with fiscal years ending in 2002, most of which end in December of 2002. When merging the accounting data with the market data, we assume that the accounting information becomes available at the end of June in each year. This follows the practice of Fama and French (1993).

Our analysis focuses on the strategic competition among a few oligopolistic firms whose products are close substitutes, therefore we use four-digit SIC codes (SIC4) to define industries following the literature (e.g., Hou and Robinson, 2006; Gomes, Kogan and Yogo, 2009; Frésard, 2010; Giroud and Mueller, 2010, 2011; Bustamante and Donangelo, 2017). We exclude all financial firms and utility firms (i.e., SIC codes between 6,000 and 6,999 and between 4,900 and 4,999). Following the literature (e.g., Frésard, 2010), at least 10 firms are required in each industry-year to ensure that the industry-level variables, such as industry-level profit margin and stock returns, are well-behaved.[26] On average, there are 123 industries in a year and 26.59 firms in an industry.

Measure of Financial Distress. The firm-level financial distress measure is constructed as the 12-month failure probability following Campbell, Hilscher and Szilagyi (2008). Industry-level financial distress measure for industry i and period t, denoted by $Distress_{i,t}$, is the average firm-level financial distress measure weighted by firms' sales. In the model, an industry's default risk is determined by both its left-tail idiosyncratic jump risk and its distance to the default boundary. The cross-sectional heterogeneity in default risk is mainly captured by industries' different level of left-tail jump risk (i.e., λ), whereas the time-series variation in default risk within an industry is mainly reflected by the time-varying distance to default. We thus also construct a distance-to-default measure according to the Merton model (see Online Appendix 2.3) for the purpose of testing the competition-distress feedback effect. The industry-level distance-to-default measure for industry i and period t, denoted by $DD_{i,t}$, is the average firm-level distance-to-default measure weighted by firms' sales.

Measure of Default Event. We retrieve and merge the information on Chapter 7 and Chapter 11 bankruptcies filed by large, public, non-financial U.S. firms over 1981 – 2014 from New Generation Research's Bankruptcydata.com, the UCLA LoPucki Bankruptcy Research Database, Public Access to Court Electronic Records (PACER), National Archives at various locations, and U.S. Bankruptcy Courts for various districts following Dou et al. (2020*a*) and Ma, Tong and Wang (2020). Similar to Campbell, Hilscher and Szilagyi (2008), we define an *default event*

[26]For the empirical results related to credit spreads, we require at least 3 firms rather than 10 firms to ensure a sufficient amount of observations in each cross section since the credit spread data are relatively sparse by nature.

as the first of the following events: chapter 7 or chapter 11 bankruptcy filing, delisting due to insolvency (delisting code 572), and a default or selective default rating by a rating agency. This expanded measure of failure (relative to measuring only bankruptcy filings) allows us to capture some instances in which firms fail but reach an agreement with creditors before an actual bankruptcy filing such as pre-court liquidation and pre-court reorganization (e.g., Gilson, John and Lang, 1990; Gilson, 1997; Dou et al., 2020*a*).

Measure of Discount Rate. The empirical proxy for discount rates is based on the smoothed earnings-price ratio motivated by the return predictability studies (e.g., Campbell and Shiller, 1988, 1998; Campbell and Thompson, 2008), and obtained from Robert Shiller's website. In our regression analyses, the discount rate in month t, denoted by $Discount_rate_t$, is calculated by fitting a time-series regression of the 12-month-ahead market return on the smoothed earnings-price ratio, and then take the fitted value at the end of month t. We construct discount-rate shocks, denoted by $\Delta Discount_rate_t$, as residuals of AR(1) time-series regressions, which are estimated at the annual frequency for the estimation of profit margin loadings and at the quarterly frequency for the estimation of excess return and credit spread loadings, aligning with the frequency of the estimation regressions for the loadings on discount-rate shocks.

Measure of Left-Tail Idiosyncratic Jump Risk. We construct the measure of left-tail idiosyncratic jump risk of industry i in month t, denoted by $IdTail_risk_{i,t}$, in the following steps. First, we construct a measure for the realized left-tail idiosyncratic jump shock for each stock in each month. Specifically, we estimate the daily residuals of the Fama-French three-factor model for each stock using a 60-month rolling window, following Boyer, Mitton and Vorkink (2010). For each stock j, the realized left-tail idiosyncratic jump shock over a year, denoted by $IdTail_shock_{j,t-11,t}$, is constructed using the 5th percentile value of the estimated daily residual distribution from the beginning of month $t-11$ to the end of month t.

Second, we construct a measure for idiosyncratic jump risk for each stock j using the measure $IdTail_shock_{j,t-11,t}$. Specifically, in each month t, we run the following panel regression

$$IdTail_shock_{j,s-11,s} = \alpha_t + \beta_t X_{j,s-12} + \epsilon_{j,s}, \tag{26}$$

where the observations include all stocks in the sample and the subscript s ranges from the beginning of the sample period to month t. The variable $X_{j,s-12}$ is a vector that includes all characteristics used by Campbell, Hilscher and Szilagyi (2008, Model 2 in Table III) for constructing the firm-level failure probability. Our panel regression specification (26) ensures that the coefficients α_t and β_t are estimated based on information up to month t. As time passes, the coefficients α_t and β_t are reestimated in each month using the same specification (26) with expanding windows. We construct the measure of left-tail idiosyncratic jump risk

for each stock j in month t as

$$IdTail_risk_{j,t} = -\left(\hat{\alpha}_t + \hat{\beta}_t X_{j,t}\right). \tag{27}$$

We flip the sign so that a larger value of $IdTail_risk_{j,t}$ intuitively implies a higher left-tail idiosyncratic jump risk for firm j in month t as the firm's stock return distribution has a fatter left tail.

Finally, the industry-level left-tail idiosyncratic jump risk is the average firm-level left-tail idiosyncratic jump risk weighted by their sales. In Online Appendix 2.1, we show that the measure of left-tail idiosyncratic jump risk is persistent at both the firm level and industry level. Moreover, we empirically verify that a higher value of the measure predicts that left-tail idiosyncratic jump shocks are more severe in the next year to justify the validity of the measure.

4.2 Calibration and Parameter Choice

The risk-free rate is $r_f = 2\%$. We set the persistence of the market price of risk to be $\varphi = 0.13$ as in Campbell and Cochrane (1999) and $\pi = 0.12$ as in Lettau and Wachter (2007). The within-industry elasticity of substitution is set at $\eta = 15$ and the cross-industry price elasticity of demand at $\epsilon = 2$, which are broadly consistent with the values of Atkeson and Burstein (2008). We set the corporate tax rate $\tau = 27\%$ and the drift term under physical measure $g = 1.89\%$ as in He and Milbradt (2014). We assume that the two firms in the industry initially have the same customer base M_0 which is normalized to be 1. We set the initial customer base of new entrants to be a fraction $\kappa = 0.3$ of the incumbent's customer base.

The remaining parameters are calibrated by matching relevant moments summarized in Panel B of Table 1. When constructing the model moments, we simulate a sample of 1,000 industries for 20 years starting from the initial customer base distribution. We then compute the model counterparts of the data. For each moment, the table reports the average value of 2,000 simulations. We set the ex-post bond recovery rate at $\nu = 0.4$ so that the model-implied average debt-asset ratio is 0.33, matching that of Baa-rated bonds in the data. The calibrated recovery rate is also close to the rate estimated by Chen (2010) based on the mean recovery rate of Baa-rated bonds, as well as the average recovery rate of debt in bankruptcy for large, public, non-financial U.S. firms from $1996-2014$ structurally estimated by Dou et al. (2020*a*). Collin-Dufresne, Goldstein and Yang (2012) and Seo and Wachter (2018) also use 40% recovery rate in normal times to match CDX spreads. The volatility of idiosyncratic shocks is $\sigma_M = 25\%$ which generates a 5-year default rate of 2.5%. The marginal cost of production $\omega = 2$ is determined to match the average net profitability. We set the punishment rate $\xi = 0.09$ so that the average gross profit margin is consistent with the data. We set $\zeta = 0.45$, $\overline{\gamma} = 0.15$, and

Table 1: Calibration and parameter choice.

Panel A: Externally determined parameters

Parameter	Symbol	Value	Parameter	Symbol	Value
Risk-free rate	r_f	2%	Persistence of market price of risk	φ	0.13
Volatility of market price of risk	π	0.12	Within-industry elasticity	η	15
Industry's price elasticity	ϵ	2	Corporate tax rate	τ	0.27
Mean growth rate of customer base	g	1.89%	Initial customer base	M_0	1
Customer base of new entrants	κ	0.3			

Panel B: Internally calibrated parameters

Parameter	Symbol	Value	Moments	Data	Model
Bond recovery rate	ν	0.4	Average debt-asset ratio (Baa rated)	0.34	0.33
Volatility of idiosyncratic shocks	σ_M	25%	5-year default rate (Baa rated)	2.2%	2.5%
Marginal cost of production	ω	2	Average net profitability	3.9%	3.6%
Punishment rate	ξ	0.09	Average gross profit margin	31.4%	26.5%
Market price of risk for Z_t	$\overline{\gamma}$	0.15	Market equity premium	7.36%	6.51%
Volatility of aggregate shocks	ς	0.04	Market Sharpe ratio	0.40	0.42
Market price of risk for $Z_{\gamma,t}$	ζ	0.45	Credit spread (Baa-rated)	138bps	163bps
Intensity of idiosyncratic jump shocks	$[\underline{\lambda}, \overline{\lambda}]$	$[0, 0.15]$	Diff. in excess returns (Q5−Q1)	−4.62%	−4.31%
Default rate upon jump shocks	ϖ	0.1	Diff. in credit spreads (Q5−Q1)	2.00%	1.81%

$\varsigma = 4\%$ so that the market portfolio's equity premium is 6.51%, Sharpe ratio is 0.42, and credit spread is 163 bps.

We calibrate the intensity of left-tail idiosyncratic jump shocks to match the difference in stock returns and credit spreads across industries sorted on the financial distress measure $Distress_{i,t}$. In particular, we assume that the intensity of left-tail idiosyncratic jump shocks λ ranges from $\underline{\lambda}$ to $\overline{\lambda}$. We discretize $[\underline{\lambda}, \overline{\lambda}]$ into $N = 10$ grids with equal spacing so that $\lambda_1 = \overline{\lambda}$ and $\lambda_N = \overline{\lambda}$. The mass of industries associated with each value of λ is the same. We normalize $\lambda_L = 0$ and set $\lambda_H = 0.15$ to generate a stock-return difference of -4.31% across quintile portfolios of industries sorted on financial distress (Q5−Q1). We set $\varpi = 0.1$ to generate a credit-spread difference of 1.81%.

4.3 Financial Distress Anomaly across Industries

We now quantitatively examine the asset pricing implications of the distressed competition mechanism. Specifically, we show that our model can quantitatively rationalize the financial distress anomaly across industries: Industries that are more financially distressed have lower expected equity excess returns and higher credit spreads. In the data, we sort all SIC4 industries into quintiles based on the industry-level financial distress measure $Distress_{i,t}$ and

Table 2: Industry portfolios sorted on financial distress.

	Equity excess return (Q5−Q1)	Credit spread (Q5−Q1)
Data (%)	−4.62	2.00
	[−8.78, −0.46]	[1.43, 2.57]
Model (%)	−4.31	1.81
Leland framework (%)	6.21	2.37

Note: The 95% confidence intervals are reported in the square brackets.

indeed find that more distressed industries have lower expected equity excess returns and higher credit spreads. Table 2 shows that the differences in expected excess returns and credit spreads between quintile portfolios of industries sorted on financial distress (Q5−Q1) are −4.62% and 2.00%, respectively. The extended empirical results on the sorting analysis of equity excess returns and credit spreads are presented in Tables 5 and 6. We perform similar portfolio sorting analysis in our model. The model-implied patterns are quantitatively consistent with the data. As discussed in Section 3.5, the difference in the left-tail idiosyncratic jump risk, captured by λ, is the primary force causing the difference in financial distress across industries. Thus, sorting industries by financial distress in the model captures the cross-industry variation in left-tail idiosyncratic jump risk, thereby generating lower expected equity excess returns for the industries that are more financial distressed. Moreover, industries with higher financial distress have higher credit spreads because they have higher left-tail idiosyncratic jump risk and thus a higher probability of default (panel B of Figure 10).

By contrast, the canonical framework (e.g., Merton, 1974; Leland, 1994) cannot rationalize the financial distress anomaly. As an illustration, we introduce the time-varying market price of risk (see equations (3) and (4)) to the standard model of Leland (1994). The time-varying market price of risk allows the canonical Leland framework to generate levered equity excess returns and credit spreads consistent with the data (e.g., Chen, Collin-Dufresne and Goldstein, 2008; Bhamra, Kuehn and Strebulaev, 2010*b*; Chen, 2010). However, Table 2 shows that the canonical Leland framework implies higher expected returns and credit spreads for more financially distressed industries. The key reason is that more financially distressed industries have higher financial leverage, amplifying the aggregate risk exposure of both equity and debt. What is unique in our model is that the endogenous competition mechanism, together with heterogenous left-tail idiosyncratic jump risk, generates more negative exposure to the discount-rate shock and thus higher expected equity excess returns for the more financially distressed industries.

Further, we also emphasize that introducing left-tail idiosyncratic jump risk alone to the canonical framework does not help explain the financial distress anomaly. This is simply because left-tail idiosyncratic jump risk is not priced, and thus it merely increases the default rate without affecting risk premia in the absence of the endogenous competition mechanism.

Table 3: Industry portfolios sorted on distress and left-tail idiosyncratic jump risk.

	Panel A: Industry portfolios sorted on $Distress_{i,t}$					
	Data			Model		
	Q1 (low)	Q5	Q5−Q1	Q1 (low)	Q5	Q5−Q1
Equity excess return (%)	8.48	3.86	−4.62	8.77	4.46	−4.31
	[3.47, 13.49]	[−2.97, 10.70]	[−8.78, −0.46]			
Excess return's exposure	−4.99	4.61	9.60	−3.70	1.28	4.98
to discount rates	[−9.58, −0.40]	[−0.74, 9.96]	[2.19, 17.01]			
Credit spread (%)	1.07	3.07	2.00	0.89	2.70	1.81
	[0.83, 1.31]	[2.29, 3.85]	[1.43, 2.57]			
5-year default rate (%)	0.50	5.21	4.71	0.04	5.43	5.39
	[0.24, 0.76]	[3.48, 6.94]	[3.07, 6.35]			
Debt-asset ratio (%)	22.44	33.44	11.00	32.82	35.19	2.37
	[20.61, 24.27]	[31.83, 35.04]	[9.05, 12.95]			
	Panel B: Industry portfolios sorted on $IdTail_risk_{i,t}$					
	Data			Model		
	Q1 (low)	Q5	Q5−Q1	Q1 (low)	Q5	Q5−Q1
Equity excess return (%)	9.04	3.55	−5.49	8.72	4.42	−4.29
	[4.64, 13.44]	[−4.11, 11.21]	[−10.63, −0.35]			
Excess return's exposure	−4.04	6.08	10.12	−3.39	1.19	4.58
to discount rates	[−9.15, 1.07]	[0.41, 11.74]	[1.49, 18.74]			
Credit spread (%)	1.09	3.25	2.16	0.88	2.68	1.80
	[0.90, 1.28]	[2.43, 4.08]	[1.48, 2.84]			
5-year default rate (%)	0.76	4.24	3.47	0.04	5.11	5.07
	[0.37, 1.15]	[2.83, 5.65]	[2.11, 4.83]			
Debt-asset ratio (%)	27.23	30.41	3.19	32.42	34.63	2.21
	[25.18, 29.28]	[28.19, 32.63]	[0.37, 6.00]			

Note: In the data, the sample period is from 1975 to 2018 for panel A and from 1976 to 2018 for panel B. A firm's 5-year default rate is computed based on an indicator that equal to one if one of the following three situations occurs: bankruptcy filings, delisting due to insolvency (delisting code 572), or a (selective) default rating by a rating agency. The industry-level default rate is the average default rate of the top six firms in the industry. The debt-asset ratio is computed as total short-term debt plus total long-term debt divided by total asset. The 95% confidence intervals are reported in the square brackets. In both the data and model, the exposure of industry portfolios' excess returns to discount rates is estimated with market returns controlled for as in Table 7. In the model, financial distress is measured by 1-year default probability as in the data, and the left-tail idiosyncratic jump risk is captured by λ.

This highlights the importance of the endogenous competition mechanism of our model. Left-tail idiosyncratic jump risk has cross-sectional asset pricing implications in our model precisely because it affects the strength of the endogenous competition mechanism (especially the strength of the competition-distress feedback effect).

In Table 3, we compare a rich set of moments between the data and model for quintile portfolios of industries sorted on financial distress and left-tail idiosyncratic jump risk. Panel A shows that in both the data and model, the portfolio with lower financial distress (Q1) is more

negatively exposed to discount rates than the portfolio with higher financial distress (Q5), after controlling for the returns of the market portfolio. This explains why more financially distressed industries are associated with lower expected equity excess returns. Moreover, the portfolio Q5 has higher credit spreads because the higher intensity of left-tail idiosyncratic jump shocks makes default more likely to occur. The model implies that the 5-year default rate is about 0.04% for Q1, which is significantly lower than 5.43% for Q5. Similar patterns on default rates are also observed in the data.

The model also implies that the more financially distressed industries (Q5) optimally choose slightly higher financial leverage than the less financially distressed industries (Q1). This is because industries with higher financial distress are associated with a higher intensity of left-tail idiosyncratic jump shocks. Firms in such industries are more impatient and less exposed to fluctuations in aggregate discount rates (see panels C and D of Figure 10). From shareholders' perspective, the default risk caused by aggregate discount-rate shocks is lower, which motivates them to increase financial leverage. We emphasize that the lower default risk caused by aggregate discount-rate shocks does not contradict with the higher 5-year default rate in these industries. This is because, for these industries with higher financial distress, a larger fraction of default events is caused by left-tail idiosyncratic jump shocks, rather than the more volatile systematic component in cash slows due to their higher λ. When left-tail jump shocks hit, firms would default with a constant probability ϖ regardless of their financial leverage. Thus, choosing higher financial leverage ex-ante does not exacerbate the default risk attributed to left-tail idiosyncratic jump shocks.

In panel B, we sort industries based on their left-tail idiosyncratic jump risk in the data (i.e., $IdTail_risk_{i,t}$) and model (i.e., λ). The patterns in the model are similar to those in panel A because cross-industry variation in financial distress is mainly determined by the cross-industry difference in left-tail idiosyncratic jump risk. This is also supported by the data. In Section 5.1, we show that the financial distress anomaly becomes much less pronounced and statistically insignificant after controlling for left-tail idiosyncratic jump risk (see Table 9).

4.4 Inspecting the Model's Mechanism

We examine the model's mechanism in Table 4 by conducting various counterfactual experiments. In column (3) of Table 4, we present the model's implications in the non-collusive equilibrium. Due to the lack of the amplification effect from competition-distress feedback, the equity premium and credit spread of the market portfolio decrease from 6.51% and 1.63% to 5.35% and 1.41%, respectively. More importantly, the return spread of the long-short portfolio (Q5−Q1) sorted on financial distress or left-tail idiosyncratic jump risk almost shrinks to zero because the cross-industry difference in λ does not affect industries' equilibrium profit margins or their exposure to discount rates in the non-collusive equilibrium. This indicates

Table 4: Inspecting the model's mechanism.

	(1) Data	(2) Model	(3) No collusion	(4) $\lambda \equiv \overline{\lambda}$	(5) $\epsilon = 4$
Equity excess return	7.36 [2.83, 11.89]	6.51	5.35	6.61	6.13
Excess return difference (Q5−Q1) sorted on $Distress_{i,t}$	−4.62 [−8.78, −0.46]	−4.31	0.23	0.19	−3.03
Excess return difference (Q5−Q1) sorted on $IdTail_risk_{i,t}$	−5.49 [−10.63, −0.35]	−4.29	0.04	0.03	−2.99
Credit spread	1.38 [1.07, 1.69]	1.63	1.41	1.79	1.55
Credit spread difference (Q5−Q1) sorted on $Distress_{i,t}$	2.00 [1.43, 2.57]	1.81	1.33	0.13	1.69
Credit spread difference (Q5−Q1) sorted on $IdTail_risk_{i,t}$	2.16 [1.48, 2.84]	1.80	1.35	0.02	1.68

Note: The 95% confidence intervals are reported in the square brackets.

that the competition-distress feedback effect is the key to explain the financial distress anomaly across industries. However, the credit spread remains significantly different between the portfolios sorted on financial distress or left-tail idiosyncratic jump risk due to the cross-industry difference in default risk caused by left-tail idiosyncratic jump shocks.

To illustrate the importance of cross-industry difference in left-tail idiosyncratic jump risk, in column (4), we assume that all industries have the same intensity $\lambda \equiv \overline{\lambda}$. Not surprisingly, the model implies that both the equity premium and credit spread are similar across industry portfolios sorted on financial distress or left-tail idiosyncratic jump risk.

As we show in Section 3.4, the competition-distress feedback effect becomes weaker when the cross-industry price elasticity of demand ϵ is larger. In column (5) of Table 4, we evaluate the model's quantitative implications for $\epsilon = 4$. As the feedback effect between competition and distress is weaker, the average equity premium and credit spread of the market portfolio decrease from 6.51% and 1.81% (column 2) to 6.13% and 1.69% (column 5), respectively. The model-implied difference in expected equity excess returns and credit spreads between industries with high and low $Distress_{i,t}$ (or $IdTail_risk_{i,t}$) also becomes less pronounced.

5 Empirical Tests

Here, we test the main predictions of our model. In Subsection 5.1, we test the main cross-sectional asset pricing implications. In Subsection 5.2, we test the implications of the feedback and contagion effect on profit margins. In Subsection 5.3, we test the implications of the

Table 5: Excess returns in the cross section of industries.

	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A: Industry portfolios sorted on financial distress					
$Distress_{i,t}$	Q1 (low)	Q2	Q3	Q4	Q5 (high)	Q5−Q1
Excess return	8.477***	10.156***	9.932***	9.160***	3.862	−4.615**
	[3.326]	[3.841]	[3.480]	[2.885]	[1.110]	[−2.179]
CAPM alpha	0.804	2.143**	1.313	−0.289	−6.089***	−6.893***
	[0.772]	[2.156]	[1.176]	[−0.216]	[−3.703]	[−3.550]
FF3 alpha	1.109	2.069**	0.986	−0.833	−7.429***	−8.538***
	[1.107]	[2.274]	[0.973]	[−0.673]	[−5.223]	[−4.584]
Observations	521	521	521	521	521	521
	Panel B: Industry portfolios sorted on left-tail idiosyncratic jump risk					
$IdTail_risk_{i,t}$	Q1 (low)	Q2	Q3	Q4	Q5 (high)	Q5−Q1
Excess return	9.044***	9.099***	8.630***	8.846***	3.550	−5.494**
	[4.028]	[3.580]	[3.046]	[2.660]	[0.908]	[−2.093]
CAPM alpha	2.472***	1.561*	0.216	−0.752	−7.217***	−9.689***
	[2.764]	[1.662]	[0.214]	[−0.550]	[−3.771]	[−4.293]
FF3 alpha	2.114**	0.890	−0.130	−0.997	−7.775***	−9.889***
	[2.379]	[1.025]	[−0.148]	[−0.868]	[−5.180]	[−5.403]
Observations	509	509	509	509	509	509

Note: This table reports (risk-adjusted) expected excess returns based on the CAPM or Fama-French three-factor model of industry portfolios sorted on financial distress ($Distress_{i,t}$) in panel A and left-tail idiosyncratic jump risk ($IdTail_risk_{i,t}$) in panel B, respectively. All numbers are in annualized percentage unit. The sample spans the period from 1975 to 2018 in panel A and from 1976 to 2018 in panel B. *t*-statistics robust to heteroskedasticity are reported in square brackets. *, **, and *** indicate statistical significance at the 10%, 5%, and 1%, respectively.

feedback and contagion effect on equity returns and credit spreads. In Subsection 5.4, we push one step further to directly test the unique predictions of our core competition mechanism.

5.1 Financial Distress Anomaly across Industries

We now test the cross-sectional asset pricing theory based on the competition-distress feedback effect in Section 3.5, which is strengthened by the quantitative analysis in Section 4.3.

Equity Returns and Credit Spreads in the Cross Section. The results in Table 3 remain robust after controlling for standard risk factors. Particularly, panel A of Table 5 shows that the (risk-adjusted) expected excess returns of industries with high $Distress_{i,t}$ (Q5) are significantly lower than those with low $Distress_{i,t}$ (Q1). The difference in annualized expected excess returns is

Table 6: Credit spreads in the cross section of industries.

	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A: Industry portfolios sorted on financial distress					
$Distress_{i,t}$	Q1 (low)	Q2	Q3	Q4	Q5 (high)	Q5−Q1
Credit spread	1.069***	1.297***	1.429***	1.756***	3.060***	1.991***
	[9.01]	[8.34]	[8.96]	[7.88]	[7.75]	[6.87]
Observations	521	521	521	521	521	521
	Panel B: Industry portfolios sorted on left-tail idiosyncratic jump risk					
$IdTail_risk_{i,t}$	Q1 (low)	Q2	Q3	Q4	Q5 (high)	Q5−Q1
Credit spread	1.092***	1.251***	1.470***	1.882***	3.254***	2.163***
	[11.41]	[9.27]	[7.53]	[7.38]	[7.72]	[6.24]
Observations	504	504	504	504	504	504

Note: This table reports credit spreads of industry portfolios sorted on financial distress measure $Distress_{i,t}$ in panel A and left-tail idiosyncratic jump risk measure $IdTail_risk_{i,t}$ in panel B, respectively. All numbers are in annualized percentage unit. The sample spans the period from 1975 to 2018 in panel A and from 1976 to 2018 in panel B. *t*-statistics robust to heteroskedasticity and autocorrelation are reported in square brackets. *, **, and *** indicate statistical significance at the 10%, 5%, and 1%, respectively.

−4.615% (Q5−Q1) and significant both statistically and economically. These industry-level patterns are consistent with the financial distress anomaly documented at the firm level (e.g., Campbell, Hilscher and Szilagyi, 2008). Panel B of Table 5 shows that similar results are obtained if we sort industries on left-tail idiosyncratic jump risk ($IdTail_risk_{i,t}$). Particularly, the (risk-adjusted) expected excess returns of industries with high $IdTail_risk_{i,t}$ (Q5) are significantly lower than those of industries with low $IdTail_risk_{i,t}$ (Q1). The difference is statistically significant and comparable to that in panel A.

In Table 6, we further study the cross-industry patterns on credit spreads. Our findings show that the industries with higher $Distress_{i,t}$ or higher $IdTail_risk_{i,t}$ are associated with higher credit spreads, which is in sharp contrast to the lower (risk-adjusted) expected equity excess returns associated with these industries.

Equity Excess Returns' Loadings on Discount Rates. Our theory suggests that the industries with higher financial distress or higher left-tail idiosyncratic jump risk have lower expected equity excess returns, because they are less negatively exposed to the aggregate discount-rate shocks. Here, we examine the exposure of equity excess returns to discount rates in the cross section of industries. In particular, we sort industries into quintiles based on $Distress_{i,t}$ and $IdTail_risk_{i,t}$. Panel A of Table 7 shows that the excess returns of industry portfolios of low financial distress (Q1) are significantly more negatively exposed to discount rates compared to those of high financial distress (Q5). Moreover, panel B shows that the industries with lower

Table 7: Stock returns' loadings on discount rates in the cross section of industries.

	(1)	(2)	(3)	(4)	(5)	(6)
			Panel A: Industry portfolios sorted on financial distress			
$Distress_{i,t}$	Q1 (low)	Q2	Q3	Q4	Q5 (high)	Q5−Q1
$\Delta Discount_rate_t$	−4.990**	−4.273***	2.122	−0.622	4.610*	9.600**
	[−2.14]	[−4.10]	[0.80]	[−0.26]	[1.70]	[2.56]
R_t^{mkt}	0.875***	1.015***	1.227***	1.225***	1.479***	0.604***
	[9.55]	[26.80]	[27.58]	[14.54]	[17.39]	[4.31]
Observations	174	174	174	174	174	174
			Panel B: Industry portfolios sorted on left-tail idiosyncratic jump risk			
$IdTail_risk_{i,t}$	Q1 (low)	Q2	Q3	Q4	Q5 (high)	Q5−Q1
$\Delta Discount_rate_t$	−4.036	−3.042**	−3.798	1.473	6.078**	10.115**
	[−1.56]	[−2.25]	[−1.46]	[0.72]	[2.12]	[2.32]
R_t^{mkt}	0.785***	1.001***	1.027***	1.400***	1.631***	0.846***
	[7.24]	[27.01]	[11.90]	[26.85]	[15.62]	[4.66]
Observations	169	169	169	169	169	169

Note: This table reports the exposure of equity excess returns to discount-rate shocks in the cross section of industries sorted on financial distress (in panel A) and left-tail idiosyncratic jump risk (in panel B). In each quintile k, we run the following time-series regression: $R_{k,t+1} - R_{f,t} = \alpha_k + \beta_k \times \Delta Discount_rate_{t+1} + \gamma_k \times (R_{t+1}^{mkt} - R_{f,t}) + \epsilon_{k,t+1}$. The variable $\Delta Discount_rate_t$ is the AR(1) residual of the discount rate measure $Discount_rate_t$ in quarter t, and R_t^{mkt} is the market return in quarter t, and $R_{f,t}$ is the risk-free rate. All numbers are in annualized percentage unit. The sample spans the period from 1975 to 2018 in panel A and from 1976 to 2018 in panel B. The t-statistics robust to heteroskedasticity and autocorrelation are reported in square brackets. *, **, and *** indicate statistical significance at the 10%, 5%, and 1%, respectively.

left-tail idiosyncratic jump risk are more negatively exposed to discount rates. The results are robust if we focus on the top six firms (ranked by sales) in each industry when constructing industry-level sorting variables and excess returns (see Table 3 of Online Appendix).

Left-Tail Idiosyncratic Jump Risk, Profit Margin, and Financial Distress. Our theory also predicts that the left-tail idiosyncratic jump risk is negatively associated with the profit margin and positively associated with the financial distress in the cross section of industries. We empirically test the relationships. In Table 8, columns (1) and (2) show that our measure of left-tail idiosyncratic jump risk is negatively associated with the profit margin. Columns (3) – (6) show that industries with higher left-tail idiosyncratic jump risk are also associated with higher financial distress, as reflected by higher values of the distress measure and credit spreads.

Financial Distress Anomaly after Controlling for $IdTail_risk_{i,t}$. Finally, in our model, the financial distress spread across industries can be explained by the heterogeneous exposure to the left-tail idiosyncratic jump risk. We now empirically examine whether the financial distress anomaly in panel A of Table 5 becomes significantly less pronounced after controlling for the left-tail idiosyncratic jump risk.

Table 8: Left-tail idiosyncratic jump risk, profit margin, and financial distress.

	(1)	(2)	(3)	(4)	(5)	(6)
	$\ln(1+PM_{i,t})$		$Distress_{i,t}$		$Credit_spread_{i,t}$	
$IdTail_risk_{i,t}$	−1.870***	−2.725***	0.044***	0.053***	0.914***	1.172***
	[−7.70]	[−8.51]	[9.25]	[7.82]	[6.23]	[8.35]
Year FE	No	Yes	No	Yes	No	Yes
Observations	4,510	4,510	4,510	4,510	444	444

Note: This table tests the relation between left-tail idiosyncratic jump risk, profit margin, and financial distress at the industry level. The sample spans the period from 1988 to 2018. We run the following panel regressions using industry-year observations: $Y_{i,t} = \alpha + \beta \times IdTail_risk_{i,t} + \delta_t + \epsilon_{i,t}$, where the dependent variable $Y_{i,t}$ is the logged one plus industry-level profit margin ($\ln(1+PM_{i,t})$), industry-level financial distress measured by $Distress_{i,t}$, or industry-level credit spread ($Credit_spread_{i,t}$). All variables are in fractional unit. Standard errors are robust to heteroskedasticity and autocorrelation. Specifically, we compute t-statistics using Driscoll-Kraay standard errors with five lags, and include t-statistics in square brackets. *, **, and *** indicate statistical significance at the 10%, 5%, and 1%, respectively.

Specifically, we perform a double-sort analysis, where we first sort industries into five quintiles based on the measure of the left-tail idiosyncratic jump risk ($IdTail_risk_{i,t}$). Within each group, we further sort industries into five quintiles based on the financial distress measure $Distress_{i,t}$. Panel A of Table 9 shows that the difference in CAPM alpha between the industry portfolio with low distress (Q1) and that with high distress (Q5) becomes statistically insignificant. The magnitude of the difference (Q5−Q1) changes from −6.893 in panel A of Table 5 to −2.037 in panel A of Table 9. The difference in the alpha of the Fama-French three-factor model (FF3 alpha) remains statistically significant, but the magnitude changes from −8.538 in panel A of Table 5 to −3.978 in panel A of Table 9.

In panel B, we perform an additional test by sorting industries on an adjusted financial distress measure ($Distress_adjusted_{i,t}$) which controls for the left-tail idiosyncratic jump risk $IdTail_risk_{i,t}$. Specifically, $Distress_adjusted_{i,t}$ is the residuals of cross-sectionally regressing the financial distress measure $Distress_{i,t}$ on the left-tail idiosyncratic jump risk measure $IdTail_risk_{i,t}$ and a constant term. Panel B shows that both the CAPM alpha and FF3 alpha become statistically insignificant once we sort industries on $Distress_adjusted_{i,t}$.

5.2 Feedback and Contagion Effects on Profit Margins

Competition-Distress Feedback Effects. Our model implies that industry-level profit margins load negatively on discount rates, and the loadings are more negative in industries where firms are closer to their default boundaries (see panel C of Figure 4). This is because the competition-distress feedback effect is stronger when the distance to default is smaller. To test this implication, we sort industries into different groups based on their distance-to-default measure $DD_{i,t}$. We then examine the sensitivity of group-level profit margins to discount rates

Table 9: Financial distress anomaly after controlling for the left-tail idiosyncratic jump risk.

	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A: Double sort on $Distress_{i,t}$ and $IdTail_risk_{i,t}$					
$Distress_{i,t}$	Q1 (low)	Q2	Q3	Q4	Q5 (high)	Q5−Q1
CAPM alpha	4.139***	4.579***	4.504***	3.664***	2.102*	−2.037
	[3.22]	[4.16]	[4.01]	[3.46]	[1.74]	[−1.28]
FF3 alpha	0.302	0.126	−0.260	−1.664*	−3.676***	−3.978***
	[0.29]	[0.13]	[−0.27]	[−1.76]	[−3.33]	[−2.66]
Observations	509	509	509	509	509	509
	Panel B: Industry portfolios sorted on $Distress_{i,t}$ adjusting for $IdTail_risk_{i,t}$					
$Distress_adjusted_{i,t}$	Q1 (low)	Q2	Q3	Q4	Q5 (high)	Q5−Q1
CAPM alpha	−3.606**	0.757	1.244	0.153	−2.147*	1.459
	[−2.07]	[0.66]	[1.23]	[0.15]	[−1.91]	[0.82]
FF3 alpha	−2.823**	0.471	0.482	−0.689	−3.126***	−0.303
	[−2.13]	[0.48]	[0.54]	[−0.72]	[−2.89]	[−0.20]
Observations	509	509	509	509	509	509

Note: This table studies the financial distress anomaly after controlling for the left-tail idiosyncratic jump risk. In panel A, we perform a double-sort analysis. We first sort industries into quintiles based on the measure of left-tail idiosyncratic jump risk measure $IdTail_risk_{i,t}$. Within each group, we further sort industries into quintiles based on the financial distress measure $Distress_{i,t}$. Panel B sorts on an adjusted financial distress measure $Distress_adjusted_{i,t}$, which is computed as the residuals of regressing the financial distress measure $Distress_{i,t}$ on the left-tail idiosyncratic jump risk measure $IdTail_risk_{i,t}$ and a constant term. The sample spans the period from 1975 to 2018. All numbers are in annualized percentage unit. t-statistics robust to heteroskedasticity are reported in square brackets. *, **, and *** indicate statistical significance at the 10%, 5%, and 1%, respectively.

by running the following time-series regression using yearly observations for each group k

$$\Delta \ln(1 + PM_{k,t}) = \alpha_k + \beta_k \times \Delta Discount_rate_t + \epsilon_{k,t}, \tag{28}$$

where the dependent variable $\Delta \ln(1 + PM_{k,t}) \equiv \ln(1 + PM_{k,t}) - \ln(1 + PM_{k,t-1})$ is the year-on-year change in group-k's profit margin measure $\ln(1 + PM_{k,t})$, which is the equal-weighted average logged one plus industry-level profit margin of all industries in group k.[27] The independent variable $\Delta Discount_rate_t$ is the AR(1) residual of the discount rate measure $Discount_rate_t$ in year t.

Column (1) in panel A of Table 10 shows that the difference in the profit-margin loading on discount rates between the tertile groups T3 and T1 of industries with high and low distance to default, respectively, is positive and statistically significant. This indicates that T1 is more

[27] To ensure that the industry-year observations of $\ln(1 + PM_{i,t})$ are well defined, we winsorize the profit margin of industry i in year t at the 1st percentile so that it is above -1. We use $\ln(1 + PM_{i,t})$ because about 20% of industry-year observations of $PM_{i,t}$ are negative, making the percentage change in profit margins not well defined. Moreover, it holds that $\ln(1 + PM_{i,t}) \approx PM_{i,t}$ when $PM_{i,t}$ is not large.

Table 10: Implications of competition-distress feedback effects on profit margins.

	(1)	(2)	(3)	(4)
	$\Delta \ln(1+PM_{k,t})$			
	All firms in the industry		Top six firms in the industry	
$DD_{i,t}$	T3−T1	Q5−Q1	T3−T1	Q5−Q1
$\Delta Discount_rate_t$	0.212**	0.369**	0.214*	0.356*
	[1.97]	[1.97]	[1.72]	[1.85]
Observations	50	50	50	50

Note: Panel A reports the difference in the sensitivity of profit margins to discount rates across group of industries sorted on the distance-to-default measure $DD_{i,t}$. The regression specification is described in (28). The dependent variable $\Delta \ln(1+PM_{k,t}) \equiv \ln(1+PM_{k,t}) - \ln(1+PM_{k,t-1})$ is the year-on-year change in group-k's profit margin measure $\ln(1+PM_{k,t})$, which is the equal-weighted average logged one plus industry-level profit margin of all industries in group k. In column (1), industries are sorted into three tertiles, and the difference in the sensitivity of profit margins to discount rates between T1 and T3 is reported. In column (2), industries are sorted into five quintiles and the difference in the sensitivity between Q1 and Q5 is reported. In columns (3) and (4), we measure industry-level variables based on the top six firms (ranked by sales) in each industry. The sample spans the period from 1969 to 2019. Standard errors are robust to heteroskedasticity and autocorrelation. Specifically, we compute t-statistics using Newey-West standard errors with five yearly lags in panel A and using Driscoll-Kraay standard errors with five yearly lags in panel B. All variables are annualized and in fractional unit. We include t-statistics in square brackets. *, **, and *** indicate statistical significance at the 10%, 5%, and 1%, respectively.

negatively exposed to discount rates, consistent with our model predictions. The result is robust if we sort industries into five quintiles (column (2)) or focus on the top six firms in the industry when constructing the industry-level variables (columns (3) and (4)).

Financial Contagion within Industries. Our model predicts that adverse idiosyncratic shocks hitting one financially distressed market leader will motivate other market leaders within the same industry to cut their profit margins under common market structure (see panel D of Figure 6). To test this prediction, we split the top six firms in each industry into three groups based on the financial distress measure $Distress_{i,t}$ in each year. Group L contains the two firms with the lowest financial distress, group H contains the two firms with the highest financial distress, and group M labels the middle group. We run the following panel regression using industry-year observations:

$$\ln(1+PM_{i,t}^{(L)}) = \beta_H \times IdShock_{i,t}^{(H)} + \beta_L \times IdShock_{i,t}^{(L)} + \sum_{j=1}^{5} \gamma_j \times \ln(1+PM_{i,t-j}^{(L)}) + \delta_t + \ell_i + \epsilon_{i,t}, \tag{29}$$

where the independent variable $IdShock_{i,t}^{(k)}$ is the idiosyncratic shock for group $k = L, H$ in industry i and year t. We construct the group-level idiosyncratic shocks based on firm-level idiosyncratic shocks, which are constructed using two different methods for robustness. The method M1 uses firms' sales growth subtracting the cross-sectional average sales growth;

Table 11: Financial contagion effect on profit margins within an industry.

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
		$\ln(1+PM_{i,t}^{(L)})$								
			Sorted on market share dispersion				Sorted on entry threat			
		All	T1 (balance)	T2	T3 (imbalance)	T3−T1	T1 (low)	T2	T3 (high)	T3−T1
$IdShock_{i,t}^{(H)}$	M1	0.023***	0.051***	0.011	0.019	−0.033**	0.055***	0.007	0.019*	−0.036**
		[2.98]	[5.30]	[0.74]	[1.34]	[−2.09]	[3.14]	[0.90]	[1.67]	[−2.17]
	M2	0.027***	0.060***	0.009	0.023	−0.037*	0.067***	0.014	0.009	−0.058***
		[2.88]	[4.65]	[0.65]	[1.15]	[−1.66]	[4.04]	[1.29]	[0.74]	[−3.69]

Note: This table studies the financial contagion effect on profit margins within an industry. The coefficient β_H capturing the contagion effect on profit margins is reported in columns (1) – (4) and (6) – (8). Column (1) presents the estimated β_H based on the whole sample, columns (2) – (4) present the estimated β_H for industry tertiles sorted on the market-share imbalance measure. Column (5) shows the difference between columns (2) and (4). Columns (6) – (8) present the estimated β_H for industry tertiles sorted on the entry threat measure. Column (9) shows the difference between columns (6) and (8). The sample spans the period from 1976 to 2018. Standard errors are robust to heteroskedasticity and autocorrelation. Specifically, we compute t-statistics using Driscoll-Kraay standard errors with five lags, and include t-statistics in square brackets. *, **, and *** indicate statistical significance at the 10%, 5%, and 1%, respectively.

and the method M2 uses time-series regression residuals of firms' sales growth on the cross-sectional average sales growth. More details are in Online Appendix 2.2. Our regression specification (29) controls for the idiosyncratic shocks to firms in group L (i.e., $IdShock_{i,t}^{(L)}$), the lagged profit margins of firms in group L (i.e., $\sum_{j=1}^{5}\gamma_j \times \ln(1+PM_{i,t-j}^{(L)})$), and the time and industry fixed effects.[28] The coefficient β_H captures the effect of idiosyncratic shocks to firms in group H (financially distressed) on the profit margin of firms in group L (financially healthy), reflecting the contagion effect on profit margins. Column (1) of Table 11 shows that the coefficient β_H is positive and statistically significant for the idiosyncratic shocks constructed by both methods, indicating that positive idiosyncratic shocks to group H robustly increase the profit margin of group L.

Our model further predicts that the within-industry contagion effect on profit margins is more pronounced in industries where market leaders have more balanced market shares (see Figure 7). To test this prediction, we split industries into three tertiles in each year based on an industry-level imbalance measure of market shares and run the same regression (29) for industries in each tertile. The imbalance measure of market shares is defined as the absolute difference in the logged sales between group L and group H of the industry. A larger value of the imbalance measure means that the market share of group L is more different from that of group H.[29] Columns (2) and (4) of Table 11 show that the contagion effect on profit margins

[28]The results are robust if we also control for industry-level sales or the idiosyncratic shocks to the two firms in the middle group, denoted by $IdShock_{i,t}^{(M)}$.

[29]For example, an industry with a sales of 5 for group H and 1 for group L is considered equally unbalanced as an industry with a sales of 1/5 for group H and 1 for group L. Note that the ratio of the sales matters, but

is significantly larger within industries with more balanced market shares, which strongly supports our model's prediction. The difference in the estimated coefficient β_H (T3−T1) is negative and statistically significant.

Finally, our model predicts that the contagion effect on profit margins is more pronounced in the industries with lower entry threat due to greater predatory incentives (see panel B of Figure 8). We test this prediction by splitting industries into three tertiles in each year based on an industry-level entry threat measure, proxied by entry costs. Because sunk entry costs mainly arise from the construction costs of business premises (e.g., Sutton, 1991; Karuna, 2007; Barseghyan and DiCecio, 2011), we measure industry-level entry costs based on the median of the firm-level trailing 5-year average of the net total property, plant, and equipment for each industry in each year. Intuitively, in industries with higher entry costs, market followers need to incur higher setup costs to compete with and eventually displace incumbent market leaders, implying that incumbent market leaders in the industry face lower entry threat. Consistent with our model's prediction, columns (6) and (8) of Table 11 show that the contagion effect on profit margins is significantly larger within the industries with lower entry threat. The difference in the estimated coefficient β_H (T3−T1) is negative and statistically significant.

Financial Contagion across Industries. Although our model focuses on the market leaders within the same industry, the financial contagion effect may well exist among market leaders in different industries following the same intuition. Let us use Figure 2 to illustrate the mechanism. Suppose two industries I and II share the same common market leader B. The model predicts that an adverse idiosyncratic shock to market leader A in industry I will motivate market leader B to significantly lower its profit margin, making B more financially distressed. Because market leader B also competes with market leader C in industry II, when B becomes more distressed, market leader C will also lower its profit margin and become more financially distressed. Taken together, the initial adverse idiosyncratic shock to market leader A would result in a lower profit margin of market leader C through the lower profit margin set by the common market leader B.

Motivated by the discussion above, we construct a competition network of industries linked by common market leaders. Based on the competition network, we test whether idiosyncratic shocks hitting market leaders in one industry can influence the profit margins of market leaders in another industry if the two industries share some common market leaders. We provide the details on the construction of the competition network and empirical design in Online Appendix 2.4.

Our empirical test has two stages. In the first stage, we estimate the impact of idiosyncratic shocks of market leaders in industry i on the profit margin of common market leaders with

whether H or L has higher sales does not.

Table 12: Financial contagion effect on profit margins across industries.

	(1)	(2)		(3)	(4)
Panel A: Construction of $\widehat{IdShock}_{i,t}^{(c_{i,j})}$ (first stage)			Panel B: Cross-industry contagion (second stage)		
	$\ln(1+PM_t^{(c_{i,j})})$			$\ln(1+PM_{i,t})$	
	M1	M2		M1	M2
$IdShock_{i,t}^{(1)}$	0.049***	0.031*	$\widehat{IdShock}_{-i,t}$	0.677**	0.760*
	[3.41]	[2.04]		[2.20]	[1.99]
$IdShock_{i,t}^{(2)}$	0.025***	0.023**	$IdShock_{i,t}$	0.167***	0.116***
	[4.38]	[2.82]		[5.25]	[6.09]
$IdShock_{i,t}^{(3)}$	−0.007	0.017			
	[−0.72]	[1.29]			
Observations	8,352	8,352	Observations	222	221

Note: This table reports the results of the two-stage estimation of the cross-industry financial contagion effect on profit margins. In panel A, we estimate the first-stage specification: $\ln(1+PM_t^{(c_{i,j})}) = \alpha + \sum_{k=1}^{3}\beta_k \times IdShock_{i,t}^{(k)} + \varepsilon_{i,t}$ and take the fitted value $\widehat{IdShock}_{i,t}^{(c_{i,j})}$. Here the term $PM_t^{(c_{i,j})}$ in the dependent variable represents the profit margin of the common market leader $c_{i,j}$, and the independent variable $IdShock_{i,t}^{(k)}$ represents the idiosyncratic shocks to the kth ($k = 1, 2, 3$) largest firm (ranked by sales) in industry i and year t, estimated by methods M1 or M2 (see Online Appendix 2.2). In panel B, we use the fitted value of the first stage to construct the independent variable $\widehat{IdShock}_{-i,t}$ as the simple average of $\widehat{\text{IdShock}}_{j,t}^{(c_{j,i})}$ over all industries connected to the industry i. $\widehat{\text{IdShock}}_{j,t}^{(c_{j,i})}$ is estimated in the first stage, and it captures the profit-margin changes of the common leader $c_{j,i}$ attributed to idiosyncratic shocks to market leaders in industry j. The cross-industry contagion effect on profit margins is estimated by specification: $\ln(1+PM_{i,t}) = \alpha + \beta_1 \times \widehat{IdShock}_{-i,t} + \beta_2 \times IdShock_{i,t} + \sum_{j=1}^{5}\gamma_j \times \ln(1+PM_{i,t-j}) + \delta_t + \ell_i + \varepsilon_{i,t}$ with time and industry fixed effects δ_t and ℓ_i. The sample spans the period from 1997 to 2018. Standard errors are robust to heteroskedasticity and autocorrelation. Specifically, we compute t-statistics using Driscoll-Kraay standard errors with five lags, and include t-statistics in square brackets. *, **, and *** indicate statistical significance at the 10%, 5%, and 1%, respectively.

industries i and j, denoted by $c_{i,j}$, in panel A of Table 12. In the second stage, we take the fitted value $\widehat{IdShock}_{i,t}^{(c_{i,j})}$ from the first stage, and we estimate the cross-industry financial contagion effect on profit margins based on the first-stage fitted values $\widehat{IdShock}_{-i,t}$, which is the average of $\widehat{IdShock}_{j,t}^{(c_{j,i})}$ over all industries connected to industry i, in panel B of Table 12.

Table 12 presents our estimation results. Panel A presents our first-stage estimates, which indicate that the common leaders' profit margins are positively associated with the idiosyncratic shocks to the top market leaders in the same industries. Panel B presents the second-stage estimates on the cross-industry contagion effect. The coefficient of $\widehat{IdShock}_{-i,t}$ is positive and statistically significant, indicating that the profit margin of industry i is positively associated with the idiosyncratic shocks to the industries that are directly connected to industry i through common market leaders. The coefficient of $\widehat{IdShock}_{-i,t}$ equals to 0.677, meaning that 1% increase in the average profit margin of common market leaders due to idiosyncratic shocks hitting the market leaders in the connected industries is associated with a 0.677% increase in the profit margin of industry i.

Table 13: Feedback effect on equity excess returns of industry portfolios.

$Profitability_{i,t}$	T1	T2	T3	T3−T1
Group 1 (low $DD_{i,t}$)	5.283	6.446***	9.529***	4.426**
	[1.51]	[1.85]	[2.74]	[2.28]
Group 2	7.243***	8.719***	10.089***	2.846*
	[2.64]	[2.99]	[3.39]	[1.75]
Group 3 (high $DD_{i,t}$)	7.822***	8.623***	9.283***	1.460
	[3.08]	[3.35]	[3.83]	[1.13]

Note: This table reports gross profitability spreads in split samples by the distance-to-default measure. We first sort industries into three groups based on their distance to default. In each group, we further sort industries into three tertiles based on their profitability. We construct industry-level gross profitability as gross profits (revenue minus cost of goods sold) scaled by assets, following the definition of Novy-Marx (2013). The sample spans the period from 1975 to 2018. The *t*-statistics are reported in square brackets. *, **, and *** indicate statistical significance at the 10%, 5%, and 1%, respectively.

5.3 Feedback and Contagion Effects on Asset Prices

Competition-Distress Feedback Effects. As discussed in Section 3.5, the competition-distress feedback is stronger when industries are closer to the default boundary. As a result, the difference in the exposure of equity excess returns to discount rates across industries with different gross profitability becomes larger when the distance to default is lower (see Figure 10). To test this prediction, we equally split all industries into three groups based on their distance-to-default measure $DD_{i,t}$. Within each group, we sort industries into three tertiles based on their gross profitability. Table 13 shows that the return spread between industries with high and low gross profitability (T3−T1) is positive and statistically significant among industries in the group with low distance to default (Group 1). The spread sorted on the gross profitability is much smaller and statistically insignificant among industries in the group with high distance to default (Group 3).

Financial Contagion within Industries. Our model implies that the financial contagion effect among market leaders within the same industry is also reflected in firms' credit spreads (panel F of Figure 6). To test this prediction, we conduct regression analysis using specification (29) except for using group-level credit spreads as the dependent variable:

$$Credit_spread_{i,t}^{(L)} = \beta_H \times IdShock_{i,t}^{(H)} + \beta_L \times IdShock_{i,t}^{(L)} + \sum_{j=1}^{5} \gamma_j \times Credit_spread_{i,t-j}^{(L)} + \delta_t + \ell_i + \epsilon_{i,t}. \tag{30}$$

Column (1) of Table 14 shows that the contagion effect on credit spreads is negative, indicating that positive idiosyncratic shocks to group H reduces the credit spread of group L. The

Table 14: Financial contagion effect on credit spreads within an industry.

		(1)	(2)	(3)	(4)	(5)
			$Credit_spread_{i,t}^{(L)}$			
			Industry portfolios sorted on market share dispersion			
		All	T1 (balance)	T2	T3 (imbalance)	T3−T1
$IdShock_{i,t}^{(H)}$	M1	−0.483*	−1.328*	−0.163	−0.273	1.055
		[−1.71]	[−1.70]	[−0.35]	[−0.88]	[1.35]
	M2	−0.308	−1.465*	0.323	0.059	1.523*
		[−1.03]	[−1.82]	[0.77]	[0.15]	[1.75]

Note: This table studies the financial contagion effect on credit spreads within an industry. In each year, we split the top six firms in each industry into three groups based on the financial distress measure $Distress_{i,t}$. Group L contains the two firms with the lowest financial distress, and group H contains the two firms with the highest financial distress. We construct the group-level idiosyncratic shocks based on firm-level idiosyncratic shocks, which are constructed using two different methods for robustness. The method M1 uses firms' sales growth subtracting the cross-sectional average sales growth; and the method M2 uses time-series regression residuals of firms' sales growth on the cross-sectional average sales growth. See Online Appendix 2.2 for more details. The results are presented in the row of M1 and M2, respectively. The coefficient β_H capturing the contagion effect on credit spreads is reported in columns (1) – (4). Column (1) presents the estimated β_H based on the whole sample, column (2) – (4) presents the estimated β_H for industry tertiles sorted on the market-share imbalance measure, which is defined as the absolute difference in the logged sales between group L and group H of the industry. Column (5) shows the difference of the columns (2) and (4). The sample spans the period from 1977 to 2018. Standard errors are robust to heteroskedasticity and autocorrelation. Specifically, we compute t-statistics using Driscoll-Kraay standard errors with five lags, and include t-statistics in square brackets. *, **, and *** indicate statistical significance at the 10%, 5%, and 1%, respectively.

coefficient is statistically insignificant due to small sample size. We further test whether the contagion effect on credit spreads is stronger in industries where market leaders have more balanced market shares, as predicted by the model. Columns (2) – (5) of Table 14 show that the contagion effect on credit spreads is much more negative within industries of the balance group (T1) than that of the imbalance group (T3). The difference is economically significant even though statistically insignificant due to small sample size.

5.4 Tests on the Core Competition Mechanism

In this section, we provide direct evidence supporting the unique predictions of our model's endogenous competition mechanism. In particular, guided by the analyses in Section 3.4, we test whether the competition-distress feedback effect and financial contagion effect become weaker when the industries' market structure becomes more competitive.

To test these predictions, we examine how the variable for market structure changes, $mkt_chg_{i,t}$, affects the feedback and contagion effect. Properly measuring market structure changes in our panel regressions is challenging. Endogeneity problems will arise if we use empirical proxies for the competitiveness of market structure such as the Herfindahl-Hirschman Index (HHI). Specifically, there could exist some omitted variables that are correlated with both the changes in the HHI and the feedback (contagion) effect through channels other than

the competitiveness of market structure. For instance, technology development can lead to changes in the HHI, and also change the sensitivity of industries' net profitability to aggregate discount rates or idiosyncratic shocks by altering the duration of firms' cash flows.

To address the endogeneity concern, we exploit exogenous variations in the competitiveness of market structure at the industry level. We follow the literature (Frésard, 2010; Valta, 2012; Frésard and Valta, 2016; Dou, Ji and Wu, 2020*a*) and use unexpected large cuts in import tariffs to identify exogenous variation in market structure.[30] The existing literature provides extensive evidence showing that tariff cuts substantially alter the competitive configuration of industries. For example, Bernard, Jensen and Schott (2006) show that import tariff cuts significantly increase the competitive pressures from foreign rivals. Valta (2012) shows that tariff reductions are followed by a significant increase in imports. Intuitively, large tariff cuts can lead to a more competitive market structure, because the reduction in trade barriers can increase (i) the industry's price elasticity of demand ϵ due to the similar products and services provided by foreign rivals and (ii) the number of market leaders n due to the entry of foreign rivals as major players.

We first examine the impact of large tariff cuts on the sensitivity of profit margins to discount rates across industries with different values of distance to default. We run the following panel regression using industry-year observations in a DID framework, essentially by adding the unexpected market structure change (i.e., the unexpected large tariff cut) dummy variable $mkt_chg_{i,t}$ to the empirical specification in Table 10:

$$\begin{aligned}\Delta \ln(1+PM_{i,t}) = {} & \beta_1 \times mkt_chg_{i,t} \times Low_DD_{i,t-1} \times \Delta Discount_rate_t \\ & + \beta_2 \times Low_DD_{i,t-1} \times \Delta Discount_rate_t + \beta_3 \times mkt_chg_{i,t} \times \Delta Discount_rate_t \\ & + \beta_4 \times \Delta Discount_rate_t + \beta_5 \times mkt_chg_{i,t} \times Low_DD_{i,t-1} \\ & + \beta_6 \times Low_DD_{i,t-1} + \beta_7 \times mkt_chg_{i,t} + \ell_i + \epsilon_{i,t}. \end{aligned} \tag{31}$$

where $Low_DD_{i,t-1}$ is the indicator variable for industries with low distance to default, equal to one if the distance-to-default measure of industry i in year $t-1$ is below the 25% quantile for the variable $DD_{i,t-1}$ across all industries in year $t-1$, and the variable $mkt_chg_{i,t}$ is the indicator variable for large tariff cuts.

As a benchmark, column (1) of Table 15 presents the results without including the terms with $mkt_chg_{i,t}$ in specification (31). It is shown that the profit margins of industries with low distance to default are more negatively exposed to discount rates, which is consistent with the implication of the competition-distress feedback. Column (2) of Table 15 reports the results of the full specification (31). The estimated coefficient $\hat{\beta}_1$ on the triple interaction term

[30] Tariff cuts as shocks to the competitiveness of industry market structure has been widely used in the literature to address endogeneity concerns (e.g., Xu, 2012; Flammer, 2015; Huang, Jennings and Yu, 2017; Dasgupta, Li and Wang, 2018).

Table 15: Impact of market structure changes on the competition-distress feedback.

	(1)	(2)	(3)	(4)
	$\Delta \ln(1+PM_{i,t})$		$\Delta PM_{i,t}$	
$Mkt_chg_{i,t} \times Low_DD_{i,t-1} \times \Delta Discount_rate_t$		1.57**		1.40**
		[2.59]		[2.53]
$Low_DD_{i,t-1} \times \Delta Discount_rate_t$	−0.47**	−0.79	−0.36*	−0.61
	[−2.08]	[−1.56]	[−1.82]	[−1.42]
$Mkt_chg_{i,t} \times \Delta Discount_rate_t$		0.39**		0.39**
		[2.20]		[2.24]
$\Delta Discount_rate_t$	−0.25**	−0.35**	−0.24***	−0.34**
	[−3.51]	[−2.03]	[−3.56]	[−2.11]
$Mkt_chg_{i,t} \times Low_DD_{i,t-1}$		0.02		0.01
		[1.18]		[1.12]
$Low_DD_{i,t-1}$	−0.02***	−0.02**	−0.01***	−0.02***
	[−4.02]	[−2.69]	[−4.03]	[−2.79]
$Mkt_chg_{i,t}$		0.00		0.00
		[0.06]		[0.08]
Observations	2,985	967	2,985	967

Note: This table examines the impact of market structure changes on the competition-distress feedback effect. We run panel regressions according to specification (31), where the independent variable is the year-on-year changes in the logged one plus industry-level profit margin (columns 1 and 2) or simply changes in the industry-level profit margin (columns 3 and 4). $Low_DD_{i,t-1}$ is an indicator variable that equals one if the distance-to-default measure of industry i in year $t-1$ is below the 25% quantile for $DD_{i,t-1}$ across all industries in year $t-1$. We measure market structure changes based on large import tariff cuts. Specifically, $Mkt_chg_{i,t}$ is an indicator variable that equals one if industry i experiences a large tariff cut in the last two years (t and $t-1$). A large tariff cut refers to the tariff cut whose magnitude is greater than three times the median tariff cut in this industry across the whole sample period (e.g., Frésard, 2010). To ensure that large tariff cuts indeed capture nontransitory changes in the competitive environment, following Frésard (2010), we exclude tariff cuts that are followed by equivalently large increases in tariffs over the subsequent two years. We obtain the tariff data for manufacturing industries at the SIC4 industry level from 1974 to 2005 from Laurent Fresard's website (Frésard, 2010), and extend the data to 2017 based on the tariff data at the Harmonized System level obtained from Peter Schott's website (Schott, 2008). We control for industry fixed effects. The sample spans the period from 1976 to 2017. Standard errors are clustered at the industry level. We include t-statistics in brackets. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

in specification (31) is positive and significant both statistically and economically, suggesting that industries with high and low distance to default display less difference in the sensitivity of profit margins to discount rates when their market structure becomes more competitive after large tariff cuts.[31] The results remain robust if we use changes in industry-level profit margin (i.e., $\Delta PM_{i,t}$) as the independent variable in columns (3) and (4).

Next, we examine the impact of large tariff cuts on the financial contagion effect. Specifically, we run the following panel regression using industry-year observations, by adding the unexpected market structure change (i.e., the unexpected large tariff cut) to the regression

[31] A positive $\hat{\beta}_1$ means that the difference in the sensitivity of profit margins to discount rates narrows because industries with low distance to default are more negatively exposed to discount rates than those with high distance to default in the absence of large tariff cuts (see column (1) of Table 15).

Table 16: Impact of market structure changes on the financial contagion effect.

	(1)	(2)	(3)	(4)
	$\ln(1+PM_{i,t}^{(L)})$			
	M1		M2	
$Mkt_chg_{i,t} \times IdShock_{i,t}^{(H)}$		-0.04^{**}		-0.04^{**}
		$[-2.39]$		$[-2.20]$
$IdShock_{i,t}^{(H)}$	0.02^{***}	0.02^{*}	0.03^{***}	0.03^{**}
	$[2.62]$	$[1.98]$	$[2.78]$	$[2.47]$
$Mkt_chg_{i,t}$		0.00		-0.01
		$[-1.37]$		$[-0.62]$
$IdShock_{i,t}^{(L)}$	0.07^{***}	0.08^{***}	0.06^{***}	0.07^{***}
	$[4.92]$	$[4.09]$	$[3.53]$	$[3.23]$
$\ln(1+PM_{i,t-1}^{(L)})$	0.29^{***}	0.24^{***}	0.29^{***}	0.24^{***}
	$[4.95]$	$[7.10]$	$[4.92]$	$[7.21]$
$\ln(1+PM_{i,t-2}^{(L)})$	0.08^{**}	0.08	0.08^{**}	0.08
	$[2.51]$	$[1.09]$	$[2.49]$	$[1.09]$
$\ln(1+PM_{i,t-3}^{(L)})$	0.03	0.06^{***}	0.02	0.06^{***}
	$[0.83]$	$[3.54]$	$[0.82]$	$[3.45]$
$\ln(1+PM_{i,t-4}^{(L)})$	0.03^{*}	0.04	0.03^{*}	0.04
	$[1.90]$	$[1.36]$	$[1.78]$	$[1.36]$
$\ln(1+PM_{i,t-5}^{(L)})$	-0.01	0.05	-0.01	0.05
	$[0.91]$	$[0.29]$	$[0.88]$	$[0.20]$
Observations	4,432	1,439	4,424	1,438

Note: This table examines the impact of market structure changes on the financial contagion effect. The independent variable is the year-on-year change in the logged one plus industry-level profit margin. Group-level idiosyncratic shocks are constructed as in Table 11. The large tariff cut variable $mkt_chg_{i,t}$ is constructed as in Table 15. We control for the year and industry fixed effects. The sample spans the period from 1976 to 2017. We include t-statistics in brackets. Standard errors are clustered at the industry level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

specification in Table 11:

$$\ln(1+PM_{i,t}^{(L)}) = \beta_1 \times mkt_chg_{i,t} \times IdShock_{i,t}^{(H)} + \beta_2 \times IdShock_{i,t}^{(H)} + \beta_3 \times mkt_chg_{i,t} + \beta_4 \times IdShock_{i,t}^{(L)} + \sum_{\tau=1}^{5} \gamma_\tau \times \ln(1+PM_{i,t-\tau}^{(L)}) + \delta_t + \ell_i + \epsilon_{i,t}. \quad (32)$$

This regression specification is similar to specification (29) except for including the terms with $mkt_chg_{i,t}$. As a benchmark, columns (1) and (3) report the results without including the terms with $mkt_chg_{i,t}$ using two different methods (M1 and M2) for constructing idiosyncratic shocks (see Online Appendix 2.2). They show that the financial contagion effect is positive, consistent with Table 11. Columns (2) and (4) show that the estimated coefficient $\hat{\beta}_1$ on the interaction term in specification (32) is negative and significant both statistically and economically, indicating that financial contagion effects on profit margins become weaker after

unexpected large tariff cuts (i.e., unexpected increase in competitiveness of market structure).

6 Conclusion

This paper investigates the implications of dynamic interactions between endogenous strategic competition and financial distress. We develop the first elements of a tractable dynamic framework for distressed competition by incorporating a supergame of strategic rivalry into a dynamic model of long-term defaultable debt. In our model, firms tend to compete more aggressively when they are in financial distress, and the intensified competition in turn reduces the profit margins for all firms in the industry, pushing everyone further into distress. Thus, the core mechanism of endogenous competition under financial distress implies novel competition-distress feedback and financial contagion effects. In addition, our model shows that, depending on the relative market share and financial strength as well as entry threats, firms in the model exhibit a rich variety of strategic interactions, including predation, self-defense, and collaboration (collective entry prevention). More important, our theory produces salient asset pricing implications: First, due to financial contagion, the credit risks of leading firms in an industry are jointly determined, whereby firm-specific shocks can significantly affect the credit spread of peer firms; second, the competition-distress feedback amplifies firms' aggregate risk exposure, more so for the industries with the lower left-tail idiosyncratic jump risk, which helps explain the puzzling cross-sectional patterns of equity and bond returns – the financial distress anomaly across industries.

References

Abreu, Dilip. 1988. "On the theory of infinitely repeated games with discounting." *Econometrica*, 56(2): 383–396.

Abreu, Dilip, David Pearce, and Ennio Stacchetti. 1990. "Toward a Theory of Discounted Repeated Games with Imperfect Monitoring." *Econometrica*, 58(5): 1041–1063.

Acemoglu, Daron, Asuman Ozdaglar, and Alireza Tahbaz-Salehi. 2015. "Systemic Risk and Stability in Financial Networks." *American Economic Review*, 105(2): 564–608.

Aggarwal, Rajesh K., and Andrew A. Samwick. 1999. "Executive compensation, strategic competition, and relative performance evaluation: theory and evidence." *Journal of Finance*, 54(6): 1999–2043.

Aguerrevere, Felipe L. 2009. "Real options, product market competition, and asset returns." *Journal of Finance*, 64(2): 957–983.

Allen, Franklin. 2000. "Capital structure and imperfect competition in product markets." In *Incentives, Organization, and Public Economics*. 281–301. Oxford University Press.

Allen, Franklin, and Douglas Gale. 2000. "Financial Contagion." *Journal of Political Economy*, 108(1): 1–33.

Alvarez, Fernando, and Urban J. Jermann. 2000. "Efficiency, equilibrium, and asset pricing with risk of default." *Econometrica*, 68(4): 775–797.

Alvarez, Fernando, and Urban J. Jermann. 2001. "Quantitative asset pricing implications of endogenous solvency constraints." *Review of Financial Studies*, 14(4): 1117–1151.

Anderson, Ronald W., and Andrew Carverhill. 2012. "Corporate Liquidity and Capital Structure." *Review of Financial Studies*, 25(3): 797–837.

Anderson, Simon P., André De Palma, and Jacques-Francois Thisse. 1989. "Demand for differentiated products, discrete choice models, and the characteristics approach." *Review of Economic Studies*, 56(1): 21–35.

Antill, Samuel. 2020. "Do the Right Firms Survive Bankruptcy?" Working Papers.

Atkeson, Andrew, and Ariel Burstein. 2008. "Pricing-to-market, trade costs, and international relative prices." *American Economic Review*, 98(5): 1998–2031.

Autor, David, David Dorn, Lawrence F. Katz, Christina Patterson, and John Van Reenen. 2019. "The fall of the labor share and the rise of superstar firms." *Quarterly Journal of Economics*, forthcoming.
Back, Kerry, and Dirk Paulsen. 2009. "Open-Loop Equilibria and Perfect Competition in Option Exercise Games." *Review of Financial Studies*, 22(11): 4531–4552.
Bagwell, Kyle, and Robert Staiger. 1997. "Collusion over the business cycle." *RAND Journal of Economics*, 28(1): 82–106.
Bakke, Tor-Erik, and Toni M. Whited. 2010. "Which Firms Follow the Market? An Analysis of Corporate Investment Decisions." *The Review of Financial Studies*, 23(5): 1941–1980.
Banerjee, Shantanu, Sudipto Dasgupta, and Yungsan Kim. 2008. "Buyer-Supplier Relationships and the Stakeholder Theory of Capital Structure." *Journal of Finance*, 63(5): 2507–2552.
Banerjee, Shantanu, Sudipto Dasgupta, Rui Shi, and Jiali Yan. 2019. "Predatory Advertising, Financial Fraud, and Leverage." Working Paper.
Barseghyan, Levon, and Riccardo DiCecio. 2011. "Entry costs, industry structure, and cross-country income and TFP differences." *Journal of Economic Theory*, 146(5): 1828 – 1851.
Bebchuk, Lucian A., and Itay Goldstein. 2011. "Self-fulfilling Credit Market Freezes." *The Review of Financial Studies*, 24(11): 3519–3555.
Belo, Frederico, and Xiaoji Lin. 2012. "The Inventory Growth Spread." *The Review of Financial Studies*, 25(1): 278–313.
Belo, Frederico, Vito Gala, Juliana Salomao, and Maria Ana Vitorino. 2019. "Decomposing Firm Value." Working Paper.
Belo, Frederico, Xiaoji Lin, and Maria Ana Vitorino. 2014. "Brand capital and firm value." *Review of Economic Dynamics*, 17(1): 150–169.
Bergin, James, and W. Bentley MacLeod. 1993. "Continuous Time Repeated Games." *International Economic Review*, 34(1): 21–37.
Bernanke, Ben, and Mark Gertler. 1989. "Agency Costs, Net Worth, and Business Fluctuations." *The American Economic Review*, 79(1): 14–31.
Bernard, Andrew B, J Bradford Jensen, and Peter K Schott. 2006. "Trade costs, firms and productivity." *Journal of Monetary Economics*, 53(5): 917–937.
Besanko, David, Ulrich Doraszelski, and Yaroslav Kryukov. 2014. "The Economics of Predation: What Drives Pricing When There Is Learning-by-Doing?" *American Economic Review*, 104(3): 868–97.
Bhamra, Harjoat S., Lars-Alexander Kuehn, and Ilya A. Strebulaev. 2010*a*. "Long Run Risks, Credit Markets, and Financial Structure." *The American Economic Review: Papers & Proceedings*, 100(2): 547–551.
Bhamra, Harjoat S., Lars-Alexander Kuehn, and Ilya A. Strebulaev. 2010*b*. "The Levered Equity Risk Premium and Credit Spreads: A Unified Framework." *Review of Financial Studies*, 23(2): 645–703.
Bolton, Patrick, and David Scharfstein. 1990. "A Theory of Predation Based on Agency Problems in Financial Contracting." *American Economic Review*, 80(1): 93–106.
Bolton, Patrick, Hui Chen, and Neng Wang. 2011. "A unified theory of Tobin's q, corporate investment, financing, and risk management." *Journal of Finance*, 66(5): 1545–1578.
Bolton, Patrick, Hui Chen, and Neng Wang. 2013. "Market timing, investment, and risk management." *Journal of Financial Economics*, 109(1): 40–62.
Bolton, Patrik, Neng Wang, and Jinqiang Yang. 2019. "Leverage Dynamics and Financial Flexibility." Working Paper.
Bond, Philip, Alex Edmans, and Itay Goldstein. 2012. "The Real Effects of Financial Markets." *Annual Review of Financial Economics*, 4(1): 339–360.
Bourveau, Thomas, Guoman She, and Alminas Zaldokas. 2020. "Corporate Disclosure as a Tacit Coordination Mechanism: Evidence from Cartel Enforcement Regulations." *Journal of Accounting Research*, 58(2): 295–332.
Boyer, Brian, Todd Mitton, and Keith Vorkink. 2010. "Expected Idiosyncratic Skewness." *Review of Financial Studies*, 23(1): 169–202.
Brander, James, and Tracy R. Lewis. 1986. "Oligopoly and Financial Structure: The Limited Liability Effect." *American Economic Review*, 76(5): 956–70.
Brock, William A, and Jose A Scheinkman. 1985. "Price setting supergames with capacity constraints." *Review of Economic Studies*, 52(3): 371–382.
Bronnenberg, Bart J., Sanjay K. Dhar, and Jean-Pierre H. Dubé. 2009. "Brand history, geography, and the persistence of brand shares." *Journal of Political Economy*, 117(1): 87–115.
Bustamante, Maria Cecilia. 2015. "Strategic Investment and Industry Risk Dynamics." *Review of Financial Studies*, 28(2): 297–341.
Bustamante, M. Cecilia, and Andres Donangelo. 2017. "Product market competition and industry returns." *Review of Financial Studies*, 30(12): 4216–4266.
Byrne, David P., and Nicolas de Roos. 2019. "Learning to Coordinate: A Study in Retail Gasoline." *American Economic Review*, 109(2): 591–619.
Caballero, Ricardo J, and Robert S Pindyck. 1996. "Uncertainty, Investment, and Industry Evolution." *International Economic Review*, 37(3): 641–662.

Cabral, Luis, and Michael Riordan. 1994. "The Learning Curve, Market Dominance, and Predatory Pricing." *Econometrica*, 62(5): 1115–40.
Campbell, John, and Samuel B. Thompson. 2008. "Predicting Excess Stock Returns Out of Sample: Can Anything Beat the Historical Average?" *Review of Financial Studies*, 21(4): 1509–1531.
Campbell, John, Jens Hilscher, and Jan Szilagyi. 2008. "In search of distress risk." *Journal of Finance*, 63(6): 2899–2939.
Campbell, John Y., and John H. Cochrane. 1999. "By Force of Habit: A Consumption-Based Explanation of Aggregate Stock Market Behavior." *Journal of Political Economy*, 107(2): 205–251.
Campbell, John Y., and Robert J. Shiller. 1988. "Stock Prices, Earnings, and Expected Dividends." *The Journal of Finance*, 43(3): 661–676.
Campbell, John Y., and Robert J. Shiller. 1998. "Valuation Ratios and the Long-Run Stock Market Outlook." *The Journal of Portfolio Management*, 24(2): 11–26.
Chen, Hui. 2010. "Macroeconomic conditions and the puzzles of credit spreads and capital structure." *Journal of Finance*, 65(6): 2171–2212.
Chen, Hui, Rui Cui, Zhiguo He, and Konstantin Milbradt. 2017. "Quantifying Liquidity and Default Risks of Corporate Bonds over the Business Cycle." *The Review of Financial Studies*, 31(3): 852–897.
Chen, Hui, Rui Cui, Zhiguo He, and Konstantin Milbradt. 2018. "Quantifying Liquidity and Default Risks of Corporate Bonds over the Business Cycle." *Review of Financial Studies*, 31(3): 852–897.
Chen, Long, Pierre Collin-Dufresne, and Robert S. Goldstein. 2008. "On the Relation Between the Credit Spread Puzzle and the Equity Premium Puzzle." *The Review of Financial Studies*, 22(9): 3367–3409.
Chen, Qi, Itay Goldstein, and Wei Jiang. 2006. "Price Informativeness and Investment Sensitivity to Stock Price." *The Review of Financial Studies*, 20(3): 619–650.
Chevalier, Judith A., and David S. Scharfstein. 1996. "Capital-Market Imperfections and Countercyclical Markups: Theory and Evidence." *American Economic Review*, 86(4): 703–725.
Cochrane, John H. 1991. " Production-based asset pricing and the link between stock returns and economic fluctuations." *Journal of Finance*, 46(1): 209–237.
Collin-Dufresne, Pierre, Robert S. Goldstein, and Fan Yang. 2012. "On the Relative Pricing of Long-Maturity Index Options and Collateralized Debt Obligations." *The Journal of Finance*, 67(6): 1983–2014.
Collin-Dufresne, Pierre, Robert S. Goldstein, and J. Spencer Martin. 2001. "The Determinants of Credit Spread Changes." *The Journal of Finance*, 56(6): 2177–2207.
Connor, John M. 2016. "The private international cartels (PIC) data set: guide and summary statistics, 1990-July 2016 (Revised 2nd Edition)." Working Paper.
Cookson, J. Anthony. 2017. "Leverage and strategic preemption: Lessons from entry plans and incumbent investments." *Journal of Financial Economics*, 123(2): 292 – 312.
Corhay, Alexandre. 2017. "Industry competition, credit spreads, and levered equity returns." University of Toronto Working Papers.
Corhay, Alexandre, Howard Kung, and Lukas Schmid. 2017. "Competition, markups, and predictable returns." Working Papers.
Corhay, Alexandre, Howard Kung, and Lukas Schmid. 2020. "Q: Risk, Rents, or Growth?" Duke University Working Papers.
Cronshaw, Mark B., and David G. Luenberger. 1994. "Strongly Symmetric Subgame Perfect Equilibria in Infinitely Repeated Games with Perfect Monitoring and Discounting." *Games and Economic Behavior*, 6(2): 220–237.
D'Acunto, Francesco, Ryan Liu, Carolin Pflueger, and Michael Weber. 2018. "Flexible prices and leverage." *Journal of Financial Economics*, 129(1): 46–68.
Dasgupta, Sudipto, and Alminas Zaldokas. 2018. "Anticollusion Enforcement: Justice for Consumers and Equity for Firms." *The Review of Financial Studies*, 32(7): 2587–2624.
Dasgupta, Sudipto, Xi Li, and Albert Y Wang. 2018. "Product market competition shocks, firm performance, and forced CEO turnover." *Review of Financial Studies*, 31(11): 4187–4231.
Davydenko, Sergei A., Ilya A. Strebulaev, and Xiaofei Zhao. 2012. "A Market-Based Study of the Cost of Default." *Review of Financial Studies*, 25(10): 2959–2999.
Delianedis, Gordon, and Robert Geske. 2001. "The Components of Corporate Credit Spreads: Default, Recovery, Tax, Jumps, Liquidity, and Market Factors." Anderson Graduate School of Management, UCLA University of California at Los Angeles, Anderson Graduate School of Management.
Dick-Nielsen, Jens. 2009. "Liquidity Biases in TRACE." *The Journal of Fixed Income*, 19(2): 43–55.
Dou, Winston Wei, and Yan Ji. 2019. "External financing and customer capital: A financial theory of markups." Working Papers.
Dou, Winston Wei, Lucian A. Taylor, Wei Wang, and Wenyu Wang. 2020*a*. "Dissecting Bankruptcy Frictions." Working Paper.
Dou, Winston Wei, Xiang Fang, Andrew W. Lo, and Harald Uhlig. 2020*b*. "Macro-Finance Models with Nonlinear Dynamics." The Wharton School at University of Pennsylvania Working Papers.
Dou, Winston Wei, Yan Ji, and Wei Wu. 2020*a*. "Competition, Profitability, and Discount Rates." *Journal of*

Financial Economcis, 22(forthcoming).
Dou, Winston Wei, Yan Ji, and Wei Wu. 2020*b*. "The Oligopoly Lucas Tree: Consumption Risk and Industry-Level Risk Exposure." Working Papers.
Dou, Winston, Yan Ji, David Reibstein, and Wei Wu. 2019. "Inalienable Customer capital, corporate liquidity, and stock returns." *Journal of Finance*, forthcoming.
Duffie, Darrell, and David Lando. 2001. "Term Structures of Credit Spreads with Incomplete Accounting Information." *Econometrica*, 69(3): 633–664.
Dumas, Bernard. 1989. "Perishable Investment and Hysteresis in Capital Formation." NBER Working Paper.
Edmans, Alex, Itay Goldstein, and Wei Jiang. 2012. "The Real Effects of Financial Markets: The Impact of Prices on Takeovers." *The Journal of Finance*, 67(3): 933–971.
Ericson, Richard, and Ariel Pakes. 1995. "Markov-perfect industry dynamics: A framework for empirical work." *Review of Economic Studies*, 62(1): 53–82.
Fama, Eugene F., and Kenneth R. French. 1993. "Common risk factors in the returns on stocks and bonds." *Journal of Financial Economics*, 33(1): 3–56.
Farrell, Joseph, and Eric Maskin. 1989. "Renegotiation in repeated games." *Games and Economic Behavior*, 1(4): 327–360.
Fershtman, Chaim, and Ariel Pakes. 2000. "A dynamic oligopoly with collusion and price wars." *RAND Journal of Economics*, 31(2): 207–236.
Fershtman, Chaim, and Kenneth L. Judd. 1987. "Equilibrium incentives in oligopoly." *American Economic Review*, 77(5): 927–940.
Flammer, Caroline. 2015. "Does product market competition foster corporate social responsibility? Evidence from trade liberalization." *Strategic Management Journal*, 36(10): 1469–1485.
Frésard, Laurent. 2010. "Financial strength and product market behavior: The real effects of corporate cash holdings." *Journal of Finance*, 65(3): 1097–1122.
Frésard, Laurent, and Philip Valta. 2016. "How does corporate investment respond to increased entry threat?" *Review of Corporate Finance Studies*, 5(1): 1–35.
Friedman, James W. 1971. "A non-cooperative equilibrium for supergames." *Review of Economic Studies*, 38(1): 1–12.
Fudenberg, Drew, and Eric Maskin. 1986. "The Folk theorem in repeated games with discounting or with incomplete information." *Econometrica*, 54(3): 533–54.
Fudenberg, Drew, and Jean Tirole. 1986. "A "Signal-Jamming" Theory of Predation." *RAND Journal of Economics*, 17(3): 366–376.
Fudenberg, Drew, and Jean Tirole. 1991. *Game theory.* The MIT Press.
Gabaix, Xavier, Jean-Michel Lasry, Pierre-Louis Lions, and Benjamin Moll. 2016. "The Dynamics of Inequality." *Econometrica*, 84(6): 2071–2111.
Gârleanu, Nicolae, Stavros Panageas, and Jianfeng Yu. 2015. "Financial Entanglement: A Theory of Incomplete Integration, Leverage, Crashes, and Contagion." *American Economic Review*, 105(7): 1979–2010.
Geroski, P.A., and S. Toker. 1996. "The turnover of market leaders in UK manufacturing industry, 1979-86." *International Journal of Industrial Organization*, 14(2): 141 – 158.
Gilchrist, Simon, Jae Sim, Raphael Schoenle, and Egon Zakrajsek. 2017. "Inflation dynamics during the financial crisis." *American Economic Review*, 107(3): 785–823.
Gilson, Stuart C. 1997. "Transactions Costs and Capital Structure Choice: Evidence from Financially Distressed Firms." *The Journal of Finance*, 52(1): 161–196.
Gilson, Stuart C., Kose John, and Larry Lang. 1990. "Troubled debt restructurings*1: An empirical study of private reorganization of firms in default." *Journal of Financial Economics*, 27(2): 315–353.
Giroud, Xavier, and Holger M. Mueller. 2010. "Does corporate governance matter in competitive industries?" *Journal of Financial Economics*, 95(3): 312 – 331.
Giroud, Xavier, and Holger M. Mueller. 2011. "Corporate governance, product market competition, and equity prices." *Journal of Finance*, 66(2): 563–600.
Glover, Brent. 2016. "The expected cost of default." *Journal of Financial Economics*, 119(2): 284 – 299.
Goldstein, Itay. 2013. "Chapter 36 Empirical Literature on Financial Crises: Fundamentals vs. Panic." In *The Evidence and Impact of Financial Globalization*. 523 – 534.
Goldstein, Itay, and Ady Pauzner. 2004. "Contagion of self-fulfilling financial crises due to diversification of investment portfolios." *Journal of Economic Theory*, 119(1): 151 – 183.
Goldstein, Robert, Nengjiu Ju, and Hayne Leland. 2001. "An EBIT-Based Model of Dynamic Capital Structure." *The Journal of Business*, 74(4): 483–512.
Gomes, Joao F., Leonid Kogan, and Motohiro Yogo. 2009. "Durability of output and expected stock returns." *Journal of Political Economy*, 117(5): 941–986.
González, Tanja Artiga, Markus Schmid, and David Yermack. 2019. "Does Price Fixing Benefit Corporate Managers?" *Management Science*, 65: 4813–4840.
Gourio, Francois, and Leena Rudanko. 2014. "Customer capital." *Review of Economic Studies*, 81(3): 1102–1136.
Graham, John R., Hyunseob Kim, Si Li, and Jiaping Qiu. 2019. "Employee Costs of Corporate Bankruptcy."

National Bureau of Economic Research, Inc NBER Working Papers 25922.
Green, Edward J, and Robert H Porter. 1984. "Noncooperative collusion under imperfect price information." *Econometrica*, 52(1): 87–100.
Grenadier, Steven R. 2002. "Option exercise games: an application to the equilibrium investment strategies of firms." *Review of Financial Studies*, 15(3): 691–721.
Grullon, Gustavo, Yelena Larkin, and Roni Michaely. 2018. "Are U.S. industries becoming more concentrated?" *Review of Finance*, forthcoming.
Gutiérrez, Germán, Callum Jones, and Thomas Philippon. 2019. "Entry Costs and the Macroeconomy." National Bureau of Economic Research, Inc NBER Working Papers.
Hackbarth, Dirk, and Bart Taub. 2018. "Does the potential to merge reduce competition?" Working Paper.
Hackbarth, Dirk, and Jianjun Miao. 2012. "The dynamics of mergers and acquisitions in oligopolistic industries." *Journal of Economic Dynamics and Control*, 36(4): 585–609.
Hackbarth, Dirk, Jianjun Miao, and Erwan Morellec. 2006. "Capital structure, credit risk, and macroeconomic conditions." *Journal of Financial Economics*, 82(3): 519–550.
Hackbarth, Dirk, Richmond Mathews, and David Robinson. 2014. "Capital structure, product market dynamics, and the boundaries of the firm." *Management Science*, 60(12): 2971–2993.
Haltiwanger, John, and Joseph E. Harrington. 1991. "The impact of cyclical demand movements on collusive behavior." *RAND Journal of Economics*, 22(1): 89–106.
He, Jie (Jack), and Jiekun Huang. 2017. "Product market competition in a world of cross-ownership: Evidence from institutional blockholdings." *Review of Financial Studies*, 30(8): 2674–2718.
He, Zhiguo, and Konstantin Milbradt. 2014. "Endogenous Liquidity and Defaultable Bonds." *Econometrica*, 82(4): 1443–1508.
Hoberg, Gerard, and Gordon Phillips. 2010. "Product market synergies and competition in mergers and acquisitions: A text-based analysis." *Review of Financial Studies*, 23(10): 3773–3811.
Hoberg, Gerard, and Gordon Phillips. 2016. "Text-based network industries and endogenous product differentiation." *Journal of Political Economy*, 124(5): 1423–1465.
Hoberg, Gerard, Gordon Phillips, and Nagpurnanand Prabhala. 2014. "Product Market Threats, Payouts, and Financial Flexibility." *Journal of Finance*, 69(1): 293–324.
Hopenhayn, Hugo A. 1992. "Entry, Exit, and Firm Dynamics in Long Run Equilibrium." *Econometrica*, 60(5): 1127–1150.
Hou, Kewei, and David T. Robinson. 2006. "Industry concentration and average stock returns." *Journal of Finance*, 61(4): 1927–1956.
Huang, Ying, Ross Jennings, and Yong Yu. 2017. "Product market competition and managerial disclosure of earnings forecasts: Evidence from import tariff rate reductions." *The Accounting Review*, 92(3): 185–207.
Jacob. 1994. "The Strategic Effects of Long-Term Debt in Imperfect Competition." *Journal of Economic Theory*, 62(2): 428–443.
Judd, Kenneth, Sevin Yeltekin, and James Conklin. 2003. "Computing Supergame Equilibria." *Econometrica*, 71(4): 1239–1254.
Kaminsky, Graciela L., Carmen M. Reinhart, and Carlos A. Végh. 2003. "The Unholy Trinity of Financial Contagion." *Journal of Economic Perspectives*, 17(4): 51–74.
Karuna, Christo. 2007. "Industry product market competition and managerial incentives." *Journal of Accounting and Economics*, 43(2-3): 275–297.
Kawakami, Toshikazu, and Yoshida Yoshihiro. 1997. "Collusion under financial constraints: Collusion or predation when the discount factor is near one?" *Economics Letters*, 54(2): 175–178.
Kelly, Bryan T., Gerardo Manzo, and Diogo Palhares. 2018. "Credit-Implied Volatility." Working Paper.
Kiyotaki, Nobuhiro, and John Moore. 1997. "Credit Cycles." *Journal of Political Economy*, 105(2): 211–248.
Kodres, Laura E., and Matthew Pritsker. 2002. "A Rational Expectations Model of Financial Contagion." *The Journal of Finance*, 57(2): 769–799.
Koijen, Ralph S. J., and Motohiro Yogo. 2015. "The Cost of Financial Frictions for Life Insurers." *The American Economic Review*, 105(1): 445–475.
Kovenock, Dan, and Gordon M Phillips. 1997. "Capital structure and product market behavior: An examination of plant exit and investment decisions." *Review of Financial Studies*, 10(3): 767–803.
Kreps, David M, and Robert Wilson. 1982. "Reputation and imperfect information." *Journal of Economic Theory*, 27(2): 253 – 279.
Kyle, Albert S., and Wei Xiong. 2001. "Contagion as a Wealth Effect." *The Journal of Finance*, 56(4): 1401–1440.
Leland, Hayne E. 1994. " Corporate debt value, bond covenants, and optimal capital structure." *Journal of Finance*, 49(4): 1213–1252.
Leland, Hayne E. 1998. " Agency costs, risk management, and capital structure." *Journal of Finance*, 53: 1213–1243.
Lettau, Martin, and Jessica A. Wachter. 2007. "Why is long-horizon equity less risky? A duration-based explanation of the value premium." *Journal of Finance*, 62(1): 55–92.
Loecker, Jan De, and Jan Eeckhout. 2019. "The rise of market power and the macroeconomic implications." *Quarterly Journal of Economics*, forthcoming.

Luttmer, Erzo G. J. 2007. "Selection, Growth, and the Size Distribution of Firms*." *The Quarterly Journal of Economics*, 122(3): 1103–1144.
Maksimovic, Vojislav, and Sheridan Titman. 1991. "Financial Policy and Reputation for Product Quality." *The Review of Financial Studies*, 4(1): 175–200.
Martin, Ian. 2013. "The Lucas Orchard." *Econometrica*, 81(1): 55–111.
Mas-Colell, Andreu, Michael Whinston, and Jerry Green. 1995. *Microeconomic Theory.* Oxford University Press.
Maskin, Eric, and Jean Tirole. 1988*a*. "A Theory of Dynamic Oligopoly, I: Overview and Quantity Competition with Large Fixed Costs." *Econometrica*, 56(3): 549–69.
Maskin, Eric, and Jean Tirole. 1988*b*. "A Theory of Dynamic Oligopoly, II: Price Competition, Kinked Demand Curves, and Edgeworth Cycles." *Econometrica*, 56(3): 571–599.
Maskin, Eric, and Jean Tirole. 2001. "Markov perfect equilibrium: I. observable actions." *Journal of Economic Theory*, 100(2): 191 – 219.
Ma, Song, Joy Tianjiao Tong, and Wei Wang. 2020. "Bankrupt Innovation Firms." Working Papers.
Matraves, Catherine, and Laura Rondi. 2007. "Product differentiation, industry concentration and market share turbulence." *International Journal of the Economics of Business*, 14(1): 37–57.
Mello, Antonio S., and John E. Parsons. 1992. "Measuring the Agency Cost of Debt." *The Journal of Finance*, 47(5): 1887–1904.
Merton, Robert C. 1974. "On the Pricing of Corporate Debt: The Risk Structure of Interest Rates." *Journal of Finance*, 29(2): 449–470.
Miao, Jianjun. 2005. "Optimal Capital Structure and Industry Dynamics." *The Journal of Finance*, 60(6): 2621–2659.
Novy-Marx, Robert. 2013. "The other side of value: The gross profitability premium." *Journal of Financial Economics*, 108(1): 1–28.
Opler, Tim C., and Sheridan Titman. 1994. "Financial Distress and Corporate Performance." *The Journal of Finance*, 49(3): 1015–1040.
Opp, Marcus M., Christine A. Parlour, and Johan Walden. 2014. "Markup cycles, dynamic misallocation, and amplification." *Journal of Economic Theory*, 154: 126–161.
Pakes, Ariel, and Paul McGuire. 1994. "Computing Markov-perfect Nash equilibria: Numerical implications of a dynamic differentiated product model." *RAND Journal of Economics*, 25(4): 555–589.
Phillips, Gordon M. 1995. "Increased debt and industry product markets an empirical analysis." *Journal of Financial Economics*, 37(2): 189–238.
Pindyck, Robert S. 1993. "A Note on Competitive Investment under Uncertainty." *American Economic Review*, 83(1): 273–277.
Pulvino, Todd C. 1998. "Do Asset Fire Sales Exist? An Empirical Investigation of Commercial Aircraft Transactions." *The Journal of Finance*, 53(3): 939–978.
Rotemberg, Julio J, and Garth Saloner. 1986. "A supergame-theoretic model of price wars during booms." *American Economic Review*, 76(3): 390–407.
Schott, Peter K. 2008. "The relative sophistication of Chinese exports." *Economic Policy*, 23(53): 6–49.
Seo, Sang Byung, and Jessica A. Wachter. 2018. "Do Rare Events Explain CDX Tranche Spreads?" *The Journal of Finance*, 73(5): 2343–2383.
Simon, Leo K., and Maxwell B. Stinchcombe. 1989. "Extensive Form Games in Continuous Time: Pure Strategies." *Econometrica*, 57(5): 1171–1214.
Snider, Connan Andrew. 2008. "Predatory Incentives and Predation Policy: The American Airlines Case."
Staiger, Robert W., and Frank A. Wolak. 1992. "Collusive pricing with capacity constraints in the presence of demand uncertainty." *RAND Journal of Economics*, 23(2): 203–220.
Sundaresan, Suresh. 2013. "A Review of Merton's Model of the Firm's Capital Structure with Its Wide Applications." *Annual Review of Financial Economics*, 5(1): 21–41.
Sutton, John. 1991. *Sunk costs and market structure: Price competition, advertising, and the evolution of concentration.* MIT press.
Sutton, John. 2007. "Market share dynamics and the "persistence of leadership" debate." *American Economic Review*, 97(1): 222–241.
Tirole, Jean. 1988. *The theory of industrial organization.* Vol. 1 of *MIT Press Books*, The MIT Press.
Titman, Sheridan. 1984. "The Effect of Capital Structure on a Firm's Liquidation Decision." *Journal of Financial Economics*, 13(1): 137–151.
Titman, Sheridan, and Roberto Wessels. 1988. "The Determinants of Capital Structure Choice." *Journal of Finance*, 43(1): 1–19.
Valta, Philip. 2012. "Competition and the cost of debt." *Journal of Financial Economics*, 105(3): 661–682.
Wiseman, Thomas. 2017. "When does predation dominate collusion." *Econometrica*, 85(2): 555–584.
Xu, Jin. 2012. "Profitability and capital structure: Evidence from import penetration." *Journal of Financial Economics*, 106(2): 427–446.
Zhou, Chunsheng. 2001. "The term structure of credit spreads with jump risk." *Journal of Banking & Finance*, 25(11): 2015–2040.