Feedback and Contagion Through Distressed Competition

Hui Chen Winston Wei Dou Hongye Guo Yan Ji*

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Abstract

Firms tend to compete more aggressively in financial distress; the intensified competition in turn reduces profit margins for everyone, pushing some further into distress. To study such feedback and contagion effects, we incorporate dynamic strategic competition into an industry equilibrium with long-term defaultable debt, which generates various peer interactions: predation, self-defense, and collaboration. Such interactions make cash flows, stock returns, and credit spreads interdependent across firms. Moreover, industries with higher idiosyncratic-jump risks are more distressed, yet also endogenously less exposed to aggregate shocks. Finally, we exploit exogenous variations in market structure – large tariff cuts – to test the core competition mechanism.

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

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1 Introduction

Product markets are often highly concentrated. Industries are increasingly characterized by a "winner takes most" feature, whereby a small number of "superstar" firms control a large share of the market (e.g., Grullon, Larkin and Michaely, 2018; Loecker and Eeckhout, 2019; Autor et al., 2020).[1] Furthermore, the positions of market leaders are highly persistent (e.g., Sutton, 2007; Bronnenberg, Dhar and Dubé, 2009). With such high levels of market concentration and persistence of leadership, strategic interactions among market leaders can play a vital role in determining not only the ways that firms compete in product markets, but also the ways that aggregate economic shocks affect industries and idiosyncratic shocks spread across firms and industries.[2]

In this paper, we study the dynamic strategic interactions among firms that face potential threats of financial distress. We show that the interplay between tactical competition and financial distress generates a competition-distress feedback loop and a new form of financial contagion. These two mechanisms have important implications for the cross section of equity returns, determinants of credit risk, and systematic stability.

Figure 1 illustrates the intuition for the feedback loop. Firms tend to compete more aggressively when they become more financially distressed. The intensified competition, in turn, reduces the profit margins for all firms in the industry, pushing some firms further into distress. This feedback effect has two asset pricing implications. First, the feedback loop amplifies the negative response of firms' profit margins and equity returns to an increase in the aggregate discount rate through the endogenous competition channel, which extends Fudenberg and Maskin (1986)'s version of folk theorems on the properties of collusive Nash equilibria.[3] Second, in the cross section, the positive feedback loop is more pronounced in less financially distressed industries, which can help explain the financial distress anomaly at industry level. This is because, as we will show, less financially distressed industries have lower left-tail idiosyncratic jump risk in the cross section. Left-tail idiosyncratic jump risk plays a vital role in pricing credit risk (e.g., Seo and Wachter, 2018). The lower level of left-tail idiosyncratic jump risk makes firms in such industries effectively more patient, and hence more willing to adhere to tacit collusion agreements, leading to higher yet more volatile profit margins as the discount rate fluctuates. This is why the feedback loop is

[1] According to the U.S. Census data, the top-four firms within each four-digit SIC (Standard Industrial Classification) industry account for about 48% of each industry's total revenue (see Dou, Ji and Wu, 2020*a*, Online Appendix B). Moreover, Gutiérrez, Jones and Philippon (2019) and Corhay, Kung and Schmid (2020*b*) investigate the forces behind the stylized fact of rising industry concentration.

[2] Recent evidence shows that peer firms strategically interact in product markets in response to changes in their financial conditions (e.g., Frésard, 2010; Hortaçsu et al., 2013; Koijen and Yogo, 2015; Gilchrist et al., 2017; Cookson, 2017; Grieser and Liu, 2019).

[3] The endogenous competition channel is established by Dou, Ji and Wu (2020*a*) for all-equity firms.

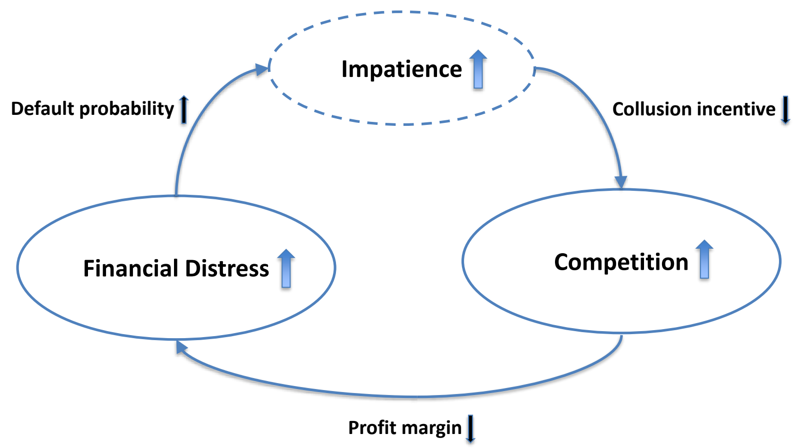

Figure 1: Interplay between financial distress and product-market competition.

stronger in such industries, and shareholders of these industries will be compensated with higher expected returns. Such heterogeneous competition-distress feedback effects across different industries help rationalize the industry-level financial distress anomaly, which otherwise seems puzzling under the canonical frameworks of Merton (1974) and Leland (1994).

Furthermore, the contagion effect enriches the set of channels through which idiosyncratic shocks can be transmitted across firms and industries. An adverse idiosyncratic shock reduces a firm's market share and distance to default and causes ripple effects: the firm's competitors also reduce their profit margins. Thus, firms' financial distress is interdependent, even across industries. The contagion effect justifies a key primitive assumption bolstering the information-based theories of credit market freezes (e.g., Bebchuk and Goldstein, 2011). Moreover, the contagion effect is stronger in industries with more balanced market shares among market leaders or in those with a lower threat of new entrants. This finding advances our understanding of how firms' credit spreads and cash flows depend on peers' financial conditions and industry structure. Our study suggests that a major competitor's market share and financial condition should be factored in when analyzing firm-level credit risk. This accomodation is absent from standard credit risk models explaining firm-level credit risk primarily through firm-specific (e.g., leverage, earnings, and idiosyncratic volatility) and aggregate (e.g., risk premium, expected growth, and uncertainty) information.

A fast-growing body of research studies the connections between strategic competition and asset pricing. Most existing work focuses on *one-shot strategic* interactions (e.g., Corhay, Kung and Schmid, 2020*a*). An exception is Dou, Ji and Wu (2020*a*,*b*), who study *dynamic strategic* interactions of all-equity firms. Crucially, we also study firms' dynamic strategic interactions by allowing collusive behavior as opposed to imposing a one-shot strategic (non-collusive) setting, not only because of the extensive empirical evidence showing that (tacit) collusion is prevalent across industries,[4] but also because of the cross-sectional patterns of feedback and contagion effects observed in the data. For instance, under one-shot strategic interactions, the stock returns of less financially distressed industries would have lower exposure to discount-rate fluctuations, and an adverse idiosyncratic shock that reduces a firm's market share and distance to default would always make its competitors raise profit margins, contradicting the empirical patterns. Our model and empirical results help us detect collusive behavior in the data. By incorporating the threat of financial distress, our model can generate a competition-distress feedback loop and a new form of financial contagion beyond the theory of Dou, Ji and Wu (2020*a*,*b*) for all-equity firms.

Our theoretical framework incorporates a supergame of strategic competition into a dynamic model of long-term defaultable debt (à la Leland, 1994). In a nutshell, the model assumes that consumers' tastes toward firms' differentiated products are embodied in firms' customer base, which fluctuates stochastically over time and is subject to large left-tail idiosyncratic jump shocks, as in Seo and Wachter (2018). Firms' cash flows are affected by not only their customer bases but also their profit margins. The latter are endogenously determined by the repeated game of Bertrand competition on profit margins with differentiated products and tacit collusion (Tirole, 1988, chap. 6). The time-varying discount rate (Cochrane, 2011) is the only aggregate state variable that drives competition intensity (Dou, Ji and Wu, 2020*a*).

More precisely, market leaders can tacitly collude with each other on setting high profit margins. Given that competitors will honor the collusive profit-margin-setting scheme, a firm may be tempted to boost its short-run revenue by reducing its profit margin to attract more customers; however, deviating from the collusive scheme may reduce revenue in the long run if the deviation 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 margin is higher when firms' deviation incentives are lower. A firm's decision to deviate is determined by its intertemporal tradeoff between short- and long-run cash flows, which is further shaped by its financial distress level and the aggregate discount rate.

Let us now elaborate more on the intuitions behind the feedback and contagions effects, as well as their important industrial organizational implications. Intuitively, a firm's incentive

[4] Connor (2016), Miller and Weinberg (2017), He and Huang (2017), Dasgupta and Zaldokas (2018), Schmitt (2018), González, Schmid and Yermack (2019), Byrne and de Roos (2019), Bourveau, She and Zaldokas (2020), and Aryal, Ciliberto and Leyden (2020), among others, offer extensive evidence on (tacit) collusion. Owing to the prevalence of collusion activities, government authorities such as the Department of Justice (DOJ) and the Federal Trade Commission (FTC) commit enormous resources to antitrust enforcement. The Thurman Arnold Project at Yale School of Management lists research related to collusion and antitrust enforcement.

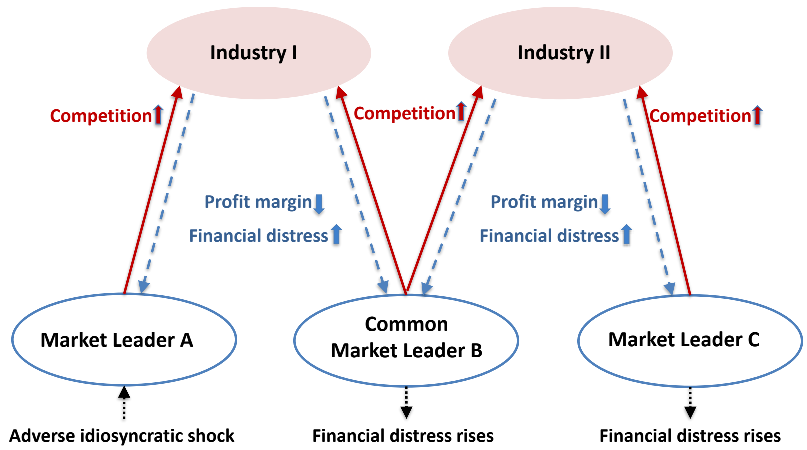

Figure 2: Financial contagion through endogenous competition in product markets.

to collude with its peers depends on how much the firm values the extra profit generated by future cooperation. Figure 1 illustrates that when firms become increasingly financially distressed, they tend to compete more intensely, resulting in lower profit margins. Firms effectively become more impatient when their default risk is higher, which renders extra profits from cooperation in the future less valuable. This makes firms become more apt to engage in undercutting behavior and become less likely to cooperate with profit-margin collusion. Lower profit margins further intensify the level of a firm's financial distress and its default risk.

As for the contagion effect, it is easy to see within an industry. When a leading firm is hit by an idiosyncratic shock and becomes financially distressed, competition tends to intensify within the industry, which results in lower profits for all firms. Consequently, the financial conditions of the firm's competitors within the same industry will also weaken. With multisector firms, financial contagion can also spread across industries. Figure 2 depicts a setting with two industries and three firms, where firm B operates in both industries. When firm A, which is in the first industry, becomes financially distressed because of an idiosyncratic shock, 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 firm C into financial distress.

As an important industrial organizational implication, we show that 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 respond or engage in a rich variety of ways, including self-defense, predation, and collaboration. Per the intuition of folk theorems, the risk of exit can change the nature of strategic competition in several ways. As already discussed, under financial distress, firms can grow more impatient, and impatience reduces a firm's collusion incentive. In response to the weaker firm's profit-margin undercutting, the firm with a stronger financial condition in the same industry might also cut its profit margin in an attempt to protect its market share. We refer to this as the incentive of self-defense. When the threat of a new entrant is sufficiently low (e.g., because of a high barrier to entry) and the distressed firm is sufficiently close to bankruptcy, the stronger firm might want to cut profit margins more aggressively, triggering the switch to a non-collusive equilibrium (i.e., a price war). In doing so, the stronger firm hopes to drive the weaker competitor out of the market sooner in order to enjoy the subsequent monopoly rent. This is the predatory incentive. Finally, if the failure of the weak competitor would open doors for a powerful new entrant, the strong firm's collaboration incentive might dominate: the strong firm might fix a high profit margin in order to help the weak firm remain solvent. Our model quantitatively evaluates the three types of incentives and offers a structural decomposition of them, thereby making an important contribution to the industrial organization (IO) literature (e.g., Besanko, Doraszelski and Kryukov, 2014).[5]

Although our contribution to the literature is mainly theoretical, we calibrate the model to assess its quantitative performance and test its main predictions in the data. We conduct our empirical analysis in four 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 higher left-tail idiosyncratic jump risk) have lower expected equity excess returns, have higher credit spreads, and are less negatively exposed to discount-rate shocks. We further show that the financial distress anomaly becomes insignificant after controlling for left-tail idiosyncratic jump risk.

Second, we test the implications of competition-distress feedback and contagion effects on firms' profit margins. We show that industry-level profit margins load negatively on the discount rate and that the loadings are more negative in industries in which firms are closer to their default boundaries. This finding is consistent with the theoretical prediction that the competition-distress feedback effect is stronger when the firm's distance to default is smaller. Further, we show that adverse idiosyncratic shocks to one financially distressed market leader can force other market leaders within the same industry to cut their profit margins. Specifically, by sorting the top firms within each industry into three groups based on their level of financial distress, we find that adverse idiosyncratic shocks to the financially distressed group diminish profit margins for the financially healthy group, but the reverse does not occur for idiosyncratic shocks to the financially healthy group. The within-industry spillover effect is more pronounced in the industries with higher entry costs or when

[5]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 the benefits of overcoming competitive disadvantage caused by rivals' aggressive competition behaviors? The predatory motive maps onto the first set of benefits and the self-defensive motive maps onto the second set.

the market shares of the two groups are more balanced. The asymmetry in the financial contagion effect is closely consistent with the theory, and, as predicted by our model, higher entry costs or more balanced market shares provide larger room for strategic predation and self-defense, thereby leading to greater spillover effects. In addition, we provide evidence for the between-industry financial contagion between market leaders in industry pairs that share common major players.

Third, we test the implications of competition-distress feedback and contagion effects on asset prices. We show that the difference in the equity excess returns across industries with different gross profitability becomes larger when the distance to default is lower. This finding supports the theoretical prediction that the competition-distress feedback effect is stronger when firms 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 by exploiting the same empirical design for testing the contagion effect on profit margins.

Finally, we directly test the model's endogenous distressed competition mechanism. On the one hand, the mechanism generates a differential sensitivity of profit margins to fluctuations in the discount rate between industries with low and high distances to default (i.e., the feedback effect). On the other hand, the mechanism generates an endogenous response of peer firms' competition behavior, 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). In accordance with the model, both feedback and contagion effects weaken 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 endogenous distressed competition mechanism is to examine how the feedback and contagion effects would change if the industry market structure becomes more competitive.

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. Intuitively, large tariff cuts can facilitate a more competitive market structure because the reduction in trade barriers can increase (i) the industry's price elasticity of demand ϵ due to foreign rivals providing similar products and services and (ii) the number of market leaders n as foreign rivals enter and become major players in domestic markets. Consistent with the model's predictions, we find that when these industries' market structures become more competitive, industries with high and low distances to default display less difference in their exposure to the discount rate and that 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 (for the seminal benchmark framework, see Merton, 1974; Leland, 1994). 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 how macroeconomic conditions affect firms' financing policies, credit risk, and asset prices. Kuehn and Schmid (2014) and Gomes, Jermann and Schmid (2016), among others, study the interaction between long-term debt financing and corporate investments. He and Xiong (2012*a*,*b*) study the interaction between the rollover risk of debt, credit risk, and fluctuations in firm fundamentals. He and Milbradt (2014) and Chen et al. (2018) study the interaction between default decisions and secondary market liquidity for defaultable corporate bonds. Existing dynamic models of capital structure and credit risk typically assume that the product market offers exogenous cash flows unrelated to firms' degree of financial distress or corporate liquidity conditions. Our model differs from the existing literature by explicitly considering an oligopoly industry in which firms' strategic competition generates endogenous cash flows. This focus 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. Similar to our paper, 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 differs from theirs along the following aspects: (i) we consider supergames and long-term debts to investigate the competition-distress feedback and contagion effects; (ii) our model explains the financial distress anomaly across industries; (iii) we emphasize the endogenous competition risk driven by variations in aggregate discount rates, whereas others emphasize the entry risk; and (iv) we directly test the endogenous distressed competition mechanism via a difference-in-differences design 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. Feedback effects can be grouped into two major classes of channels: 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 constraints can spur an adverse feedback loop: when firms become more financially constrained, they are forced to reduce real investment and hiring, which, in turn, exacerbates their financial constraints. Dou et al. (2020*b*) survey this class of macro-finance models. In an influential work, He and Milbradt (2014) show the existence of a fundamental-liquidity feedback loop in the context of corporate bond markets. Bond, Edmans and Goldstein (2012) emphasize that 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; Cespa and Foucault, 2014). This paper introduces a novel fundamental-based feedback effect between imperfect primary capital markets and imperfect product markets arising from 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 occurs through real linkages among 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 cross-asset learning and self-fulfilling beliefs (e.g., Goldstein and Pauzner, 2004; Cespa and Foucault, 2014). 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 literature exploring how industry competition and customer markets affect firms' financial decisions and valuations. Titman (1984), Titman and Wessels (1988), and Maksimovic (1988) undergird subsequent work in this line of the literature. Banerjee, Dasgupta and Kim (2008), Hoberg, Phillips and Prabhala (2014), and D'Acunto et al. (2018) empirically investigate the effects of industry competition and customer base on firms' leverage decisions. 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 (2020) investigate how industry competition and the customer base affect various corporate policies, such as investment, cash holdings, mergers and acquisitions, and entries and exits. Gârleanu, Kogan and Panageas (2012), Kogan et al. (2017), and Kogan, Papanikolaou and Stoffman (2018) study the asset pricing implications of the displacement risk mechanism in which innovation increases competitive pressure on existing firms in the same industry and workers, reducing profits of existing firms and eroding the human capital of older workers. Finally, a growing theoretical literature focuses on how strategic industry competition and the customer base affect firms' valuation and equity returns (e.g., Aguerrevere, 2009; Belo, Lin and Vitorino, 2014; Opp, Parlour and Walden, 2014; Bustamante, 2015; Dou et al., 2019; Belo et al., 2019; Loualiche, 2019; Corhay, Kung and Schmid, 2020*a*; Dou, Ji and Wu, 2020*a*,*b*). Our model highlights the dynamic interaction of endogenous competition and financial distress, generating competition-distress feedback and financial contagion effects. These results and findings are new to the literature.

Our paper is also related to the burgeoning literature probing how financial characteristics influence firms' performance and decisions in the product market. In 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 the firm's product warranties. Brander and Lewis (1986) focus on the "limited liability" effect of short-term debt financing on product competition behavior. Bolton and Scharfstein (1990) show that financial constraints induce rational predation behavior. Allen (2000) shows that firms with greater debt increases the probability of bankruptcy and liquidation, which is costly, and thus, higher leverage will be subsequently associated with less aggressive product market behavior. Phillips (1995), Chevalier and Scharfstein (1996), Hortaçsu et al. (2013), Koijen and Yogo (2015), Hoberg and Phillips (2016), Cookson (2017), Gilchrist et al. (2017), Hackbarth and Taub (2018), Banerjee et al. (2019), and Grieser and Liu (2019), among others, advance the empirical study of the product-market implications of financial frictions. Different from these existing works, our paper combines a dynamic Leland framework of long-term defaultable debt with dynamic strategic competition featuring collusive behavior.

Finally, our paper contributes to the literature on the financial distress anomaly of equity returns (e.g., Dichev, 1998; Campbell, Hilscher and Szilagyi, 2008; Garlappi, Shu and Yan, 2008; George and Hwang, 2010; Garlappi and Yan, 2011; Chen, Hackbarth and Strebulaev, 2019). We use the probability of failure in Campbell, Hilscher and Szilagyi (2008) to measure financial distress. However, we focus on the anomaly across industries, as opposed to that across firms. Further, we propose a novel explanation of the industry financial distress anomaly based on the distressed strategic competition between peer firms. Importantly, we show that the asset pricing implications of industry-level financial distress in the cross section is mainly generated through industries' heterogeneous left-tail idiosyncratic jump risk. Our results complement the existing findings on financial distress anomaly.

2 Model

Our model essentially extends that of Leland (1994) by incorporating Bertrand competition between n firms with tacit collusion. For tractability, we assume that the industry has two dominant firms ($n = 2$), referred to as *market leaders*, and many followers of measure zero. We label a generic market leader by i and its competitor by j below.

2.1 Financial Distress

Financial Frictions. Firms are financed by long-term debt and equity. For tractability, we model long-term debt as a consol with perpetual coupon payments at rate b_i for firm i;

further, we follow Leland (1994) and adopt a framework of static capital structure: the coupon rate b_i is optimally chosen at the beginning upon the firm entering the market to maximize firm value given the tradeoff between tax shield benefits and distress costs.[6] 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 to maximize the firm's equity value. Shareholders have limited liability, and managers have the option to default on debt. When operating cash flows cannot cover interest expenses, the firm can issue equity to cover the shortfalls without paying any extra financing costs. When the equity value falls to zero, managers will choose to file bankruptcy and exit. Upon exiting the market, the firm is sold as an intact business or is liquidated piecemeal, and its debtholders obtain a fraction ν of the asset value, with $\nu \in (0, 1)$.

Cash Flows. Firm i's earnings flow after interest expenses and taxes over $[t, t + \mathrm{d}t]$ is

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

where $\Pi_{i,t} M_{i,t}$ is the operating cash flow, $M_{i,t}$ is the firm's customer base,[7] 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 assume that firm i's customer base $M_{i,t}$ evolves with the following 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 parameter g captures the growth rate of the customer base, the standard Brownian motion Z_t captures aggregate shocks,[8] 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 jumps in firm i's customer base. Upon the occurrence of a Poisson 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 that of Seo and Wachter (2018), who emphasize that idiosyncratic jump risk is a crucial ingredient in understanding credit spreads. For simplicity, Seo and Wachter (2018) also calibrate a disastrous idiosyncratic

[6]Models with a 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. Adopting the static optimal capital structure makes the model more tractable, given the complexity of the current setup, and does not change the main insights or results of this paper.

[7]A firm's customer base helps stabilize the firm's capacity for demand flows by creating entry barriers and durable advantages over competitors. The customer base plays an essential role in determining the short-run demand for a firm's products (e.g., Bronnenberg, Dubé and Gentzkow, 2012; Gourio and Rudanko, 2014; Dou et al., 2019; Dou, Ji and Wu, 2020*a*,*b*).

[8]The aggregate shock can be an economy-wide or industry-wide shock that is priced.

jump of almost -100%, under which a firm's exit is certain.

The firm's financial distress is determined not only by the cash flow level $E_{i,t}$ but also jump intensity λ. A higher jump intensity λ promotes a higher probability of failure, regardless of the current cash flow level $E_{i,t}$. Moreover, we will show later that the jump intensity λ affects the endogenous profitability $\Pi_{i,t}$, as well as firms' aggregate risk exposure, even though the left-tail idiosyncratic jump risk itself is not priced because of full diversification. As we observe in the data, the time-series variation in the financial distress of an industry is mainly driven by the fluctuation in the average distance to default of its firms, but the cross-industry variation in the degree of financial distress is mainly caused by the heterogeneous intensity of idiosyncratic jumps (λ). Exploiting ex-ante heterogeneity in λ across industries, our model generates cross-industry variations in financial distress, profitability, and aggregate risk exposure.

Stochastic Discount Factor. Countercyclical risk premiums crucially allow Leland-type models to quantitatively reconcile joint patterns of low leverage, high credit spread, and low default frequency (e.g., Chen, Collin-Dufresne and Goldstein, 2008; Chen, 2010). Motivated by previous studies, we specify the stochastic discount factor (SDF) Λ_t as

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

where Z_t and $Z_{\gamma,t}$ are independent standard Brownian motions, r_f is the equilibrium risk-free rate, and γ_t is the time-varying market price of risk (also referred to as the "discount rate" in our paper) 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 for the time-varying aggregate 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).

Interpretation of the Shocks. The aggregate Brownian shock Z_t in equations (2) and (3) can be interpreted as the economy-wide or industry-wide demand shock. The shock ensures that variation in the discount rate γ_t affects the valuation of firms' cash flows, and thus can 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 affect 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 Brownian shocks, $W_{1,t}$ and $W_{2,t}$, can be interpreted as idiosyncratic demand (or taste) shocks. Idiosyncratic shocks are needed for the model to quantitatively match the default frequency and generate a nondegenerate cross-sectional distribution of the customer base in the stationary equilibrium.

The left-tail idiosyncratic Poisson shocks, $J_{1,t}$ and $J_{2,t}$, play a crucial role in our theory and empirical results. Idiosyncratic jump risk has been proven useful in explaining credit spreads and credit default swap index (CDX) spreads (e.g., Delianedis and Geske, 2001; Collin-Dufresne, Goldstein and Yang, 2012; Kelly, Manzo and Palhares, 2018; Seo and Wachter, 2018). We treat it as a crucial and fundamental industry characteristic in our model. We provide evidence that the heterogeneity in industry-level left-tail idiosyncratic jump risk λ is a crucial determinant for the cross-industry differences in financial distress.

One interpretation of the left-tail idiosyncratic Poisson shock is that it captures exogenous displacement. Small market followers in an industry are constantly challenging and trying to displace market leaders, and they typically do so through distinctive innovation or rapid business expansion. A change in market leaders does not occur gradually over an extended period of time; rather, market leaders are displaced rapidly and disruptively (e.g., Christensen, 1997). For instance, Apple and Samsung displaced Nokia and Motorola as new market leaders in the mobile phone industry over a brief period of time.

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

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 IO 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 incumbent firm i's exit, a new firm enters immediately with an initial customer base $M_{new} = \kappa M_{j,t} > 0$ and coupon rate b_{new}, where b_{new} is optimally chosen to maximize the new firm's value. The parameter $\kappa > 0$ captures the relative size of the new entrant and the surviving incumbent firm j. Upon entry, the dynamic game of Bertrand duopolistic competition, which we describe next in Section 2.3, is "reset" to a new one between the surviving incumbent market leader and the new entrant.

2.2 Product Market Competition

The setup in Section 2.1 almost follows the standard model of Leland (1994), except for the endogenous profitability $\Pi_{i,t}$, which results from the strategic competition among firms. We now explain the determination of $\Pi_{i,t}$.

Demand System for Differentiated Products. We first introduce the demand system for differentiated products within an industry. Consumers derive utility from a basket of differentiated goods, produced by the firms. The industry-level consumption C_t is determined by a Dixit-Stiglitz constant-elasticity-of-substitution (CES) aggregator:

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

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 tastes 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:

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

All else equal, the demand for firm i's goods $C_{i,t}$ increases with consumers' relative tastes $M_{i,t}/M_t$ in equilibrium. One can naturally think of consumers' tastes $M_{i,t}$ 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, whereby a larger $M_{i,t}/M_t$ implies that firm i's price $P_{i,t}$ has greater influence on the price index P_t (see equation (6)).

To characterize how industry demand C_t depends on the industry's 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-level price elasticity of demand.[9] We assume that $\eta \geq \epsilon > 1$, meaning that products are more substitutable within the same industry than across industries. For example, the elasticity of substitution between the Apple iPhone and the Samsung Galaxy is likely much higher than that between a cell phone and a cup of coffee.[10]

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

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

Equations (8) and (9) show that 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 with $\mu_{i,t} = 0$, 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 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 optimal decisions about defaulting to maximize their equity value. The marginal cost for a firm to produce a

[9]For microfounding such an isoelastic industry demand curve, consider a continuum of industries that exist in the economy and produce differentiated industry-level baskets of goods. The elasticity of substitution across industry-level baskets is ϵ and the preference weight for an industry's goods is equal to its customer base M_t. 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).

[10]This assumption is consistent with assumptions made in the literature (e.g., Atkeson and Burstein, 2008; Corhay, Kung and Schmid, 2020*a*; Dou, Ji and Wu, 2020*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, that is, $Y_{i,t} = C_{i,t}$, because production is costly and goods are immediately perishable. Firm i's operating profits per unit of its customer base are

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

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

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

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 $\Pi_i(\theta_{i,t}, \theta_{j,t})$. Below, we will explain the Nash equilibrium, which determines profit margin strategies $(\theta_{i,t}, \theta_{j,t})$.

2.3 Nash Equilibrium

The two firms in an industry play a supergame (Friedman, 1971), in which the stage games of setting profit margins are continuously played and infinitely repeated 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 can also exist, in which profit-margin strategies are sustained by conditional punishment strategies.[11]

Formally, a subgame perfect Nash equilibrium for the supergame consists of a collection

[11] In the IO and macroeconomics literature, this type of equilibrium is called a collusive equilibrium or collusion (e.g., Green and Porter, 1984; Rotemberg and Saloner, 1986). The game-theoretic literature generally refers to it as the equilibrium of repeated games (Fudenberg and Tirole, 1991) in order to distinguish it from the one-shot Nash equilibrium (i.e., our non-collusive equilibrium).

of profit-margin strategies that constitute a Nash equilibrium for every history of the game. We do not consider all such equilibria; instead, we focus on those that allow for collusive arrangements enforced by punishment schemes. All strategies depend on "payoff-relevant" states $x_t = \{M_{1,t}, M_{2,t}, \gamma_t\}$ in the state space $\mathcal{X}$, as in Maskin and Tirole (1988*a*,*b*), as well as a pair of indicator functions that track whether either firm has previously deviated from the collusive agreement, as in Fershtman and Pakes (2000, p. 212).[12]

Non-Collusive Equilibrium. The non-collusive equilibrium is characterized by a profit-margin-setting 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 chooses profit margin $\theta_{i,t} \equiv \theta_i(x_t)$ to maximize its equity value $V_i^N(x_t)$, under the assumption that its competitor j will stick to 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,[13] we formulate optimization problems conditioning on no endogenous default at time t as a pair of Hamilton-Jacobi-Bellman (HJB) equations:

$$\lambda V_i^N(x_t)\mathrm{d}t = \max_{\theta_{i,t}} \underbrace{(1-\tau)[\Pi_i(\theta_{i,t}, \theta_{j,t}^N)M_{i,t} - b_i]\mathrm{d}t}_{\text{dividends}} + \underbrace{\Lambda_t^{-1}\mathbb{E}_t\left[\mathrm{d}(\Lambda_t V_i^N(x_t))\right]}_{\text{value gain if no jump shock}}, \quad \text{for } i = 1, 2. \tag{13}$$

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

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 $\underline{M}_{i,t}^N$, the equity value of firm i is equal to zero (i.e., the value matching condition), and the optimality of the boundary implies the smooth pasting condition:

$$V_i^N(x_t)\Big|_{M_{i,t}=\underline{M}_{i,t}^N} = 0 \quad \text{and} \quad \frac{\partial}{\partial M_{i,t}} V_i^N(x_t)\Big|_{M_{i,t}=\underline{M}_{i,t}^N} = 0, \quad \text{respectively.} \tag{14}$$

As $M_{i,t} \to +\infty$, firm i essentially becomes an industry monopoly, which sets another boundary condition (see Online Appendix 1.4).

Collusive Equilibrium. For the collusive equilibrium, firms tacitly collude with each other in setting higher profit margins, where any deviation would trigger 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 the fiercest competition (i.e., the non-collusive equilibrium

[12]For notational simplicity, we omit the indicator states of historical deviations.
[13]For example, Pakes and McGuire (1994) and Ericson and Pakes (1995).

in our model).

Consider a generic collusive equilibrium in which the two firms follow a collusive profit-margin-setting scheme. Both firms can costlessly observe the other's profit margin, such that deviant behavior can be detected and punished. The assumption of perfect information follows the literature.[14] If one firm deviates from the collusive profit-margin-setting 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 punishes the deviating firm because this equilibrium features the lowest profit margin.[15] We use an idiosyncratic Poisson process $N_{i,t}$ with intensity ξ to characterize whether a firm can successfully implement a punishment strategy after the competitor's deviation.[16] Thus, a higher ξ makes the threat of punishment more credible, which reduces any incentives to deviate and enables collusion at higher profit margins.

Formally, the set of incentive-compatible collusion agreements, denoted by $\mathcal{C}$, consists of all continuous profit-margin-setting 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:

$$V_i^N(x) \leq V_i^C(x), \quad \text{for all } x \in \mathcal{X} \text{ and } i = 1, 2; \qquad \text{(PC)} \qquad (15)$$

$$V_i^D(x) \leq V_i^C(x), \quad \text{for all } x \in \mathcal{X} \text{ and } i = 1, 2, \qquad \text{(IC)} \qquad (16)$$

where $V_i^D(x)$ 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. Conditioned on no endogenous default at time t, $V_i^C(x)$ satisfies

$$\lambda V_i^C(x_t)\mathrm{d}t = \underbrace{(1-\tau)[\Pi_i(\theta_{i,t}^C, \theta_{j,t}^C)M_{i,t} - b_i]\mathrm{d}t}_{\text{dividends}} + \underbrace{\Lambda_t^{-1}\mathbb{E}_t\left[\mathrm{d}(\Lambda_t V_i^C(x_t))\right]}_{\text{value gain if no jump shock}}, \quad \text{for } i = 1, 2, \qquad (17)$$

subject to the PC and IC constraints (15) and (16). The variables $\theta_{i,t}^C \equiv \theta_i^C(x_t)$ are the collusive profit margins for $i = 1, 2$. 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,

[14] Examples include Rotemberg and Saloner (1986), Haltiwanger and Harrington (1991), Staiger and Wolak (1992), and Bagwell and Staiger (1997).

[15] We follow the literature and adopt the non-collusive equilibrium as the incentive-compatible punishment for deviation (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 significantly altered provided that the punishment lasts long enough.

[16] 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 equilibrium over $[t, t+\mathrm{d}t]$. 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 the indeterminacy of outcomes (e.g., Simon and Stinchcombe, 1989; Bergin and MacLeod, 1993).

determined by the following value matching and smooth pasting conditions:

$$V_i^C(x_t)\Big|_{M_{i,t}=\underline{M}_{i,t}^C} = 0 \ \text{ and } \ \frac{\partial}{\partial M_{i,t}} V_i^C(x_t)\Big|_{M_{i,t}=\underline{M}_{i,t}^C} = 0, \text{ respectively.} \tag{18}$$

The boundary condition at $M_{i,t} \to +\infty$ is identical to that in the non-collusive equilibrium. This is because when $M_{i,t} \to +\infty$, firm i is essentially an industry monopoly and there is no benefit from collusion.

Equilibrium Deviation Values. Conditioned on no endogenous default at time t, the equity value $V_i^D(x_t)$ of deviation evolves as follows:

$$\begin{aligned}\lambda V_i^D(x_t)\mathrm{d}t = \max_{\theta_{i,t}} & \underbrace{(1-\tau)[\Pi_i(\theta_{i,t}, \theta_{j,t}^C)M_{i,t} - b_i]\mathrm{d}t}_{\text{dividends}} \\ & - \underbrace{\xi\left[V_i^D(x_t) - V_i^N(x_t)\right]\mathrm{d}t}_{\text{value loss if punished}} + \underbrace{\Lambda_t^{-1}\mathbb{E}_t\left[\mathrm{d}(\Lambda_t V_i^D(x_t))\right]}_{\text{value gain if no jump shock}}, \quad \text{for } i = 1, 2, \end{aligned} \tag{19}$$

The non-default region is 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 optimal default boundary if it chooses to deviate from collusion, determined by the value matching and smooth pasting conditions:

$$V_i^D(x_t)\Big|_{M_{i,t}=\underline{M}_{i,t}^D} = 0 \ \text{ and } \ \frac{\partial}{\partial M_{i,t}} V_i^D(x_t)\Big|_{M_{i,t}=\underline{M}_{i,t}^D} = 0, \ \text{ respectively.} \tag{20}$$

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

Two points are worth further discussion. First, the PC constraints (15) can become binding in the collusive equilibrium, triggering the two firms to switch to the non-collusive equilibrium. The endogenous switch captures the endogenous outbreak of price wars, which we will examine in Section 3.3. We assume that once the two firms switch to the non-collusive equilibrium, they will stay there forever.[17] Endogenous switching between the collusive to the non-collusive equilibrium because of increased financial distress (i.e., lower distance to default) is one of our model's key differences from that of Dou, Ji and Wu (2020*a*), in which firms are financed wholly by equity and never suffer from financial distress. In their model, the PC constraints are never binding because higher profit margins always lead to higher equity values in the absence of default or exit.

There exist infinitely many elements in $\mathcal{C}$ and hence infinitely many collusive equilibria.

[17]The firm that proposes switching to the non-collusive equilibrium is essentially deviating, and, thus, we assume that they will not return to the collusive equilibrium. We make this assumption to be consistent with our specification for the punishment strategies.

We focus on a subset of $\mathcal{C}$, denoted by $\overline{\mathcal{C}}$, consisting of all profit-margin-setting schemes $\Theta^C(\cdot)$ such that the IC constraints (16) are binding state by state, that is, $V_i^D(x_t) = V_i^C(x_t)$ for all $x_t \in \mathcal{X}$ and $i = 1,2$.[18] The subset $\overline{\mathcal{C}}$ is nonempty because it contains the profit-margin-setting scheme in the non-collusive 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 $\Theta^C(\cdot)$ such that there does not exist another pair $\widetilde{\Theta}^C(\cdot) = (\widetilde{\theta}_1^C(x_t), \widetilde{\theta}_2^C(x_t)) \in \overline{\mathcal{C}}$ with $\widetilde{\theta}_i^C(x_t) \geq \theta_i^C(x_t)$ for all $x_t \in \mathcal{X}$ and $i = 1,2$, with strict inequality holding for some i and x_t.[19] Our numerical algorithm is similar to that of Abreu, Pearce and Stacchetti (1990).[20] Deviation never occurs on the equilibrium path. The one-shot deviation principle (Fudenberg and Tirole, 1991) makes it clear that the collusive equilibrium characterized above is a subgame perfect Nash equilibrium.

Debt Value. Debt value equals the sum of the present value of the cash flows that accrue to debtholders until the occurrence of endogenous default or the left-tail idiosyncratic jump shock (i.e. the exogenous displacement), whichever occurs first, plus the recovery value of the endogenous default or exogenous displacement.

When the left-tail idiosyncratic jump shock hits firm i over $[t, t + \mathrm{d}t]$ (i.e., $\mathrm{d}J_{i,t} = 1$), two outcomes are possible: with probability ϖ, the firm is wiped out with no debt recovery; and with probability $1 - \varpi$, the firm is restructured by the new entrant firm, the old debt is retired at par value, and new debt is optimally issued. We follow the literature on dynamic debt models (e.g., Mello and Parsons, 1992; Leland, 1994; Hackbarth, Miao and Morellec, 2006) and set the recovery value of endogenous default to be a fraction ν of the firm's unlevered asset value, which is the value of an all-equity firm. In the collusive equilibrium, the unlevered asset value $A_i^C(x_t)$ is similarly determined by equations (13) to (20) except we set $b_i = 0$ and remove the default boundary conditions (14), (18), and (20).

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 HJB equation:

$$\left[\varpi D_i^C(x_t) + (1-\varpi)(D_i^C(x_t) - D_i^C(x_{t_0}))\right] \lambda \mathrm{d}t = \underbrace{b_i \mathrm{d}t}_{\text{coupons}} + \underbrace{\Lambda_t^{-1} \mathbb{E}_t \left[\mathrm{d}(\Lambda_t D_i^C(x_t))\right]}_{\text{value gain if no jump shock}}, \tag{21}$$

[18] This equilibrium refinement is similar in the spirit of Abreu (1988), Alvarez and Jermann (2000, 2001), and Opp, Parlour and Walden (2014).

[19] One can show that the "Pareto-efficient frontier" is nonempty based on the fundamental theorem of the 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.

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

with the following boundary conditions:

$$D_i^C(x_t)\Big|_{M_{i,t}=\underline{M}_{i,t}^C} = \nu A_i^C(x_t)\Big|_{M_{i,t}=\underline{M}_{i,t}^C} \text{ and } \lim_{M_{i,t}\to+\infty} D_i^C(x_t) = \frac{b_i + (1-\varpi)\lambda D_i^C(x_{t_0})}{r_f + \lambda}, \quad (22)$$

where $i = 1, 2$, $D_i^C(x_{t_0})$ is the par value of the debt issued at the initial time t_0, when firm i enters the industry.

The left-hand side of equation (21) is the expected loss of debt due to the left-tail idiosyncratic jump shock, and the right-hand side is the expected gain of debtholders if the jump shock does not occur over $[t, t + \mathrm{d}t]$. The first condition in equation (22) is the recovery value to debtholders at the default boundary, and the second condition captures the asymptotic behavior of debt when the customer base $M_{i,t}$ approaches infinity, which is basically the value of a bond with constant coupon rate b_i until it retires at the par value with rate $(1-\varpi)\lambda$ or it defaults with rate $\varpi\lambda$, whichever occurs first.

3 Main Theoretical Results

We have two main theoretical results: (i) the financial contagion effect (discussed in Section 3.1), and (ii) the positive feedback loop between competition and financial distress (discussed in Section 3.2). Further implications from the model include: (iii) predatory price wars or collective entry preventions may arise endogenously, depending on the threat of new entrants (Section 3.3); (iv) both feedback and contagion effects are dampened when industries' market structure becomes more competitive (Section 3.4); and (v) the feedback effect helps rationalize the industry-level financial distress anomaly (Section 3.5).

3.1 Financial Contagion Through Strategic Competition

We show financial contagion exists among firms within the same industry through the endogenous distressed competition mechanism: negative idiosyncratic shocks to a firm may also increase the default risk of the firm's competitor.

To elaborate on the financial contagion effect, panels A and B of Figure 3 plot the profit margins of firms i and j, respectively, as a function of firm i's customer base $M_{i,t}$, with firm j's customer base fixed at $M_{j,t} = 1$. Both firms have higher profit margins in the collusive equilibrium (blue solid lines) than in the non-collusive equilibrium (red dotted lines). Moreover, firm i's default boundary (represented by the vertical lines) in the collusive equilibrium is lower than that in the non-collusive equilibrium (i.e., $\underline{M}_{i,t}^C < \underline{M}_{i,t}^N$). The blue solid line in panel A shows that firm i reduces its profit margin when it becomes

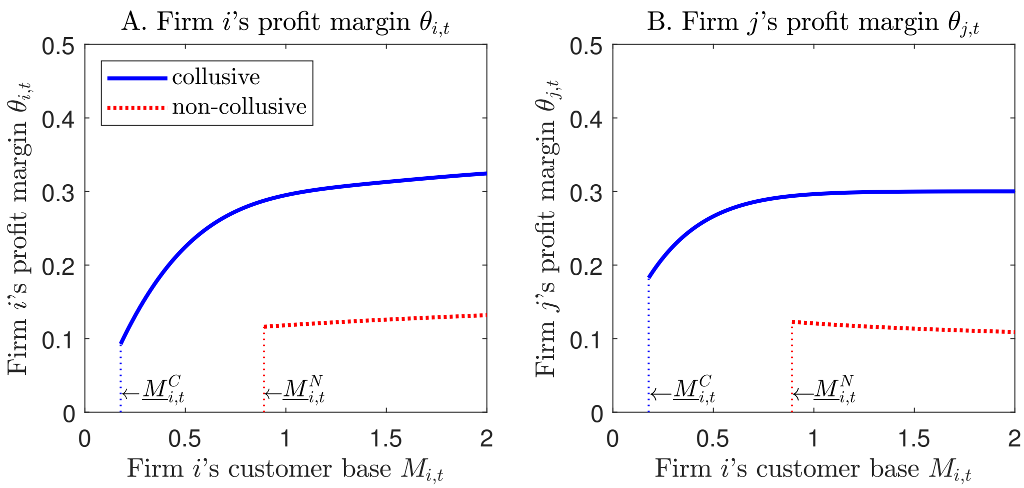

Figure 3: Financial contagion between the two firms in the same industry. This figure plots the profit margins of firms i and j as a function of firm i's customer base $M_{i,t}$. The blue solid and red dotted lines represent the collusive and non-collusive equilibrium. The vertical dotted lines represent the default boundaries of firm i in the corresponding cases. We set $\gamma_t = \overline{\gamma}$ and $M_{j,t} = 1$. Other parameters are set according to our calibration in Section 4.2.

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 (blue solid line in panel B) even though firm j's customer base $M_{j,t}$ remains unchanged.

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

By contrast, in the non-collusive equilibrium, firm i's profit margin increases with its own customer base (red dotted line in panel A), and firm j's profit margin decreases with its competitor firm i's customer base (red dotted line in panel B). In other words, both firms' non-collusive profit margins increase with their own customer base share. This is a standard result in the literature: non-collusive profit margins (i.e., the one-shot Nash equilibrium of Bertrand competition) are solely determined by the short-run price elasticity of demand. As shown in equation (8), a firm's short-run price elasticity of demand decreases with its share of the customer base $M_{i,t}/M_t$.

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

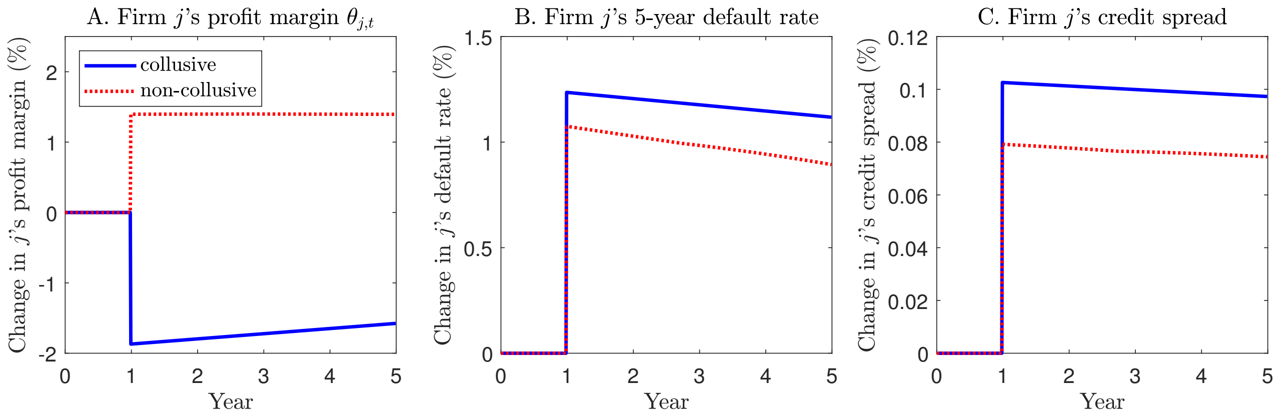

Figure 4: IRFs of firm j to illustrate the financial contagion effect. This figure plots the IRFs of firm j after a negative idiosyncratic shock to firm i's customer base. We assume that firm i's customer base is unexpectedly reduced by half at $t = 1$, that is, from $M_{i,1}$ to $M_{i,1}/2$. The blue solid and red dotted lines plot the change in firm j's profit margins, 5-year default rates, and credit spreads relative to the scenario without a shock to firm i's customer base in the collusive and non-collusive equilibrium, respectively. The initial customer base at $t = 0$ is $M_{i,0} = M_{j,0} = 1$ in the collusive equilibrium. The initial debt-to-asset ratio is 0.35 for both firms. For the non-collusive equilibrium, we set $M_{i,0} = M_{j,0} = 2.2$ so that both firms' 5-year default rate is the same as that in the collusive equilibrium at $t = 0$. We set $\gamma_t = \overline{\gamma}$ and other parameters according to our calibration in Section 4.2.

To further illustrate the contagion effect, Figure 4 plots the impulse response functions (IRFs) of firm j after a negative idiosyncratic shock to firm i's customer base. In particular, we assume that firm i's customer base is unexpectedly reduced by half at $t = 1$. In panel A, we plot the change in firm j's profit margin relative to the scenario without a shock to firm i's customer base in the collusive (blue solid line) and non-collusive equilibrium (red dotted line). Per our discussion of Figure 3, when firm i is hit by the adverse idiosyncratic shock, firm j's profit margin decreases in the collusive equilibrium, but increases in the non-collusive equilibrium. Panels B and C show that in the collusive equilibrium, firm j's default rate increases by 1.3% and credit spread increases by about 10 basis points when its competitor, firm i, is hit by the adverse idiosyncratic shock at $t = 1$. In the non-collusive equilibrium, firm j's default rate and credit spread also increase at $t = 1$, despite the increase in its profit margin (panel A). This is because firm i cuts its profit margin more aggressively in the non-collusive equilibrium when being hit by the adverse idiosyncratic shock, attracting demand from firm j, which consequently reduces firm j's cash flows.

In Figure 5, we further study how the relative sizes and leverage ratios of the two firms in the industry influence the contagion effect on profit margins in the collusive equilibrium. Compared with panel A, panel B shows that when the two firms have imbalanced customer bases, the negative impact on firm j's profit margin is smaller for the same shock to firm i's customer base at $t = 1$. Intuitively, when the two firms have similar size of customer base, both firms influence the industry's price index in a large way through equation (6).

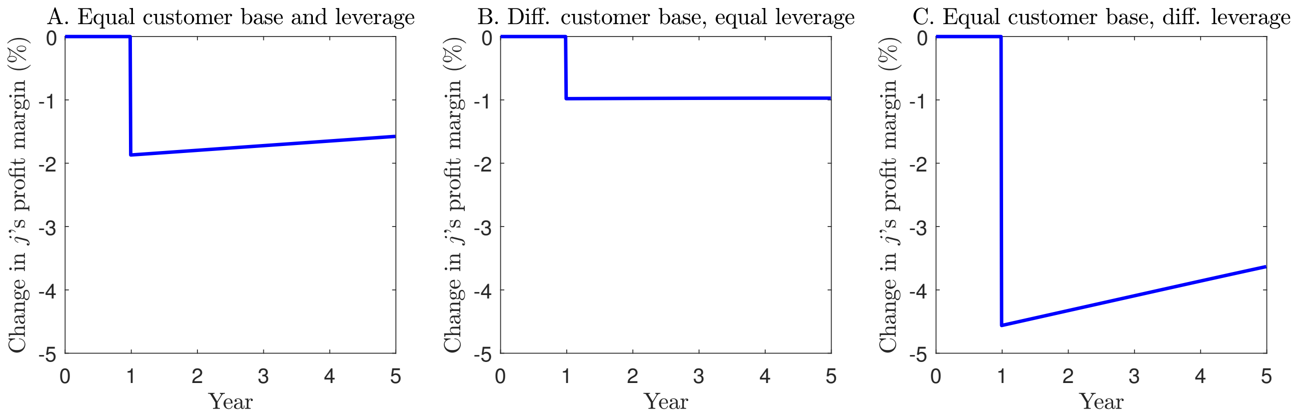

Figure 5: Financial contagion when firms have different customer bases or leverage ratios. This figure illustrates the IRFs of firm j's profit margin after a negative idiosyncratic shock to firm i's customer base. In particular, we assume that firm i's customer base is unexpectedly reduced by half at $t = 1$, i.e., from $M_{i,1}$ to $M_{i,1}/2$. We consider three industries with the same average customer bases and debt-to-asset ratios across the three panels. In panel A, the two firms are symmetric with identical customer bases and debt-to-asset ratios ($lev_{i,0} \equiv D_{i,0}^C/(D_{i,0}^C + V_{i,0}^C)$ for $i = 1, 2$) at $t = 0$, i.e., $M_{i,0} = M_{j,0} = 1$ and $lev_{i,0} = lev_{j,0} = 0.35$. In panel B, the two firms have different customer bases but identical debt-to-asset ratios, i.e., $M_{i,0} = 1.25$, $M_{j,0} = 0.75$, and $lev_{i,0} = lev_{j,0} = 0.35$. In panel C, the two firms have identical customer bases but different debt-to-asset ratios, i.e., $M_{i,0} = M_{j,0} = 1$, $lev_{i,0} = 0.4$, and $lev_{j,0} = 0.3$. The blue solid line plots the change in firm j's profit margin in the collusive equilibrium relative to the benchmark case without the shock to firm i's customer base. In all three panels, we set $\gamma_t = \overline{\gamma}$. Other parameters are set according to our calibration in Section 4.2.

This generates large externality and strong strategic concerns because both firms know that the industry's price index is sensitive not only to their own profit margins but also to their competitor's. As a result, a change in one firm's distance to default would generate a large impact on the other firm's profit margins. In industries with more imbalanced customer base distributions, profit margins reflect more about firms' own financial conditions rather than their competitors' financial conditions because of weaker strategic interactions.

Comparing panels A and C of Figure 5, we show that the contagion effect is larger when firm i is more leveraged than firm j, holding the industry's average leverage ratio constant. This is because both self-defensive and predatory incentives become more significant when the two firms' degrees of financial distress become increasingly differentiated.

3.2 Feedback Between Competition and Financial Distress

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

Profit Margins and Distance to Default. To fix ideas, we consider an industry with two identical firms such that $M_{i,t} = M_{j,t} = M_t/2$ constantly holds. Panel A of Figure 6 plots

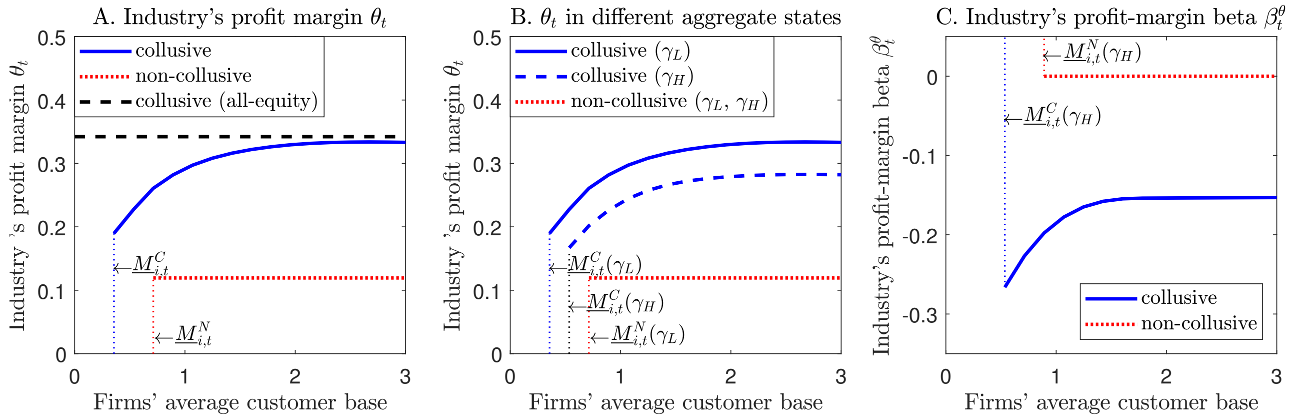

Figure 6: Positive feedback loop between competition and financial distress. We consider an industry with two identical firms such that $M_{i,t} = M_{j,t} = M_t/2$ constantly holds. In panel A, the blue solid and red dotted lines plot the industry's profit margin θ_t in the collusive and non-collusive equilibrium. As a benchmark, the black dashed line represents the industry's profit margin in the collusive equilibrium when both firms are wholly financed by equity. We set $\gamma_t = \overline{\gamma}$. Panel B plots the industry's profit margin θ_t for different aggregate states γ_t. The blue solid and 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 $\gamma_H = \overline{\gamma} + 2\text{std}(\gamma_t)$. Panel C plots the profit-margin beta to γ_t defined in equation (23). The blue solid and red-dotted lines represent the collusive and non-collusive equilibrium respectively. In all panels, the vertical dotted lines represent firm i's default boundaries in the corresponding cases. Parameters are set according to our calibration in Section 4.2.

the industry's profit margin as a function of firms' average customer base and endogenous default boundaries. The vertical lines show that firms' default boundary in the collusive equilibrium is lower than that in the non-collusive equilibrium. Therefore, given the same average customer base of firms, the distance to default decreases when competition intensifies. Moreover, zeroing in on the collusive equilibrium (blue solid line), we learn that, as competition intensifies (i.e., the profit margin narrows), the distance to default decreases; that is, higher competition intensity leads to more financial distress because undercutting profit margins erodes firms' cash flows.

Panel A of Figure 6 also shows that the profit margin in the collusive equilibrium (blue solid line) endogenously decreases as firms' distance to default decreases. 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 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 because of their higher probability of default. As a result, firms become effectively more impatient and care less about future cooperation. Instead, firms are motivated to undercut their competitors' profit margins. Thus, to ensure that deviation does not occur in the collusive equilibrium (i.e., the IC constraints (16) are satisfied), the mutually agreed-upon 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.[22]

Taken together, panel A of Figure 6 shows a positive feedback loop between competition and financial distress. By contrast, the non-collusive equilibrium (red dotted line) does not have a feedback loop, because 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 industry competition. In addition, the industry with all-equity firms does not have a feedback loop, which can be seen from the constant profit margin (flat black dashed line). Thus, the endogenous distressed competition mechanism is the key to generating the positive feedback loop.

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 are closer to the default boundary because of the competition-distress feedback.

Panel B of Figure 6 plots the industry's profit margin in the collusive equilibrium of states with a low discount rate γ_L (blue solid line) and a high discount rate γ_H (blue dashed line). The industry's profit margin is lower when the discount rate is higher.[23] 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 future cooperation. As a result, future punishment becomes less threatening and higher profit margins are more difficult to sustain. By contrast, in the non-collusive equilibrium, profit margins remain unchanged when the discount rate rises (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 industry-level profit-margin beta β_t^θ to the discount rate, defined as the ratio of the industry's profit margin between the two aggregate states:

$$\beta_t^\theta \equiv \theta_t^C(\gamma_H)/\theta_t^C(\gamma_L) - 1. \tag{23}$$

[22]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.

[23]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; instead, they may 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.

Importantly, the blue solid line in panel C of Figure 6 shows that the profit-margin beta becomes more negative when the industry becomes more financially distressed in the collusive equilibrium. 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 response to a two-standard-deviation increase in the discount rate γ_t. This is because the endogenously intensified competition is further amplified by the competition-distress feedback loop, dramatically amplifying the industry's exposure to discount rates, especially when the industry is financially distressed.[24] By contrast, the profit-margin beta is always zero in the non-collusive equilibrium (red dotted line).

3.3 Self-Defense, Predation, and Collaboration

Although our calibration suggests that the contagion effect is mainly caused by 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. A smaller value of κ implies that the industry has a lower threat of new entrants. While our benchmark calibration focuses on average industries with $\kappa = 0.3$ (see Section 4.2 for our calibration), here we illustrate two extreme cases with $\kappa = 0$ and $\kappa = 3$, representing 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 7 show that profit margins are lower compared to the baseline industry (Figure 3) as 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 7, 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 wage a price war by jumping into the non-collusive equilibrium. The profit margin suddenly jumps downward at $M_{i,t} = 0.85$, and stays at the level of non-collusive profit margins for $\underline{M}_{i,t}^{C} < M_{i,t} < 0.85$, with $\underline{M}_{i,t}^{C}$ being the endogenous default boundary of firm i.[25] Thus, our model implies that the within-industry contagion effect on profit margins is more dramatic in industries with lower entry threat.[26]

[24] Online Appendix 1.1 discusses equity's risk exposure in more detail.

[25] Online Appendix 1.2 shows 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 a price war. The downward jump in firm j's profit margin reflects firm j's high predatory incentives.

[26] In fact, when the entry threat is lower, the contagion effect on credit spreads implied by the model could

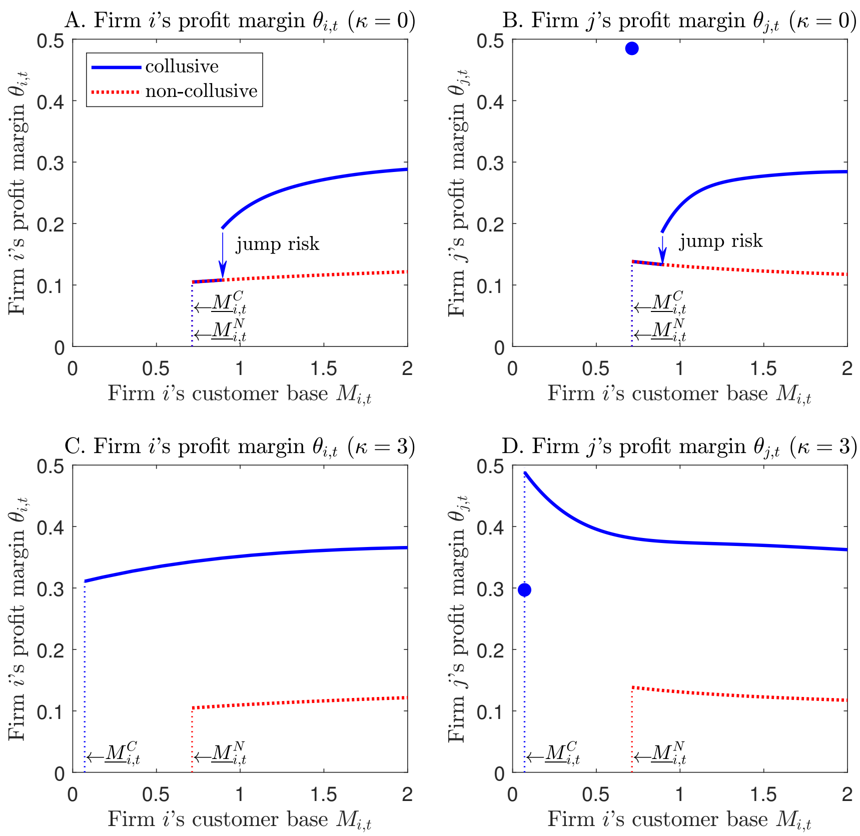

Figure 7: Illustration of endogenous price wars and collaboration. In panels A and B, we consider an industry with no entry threat ($\kappa = 0$) and plot the two firms' profit margins as a function of firm i's customer base $M_{i,t}$. In panels C and D, we consider an industry with high entry threat ($\kappa = 3$). In all panels, the blue solid and red dotted lines represent the collusive and 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 $\gamma_t = \overline{\gamma}$, $M_{j,t} = 2$. For comparison, we use the same coupon rates from Figure 3. Other parameters are set according to our calibration in Section 4.2.

In the industry with $\kappa = 3$ (i.e., extremely high entry threat), panels C and D of Figure 7 show that firms collude on much higher profit margins compared to the baseline industry (Figure 3). This is because both firms worry about losing market power to the large new

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 model's 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 because of increased predatory incentives (see panel B of Figure 7), 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 (because of low entry threat) and set higher profit margins in the near future, leading to lower default rates and credit risk for firm j.

entrants, and thus they collaborate with each other to reduce the default risk. 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.

An extensive IO literature 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).[27] Our model complements these theories by establishing the connection between predatory pricing and financial distress. Our numerical illustration in panel B of Figure 7 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. A predatory price war breaks out endogenously if the predatory incentive dominates, which occurs when the entry threat is sufficiently low (κ is small) and one of the two firms is sufficiently close to default.

3.4 Distressed Competition and Market Structure

The endogenous distressed competition mechanism generates both competition-distress feedback and financial contagion effects. Here, we examine these effects 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.

In panels A and B of Figure 8, we focus on the collusive equilibrium. Panel A illustrates how industries' market structure influences the competition-distress feedback effect. The blue solid line plots the profit-margin beta to the discount rate γ_t under our baseline duopoly market structure with a low cross-industry price elasticity of demand (i.e., $\epsilon = 2$ and $n = 2$). The black dashed and red dotted lines represent a more competitive market structure by increasing the elasticity to $\epsilon = 4$ or the number of market leaders to $n = 3$, respectively. Relative to the baseline calibration, the profit margin beta in these two cases is less negative, especially when the industry is close to the default boundary (i.e., the black dashed and red dotted lines are flatter than the blue solid line). Intuitively, firms have less incentive to collude with each other when industry market structure becomes more competitive. The dampened collusion incentive weakens the response of competition intensity to changes in

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

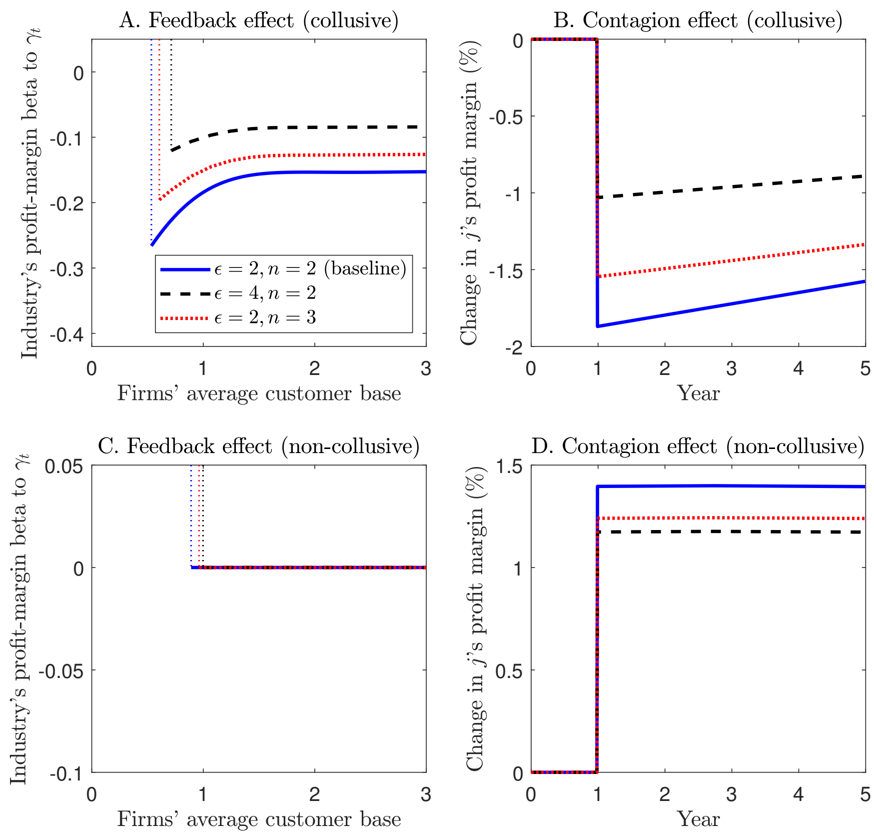

Figure 8: Feedback and contagion effects under various market structures. Panel A illustrates the profit-margin beta (defined in equation (23)) in the collusive equilibrium under various market structures. We focus on the industry within which firms have identical customer bases for expository purposes. The blue solid line represents the market structure with $\epsilon = 2$ and $n = 2$ in accordance with our baseline calibration in Section 4.2. The black dashed line represents the case with $\epsilon = 4$ and $n = 2$, and the red dotted line represents the case with $\epsilon = 2$ and $n = 3$. The vertical dotted lines represent firms' default boundaries in the corresponding cases. We set $\gamma_L = \overline{\gamma}$ and $\gamma_H = \overline{\gamma} + 2\text{std}(\gamma_t)$. Panel B illustrates the contagion effect on profit margins under various market structures in the collusive equilibrium. To measure the contagion effect, we conduct an experiment similar to that in Figure 4. In particular, we compute the change 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 $t = 1$. Panels C and D illustrate the feedback and contagion effects in the non-collusive equilibrium. Other parameters are set according to our calibration in Section 4.2.

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 industries with a low distance to default.

Panel B shows that the financial contagion effect is also weaker when industry market structure becomes more competitive. We conduct impulse-response experiments similar to those in Figure 4. In particular, we measure the within-industry contagion effect on profit margins by computing the change in firm j's profit margin, relative to the scenario without shocks, in response to an unexpected idiosyncratic shock that reduces the customer base of firm i by half at $t = 1$. 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.

By contrast, panel C shows that the profit margin beta is always zero in the non-collusive equilibrium irrespective of the competitiveness of the market structure. As we explain for panel C of Figure 6, this is because profit margins do not respond to the discount rate in one-shot games. Panel D shows that the contagion effect in the non-collusive equilibrium becomes less significant when the market structure is more competitive simply because of the weakened strategic interactions. However, the sign in panel D is opposite to that of panel B as explained for panel A of Figure 4.

3.5 Financial Distress Anomaly across Industries

We now discuss the asset pricing implications of the competition-distress feedback in across industries with different intensities λ of the left-tail idiosyncratic jump shocks.

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., a higher probability of exogenous replacement). The higher exit rate makes firms less concerned about 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; 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 intensities, λ_L and λ_H, with $\lambda_L < \lambda_H$. We assume that firms in the same industry have identical customer base. Panels A to C of Figure 9 display the collusive equilibrium. Panels A and B 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 compare the equity exposure of the two industries, we define the industry-level equity beta β_t^V to the discount rate as the value-weighted firm-level

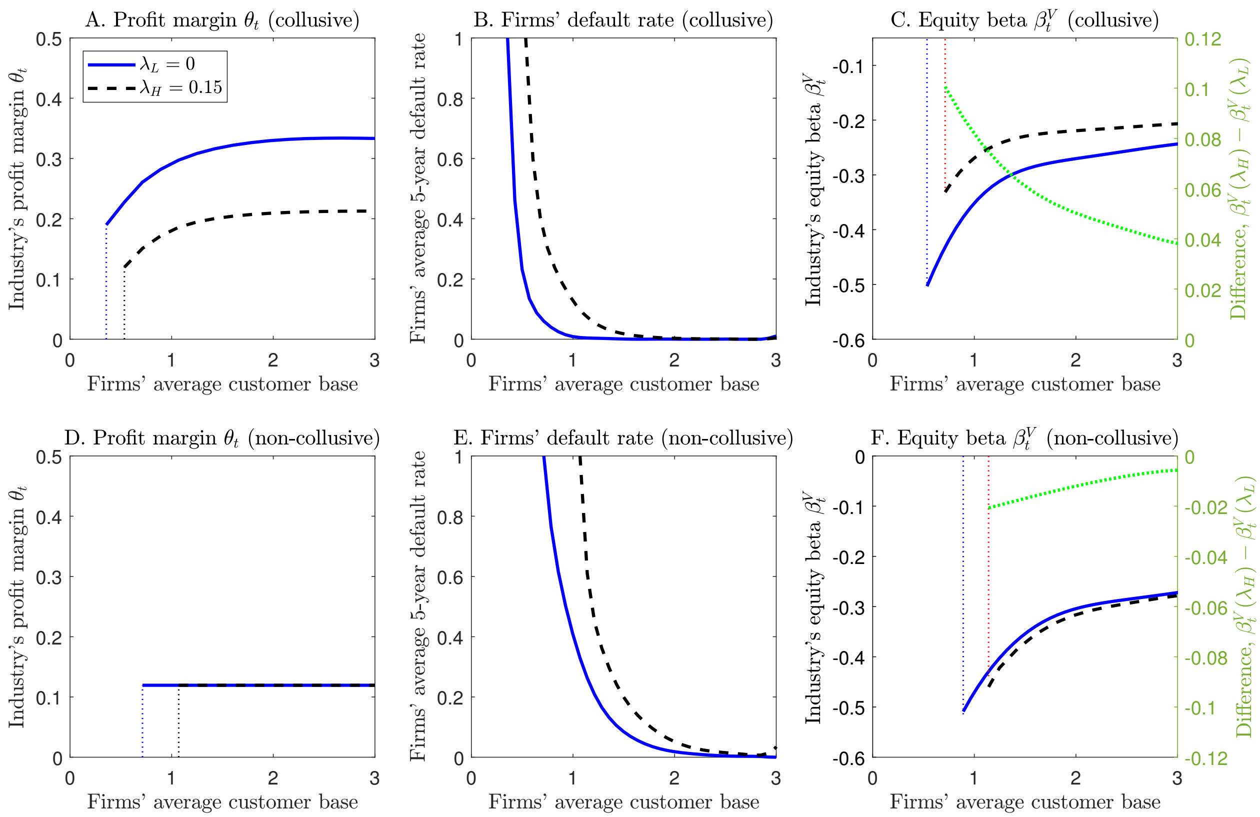

Figure 9: Industry exposure to discount-rate shocks in the cross section. We consider duopoly industries with two identical firms (i.e., $M_{i,t} = M_{j,t}$). Panels A to C target the collusive equilibrium. Panel A plots the profit margin θ_t of industries with λ_L and λ_H as functions of firms' average customer base in the state of γ_L. The vertical dotted lines represent firms' default boundaries in the 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 (24)) of the two industries. The green dotted line in panel C (corresponding to the right y-axis) plots the difference in the equity beta between the two industries. Panels D to F target the non-collusive equilibrium and plot the same dimensions as panels A to C. 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.

equity beta:

$$\beta_t^V = \sum_{i=1}^{2} w_{i,t}^V \beta_{i,t}^V, \text{ where } \beta_{i,t}^V = \frac{V_{i,t}^C(\gamma_H)}{V_{i,t}^C(\gamma_L)} - 1 \text{ and } w_{i,t}^V = \frac{V_{i,t}^C(\gamma_L)}{\sum_{j=1}^{2} V_{j,t}^C(\gamma_L)}, \tag{24}$$

for all $M_{i,t}, M_{j,t} > 0$. Panel C shows that 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 (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 the industries are closer to the default boundary, as this is the time when the economic mechanism of competition-distress feedback becomes more relevant. The green dotted line (corresponding to the right y-axis) shows that the equity-beta gap between the two industries is indeed wider when the distance to default is smaller.

The cross-industry implications are very different in the non-collusive equilibrium, as demonstrated in panels D to F of Figure 9. The profit margins (panel D) stay constant and lower than those in the collusive equilibrium. Conditional on the same average customer base, both industries have higher default rates (panel E), and their equity betas are more negative (panel F). Importantly, panel F shows that the equity beta of the industry with λ_H is more negative than that of the industry with λ_L because of the higher leverage, which is opposite to the cross-industry pattern in the collusive equilibrium (panel C). Echoing the analysis in Section 4.4, the implications of one-shot strategic interactions (non-collusive equilibrium) 8in panel F contradict the observed financial distress anomaly in the data.

4 Quantitative Analysis

In this section, we conduct our quantitative analysis. Section 4.1 describes the data and empirical measures. Section 4.2 presents our calibration analysis. In Section 4.3, we study the model's implications about stock returns and credit spreads. Finally, in Section 4.4, we conduct counterfactual experiments.

4.1 Data and Empirical Measures

We obtain firm-level accounting data from Compustat and stock returns from the Center for Research in Security Practices (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. (2018), 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 data span from 1973 to 2018 and cover 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 2002 is categorized with other observations with fiscal years ending in 2002, most of which end in December 2002. When merging the accounting data with the market data, we assume that the accounting information becomes available at the end of June 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 SIC4 codes 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 (e.g., industry-level profit margin and stock return) are well-behaved.[28] On average, there are 123 industries in a year and 26.6 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). The 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-industry heterogeneity in default risk is mainly captured by industries' different levels of left-tail idiosyncratic 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. Thus, we also construct a distance-to-default measure following 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, nonfinancial U.S. firms from 1981 to 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 a *default event* 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

[28]For the empirical analyses involving credit spreads, we lower the threshold from 10 firms in each industry-year to 3 due to the sparsity of credit spread data.

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 or 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 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 taking 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 extracted at an annual frequency for the estimation of profit-margin betas and at a quarterly frequency for the estimation of equity and credit spread betas, aligning with the frequency of the beta-estimation regressions.

Measure of Left-Tail Idiosyncratic Jump Risk. Our measure for left-tail idiosyncratic jump risk of industry i in month t, denoted by $IdTail\_risk_{i,t}$, is constructed as follows. 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. 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 at the firm level.

Second, we construct a measure for ex-ante left-tail idiosyncratic jump risk for each stock j. In each month t, we run the following panel regression for all stocks in the subsample from the first month up to month t:

$$IdTail\_shock_{j,s+1,s+12} = \alpha_t + \beta_t X_{j,s} + \epsilon_{j,s+12}, \quad s = 1, \cdots, t-12. \tag{25}$$

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 (25) ensures that the coefficients α_t and β_t are estimated based on information up to month t. The coefficients α_t and β_t are reestimated in each month using the same specification (25) with expanding windows (see Online Appendix 2.1 for estimated coefficients). We construct the measure of left-tail idiosyncratic jump risk for each stock j in month t as

$$IdTail\_risk_{j,t} = -\left(\hat{\alpha}_t + \hat{\beta}_t X_{j,t}\right). \tag{26}$$

Table 1: 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 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			

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.

Finally, the industry-level left-tail idiosyncratic jump risk is the average firm-level left-tail idiosyncratic jump risk weighted by sales. Online Appendix 2.1 shows that the measure of left-tail idiosyncratic jump risk is persistent at both firm and industry levels. Moreover, we empirically verify that a higher value of the ex-ante measure predicts that left-tail idiosyncratic jump shocks are more severe in the next year (with high out-of-sample R^2) to justify the validity of the measure.

4.2 Calibration and Parameter Choices

Table 1 presents the externally calibrated parameters. The real 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 calibration and estimation in the IO and international trade literature (e.g., Harrigan, 1993; Head and Ries, 2001; 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) to match the growth rate of real cash flows. 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 the relevant moments summarized in Table 2. 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-to-asset ratio is 0.33, matching that of Baa-rated bonds in the data.[29] The

[29] The calibrated recovery rate is also close to the rate estimated by Chen (2010) based on the mean recovery

Table 2: Internally calibrated parameters and targeted moments.

Parameter	Symbol	Value	Moments	Data	Model
Bond recovery rate	ν	0.4	Average debt-to-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	$\overline{\gamma}$	0.45	Market equity premium	7.36%	7.27%
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%	−5.01%
Default rate upon jump shocks	ϖ	0.1	Diff. in credit spreads (Q5−Q1)	2.00%	2.05%

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 $\zeta = 0.45$, $\overline{\gamma} = 0.45$, and $\varsigma = 4\%$ so that the market portfolio's equity premium is 7.27%, 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 $\lambda_1 = \underline{\lambda}$ and $\lambda_N = \overline{\lambda}$. The mass of industries associated with each value of λ is the same. We normalize $\underline{\lambda} = 0$ and set $\overline{\lambda} = 0.15$ to generate a stock-return difference of -5.01% across quintile portfolios of industries sorted on financial distress (Q5−Q1). We set $\varpi = 0.1$ to generate a credit spread difference of 2.05%.

4.3 Financial Distress Anomaly across Industries

We now quantitatively examine the asset pricing implications of the endogenous distressed competition mechanism. Specifically, we show that our model can quantitatively rationalize the financial distress anomaly across industries: more financially distressed industries 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 indeed find that more distressed industries have lower expected equity excess returns and higher credit spreads. Table 3 shows that the differences in expected excess returns and credit spreads between quintile portfolios of industries sorted

rate of Baa-rated bonds, as well as the average recovery rate of debt in bankruptcy for large, public, nonfinancial U.S. firms from 1996 to 2014 structurally estimated by Dou et al. (2020*a*). Collin-Dufresne, Goldstein and Yang (2012) and Seo and Wachter (2018) also use a 40% recovery rate in normal times to match CDX spreads.

on financial distress (Q5−Q1) are −4.62% and 2.00%, respectively. Section 5.1 presents extended empirical results on the sorting analysis.[30] 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 financially 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 9).

By contrast, the canonical framework (e.g., Merton, 1974; Leland, 1994) cannot rationalize the financial distress anomaly. After incorporating the time-varying market price of risk (equations (3) and (4)) to the standard model of Leland (1994),[31] we find that the extended Leland framework implies higher expected returns and credit spreads for more financially distressed industries, with the difference (Q5−Q1) being 6.21% and 2.37%, respectively. This is because more financially distressed industries are closer to default and thus have higher financial leverage, which amplifies the exposure of both equity and debt to aggregate shocks. Unique to our model is that the endogenous distressed competition mechanism, together with heterogenous left-tail idiosyncratic jump risk, generates less negative exposure to the discount-rate shock and thus lower expected equity excess returns for the more financially distressed industries.

Further, we emphasize that introducing left-tail idiosyncratic jump risk alone to the canonical framework does not help explain the industry-level financial distress anomaly. This is simply because left-tail idiosyncratic jump risk is not priced, so it merely increases the default rate without affecting risk premium in the absence of the endogenous distressed competition mechanism. This highlights the importance of the endogenous distressed competition mechanism of our model. Left-tail idiosyncratic jump risk has cross-sectional asset pricing implications precisely because it affects the strength of the endogenous distressed competition mechanism (especially the strength of the competition-distress feedback effect). Moreover, what if we alternatively introduce heterogeneous volatility of idiosyncratic Brownian motion shock (i.e., heterogeneous σ_M in Equation (2)) instead of introducing heterogeneous left-tail idiosyncratic jump risk? This does not help explain the industry-level financial distress anomaly, because industries with larger σ_M tend to be more financially

[30]Table 5 of Online Appendix shows that financial distress anomaly is significant both across industries and across firms within the same industry. We focus on the industry-level financial distress anomaly.

[31]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).

Table 3: Industry portfolios sorted on financial distress in model and data.

	Data			Model		
	Q1 (low)	Q5	Q5−Q1	Q1 (low)	Q5	Q5−Q1
Equity excess return (%)	8.48	3.86	−4.62	9.88	4.87	−5.01
	[3.47, 13.49]	[−2.97, 10.70]	[−8.78, −0.46]			
Equity beta to discount rate	−4.99	4.61	9.60	−6.09	7.06	13.15
	[−9.58, −0.40]	[−0.74, 9.96]	[2.19, 17.01]			
Credit spread (%)	1.07	3.07	2.00	0.77	2.82	2.05
	[0.83, 1.31]	[2.29, 3.85]	[1.43, 2.57]			
5-year default rate (%)	0.50	5.21	4.71	0.02	7.57	7.55
	[0.24, 0.76]	[3.48, 6.94]	[3.07, 6.35]			
Debt-to-asset ratio (%)	22.44	33.44	11.00	27.96	37.87	9.91
	[20.61, 24.27]	[31.83, 35.04]	[9.05, 12.95]			

Note: In the data, the sample period is from 1975 to 2018. The industry-level default rate is the average default rate of the top six firms in the industry. Default event is defined in Section 4.1. The debt-to-asset ratio is total short-term debt plus total long-term debt divided by total assets. The 95% confidence intervals are reported in brackets. The equity beta to the discount rate is estimated controlling for market returns as in panel B of Table A in Appendix. In the model, financial distress is measured by the 1-year default probability as in the data.

distressed due to lower distance to default, thereby having more negative betas to the discount-rate shock.

Table 3 also shows that, in both the data and the model, the portfolio with lower financial distress (Q1) is more negatively exposed to the discount rate than that 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. The model implies that the 5-year default rate is about 0.02% for Q1, which is significantly lower than 7.57% for Q5. Similar patterns for default rates are also observed in the data.

The model also implies that the more financially distressed industries (Q5) have higher debt-to-asset ratios than the less financially distressed industries (Q1) because the former optimally chooses higher financial leverage ex-ante. In our model, 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 the aggregate discount rate (panel C of Figure 9). From the perspective of shareholders, 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 the higher 5-year default rate in these industries. This is because a large fraction of default events is caused by left-tail idiosyncratic jump shocks due to the higher λ of these industries rather than the volatile systematic component in cash flows. 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.

Table C in Appendix further strengthens the empirical support for our mechanism. There we sort industries based on their left-tail idiosyncratic jump risk in both the data (i.e., $IdTail\_risk_{i,t}$) and the model (i.e., λ). The patterns are similar to those in Table 3 because cross-industry variation in financial distress is mainly determined by the cross-industry difference in left-tail idiosyncratic jump risk. This is further supported by the additional empirical results in Section 5.1, showing that the industry-level financial distress anomaly becomes much less pronounced and statistically insignificant after controlling for left-tail idiosyncratic jump risk (see Table 6).

4.4 Inspecting the Model's Mechanism

In Table 4, we conduct various counterfactual experiments with the aim of examining the model's mechanism. Column (3) of Table 4 presents the model's implications in the non-collusive equilibrium, wherein firms are allowed to optimally set their initial coupons. Because endogenous competition risk is absent, firms choose a higher initial leverage, leading to a higher debt-to-asset ratio, compared with the collusive equilibrium. For the same reason, the equity premium and credit spread of the market portfolio decrease from 7.27% and 1.63% to 4.92% and 1.41%, respectively. More importantly, the excess return difference (Q5−Q1) of portfolios sorted on financial distress or left-tail idiosyncratic jump risk becomes positive with small magnitude because the cross-industry difference in λ does not affect industries' profit margins or their exposure to the discount rate in the non-collusive equilibrium. The positive excess return difference (Q5−Q1) reflects the higher financial leverage of more financially distressed industries (Q5). The comparison between collusive and non-collusive outcomes indicates that the competition-distress feedback effect is the key to explaining the financial distress anomaly across industries in our model. But, 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.

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 the credit spread are similar across industry portfolios sorted on left-tail idiosyncratic jump risk. The small and positive excess return difference (Q5−Q1) for industry portfolios sorted on financial distress reflects a pure leverage effect.

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

Table 4: Inspecting the model's mechanism.

	(1) Data	(2) Model	(3) No collusion	(4) $\lambda \equiv \overline{\lambda}$	(5) $\epsilon = 4$	(6) $\eta = 12$
Debt-to-asset ratio	0.29	0.33	0.36	0.33	0.34	0.33
Equity excess return (%)	7.36	7.27	4.92	7.41	6.84	7.02
Diff in excess return sorted on $Distress_{i,t}$ (%)	−4.62	−5.01	0.94	1.41	−4.03	−4.75
Diff in excess return sorted on $IdTail\_risk_{i,t}$ (%)	−5.49	−5.54	0.53	0.03	−4.48	−5.12
Credit spread (%)	1.38	1.63	1.41	1.72	1.55	1.60
Diff in credit spread sorted on $Distress_{i,t}$ (%)	2.00	2.05	1.33	0.37	1.78	1.88
Diff in credit spread sorted on $IdTail\_risk_{i,t}$ (%)	2.16	1.90	1.35	0.02	1.76	1.84

evaluate the model's quantitative implications for $\epsilon = 4$. As the feedback effect is weaker, the average equity premium and credit spread of the market portfolio decrease from 7.27% and 1.63% (column 2) to 6.84% and 1.55% (column 5), respectively. The model-implied difference in expected equity excess returns and credit spreads between industries with high and low financial distress (or left-tail idiosyncratic jump risk) also becomes less pronounced.

The strength of the endogenous distressed competition mechanism also depends on the gap between η and ϵ. If $\eta = \epsilon$, firms are monopolistically competitive, leaving no room for colluding on higher profit margins. Column (6) of Table 4 shows that changing η to 12 reduces the equity premium and credit spread, as well as their cross-industry differences.

5 Empirical Tests

Section 5.1 tests the cross-industry asset pricing implications. Section 5.2 and 5.3 test the implications of the feedback and contagion effects on profit margins and asset prices, respectively. Section 5.4 directly tests the unique predictions of the central mechanism.

5.1 Left-Tail Idiosyncratic Jump Risk and Financial Distress Anomaly

We now test the cross-industry asset pricing implications of Section 3.5, which is strengthened by the quantitative analysis in Section 4.3.

Equity Returns and Credit Spreads in the Cross Section. The empirical results on equity returns and credit spreads in Table 3 remain robust after controlling for standard risk factors. Particularly, Appendix A shows that more financially distressed industries have lower CAPM alphas. These industry-level patterns are consistent with the financial distress anomaly documented at the firm level (e.g., Campbell, Hilscher and Szilagyi, 2008). Moreover, the results are similar if we sort industries on left-tail idiosyncratic jump risk (i.e., $IdTail\_risk_{i,t}$).

Table 5: 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

Note: This table tests the relation between left-tail idiosyncratic jump risk, profit margin, and financial distress at the industry level. 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 the industry-level profit margin ($\ln(1+PM_{i,t})$), industry-level financial distress measure ($Distress_{i,t}$), or industry-level credit spread ($Credit\_spread_{i,t}$). All variables are in fractional unit. The sample spans the period from 1988 to 2018. The number of observations is 4,510 for columns (1) to (4) and 444 for columns (5) and (6). Standard errors are robust to heteroskedasticity and autocorrelation. Specifically, we compute t-statistics using Driscoll-Kraay standard errors with five lags, and report t-statistics in brackets. *, **, and *** indicate statistical significance at 10%, 5%, and 1%, respectively. FE is fixed effects.

Equity Betas to the Discount Rate. Our model suggests that industries with higher financial distress or left-tail idiosyncratic jump risk have lower expected equity excess returns because they are less negatively exposed to the aggregate discount-rate shocks, opposite to the prediction of non-collusive settings. Appendix B shows that, in the data, the excess returns of more financially distressed industries are significantly less negatively exposed to the discount rate. The results are similar if we sort industries based on $IdTail\_risk_{i,t}$.

Left-Tail Idiosyncratic Jump Risk, Profit Margin, and Financial Distress. Our model predicts that the left-tail idiosyncratic jump risk is negatively associated with the profit margin and positively associated with the level of financial distress across industries (panels A and B of Figure 9). We empirically test this relationship. Table 5 shows that industries with higher $IdTail\_risk_{i,t}$ are associated with lower profit margins (columns (1) and (2)), and higher financial distress, as reflected by higher values of the distress measure and credit spread (columns (3) to (6)).

Financial Distress Anomaly after Controlling for $IdTail\_risk_{i,t}$. 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 (see panel A of Table A in Appendix) becomes significantly less pronounced after controlling for the left-tail idiosyncratic jump risk. 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 6 shows

Table 6: 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]
		Panel B: Industry portfolios sorted on $Distress\_adjusted_{i,t}$				
$Distress\_adjusted_{i,t}$	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]

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 $IdTail\_risk_{i,t}$. Within each group, we further sort industries into quintiles based on $Distress_{i,t}$. Panel B sorts on the adjusted financial distress measure ($Distress\_adjusted_{i,t}$), which is computed as the residuals of regressing $Distress_{i,t}$ on $IdTail\_risk_{i,t}$ and a constant term. The sample spans the period from 1975 to 2018. The number of observations is 509 for both panels. All numbers are in annualized percentage unit. t-statistics robust to heteroskedasticity are reported in brackets. *, **, and *** indicate statistical significance at 10%, 5%, and 1%, respectively.

that the difference in CAPM alpha between the industry portfolio with low (Q1) and high (Q5) distress becomes statistically insignificant. The magnitude of the difference (Q5−Q1) changes from −6.893 in panel A of Table A in Appendix to −2.037 in panel A of Table 6.

Panel B of Table 6 performs 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. It is shown that the CAPM alpha becomes 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 the discount rate and that the loadings are more negative in industries where firms are closer to their default boundaries (panel C of Figure 6), due to the stronger competition-distress feedback effect. To test this implication, we sort industries into different groups based on the distance-to-default measure ($DD_{i,t}$). We then examine the profit-margin beta to the discount rate by running the following time-series regression using yearly

Table 7: Implications of the competition-distress feedback effect 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]

Note: This table reports the difference in the profit-margin beta to the discount rate across groups of industries sorted on the distance-to-default measure ($DD_{i,t-1}$). The regression specification is described in (27). In column (1), we sort industries into three tertiles, and report the difference in the profit-margin beta between T1 and T3. In column (2), industries are sorted into five quintiles and the difference in the profit-margin beta 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. The number of observations is 50 for all columns. Standard errors are robust to heteroskedasticity and autocorrelation. Specifically, we compute t-statistics using Newey-West standard errors with five yearly lags. All variables are annualized and in fractional unit. We report t-statistics in brackets. *, **, and *** indicate statistical significance at 10%, 5%, and 1%, respectively.

observations for each group k:

$$\Delta \ln(1+PM_{k,t}) = \alpha_k + \beta_k \times \Delta Discount\_rate_t + \epsilon_{k,t}, \tag{27}$$

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 of logged one plus the industry-level profit margin of all industries in group k.[32]

Column (1) of Table 7 shows that the difference in the profit-margin beta to the discount rate between the tertile groups of industries with high (T3) and low (T1) distances to default, respectively, is positive and statistically significant. This indicates that T1 is more negatively exposed to the discount rate, consistent with the prediction of our model (but not with that of non-collusive settings). 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 to a financially distressed market leader will motivate other market leaders within the same

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

industry to cut their profit margins under a common market structure (see panel A of Figure 4). 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:

$$\ln(1 + PM_{i,t}^{(L)}) = \sum_{j \in \{H,L\}} \beta_j \times IdShock_{i,t}^{(j)} + \sum_{j=1}^{5} \gamma_j \times \ln(1 + PM_{i,t-j}^{(L)}) + \delta_t + \ell_i + \epsilon_{i,t}, \qquad (28)$$

where the independent variable $IdShock_{i,t}^{(k)}$ is the idiosyncratic shock of 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. Method M1 uses firms' sales growth minus the cross-sectional average sales growth; and 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. Our regression specification (28) 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.[33] 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 8 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, opposite to the prediction of non-collusive settings. Conversely, we find that idiosyncratic shocks to group L do not significantly affect the profit margin of group H, as implied by our model.

Our model further predicts that the within-industry contagion effect on profit margins is more pronounced in industries in which market leaders have more balanced market shares (Figure 5). 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 (28) 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.[34] A larger value of the imbalance measure means that the market share of group L is more different

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

[34] For example, an industry with sales 5 for group H and 1 for group L is considered equally unbalanced as an industry with sales 1/5 for group H and 1 for group L. Note that according to the model, the ratio of sales matters, but whether H or L has higher sales does not.

Table 8: 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			
$IdShock_{i,t}^{(H)}$	All	T1 (balance)	T2	T3 (imbalance)	T3−T1	T1 (low)	T2	T3 (high)	T3−T1
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 in specification (28) captures the contagion effect on profit margins. Column (1) presents the estimated β_H based on the whole sample, and columns (2) to (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) to (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 report *t*-statistics in brackets. *, **, and *** indicate statistical significance at 10%, 5%, and 1%.

from that of group H. Columns (2) and (4) of Table 8 show that the contagion effect on profit margins 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 industries with lower entry threat due to greater predatory incentives (panel B of Figure 7). 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 8 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.

Table 9: 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)	
	$\ln(1+PM_t^{(c_{i,j})})$			$\ln(1+PM_{i,t}^{(-c)})$	
	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 for 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 $\widehat{IdShock}_{i,t}^{(c_{i,j})}$. 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 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 construct the independent variable $\widehat{IdShock}_{-i,t}$ as the simple average of $\widehat{IdShock}_{j,t}^{(c_{j,i})}$ (estimated in first stage) over all industries (j) connected to industry i. The cross-industry contagion effect on profit margins is estimated by the following specification: $\ln(1+PM_{i,t}^{(-c)}) = \alpha + \beta_1 \times \widehat{IdShock}_{-i,t} + \beta_2 \times IdShock_{i,t} + \sum_{j=1}^{5}\gamma_j \times \ln(1+PM_{i,t-j}^{(-c)}) + \delta_t + \ell_i + \varepsilon_{i,t}$ with time and industry fixed effects δ_t and ℓ_i. The variable $PM_{i,t}^{(-c)}$ is the profit margin of industry i excluding its common market leaders in year t. 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 brackets. *, **, and *** indicate statistical significance at 10%, 5%, and 1%, respectively.

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 economic intuition illustrated in Figure 2.

To test the cross-industry financial contagion effect, we construct a competition network of industries linked by common market leaders. Based on the competition network, we test whether idiosyncratic shocks to market leaders in one industry influence the profit margins of market leaders in another industry if the two industries share some common market leaders. Online Appendix 2.4 provides the details about the construction of the competition network and empirical design.

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 the common market

Table 10: Feedback effect on the 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 ($DD_{i,t}$). We first sort industries into three groups based on their $DD_{i,t}$. In each group, we further sort industries into three tertiles based on their gross profitability, which is constructed 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. t-statistics are reported in brackets. *, **, and *** indicate statistical significance at 10%, 5%, and 1%, respectively.

leader $c_{i,j}$ with industries i and j. The fitted value of the regression, $\widehat{IdShock}_{i,t}^{(c_{i,j})}$, captures the changes in the common market leader $c_{i,j}$'s profit margin attributed to idiosyncratic shocks to market leaders in industry i. In the second stage, we estimate the cross-industry financial contagion effect on profit margins by regressing logged one plus the profit margin of industry i excluding its common market leaders on $\widehat{IdShock}_{-i,t}$, which is the average of $\widehat{IdShock}_{j,t}^{(c_{j,i})}$ (estimated in first stage) over all industries (j) connected to industry i through common market leaders.

Panel A of Table 9 presents our first-stage estimates, indicating 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 for $\widehat{IdShock}_{-i,t}$ 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 for $\widehat{IdShock}_{-i,t}$ equals 0.677, meaning that a 1% increase in the average profit margin of common market leaders due to idiosyncratic shocks to the market leaders in the connected industries is associated with a 0.677% increase in the profit margin of industry i.

5.3 Feedback and Contagion Effects on Asset Prices

Competition-Distress Feedback Effects. As discussed in Section 3.5, competition-distress feedback is stronger when industries are closer to the default boundary. As a result, the difference in the equity beta to the discount rate across industries with different gross profitability becomes larger when the distance to default is lower (panels A and C of Figure 9). To test this prediction, we equally split all industries into three groups based on the distance-to-default measure ($DD_{i,t}$). Within each group, we sort industries into three tertiles based on their gross profitability. Table 10 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 a low $DD_{i,t}$ (group 1). The gross profitability spread is much smaller and statistically insignificant among industries in the group with a high $DD_{i,t}$ (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 C of Figure 4). To test this prediction, we conduct regression analysis using specification (28) except for using the group-level credit spreads on both sides:

$$Credit\_spread^{(L)}_{i,t} = \sum_{j \in \{H,L\}} \beta_j \times IdShock^{(j)}_{i,t} + \sum_{j=1}^{5} \gamma_j \times Credit\_spread^{(L)}_{i,t-j} + \delta_t + \ell_i + \epsilon_{i,t}. \quad (29)$$

Column (1) of Table 11 shows that the contagion effect on credit spreads is negative, indicating that positive idiosyncratic shocks to group H reduce the credit spread of group L. The coefficient is statistically insignificant because of the small sample size. Columns (2) to (5) further 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 despite statistical insignificance due to a small sample size.

5.4 Testing the Endogenous Distressed Competition Mechanism

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

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, some omitted variables correlated with both changes in HHI and the feedback (contagion) effect could exist through channels other than the competitiveness of market structure. For instance, technology development can lead to both the changes in HHI and the changes in 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 variation in the competitive-

Table 11: Financial contagion effect on credit spreads within an industry.

	(1)	(2)	(3)	(4)	(5)
	$Credit\_spread^{(L)}_{i,t}$				
		Industry portfolios sorted on market share dispersion			
$IdShock^{(H)}_{i,t}$	All	T1 (balance)	T2	T3 (imbalance)	T3−T1
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*
	[−1.93]	[−1.82]	[0.77]	[0.15]	[1.75]

Note: This table studies the financial contagion effect on credit spreads within an industry. The empirical design is the same as that used for Table 8. Columns (1) to (4) report the coefficient β_H, which captures the contagion effect on credit spreads. Column (1) presents the estimated β_H based on the whole sample, and columns (2) to (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). 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 report t-statistics in brackets. *, **, and *** indicate statistical significance at 10%, 5%, and 1%, respectively.

ness 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 structures.[35] 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 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 because of the similar products and services provided by foreign rivals and (ii) the number of market leaders n because of 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 the distance to default. We run the following panel regression using industry-year observations in a difference-in-differences framework, essentially by adding unexpected market structure changes (i.e., unexpected

[35]Tariff cuts are widely used as a shock to the competitiveness of industry market structure to address endogeneity concerns (Xu, 2012; Huang, Jennings and Yu, 2017; Dasgupta, Li and Wang, 2018).

Table 12: 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 from specification (30), where the independent variable is year-on-year change in the logged one plus the industry-level profit margin (columns 1 and 2) or the industry-level profit margin (columns 3 and 4). $Low\_DD_{i,t-1}$ is an indicator variable that equals 1 if $DD_{i,t-1}$ is below the 25% quantile of the distance-to-default measure 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 1 if industry i experiences a large tariff cut in the last two years (t and $t-1$). A large tariff cut refers to a cut with a magnitude 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 followed by equivalently large increases in tariffs over the subsequent two years. We obtain tariff data for manufacturing industries at the SIC4 level from 1974 to 2005 from Laurent Fresard's website (Frésard, 2010) and extend these 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 report t-statistics in brackets. *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels.

large tariff cuts) dummy variable $mkt\_chg_{i,t}$ to the empirical specification in Table 7:

$$\begin{aligned}\Delta\ln(1+PM_{i,t}) = {} & \beta_1 \times mkt\_chg_{i,t} \times Low\_DD_{i,t-1} \times \Delta Discount\_rate_t \\ & + \beta_2 \times Low\_DD_{i,t-1} \times \Delta Discount\_rate_t + \beta_3 \times mkt\_chg_{i,t} \times \Delta Discount\_rate_t \\ & + \beta_4 \times \Delta Discount\_rate_t + \beta_5 \times mkt\_chg_{i,t} \times Low\_DD_{i,t-1} \\ & + \beta_6 \times Low\_DD_{i,t-1} + \beta_7 \times mkt\_chg_{i,t} + \ell_i + \epsilon_{i,t}. \end{aligned} \tag{30}$$

where $Low\_DD_{i,t-1}$ is the indicator variable for industries with a low distance to default, equal to 1 if $DD_{i,t-1}$ is below the 25% quantile of the distance-to-default measure across all industries in year $t-1$, and $mkt\_chg_{i,t}$ is the indicator variable for large tariff cuts.

Column (1) of Table 12 presents the benchmark results without including the terms with $mkt\_chg_{i,t}$ in specification (30). The profit margins of industries with a low distance to default are more negatively exposed to the discount rate, a finding that is consistent with the implication of the competition-distress feedback. Column (2) of Table 12 reports the results for the full specification (30). The estimated coefficient $\hat{\beta}_1$ for the triple interaction term is positive and significant both statistically and economically, suggesting that industries with high and low distances to default display less difference in the sensitivity of profit margins to the discount rate when their market structure becomes more competitive after large tariff cuts.[36] The results remain robust if we use changes in the 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, essentially by adding the unexpected market structure change $mkt\_chg_{i,t}$ (i.e., the unexpected large tariff cut) to the regression specification in Table 8:

$$\begin{aligned}\ln(1+PM_{i,t}^{(L)}) = \beta_1 \times mkt\_chg_{i,t} \times IdShock_{i,t}^{(H)} + \beta_2 \times IdShock_{i,t}^{(H)} + \beta_3 \times mkt\_chg_{i,t} \\ + \beta_4 \times IdShock_{i,t}^{(L)} + \sum_{j=1}^{5} \gamma_j \times \ln(1+PM_{i,t-j}^{(L)}) + \delta_t + \ell_i + \epsilon_{i,t}. \end{aligned} \tag{31}$$

Columns (1) and (3) of Table 13 report the benchmark results without including the terms with $mkt\_chg_{i,t}$. They show that the financial contagion effect is positive, consistent with the results for Table 8. Columns (2) and (4) report the results of the full specification (31). The estimated coefficient $\hat{\beta}_1$ for the interaction term is negative and significant both statistically and economically, indicating that the financial contagion effect on profit margins becomes weaker after unexpected large tariff cuts (i.e., unexpected increase in the competitiveness of market structure).

6 Conclusion

This paper investigates the 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, diminishes profit margins for all firms in the industry, pushing some further into distress. Thus, the endoge-

[36] A positive $\hat{\beta}_1$ means that the difference in the sensitivity of profit margins to the discount rate narrows because industries with a low distance to default are more negatively exposed to discount rates than are those with a high distance to default in the absence of large tariff cuts (see column (1) of Table 12).

Table 13: Impact of market structure changes on the financial contagion effect.

	(1)	(2)	(3)	(4)
		$\ln(1+PM^{(L)}_{i,t})$		
	M1		M2	
$Mkt\_chg_{i,t} \times IdShock^{(H)}_{i,t}$		-0.04^{**}		-0.04^{**}
		[−2.39]		[−2.20]
$IdShock^{(H)}_{i,t}$	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]
$IdShock^{(L)}_{i,t}$	0.07^{***}	0.08^{***}	0.06^{***}	0.07^{***}
	[4.92]	[4.09]	[3.53]	[3.23]
$\ln(1+PM^{(L)}_{i,t-1})$	0.29^{***}	0.24^{***}	0.29^{***}	0.24^{***}
	[4.95]	[7.10]	[4.92]	[7.21]
$\ln(1+PM^{(L)}_{i,t-2})$	0.08^{**}	0.08	0.08^{**}	0.08
	[2.51]	[1.09]	[2.49]	[1.09]
$\ln(1+PM^{(L)}_{i,t-3})$	0.03	0.06^{***}	0.02	0.06^{***}
	[0.83]	[3.54]	[0.82]	[3.45]
$\ln(1+PM^{(L)}_{i,t-4})$	0.03^{*}	0.04	0.03^{*}	0.04
	[1.90]	[1.36]	[1.78]	[1.36]
$\ln(1+PM^{(L)}_{i,t-5})$	−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 year-on-year change in the logged one plus the industry-level profit margin. Group-level idiosyncratic shocks are constructed using methods M1 and M2, as in Table 8. The large tariff cut variable $mkt\_chg_{i,t}$ is constructed as in Table 12. We control for the year and industry fixed effects. The sample spans the period from 1976 to 2017. We report t-statistics in brackets. Standard errors are clustered at the industry level. *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels, respectively.

nous distressed competition mechanism implies novel competition-distress feedback and financial contagion effects. In addition, depending on the relative market share and financial strength, as well as entry threat, firms can exhibit a rich variety of strategic interactions, including predation, self-defense, and collaboration (collective entry prevention). More important, our model has salient asset pricing implications: first, because of 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, competition-distress feedback amplifies firms' aggregate risk exposure, more so for industries with lower left-tail idiosyncratic jump risk, which helps explain the puzzling cross-sectional patterns of equity and bond returns, namely, the financial distress anomaly across industries.

Our study raises interesting questions for future research. Equity issuance is costless in our model but costly in reality. The costless issuance of equity is a simplification widely adopted in standard credit risk models. Do firms compete more aggressively when they become more liquidity constrained, but not yet more financially distressed? We focus on frictions related to debt financing, but the equity financing friction should also be investigated. Extending the model to incorporate external equity financing costs and allow firms to hoard cash, as in Bolton, Chen and Wang (2011, 2013), Dou et al. (2019), and Dou and Ji (2020), would be interesting for future research. Also, our paper highlights an important source of cash flow risk — endogenous competition risk — that depends on industries' market structures. Extending the model to study the joint determination of optimal capital structure and risk management, as in Rampini and Viswanathan (2010, 2013), would be another potentially fruitful research area.

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, 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.

Aryal, Gaurab, Federico Ciliberto, and Benjamin T Leyden. 2020. "Coordinated capacity reductions and public communication in the airline industry." Working Paper.

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. 2020. "The Fall of the Labor Share and the Rise of Superstar Firms." *The Quarterly Journal of Economics*, 135(2): 645–709.

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.

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.

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., Jean-Pierre H. Dubé, and Matthew Gentzkow. 2012. "The Evolution of Brand Preferences: Evidence from Consumer Migration." *American Economic Review*, 102(6): 2472–2508.

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.

Cespa, Giovanni, and Thierry Foucault. 2014. "Illiquidity Contagion and Liquidity Crashes." *Review of Financial Studies*, 27(6): 1615–1660.

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. 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.

Chen, Zhiyao, Dirk Hackbarth, and Ilya A. Strebulaev. 2019. "A Unified Model of Distress Risk Puzzles." Working Paper.

Chevalier, Judith A., and David S. Scharfstein. 1996. "Capital-Market Imperfections and Countercyclical Markups: Theory and Evidence." *American Economic Review*, 86(4): 703–725.

Christensen, Clayton. 1997. *The innovator's dilemma: When new technologies cause great firms to fail.* Harvard Business Review Press.

Cochrane, John H. 2011. "Presidential address: discount rates." *Journal of Finance*, 66(4): 1047–1108.

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. 2020*a*. "Competition, markups, and predictable returns." *Review of Financial Studies*, forthcoming.

Corhay, Alexandre, Howard Kung, and Lukas Schmid. 2020*b*. "Q: Risk, Rents, or Growth?" Duke University Working Papers.

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.

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.

Dichev, Ilia D. 1998. "Is the Risk of Bankruptcy a Systematic Risk?" *The Journal of Finance*, 53(3): 1131–1147.

Dick-Nielsen, Jens. 2009. "Liquidity Biases in TRACE." *The Journal of Fixed Income*, 19(2): 43–55.

Dou, Winston, and Yan Ji. 2020. "External financing and customer capital: A financial theory of markups." *Management Science*, forthcoming.

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*, 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.

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.

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.

Garlappi, Lorenzo, and Hong Yan. 2011. "Financial Distress and the Cross-section of Equity Returns." *The Journal of Finance*, 66(3): 789–822.

Garlappi, Lorenzo, Tao Shu, and Hong Yan. 2008. "Default Risk, Shareholder Advantage, and Stock Returns." *The Review of Financial Studies*, 21(6): 2743–2778.

Gârleanu, Nicolae, Leonid Kogan, and Stavros Panageas. 2012. "Displacement risk and asset returns." *Journal of Financial Economics*, 105(3): 491 – 510.

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.

George, Thomas J., and Chuan-Yang Hwang. 2010. "A resolution of the distress risk and leverage puzzles in the cross section of stock returns." *Journal of Financial Economics*, 96(1): 56 – 79.

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.

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.

Gomes, João, Urban Jermann, and Lukas Schmid. 2016. "Sticky Leverage." *American Economic Review*, 106(12): 3800–3828.

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.

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.

Grieser, William, and Zack Liu. 2019. "Corporate Investment and Innovation in the Presence of Competitor Constraints." *The Review of Financial Studies*, 32(11): 4271–4303.

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.

Harrigan, James. 1993. "OECD imports and trade barriers in 1983." *Journal of International Economics*, 35(1-2): 91–111.

Head, Keith, and John Ries. 2001. "Increasing returns versus national product differentiation as an explanation for the pattern of U.S.-Canada trade." *American Economic Review*, 91(4): 858–876.

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.

He, Zhiguo, and Wei Xiong. 2012*a*. "Dynamic Debt Runs." *Review of Financial Studies*, 25(6): 1799–1843.

He, Zhiguo, and Wei Xiong. 2012*b*. "Rollover Risk and Credit Risk." *Journal of Finance*, 67(2): 391–430.

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.

Hortaçsu, Ali, Gregor Matvos, Chad Syverson, and Sriram Venkataraman. 2013. "Indirect Costs of Financial Distress in Durable Goods Industries: The Case of Auto Manufacturers." *The Review of Financial Studies*, 26(5): 1248–1290.

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.

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.

Kogan, Leonid, Dimitris Papanikolaou, Amit Seru, and Noah Stoffman. 2017. "Technological innovation, resource allocation, and growth." *Quarterly Journal of Economics*, 132(2): 665–712.

Kogan, Leonid, Dimitris Papanikolaou, and Noah Stoffman. 2018. "Left behind: Creative destruction, inequality, and the stock market." *Journal of Political Economy*, forthcoming.

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.

Kuehn, Lars-Alexander, and Lukas Schmid. 2014. "Investment-Based Corporate Bond Pricing." *The Journal of Finance*, 69(6): 2741–2776.

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.

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.

Loualiche, Erik. 2019. "Asset pricing with entry and imperfect competition." Working Papers.

Luttmer, Erzo G. J. 2007. "Selection, Growth, and the Size Distribution of Firms*." *The Quarterly Journal of Economics*, 122(3): 1103–1144.
Maksimovic, Vojislav. 1988. "Capital Structure in Repeated Oligopolies." *RAND Journal of Economics*, 19(3): 389–407.
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.
Ma, Song, Joy Tianjiao Tong, and Wei Wang. 2020. "Bankrupt Innovation Firms." Working Papers.
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.
Miller, Nathan H, and Matthew C Weinberg. 2017. "Understanding the price effects of the MillerCoors joint venture." *Econometrica*, 85(6): 1763–1791.
Novy-Marx, Robert. 2013. "The other side of value: The gross profitability premium." *Journal of Financial Economics*, 108(1): 1–28.
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.
Rampini, Adriano A., and S. Viswanathan. 2010. "Collateral, Risk Management, and the Distribution of Debt Capacity." *Journal of Finance*, 65(6): 2293–2322.
Rampini, Adriano A., and S. Viswanathan. 2013. "Collateral and capital structure." *Journal of Financial Economics*, 109(2): 466–492.
Rotemberg, Julio J, and Garth Saloner. 1986. "A supergame-theoretic model of price wars during booms." *American Economic Review*, 76(3): 390–407.
Schmitt, Matt. 2018. "Multimarket contact in the hospital industry." *American Economic Journal: Economic Policy*, 10(3): 361–87.
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.
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.

Appendix

A Equity Returns and Credit Spreads in the Cross Section

The results in Table 3 remain robust after controlling for standard risk factors. Panel A of Table A 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 -4.615% (Q5−Q1) and significant both statistically and economically. In terms of credit spreads, our findings show that the industries with higher $Distress_{i,t}$ are associated with higher credit spreads, which is in sharp contrast to the lower (risk-adjusted) expected equity excess returns associated with these industries. Panel A of Table B shows that similar results are obtained if we sort industries on left-tail idiosyncratic jump risk ($IdTail\_risk_{i,t}$). Particularly, industries with high $IdTail\_risk_{i,t}$ have significantly lower (risk-adjusted) expected excess returns and significantly higher credit spreads than those of industries with low $IdTail\_risk_{i,t}$.

B Equity Beta to the Discount Rate

Panel B of Table A examines the equity beta to the discount rate in the cross section of industries in the data. Particularly, we sort industries into quintiles based on $Distress_{i,t}$ and find that the excess returns of industry portfolios of low financial distress (Q1) are significantly more negatively exposed to the discount rate compared to those of high financial distress (Q5). Similar results hold if we sort industries based on $IdTail\_risk_{i,t}$ (see panel B of Table B). 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 4 of Online Appendix).

Table A: Industry portfolios sorted on financial distress.

	(1)	(2)	(3)	(4)	(5)	(6)
$Distress_{i,t}$	Q1 (low)	Q2	Q3	Q4	Q5 (high)	Q5−Q1
			Panel A: Equity returns and credit spreads			
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]
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]
			Panel B: Equity betas to the discount rate			
$\Delta Discount\_rate_{t+1}$	−4.990**	−4.273***	2.122	−0.622	4.610*	9.600**
	[−2.14]	[−4.10]	[0.80]	[−0.26]	[1.70]	[2.56]
$R^{mkt}_{t+1} - R_{f,t}$	0.875***	1.015***	1.227***	1.225***	1.479***	0.604***
	[9.55]	[26.80]	[27.58]	[14.54]	[17.39]	[4.31]

Note: Panel A reports (risk-adjusted) expected excess returns and credit spreads of industry portfolios sorted on financial distress ($Distress_{i,t}$). Panel B reports the equity beta to the discount rate. In each quintile k, we run the following time-series regression: $R_{k,t+1} - R_{f,t} = \alpha_k + \beta_k \times \Delta Discount\_rate_{t+1} + \gamma_k \times (R^{mkt}_{t+1} - R_{f,t}) + \epsilon_{k,t+1}$. The variable $\Delta Discount\_rate_t$ is the AR(1) residual of the discount rate measure $Discount\_rate_t$ in quarter t, R^{mkt}_t 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. The number of observations is 521 for panel A and 174 for panel B. t-statistics robust to heteroskedasticity and autocorrelation are reported in brackets. *, **, and *** indicate statistical significance at 10%, 5%, and 1%, respectively.

Table B: Industry portfolios sorted on left-tail idiosyncratic jump risk.

	(1)	(2)	(3)	(4)	(5)	(6)
$IdTail\_risk_{i,t}$	Q1 (low)	Q2	Q3	Q4	Q5 (high)	Q5−Q1
			Panel A: Equity returns and credit spreads			
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]
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]
			Panel B: Equity beta to the discount rate			
$\Delta Discount\_rate_{t+1}$	−4.036	−3.042**	−3.798	1.473	6.078**	10.115**
	[−1.56]	[−2.25]	[−1.46]	[0.72]	[2.12]	[2.32]
$R^{mkt}_{t+1} - R_{f,t}$	0.785***	1.001***	1.027***	1.400***	1.631***	0.846***
	[7.24]	[27.01]	[11.90]	[26.85]	[15.62]	[4.66]

Note: This table performs the same analysis as in Table A, except for sorting industries on the left-tail idiosyncratic jump risk measure ($IdTail\_risk_{i,t}$). All numbers are in annualized percentage unit. The sample spans the period from 1976 to 2018. The number of observations is 509 for panel A and 169 for panel B. t-statistics robust to heteroskedasticity and autocorrelation are reported in brackets. *, **, and *** indicate statistical significance at 10%, 5%, and 1%, respectively.

Table C: Industry portfolios sorted on left-tail idiosyncratic jump risk in model and data.

	Data			Model		
	Q1 (low)	Q5	Q5−Q1	Q1 (low)	Q5	Q5−Q1
Equity excess return (%)	9.04	3.55	−5.49	10.10	4.55	−5.54
	[4.64, 13.44]	[−4.11, 11.21]	[−10.63, −0.35]			
Equity beta to discount rate	−4.04	6.08	10.12	−6.13	6.68	12.81
	[−9.15, 1.07]	[0.41, 11.74]	[1.49, 18.74]			
Credit spread (%)	1.09	3.25	2.16	0.79	2.69	1.90
	[0.90, 1.28]	[2.43, 4.08]	[1.48, 2.84]			
5-year default rate (%)	0.76	4.24	3.47	0.04	5.26	5.22
	[0.37, 1.15]	[2.83, 5.65]	[2.11, 4.83]			
Debt-to-asset ratio (%)	27.23	30.41	3.19	29.14	34.90	5.76
	[25.18, 29.28]	[28.19, 32.63]	[0.37, 6.00]			

Note: This table performs the same analysis as in Table 3, except for sorting industries on the left-tail idiosyncratic jump risk measure ($IdTail\_risk_{i,t}$) in the data and λ in the model. The sample period is from 1976 to 2018.