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 when they are in financial distress; the intensified competition reduces the profit margins for all firms in the industry, pushing everyone further into distress. To study such feedback and contagion effects, we incorporate a supergame of strategic competition into a dynamic model of long-term defaultable debt. Depending on the relative market share and financial strength as well as entry threats, firms in the model exhibit a rich variety of strategic interactions, including predation, self-defense, and collaboration. A key result of our model is that, due to financial contagion, the credit risks of leading firms in an industry are jointly determined, whereby firm-specific shocks can significantly affect the credit risk of peer firms. In addition, the competition-distress feedback affects firms’ aggregate risk exposure, which helps explain the puzzling joint cross-sectional patterns of equity and bond returns. Finally, we also provide empirical support for our model’s predictions. In particular, we exploit exogenous variations in market structure – large tariff cuts – to test the endogenous competition mechanism directly.

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

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1 Introduction

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

Motivated by the facts above, this paper studies the feedback and contagion effects generated by the dynamic interactions between strategic competition and financial distress. More important, we show that incorporating the feedback effect due to the distressed competition mechanism, a single deviation from the benchmark asset pricing models, can explain various joint patterns of equity returns and credit spreads that otherwise seem puzzling under the canonical framework of Merton (1974) and Leland (1994). The feedback effect arises because firms tend to compete more aggressively when they are in financial distress, and the intensified competition reduces the profit margins for all firms in the industry, pushing everyone further into distress (see Figure 1). The effect further amplifies the asset pricing implications of industry competition, and more so in more financially distressed industries. Moreover, the financial contagion effect, even across industries (see Figure 2), renders the financial distress of leading firms interdependent, thereby microfounding the key primitive in the theories of aggregate credit market dynamics (e.g., Bebchuk and Goldstein, 2011).

We incorporate a supergame of strategic competition into a dynamic model of long-term defaultable debt (à la Leland, 1994). The industry features a dynamic Bertrand oligopoly with differentiated products and tacit collusion (Tirole, 1988, Chapter 6). Consumers’ tastes toward firms’ differentiated products, which are embodied in customer base. Firms’ cash flows are endogenously determined by their profit margins and customer base. The aggregate discount rate is time varying, as emphasized in Cochrane.

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

2 According to Merton (1974), Leland (1994) and their many extensions, more profitable firms have lower credit spreads and should compensate shareholders with lower equity returns because of the lower default risk. Moreover, financially distressed firms have higher credit spreads and should compensate shareholders with higher equity returns because of the higher default risk. However, the opposite patterns are observed in the data (e.g., Campbell, Hilscher and Szilagyi, 2008; Novy-Marx, 2013).
In our model, oligopolists can tacitly collude with each other on setting high profit margins. Given that the competitor will honor the collusive profit-margin scheme, a firm can boost up its short-run revenue by undercutting profit margins to attract more customers; however, deviating from the collusive profit-margin scheme may reduce revenue in the long run if the profit-margin undercutting behavior is detected and punished by the competitor. Following the literature (e.g., Green and Porter, 1984; Brock and Scheinkman, 1985; Rotemberg and Saloner, 1986), we adopt the non-collusive Nash equilibrium as the incentive-compatible punishment for deviation. The collusive profit margins depend on firms’ deviation incentives: a higher collusive profit margin can only be sustained by a lower deviation incentive, which is determined by firms’ intertemporal tradeoff between short- and long-run cash flows. The intertemporal tradeoff is further shaped by the firm-specific financial condition and the aggregate discount rate.

Based on the core mechanism above, our model has the following main theoretical results. First, there exists a positive feedback loop between competition and financial distress. Intuitively, a firm’s incentive to collude with its peers in strategic competition depends on how much it values the extra profit from cooperation in the future, following the idea of Fudenberg and Maskin (1986)’s “Folk theorem.” As illustrated in Figure 1, when a firm becomes more financially distressed, it tends to compete more intensely, resulting lower profit margins. This is because higher default risk makes the firm effectively more impatient, which renders the punishment for deviation from collusion less costly and the incentive for undercutting its competitors on profit margins stronger. Lower profit margins further elevate the level of financial distress and default risk.

Second, strategic competition in the product markets leads to financial contagion. This
Figure 2: Financial contagion through endogenous competition in product markets.

effect is easy to see within an industry. When a leading firm is hit by a firm-specific shock and pushed into financial distress, competition tends to intensify within the industry (due to the higher impatience explained above), which results in lower profits for all firms. Consequently, the financial conditions of the competitors in the same industry will also weaken.

With multi-sector firms, the financial contagion can also spread across industries. For example, Figure 2 illustrates a setting with two industries and three firms, where firm B operates in both industries. When firm A in the first industry becomes financially distressed due to a firm-specific shock, the heightened competition raises the level of financial distress for firm B. Firm B responds by competing more aggressively in both industries, which eventually hurts the profitability of firm C in the second industry and potentially pushes it into financial distress.

Third, depending on the heterogeneity in market shares and financial conditions across firms in an industry as well as between incumbent firms and new entrants, firms can exhibit a rich variety of strategic interactions, including self-defense, predation (price war), and collaboration. Per the intuition of the “Folk theorem,” bankruptcy risk can change the nature of strategic competition in several ways. As already discussed above, it can endogenously make a firm more impatient, which reduces its collusion incentive. In response to the profit-margin undercutting by the weaker firm, the financially strong firm in the same industry might also cut profit margins to protect its market share. We refer to this as the self-defensive incentive. Next, when the threat of new entrant is sufficiently low (e.g., due to a high entry barrier) and the distressed firm is sufficiently close to bankruptcy,
the strong firm might want to cut profit margins even more aggressively, even switching to a non-collusive equilibrium (a price war), in the hope that it could drive the weaker competitor out of the market sooner and enjoy the monopoly rent subsequently. This is the predatory incentive. However, if the failure of the weaker competitor results in the emergence of a powerful new entrant, the stronger firm’s collaboration incentive might dominate: it might keep the level of its profit margin high in order to help the weaker firm remain solvent. Our model provides a quantitative evaluation and structural decomposition of the three types of incentives, which constitutes an important contribution to the industrial organization (IO) literature like Besanko, Doraszelski and Kryukov (2014).³

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

As the second set of asset pricing implications, we show that there is an amplification effect on the industry’s exposure to aggregate discount-rate shocks owing to the competition-distress feedback. The exposure of profit margins to aggregate discount-rate shocks is considerably higher for the industries with higher market leadership persistence than those with lower leadership persistence. As a result, the exposure of stock returns and credit spreads to aggregate discount-rate shocks is also higher for the industries with higher market leadership persistence. More importantly, such a gap in exposure of profit margins, stock returns, and credit spreads to aggregate discount-rate shocks becomes significantly more pronounced when industries are more financially distressed, in line with the main theoretical prediction on the competition-distress feedback.

As the third set of asset pricing implications, our model provides a novel mechanism for explaining both the gross profitability premium puzzle and the distress anomaly at industry level, the joint patterns of stock returns and credit spreads at odds with the canonical models of Merton (1974) and Leland (1994). In a related paper, Dou, Ji and

³Our structural decomposition is reminiscent of that of Besanko, Doraszelski and Kryukov (2014). The structural decomposition corresponds to the common practice of antitrust authorities to question the intent behind a business strategy: Is the firm’s aggressive pricing behavior primarily driven by the benefits of acquiring competitive advantage or by the benefits of overcoming competitive disadvantage caused by rivals’ aggressive competition behaviors? The predatory motive maps into the first set of benefits and the self-defensive motive into the second set.
Wu (2020) build a model with endogenous competition risk like our model, but focus on all-equity firms. They show that the gross profitability premium cross industries can be explained by the heterogeneous persistence of market leadership and the endogenous competition risk. We extend the framework of Dou, Ji and Wu (2020) by endogenizing the interaction between strategic competition and financial distress. Our model is able to explain the joint patterns of equity returns and credit spreads associated with gross profitability as well as the financial distress anomaly at the industry level.

More precisely, as shown extensively in the empirical IO literature, the turnover rate of market leadership is a fundamental industry characteristic that is largely heterogeneous across industries. In our model, upon a leadership turnover, existing market leaders are displaced by new market leaders who used to be market followers. The change of market leadership does not occur gradually; instead, market leaders are replaced rapidly and disruptively (e.g., Christensen, 1997) and their customer base erodes dramatically over a short period of time due to distinctive innovation or rapid business expansion of market followers. Thus, in industries with a higher turnover rate of market leadership, existing market leaders face higher financial distress risk because they are more likely to be displaced and suffer substantial losses of customer base, a key determinant for their cash flows. Further, in such industries, existing market leaders find it more difficult to collude because the higher displacement risk makes the future punishment for deviation behavior less threatening. The lack of collusion incentives results in lower profit margins, which yet are more immune to fluctuations in discount rates, implying more stable competition intensity in these industries. Consequently, our model implies that conditional on the same financial leverage, shareholders are compensated with lower expected returns in industries with a higher turnover rate of market leadership because the competition intensity is more stable. For the industries with lower leadership persistence are those with lower gross profitability and higher financial distress (after controlling for leverage), our model in turn implies that shareholders are compensated with lower expected returns in less profitable and more financially distressed industries. Therefore, on the equity return side, this provides insight to explain the profitability premium puzzle and the financial distress anomaly. By contrast, on the credit spread front, the model implies higher credit spreads for the less profitable and more financially distressed industries because the lower profitability generates lower cash flows, resulting in higher credit risk.

While our contribution is mainly theoretical, we empirically test the main predictions of our model and find strong evidence that supports the theoretical implications. The industry-level distress measure is constructed by averaging firm-level financial distress measure constructed as in Campbell, Hilscher and Szilagyi (2008). The central aggregate
shock in our theory is the discount-rate shock, which drives the competition intensity across all industries. The empirical proxy for discount rates is based on the smoothed earnings-price ratio motivated by the return predictability studies (e.g., Campbell and Shiller, 1988, 1998; Campbell and Thompson, 2008). We construct a proxy for the likelihood of market leadership turnover. Specifically, we first use patent data to construct a measure that captures the innovation similarity among industries. In light of previous studies (e.g., Jaffe, 1986; Bloom, Schankerman and Van Reenen, 2013), a higher innovation similarity predicts a lower likelihood of radical innovation in the industry and, hence, a lower likelihood of market leadership turnovers. Using the innovation similarity measure, as well as other industry characteristics, we construct an estimate of the turnover rate of market leaders based on a logistic regression, which is referred to as the *leadership turnover measure*.

We conduct our empirical analysis in three major steps as follows. First, we test the model’s predictions on profit margins and provide empirical support on our three main results. Particularly, we show that profit margins of more distressed industries are more exposed to discount-rate shocks. We also show that there exists a significant contemporaneous feedback between profit margin and financial distress in the data. Further, we provide evidence for financial contagion. By sorting the top firms within each industry into three groups based on their financial distress level, we find that adverse idiosyncratic shocks to the financially distressed group lead to lower profit margins of the financially healthy group, and that such within-industry spillover effect is more pronounced in the industries with higher entry costs or when the market shares of the two groups are more balanced. In addition, we provide evidence for the between-industry financial contagion effect for market leaders in two different industries which share common market leaders.

Second, we test the model’s asset pricing implications. We first provide empirical evidence that support the feedback and contagion effect on credit spreads. We then show the joint patterns of stock returns and credit spreads in the data. Specifically, industries with higher profitability are associated with higher average excess returns and risk-adjusted returns; on the contrary, these industries are associated with lower credit spreads. Consistent with the competition-distress feedback effect, these patterns are more pronounced among financially distressed industries. Further, we show that industries with higher market leadership persistence are associated with higher profitability, thereby having lower financial distress (lower credit spreads) and higher expected stock returns even after controlling for leverages. The “misalignment” of stock excess returns and bond credit spreads in the cross section seems puzzling in the canonical models (Merton, 1974;
but can be reconciled in our model based on the endogenous competition mechanism.

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

We exploit a widely-used empirical setting to introduce variation in the competitiveness of industry market structure. In particular, we follow the literature (Frésard, 2010; Valta, 2012; Frésard and Valta, 2016) and use unexpected large cuts in import tariffs to identify exogenous variation in market structure.\(^4\) 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 $\epsilon$ due to the similar products and services provided by foreign rivals and (ii) the number of market leaders $n$ due to the entry of foreign rivals as major players. Consistent with the implications of the model, we find that industries with high and low profitability industries display less difference in their exposure to discount rates and the within-industry financial contagion effect becomes weaker when these industries’ market structure becomes more competitive.

**Related Literature.** Our paper contributes to the growing literature on feedback effects between the capital markets and real economy. Understanding the feedback effects has become particularly relevant in the light of the recent financial crisis. There are two major classes of channels for the feedback effects — the fundamental-based and information-based channels. Seminal examples of the fundamental-based channel include Bernanke and Gertler (1989) and Kiyotaki and Moore (1997), demonstrating how adverse selection or moral hazard problems cause frictions for the firms to raise external funding. Particularly,

\(^4\)Many other papers in the literature use tariff cuts as shocks to the competitiveness of industry market structure to address endogeneity concerns (e.g., Xu, 2012; Flammer, 2015; Huang, Jennings and Yu, 2017; Dasgupta, Li and Wang, 2018).
when the financing constraint is price dependent, there is an adverse feedback loop: firms are more financially constrained and thus forced to reduce real investment and hiring, and this in turn makes firms more financially constrained. Dou et al. (2020b) provide a recent survey for this class of macro-finance models. As emphasized by Bond, Edmans and Goldstein (2012), the fundamental-based channel is about primary financial markets, and the feedback effect between secondary financial markets and real economy is also crucial yet mainly through the information-based channel (e.g., Chen, Goldstein and Jiang, 2006; Bakke and Whited, 2010; Edmans, Goldstein and Jiang, 2012). This paper introduces a novel fundamental-based feedback channel — the feedback effect between imperfect capital markets and imperfect product markets as a result of predation incentives and predation-like behavior (i.e. self-defense incentives).

Financial contagion also takes place through two major classes of channels — the fundamental-based and information-based channels (see Goldstein, 2013). The fundamental-based channel is through real linkages between economic entities, such as common (levered) investors (e.g., Kyle and Xiong, 2001; Kodres and Pritsker, 2002; Kaminsky, Reinhart and Végh, 2003; Martin, 2013; Gărleanu, 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 self-fulfilling beliefs (e.g., Goldstein and Pauzner, 2004). This paper proposes a novel product-market competition channel through which financial distress becomes contagious among product-market peers.

Our paper contributes to the large and growing literature on the structural model of corporate debt and default (see Merton, 1974; Leland, 1994, for the seminal benchmark framework). Sundaresan (2013) provides a comprehensive review on this literature. Particularly, Fischer, Heinkel and Zechner (1989), Leland and Toft (1996), Anderson and Sundaresan (1996), Goldstein, Ju and Leland (2001), DeMarzo and Sannikov (2006), Broadie, Chernov and Sundaresan (2007), and DeMarzo and Fishman (2007), among others, study dynamic theory of capital structure. Specifically, Hack Barth, Miao and Morellec (2006), Chen, Collin-Dufresne and Goldstein (2008), Bhamra, Kuehn and Strebfalae (2010a,b), Chen (2010), and Chen et al. (2018) focus on the impact of macroeconomic conditions on firms’ financing policies, credit risk, and asset prices. Further, Anderson and Carverhill (2012) and Bolton, Wang and Yang (2019) focus on the impact of financial flexibility on firms’ capital structure dynamics. Existing dynamic models of capital structure and credit risk typically assume that the product market offers exogenous cash flows unrelated to firms’ debt-equity positions or corporate liquidity conditions. Our model differs from those in this literature by explicitly considering an oligopoly industry in which firms’ strategic price competition generates endogenous cash flows. This allows us
to jointly study firms’ financial decisions in the financial market and their markup-setting decisions in the product market, as well as the interactions. Like ours, Brander and Lewis (1986) and Corhay (2017) also develop models in which firms’ cash flows are determined by strategic competition in the product market. Particularly, Corhay (2017) shows that more competitive industries (i.e., industries with more firms) are characterized by higher credit spreads, but lower expected equity returns. Our paper is different in the following aspects: (i) the core mechanism is different since we consider supergames and long-term debts, which allows us to investigate the feedback and contagion effects; (ii) we focus on different cross sections since the key industry characteristic we emphasize is not the number of firms per se rather the persistence of market leadership; (iii) we emphasize the endogenous competition-intensity risk driven by variations in aggregate discount rates, whereas Corhay (2017) emphasizes the entry risk over business cycles; (iv) our model has much richer and broader implications on asset prices and profit margins; and (v) we provide direct tests on the core competition mechanism in difference-in-difference designs by exploiting the unexpected large tariff cuts as instruments for exogenous shifts in the competitiveness of industries’ market structure.

Our paper is also related to the literature highlighting the importance of customer base in determining profit margins (e.g., Phelps and Winter, 1970; Rotemberg and Woodford, 1991, 1992; Ravn, Schmitt-Grohe and Uribe, 2006; van Binsbergen, 2016). In a seminal work, Ravn, Schmitt-Grohe and Uribe (2006) provide a microfoundation for customer market based on consumers’ deep habits, which can generate countercyclical markups. Our model differs from these models by focusing on oligopoly industries with endogenous leverage and default decisions – we emphasize the collusive equilibrium of dynamic strategic price competition and its interaction with firms’ financial conditions.

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

Our paper is also related to the burgeoning literature on how financial characteristics influence firms’ performance and decisions in the product market. In the early seminal works, Titman (1984) and Maksimovic and Titman (1991) study how capital structure affects a firm’s choice of product quality and the viability of its products’ warranties. Brander and Lewis (1986) focuses on the “limited liability” effect of short-term debt financing on product competition behavior. Bolton and Scharfstein (1990) show that financial constraints give rise to rational predation behavior. Jacob (1994) focuses on the role of long-term debt and shows that the accumulated profit is important in determining product market behavior. In Allen (2000), greater debt increases the probability of bankruptcy and liquidation which is costly, and thus, higher leverage will be associated with less aggressive product market behavior subsequently. Phillips (1995) empirically investigates whether a firm’s capital structure affects its own and its competitors’ output and product pricing decisions. Chevalier and Scharfstein (1996) and Gilchrist et al. (2017) show both in model and data that liquidity-constrained firms tend to set higher markups to increase their short-term cash flows. Hoberg and Phillips (2016) investigate how R&D expenses affect product market competition behavior, and Hackbarth and Taub (2018) study how M&A activities affect product market competition behavior. Banerjee et al. (2019) document evidence of rival firms conducting predatory advertising and predatory pricing (i.e., decrease in profit margins) when major firms commit financial frauds. They show that this effect is particularly stronger when the fraud firm has higher leverage and when the rival firms have lower leverage. Opp, Parlour and Walden (2014) and Dou, Ji and Wu (2020) show that the time-varying discount rates affect firms’ collusion incentive and thus their market power. Different from the existing works, our paper combines Brander and Lewis (1986) and Dou, Ji and Wu (2020), and then extends the hybrid to a dynamic Leland framework with long-term debt with endogenous default, customer base accumulation, and dynamic strategic competition allowing for collusive behavior.
2 The Baseline Model

We develop an industry-equilibrium model with supergames, long-term bonds, and time-varying risk premia. For simplicity, we assume that the industry has two firms (i.e., \( n = 2 \)), referred to as market leaders, indexed by \( i \in \{1, 2\} \) and many followers with measure zero; so each industry is essentially a duopoly. We label a generic leading firm by \( i \) and its competitor by \( j \). Essentially, our model extends that of Leland (1994) by incorporating Bertrand competition with tacit collusion.

2.1 Financial Distress

Financial Frictions. Firms are financed by debt and equity, and they issue long-term debt to take advantage of the tax shield but do not hold cash reserves, as in the standard Leland model. The corporate tax rate is \( \tau > 0 \). A levered firm first uses its cash flow to make interest payments, then pays taxes, and distributes the rest to equityholders as dividends. Equityholders have limited liability and the option to default: When internally generated cash cannot cover the interest expenses, the firm can costlessly issue equity to cover the shortfalls;\(^5\) but, if equityholders are no longer willing to inject more capital, the firm defaults and exits. In other words, if the equity value falls to zero, equityholders will choose to default and exit. Upon equityholders’ defaulting on the debt, the firm is liquidated or reorganized, and its debtholders would obtain a fraction \( \nu \) of the abandonment value (unlevered asset value). The bankruptcy loss incurred by the debtholders in the large cases is quite significant mainly due to the prolonged bankruptcy process (e.g., Dou et al., 2020a).\(^6\) This is the only financial friction in our model, as in the standard Leland model.

Cash Flows. The long-term debt is modeled as a consol bond, which promises perpetual coupon payments at rate \( b_i \) with \( i = 1, 2 \). This is a standard assumption in the literature (Leland, 1994; Duffie and Lando, 2001), which helps maintain a time-homogeneous setting. Thus, firm \( i \)'s flow intensity of earnings after interest expenses and taxes over \([t, t + dt]\) is

\[
\text{Earnings}_{i,t} = (1 - \tau) \left[ \Pi_{i,t} M_{i,t} - b_i \right],
\]

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

\(^5\)In a recent paper, Antill (2020) also finds large bankruptcy loss for US corporations.
where $M_{i,t}$ is the customer capital of the firm $i$, $\Pi_{i,t}$ is the profitability per unit of customer capital, and $M_{i,t}$ evolves as follows:

$$
\frac{dM_{i,t}}{M_{i,t}} = gd\tau + \varsigma dZ_t + \sigma_M dW_{i,t} - M_{i,t}dJ_{i,t}.
$$

The constant term $g$ in equation (2) captures customer base growth. The standard Brownian motion $Z_t$ captures economy-wide aggregate shocks. The standard Brownian motion $W_{i,t}$ captures idiosyncratic shocks to firm $i$’s customer base. The Poisson process $J_{i,t}$ with intensity $\lambda$ captures idiosyncratic jumps of firm $i$’s customer base, and upon the occurrence of jumps, the firm $i$ loses all the customer base and chooses to exit. These shocks are mutually independent.

**Stochastic Discount Factor (SDF).** Countercyclical risk premia are crucial for the Leland framework to quantitatively reconcile the low leverage, high credit spread, and low default frequency (e.g., Chen, Collin-Dufresne and Goldstein, 2008; Chen, 2010). Motivated by the previous studies, we directly specify the stochastic discount factor (SDF), denoted by $\Lambda_t$, for tractability. The SDF evolves as follows:

$$
\frac{d\Lambda_t}{\Lambda_t} = -r_f dt - \gamma_t dZ_t - \zeta dZ_{\gamma,t},
$$

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

$$
d\gamma_t = -\varphi(\gamma_t - \overline{\gamma})dt - \pi dZ_{\gamma,t} \text{ with } \varphi, \overline{\gamma}, \pi > 0.
$$

Our specification of time-varying discount rate $\gamma_t$ follows the literature on cross-sectional return predictability (e.g., Lettau and Wachter, 2007; Belo and Lin, 2012; Dou, Ji and Wu, 2020). We assume $\zeta > 0$ to capture the well-documented countercyclical price of risk. The primitive economic mechanism driving the countercyclical price of risk can be, for example, time-varying risk aversion, as in Campbell and Cochrane (1999). Therefore, our model is similar to Chen, Collin-Dufresne and Goldstein (2008), who show that the strongly countercyclical risk prices generated by the habit formation model (Campbell and Cochrane, 1999), combined with exogenously imposed countercyclical asset value default boundaries, can generate high credit spreads. However, by contrast, default boundaries are highly endogenous in our model due to the endogenous time-varying competition intensity.
Interpretation of Shocks. We have introduced all aggregate and idiosyncratic shocks in equations (2) and (3). We provide more economic interpretation here. First, the aggregate shock $Z_t$ can be interpreted as the aggregate demand shock. We introduce the aggregate shock mainly to ensure that variations in the aggregate discount rate $\gamma_t$ matter for valuation of firms’ cash flows and thus competition intensity variation. In other words, the aggregate demand shock $Z_t$ is needed for the discount-rate shock $Z_{\gamma,t}$ to have large impact on valuation and thus competition intensity. The discount rate $\gamma_t$ is the only aggregate state variable. Economic downturns in our model are characterized by those states with a high $\gamma_t$.

Second, the idiosyncratic shocks $W_{1,t}$ and $W_{2,t}$ can be interpreted as idiosyncratic demand (or “taste”) shocks. We introduce the idiosyncratic shock mainly for the following two reasons: (i) they are needed to quantitatively generate sizeable credit spreads given low leverage and low default frequency; and (ii) they are helpful for generating a non-degenerate cross-sectional distribution of customer base in the stationary equilibrium.

Third, the idiosyncratic jump shocks $J_{1,t}$ and $J_{2,t}$ play a crucial role in our theory. Idiosyncratic jump risk is shown to be useful to explain credit spreads. For example, in theory, incorporating idiosyncratic jumps leads to a better explanation for the level of credit spreads (e.g., Delianedis and Geske, 2001; Zhou, 2001), and in the data, some empirical findings suggest that the jump risk matters for credit spreads (e.g., Cremers, Driessen and Maenhout, 2008; Cremers et al., 2008; Zhang, Zhou and Zhu, 2009).

More importantly, we use the idiosyncratic jumps $J_{1,t}$ and $J_{2,t}$ to characterize the occurrence of leadership turnover in the industry. Market followers in an industry are constantly challenging and trying to replace the 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; instead, market leaders are replaced rapidly and disruptively (e.g., Christensen, 1997). For example, Apple and Samsung replaced Nokia and Motorola to become the leaders in the mobile phone industry over a very short period of time. The economy comprises a continuum of industries, and thus the firm-specific turnover event of market leaders (i.e., $d_{J_{i,t}} = 1$) is an idiosyncratic event to the representative investor. Particularly, upon such a change ($d_{J_{i,t}} = 1$), the existing market leader $i$ is replaced by a new market leader who used to be a follower.

The persistence of the position of market leaders, captured by $\lambda^{-1}$ in our model and the data, is significantly heterogeneous across industries.\footnote{See, e.g., Baldwin (1995), Geroski and Toker (1996), Caves (1998), Matraves and Rondi (2007), Sutton (2007), Bronnenberg, Dhar and Dubé (2009), and Ino and Matsumura (2012) for empirical evidence on the...} In this paper, we focus on the
ex-ante heterogeneity in market leadership persistence \( \lambda^{-1} \) as a crucial and fundamental industry characteristic across industries.

**Exit and Entry.** In our model, the market leader \( i \) can exit the industry in two ways, either exogenously or endogenously. On the one hand, the market leader \( i \) can be replaced by a new market leader who used to be a follower (i.e., \( dJ_{i,t} = 1 \)). On the other hand, the market leader \( i \) can choose optimally when to default and exit.

To maintain tractability, we assume that a new firm enters the industry only after an incumbent firm exits such that the number of firms stays exactly constant. This is inspired by the “return process” in Luttmer (2007) and the model with “exit and reinjection” in Miao (2005) and Gabaix et al. (2016). This is a commonly-adopted assumption in the industrial organization literature on oligopolistic competition and predation (e.g., Besanko, Doraszelski and Kryukov, 2014). This assumption can be interpreted as the reorganization of the old exiting firm. Essentially, this assumption implies that we always focus on the competition between the two top leaders in the industry.

In particular, upon an incumbent firm \( i \)’s exiting, a new entrant firm with initial customer base \( M_{new} = \kappa M_{j,t} > 0 \) with \( j \neq i \) and coupon rate \( b_{new} \) will enter the market, where \( b_{new} \) is chosen so that the initial debt-asset ratio, the market value of debt divided by the market value of assets, is set to be \( \ell_{new} \). The parameter \( \kappa > 0 \) captures the relative size of the new entrant firm and the non-exiting incumbent firm \( j \). Therefore, when one old firm exits and one new firm enters, the game of Bertrand duopolistic competition is “reset” to a new one. We highlight that the coefficient \( \kappa \) captures the entry threat (or entry bar) to the market leaders of the industry: A higher \( \kappa \) implies that the incumbent market leader faces a greater entry threat.

### 2.2 Product Market Competition

The setup in Section 2.1 almost follows the standard model of Leland (1994), except that the profitability per unit of customer base \( \Pi_{i,t} \) would be determined endogenously in our model through strategic competition. In this section, we shall elaborate in detail on how the endogenous profitability \( \Pi_{i,t} \) would be generated from the tacit collusion and endogenous variation in competition intensity.

**Demand System for Differentiated Products.** We first introduce the demand system for differentiated products within an industry. We assume that firms within the same significant heterogeneity of \( \lambda \).
industry produce differentiated products. To model product differentiation, we assume that consumers derive utility from purchasing a basket of differentiated goods with imperfect substitution. We assume that the industry-level consumption index by $C_t$ is determined by a Dixit-Stiglitz constant-elasticity-of-substitution (CES) aggregation:

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

where $C_{i,t}$ is the amount of firm $i$’s products purchased by consumers, and the parameter $\eta > 1$ captures the elasticity of substitution among goods produced by different firms in the same industry. Further, we assume that consumer’s utility is monotonic. The weight $M_{i,t}/M_t$ captures consumers’ relative taste for firm $i$’s products.

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

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

The demand for firm $i$’s goods $C_{i,t}$ increases with $M_{i,t}$ in equilibrium, all else unchanged. From a firm’s perspective, it is natural to think of consumers’ taste $M_{i,t}$ as firm $i$’s customer base (or customer capital) and $M_t$ as the industry’s total customer base (e.g., Gourio and Rudanko, 2014; Dou et al., 2019). The share $M_{i,t}/M_t$ is the customer base
share of firm $i$, and firm $i$ has a greater influence on the price index $P_t$ when it possesses a larger share of the customer base $M_{i,t}/M_t$ (see equation (6)).

To characterize how the aggregate demand $C_t$ depends on the price index $P_t$ at the industry level, we follow the seminal works on industry dynamics by Hopenhayn (1992), Pindyck (1993), and Caballero and Pindyck (1996), postulating an isoelastic industry demand curve:

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

where $M_t$, as defined in equation (5), is an endogenous stochastic process that captures the total customer base of the industry. The coefficient $\epsilon > 1$ captures the industry’s price elasticity of demand. A common micro-foundation for such an isoelastic industry demand curve is that a continuum of industries exist in the economy producing differentiated industry-level baskets of goods, with the elasticity of substitution across industries being $\epsilon$ and the preference weight for an industry’s goods equal to its customer base $M_t$.\[^8\]

We assume that $\eta \geq \epsilon > 1$, meaning that products within the same industry are more substitutable. For example, the elasticity of substitution between the Apple iPhone and the Samsung Galaxy is much higher than that between a cell phone and a cup of coffee.\[^9\]

The short-run price elasticity of demand for product $j$, taking into account the externality, is

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

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

$$\mu_{i,t} = \frac{P_{i,t} C_{i,t}}{P_t C_t} = \left( \frac{P_{i,t}}{P_t} \right)^{1-\eta} \frac{M_{i,t}}{M_t}.$$ \hspace{1cm} (8)

The short-run price elasticity of demand is given by a weighted average of $\eta$ and $\epsilon$, 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 heavily on $\eta$. In the extreme case where $\mu_{i,t} = 0$, firm $i$ becomes atomistic and takes the industry price index $P_t$ as given. As a result, firm $i$’s

\[^8\] 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).

\[^9\] This assumption is consistent with the literature (e.g., Atkeson and Burstein, 2008; Corhay, Kung and Schmid, 2017; Dou, Ji and Wu, 2020).
price elasticity of demand is exactly \( \eta \). 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 strongly on \( \epsilon \). In the extreme case where \( \mu_{i,t} = 1 \), firm \( i \) monopolizes the industry, and its price elasticity of demand is exactly \( \epsilon \).

**Endogenous Profitability.** Firms’ equityholders choose production, profit margins, and default decisions optimally to maximize their market equity value. The marginal cost for a firm to produce a flow of goods is \( \omega \) with \( \omega > 0 \). That is, when firm \( i \) produces goods at rate \( Y_{i,t} \), its total costs of production are \( \omega Y_{i,t} dt \) over \([t, t + dt]\).

**Proposition 2.1.** In equilibrium, the firm finds it optimal to choose \( P_{i,t} > \omega \) and produce goods to exactly meet the demand, i.e., \( Y_{i,t} = C_{i,t} \).

Denote by \( \theta_{i,t} \) and \( \theta_t \) the firm-level and industry-level profit margins, defined as follows:

\[
\theta_{i,t} \equiv \frac{P_{i,t} - \omega}{P_{i,t}} \quad \text{and} \quad \theta_t \equiv \frac{P_t - \omega}{P_t}.
\]

(9)

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

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

(10)

Firm \( i \)'s operating profits per customer base depend on both its own and its competitor’s profit margin decisions:

\[
\Pi_i(\theta_{i,t}, \theta_{j,t}) \equiv (P_{i,t} - \omega) C_{i,t} / M_{i,t} = \omega^{1-\epsilon} \theta_{i,t} (1 - \theta_{i,t})^{\eta - 1} (1 - \theta_t)^{\epsilon - \eta}.
\]

(11)

Equation (11) shows that the profitability per unit of customer base of firm \( i \), in equation (1), depends on its competitor \( j \)'s profit margin \( \theta_{j,t} \) through the industry’s profit margin \( \theta_t \). This reflects the externality of firm \( j \)'s 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 \( \theta_t \) will drop, which will reduce the demand for firm \( i \)'s goods \( C_{i,t} \) (see equation (6)), and in turn firm \( i \)'s profits \( \Pi_i(\theta_{i,t}, \theta_{j,t}) \). Therefore, when the competitor \( j \) sets a lower profit margin \( \theta_{j,t} \), firm \( i \) will also be motivated to lower its own profit margin \( \theta_{i,t} \) in order to maintain the demand for its goods. As a result, the two firms’ profit-margin setting decisions exhibit strategic complementarity in equilibrium.

Therefore, the cash flow in (1) can be rewritten as

\[
\text{Earnings}_{i,t} = (1 - \tau) \left[ \Pi_i(\theta_{i,t}, \theta_{j,t}) M_{i,t} - b_i \right],
\]

(12)
which is determined by the competitors’ optimal profit margin choice $\theta_{i,t}$ and $\theta_{j,t}$. As we emphasized above, this is the key deviation from the standard Leland model. Below we illustrate how firms optimally choose profit margins and default.

2.3 Nash Equilibrium

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

Subgame Perfect Nash Equilibrium. The two firms in an industry play a supergame (Friedman, 1971), in which the stage games of setting profit margins are played continuously and repeated infinitely with exogenous and endogenous state variables varying over time. Formally, a subgame perfect Nash equilibrium for the dynamic game consists of a collection of profit-margin strategies that constitute a Nash equilibrium for every history of the game. We do not consider all such equilibria; instead, we only focus on those which allow for collusive arrangements enforced by punishment schemes. All strategies are allowed to depend upon both “payoff-relevant” states $x_t = \{M_{1,t}, M_{2,t}, \gamma_t\}$ in state space $\mathcal{X}$, as in Maskin and Tirole (1988a,b), and a set of indicator functions that track whether any firm has previously deviated from a collusive profit-margin agreement, as in Fershtman and Pakes (2000, Page 212). Thus, the industry’s state is the vector of firms’ payoff-relevant states $x_t = \{M_{1,t}, M_{2,t}, \gamma_t\}$.

In particular, there exists a non-collusive equilibrium, which is the repetition of the one-shot Nash equilibrium and thus is Markov perfect. Meanwhile, multiple subgame perfect collusive equilibria also exist in which profit-margin strategies are sustained by conditional punishment strategies.\footnote{For notational simplicity, we omit the indicator states of historical deviations.}

Non-Collusive Equilibrium with Endogenous Default Boundaries. The non-collusive equilibrium is characterized by profit-margin scheme $\Theta^N(.) = (\theta^N_1(.), \theta^N_2(.))$, 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 equity value $V^N_{i,t} \equiv V^N_i(x_t)$, under the assumption that its competitor $j$ will set the one-shot Nash-equilibrium profit margin $\theta^N_{j,t} \equiv \theta^N_j(x_t)$. Following \footnote{In the industrial organization and macroeconomics literature, this equilibrium is called the collusive equilibrium or collusion (see, e.g., Green and Porter, 1984; Rotemberg and Saloner, 1986). Game theorists generally call it the equilibrium of repeated game (see Fudenberg and Tirole, 1991) in order to distinguish it from the one-shot Nash equilibrium (i.e., our non-collusive equilibrium).}
the recursive formulation in dynamic games for characterizing the Nash equilibrium,\textsuperscript{12} optimization problems can be formulated recursively by the coupled pair of Hamilton-Jacobi-Bellman (HJB) equations:

\[
\lambda V^N_i(x_t)dt = \max_{\theta_{i,t}} (1 - \tau)[\Pi_i(\theta_{i,t}, \theta^N_{j,t})M_{i,t} - b_i]dt + \Lambda_i^{-1}E_t\left[d(\Lambda_t V^N_i(x_t))\right],
\]

with \(i = 1, 2\). The left hand side \(\lambda V^N_i(x_t)dt\) is the expected loss of equity value due to disruption, while the right hand side is the expected gain of equityholders if disruption does not occur over \([t, t + dt]\). The solutions to the coupled HJB equations give the non-collusive-equilibrium profit margin \(\theta^N_{i,t} \equiv \theta^N_i(x_t)\) with \(i = 1, 2\).

Firm \(i\)'s endogenous default boundary in the non-collusive equilibrium, which is in terms of its customer base, is denoted by \(M^N_{i,t} \equiv M^N_i(M_{j,t}, \gamma_t)\). At the optimal default boundary, the equity value of firm \(i\) is equal to zero (the value matching condition) and the boundary is optimal in terms of maximizing the equity value (the smooth pasting condition):

\[
V^N_i(x_t)\bigg|_{M_{i,t} = M^N_{i,t}} = 0 \quad \text{and} \quad \frac{\partial}{\partial M_{i,t}} V^N_i(x_t)\bigg|_{M_{i,t} = M^N_{i,t}} = 0, \quad \text{respectively.} \quad (14)
\]

The boundary condition at \(M_{i,t} = +\infty\) is given and explained by Appendix A.4 in detail. Intuitively, firm \(i\) is essentially a monopoly in the industry with negligible default risk because its competitor \(j\) is negligible for any value of \(M_{j,t}\).

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

Consider a generic collusive equilibrium in which the two firms follow a collusive profit-margin scheme. Both firms can costlessly observe the other’s profit margin, so that deviation can be detected and punished. The assumption of perfect information follows the literature.\textsuperscript{13} In particular, if one firm deviates from the collusive profit-margin scheme, then with probability \(\xi dt\) over \([t, t + dt]\) the other firm will implement a punishment


\textsuperscript{13}A few examples include Rotemberg and Saloner (1986), Haltiwanger and Harrington (1991), Staiger and Wolak (1992), and Bagwell and Staiger (1997).
strategy in which it will forever set the non-collusive profit margin. Entering the non-collusive equilibrium is considered as the punishment for the deviating firm, because the industry will switch from the collusive to the non-collusive equilibrium featuring the lowest profit margin.\(^{14}\) We use the idiosyncratic Poisson process \(N_{i,t}\) to characterize whether a firm can successfully implement a punishment strategy. One interpretation of \(N_{i,t}\) is that, with \(1 - \xi dt\) probability over \([t, t + dt]\), the deviator can persuade its competitor not to enter the non-collusive Nash equilibrium over \([t, t + dt]\).\(^{15}\) Thus, the punishment intensity \(\xi\) can be viewed as a parameter governing the credibility of the punishment for deviating behavior. A higher \(\xi\) leads to a lower deviation incentive.

Formally, the set of incentive-compatible collusion agreements, denoted by \(C\), consists of all continuous profit-margin schemes \(\Theta_C(\cdot) \equiv (\theta^{C}_1(\cdot), \theta^{C}_2(\cdot))\), such that the following participation constraints (PC) and incentive compatibility (IC) constraints are satisfied:

\[
\begin{align*}
V^N_i(x) &\leq V^C_i(x), \quad \text{for all } x \in X \text{ and } i = 1, 2; \quad \text{(PC constraints)} \quad (15) \\
V^D_i(x) &\leq V^C_i(x), \quad \text{for all } x \in X \text{ and } i = 1, 2. \quad \text{(IC constraints)} \quad (16)
\end{align*}
\]

Here, \(V^N_i(x)\) is firm \(i\)'s equity value in the non-collusive equilibrium, \(V^D_i(x)\) is firm \(i\)'s equity value if it chooses to deviate from the collusion, and \(V^C_i(x)\) is firm \(i\)'s equity value in the collusive equilibrium, pinned down recursively according to

\[
\lambda V^C_i(x)dt = (1 - \tau) [\Pi_i(\theta^{C}_i(x_i), \theta^{C}_j(x_j)) M_{i,t} - b_i]dt + \Lambda_i^{-1} E_t \left[ d(\Lambda_t V^C_i(x_i)) \right],
\]

subject to the PC and IC constraints in equations (15) and (16), where \(\theta^{C}_i(x)\) with \(i = 1, 2\) are the collusive profit margins. The left hand side \(\lambda V^C_i(x)dt\) is the expected loss of equity value due to disruption, while the right hand side is the expected gain of equityholders if disruption does not occur in the next instant \(dt\). Obviously, the equilibrium recursive relation in equation (17) only holds within the non-default region, characterized by \(M_{i,t} > M^C_{i,t} \equiv M^C_i(M_{j,t}, \gamma_t)\) where \(M^C_{i,t}\) is firm \(i\)'s default boundary in the collusive equilibrium. The value matching and smooth pasting conditions for the

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\(^{14}\)We adopt the non-collusive equilibrium as the incentive-compatible punishment for deviation, which follows the literature (see, e.g., Green and Porter, 1984; Rotemberg and Saloner, 1986). We can extend the setup to allow for finite-period punishment. The quantitative implications are not altered significantly provided that the punishment lasts long enough.

\(^{15}\)Ex-post renegotiations can occur because the non-collusive equilibrium is not renegotiation-proof or “immune to collective rethinking” (see Farrell and Maskin, 1989). The strategy we consider is essentially a probabilistic punishment strategy. This “inertia assumption” also solves the technical issue of continuous-time dynamic games about indeterminacy of outcomes (see, e.g., Simon and Stinchcombe, 1989; Bergin and MacLeod, 1993).
optimal default boundary are

\[ V^C_i(x_t) \bigg|_{M_{i,t} = M^D_{i,t}} = 0 \quad \text{and} \quad \frac{\partial}{\partial M_{i,t}} V^C_i(x_t) \bigg|_{M_{i,t} = M^D_{i,t}} = 0, \quad \text{respectively.} \quad (18) \]

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

**Equilibrium Deviation Values.** Let \( V^D_i(x_t) \equiv V^D_i(x_t) \) be firm \( j \)'s highest equity value if it deviates from implicit collusion. The highest deviation value evolves as follows:

\[
\lambda V^D_i(x_t) dt = \max_{\theta_i,t} \left( \Pi_i(\theta_i,t, \theta^C_j, M_{i,t}) - b_i \right) dt - \xi \left( V^D_i(x_t) - V^N_i(x_t) \right) dt + \Lambda_t^{-1} \mathbb{E}_t \left[ d(\Lambda_t V^D_i(x_t)) \right],
\]

for \( i = 1, 2 \). The left hand side \( \lambda V^D_i(x_t) dt \) is the expected loss of equity value due to disruption, while the right hand side is the expected gain of equityholders if disruption does not occur in the next instant \( dt \). The equilibrium recursive relation characterized by the coupled equations above only hold within non-default region, characterized by \( M_{i,t} > M^D_{i,t} \equiv M^D_i(M_{j,t}, \gamma_t) \) where \( M^D_{i,t} \) is firm \( i \)'s default boundary if it chooses to deviate from the collusion. The value matching and smooth pasting conditions for the optimal default boundary are

\[ V^D_i(x_t) \bigg|_{M_{i,t} = M^D_{i,t}} = 0 \quad \text{and} \quad \frac{\partial}{\partial M_{i,t}} V^D_i(x_t) \bigg|_{M_{i,t} = M^D_{i,t}} = 0, \quad \text{respectively.} \quad (20) \]

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

**More Discussions.** Several points are worth mentioning. First, the equity value in the collusive equilibrium may be equal to that in the non-collusive equilibrium, i.e., the PC constraints (15) are binding. When one firm’s PC constraint starts to bind, the two firms switch to the non-collusive equilibrium. The endogenous switch to the non-collusive equilibrium captures endogenous price wars, which we illustrate in Subsection 3.3. We assume that once the two firms switch to the non-collusive equilibrium, they will stay
The endogenous equilibrium switching is our model’s key difference from that of Dou, Ji and Wu (2020), in which firms finance only by issuing equity and never suffer from financial distress. In their model, the PC constraints for profit-margin collusion are always not binding since higher profit margins always lead to higher equity value without default or exit.

Second, there exist infinitely many elements in $\mathcal{C}$ and hence infinitely many collusive equilibria. We focus on a subset of $\mathcal{C}$, denoted by $\overline{\mathcal{C}}$, consisting of all profit-margin schemes $\Theta_i^C(\cdot)$ such that the IC constraints (16) are binding state by state, i.e., $V_i^D(x_t) = V_i^C(x_t)$ for all $x_t \in \mathcal{X}$ and $i = 1, 2$. It is obvious that the subset $\overline{\mathcal{C}}$ is nonempty since it contains the profit-margin scheme in the non-collusive Nash equilibrium. We further narrow our focus to the “Pareto-efficient frontier” of $\overline{\mathcal{C}}$, denoted by $\overline{\mathcal{C}}_p$, consisting of all pairs of $\Theta_i^C(\cdot)$ such that there does not exist another pair $\tilde{\Theta}_i^C(\cdot) \in \overline{\mathcal{C}}$ with $\tilde{\theta}_i(x_t) \geq \theta_i^C(x_t)$ for all $x_t \in \mathcal{X}$ and $i = 1, 2$, and with strict inequality holding for some $x_t$ and $i$. Our numerical algorithm follows a method similar to that of Abreu, Pearce and Stacchetti (1990). Deviation never occurs on the equilibrium path. Using the one-shot deviation principle (Fudenberg and Tirole, 1991), it is clear that the collusive equilibrium characterized above is a subgame perfect Nash equilibrium.

**Debt Value.** We derive the levered equity value, together with the optimal profit margins and default boundaries, in the collusive Nash equilibrium above. Now, we can directly calculate the value of corporate debt. Debt value equals the sum of the present value of the cash flows that accrue to debtholders until the default time or the replacement time by market followers, whichever is earlier, and the change in this present value that arises in default or replacement. Since the latter component depends on the firm’s abandonment value, we start by deriving this value below.

We set the abandonment value to be zero for disruption-driven exits because being replaced by market followers reflects economic distress. We set the abandonment value

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

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

18 It can be shown that the “Pareto-efficient frontier” is nonempty based on the fundamental theorem of the existence of Pareto-efficient allocations (see, 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.

19 Alternative methods include Cronshaw and Luenberger (1994), Pakes and McGuire (1994), and Judd, Yeltkin and Conklin (2003), which contain similar ingredients to those of our solution method. Proving the uniqueness of the equilibrium under our selection criterion is beyond the scope of the paper. We use different initial points in our numerical algorithm and find robust convergence to the same equilibrium.
to be a fraction \( \nu \) of the value of unlevered assets \( A^C_i(x_t) \) for default-driven exits, which are caused by financial distress. This assumption follows the literature on dynamic debt models (e.g., Mello and Parsons, 1992; Leland, 1994; Hackbarth, Miao and Morellec, 2006). The unlevered-asset value \( A^C_i(x_t) \) is the value of an all-equity firm. In the collusive equilibrium, the unlevered asset value \( A^C_i(x_t) \) is determined similarly by equations (13) – (20) except for setting \( b_i = 0 \) and removing the default boundary conditions (14), (18), and (20).

The value of debt in the collusive equilibrium, denoted by \( D^C_i(x_t) \), can be characterized as follows. In the non-default region (i.e., \( M_{i,t} > M^C_{i,t} \)), the debt value is given by the following coupled HJB equation:

\[
\lambda D^C_i(x_t) dt = \frac{b_i dt}{\text{coupons}} + \Lambda_i^{-1} \mathbb{E}_t \left[ d(\Lambda_i D^C_i(x_t)) \right], \quad \text{for } i = 1, 2, \tag{21}
\]

with boundary conditions:

\[
D^C_i(x_t) \bigg|_{M_{i,t}=M^C_{i,t}} = \nu A^C_i(x_t) \bigg|_{M_{i,t}=M^C_{i,t}} \quad \text{and} \quad \lim_{M_{i,t} \to +\infty} D^C_i(x_t) = \frac{b_i}{r_f}, \quad \text{for } i = 1, 2. \tag{22}
\]

The left hand side of (21) is the expected loss of debt due to disruption, while the right hand side is the expected gain of the debtholders if the disruption does not occur in the next instant \( dt \). The first condition in equation (22) is the liquidation payoff to the debtholders at the default boundary, and the second condition in equation (22) captures the asymptotic behavior of debt value when customer base \( M_{i,t} \) approach to infinity, which is basically the value of a default-free consol bond with constant coupon rate \( b_i \).

### 3 Main Theoretical Results

Our model has the following main theoretical results. First, there exists a positive feedback loop between competition and financial distress as a firm’s financial condition becomes worse, it becomes more impatient and thus competes more aggressively; further, the intensified competition narrows profit margins for every firm, which in turn elevates the level of financial distress and default risk. The feedback effect largely amplifies the industry’s risk exposure to aggregate discount-rate shocks.

Second, strategic and distressed competition in the product markets leads to financial contagion. For example, a negative idiosyncratic shock hitting one leading firm may

\[20\] The exact and detailed solution for the value of all-equity firms can be found in Dou, Ji and Wu (2020).
intensify competition within the industry, resulting in lower profit margins and higher
default risk for all firms. Such financial contagion effects are more pronounced in
industries where market leaders have more balanced market shares.

Third, depending on the heterogeneity in market shares between incumbent firms and
new entrants (i.e., the entry threat), firms can also exhibit strategic behavior including pre-
dation (price war) and collaboration. Our calibrated model can quantitatively characterize
the cases in which predatory price war can endogenously arise from financial distress
shocks to the competitors and collaboration can take place to protect the distressed
incumbent competitor to prevent a more threatening potential entrant from entering the
industry as a new market leader. Our quantitative model can also isolate and quantify
a firm’s predatory incentives by decomposing the equilibrium product-market pricing
conditions, similar to Besanko, Doraszelski and Kryukov (2014).

Finally, we discuss the core competition mechanism under various market structure.
We show that the cross-industry difference in profit-margin sensitivity to discount rates
and the within-industry contagion effect are smaller when industries’ market structure
becomes more competitive. These implications lay the foundations for directly testing the
core competition mechanism by exploiting the exogenous variation in competitiveness of
market structure in Section 5.4.

### 3.1 Feedback between Competition and Distress

**Profit Margins and Default Boundaries.** To fix ideas, consider a duopoly industry with
two identical firms. Panel A of Figure 4 plots the industry’s profit margin as a function
of firms’ average customer base. The industry has higher profit margins in the collusive
equilibrium (the blue solid line) than in the non-collusive equilibrium (the red dotted
line). Moreover, compared to an industry of monopolistic competition with a continuum
of firms (the black dashed line), firms in the duopoly industry have higher profit margins.
Intuitively, firms’ profit margins reflect the competition intensity they face in the product
market. Higher competition intensity effectively means a higher price elasticity of
demand, which results in lower equilibrium profit margins. The lower profit margins in
turn increase the probability of default.

As shown by the vertical lines in the figure, firms’ default boundary in the collusive
equilibrium are lower than that in the non-collusive equilibrium of the duopoly industry,

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21 We consider identical firms for illustration purposes because it implies that the industry’s profit
margin and financial distress is the same as each firm’s profit margin and financial distress. The feedback
mechanism also exists when firms are assymmetric.
Note: We consider a duopoly industry with two identical firms (i.e., $M_i = M_j$). The blue solid and red dotted lines in panel A plots the duopoly industry’s profit margin $\theta_t$ as a function of firms’ average customer base. The black dashed line plots the profit margin of an industry of monopolistic competition where a continuum of firms exists. We use $\gamma_t = \gamma$ in panel A. Panel B plots the same duopoly industry’s profit margin $\theta_t$ for different aggregate states $\gamma_t$. The blue solid and black dashed lines represent a low $\gamma_t = \gamma_L$ and a high $\gamma_t = \gamma_H$ in the collusive equilibrium. The red dotted dash-dotted line represents the non-collusive equilibrium with $\gamma_t$. In panel B, we set $\gamma_L = \gamma$ and $\gamma_H = \gamma + 2\text{std}(\gamma_t)$. Panel C plots the profit-margin beta to $\gamma_t$ defined in equation (23). The blue solid and red-dotted lines represent collusive and non-collusive equilibria respectively. In all panels, the vertical dotted lines represent firms’ default boundaries in respective cases. Other parameters are set according to our calibration in Section 6.1.

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

which are lower than that in the industry of monopolistic competition (i.e., $M_{i,t}^M > M_{i,t}^N > M_{i,t}^C$). This implies that financial distress becomes worse with increased competition intensity, because undercutting profit margins erodes firms’ cash flows.

More important, Panel A of Figure 4 shows that, different from the non-collusive case (the red dotted line) and the monopolistic competitive case (the black dashed line), the profit margin of the collusive case (the blue solid curve) is endogenously decreasing as financial distress becomes worse (i.e., as the average customer base decreases with coupon fixed), which is caused by the competition-distress feedback. The blue solid line in panel A shows that the profit margin decreases when the industry becomes more financially distressed (i.e., when firms’ average customer base decreases). This indicates that financial distress leads to more competition and lower 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 collusive profit-margin-setting schemes, firms can obtain higher contemporaneous cash flows; however, firms run into the risk of losing future cash flows because once the deviation is punished by the other firm, the non-collusive equilibrium will be implemented. When firms are closer to the default boundary, they are more likely to exit the market in the near future due to the higher probability of default. As a result, firms become effectively more impatient and value their cash flows in the short run more than those in the long run. This motivates firms to undercut their competitors’ profit margins. Thus, if the two firms were to maintain the collusive equilibrium, the mutually agreed profit margins must fall
when firms are more distressed to ensure that deviation does not occur in equilibrium (i.e., the IC constraints are satisfied). Thus, increased financial distress would generate lower profit margins and intensify competition.

Our idea echoes and formalizes the important generic insight of Maskin and Tirole (1988a) and Fershtman and Pakes (2000): the tacit collusion among oligopolists arises in industries where each firm expects others to remain in the market for a long time; but if firms are more likely to exit the market in the future, the incentive for collusive behavior becomes weaker. Taken together, panel A of Figure 4 implies a positive feedback loop between competition and financial distress.22

Profit-Margin Exposure to Discount-Rate Shocks. In the rest of this section, we focus on the collusive equilibrium where interesting dynamics of strategic competition are present. Dou, Ji and Wu (2020) show that high discount rates lead to high competition intensity in industries. We make a further point by showing that high discount rates lead to a larger increase in competition intensity of financially distressed industries, owing to the positive feedback loop between competition and financial distress. In other words, our model implies that the profit margin of more financially distressed industries is more exposed to discount-rate shocks (i.e., \( dZ_{\gamma_t} \) in equation 4).

To illustrate this idea, panel B of Figure 4 plots the duopoly industry’s profit margin in the collusive equilibrium in the state with a low discount rate \( \gamma_L \) (the blue solid line) and a high discount rate \( \gamma_H \) (the black dashed line). It is shown that the industry’s profit margin is lower when the discount rate is higher.23 This is because a higher discount rate \( \gamma_H \) makes firms more impatient and focus more on short-term cash flows. As a result, future punishment becomes less threatening and higher profit margins are more difficult to be sustained.24

22 By contrast, there is no feedback look in the non-collusive equilibrium or (the red dotted line in panel A) or in the industry of monopolistic competition (the black dashed line in panel A). In these two cases, the industry’s profit margin is flat regardless of the average customer base of firms within the industry. This is because in both cases, the intensity of competition is exogenously determined by the price elasticity of demand. Thus, by definition, there is no feedback effect from financial distress on competition intensity.

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, and instead they enter into a price war until only one firm in the industry is alive. This is not the case under our baseline calibration because we assume that new firms enter the industry when existing firms exit after default.

24 By contrast, in the non-collusive equilibrium, profit margins remain almost unchanged when the discount rate rises (see the red-dotted line) because competition intensity is exogenously determined by the price elasticity of demand, which does not vary with \( \gamma_t \). For clarity, we only draw the non-collusive profit margin in the state with a low discount rate \( \gamma_L \) in panel B of Figure 4, which is slightly different from the profit margin in the state with a high discount rate \( \gamma_H \), reflecting the change in firms’ incentive in accumulating customer base.
We measure the sensitivity of profit margins to discount rates using the industry-level profit-margin beta $\beta^\theta_t$, defined by the ratio of industry-level profit margins between the two aggregate states:

$$\beta^\theta_t \equiv \frac{\theta^C_t(\gamma_H)}{\theta^C_t(\gamma_L)} - 1. \quad (23)$$

The blue solid line in panel C of Figure 4 shows that in the collusive equilibrium, the profit-margin beta becomes more negative when the industry becomes more financially distressed. In particular, when the industry is close to the default boundary, the profit-margin beta is as large as $-0.3$, indicating that the industry’s profit margin decreases by 30% in responding to a rise in the discount rate.

The significant comovement between profit margins and discount rates implies that a higher discount rate depresses the industry’s value not only through the standard discounting effect but also by reducing profit margins due to higher competition. The endogenously intensified competition is further amplified by the feedback loop between competition and financial distress, dramatically increasing the industry’s equity and debt exposure to discount-rate shocks, especially when the industry is financially distressed. We illustrate the amplification effect on industry risk exposure in Appendix A.1.

### 3.2 Financial Contagion

In this subsection, we show that there is financial contagion among firms within the same industry: negative firm-specific shocks hitting one firm may increase both firms’ default risk. To elaborate on the financial contagion effect, panels A and B of Figure 5 plot the two firms’ profit margins as a function of firm $i$’s customer base $M_{i,t}$, given firm $j$’s customer base fixed at $M_{j,t} = 2$. The blue solid line in panel A shows that firm $i$ reduces its profit margin when it becomes more financially distressed (i.e., $M_{i,t}$ decreases) due to negative firm-specific shocks (i.e., $dW_{i,t}$ in equation (2)). Moreover, its financially strong competitor, firm $j$, also lowers its profit margin (see the blue solid line in panel B) even though firm $j$’s customer base $M_{j,t}$ remains unchanged.

The peer firm $j$’s profit-margin undercutting is mainly due to its self-defensive incentives. Intuitively, firm $j$ has the self-defensive incentive because it knows that the financially weak firm $i$ will cut its profit margin to steal customers (see the blue solid line in panel A). The intention of setting a lower profit margin is partly to prevent its financially weak competitor from stealing demand. To be more specific, if firm $j$ were...
Note: Panels A and B plot the profit margins of firm i and j as a function of firm i’s customer base $M_i$. The blue solid and red dotted lines represent the collusive equilibrium and the non-collusive equilibrium in our calibrated industry. The vertical dotted lines represent default boundaries of firm i in respective cases. We set $\gamma_t = \gamma_f$ and $M_j = 2$. Panels C – F illustrate the IRF of profit margins and default rates after a negative idiosyncratic shock to firm i’s customer base. The black dashed lines plot the benchmark case without aggregate or idiosyncratic shocks for both firms. The blue solid lines plot the IRF when there is an unexpected idiosyncratic shock at $t = 1$, which reduces firm i’s customer base by 50%, from $M_i$ to $M_i / 2$. We set $M_i,0 = M_j,0 = 1$ and $\gamma_t = \gamma_f$. Other parameters are set according to our calibration in Section 6.1.

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

to keep its profit margin unchanged, its financially weak competitor, firm i, will deviate from the collusive equilibrium by significantly undercutting the profit margin. To prevent firm i from deviating, firm j has to cut its own profit margin, which itself is an optimal response to increased financial distress of firm i.

To better illustrate the contagious effect, panels C – F of Figure 5 plot the two firms’ impulse response functions (IRF) of profit margins and 10-year default rate after a negative shock to firm i’s customer base. In panels C and E, the blue solid lines plot the IRF of margins are increasing in their own customer base and deceasing in their competitor’s customer base. This is because non-collusive profit margins are one-shot Nash equilibrium outcomes. When customer base is sticky (i.e., small $\alpha$), firms’ non-collusive profit margins simply reflect the short-run price elasticity of demand they face. As shown by equation (8), a firm’s short-run price elasticity of demand decreases with its customer base share, and thus a larger customer base share leads to a lower elasticity and a higher non-collusive profit margin.
Figure 6: Financial contagion in industries with different distribution of customer base.

In Figure 6, we further study how the relative size of the two firms in the industry affect the financial contagion effect. In particular, we consider industries with different initial distribution of customer base in panels A, B, and C. For the same shock to firm i’s customer base at $t = 1$, the negative impact on firm j’s profit margin is the largest when the two firms’ customer base is comparable (panel A), and the impact becomes smaller when their customer base is more different (panels B and C). Intuitively, when the two firms have similar customer base, both firms have large influence on the industry’s price index through equation (6). This generates stronger strategic concerns in profit-margin decisions as both firms know that the industry’s price index is sensitive not only to their own profit margins but also to their competitor’s profit margins. As a result, a change in one firm’s financial condition would generate a larger impact on the other firm’s profit.
margins.

By contrast, when the two firms’ customer base is more different, both firms would have less strategic concerns. On the one hand, the small firm knows that it has less impact on the industry’s price index, and thus it optimally chooses not to respond much to the big firm’s financial conditions. On the other hand, the big firm knows that the small firm has less impact on the industry’s price index, and thus it does not care too much about how the small firm behaves. Therefore, in industries with more unbalanced distribution of customer base, both the small and the big firms’ profit margins reflect more about their own financial conditions rather than their competitors’ financial conditions due to less strategic concerns.

3.3 Self-defense, Predation, and Collaboration

Although we focus on the self-defense incentive of peers in the contagion effect, we emphasize that our model can also generate a rich set of strategic competitive behavior depending on the relative size of incumbent firms and new entrants, which is determined by the parameter $\kappa$. Recall that when firm $i$ defaults, a new entrant with initial customer base $M_{new} = \kappa M_{j,t}$ immediately enters the market. A smaller value of $\kappa$ implies that the industry has a lower level of entry barrier for market leaders. While our benchmark calibration focuses on average industries with $\kappa = 0.3$ (see Section 6.1 for our calibration), we illustrate two extreme industries with $\kappa = 0$ and $\kappa = 3$, representing an industry with extremely high entry and low entry barrier for 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 (see panels A and B of Figure 5) due to the lack of collusion. Intuitively, both firms know that by driving their competitor 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. Even more dramatically, the two firms abandon collusion when firm $i$’s customer base $M_{i,t}$ drops below 0.85 and becomes financially distressed. The collusive profit margins suddenly jump downward at $M_{i,t} = 0.85$ and become equal to the non-collusive profit margins for $M_{i,t} < 0.85$.\footnote{In Appendix A.3, we show that it is the financially strong firm, firm $j$ in this example, that wants to drive its financially weak competitor, firm $i$, into default by waging the price war. The downward jump in firm $j$’s profit margins reflects its high real predatory incentives.}

Thus, our model implies that the within-industry contagion effect on profit margins is more dramatic in industries with higher entry barrier. However, the larger contagion...
Note: In panels A and B, we consider an industry with no entry ($\kappa = 0$) 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 large new entrants ($\kappa = 3$). In all panels, the blue solid and red dash-dotted lines represent the collusive equilibrium and the non-collusive equilibrium. The blue dots in panels B and D represent the profit margin that firm $j$ would set immediately after firm $i$ defaults and exits the market. We set $\gamma_t = \bar{\gamma}$ and $M_{j,t} = 2$. Other parameters are set according to our calibration in Section 6.1.

Figure 7: Illustration of endogenous price wars and jump risks in cash flows.

effect on profit margins does not necessarily lead to a larger contagion effect on default rates or credit risk. This is because the lower profit margins set by the financially strong firm may quickly drive its financially weak competitor out of the market. In the industries with high entry barrier, this allows the financially strong firm to enjoy the monopoly rent and set higher profit margins thereafter, leading to lower default rates and credit risk ex-ante. In fact, because of this monopoly rent channel, the model predicts that increasing the industry’s entry barrier has an ambiguous effect on the magnitude of contagion on default rate and credit risk, even though the model predicts that the contagion effect on profit margins always becomes stronger.

In the industry with $\kappa = 3$ (i.e., extremely high entry threat), panels C and D of Figure 7 show that the two firms collude on much higher profit margins compared to
the baseline industry (see panels A and B of Figure 5). This is because both firms worry about losing market power to the large new entrants, and they thus collaborate with each other on maintaining higher profit margins in order 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 significantly increasing its profit margin, with the intention to help increase firm $i$’s cash flows.

There is an extensive industrial organization (IO) literature that attempts to rationalize predatory pricing as an equilibrium phenomenon by means of reputation effects (e.g., Kreps and Wilson, 1982), informational asymmetries (e.g., Fudenberg and Tirole, 1986), financial constraints (e.g., Bolton and Scharfstein, 1990), or learning-by-doing (e.g., Cabral and Riordan, 1994; Snider, 2008; Besanko, Doraszelski and Kryukov, 2014). To fix idea, our model forgoes these features and focuses on the interaction between predatory pricing and financial distress. Our numerical analysis nevertheless reveals the widespread existence of equilibria involving 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. More importantly, the full-blown price war endogenously breaks out when the predatory incentives dominate. The predation price war would happen when the financial condition is very imbalanced among the competitors and the entry threat is very weak.

### 3.4 Competition Mechanism under Different Market Structure

Our above analyses focus on industries with the same market structure. In this subsection, we further shed light on the core competition mechanism under various market structures. Like in many other studies in the literature, the competitiveness of a market structure is characterized by the industry’s price elasticity of demand $\epsilon$ and the number of market leaders $n$ in our model.

First, we analyze how industry market structure influences the difference in the sensitivity of profit margins to discount rates between industries with low ($\lambda_L$) and high ($\lambda_H$) turnover rates of market leadership. Panel A of Figure 8 plots the profit-margin beta to an increase in the discount rate from $\gamma_L$ to $\gamma_H$ under our baseline duopoly market structure with $\epsilon = 2$ and $n = 2$ for the two industries whose market leadership changes at different rates. Consistent with panel B of Figure 9, the profit-margin beta is much more negative in the industry with a low turnover rate $\lambda_L$.

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27 There are also early papers that investigate the interaction between compensation contracting and oligopolistic competition (e.g., Fershtman and Judd, 1987; Aggarwal and Samwick, 1999).
Note: Panels A – C illustrate the profit-margin beta (defined in equation (23)) under various market structure. The blue solid and black dashed lines in each panel plot the profit-margin beta in industries with $\lambda_L$ and $\lambda_H$, respectively. Conditional on the same value of $b_0$, the industry with $\lambda_H$ has a higher leverage ratio. To adjust for the leverage effect for profit-margin beta in the industry with $\lambda_H$, we define $\beta_{\theta_t}^{(\lambda_H)} = \beta_{\theta_t}(\lambda_H)(1 - \text{debt-asset-ratio}_{\lambda_H})/(1 - \text{debt-asset-ratio}_{\lambda_L})$. In panel A, we consider the market structure with $\epsilon = 2$ and $n = 2$ according to our baseline calibration in Appendix Table 13. In panel B, we set $\epsilon = 4$ and $n = 2$; and in panel C, we set $\epsilon = 2$ and $n = 3$. In all panels, we focus on the industries within which firms have identical customer base for expository purposes. The vertical dotted lines represent firms’ default boundaries in respective cases. We use $\lambda_L = 0$, $\lambda_H = 0.12$, $\gamma_L = \gamma$ and $\gamma_H = \gamma + 2\text{std}(\gamma_t)$. Panels D – F illustrate the difference in the contagion effect on profit margins between industries with low ($\lambda_L = 0$) and high ($\lambda_H = 0.12$) turnover rates of market leadership under various market structure. To measure the contagion effect, we conduct the experiment similar to that in panels C – F of Figure 5. In particular, we compute the percentage deviation in firm $j$’s profit margin in response to an unexpected idiosyncratic shock that reduces the customer base of its competitor, firm $i$, by half at $t = 1$. That is, the contagion effect in an industry is measured by calculating the percentage deviation of the blue solid line from the black dashed line in panel C of Figure 5. Other parameters are set according to our calibration in Section 6.1.

Figure 8: Profit-margin beta and financial contagion under various market structure.

Panel B considers a more competitive market structure by setting the industry’s price elasticity of demand to $\epsilon = 4$, keeping the number of market leaders $n = 2$ unchanged. The industry with a low turnover rate $\lambda_L$ still has a higher profit-margin beta than the industry with a high turnover rate $\lambda_H$. However, the difference in profit-margin betas between the two industries narrows significantly relative to that in panel A. In panel C, we consider a more competitive market structure by setting the number of market leaders to $n = 3$, keeping the industry’s price elasticity of demand $\epsilon$ unchanged. Relative to the baseline case in panel A, again we find that the difference in profit-margin betas
diminishes when the market structure becomes more competitive.

Taken together, Figure 8 implies that when the industry market structure becomes more competitive, the difference in the sensitivity of profitability to discount-rate shocks between industries with low and high market leadership persistence (i.e., low and high \( \lambda \), respectively) subsides. Intuitively, with a more competitive market structure, the market leaders within the same industry have less incentive to collude, irrespective of their market leadership persistence. As a result, profit-margin betas becomes less different across industries with different levels of leadership persistence (i.e., different values of \( \lambda \)).

Next, we show that the difference in the financial contagion effect between industries with low \( (\lambda_L) \) and high \( (\lambda_H) \) turnover rates of market leadership becomes less significant when industries’ market structure becomes more competitive. We conduct the experiment similar to that in Figure 5. In particular, we measure the within-industry contagion effect on profit margins by computing the percentage deviation in firm \( j \)'s profit margin (relative to the scenario without shocks, i.e., the black dashed line in panel C of Figure 5) in response to an unexpected idiosyncratic shock that reduces the customer base of its competitor, firm \( i \), by half at \( t = 1 \). Panel D of Figure 8 plots the difference in this contagion effect between the industries with low \( (\lambda_L) \) and high \( (\lambda_H) \) turnover rates of market leadership. The difference is negative, indicating that the industry with \( \lambda_L \) has larger contagion effect because firms collude on higher profit margins as shown in panel A of Figure 9. Importantly, the contagion effect on profit margins becomes less significant as we increase the industry’s price elasticity of demand \( \epsilon \) (panel E) or the number of market leaders \( n \) (panel F). Thus, our model implies that when the industry market structure becomes more competitive, the difference in the financial contagion effect between industries with low and high market leadership persistence (i.e., low and high \( \lambda \), respectively) also subsides.

4 Asset Pricing Implications

We shed light on the asset pricing implications of the competition-distress feedback in the cross section of industries with different persistence of market leadership \( \lambda^{-1} \). Basically, such feedback effect is stronger in industries with lower \( \lambda \) (i.e., higher market leadership persistence). Our competition-distress feedback provides one explanation for the important joint patterns of stock returns and credit spreads in the cross section which at odds with the standard credit models (e.g., Merton, 1974; Leland, 1994). The model implies that in the industries with higher \( \lambda \), market leaders face higher financial distress
and have lower profit margins which are also less sensitive to aggregate discount rate shocks. As a result, in the industries with higher $\lambda$, stock returns are less exposed to aggregate discount rate shocks after controlling for financial leverage; but on the contrary, credit spreads are more exposed to aggregate discount rate shocks since the debtholders in industries with higher $\lambda$ are subject to greater future default loss.

Moreover, the model implies that in the industries with higher financial distress level, firm’s equity is less exposed to aggregate discount rate shocks and thus has lower expected return after controlling for financial leverage; but naturally, in the more distressed industries, firm’s debt is more exposed to aggregate discount rate shocks and has higher credit spread simply because the debtholders in industry of higher financial distress level are subject to greater default likelihood and loss.

To fix the idea, consider duopoly industries with identical firms as in Subsection 3.1. For comparison, we focus on two industries with different leadership turnover rates, $\lambda_L$ and $\lambda_H$. Panel A of Figure 9 plots the two industries’ profit margins in the aggregate state with a high ($\gamma_H$) and a low discount rate ($\gamma_L$). Profit margins are much higher in the industry with a low leadership turnover rate ($\lambda_L$). Moreover, in this industry, profit margins drop more substantially in response to an increase in the discount rate from $\gamma_L$ to $\gamma_H$. Panel B makes this point clearer by comparing the two industries’ profit-margin beta defined in equation (23). In both industries, the profit-margin beta is more negative when firms within the industry are more financially distressed, reflecting the competition-distress feedback. Importantly, the profit-margin beta is much more negative in the industry with $\lambda_L$ (the blue solid line). Intuitively, a higher rate of market leadership turnover has a similar effect to that of a higher discount rate. It motivates firms to compete more aggressively to generate more profits now rather than in the future, which dampens the collusion incentive, resulting in both lower levels and lower sensitivity of profit margins to aggregate discount-rate shocks.

In industries with lower turnover rates of market leadership, shareholders are more exposed to discount-rate shocks because of the larger fluctuations in profit margins and cash flows. To illustrate the exposure of debt and equity, we define the industry-level beta of equity ($\beta^V_t$) and debt ($\beta^D_t$) with respect to discount-rate shocks as the value-weighted firm-level beta:

$$\beta^V_t = \sum_{i=1}^{2} w^V_{i,t} \beta^V_{i,t}, \text{ where } \beta^V_{i,t} = \frac{V^C_{i,t}(\gamma_H)}{V^C_{i,t}(\gamma_L)} - 1 \text{ and } w^V_{i,t} = \frac{V^C_{i,t}(\gamma_L)}{\sum_{j=1}^{2} V^C_{j,t}(\gamma_L)},$$

$$\beta^D_t = \sum_{i=1}^{2} w^D_{i,t} \beta^D_{i,t}, \text{ where } \beta^D_{i,t} = \frac{D^C_{i,t}(\gamma_H)}{D^C_{i,t}(\gamma_L)} - 1 \text{ and } w^D_{i,t} = \frac{D^C_{i,t}(\gamma_L)}{\sum_{j=1}^{2} D^C_{j,t}(\gamma_L)},$$

(24)
Note: We consider duopoly industry with two identical firms (i.e., \( M_i, t = M_j, t \)). Panel A, C, and E plot the industry’s leverage-adjusted profit-margin beta \( \beta^\theta_t \) (equation (23)), equity beta \( \beta^V_t \) (equation (24)), and debt beta \( \beta^D_t \) (equation (25)) of industries with \( \lambda_L \) and \( \lambda_H \), respectively. Conditional on the same value of \( b_0 \), the industry with \( \lambda_H \) has a higher leverage ratio. To adjust for the leverage effect for profit-margin beta in the industry with \( \lambda_H \), we define \( \beta^\theta_t, \text{adj}(\lambda_H) = \beta^\theta_t(\lambda_H)(1 - \text{debt-asset-ratio}_{\lambda_H})/(1 - \text{debt-asset-ratio}_{\lambda_L}) \). The leverage-adjusted equity beta \( \beta^V_t, \text{adj}(\lambda_H) \) is defined in a similar way. Panels B, D, and F plot the difference in the betas of the two industries. In all panels, the vertical dotted lines represent firms’ default boundaries in respective cases. We use \( \lambda_L = 0, \lambda_H = 0.12, \gamma_L = \overline{\gamma} \) and \( \gamma_H = \overline{\gamma} + 2\text{std}(\gamma_t) \). Other parameters are set according to our calibration in Section 6.1.

Figure 9: Leadership turnover rates, profit margins, and industry risk exposure.

for all \( M_{i,t}, M_{j,t} > 0 \).

Panel C of Figure 9 compares the equity beta of the two industries. The industry with \( \lambda_L \) is more exposed to the discount-rate shocks than the industry with \( \lambda_H \). Moreover, panel D shows that the difference in equity beta is particularly large when firms within the industry are financially distressed (i.e., close to default boundaries) thanks to the competition-distress feedback.

However, our model implies that debtholders are less exposed to discount-rate shocks in industries with lower turnover rates of market leadership. This is because these industries have higher profit margins, which imply that debt holders face lower default risk (see the default boundaries in panel A of Figure 9). Panel E shows that the debt beta in the industry with \( \lambda_L \) is less negative (the blue solid line), which is opposite to
the pattern of equity beta (the blue solid line in panel C). Moreover, panel F shows that similar to equity beta, the difference in debt beta between the two industries is larger when firms within the industry are more financially distressed.

Taken together, our model implies that in industries with higher gross profitability (i.e., lower \( \lambda \)), shareholders are more exposed but debtholders are less exposed to aggregate discount-rate shocks. Thus, our model provides one explanation for the joint patterns on the cross-industry relation between gross profitability, equity returns, and credit spreads, which is generally viewed as a strengthened version of gross profitability premium.\(^{28}\) Further, our model implies that this relation would be more pronounced among financially distressed industries.

By focusing on the cross-section of market leadership turnovers, our model also sheds light on the channels that explain the financial distress anomaly across industries. Specifically, in the industries with a higher \( \lambda \), firms face greater financial distress risk because they are more likely to be displaced by market followers. Our model implies that the shareholders of these industries are less exposed to discount-rate shocks after controlling for financial leverage (see panel C of Figure 9).

5 Empirical Evidence

In this section, we empirically test the main predictions of our model. Section 5.1 describes the data and the discount rate measure. We then conduct our empirical tests in three steps. In Section 5.2, we first provide empirical evidence to support our model’s main theoretical implications on profit margins. In Section 5.3, we provide empirical evidence on our model’s asset pricing implications. In Section 5.4, we push another step further to directly test the unique predictions of our core competition mechanism. We explore the impact of the variation in the industry market structure on firms’ endogenous competition behavior by examining the changes in the sensitivity of profitability to discount-rate shocks and the response of competitors’ profit margins to firm-specific shocks to market leaders in the same industry. The empirical evidence strongly supports our core competition mechanism.

\(^{28}\)Dou, Ji and Wu (2020) focus on all-equity firms and thus their model does not have any prediction on the relation between gross profitability and credit spreads, or how they interact with financial distress.
5.1 Data Description

In the empirical section, we take firm-level accounting data from Compustat, stock return data from CRSP, and credit spread data from Chen et al. (2017). More precisely, our data of bond spreads combine the Mergent Fixed Income Securities Database (FISD) from January 1994 to December 2004 and the TRACE Database from January 2005 to June 2012. 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 bond credit spread by taking the difference between the bond yield and the treasury yield with corresponding maturity. The credit spread dataset we use spans from 1973 to 2018, with cross sectional coverage of 400 to 750 firms.

The firm-level financial distress measure is constructed as in Campbell, Hilscher and Szilagyi (2008). Industry-level fundamental variables—profit margin, distress, leverage, idiosyncratic shocks—are aggregated based on averaging firm-level fundamental variables weighted by sales. Industry-level stock return is weighted by market capitalization. Industry-level credit spreads are weighted by the bonds’ par value. When organizing the cross section of accounting data, we first map fiscal year to calendar year and when applicable, map to market data starting from the June of the next year, following the practice of Fama and French (1993). The industry-level market leadership turnover measure is constructed as in Dou, Ji and Wu (2020) using logistic regressions. We exclude all financial firms and utility firms (SIC codes between 6,000 and 6,999 and between 4,900 and 4,999, respectively). Following the literature (e.g., Frésard, 2010), at least 10 firms are required in each industry-year to ensure that the industry-level variables, such as industry-level profit margin and returns, are well-behaved.

The central aggregate shocks in our theory is the discount rate shock, which drives the competition intensity across all industries. The empirical proxy for discount rates is based on the smoothed earnings-price ratio motivated by the return predictability studies (e.g., Campbell and Shiller, 1988, 1998; Campbell and Thompson, 2008), and is obtained from Robert Shiller’s website. In our regression analyses, discount rate, is calculated by fitting a time-series regression of the 12-month-ahead market return on the smoothed earnings-price ratio, and then take the fitted value at the end of the period $t$.

5.2 Theoretical Implications on Profit Margins

Profit Margins’ Exposure to Discount Rates. Table 1 reports the loadings of the change in industry profit margin on the discount-rate shock. Industries are sorted into five
Table 1: Financial distress and profit margins’ loading on discount rates.

<table>
<thead>
<tr>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
</tr>
</thead>
<tbody>
<tr>
<td>∆ln(1 + PM_{ij}, t)</td>
<td>∆ln(1 + PM_{ij}, t−1)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>∆Discount rate, t</td>
<td>−0.010</td>
<td>−0.088</td>
<td>0.029</td>
<td>−0.251</td>
<td>−0.382</td>
</tr>
<tr>
<td>[−0.12]</td>
<td>[−1.48]</td>
<td>[0.51]</td>
<td>[−1.29]</td>
<td>[−1.59]</td>
<td>[−2.07]</td>
</tr>
<tr>
<td>Observations</td>
<td>47</td>
<td>47</td>
<td>47</td>
<td>47</td>
<td>47</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.000</td>
<td>0.021</td>
<td>0.001</td>
<td>0.050</td>
<td>0.064</td>
</tr>
</tbody>
</table>

Note: This table reports results from the following five annual time-series regressions: ∆ln(1 + PM_{ij}, t) = a_j + b_j ∆Discount rate, t + ε_{ij,t} with j = 1, · · · , 5. The exposure of profit margins to discount rates, b_j, is reported in the table, and we omit the coefficients for the constant terms a_j in the table for brevity. Here industries are sorted into 5 quintiles based on the industry-level financial distress measure. ∆ln(1 + PM_{ij}, t) ≡ ln(1 + PM_{ij}, t) − ln(1 + PM_{ij}, t−1), where ln(1 + PM_{ij}, t) is the equally-weighted average logged one plus the industry-level profit margin (weighted based on sales) of the industries in the jth quintile. ∆Discount rate, t is the AR(1) residual of the discount rate measure in year t. The sample here spans the period from 1972 to 2018. The discount rate and the log profit margins are both in annual, fractional unit. The standard errors are robust to heteroskedasticity and autocorrelation. We include t-statistics in square brackets. *, **, and *** indicate statistical significance at the 10%, 5%, and 1%, respectively.

groups based on industry-level financial distress level. Average profit margin and its change are then computed for each group. The exposure of industry-level profit margins to discount-rate shocks is estimated for each group. The table shows that industries with higher financial distress have more negative exposure to discount-rate shocks, consistent with the model implications (see Figure 4). The estimated relationship between financial distress and exposure to discount rates is (almost) strictly monotonic, and the difference in loadings between group 5 (high financial distress) and group 1 (low financial distress) is statistically significant. We consider ln(1 + PM_{it}) in our empirical analyses for the following two reasons: (i) we need to consider percentage changes of profit margins, but about 20% of the industry-year observations PM_{it} are negative; and (ii) when PM_{it} is not large, it holds that ln(1 + PM_{it}) ≈ PM_{it}.

**Contemporaneous Feedback between Profit Margin and Financial Distress.** Table 2 shows the feedback between industry profit margin and financial distress. The standard econometric specification for testing the contemporaneous feedback effects is as follows (e.g., Brooks, 2019, Section 6.12):²⁹

\[
\begin{bmatrix}
\ln(1 + PM_{it})  \\
\text{Distress}_{i,t}
\end{bmatrix} = A_{i,t} + \Gamma \begin{bmatrix}
\ln(1 + PM_{it-1})  \\
\text{Distress}_{i,t-1}
\end{bmatrix} + B \begin{bmatrix}
\text{Distress}_{i,t}  \\
\ln(1 + PM_{it})
\end{bmatrix} + \begin{bmatrix}
\epsilon_{1,i,t}  \\
\epsilon_{2,i,t}
\end{bmatrix},
\]

²⁹ This econometric methodology is first proposed and used by Blanchard and Watson (1986) and Bernanke (1986).
Table 2: Contemporaneous feedback between profit margin and distress.

<table>
<thead>
<tr>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Panel A: All firms in the industry</td>
<td>Panel B: Top 6 firms in the industry</td>
<td></td>
<td></td>
</tr>
<tr>
<td>ln(1 + PM_i,t)</td>
<td>ln(1 + PM_i,t)</td>
<td>ln(1 + PM_i,t)</td>
<td>ln(1 + PM_i,t)</td>
</tr>
<tr>
<td>Distress_i,t</td>
<td>Distress_i,t</td>
<td>Distress_i,t</td>
<td>Distress_i,t</td>
</tr>
<tr>
<td>(-9.415^{***})</td>
<td>(-7.018^{***})</td>
<td>([-3.44])</td>
<td>([-4.71])</td>
</tr>
<tr>
<td>([-5.65])</td>
<td>([-4.39])</td>
<td>([1.34])</td>
<td>([1.17])</td>
</tr>
<tr>
<td>ln(1 + PM_i,t)</td>
<td>ln(1 + PM_i,t)</td>
<td>ln(1 + PM_i,t)</td>
<td>ln(1 + PM_i,t)</td>
</tr>
<tr>
<td>Distress_i,t-1</td>
<td>Distress_i,t-1</td>
<td>Distress_i,t-1</td>
<td>Distress_i,t-1</td>
</tr>
<tr>
<td>0.083</td>
<td>0.056</td>
<td>0.419^{***}</td>
<td>0.399^{***}</td>
</tr>
<tr>
<td>([1.34])</td>
<td>([1.17])</td>
<td>([6.04])</td>
<td>([7.58])</td>
</tr>
<tr>
<td>Observations</td>
<td>Observations</td>
<td>Observations</td>
<td>Observations</td>
</tr>
<tr>
<td>4,754</td>
<td>4,754</td>
<td>4,754</td>
<td>4,754</td>
</tr>
<tr>
<td>R-squared</td>
<td>R-squared</td>
<td>R-squared</td>
<td>R-squared</td>
</tr>
<tr>
<td>0.467</td>
<td>0.490</td>
<td>0.255</td>
<td>0.215</td>
</tr>
<tr>
<td>([-5.65])</td>
<td>([-4.39])</td>
<td>([1.34])</td>
<td>([1.17])</td>
</tr>
</tbody>
</table>

Note: This table reports results from the following industry-annual level panel regressions:

\[
\ln(1 + PM_i,t) = a_1 + \gamma_1 \ln(1 + PM_i,t-1) + b_1 \text{Distress}_{i,t} + \delta_1 + \ell_1 + \epsilon_{1,i,t}, \text{ and Distress}_{i,t} = a_2 + \gamma_2 \text{Distress}_{i,t-1} + b_2 \ln(1 + PM_i,t) + \delta_2 + \ell_2 + \epsilon_{2,i,t}. \]

We omit the coefficients for the constant terms \(a_1\) and \(a_2\) in the table for brevity. The variable Distress_{i,t} is the average distress of the industry \(i\) in year \(t\). The variables \(\delta_1\), \(\delta_2\), \(\ell_1\), and \(\ell_2\) are time and industry fixed effect. Average within an industry is weighted by sales. All variables are in fractional unit. The sample of this table spans the period from 1972 to 2018. The standard errors are robust to heteroskedasticity and autocorrelation among nearby cross sections. Specifically, we compute t-statistics using Driscoll-Kraay standard errors with 5 lags, and include t-statistics in square brackets. *, **, and *** indicate statistical significance at the 10%, 5%, and 1%, respectively.

where \(A_{i,t} \equiv [a_1, a_2] + [\delta_1, \delta_2]^T + [\ell_1, \ell_2]^T\), \(\Gamma \equiv \text{diag}\{\gamma_1, \gamma_2\}\), and \(B \equiv \text{diag}\{b_1, b_2\}\). Our theory predicts that both \(b_1\) and \(b_2\) are negative.

The first two columns show that when the industry is more financially distressed this year, it is likely to have lower profit margin in the same year even after controlling for the lagged profit margin. The next two columns show that when the profit margin of the industry becomes lower, the industry is likely to become more financially distressed in the same year, after controlling for the lagged financial distress level. These results are consistent with the feedback effect of the endogenous competition mechanism.

Financial Contagion within Industries. Table 3 tests our model’s prediction on the financial contagion effect among the market leaders within the same industry. The model predicts that the adverse idiosyncratic shock to a financially distressed market leader within an industry will lead to more aggressive price-setting behavior with narrowed profit margin. In most industries, other market leaders within the same industry will in turn behave aggressively by pushing down their profit margins (see Panel A and Panel D of Figure 5), which can be mainly driven by both predatory and defensive incentives (see Panel C and Panel E of Figure 5). Additionally, the model predicts that the financial
contagion effect is greater in industries with more balanced market shares among the market leaders (see Figure 6), and the model also predicts that the financial contagion effect is more pronounced in industries with higher entry costs to become market leaders (see Figure 7). We will show empirical evidence that supports the predictions below.

To see the financial contagion effect in the data, in each year we split the top 6 firms of each industry into 3 groups, tertile-sorting based on their financial distress level. Group L (the first tertile) contains the financially healthy firms (i.e., the firms whose financial distress measure is in the lowest tertile), and group H (the third tertile) contains the financially distressed ones (i.e., the firms whose financial distress measure is in the highest tertile). We then construct the group-level idiosyncratic shocks based on firm-level idiosyncratic shocks. Two methods of constructing the idiosyncratic shocks are adopted for robustness, and the details are described in Appendix C. We run the following industry-year level panel regression:

$$\ln(1 + PM_{it}^{(L)}) = b_H \text{IdShock}_{it}^{(H)} + b_L \text{IdShock}_{it}^{(L)} + \sum_{j=1}^{5} \gamma_j \ln(1 + PM_{it-j}^{(L)}) + \delta_i + \ell_i + \epsilon_{it}. $$

Here the coefficient $b_H$ captures the effect of group H (financially distressed) firms’

### Table 3: Financial contagion effect among market leaders within the same industry.

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
<th>(7)</th>
<th>(8)</th>
<th>(9)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Market share imbalance tertiles</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(M1) IdShock$_{it}^{(H)}$</td>
<td>0.030***</td>
<td>0.051***</td>
<td>0.027*</td>
<td>0.023**</td>
<td>-0.028*</td>
<td>0.031**</td>
<td>0.020***</td>
<td>0.061***</td>
<td>0.030</td>
</tr>
<tr>
<td></td>
<td>[3.36]</td>
<td>[4.16]</td>
<td>[1.96]</td>
<td>[2.16]</td>
<td>[-1.94]</td>
<td>[2.02]</td>
<td>[2.93]</td>
<td>[3.40]</td>
<td>[1.52]</td>
</tr>
<tr>
<td>(M2) IdShock$_{it}^{(H)}$</td>
<td>0.033***</td>
<td>0.055***</td>
<td>0.029*</td>
<td>0.024</td>
<td>-0.031*</td>
<td>0.020*</td>
<td>0.024**</td>
<td>0.073***</td>
<td>0.053***</td>
</tr>
<tr>
<td></td>
<td>[3.33]</td>
<td>[4.86]</td>
<td>[1.94]</td>
<td>[1.65]</td>
<td>[-1.81]</td>
<td>[1.28]</td>
<td>[2.52]</td>
<td>[3.71]</td>
<td>[3.02]</td>
</tr>
</tbody>
</table>

Note: This table reports results from the following industry-year level panel regressions: $\ln(1 + PM_{it}^{(L)}) = b_H \text{IdShock}_{it}^{(H)} + b_L \text{IdShock}_{it}^{(L)} + \sum_{j=1}^{5} \gamma_j \ln(1 + PM_{it-j}^{(L)}) + \delta_i + \ell_i + \epsilon_{it}$. The idiosyncratic shocks to each group of market leaders within an industry are constructed using two methods: (i) method 1 is firm’s sales growth subtracting the cross sectional average sales growth; and (ii) method 2 is time-series regression residual of firm’s sales growth on the cross sectional average sales growth. The result of method 1 is presented in the row of (M1), and that of the method 2 is presented in the row of (M2). The financial contagion coefficient, denoted by $b_H$, is reported in columns (1) – (4) and (6) – (8). Column (1) shows $b_H$ estimates based on the whole sample, column (2) shows $b_H$ estimates based on the subsample containing the most balanced industries in terms of leaders’ market shares, column (3) shows $b_H$ estimates based on the subsample containing the moderately balanced industries, column (4) shows $b_H$ estimates based on the subsample containing the most imbalanced industries, column (5) shows the difference of the columns (4) and (2), column (6) shows $b_H$ estimates based on the subsample containing the industries with the lowest entry cost, column (7) shows $b_H$ estimates based on the subsample containing the industries with the moderate entry cost, column (8) shows $b_H$ estimates based on the subsample containing the industries with the highest entry cost, and column (9) shows the difference of the columns (8) and (6). Results in this table are based on the market leaders within each SIC-4 industry, defined as the top 6 firms by sales. Entry costs of each industry-year is computed as the median of the trailing five year average of the net total property, plant, and equipment of each industry. Data in this regression ranges from 1976 to 2018. The standard errors are robust to heteroskedasticity and autocorrelation among nearby cross sections. Specifically, we compute t-statistics using Driscoll-Kraay standard errors with 5 lags, and include t-statistics in square brackets. *, **, and *** indicate statistical significance at the 10%, 5%, and 1%, respectively.
idiosyncratic shock on the profit margin of group L (financially healthy) firms, hence captures the financial contagion effect. We emphasize that the regression above controls for the group L (financially healthy) firms’ own idiosyncratic shock $\text{IdShock}^{(L)}_{i,t}$, the group L (financially healthy) firms’ past profit margins $\sum_{j=1}^{5} \gamma_j \ln(1 + \text{PM}^{(L)}_{i,t-j})$, the time fixed effects, and the industry fixed effects.$^{30}$

The first column, titled “All”, of Table 3 shows that the financial contagion effect is strong and robust to the choice of the specific measure for idiosyncratic shocks. Columns (2) – (4), titled “Market share imbalance tertiles”, show that the financial contagion effect is greater when the market shares of the distressed and healthy market leaders are more balanced. More precisely, we split the aforementioned panel regression into three subsamples based on an imbalance measure, defined as the absolute value of the difference between the logged sales of the group L (financially healthy) and that of the group H (financially distressed). For example, when the group L (financially healthy) and group H (financially distressed) firms are of equal size (i.e. they have the same sales), the absolute value would achieve zero — the theoretical minimum. By contrast, when the group L (financially healthy) firms are much larger or smaller than the group H (financially distressed) firms, the absolute value would be a large positive number. Column (2) is about the balanced industries whose imbalance measure lies in the first tertile in a particular year, and column (4) is about the industries whose imbalance measure lies in the third tertile in a particular year. Consistent with our model’s predictions (see Figure 6), the financial contagion effect is the largest in column (2) and the smallest in column (4). The difference between the estimated coefficients in columns (4) and (2) is negative and statistically significant.

Moreover, columns (6) – (8), titled “Entry cost tertiles”, show that the financial contagion effect is greater in industries with higher entry costs. Entry costs of each industry-year is computed as the median of the trailing five year average of the net total property, plant, and equipment for each industry and year. The key idea behind the empirical measure is that sunk entry costs mainly arise from construction costs of business premises (e.g., Sutton, 1991; Karuna, 2007; Barseghyan and DiCecio, 2011). It is very intuitive: the market followers need to incur higher setup costs to compete with and eventually displace the existing market leaders if it requires higher business premises to operate as market leaders in this industry. We split the panel regression into three subsamples based on the entry cost measure. Column (6) is about the industries whose entry cost measure lies in the first tertile in a particular year, and column (8) is about the

$^{30}$The results are robust when we additionally control for industry-level sales or $\text{IdShock}^{(M)}_{i,t}$ for the group of firms with the median financial distress measure.
Panel A: Cross-industry spillover

<table>
<thead>
<tr>
<th></th>
<th>Panel B: Construction of IdShock(_{ij})</th>
</tr>
</thead>
<tbody>
<tr>
<td>(1) (\ln(1 + PM_{ij}))</td>
<td>(3) (\ln(1 + PM_{ij}^{(c)}))</td>
</tr>
<tr>
<td>(M1) (\hat{\text{IdShock}}_{ij})</td>
<td>(M1) (\hat{\text{IdShock}}_{ij}^{(1)}) (largest)</td>
</tr>
<tr>
<td>(0.167^{***})</td>
<td>(0.049^{***})</td>
</tr>
<tr>
<td>[5.25]</td>
<td>[3.41]</td>
</tr>
<tr>
<td>(0.677^{**})</td>
<td>(0.025^{***})</td>
</tr>
<tr>
<td>[2.20]</td>
<td>[4.38]</td>
</tr>
<tr>
<td>(0.760^{*})</td>
<td>(-0.007)</td>
</tr>
<tr>
<td>[1.99]</td>
<td>[-0.72]</td>
</tr>
<tr>
<td>Observations</td>
<td>222</td>
</tr>
</tbody>
</table>

Note: This table reports estimation results of panels A and B. In panel B, we estimate the “first-stage” industry-year regression \(\ln(1 + PM_{ij}^{(c)}) = a + \sum_{k=1}^{3} b_k \hat{\text{IdShock}}_{ij}^{(k)} + \epsilon_{ij}\). And, we compute the fitted value \(\hat{\text{IdShock}}_{ij} = a + \sum_{k=1}^{3} b_k \hat{\text{IdShock}}_{ij}^{(k)}\). The estimated coefficients are reported in panel B, and columns (3) and (4) correspond to the two construction methods for idiosyncratic shocks, denoted by M1 and M2, respectively. We omit the estimated constant terms in the table for brevity. The idiosyncratic shock \(\hat{\text{IdShock}}_{ij}^{(c)}\) is the \(k\)-th largest (in terms of sales) in the same industry of the common market leader with profit margin \(PM_{ij}^{(c)}\). The estimation results are robust when using the top 2 – 6 firms. Panel A uses the fitted values \(\hat{\text{IdShock}}_{ij}^{(c)}\) to estimation the industry-year regression: \(\ln(1 + PM_{ij}^{(c)}) = a + b \hat{\text{IdShock}}_{ij}^{(c)} + \epsilon_{ij}\). We explain the construction of the competition network through the common market leaders and \(\hat{\text{IdShock}}_{ij}^{(c)}\) in Appendix D. Results in this table are based on the market leaders within each SIC-4 industry. Data in this regression ranges from 1976 to 2018. The standard errors are robust to heteroskedasticity and autocorrelation among nearby cross sections. Specifically, we compute t-statistics using Driscoll-Kraay standard errors with 5 lags, and include t-statistics in square brackets. *, **, and *** indicate statistical significance at the 10%, 5%, and 1%, respectively.

Industries whose entry cost measure lies in the third tertile in a particular year. Columns (6) – (8) report the financial contagion coefficient \(b_H\) for the three subsamples. Consistent with the model’s predictions, the financial contagion effect is the largest in column (6) for the industries with the lowest entry costs and the smallest in column (8) for those with the highest entry costs. The difference between the estimated coefficients in columns (8) and (6) is positive and statistically significant.

**Financial Contagion across Industries.** Table 4 tests our model’s prediction on the financial contagion effect between the market leaders in two different industries yet sharing common major competitors. Let’s use Figure 2 for demonstration. Suppose there are two industries I and II sharing the same common market leader B. The model predicts that the adverse idiosyncratic shock to market leader A in industry I will lead to more aggressive price-setting behavior with narrowed profit margin, which causes the common competitor B more financially distressed. As a result, the common competitor becomes effectively more impatient and are likely to compete more aggressively in both industries. Thus, the market leader C in industry II in turn lower its profit margin and
Table 5: Equity return’s and credit spread’s loading on discount rates across different financial distress.

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
<th>(7)</th>
<th>(8)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Panel A: All firms in the industry</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Excess return,</td>
<td>1(Low)</td>
<td>2</td>
<td>3(High)</td>
<td>3 - 1</td>
<td>1(Low)</td>
<td>2</td>
<td>3(High)</td>
<td>3 - 1</td>
</tr>
<tr>
<td>ΔDiscount rate,</td>
<td>[1.61]</td>
<td>[2.40]</td>
<td>[1.93]</td>
<td>[1.73]</td>
<td>0.078</td>
<td>0.178**</td>
<td>0.095**</td>
<td>0.018*</td>
</tr>
<tr>
<td>ΔCredit spread,</td>
<td>180</td>
<td>180</td>
<td>180</td>
<td>180</td>
<td>180</td>
<td>180</td>
<td>180</td>
<td>180</td>
</tr>
<tr>
<td>Panel B: Top 6 firms in the industry</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Excess return,</td>
<td>1(Low)</td>
<td>2</td>
<td>3(High)</td>
<td>3 - 1</td>
<td>1(Low)</td>
<td>2</td>
<td>3(High)</td>
<td>3 - 1</td>
</tr>
<tr>
<td>ΔDiscount rate,</td>
<td>[1.90]</td>
<td>[1.53]</td>
<td>[2.47]</td>
<td>[1.78]</td>
<td>0.071*</td>
<td>0.106</td>
<td>0.149**</td>
<td>0.078*</td>
</tr>
<tr>
<td>ΔCredit spread,</td>
<td>180</td>
<td>180</td>
<td>180</td>
<td>180</td>
<td>180</td>
<td>180</td>
<td>180</td>
<td>180</td>
</tr>
</tbody>
</table>

Note: This table reports results from the following quarterly time-series regressions:

\[
\Delta \text{Credit spread}_{i,t} = \alpha_i + \beta_i \Delta \text{Discount rate}_t + \epsilon_{i,t}.
\]

Here the cross section of industries are sorted into 3 bins based on industry financial distress level. The average credit spread among firms within ith bin. Discount rate, is calculated by fitting a time series regression of forward 12-month stock market return on the smoothed EP ratio, and then take the fitted value at the end of year t. ΔDiscount rate, is the AR1 residual of the discount rate at year t. Top 6 firms are determined by sales. Annual accounting data of year t are mapped to credit spread data from Q2 of year t + 1 to Q1 of year t + 2, as in Fama and French (1993). Each group’s credit spread loadings, βi, are reported in the table. The credit spreads and the discount rates in this table are both in annualized fractional units. The t-statistics robust to heteroskedasticity and autocorrelation are reported in square brackets.

becomes more financially distressed. Therefore, the model predicts that the adverse idiosyncratic shock to market leader A would lower the profit margin of market leader C though the decreased profit margin of the common market leader B.

In panel A of table 4, the positive coefficient on \( \text{IdShock}_{i,t} \) shows that higher idiosyncratic shock to an industry corresponds to higher profit margin in itself. This is our control. The coefficient on \( \hat{\text{IdShock}}_{i,t} \) means that, on top of this control, higher idiosyncratic shocks to linked industries, to the extent that they impact the profit margin of the common leader, also corresponds to higher profit margin in the base industry. The coefficient of 0.677 means that 1% of the predicted common leader profit margin corresponds to 0.677% of profit margin in the base industry. This is consistent with the model’s prediction.

5.3 Asset Pricing Implications

5.3.1 Feedback Effect

Table 5, as a companion result of Table 1, reports the loadings of firms’ credit spread on the discount rate. Here industries are sorted into three groups based on the industry-level financial distress level. Average credit spread is then computed for each group, and each
Table 6: Financial contagion effect on credit spreads among market leaders within the same industry.

<table>
<thead>
<tr>
<th></th>
<th>1 (Balance)</th>
<th>2</th>
<th>3 (Imbalance)</th>
<th>3 – 1</th>
</tr>
</thead>
<tbody>
<tr>
<td>(M1) IdShock\textsubscript{(H)}</td>
<td>-0.595\textsuperscript{***}</td>
<td>-0.960\textsuperscript{*}</td>
<td>-0.383</td>
<td>-0.328</td>
</tr>
<tr>
<td></td>
<td>[-2.77]</td>
<td>[-1.98]</td>
<td>[-0.93]</td>
<td>[-0.81]</td>
</tr>
<tr>
<td>(M2) IdShock\textsubscript{(H)}</td>
<td>-0.510\textsuperscript{***}</td>
<td>-0.961\textsuperscript{*}</td>
<td>0.032</td>
<td>-0.142</td>
</tr>
<tr>
<td></td>
<td>[-1.95]</td>
<td>[-1.90]</td>
<td>[0.08]</td>
<td>[-0.36]</td>
</tr>
</tbody>
</table>

Note: This table reports results from the following industry-year panel regressions: Credit spread\textsubscript{it} = b\textsubscript{H}IdShock\textsubscript{it} + b\textsubscript{L}IdShock\textsubscript{it} + \sum\textsubscript{j=1}^{5} \gamma\textsubscript{j} Credit spread\textsubscript{it,j} + \delta\textsubscript{i} + \ell\textsubscript{t} + \epsilon\textsubscript{it}. The idiosyncratic shocks to each group of market leaders within an industry are constructed using two methods: (i) method 1 is firm’s sales growth subtracting the cross sectional average sales growth; and (ii) method 2 is time-series regression residual of firm’s sales growth on the cross sectional average sales growth. The result of method 1 is presented in the row of (M1), and that of the method 2 is presented in the row of (M2). The financial contagion coefficient, denoted by b\textsubscript{H}, is reported in columns (1) – (4). Column (1) shows b\textsubscript{H} estimates based on the whole sample, column (2) shows b\textsubscript{H} estimates based on the subsample containing the most balanced industries in terms of leaders’ market shares, column (3) shows b\textsubscript{H} estimates based on the subsample containing the moderately balanced industries, column (4) shows b\textsubscript{H} estimates based on the subsample containing the most imbalanced industries, column (5) shows the difference of the columns (4) and (2). Results in this table are based on the market leaders within each SIC-4 industry, defined as up to the top 6 firms. We relax the requirement of the number of firms from 10 to 3 in this exercise to prevent the sample from getting too small. Data in this regression ranges from 1976 to 2018. The standard errors are robust to heteroskedasticity and autocorrelation among nearby cross sections. Specifically, compute t-statistics using Driscoll-Kraay standard errors with 5 lags, and include t-statistics in square brackets. *, **, and *** indicate statistical significance at the 10%, 5%, and 1%, respectively.

5.3.2 Financial Contagion Effect

Table 6, as a companion result of Table 3, shows that the financial contagion effect among market leaders within the same industry can also be reflected in credit spreads as predicted by the model. Moreover, the empirical pattern shown in Columns (4) – (5) of Table 6 is also consistent with the theoretical prediction that the financial contagion effect is more pronounced in those industries with more balanced market shares among the market leaders.

Group’s loading on the discount rate is estimated using a time-series regression. The table shows that credit spreads have positive loadings on the discount rate, which means that corporate bond prices are on average pro-cyclical. Importantly, the credit spread loadings become more positive as the financial distress level increases, and thus, the corporate bond price loadings on the discount rate become more negative as the financial distress level increases, consistent with the model’s implication shown in Panel B of Figure A.1. The difference in loadings for group 1 and 3 is statistically significant.
Table 7: Excess returns, credit spreads, and gross profitability

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Panel A: Equity Returns</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Excess Return</td>
<td>(-1.670^{**})</td>
<td>(-0.657)</td>
<td>0.135</td>
<td>0.833</td>
<td>(1.345^{*})</td>
<td>(3.015^{**})</td>
</tr>
<tr>
<td>([-2.33])</td>
<td>([-1.17])</td>
<td>[0.25]</td>
<td>[1.42]</td>
<td>[1.83]</td>
<td>[2.35]</td>
<td></td>
</tr>
<tr>
<td>CAPM Alpha</td>
<td>(-1.768^{**})</td>
<td>(-0.897)</td>
<td>0.003</td>
<td>0.981*</td>
<td>(1.682^{**})</td>
<td>(3.449^{***})</td>
</tr>
<tr>
<td>([-2.42])</td>
<td>([-1.59])</td>
<td>[0.01]</td>
<td>[1.66]</td>
<td>[2.28]</td>
<td>[2.66]</td>
<td></td>
</tr>
<tr>
<td>FF3 Alpha</td>
<td>(-1.909^{***})</td>
<td>(-1.106^{*})</td>
<td>0.124</td>
<td>1.305**</td>
<td>(1.599^{**})</td>
<td>(3.508^{***})</td>
</tr>
<tr>
<td>([-2.62])</td>
<td>([-1.93])</td>
<td>[0.23]</td>
<td>[2.21]</td>
<td>[2.17]</td>
<td>[2.72]</td>
<td></td>
</tr>
<tr>
<td>Observations</td>
<td>654</td>
<td>654</td>
<td>654</td>
<td>654</td>
<td>654</td>
<td>654</td>
</tr>
</tbody>
</table>

| **Panel B: Bond Returns** |           |           |           |           |           |           |
| Credit Spread       | 2.355^{***} | 1.880^{***} | 1.642^{***} | 1.448^{***} | 1.307^{***} | \(-1.048^{***}\) |
| \([8.26]\)          | \([8.32]\) | \([7.15]\) | \([8.62]\) | \([7.41]\) | \([-7.95]\) |           |
| Observations        | 545       | 545       | 545       | 545       | 545       | 545       |

Note: This table reports results from the following monthly time-series regressions: \(Spread_{it} = \alpha_i + \epsilon_{it}\) and \(Ret_{it} = \alpha_i + \epsilon_{it}\), controlling for industry leverage. Here, the cross section of industries are sorted into 5 bins based on industry level gross profitability, defined as in Novy-Marx (2013). \(Ret_{it}\) is the market value weighted returns among the stocks in the bin \(i\). \(Spread_{it}\) is the par value weighted average credit spread among firms within bin \(i\). Annual accounting data of year \(t\) are assumed to be known at the end of June of year \(t+1\) and are mapped to credit spread and return data accordingly, as in Fama and French (1993) and Novy-Marx (2013). The coefficient \(\alpha\) equals the time series mean of the bin’s return and credit spread. Returns are in monthly fractional unit, and credit spreads are in annualized fractional unit. The sample for the credit spread range from 1973 to 2018. The sample for stock return range from 1963 to 2018. For the credit spread regression, \(t\)-statistics robust to autocorrelation are reported in square brackets.

5.3.3 Joint Patterns of Stock Returns and Credit Spreads

**Cross Section of Gross Profitability.** Table 7 shows the relationship between profitability, defined in Novy-Marx (2013), and stock returns and credit spreads. Panel A shows that when an industry has high profitability, firms in it have higher stock returns relative to those in the low profitability industries. This confirms the profitability puzzle in Novy-Marx (2013) at the industry level. Panel B shows that when an industry has high profitability, firms in it have lower credit spread relative to those in the low profitability industries.

**Cross Section of Financial Distress.** Our model predicts that the industries with higher financial distress have lower expected stock returns, even after controlling for firms’ leverage. Our theory on the cross-industry financial distress anomaly is particularly meaningful since the financial distress premium puzzle concentrates on the cross-industry spread rather than the within-industry spread in the data. The empirical results in Table 8 are new to the literature and consistent with our model’s prediction.
Table 8: Excess returns, credit spreads, and financial distress.

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Panel A: Equity Returns</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Excess Return</td>
<td>2.694**</td>
<td>0.709</td>
<td>0.325</td>
<td>−0.257</td>
<td>−4.485***</td>
<td>7.180***</td>
</tr>
<tr>
<td>CAPM Alpha</td>
<td>3.929***</td>
<td>1.540**</td>
<td>0.515</td>
<td>−1.143*</td>
<td>−5.724***</td>
<td>9.653***</td>
</tr>
<tr>
<td>FF3 Alpha</td>
<td>4.370***</td>
<td>1.456**</td>
<td>0.632</td>
<td>−1.001</td>
<td>−6.414***</td>
<td>10.784***</td>
</tr>
<tr>
<td>Observations</td>
<td>521</td>
<td>521</td>
<td>521</td>
<td>521</td>
<td>521</td>
<td>521</td>
</tr>
</tbody>
</table>

|                  | (1)      | (2)      | (3)      | (4)      | (5)      | (6)      |
| **Panel B: Bond Returns** |          |          |          |          |          |          |
| Credit Spread    | 1.396*** | 1.342*** | 1.374*** | 1.790*** | 3.401*** | 2.004*** |
| Observations     | 521      | 521      | 521      | 521      | 521      | 521      |

Note: Here the cross section of industries are sorted into 5 bins based on industry level financial distress, where the distress is weighted by sales.

**The Interaction of Gross Profitability and Financial Distress.** Table 9 shows the average returns of 9 double-sorted portfolios. The cross section of industry level stock returns are first sorted into 3 bins based on their respective distress level, and then each bin is sorted into 3 bins based on their profitability. The positive numbers in column “3 − 1” shows that a strategy that longs high profitability stocks and short low profitability industries earns positive returns on average. This repeats the message in Panel A of Table 7. The new point of Table 9 is that this return increases with the industries’ distress level. Among the high distress industries, a portfolio that long high profitability and short low profitability earns 70 basis points per month. In contrast, among the low distress industries, the return is only 2 basis points. The difference of 68 basis points is statistically significant at the 5% level.

In our theory, the economic mechanism behind the rationale for the financial distress premium puzzle can be summarized as follows: On the one hand, industries with higher leadership persistence have higher expected stock returns due to higher sensitivity of competition intensity to the discount-rate shock; and on the other hand, industries with higher leadership persistence are less financially distressed since they face less industry-specific displacement risk (as a type of downward jump risk). Table 10 shows that the data is consistent with the model’s prediction that industries with higher market leadership persistence (i.e., lower λ measure), on average, have higher profitability, lower financial
Table 9: Interaction between gross profitability and financial distress

<table>
<thead>
<tr>
<th></th>
<th>Panel A: Excess Return</th>
<th></th>
<th>Panel B: Credit Spread</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>1 (Low Profit)</td>
<td>2</td>
<td>3 (High Profit)</td>
<td>3 – 1</td>
</tr>
<tr>
<td>1 (Low Distress)</td>
<td>1.313</td>
<td>1.523</td>
<td>1.478</td>
<td>0.238</td>
</tr>
<tr>
<td></td>
<td>[0.91]</td>
<td>[1.41]</td>
<td>[1.16]</td>
<td>[0.14]</td>
</tr>
<tr>
<td>2</td>
<td>−0.317</td>
<td>0.964</td>
<td>1.884*</td>
<td>2.201</td>
</tr>
<tr>
<td></td>
<td>[−0.28]</td>
<td>[1.18]</td>
<td>[1.89]</td>
<td>[1.32]</td>
</tr>
<tr>
<td>3 (High Distress)</td>
<td>−4.667***</td>
<td>−3.479***</td>
<td>0.861</td>
<td>5.528***</td>
</tr>
<tr>
<td></td>
<td>[−2.81]</td>
<td>[−2.65]</td>
<td>[0.64]</td>
<td>[2.60]</td>
</tr>
<tr>
<td>3 – 1</td>
<td>−5.990**</td>
<td>−5.003**</td>
<td>−0.617</td>
<td>5.382**</td>
</tr>
<tr>
<td></td>
<td>[−2.45]</td>
<td>[−2.38]</td>
<td>[−0.30]</td>
<td>[2.09]</td>
</tr>
</tbody>
</table>

Note: This table reports average monthly returns of 9 portfolios consisting of industries, sequentially sorted on the industry’s distress and then profitability. The portfolio returns are weighted by market cap-weighted returns. Annual accounting data, used in the construction of the profitability measure, of year $t$ are mapped to return data from July of year $t + 1$ to June of year $t + 2$, as in Fama and French (1993) and Novy-Marx (2013). Sample starts in 1975m8 and ends 2018m12, as before that month the data coverage is too unstable to performance double sorting. The $t$-statistics are reported in square brackets.

distress, and lower credit spreads.

5.4 Empirical Tests on the Core Competition Mechanism

In this subsection, we first provide evidence supporting the unique predictions of our core competition mechanism. Our core competition mechanism generates an endogenous differential response of firms’ competition intensity, as reflected in profit margins, to aggregate discount-rate shocks between industries featuring low and high financial distress (i.e., the feedback effect), which rationalizes the joint patterns of stock returns and credit spreads — gross profitability premium and financial distress puzzle. To check whether the observed differential sensitivity of profit margins to fluctuation in discount rates is mainly driven by the endogenous competition mechanism, a direct test is to examine how such differential sensitivity would change if the industry market structure shifts to a more competitive one. As shown in Section 3.4, such differential sensitivity is weaker if the industry market structure becomes more competitive (i.e., if the industry’s price elasticity of demand $\epsilon$ or number of market leaders $n$ increases).

Moreover, our core competition mechanism also generates an endogenous response of peer firms’ competition intensity, as reflected in their profit margins, to idiosyncratic shocks of the financially distressed market leaders in the same industry (i.e., the financial contagion effect). To check whether the observed financial contagion effect is mainly driven by the endogenous competition mechanism, a direct test is to examine how such
Table 10: Leadership turnover, profitability, financial distress, and credit spreads.

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Profitability(_{i,t})</td>
<td>Distress(_{i,t})</td>
<td>Credit spread(_{i,t})</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(\lambda(_{i,t}))</td>
<td>-1.014</td>
<td>-1.812***</td>
<td>0.006**</td>
<td>0.006**</td>
<td>0.147*</td>
<td>0.328**</td>
</tr>
<tr>
<td>Year FE</td>
<td>No</td>
<td>Yes</td>
<td>No</td>
<td>Yes</td>
<td>No</td>
<td>Yes</td>
</tr>
<tr>
<td>Observations</td>
<td>2047</td>
<td>2047</td>
<td>2047</td>
<td>2047</td>
<td>286</td>
<td>286</td>
</tr>
</tbody>
</table>

Note: This table reports results from the following industry-annual level panel regressions: Profitability\(_{i,t}\) = \(a_1 + b_1 Leadership Turnover\(_{i,t}\) + \delta_{1,t} + \epsilon_{i,t}\), Distress\(_{i,t}\) = \(a_1 + b_1 Leadership Turnover\(_{i,t}\) + \delta_{1,t} + \epsilon_{i,t}\), and Credit Spread\(_{i,t}\) = \(a_1 + b_1 Leadership Turnover\(_{i,t}\) + \delta_{1,t} + \epsilon_{i,t}\). The variables \(\delta_{1,t}\) is time fixed effect. We omit the coefficients for the constant terms \(a_1\) in the table for brevity. The variables Profitability\(_{i,t}\), Distress\(_{i,t}\), and Credit Spread\(_{i,t}\) is the average profitability, distress, and credit spread of the industry \(i\) in year \(t\). Within industry they are weighted by sales, market cap, and nominal value outstanding respectively, as in other places. Firm level profitability is computed as gross profit divided by total asset, and then winsorized at the 1st and the 99th percentiles. When the dependent variable is credit spread, we require the firm to have at least 6 firms, as opposed to 10. This is to prevent the number of observations from getting too small. All variables are in fractional unit. The sample of this table spans the period from 1988 to 2018. The standard errors are robust to heteroskedasticity and autocorrelation among nearby cross sections. Specifically, we compute t-statistics using Driscoll-Kraay standard errors with 5 lags, and include t-statistics in square brackets. *, **, and *** indicate statistical significance at the 10%, 5%, and 1%, respectively.

The financial contagion effect would change if the industry market structure shifts to a more competitive one. As shown in Section 3.4, such contagion effect is weaker if the industry market structure becomes more competitive (i.e., if the industry’s price elasticity of demand \(\epsilon\) or number of market leaders \(n\) increases).

We directly test the unique predictions of our core competition mechanism described above. Empirically, we exploit a widely-used setting to introduce variation in the competitiveness of industry market structure. More precisely, 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.\(^{31}\) The vast literature on barriers to trade suggests that globalization and trade openness substantially alter the competitive configuration of industries (see Tybout (2003) for a survey). For example, Bernard, Jensen and Schott (2006) show that tariff cuts significantly intensify the competitive pressures from foreign rivals. Valta (2012) shows that import tariff cuts are followed by a significant increase in imports. Thus, tariff reductions bring real changes to the competitiveness of industry market structure. 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 \(\epsilon\) due to the similar products and services provided by foreign rivals and (ii) the number of market leaders \(n\) due to the entry of foreign rivals as major

\(^{31}\)Many other papers in the literature use tariff cuts as shocks to the competitiveness of industry market structure to address endogeneity concerns (e.g., Xu, 2012; Flammer, 2015; Huang, Jennings and Yu, 2017; Dasgupta, Li and Wang, 2018).
Table 11: Impact of market structure changes on the feedback effect.

<table>
<thead>
<tr>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
</tr>
</thead>
<tbody>
<tr>
<td>∆ln(1 + PM_{i,t})</td>
<td>∆Net profitability_{i,t}</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mkt_chg_{i,t} × high_distress_{i,t-1} × Δsmooth_EP_{t}</td>
<td>0.13**</td>
<td>0.28**</td>
<td></td>
</tr>
<tr>
<td></td>
<td>[2.39]</td>
<td>[2.06]</td>
<td></td>
</tr>
<tr>
<td>High_distress_{i,t-1} × Δsmooth_EP_{t}</td>
<td>-0.08**</td>
<td>-0.06*</td>
<td>-0.11**</td>
</tr>
<tr>
<td></td>
<td>[-2.01]</td>
<td>[-1.75]</td>
<td>[-2.32]</td>
</tr>
<tr>
<td>Mkt_chg_{i,t} × Δsmooth_EP_{t}</td>
<td>0.05</td>
<td></td>
<td>-0.14</td>
</tr>
<tr>
<td></td>
<td>[1.34]</td>
<td></td>
<td>[-1.04]</td>
</tr>
<tr>
<td>ΔSmooth_EP_{t}</td>
<td>-0.01</td>
<td>-0.03</td>
<td>0.00</td>
</tr>
<tr>
<td></td>
<td>[-0.75]</td>
<td>[-1.15]</td>
<td>[0.11]</td>
</tr>
<tr>
<td>Mkt_chg_{i,t} × high_distress_{i,t-1}</td>
<td>-0.00</td>
<td></td>
<td>-0.02*</td>
</tr>
<tr>
<td></td>
<td>[-0.50]</td>
<td></td>
<td>[-1.80]</td>
</tr>
<tr>
<td>High_distress_{i,t-1}</td>
<td>0.01</td>
<td>0.02***</td>
<td>0.01</td>
</tr>
<tr>
<td></td>
<td>[3.35]</td>
<td>[3.27]</td>
<td>[3.73]</td>
</tr>
<tr>
<td>Mkt_chg_{i,t}</td>
<td>0.00</td>
<td></td>
<td>0.01</td>
</tr>
<tr>
<td></td>
<td>[0.09]</td>
<td></td>
<td>[0.81]</td>
</tr>
<tr>
<td>Observations</td>
<td>4443</td>
<td>1428</td>
<td>2712</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.022</td>
<td>0.034</td>
<td>0.015</td>
</tr>
</tbody>
</table>

Note: This table examines the impact of market structure changes on the feedback effect using industries with different levels of financial distress. The independent variable is the year-on-year change in the industry-level ln(1 + profit margin) and net profitability. High_distress_{i,t-1} is an indicator variable that equals one if the one-year-lagged financial distress of industry i is above the median gross profitability across all industries. The sample in columns (1) and (2) spans the period from 1972 to 2017. We measure market structure changes based on import tariff. Specifically, mkt_chg_{i,t} is an indicator variable that equals one if an industry experiences a large tariff cut in the last two years (t and t - 1). A large tariff cut refers to the tariff cut whose magnitude is greater than three times the median tariff cut in this industry across the whole sample period (e.g., Frésard, 2010). To ensure that large tariff cuts indeed capture nontransitory changes in the competitive environment, following Frésard (2010), we exclude tariff cuts that are followed by equivalently large increases in tariffs over the subsequent two years. We download the tariff data for manufacturing industries at the SIC4 industry level from 1974 to 2005 from Laurent Fresard’s website. We extend the data to 2017 based on the tariff data at the Harmonized System level, which are downloaded from Peter Schott’s website. Standard errors are clustered at the industry level. We include t-statistics in brackets. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

We first examine the impact of market structure changes on the sensitivity of net profitability to discount rates across industries with different financial distress. Table 11 presents the results. The regression includes the indicator variable for market structure changes, as well as its interaction terms, in the panel specification:

\[ \Delta \ln(1 + PM_{i,t}) = \beta_1 mkt_{chg_{i,t}} \times high_{distress_{i,t-1}} \times \Delta smooth_{EP_{t}} \]
\[ + \beta_2 high_{distress_{i,t-1}} \times \Delta smooth_{EP_{t}} + \beta_3 mkt_{chg_{i,t}} \times \Delta smooth_{EP_{t}} \]
\[ + \beta_4 \Delta smooth_{EP_{t}} + \beta_5 mkt_{chg_{i,t}} \times high_{distress_{i,t-1}} \]
\[ + \beta_6 high_{distress_{i,t-1}} + \beta_7 mkt_{chg_{i,t}} + \epsilon_{i,t}. \]

Here, mkt_{chg_{i,t}} is the indicator variable for market structure changes, which are measured by large tariff cuts. We find that the estimated coefficient on the triple interaction...
term $\hat{\beta}_1$ is positive and statistically significant, suggesting that high- and low-profitability industries display less difference in the exposure to discount rates when their market structure shifts to a more competitive one.\footnote{A positive $\hat{\beta}_1$ means that the difference in discount-rate exposure narrows because high-profitability industries are more negatively exposed to discount rates than low-profitability industries in the absence of large tariff cuts or large increases in cross-industry product similarity.} The magnitude of $\hat{\beta}_1$ in columns (1) is economically large. The result remains unchanged if we use $\Delta$Net profitability$_{i,t}$ in column (2).

Next, we examine the impact of market structure on the financial contagion effect. Specifically, we consider the following panel regression:

$$
\ln(1 + PM_{i,t}^{(L)}) = \beta_1 mkt\_chg_{i,t} \times \text{IdShock}_{i,t}^{(H)} + \beta_2 \text{IdShock}_{i,t}^{(H)} + \beta_3 mkt\_chg_{i,t} \\
+ \beta_4 \text{IdShock}_{i,t}^{(L)} + \sum_{\tau=1}^{5} \gamma_\tau \ln(1 + PM_{i,t-\tau}^{(L)}) + \epsilon_{i,t}. \tag{28}
$$

The estimated coefficient on the interaction term $\hat{\beta}_1$ in Table 12 is negative and significant both statistically and economically.

6 Quantitative Analyses

In this section, we quantitatively study the model’s ability to explain the asset pricing patterns in the data.

6.1 Calibration and Parameter Choice

The risk-free rate is $r_f = 2\%$. We set the persistence of the market price of risk to be $\varphi = 0.13$ as in Campbell and Cochrane (1999) and $\pi = 0.12$ as in Lettau and Wachter (2007). The within-industry elasticity of substitution is set at $\eta = 15$ and the industry’s price elasticity of demand at $\epsilon = 2$, which are broadly consistent with the values of Atkeson and Burstein (2008). We set the corporate tax rate $\tau = 27\%$ and the drift term under physical measure $g = 1.8\%$ as in He and Milbradt (2014). We set the bond recovery rate at $\nu = 0.41$ based on the mean recovery rate of Baa-rated bonds estimated by Chen (2010). This is fairly close to the estimated average recovery rate of debt in bankruptcy for large, public, non-financial U.S. firms from 1996 – 2014 (see Dou et al., 2020a). The initial debt-asset ratio of new entrant is set at $l_{new} = 0.4$. We set the initial customer base of new entrant to be a fraction $\kappa = 0.3$ of the non-exiting firm’s customer base.
Table 12: Impact of market structure changes on the financial contagion effect.

<table>
<thead>
<tr>
<th></th>
<th>Method (M1)</th>
<th>Method (M2)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mkt_chg_{i,t} \times IdShock_{i,t}^{(H)}</td>
<td>(-0.03^{**})</td>
<td>(-0.03^{**})</td>
</tr>
<tr>
<td>IdShock_{i,t}^{(H)}</td>
<td>(0.03^{***})</td>
<td>(0.03^{***})</td>
</tr>
<tr>
<td></td>
<td>[3.36]</td>
<td>[3.33]</td>
</tr>
<tr>
<td>Mkt_chg_{i,t}</td>
<td>(-0.01^*)</td>
<td>(-0.00)</td>
</tr>
<tr>
<td></td>
<td>([-1.84])</td>
<td>([-0.85])</td>
</tr>
<tr>
<td>IdShock_{i,t}^{(L)}</td>
<td>(0.07^{***})</td>
<td>(0.08^{***})</td>
</tr>
<tr>
<td></td>
<td>[7.56]</td>
<td>[6.40]</td>
</tr>
<tr>
<td>ln(1 + PM_{i,t-1}^{(L)})</td>
<td>(0.29^{***})</td>
<td>(0.18^{***})</td>
</tr>
<tr>
<td></td>
<td>[8.85]</td>
<td>[3.36]</td>
</tr>
<tr>
<td>ln(1 + PM_{i,t-2}^{(L)})</td>
<td>(0.05)</td>
<td>(0.10^{***})</td>
</tr>
<tr>
<td></td>
<td>[1.65]</td>
<td>[2.91]</td>
</tr>
<tr>
<td>ln(1 + PM_{i,t-3}^{(L)})</td>
<td>(-0.01)</td>
<td>(0.04^{**})</td>
</tr>
<tr>
<td></td>
<td>([-0.36])</td>
<td>[2.44]</td>
</tr>
<tr>
<td>ln(1 + PM_{i,t-4}^{(L)})</td>
<td>(0.00)</td>
<td>(-0.00)</td>
</tr>
<tr>
<td></td>
<td>[0.09]</td>
<td>([-0.02])</td>
</tr>
<tr>
<td>ln(1 + PM_{i,t-5}^{(L)})</td>
<td>(0.03)</td>
<td>(0.01)</td>
</tr>
<tr>
<td></td>
<td>[0.91]</td>
<td>[0.29]</td>
</tr>
<tr>
<td>Observations</td>
<td>14130</td>
<td>3932</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.335</td>
<td>0.320</td>
</tr>
</tbody>
</table>

Note: This table examines the impact of market structure changes on the financial contagion effect. The independent variable is the year-on-year change in the industry-level logged one plus profit margin. Other variables are explained in Table 11. The sample spans the period from 1976 to 2017. We include \(t\)-statistics in brackets. Standard errors are clustered at the industry level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

When studying the cross-sectional implications, we assume that the industry-level rate of market leadership turnover \(\lambda\) ranges from \(\lambda_L\) to \(\lambda_H\). We discretize \([\lambda_L, \lambda_H]\) into \(N = 5\) grids with equal spacing so that \(\lambda_1 = \lambda_L\) and \(\lambda_N = \lambda_H\). The mass of industries associated with each value of \(\lambda\) is the same. We set \(\lambda_L = 0\) as in our baseline industry and \(\lambda_H = 0.12\). To generate reasonable credit spreads across industries, we assume that a fraction \(\varpi = 0.85\) of leadership-turnover events only involves the turnovers of management teams without resulting in bankruptcy.

The remaining parameters are calibrated by matching relevant moments in Panel B of Table 13. We assume that the two firms in the baseline industry initially have the same coupon rate \(b_0\) and customer base \(M_0\). The initial customer base \(M_0\) is normalized to be 1 and we set \(b_0 = 10\) to generate an average debt-asset ratio of 0.35. The volatility of idiosyncratic shocks is \(\sigma_M = 25\%\) which generates a 10-year default rate of 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. Duffee (1998) reports that the average credit spread between a Baa-rated
### Table 13: Calibration and parameter choice.

<table>
<thead>
<tr>
<th>Panel A: Externally Determined Parameters</th>
</tr>
</thead>
<tbody>
<tr>
<td>Parameter</td>
</tr>
<tr>
<td>Risk-free rate</td>
</tr>
<tr>
<td>Volatility of market price of risk</td>
</tr>
<tr>
<td>Industry’s price elasticity</td>
</tr>
<tr>
<td>Mean growth rate of customer base</td>
</tr>
<tr>
<td>Debt-asset ratio of new entrant</td>
</tr>
<tr>
<td>Leadership turnover rate</td>
</tr>
<tr>
<td>Fraction of management turnover</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Panel B: Internally Calibrated Parameters</th>
</tr>
</thead>
<tbody>
<tr>
<td>Parameter</td>
</tr>
<tr>
<td>Initial coupon rate</td>
</tr>
<tr>
<td>Volatility of idiosyncratic shocks</td>
</tr>
<tr>
<td>Marginal cost of production</td>
</tr>
<tr>
<td>Punishment rate</td>
</tr>
<tr>
<td>Market price of risk for ( Z_t )</td>
</tr>
<tr>
<td>Volatility of aggregate shocks</td>
</tr>
<tr>
<td>Market price of risk for ( Z_{\gamma,t} )</td>
</tr>
</tbody>
</table>

10-year bond in the industrial sector and the Treasury is 138 bps. We set \( \zeta = 0.45 \), \( \gamma = 0.15 \), and \( \varsigma = 4\% \) so that the average equity premium is 6.7\%, the Sharpe ratio is 0.42, and the credit spread is 143 bps.

### 6.2 Quantitative Results

Panel A of Table 14 studies the cross-section of industry portfolios sorted on gross profitability. In the data, the average equity return of the industry portfolio with high gross profitability (Q5) is 3.02\% higher than that of the industry portfolio with low gross profitability (Q1) after controlling for leverage; however, the credit spread of the former is 1.05\% lower than the latter. Our model-implied patterns are consistent with the data. In the collusive equilibrium, the differences are 5.07\% for equity returns and −1.55\% for credit spreads (Q5–Q1). To highlight the importance of competition risk premium in rationalizing the gross profitability premium puzzle across industries, we also present the model-implied values in the non-collusive equilibrium. The magnitudes are -0.05\% for equity returns and 0.03\% for credit spreads, both of which are indistinguishable from zero because there is essentially no variation in gross profitability across industries in the
non-collusive equilibrium.

Panel B studies the cross-section of industry portfolios sorted on financial distress. In the data, the average equity return of the industry portfolio with high distress (Q5) is 7.18% lower than that of the industry portfolio with high distress (Q1) after controlling for leverage; however, the credit spread of the former is 2.00% higher than the latter. In the model, we use the expected 5-year default rate as a measure of financial distress. Performing the same sorting analysis, we find that in the collusive equilibrium, the model-implied average equity return for Q5 is 4.97% lower than that of Q1 after controlling for leverage and the average credit spread is 2.73% higher, which are roughly in line with the data. By contrast, in the non-collusive equilibrium, the model-implied difference in equity returns (Q5−Q1) is merely 0.09% because the competition intensity is not affected by the degree of industry distress. The model-implied credit spreads are 0.70% (Q1) and 4.42% (Q5) in the non-collusive equilibrium, larger than those in the collusive equilibrium. This is because all else equal, firms in the non-collusive equilibrium have greater default rates than those in the collusive equilibrium due to more intensive competition and lower profitability (see panel A of Figure 4).

In our model, the cross-sectional difference in gross profitability and financial distress is driven by the same fundamental industry characteristic – the heterogeneous persistence of market leadership. Industries with higher leadership turnover rates are associated with lower gross profitability and higher financial distress. To uncover the impact of this fundamental heterogeneity, we study the cross-section of industry portfolios sorted on leadership turnover rates \( \lambda \) in panel C. In the data, the average equity return of the industry portfolio with high turnover rate (Q5) is 2.56% lower than that of the industry portfolio with low turnover rate (Q1) after controlling for leverage; however, the credit spread of the former is 0.75% higher than the latter. Our model generates consistent patterns in the collusive equilibrium, though with larger magnitudes for both equity returns and credit spreads. By contrast, in the non-collusive equilibrium, the model cannot generate a significant difference in equity returns between Q1 and Q5 because leadership persistence does not affect industry competition. This again highlights the importance of competition risk premium.

In panel D, we study how financial distress affects gross profitability premium puzzle. In both the model and data, we split industries into two groups based on their financial distress. Within each group, we further sort industries into tertiles based on their gross profitability. The data suggest that the differences in equity returns and credit spreads between Q1 and Q5 are more pronounced in the high-distress group. Our model rationalizes this pattern thanks to the competition-distress feedback in the collusive
Table 14: Quantitative implications in model and data.

Panel A: Industry portfolios sorted on gross profitability

<table>
<thead>
<tr>
<th></th>
<th>equity returns (%)</th>
<th>credit spreads (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Q1 (low)</td>
<td>Q5 (high)</td>
</tr>
<tr>
<td>Data</td>
<td>−1.67</td>
<td>1.35</td>
</tr>
<tr>
<td>Model</td>
<td></td>
<td></td>
</tr>
<tr>
<td>collusive</td>
<td>−1.83</td>
<td>3.24</td>
</tr>
<tr>
<td>non-collusive</td>
<td>0.02</td>
<td>−0.03</td>
</tr>
</tbody>
</table>

Panel B: Industry portfolios sorted on financial distress

<table>
<thead>
<tr>
<th></th>
<th>equity returns (%)</th>
<th>credit spreads (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Q1 (low)</td>
<td>Q5 (high)</td>
</tr>
<tr>
<td>Data</td>
<td>2.69</td>
<td>−4.49</td>
</tr>
<tr>
<td>Model</td>
<td></td>
<td></td>
</tr>
<tr>
<td>collusive</td>
<td>2.26</td>
<td>−2.71</td>
</tr>
<tr>
<td>non-collusive</td>
<td>−0.04</td>
<td>0.05</td>
</tr>
</tbody>
</table>

Panel C: Industry portfolios sorted on leadership turnover rate

<table>
<thead>
<tr>
<th></th>
<th>equity returns (%)</th>
<th>credit spreads (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Q1 (low)</td>
<td>Q5 (high)</td>
</tr>
<tr>
<td>Data</td>
<td>1.06</td>
<td>−1.50</td>
</tr>
<tr>
<td>Model</td>
<td></td>
<td></td>
</tr>
<tr>
<td>collusive</td>
<td>2.33</td>
<td>2.79</td>
</tr>
<tr>
<td>non-collusive</td>
<td>−0.04</td>
<td>0.08</td>
</tr>
</tbody>
</table>

Panel D: Long-short portfolios sorted on gross profitability (T3–T1) in split samples by distress

<table>
<thead>
<tr>
<th></th>
<th>equity returns (%)</th>
<th>credit spreads (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>low distress</td>
<td>high distress</td>
</tr>
<tr>
<td>Data</td>
<td>0.24</td>
<td>5.53</td>
</tr>
<tr>
<td>Model</td>
<td></td>
<td></td>
</tr>
<tr>
<td>collusive</td>
<td>3.46</td>
<td>7.29</td>
</tr>
<tr>
<td>non-collusive</td>
<td>0.03</td>
<td>0.02</td>
</tr>
</tbody>
</table>

Panel E: Regressing leadership turnover rates on profitability and distress

<table>
<thead>
<tr>
<th></th>
<th>profitability</th>
<th>distress</th>
</tr>
</thead>
<tbody>
<tr>
<td>Data</td>
<td>−1.81</td>
<td>0.006</td>
</tr>
<tr>
<td>Model</td>
<td></td>
<td></td>
</tr>
<tr>
<td>collusive</td>
<td>−1.74</td>
<td>0.21</td>
</tr>
<tr>
<td>non-collusive</td>
<td>0.00</td>
<td>0.74</td>
</tr>
</tbody>
</table>

Note: In the model, financial distress is measured by the expected 5-year default rate. In both the model and data, the results for equity returns control for financial leverage, but the results for credit spreads do not control for financial leverage. In particular, the results for equity returns are obtained in the following steps. First, we sort industries into five bins based on their financial leverage. Second, for each industry, we calculate its leverage-adjusted gross profitability by subtracting the average gross profitability of all industries in the same bin. The leverage-adjusted financial distress, leadership turnover rate, and equity returns are constructed in the same way. Third, we perform sorting analysis based on leverage-adjusted gross profitability, financial distress, and leadership turnover in panels A, B, and C for equity returns. In panel D, we split sample based on financial distress, and perform sorting analysis based on leverage-adjusted gross profitability for equity returns. When constructing the model moments, we simulate a sample of 1,000 industries for 150 years with an 80-year burn-in period. We then compute the model-implied moments similar to the data. For each moment, the table reports the average value of 2,000 simulations.
equilibrium (see panels D and F of Figure 9).

Finally, panel E formally studies the relation between leadership turnover rates, gross profitability, and financial distress. In the data, industries with higher leadership turnover rates are associated with lower profitability and higher distress. In the model, we run similar regressions and show that a one-percentage-point increase in turnover rate reduces the gross profit margin by 1.74 percentage points and increases the 5-year default rate by 0.21 percentage point on average in the collusive equilibrium. However, in the non-collusive equilibrium, leadership turnover rate does not affect the gross profit margin, and its impact on 5-year default rate is larger due to the higher level of distress.

7 Conclusion

In this paper, we explore the implication of endogenous competition on credit risks. We develop a general-equilibrium asset pricing model incorporating dynamic supergames of profit-margin competition among firms. In our model, firms compete more fiercely in recessions through profit-margin undercutting, resulting in low cash flows and high credit risks. The high credit risks induce more intense competition in product markets, further reducing profit margins and cash flows. This feedback mechanism between product market competition and financial leverage increases credit risks and generates high credit spreads.

References


Appendix

A Supplementary Information on Model Analyses

A.1 Amplification Effect on Industry Risk Exposure

In this appendix section, we show that industries’ exposure to discount-rate shocks is amplified due to the competition-distress feedback.
Figure 4 implies that a higher discount rate depresses the industry’s value not only through the standard discounting effect but also by reducing profit margins due to higher competition. The endogenously intensified competition is further amplified by the feedback loop between competition and financial distress, dramatically increasing the industry’s exposure to discount-rate shocks. In particular, the intensified competition in the aggregate states of high discount rates lowers firms’ cash flows, which raises the default risk of levered firms. The rising default risk makes financially distressed firms compete more aggressively, which further reduces profit margins and increases the default risk across firms.

To illustrate this amplification effect, consider the same duopoly industry as in Subsection 3.1. Figure A.1 plots the industry-level beta of equity $\beta^V_t$ (defined in equation 24) and debt $\beta^D_t$ (defined in equation 24) with respect to discount-rate shocks, calculated as the value-weighted firm-level beta:

![Graph](image)

Note: We consider a duopoly industry with two identical firms (i.e., $M_{i,t} = M_{j,t}$). Panel A plots the industry’s equity exposure (defined in equation 24) as a function of firms’ average customer base; and panel B plots industry’s debt exposure (defined in equation 25). The blue solid line represents the collusive equilibrium of our baseline model and the black dashed line represents the counterfactual case where industries profit margins remain unchanged when the discount rate rises. The vertical dotted lines represent firms’ default boundary in the state of $\gamma_H$. In both panels, we use $\gamma_L = \tau$ and $\gamma_H = \tau + 2\text{std}(\gamma_t)$. Other parameters are set according to our calibration in Section 6.1.

Figure A.1: Amplification effect of competition-distress feedback on industry risk exposure.

The blue solid lines in panels A and B plot the industry’s beta of equity and debt when the discount rate increases from $\gamma_L$ to $\gamma_H$. As a benchmark, the black dashed lines plot the industry’s beta in a counterfactual experiment where profit margins remain fixed when the discount rate increases. Our baseline model implies that the industry’s equity and debt are much more exposed to discount-rate shocks because profit margins negatively comove with the discount rate. This implication is consistent with that of Dou, Ji and Wu (2020) whose model focuses on all-equity industries (i.e., all firms in the industry are unlevered). Different from Dou, Ji and Wu (2020), our model further implies that the magnitude of the amplification effect, as measured by the distance between the blue solid and red dotted lines, is larger when the industry is more financially distressed. This is due to the positive feedback loop between competition and distress (see panel C of Figure 4).
Note: We set the initial customer base of both firms at $M_{i,0} = M_{j,0} = 2$. Then, we hold firm $j$’s customer base fixed and introduce a sequence of negative idiosyncratic shocks to firm $i$, which gradually reduce its customer base until it hits the default boundary. The blue solid line traces out how firm $j$’s profit margin $\theta_{j,t}$ varies with firm $i$’s customer base $M_{i,t}$ over time in the industry with a low entry barrier ($\kappa = 0.3$, panel A) and the industry with a high entry barrier ($\kappa = 0.15$, panel B). The black dashed line represents the industry in which firms have no predatory incentives (i.e., the new entrant has the same amount of customer base as the exiting firm). In all panels, the vertical dotted lines represent default boundaries of firm $i$ in respective cases and we set $\gamma_t = \gamma$. Other parameters are set according to our calibration in Section 6.1.

Figure A.2: Isolating the real predatory incentives.

A.2 Isolating the Predatory Incentive

As discussed in Subsection 3.2, both firms cut profit margins in response to negative idiosyncratic shocks to customer base. The profit-margin undercutting of the financially strong firm reflects both its self-defensive and predatory incentives. In this appendix, we use the model to isolate firms’ predatory incentives from their self-defensive incentives. To this end, we compare the financially strong firm’s profit margin in our baseline model (the blue solid lines in Figure A.2) to that in a counterfactual scenario (the black dashed lines in Figure A.2) where the new entrant has the same amount of customer base as the financially distressed firm that exits the industry, i.e., $M_{new} = M_{i,t}$ when firm $i$ defaults at $t$.

In this counterfactual scenario, by definition, the financially strong firm would not have any predatory incentives because driving its financially weak competitor out of the market does not increase its monopoly power or profitability in the future.

Specifically, in Figure A.2, we consider an experiment where the initial customer base of both firms are set at $M_{i,0} = M_{j,0} = 2$. Then, we hold firm $j$’s customer base fixed and introduce a sequence of negative idiosyncratic shocks to firm $i$, which gradually reduce its customer base until it hits the default boundary. Panel A shows that the financially strong firm $j$ cuts its profit margin more significantly in our baseline industry (the blue solid line) than in the counterfactual scenario (the black dashed line) when firm $i$ becomes more financially distressed due to idiosyncratic shocks (i.e., lower $M_{i,t}$). The difference between the two curves quantifies firm $j$’s real predatory incentives. As a further illustration, in panel B, we consider an

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33 We assume that the new entrant chooses its initial coupon rate $b_{new}$ to keep the initial debt ratio at $l_{new}$. This ensures that the new entrant does not default immediately even though it has the same amount of customer base as the exiting firm.

34 The predatory incentives of firm $j$ quantified by the difference between the two curves also reflect the feedback effect from firm $i$’s profit margin. Intuitively, when firm $j$ lowers its profit margin due to pure
Note: Panels A plots firm $i$’s equity value as a function of its own customer base $M_{i,t}$; and panel B plots firm $j$’s equity value as a function of firm $i$’s customer base $M_{i,t}$. The blue solid and red dash-dotted lines represent the collusive equilibrium and the non-collusive equilibrium in the industry with $\kappa = 0$. The vertical red dotted line represents default boundaries of firm $i$. The vertical dash-dotted line represents the endogenous jump (i.e., switching between collusion and non-collusion) boundary. In all panels, we use $\gamma_t = \overline{\gamma}$ and $M_{j,t} = 2$. Other parameters are set according to our calibration in Section 6.1.

Figure A.3: Illustration of the price-war boundary in the industry with $\kappa = 0$.

industry with higher entry barrier by assuming that the new entrant has a smaller size than that in our baseline industry (i.e., reducing $\kappa$ from 0.3 to 0.15). This implies that the financially strong firm $j$ would have more predatory incentives because it can capture a larger market share by successfully driving its weak competitor $i$ into default. Comparing the difference between the blue solid and black dashed lines in panels A and B, it is clear that firm $j$ has higher predatory incentives in the latter industry. In particular, when firm $i$ is close to its default boundary, firm $j$ is willing to forgo 4% of its profit margin to drive firm $i$ into default.

A.3 Determination of the Price-War Boundary

In this appendix, we illustrate how the price-war boundary is determined in the industry with $\kappa = 0$. In Figure A.3, we compare each firm’s equity value in the collusive and non-collusive equilibria. Panel B shows that firm $j$’s equity value in the collusive equilibrium (the blue solid line) intersects with that in the non-collusive equilibrium (the red-dotted line) at $M_{i,t} = 0.9$. This is the critical point when firm $j$’s PC constraint (15) becomes binding. For $M_{i,t} > 0.9$, both firms’ PC constraints are always satisfied and not binding for the collusive profit-margin schemes that satisfy the IC constraints (16), and thus they want to collude with each other. For $M_{i,t} < 0.9$, the PC constraint (15) becomes binding for firm $j$. This implies that if the two firms collude on profit margins that are higher than the non-collusive ones, the PC constraint of firm $j$ will be violated even though the IC constraints (16) are honored.

On the other hand, panel A of Figure A.3 shows that firm $i$’s equity value in the collusive equilibrium is strictly higher than that in the non-collusive equilibrium when $M_{i,t} \geq 0.9$, indicating that firm $i$ would always want to collude with firm $j$. Only when $M_{i,t} < 0.9$, firm $i$’s equity value in the collusive equilibrium is equal to that in the non-collusive equilibrium because firm $j$ chooses not to collude. At $M_{i,t} = 0.9$, there predatory incentives, firm $i$ will respond by setting a lower profit margin due to strategic complementarity. This in turn will further lower firm $j$’s profit margin.
is an endogenous jump in firm \( i \)'s equity value. Therefore, our model implies that it is the firm with a stronger financial condition (or larger customer base when the two firms pay the same coupon rates) that wants to abandon collusion and wages a price war.

### A.4 Boundary Condition at \( M_{i,t} = +\infty \)

When \( M_{i,t} = +\infty \), firm \( i \) is essentially a monopoly in the industry with negligible default risk because its competitor \( j \) is negligible for any value of \( M_{j,t} \). Thus, the boundary condition of firm \( i \)'s equity value at \( M_{i,t} = +\infty \) should satisfy:

\[
\lim_{M_{i,t} \to \infty} \frac{\partial}{\partial M_{i,t}} V_i^N(x_t) = \lim_{M_{i,t} \to \infty} \frac{\partial}{\partial M_{i,t}} V_i^C(x_t) = \lim_{M_{i,t} \to \infty} \frac{\partial}{\partial M_{i,t}} V_i^D(x_t) = \lim_{M_{i,t} \to \infty} \frac{\partial}{\partial M_{i,t}} U_i(M_{i,t}, \gamma_t),
\]

(29)

where \( U_i(M_{i,t}, \gamma_t) \) is the equity value of an unlevered monopoly industry with customer base \( M_{i,t} \equiv M_t \). In this monopoly industry, the demand curve facing the monopoly firm is given by equation (7)

\[
C_{i,t} = C_t = M_{i,t}P_t^{-\epsilon},
\]

(30)

and the evolution of the single firm’s customer base \( M_{i,t} \) is

\[
dM_{i,t}/M_{i,t} = gdt + \zeta dZ_t + \sigma_M dW_{i,t} - M_{i,t}dJ_{i,t},
\]

(31)

Thus, the HJB equation that determines \( U_i(M_{i,t}, \gamma_t) \) can be written as

\[
\lambda U_i(M_{i,t}, \gamma_t)dt = \max_{b_i}(1 - \tau)[\omega^{1-\epsilon}\theta_t(1 - \theta_t)^{1-\epsilon} M_{i,t} - b_i]dt + \Lambda_t^{-1}E_t[d(\Lambda_tU_i(M_{i,t}, \gamma_t))].
\]

(32)

The boundary condition of firm \( i \)'s debt value at \( M_{i,t} = +\infty \) is the value of a default-free consol bond with constant coupon rate \( b_t \) and value \( b_t/r_f \).

### A.5 Industry of Monopolistic Competition

Consider an industry of monopolistic competition with a continuum of firms. The demand for each firm’s good is determined by

\[
C_{i,t} = \left( \frac{P_{i,t}}{P_t} \right)^{-\eta} P_t^{-\epsilon} M_{i,t},
\]

(33)

where \( P_t \) is

\[
P_t = \left[ \int_{j \in J} \left( \frac{M_{j,t}}{M_t} \right) P_{j,t}^{1-\eta} dt \right] ^{1/\eta}.
\]

(34)

The key difference between the price index (6) of a duopoly industry and the price index (34) is that for the latter, each firm is atomistic and takes the price index \( P_t \) as exogenously given when choosing \( P_{i,t} \).

The optimal profit margin chosen by any firm \( i \) is \( \theta^*_i = 1/\eta \). Thus, the profit margin index in the industry of monopolistic competition is \( \theta^*_i = \frac{1}{\eta} \). In equilibrium, firm \( i \)'s operating profit rate per unit of customer base is

\[
\Pi(\theta^*_{i,t}, \gamma_t) = \omega^{1-\epsilon} \left( \frac{1}{\eta} \right) \left( \frac{n - 1}{\eta} \right)^{\epsilon - 1} M_{i,t}.
\]

(35)
Note: This figure plots firm $i$’s conditional cash flow volatility normalized by its own customer base $M_{i,t}$. Specifically, we fix the values of $\gamma_0 = \gamma$ and $M_{j,0} = 2$ at $t = 0$. For each value of $M_{i,0}$, we run $N = 200,000$ parallel simulations for one year until $t = 1$. We then calculate firm $i$’s cumulative cash flows $A_{i,0}^{k} \rightarrow^{t=1}$ from $t = 0$ to $t = 1$ for each simulation $k = 1, \ldots, N$. That is, $A_{i,0}^{k} \rightarrow^{t=1} = \int_{t=0}^{1} \Pi_i(\theta_{i,t}, \theta_{j,t}) M_{i,t} dt$, where $\Pi_i(\theta_{i,t}, \theta_{j,t})$ is defined by equation (11). The conditional cash flow volatility per customer base corresponding to each value of $M_{i,0}$ is computed by the standard deviation of $A_{i,0}^{k} \rightarrow^{t=1}$ over $N$ simulations. The blue solid and red dotted lines represent the collusive equilibrium and the non-collusive equilibrium in a duopoly industry. The black dashed line represents a generic firm in an industry of monopolistic competition with a continuum of firms. The vertical dotted lines represent default boundaries of firm $i$ in respective cases. Other parameters are set according to our calibration in Section 6.1.

Figure A.4: Conditional cash flow volatility per customer base.

### A.6 Additional Model Analyses

#### Cash Flow Volatility.

Figure A.4 plots firm $i$’s conditional cash flow volatility normalized by its customer base. In the industry of monopolistic competition, the conditional cash flow volatility is a constant (see the black dashed line) regardless of the firm’s customer base $M_{i,t}$ because the profit margin is a constant. In the duopoly industry, the conditional cash flow volatility slightly increases with the firm’s customer base $M_{i,t}$ in the non-collusive equilibrium (see the red dotted line), reflecting the change in profit margins due to the change in short-run price elasticity of demand (see equation 8). By contrast, in the collusive equilibrium, firm $i$’s cash flow volatility increases substantially when the firm becomes financially distressed (see the blue solid line). This is because the feedback between financial distress and competition makes the firm’s profit margins more expose to shocks in $M_{i,t}$ when the firm becomes financially distressed (see the blue solid line in panel A of Figure 4).

#### Exposure to Aggregate Shocks in Customer Base.

Figure A.5 illustrates firm $i$’s exposure to aggregate shocks in customer base (i.e., the term $dZ_t$ in equation 2). Panel A shows that the firm’s equity is more exposed to aggregate shocks in customer base in the collusive equilibrium (see the blue solid line) due to the significant endogenous movement in profit margins (see the blue solid and black dashed lines in panel B of Figure 4). However, panel B shows that, for any customer base $M_{i,t}$, the firm’s debt is less exposed to these shocks in the collusive equilibrium (see the blue solid line). This is because firm $i$’s default risk is lower in the collusive equilibrium (comparing the blue and red vertical dotted lines in panel B).
Note: This figure illustrates firm $i$’s exposure to aggregate shocks in customer base. Panel A plots firm $i$’s equity exposure to aggregate shocks in customer base, i.e., $\partial V_i / \partial M_{i,t}$; panel B plots firm $i$’s debt exposure to aggregate shocks in customer base, i.e., $\partial D_i / \partial M_{i,t}$. The blue solid and red dotted lines represent the collusive equilibrium and the non-collusive equilibrium, respectively. The vertical dotted lines represent default boundaries of firm $i$ in respective cases. In both panels, we use $\gamma_t = \gamma$, and $M_{j,t} = 2$. Other parameters are set according to our calibration in Section 6.1.

**Figure A.5:** Exposure to aggregate shocks in customer base.

**Comparative Statics on Coupon Rates.** We study the comparative statics on firms’ coupon rates. Panels A and B of Figure A.6 compare the profit margins of the baseline industry with the industry where both firms’ initial coupon rates are $b_0 = 15$. Both firms in the industry with a higher coupon rate set lower profit margins in the collusive equilibrium (see the red dotted line), reflecting the feedback between competition and financial distress. Moreover, panels C and D show that both the equity and debt of firms in the industry with a higher coupon rate are more exposed to aggregate discount rate shocks.

**B Numerical Algorithm**

In this section, we detail the numerical algorithm that solves the model. To give an overview, our algorithm proceeds in the following steps:

1. We solve the non-collusive equilibrium. This requires us to solve the subgame perfect equilibrium of the dynamic game played by two firms. The simultaneous-move dynamic game requires us to solve the intersection of the two firms’ best response (i.e., optimal decisions on profit margins and default) functions, which themselves are optimal solutions to coupled PDEs.

2. We solve the collusive equilibrium using the value functions in the non-collusive equilibrium as punishment values. Because we are interested in the highest collusive profit margins with binding incentive-compatibility constraints, this requires us to solve a high-dimensional fixed-points problem. We thus use an iteration method inspired by Abreu, Pearce and Stacchetti (1986, 1990b), Ericson and Pakes (1995), and Fershtman and Pakes (2000) to solve the problem.

Note that standard methods for solving PDEs with free boundaries (e.g., finite difference or finite element) can easily lead to non-convergence of value functions. To mitigate such problems and obtain accurate solutions, we solve the continuous-time game using a discrete-time dynamic programming method, as in Dou, Ji and Wu (2020). In Appendix B.1, we present the discretized recursive formulation for the
Note: Panel A plots firm i’s profit margin as a function of its own customer base $M_{ij}$; and panel B plots firm j’s profit margin as a function of firm i’s customer base $M_{ij}$. Panel C plots firm i’s equity exposure (defined in equation 24) as a function of its customer base $M_{ij}$; and panel D plots firm i’s debt exposure (defined in equation 25) as a function of its customer base $M_{ij}$. In all panels, the blue solid line represents the baseline industry with coupon rate $b_0 = 10$ in the collusive equilibrium. The red dotted line represents the industry with coupon rate $b_0 = 15$ in the collusive equilibrium. The vertical dotted lines represent default boundaries of firm i in respective cases. In all panels, we use $\gamma_t = \overline{\gamma}$, $\gamma_H = \overline{\gamma} + 2\text{std}(\gamma_t)$, and $M_{ij} = 2$. Other parameters are set according to our calibration in Section 6.1.

Figure A.6: Firms’ profit margins and risk exposure with different coupon rates $b_0$.

model, including firms’ problems in non-collusive equilibrium, collusive equilibrium, and deviation. In Appendix B.2, we discuss how we discretize the stochastic processes, time grids, and state variables in the model. Finally, in Appendix B.3, we discuss the details on implementing our numerical algorithms, including finding the equilibrium profit margins in the non-collusive equilibrium and solving the optimal collusive profit margins and default boundaries.

### B.1 Discretized Dynamic Programming Problem

We solve the model in risk-neutral measure, where we have

$$dZ_t = -\gamma_t dt + d\tilde{Z}_t,$$

$$dZ_{\gamma,t} = -\zeta dt + d\tilde{Z}_{\gamma,t}. \tag{36}$$
Because firm 1 and firm 2 are symmetric, one firm’s equity value and policy functions are obtained directly given the other firm’s equity value and policy functions. We first illustrate the non-collusive equilibrium and then we illustrate the collusive equilibrium.

### B.1.1 Non-Collusive Equilibrium

Below, we first present the recursive formulation for the firm’s equity value in the non-collusive equilibrium. Next, we present the conditions that determine the non-collusive (Nash) equilibrium.

#### Recursive Formulation for The Value of Equity in Non-Collusive Equilibrium

Firm $i$’s state is characterized by three state variables, including firm $i$’s customer base $M_{i,t}$, firm $j$’s customer base $M_{j,t}$, and the aggregate state $\gamma_t$. Denote the equity value functions in the non-collusive equilibrium as $V^N_i(M_{i,t}, M_{j,t}, \gamma_t; \theta_{i,t}, d_{i,t}; b_i, b_j)$ for $i=1,2$, where $b_i$ and $b_j$ are the two firms’ coupon rates. In our baseline calibration, we set $b_i = b_j = b_0$. We make coupon rate explicitly as state variables because upon defaults of any incumbent firms, the coupon rate of new entrants is $b_{new}$, which may be different from $b_0$.

To characterize the equilibrium value functions, it is more convenient to introduce two off-equilibrium value functions. Let $\tilde{V}^N_i(M_{i,t}, M_{j,t}, \gamma_t; \theta_{i,t}, d_{i,t}; b_i, b_j)$ be firm $i (= 1, 2)$’s value when its competitor $j$’s profit margin is any (off-equilibrium) value $\theta_{j,t}$ and default status is any (off-equilibrium) value $d_{j,t} = 0, 1$.

Firm $i=1,2$ solves the following problem:

$$
\tilde{V}^N_i(M_{i,t}, M_{j,t}, \gamma_t; \theta_{i,t}, d_{i,t}; b_i, b_j) = \max_{\theta_{j,t}, d_{j,t}} \left(1 - d_{i,t}\right) \left\{ \left(1 - \tau\right) \left[ \omega \left(1 - \theta_{j,t}\right) (1 - \theta_{i,t})\eta - \left(1 - \theta_{i,t}\right) \eta - \eta M_{i,t} - b_i \right] \Delta t + e^{-(r_f + \lambda)\Delta t} E_t \left[ (1 - d_{j,t}) V^N_i(M_{i,t+\Delta t}, M_{j,t+\Delta t}, \gamma_{t+\Delta t}; b_i, b_j) + d_{j,t} V^N_i(M_{i,t+\Delta t}, M_{new}, \gamma_{t+\Delta t}; b_i, b_{new}) \right] \right\},
$$

(38)

subject to the following constraints. (1) The industry’s profit margin is given by

$$
1 - \theta_t = \left[ \frac{M_{i,t}(1 - \theta_{i,t})\eta^{-1} + M_{j,t}(1 - \theta_{j,t})\eta^{-1}}{M_t} \right]^{\frac{1}{\eta-1}} \text{ with } M_t = M_{i,t} + M_{j,t}.
$$

(39)

(2) The customer base evolves according to

$$
M_{i,t+\Delta t} = M_{i,t} + g M_{i,t}\Delta t + \zeta M_{i,t}(-\gamma_t\Delta t + \Delta Z_t) + \sigma M_{i,t}\Delta W_{i,t},
$$

(40)

$$
M_{j,t+\Delta t} = M_{j,t} + g M_{j,t}\Delta t + \zeta M_{j,t}(-\gamma_t\Delta t + \Delta Z_t) + \sigma M_{j,t}\Delta W_{j,t}.
$$

(41)

The jump terms $d_{i,t}$ and $d_{j,t}$ are omitted because they trigger immediate default and are reflected by the term $e^{-\lambda\Delta t}$ in the objective function (38).

(3). The aggregate state $\gamma_t$ evolves according to

$$
\gamma_{t+\Delta t} = \gamma_t - \varphi (\gamma_t - \bar{\gamma}) \Delta t - \pi (-\zeta\Delta t + \Delta \hat{Z}_{\gamma,t}).
$$

(42)

#### Non-Collusive (Nash) Equilibrium

Denote the equilibrium profit margin and default functions as $\theta^N_i(M_{i,t}, M_{j,t}, \gamma_t; b_i, b_j)$ and $d^N_i(M_{i,t}, M_{j,t}, \gamma_t; b_i, b_j)$. Denote the off-equilibrium profit margin and default functions as $\tilde{\theta}^N_i(M_{i,t}, M_{j,t}, \gamma_t; \theta_{i,t}, d_{i,t}; b_i, b_j)$ and $\tilde{d}^N_i(M_{i,t}, M_{j,t}, \gamma_t; \theta_{j,t}, d_{j,t}; b_i, b_j)$.
Given firm $j$'s profit margin $\theta_{j,t}$ and default decision $d_{j,t}$, firm $i$ optimally sets the profit margin $\theta_{i,t}$ and makes default decision $d_{i,t}$. The non-collusive (Nash) equilibrium is derived from the fixed point—each firm’s profit margin and default are optimal given the other firm’s optimal profit margin and default:

$$
\theta_{i,t}^N(M_{i,t}, M_{j,t}, \gamma_i; b_i, b_j) = d_{i,t}^N(M_{i,t}, M_{j,t}, \gamma_i; b_i, b_j),
$$

$$
d_{i,t}^N(M_{i,t}, M_{j,t}, \gamma_i; b_i, b_j) = \theta_{i,t}^B(M_{i,t}, M_{j,t}, \gamma_i; b_i, b_j),
$$

The equilibrium value functions are given by

$$
V_i^N(M_{i,t}, M_{j,t}, \gamma_i; b_i, b_j) = V_i^B(M_{i,t}, M_{j,t}, \gamma_i; b_i, b_j),
$$

B.1.2 Collusive Equilibrium

Below, we present the recursive formulation for the firm’s value in the collusive equilibrium. Then we present the recursive formulation for the firm’s value when it deviates from the collusive equilibrium.

Finally, we present the incentive compatibility constraints to determine the equilibrium collusive profit margins. After finding the equilibrium collusive profit margin scheme, we check whether the participation constraints are satisfied. There are two cases, if the participation constraints are satisfied, the two firms will collude on the equilibrium profit margin scheme. If the participation constraints are not satisfied, the two firms will set profit margins according to their non-collusive ones.

Recursive Formulation for The Value of Equity in The Collusive Equilibrium Denote $V_i^C(M_{i,t}, M_{j,t}, \gamma_i; d_{i,t}; b_i; \sigma^C(\cdot))$ as firm $i (=1,2)$’s value in the collusive equilibrium with collusive profit margin scheme $\sigma^C(\cdot)$. Denote $V_j^C(M_{i,t}, M_{j,t}, \gamma_i; d_{j,t}; b_i; b_j; \sigma^C(\cdot))$ be firm $i (=1,2)$’s value in the collusive equilibrium with collusive profit margin scheme $\sigma^C(\cdot)$ when its competitor $j$’s default status is any (off-equilibrium) value $d_{j,t} = 0, 1$.

Firm $i$ solves the following problem:

$$
V_i^C(M_{i,t}, M_{j,t}, \gamma_i; d_{i,t}; b_i; b_j; \sigma^C(\cdot)) = \max_{d_{i,t}} (1 - d_{i,t}) \left\{ (1 - \tau) \left[ \omega^{1 - \varepsilon} \theta_{i,t}^C(1 - \theta_{i,t}^C)^{\eta - 1}(1 - \theta_{i,t}^C)^{\varepsilon - \eta} M_{i,t} - b_i \right] \Delta t 
+ e^{-(r_f + \lambda)\Delta t} \mathbb{E}_t \left[ (1 - d_{j,t}) V_j^C(M_{i,t+\Delta t}, M_{j,t+\Delta t}, \gamma_{i,t+\Delta t}; b_i, b_j; \sigma^C(\cdot)) + d_{j,t} V_j^C(M_{i,t+\Delta t}, M_{new}, \gamma_{i,t+\Delta t}; b_i, b_{new}, \sigma^C(\cdot)) \right] \right\},
$$

subject to the following constraints. (1) The industry’s profit margin is given by

$$
1 - \theta_i^C = \left[ \frac{M_{i,t}(1 - \theta_{i,t}^C)^{\eta - 1} + M_{j,t}(1 - \theta_{j,t}^C)^{\eta - 1}}{M_t} \right]^{1/(\eta - 1)}
$$

with $M_t = M_{i,t} + M_{j,t}$.

(2) The customer base evolves according to

$$
M_{i,t+\Delta t} = M_{i,t} + g M_{i,t} \Delta t + \xi M_{i,t} (\gamma_{i,t} \Delta t + \Delta \tilde{Z}_t) + \sigma_M M_{i,t} \Delta W_{i,t},
$$

$$
M_{j,t+\Delta t} = M_{j,t} + g M_{j,t} \Delta t + \xi M_{j,t} (\gamma_{j,t} \Delta t + \Delta \tilde{Z}_t) + \sigma_M M_{j,t} \Delta W_{j,t}.
$$
subject to the following constraints. (1) The industry’s profit margin is given by

\[ \gamma_t = \gamma_t - \varphi(\gamma_t - \bar{\gamma})\Delta t - \pi(-\zeta \Delta t + \Delta \bar{\gamma}_t). \] (50)

Denote the equilibrium default function as \( \tilde{d}_i^C(M_{i,t}, M_{j,t}, \gamma_t; b_i, b_j; \tilde{\Theta}^C(\cdot)) \). Denote the off-equilibrium default function as \( \tilde{d}_i^C(M_{i,t}, M_{j,t}, \gamma_t; d_{ij,t}; b_i, b_j; \tilde{\Theta}^C(\cdot)) \). The default decisions are determined in Nash equilibrium. In particular, given firm \( j \)'s default decision \( d_{ij,t} \), firm \( i \) optimally makes default decision \( d_{ij,t} \). The Nash equilibrium is derived from the fixed point—each firm’s default is optimal given the other firm’s optimal default:

\[ \tilde{d}_i^C(M_{i,t}, M_{j,t}, \gamma_t; b_i, b_j; \tilde{\Theta}^C(\cdot)) = \tilde{d}_i^C(M_{i,t}, M_{j,t}, \gamma_t; \tilde{d}_j^C(M_{i,t}, M_{j,t}, \gamma_t; b_j, b_j; \tilde{\Theta}^C(\cdot)); b_i, b_j; \tilde{\Theta}^C(\cdot)). \] (51)

The equilibrium value functions are given by

\[ \tilde{V}_i^C(M_{i,t}, M_{j,t}, \gamma_t; b_i, b_j; \tilde{\Theta}^C(\cdot)) = \tilde{V}_i^C(M_{i,t}, M_{j,t}, \gamma_t; \tilde{d}_j^C(M_{i,t}, M_{j,t}, \gamma_t; b_j, b_j; \tilde{\Theta}^C(\cdot)); b_i, b_j; \tilde{\Theta}^C(\cdot)). \] (52)

**Recursive Formulation for The Value of Equity upon Deviation**

The deviation value is obtained by assuming that firm \( i \) optimally sets its profit margin conditional on firm \( j \) setting the profit margin according to the collusive profit margin scheme, i.e., \( \tilde{d}_{j}^C(M_{i,t}, M_{j,t}, \gamma_t; b_i, b_j; \tilde{\Theta}^C(\cdot)) \) and default decision \( \tilde{d}_j^N(M_{i,t}, M_{j,t}, \gamma_t; b_i, b_j; \tilde{\Theta}^C(\cdot)) \). Denote \( \tilde{V}_i^D(M_{i,t}, M_{j,t}, \gamma_t; b_i, b_j; \tilde{\Theta}^C(\cdot)) \) as firm \( i \)'s deviation value.

Firm \( i \) solves the following problem:

\[
\tilde{V}_i^D(M_{i,t}, M_{j,t}, \gamma_t; b_i, b_j; \tilde{\Theta}^C(\cdot)) = \max_{b_i, d_{ij,t}} \left\{ (1 - d_{ij,t}) \left[ (1 - \gamma_t) \left[ \omega^{-\kappa_0} \gamma_t (1 - \theta_{ij,t})^{-1} (1 - \tilde{\Theta}_i^D)^{-\eta} M_{i,t} - b_i \right] \right. \right. \Delta t \\
+ e^{-(\tau_f + \lambda)\Delta t} \mathbb{E}_t \left[ d_{ij,t} \left( 1 - \xi \Delta t \right) \tilde{V}_i^D(M_{i,t+\Delta t, M_{new}, \gamma_{t+\Delta t}; b_i, b_{new}; \tilde{\Theta}^C(\cdot)) + \xi \Delta t \tilde{V}_i^N(M_{i,t+\Delta t, M_{new}, \gamma_{t+\Delta t}; b_i, b_{new})) \right] \\
\left. \left. \left. (1 - d_{ij,t}) \left[ (1 - \gamma_t) \tilde{V}_i^D(M_{i,t+\Delta t, M_{new}, \gamma_{t+\Delta t}; b_i, b_{new}; \tilde{\Theta}^C(\cdot)) + \xi \Delta t \tilde{V}_i^N(M_{i,t+\Delta t, M_{new}, \gamma_{t+\Delta t}; b_i, b_{new})) \right] \right] \right\} \right\}
\] (53)

subject to the following constraints. (1) The industry’s profit margin is given by

\[ 1 - \tilde{\Theta}_i^D = \left[ \frac{M_{i,t} (1 - \theta_{ij,t})^{-1} + M_{j,t} (1 - \tilde{\Theta}_j^C)^{-1}}{M_{i,t}} \right] \frac{1}{\varphi} \quad \text{with} \quad M_t = M_{i,t} + M_{j,t}. \] (54)

(2) The customer base evolves according to

\[
M_{i,t+\Delta t} = M_{i,t} + g_{i} M_{i,t} \Delta t + \varsigma M_{i,t} (\gamma_t \Delta t + \Delta \bar{\gamma}_t) + \sigma_{M} M_{i,t} \Delta W_{i,t},
\]

\[
M_{j,t+\Delta t} = M_{j,t} + g_{j} M_{j,t} \Delta t + \varsigma M_{j,t} (\gamma_t \Delta t + \Delta \bar{\gamma}_t) + \sigma_{M} M_{j,t} \Delta W_{j,t}.
\] (55)

(3) The aggregate state \( \gamma_t \) evolves according to

\[ \gamma_{t+\Delta t} = \gamma_t - \varphi(\gamma_t - \bar{\gamma})\Delta t - \pi(-\zeta \Delta t + \Delta \bar{\gamma}_t). \] (57)

72
Solving For Equilibrium Profit Margins  The collusive equilibrium is a subgame perfect Nash equilibrium if and only if the collusive profit margin scheme $\Theta^C(\cdot)$ satisfies the following PC and IC constraints:

$$V_i^C(M_{i,t}, M_{j,t}, \gamma_t; b_i, b_j; \Theta^C(\cdot)) \geq V_i^N(M_{i,t}, M_{j,t}, \gamma_t; b_i, b_j),$$  \hspace{1cm} (58)

$$V_i^C(M_{i,t}, M_{j,t}, \gamma_t; b_i, b_j; \Theta^C(\cdot)) = V_i^D(M_{i,t}, M_{j,t}, \gamma_t; b_i, b_j; \Theta^C(\cdot)),$$  \hspace{1cm} (59)

for all $M_{i,t} \in [0, +\infty)$, $\gamma_t \in \mathbb{R}$, and $i = 1, 2$.

There exist infinitely many subgame perfect Nash equilibria. We focus on the collusive equilibrium with the collusive profit margins lie on the “Pareto efficient frontier” (denoted by $\Theta^C(\cdot)$), which are obtained when all incentive compatibility constraints are binding, i.e.

$$V_i^C(M_{i,t}, M_{j,t}, \gamma_t; b_i, b_j; \Theta^C(\cdot)) = V_i^D(M_{i,t}, M_{j,t}, \gamma_t; b_i, b_j; \Theta^C(\cdot)),$$  \hspace{1cm} (60)

for all $M_{i,t} \in [0, +\infty)$, $\gamma_t \in \mathbb{R}$, and $i = 1, 2$. The collusive equilibrium is solved by finding profit margin scheme $\Theta^C(\cdot)$ such that the PC constraint (58) and the IC constraint (60) are satisfied simultaneously.

We denote $V_i^C(M_{i,t}, M_{j,t}, \gamma_t; b_i, b_j)$ as firm $i$’s value in the collusive equilibrium with collusive profit margin scheme $\Theta^C(\cdot)$. In solving the equilibrium, we first ignore the PC constraint (58) and solve for $\Theta^C(\cdot)$ that satisfies the IC constraint (60). Then given $\Theta^C(\cdot)$, we check whether the PC constraint (58) is satisfied for each value of $M_{i,t}$, $M_{j,t}$, and $\gamma_t$. If it is satisfied, we have

$$V_i^C(M_{i,t}, M_{j,t}, \gamma_t; b_i, b_j) = V_i^N(M_{i,t}, M_{j,t}, \gamma_t; b_i, b_j),$$  \hspace{1cm} (61)

$$\theta_i^C(M_{i,t}, M_{j,t}, \gamma_t; b_i, b_j) = \Theta_i^C(M_{i,t}, M_{j,t}, \gamma_t; b_i, b_j; \Theta^C(\cdot)).$$  \hspace{1cm} (62)

If it is not satisfied, we guess the endogenous collusion boundary $\zeta(M_{i,t}, \gamma_t; b_i, b_j)$ (through iterations) at which one of the firm’s participation constraint is just binding. For $M_{i,t} \leq \zeta(M_{i,t}, \gamma_t; b_i, b_j)$, we set

$$V_i^C(M_{i,t}, M_{j,t}, \gamma_t; b_i, b_j) = V_i^N(M_{i,t}, M_{j,t}, \gamma_t; b_i, b_j),$$  \hspace{1cm} (63)

$$\theta_i^C(M_{i,t}, M_{j,t}, \gamma_t; b_i, b_j) = \Theta_i^N(M_{i,t}, M_{j,t}, \gamma_t; b_i, b_j).$$  \hspace{1cm} (64)

For $M_{i,t} > \zeta(M_{i,t}, \gamma_t; b_i, b_j)$, we have

$$V_i^C(M_{i,t}, M_{j,t}, \gamma_t; b_i, b_j) = V_i^C(M_{i,t}, M_{j,t}, \gamma_t; b_i, b_j; \Theta^C(\cdot)), $$  \hspace{1cm} (65)

$$\theta_i^C(M_{i,t}, M_{j,t}, \gamma_t; b_i, b_j) = \Theta_i^C(M_{i,t}, M_{j,t}, \gamma_t; b_i, b_j; \Theta^C(\cdot)).$$  \hspace{1cm} (66)

Value of Debt  Firm $i$’s value of debt in the collusive equilibrium is given by

$$D_i^C(M_{i,t}, M_{j,t}, \gamma_t; b_i, b_j) = (1 - d_i^C(M_{i,t}, M_{j,t}, \gamma_t; b_i, b_j)) \left\{ b_i \Delta t + e^{-(r_f + \lambda + \omega)\Delta t} \mathbb{E}_t \left[ D_i^C(M_{i,t+\Delta t}, M_{j,t+\Delta t}, \gamma_t+\Delta t; b_i, b_j) \right] \right\} + d_i^C(M_{i,t}, M_{j,t}, \gamma_t; b_i, b_j) \nu A_i^C(M_{i,t}, M_{j,t}, \gamma_t; 0, b_j),$$  \hspace{1cm} (67)

where $d_i^C(M_{i,t}, M_{j,t}, \gamma_t; b_i, b_j)$ and $A_i^C(M_{i,t}, M_{j,t}, \gamma_t; 0, b_j)$ are the optimal default decision and the unlevered asset value in the collusive equilibrium under the collusive profit margin scheme $\Theta^C(\cdot)$.

Firm $i$’s value of debt in the non-collusive equilibrium is determined similarly using the optimal default
decision and the unlevered asset value in the non-collusive equilibrium.

B.2 Discretization

We discretize the aggregate state $\gamma_t$ based on $n_\gamma$ grids using the method of Tauchen (1986). We approximate the persistent AR(1) process of long-run growth rates $\theta_t$ using $n_\theta$ discrete states based on the method of Rouwenhorst (1995). The time line is discretized into intervals with length $\Delta t$. We choose a large $n_\gamma$ to ensure the continuous process is accurately approximated.

We use collocation methods to solve each firm’s problem. Let $S_M \times S_M \times S_\gamma \times S_b \times S_b$ be the grid of collocation nodes for a firm’s equilibrium value, $S_M \times S_M \times S_\gamma \times S_\theta \times S_d \times S_b \times S_b$ be the grid of collocation nodes for a firm’s off-equilibrium value in the non-collusive equilibrium, and $S_M \times S_M \times S_\gamma \times S_d \times S_b \times S_b$ be the grid of collocation nodes for a firm’s off-equilibrium value in the collusive equilibrium. We have $S_M = \{M_1, M_2, ..., M_{n_M}\}, S_\gamma = \{\gamma_1, \gamma_2, ..., \gamma_{n_\gamma}\}, S_\theta = \{\theta_1, \theta_2, ..., \theta_{n_\theta}\}, S_d = \{0, 1\}$, and $S_b = \{b_1, b_2, ..., b_{n_b}\}$.

We approximate the firm’s value function $V(\cdot)$ and $D(\cdot)$ on the grid of collocation notes using a linear spline with coefficients corresponding to each grid point. We first form a guess for the spline’s coefficients, then we iterate to obtain a vector that solves the system of Bellman equations.

B.3 Implementation

The numerical algorithms are implemented using C++. The program is run on the server of MIT Economics Department, supply.mit.edu and demand.mit.edu, which are built on Dell PowerEdge R910 (64 cores, Intel(R) Xeon(R) CPU E7-4870, 2.4GHz) and Dell PowerEdge R920 (48 cores, Intel(R) 4 Xeon E7-8857 v2 CPUs). We use OpenMP for parallelization when iterating value functions and simulating the model.

Selection of Grids  We set $n_\gamma = 51$, $n_M = 101$, $n_\theta = 11$, $n_b = 5$, $\Delta t = 1/24$. The grid of customer base $S_M$ is discretized into 22 nodes from $M_1 = 0$ to $M_{n_M} = 8$. We use 80 grids with equal spaces to discretize the region $[0, 1.5]$ to capture the large nonlinearity around the default boundary and use 20 grids with equal spaces to discretize the region $[1.5, 8]$. The upper bound $M_{n_M} = 8$ is determined so that the marginal value of $M_{ij}$ becomes a constant. This ensures that the boundary condition at infinity is accurately solved and satisfied. The time interval $\Delta t$ is set to be $1/24$ (i.e., half month). A higher $\Delta t$ implies faster convergence for the same number of iterations but lower accuracy. We checked that the solution is accurate enough for $\Delta t = 1/24$, further reducing $\Delta t$ would not improve the accuracy much. With $\Delta = 1/24$, 5000 times iterations allow us to achieve convergence in value functions. The profit margin grid is discretized into 11 nodes from 0 to $1/\epsilon$ with equal spaces. The lowest coupon rate is set to be zero to consider unlevered firms. The highest coupon rate is set to be 20.

Solving the Non-Collusive Equilibrium  Given the value functions from the previous iteration, we use the golden section search method to find the optimal profit margins. The computational complexity of this algorithm is at the order of $\log(n)$, much faster and more accurate than a simple grid search. The optimal default decisions can be trivially solved by checking two cases with $d_{ij}^N = 0$ and $d_{ij}^N = 1$.

Searching for the equilibrium profit margin is challenging because we have to solve a fixed-point problem that involves both firms’ simultaneous profit margin decisions. Our solution technique is to
iteratively solve the following three steps.

First, given $V_i^N(M_{i,t}, M_{j,t}, \gamma_t; b_i, b_j)$, we solve the off-equilibrium value $\tilde{V}_i^N(M_{i,t}, M_{j,t}, \gamma_t; \theta_j, d_{j,t}; b_i, b_j)$ and the off-equilibrium policy functions $\tilde{\theta}_i^N(M_{i,t}, M_{j,t}, \gamma_t; \theta_j, d_{j,t}; b_i, b_j)$ and $\tilde{d}_i^N(M_{i,t}, M_{j,t}, \gamma_t; \theta_j, d_{j,t}; b_i, b_j)$. Second, for each $(M_{i,t}, M_{j,t}, \gamma_t; b_i, b_j) \in S_M \times S_M \times S_{\gamma} \times S_{b} \times S_{b}$, we solve equations (43 – 44) and obtain the equilibrium profit margins $\theta_i^N(M_{i,t}, M_{j,t}, \gamma_t; b_i, b_j)$ and defaults $d_i^N(M_{i,t}, M_{j,t}, \gamma_t; b_i, b_j)$. Third, we solve equations (45) and obtain equilibrium value functions $V_i^N(M_{i,t}, M_{j,t}, \gamma_t; b_i, b_j)$.

**Solving the Collusive Equilibrium** To solve the collusive equilibrium, we have to simultaneously solve the endogenous default boundaries and the endogenous collusive profit margins within the collusion boundaries. We implement a nested iteration method. First, we guess the default boundaries. Second, we solve for the highest collusion profit margins within the boundary using the iteration algorithm below. The profit margins associated with the states below the default boundaries are indeterminate because firms are in default. For these states, we set firms’ profit margins at the non-collusive profit margins $\theta_i^N(M_{i,t}, M_{j,t}, \gamma_t; b_i, b_j)$. Third, we check whether the implied default boundaries are consistent with our guessed boundaries. If not, we update our guess and resolve the highest collusion profit margins.

We modify the golden section search method to find the highest collusion profit margins $\theta_C^C(M_{i,t}, M_{j,t}, \gamma_t; b_i, b_j)$ within the default boundaries by iterations. For each iteration, we guess collusion profit margins $\theta_C^C(M_{i,t}, M_{j,t}, \gamma_t; b_i, b_j)$, and given the guessed profit margins, we solve firms’ collusion value and deviation value using standard recursive methods. We update the guessed collusion profit margins until the incentive compatibility constraints (60) are binding for all states.

There are two key differences between our method and a standard golden section search method. First, to increase efficiency, we guess and update the collusion profit-margin scheme $\theta_i^C(M_{i,t}, M_{j,t}, \gamma_t; b_i, b_j)$ simultaneously for all $(M_{i,t}, M_{j,t}, \gamma_t) \in S_M \times S_M \times S_{\gamma}$, instead of doing it one by one for each state. A natural problem introduced by the simultaneous updating is that there might be overshooting. For example, if for some particular state $(M_{i,t}, M_{j,t}, \gamma_t)$, we updated a collusion profit margin $\theta_i^C(M_{i,t}, M_{j,t}, \gamma_t; b_i, b_j)$ too high in the previous iteration, the collusion profit margin for some other states $(M_{i,t}, M_{j,t}, \gamma_t) \neq (M_{i,t}, M_{j,t}, \gamma_t)$ might be affected in this iteration and never achieve a binding incentive compatibility constraint. Eventually, this may lead to non-convergence.

We solve this problem by gradually updating the collusion profit margins. In particular, in each round of iteration, we first compute the updated collusion profit-margin scheme $\theta_i^C(M_{i,t}, M_{j,t}, \gamma_t)$ implied by the golden section search method. Then, instead of changing the upper search bound or lower search bound to $\theta_i^C(M_{i,t}, M_{j,t}, \gamma_t; b_i, b_j)$ directly, we change it to $(1 - adj) \times \theta_i^C(M_{i,t}, M_{j,t}, \gamma_t; b_i, b_j) + adj \times \theta_i^C(M_{i,t}, M_{j,t}, \gamma_t; b_i, b_j)$, i.e., a weighted average of the current iteration’s collusion profit margin $\theta_i^C(M_{i,t}, M_{j,t}, \gamma_t; b_i, b_j)$ and the updated collusion profit margin $\theta_i^C(M_{i,t}, M_{j,t}, \gamma_t; b_i, b_j)$. If $adj = 0.5$, our algorithm is essentially the same as bisection search algorithm. A lower $adj$ is more suitable to solve the problem in which different states have a higher degree of interdependence. We set a relatively low $adj = 0.05$ to ensure convergence.

**C Construction of Idiosyncratic Shocks**

**Method 1:**
(i) Compute the annual sales growth of individual firms, censoring the rare instances where the sales of the last year is negative.

(ii) Compute the panel means of the sales growth on top 100 firms of each cross section.

(iii) Winsorize the sales growth at the panel means plus and minus 30%.

(iv) Compute the aggregate sales growth as the average of the winsorized sales growth on the top 100 firms.

(v) Compute firm level idiosyncratic shock as winsorized sales growth subtracting the average sales growth.

(vi) Aggregate idiosyncratic shock to the industry-year level, weighting by last year’s sale.

This methodology closely aligns with the method used in (Gabaix, 2011) with the exception of the winsorization bounds. The bounds were 20% in (Gabaix, 2011), which we relax to 30%.

Method 2:

(i) Compute the aggregate sales growth as in Method 1.

(ii) Conduct firm level time series regression of sales growth on aggregate sales growth and a constant. Take the residual as the idiosyncratic shock.

(iii) Aggregate idiosyncratic shock to the industry-year level, weighting by last year’s sale.

D Construction of Competition Networks

In Table 4, the competition network through the common market leaders is constructed according to the following step.

First, we identify industry pairs that share common leaders in each year. A company is a common leader in two industries if it satisfies the following conditions: (1) its SIC4 code ends in 0, and (2) it is ranked top 6 in terms of sales in both industries, as indicated by the segment level sales and segment-industry mapping in Compustat Segment. This results in a competition network of industries at an annual frequency.

Second, we organize the network into a year-industry pair panel. If industry \( i \) and industry \( j \) have common leaders in year \( t \), then \( (t, i, j) \) and \( (t, j, i) \) are two observations in the panel.

Third, in panel B of Table 4, we run industry-year pair-level regression of the log one plus profit margin of the common leaders of the pair of industries on a constant term and the idiosyncratic shocks of top 3 firms (in terms of sales) of the industry \( i \) or industry \( j \). In the panel regression, missing idiosyncratic shocks are replaced with 0, and the log profit margins are winsorized at the 1st and 99th percentiles. Coefficients from these regressions are reported in panel B of Table 4. The estimation results are similar when using top 2 – 6 firms of the industry on the right-hand side of the regression.

Fourth, we identify the industries which shares common leaders with industry \( i \) for each industry \( i \) in year \( t \), requiring that the linked industry’s SIC4 code starts with the same digit and end with the digit 1 – 8, inclusive. For each of the linked industry, we use the fitted value \( \hat{\text{IdShock}}^{(c)}_{i,j} \) to capture the
Table E.1: Profit margin volatility across industries

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>All Firms</td>
<td>Top 6</td>
</tr>
<tr>
<td>$H_{H I, t}$</td>
<td>$-0.035^{***}$</td>
<td>$-0.026^{**}$</td>
</tr>
<tr>
<td></td>
<td>$[-2.78]$</td>
<td>$[-2.49]$</td>
</tr>
<tr>
<td>$P M V o l_{i,t}$</td>
<td>$0.246^{***}$</td>
<td>$0.191^{***}$</td>
</tr>
<tr>
<td></td>
<td>$[8.13]$</td>
<td>$[6.67]$</td>
</tr>
<tr>
<td>$D i s t r e s s_{i,t}$</td>
<td>$5.187^{***}$</td>
<td>$4.030^{***}$</td>
</tr>
<tr>
<td></td>
<td>$[5.76]$</td>
<td>$[4.03]$</td>
</tr>
<tr>
<td>$O L_{i,t}$</td>
<td>$-0.002$</td>
<td>$-0.009^{***}$</td>
</tr>
<tr>
<td></td>
<td>$[-0.59]$</td>
<td>$[-2.79]$</td>
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<tr>
<td>Observations</td>
<td>148,615</td>
<td>29,594</td>
</tr>
<tr>
<td>R-square</td>
<td>0.173</td>
<td>0.175</td>
</tr>
</tbody>
</table>

Note: This table reports results from the following firm-year level panel regressions:

$$P M V o l_{i,t+1} = a + b_1 H_{H I_{i,t}} + b_2 P M V o l_{i,t} + b_3 D i s t r e s s_{i,t} + b_4 O L_{i,t} + \sum \delta_t F E_t + \sum \rho_i F E_i + \epsilon_{i,t}.$$ Here, $P M V o l_{i,t+1}$ is the volatility of logged one plus the quarterly winsorized profit margin for firm $i$ over year $t + 1$. The variables $H_{H I_{i,t}}, D i s t r e s s_{i,t},$ and $O L_{i,t}$ are the Herfindahl-Hirschman Index (HHI) for the industry of firm $i$, the average financial distress level for the industry of firm $i$, and the average operating leverage for the industry of firm $i$ in year $t$. $F E_t$ and $F E_i$ are time and industry fixed effect. The computation of the HHI requires at least 6 firms in each industry-year, and it is based on all firms in the industry for Column 1 and top 6 firms for Column 2. Average within an industry is weighted by sales. The regression is weighted by the firm’s sale in year $t$. For each firm $i$, we compute its quarterly profit margin, and then winsorize at the 5th and 95th percentile values on the panel. This winsorization step is necessary as firm level profit margin can attain very extreme values. We then compute each firm’s profit margin volatility over the next four quarters, and regress it on the industry’s HHI. All other variables are in fractional unit. The standard errors are robust to heteroskedasticity and autocorrelation. We compute t-statistics using Driscoll-Kraay standard errors with 5 lags, and include t-statistics in square brackets. *, **, and *** indicate statistical significance at the 10%, 5%, and 1%, respectively.

variation in the common leaders’ profit margin associated with the idiosyncratic shocks of the top 3 firms in the linked industry. If there are more than 1 linked industries, we compute $I d i o S h o c k_{l,t}^{(c)}$ based on their equally-weighted average.

E Volatility and Market Concentration

Profit Margin Volatility and Market Concentration. Here we test the model’s prediction that more concentrated industries tend to have lower volatility in profit margin in the future. We measure each industry’s concentration level with the Herfindahl-Hirschman Index (HHI). As a crude way to make sure that this measure behaves well, we require at least 6 firms in each industry-year. The first row of the table shows that firms in more concentrated industries (i.e., the industries with a higher HHI), the volatility of
Credit Spread Volatility and Market Concentration. Here we test the model’s prediction that more concentrated industries tend to have lower volatility in credit spread in the future. We measure each industry’s concentration level with the Herfindahl-Hirschman Index (HHI). As a crude way to make sure that this measure behaves well, we require at least 6 firms in each industry-year. The first row of the table shows that firms in more concentrated industries (i.e., the industries with a higher HHI), the volatility of credit spreads in the next 12 months is lower. Here both credit spread volatility and HHI are in fractional units.

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
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</thead>
<tbody>
<tr>
<td></td>
<td>CSVol_{i,t}</td>
<td></td>
</tr>
<tr>
<td></td>
<td>All Firms</td>
<td>Top 6</td>
</tr>
<tr>
<td>$HHI_{i,t}$</td>
<td>-0.252***</td>
<td>-0.162**</td>
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<td>0.353***</td>
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<td></td>
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<td>[12.16]</td>
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<tr>
<td>$Distress_{i,t}$</td>
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</tr>
<tr>
<td></td>
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<td>[1.56]</td>
</tr>
<tr>
<td>$OL_{i,t}$</td>
<td>-0.038*</td>
<td>-0.008</td>
</tr>
<tr>
<td></td>
<td>[-1.80]</td>
<td>[-0.46]</td>
</tr>
<tr>
<td>N</td>
<td>7253</td>
<td>4870</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.415</td>
<td>0.426</td>
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</table>

Note: This table reports results from the following firm-year level panel regressions: 

$$CSVol_{i,t+1} = a + b_1 HHI_{i,t} + b_2 CSVol_{i,t} + b_3 Distress_{i,t} + b_4 OL_{i,t} + \sum \delta_t FE_t + \sum \rho_i FE_i + \epsilon_{i,t}$$

Here, $CSVol_{i,t+1}$ is the volatility of the monthly credit spread for firm $i$ over year $t + 1$. The variables $HHI_{i,t}$, $Distress_{i,t}$, and $OL_{i,t}$ are the Herfindahl-Hirschman Index (HHI) for the industry of firm $i$, the average distress level for the industry of firm $i$, and the average operating leverage for the industry of firm $i$ in year $t$. $FE_t$ and $FE_i$ are time and industry fixed effect. Average within an industry is weighted by sales. The regression is weighted by the bond’s par value. The spread on which we compute the volatility are in annualized, percentage unit. All other variables are in fractional unit. The standard errors are robust to heteroskedasticity and autocorrelation. We include t-statistics in square brackets. *, **, and *** indicate statistical significance at the 10%, 5%, and 1%, respectively.