Industry Distress Anomaly

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Abstract

We document a robust and significant industry financial distress anomaly. The industry distress anomaly remains significant after controlling for the firm distress anomaly, but it does not exist in placebo industries, constructed by reshuffling firms across real industries. To rationalize the industry distress anomaly, we propose an industry equilibrium model with endogenous strategic competition. Central to the model is the competition-distress feedback within industries, which amplifies the exposure of industries' profit margins and equity returns to aggregate discount-rate shocks. Industries with higher idiosyncratic left-tail risks are more distressed, yet are endogenously less exposed to aggregate shocks due to the weaker competition-distress feedback, implying lower expected equity returns.

Keywords: Stock and Bond Returns, Supergames, Tacit Collusion, Financial Distress Anomaly (**JEL**: G12, L13, O33, C73)

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1 Introduction

The financial distress anomaly documented by Campbell, Hilscher and Szilagyi (2008) has attracted great attention due to the central role of distress risk in corporate decisions and asset valuation. It is a puzzling phenomenon that more distressed industries exhibit lower expected equity returns, as the canonical frameworks of Merton (1974) and Leland (1994) imply the opposite pattern. There could exist an industry component to this phenomenon as idiosyncratic distress risk can propagate within industries due to firms' strategic price competition in product markets.[1] This paper revisits the distress anomaly from an industry perspective. We empirically document a robust and significant industry distress anomaly, and further provide a theoretical explanation through the lens of an industry equilibrium model with endogenous strategic competition.

While many capital market anomalies tend to disappear when examined at the industry level, we show that the distress anomaly persists consistently across industries at the four-digit Standard Industrial Classification (SIC4) code level. The industry-level distress spread (i.e., the equity returns of the long-short portfolio of industries sorted on the industry-level financial distress measure) is statistically significant and its economic magnitude is comparable to that at the firm level. Importantly, the industry-level distress spread remains significant after controlling for the firm-level distress spread. Further, we show that the industry distress spread is no longer significant in hypothetical industries, which are constructed by reshuffling firms across real industries, even though these hypothetical industries are created to have similar distress risk as the real industries.

The implications of these new empirical facts are threefold: First, there exists a robust and significant industry component of the distress anomaly; second, the distress anomalies at the industry and the firm level are likely driven by different economic mechanisms; and third, the industry distress anomaly is tied to some economic mechanism within real industries, with its strength depending on certain industry characteristics.

Explaining industry-level anomalies introduces an additional layer of complexity. Financial economists often struggle to link industry-level risk exposures with the fundamental characteristics of an industry (e.g., Fama and French, 1997; Dittmar and Lundblad, 2017). To theoretically justify the industry component of the distress anomaly, we propose an industry equilibrium model with endogenous strategic competition. We show that competition among distressed market leaders within oligopoly industries determines the joint patterns of industry-level credit spreads and levered equity returns. Through a competition-distress

[1] See Chen et al. (2024) for illustrating the financial contagion effects in an analytically tractable model of concentrated industries. See Dou and Wu (2023) and Dou, Johnson and Wu (2025) for causal evidence of the financial contagion effects.

feedback mechanism, our model can quantitatively explain the industry distress anomaly. For tractability, our model focuses on rationalizing the industry component of the distress anomaly while remaining silent on the economic mechanism that explains the distress anomaly across firms. Thus, our model complements the existing theories that focus on explaining the firm distress anomaly (e.g., Garlappi, Shu and Yan, 2008; Garlappi and Yan, 2011).

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

In our model, market leaders can tacitly collude with each other on setting high profit margins. Given that competitors will honor the collusive profit-margin-setting scheme, a firm may be tempted to boost its short-run revenue by reducing its profit margin to attract more customers; however, deviating from the collusive scheme may reduce revenue in the long run if the deviation is detected and punished by the competitor. Following the literature (e.g., Green and Porter, 1984; Brock and Scheinkman, 1985; Rotemberg and Saloner, 1986), we adopt the non-collusive Nash equilibrium as the incentive-compatible punishment for deviation. The collusive profit margin is higher when firms' deviation incentives are lower. A firm's decision to deviate is determined by its intertemporal tradeoff between short- and long-run cash flows, which is further shaped by its financial distress level and the aggregate discount rate.

There is a competition-distress feedback. Firms tend to compete more aggressively when they become more financially distressed. The intensified competition, in turn, reduces the profit margins for all firms in the industry, pushing some firms further into distress. Intuitively, a firm's incentive to collude with its peers depends on how much the firm values the extra profit generated by future cooperation. When firms become increasingly financially distressed, they tend to compete more intensely, resulting in lower profit margins. Firms effectively become more impatient when their default risk is higher, which renders extra profits from cooperation in the future less valuable. This makes firms more apt to engage in undercutting behavior and less likely to cooperate with profit-margin collusion. Lower

profit margins further intensify the level of a firm's financial distress and its default risk.

The competition-distress feedback is central to our model's explanation for the industry distress anomaly. In an analytically tractable model, this economic mechanism is demonstrated by Chen et al. (2024). Their model emphasizes how distressed competition affects firms' capital structure choices, rather than exploring the asset pricing implications of the competition-distress feedback. Our paper instead focuses on establishing the cross-industry interdependence between financial distress, expected equity returns, and credit spreads. To rationalize the industry distress anomaly, our model considerably extends theirs in three main aspects: (i) Our model introduces aggregate discount-rate fluctuations and focuses on the interaction of the competition-distress feedback and the aggregate discount rate; (ii) Our model focuses on cross-sectional heterogeneity, demonstrating that industries with higher idiosyncratic left-tail risk are more distressed yet have a weaker competition-distress feedback; and (iii) Our model is quantitative, while their main focus is qualitative.

In our model, industries' exposure to aggregate discount-rate fluctuations is significantly amplified by the competition-distress feedback. Intuitively, when the discount rate rises, future cash flows are discounted at a higher rate, reducing the firms' continuation value. The lower continuation value directly affects the strategic decisions of shareholders through two channels: first, it motivates shareholders to default early, effectively reducing firms' distances to default and increasing firms' distress levels; second, it reduces firms' capacity to collude because a lower continuation value increases firms' deviation incentives. This leads to more intensive competition within the industry, resulting in lower profit margins. Therefore, a higher discount rate directly increases both the financial distress level and competition intensity within the industry. Such direct effects are further amplified by the competition-distress feedback, increasing firms' exposure to aggregate discount-rate fluctuations. Therefore, the strength of the competition-distress feedback determines industries' exposure to aggregate discount-rate fluctuations.

Our model offers a way to explain the industry distress anomaly by focusing on the cross-industry differences in the amplification effects of competition-distress feedback on industries' exposure to aggregate discount-rate fluctuations. Specifically, in our model, idiosyncratic left-tail risk is a fundamental industry characteristic driving cross-industry differences in distress. Idiosyncratic left-tail risk captures a market leader's vulnerability to exogenous displacement by market followers due to distinctive innovation or rapid business expansion (e.g., Gârleanu, Panageas and Yu, 2012; Kogan, Papanikolaou and Stoffman, 2020; Kogan et al., 2021). This risk influences industries' exposure to aggregate discount-rate fluctuations via the competition-distress feedback, thereby affecting expected equity returns at the industry level. Intuitively, in industries more exposed to idiosyncratic left-tail

shocks, firms are more financially distressed and face higher exit rates. The higher exit rate reduces firms' concerns about future cooperation, dampening incentives to collude. As the competition-distress feedback effect stems from endogenous collusion, it weakens when collusion incentives diminish. Consequently, in industries with greater idiosyncratic left-tail risk, profit margins and equity returns respond less negatively to aggregate discount-rate shocks. Since these shocks are negatively priced, investors require lower expected excess returns for holding stocks in these industries. Thus, our model suggests that industries with higher idiosyncratic left-tail risk are less profitable and more financially distressed due to increased default probabilities, while also being less negatively exposed to discount-rate shocks, resulting in lower expected stock returns. This provides an explanation for the industry distress anomaly.

We provide empirical support to the model in three steps as follows. First, we provide evidence showing that the industry-level idiosyncratic left-tail risk is the fundamental industry characteristic that explains the industry distress anomaly. Specifically, we show that industries with higher idiosyncratic left-tail risk are associated with higher financial distress but lower profit margins. Moreover, these industries have lower expected equity excess returns and lower CAPM alphas, but higher credit spreads and higher CDS spreads. Further, we show that the industry-level distress spread becomes statistically insignificant after controlling for the industry-level idiosyncratic left-tail risk.

Second, we provide evidence for the economic mechanism behind the industry-level distress spread implied by our model, that is, the industry-level distress spread is owing to industries' differential exposure to discount-rate shocks. Specifically, we show that industries with higher financial distress or idiosyncratic left-tail risk are less negatively exposed to discount-rate shocks. Moreover, the industry-level distress spread is highly correlated with the industry-level discount-rate spread (i.e., the equity returns of the long-short portfolio of industries sorted on the expected loadings of industry returns on discount-rate shocks), and becomes statistically insignificant after controlling for the industry-level discount-rate spread. Further, we show that the industry-level discount-rate spread and distress spread have similar explanatory power for the cross-sectional equity returns of 21 test portfolios that vary in the level of distress risk.

Third, we test the model's competition-distress feedback mechanism. We show that industry-level profit margins load negatively on the discount rate and that the loadings are more negative in industries in which firms are closer to their default boundaries. Moreover, the difference in the expected equity excess returns across industries with different gross profitability becomes larger when the distance to default is lower. These findings are consistent with the theoretical predictions that the competition-distress feedback mechanism

is stronger when firms are closer to their default boundaries. Furthermore, we examine the variation in feedback effects across industries. Consistent with the model's prediction, the feedback effect on profit margins and equity returns is stronger in industries where market leaders have more evenly distributed market shares. Finally, we directly test the competition-distress feedback mechanism by exploiting exogenous variations in market structure caused by unexpected large cuts in import tariffs (Frésard, 2010; Valta, 2012; Frésard and Valta, 2016). Intuitively, large tariff cuts can facilitate a more competitive market structure due to increased imports and thus higher competitive pressures from foreign rivals. We find that after large tariff cuts, industries with high and low distances to default display less difference in their exposure to the discount rate, which supports the model's prediction that the competition-distress feedback effect weakens when industries' market structure becomes more competitive.

Related Literature. Our paper contributes to the literature on the financial distress anomaly of equity returns (e.g., Dichev, 1998; Campbell, Hilscher and Szilagyi, 2008; Garlappi, Shu and Yan, 2008; George and Hwang, 2010; Garlappi and Yan, 2011; Friewald, Wagner and Zechner, 2014; Boualam, Gomes and Ward, 2020; Chen, Hackbarth and Strebulaev, 2022; Friewald, Nagler and Wagner, 2022). Empirically, we document a robust and significant industry component of the distress anomaly, which survives after controlling for the firm-level distress spread but becomes insignificant in hypothetical industries constructed by reshuffling firms across real industries. Our findings suggest that the industry distress anomaly is tied to some economic mechanism within real industries, which is not likely the same as the mechanism that explains the firm distress anomaly. Our theoretical analysis complements the existing literature that focuses on explaining the firm distress anomaly. For example, by allowing shareholders to recover part of the residual firm value upon default, Garlappi and Yan (2011) develop a model to generate an intriguing hump-shaped relationship between financial distress and expected equity returns, providing an explanation for the distress anomaly across firms. Our contribution lies in proposing a novel explanation for the distress anomaly across industries. We show that the industry distress anomaly can be rationalized by industries' heterogeneous idiosyncratic left-tail risk, which determines their exposure to the aggregate discount-rate fluctuation through the competition-distress feedback mechanism.

Our paper also contributes to the large and growing literature on the structural model of corporate debt, default, and equity returns (for the seminal benchmark framework, see Merton, 1974; Leland, 1994). Specifically, Hackbarth, Miao and Morellec (2006), Chen, Collin-Dufresne and Goldstein (2008), Bhamra, Kuehn and Strebulaev (2010*a*,*b*), Chen (2010), and

Chen et al. (2018) focus on how macroeconomic conditions affect firms' financing policies, credit risk, and asset prices. Kuehn and Schmid (2014) and Gomes, Jermann and Schmid (2016), among others, study the interaction between long-term debt financing and corporate investments. He and Xiong (2012*a*,*b*) study the interaction between the rollover risk of debt, credit risk, and fluctuations in firm fundamentals. He and Milbradt (2014) and Chen et al. (2018) study the interaction between default decisions and secondary market liquidity for defaultable corporate bonds. Existing dynamic models of capital structure and credit risk typically assume that the product market offers exogenous cash flows unrelated to firms' financial distress levels or liquidity conditions. An exception is Corhay (2017) who develops structural credit models in which firms' cash flows are determined by strategic competition in the product market. Corhay (2017) examines equity returns and credit risk in an oligopoly model, focusing on non-collusive competition and short-term debts. In contrast, our model centers on long-term debts and tacit collusion. Our model provides a mechanism to quantitatively rationalize the industry distress anomaly, which cannot be explained by the aforementioned works.

Our paper is related to the literature exploring how industry competition and customer markets affect firms' financial decisions and valuations. Titman (1984), Maksimovic (1988), and Titman and Wessels (1988) undergird subsequent work in this line of the literature. Banerjee, Dasgupta and Kim (2008), Hoberg, Phillips and Prabhala (2014), and D'Acunto et al. (2018) empirically investigate the effects of industry competition and customer base on firms' leverage decisions. Dumas (1989), Kovenock and Phillips (1997), Grenadier (2002), Aguerrevere (2009), Back and Paulsen (2009), Hoberg and Phillips (2010), Hackbarth and Miao (2012), Gourio and Rudanko (2014), Hackbarth, Mathews and Robinson (2014), Bustamante (2015), Dou and Ji (2021), and Dou et al. (2021*b*) investigate how industry competition and the customer base affect various corporate policies, such as investment, cash holdings, mergers and acquisitions, and entries and exits. Gârleanu, Kogan and Panageas (2012), Kogan et al. (2017), and Kogan, Papanikolaou and Stoffman (2020) study the asset pricing implications of the displacement risk mechanism whereby innovation increases competitive pressure faced by existing firms in the same industry, reducing these firms' profits and eroding the human capital of older workers. Finally, a growing theoretical literature focuses on how strategic industry competition and the customer base affect firms' valuation and equity returns (e.g., Aguerrevere, 2009; Belo, Lin and Vitorino, 2014; Opp, Parlour and Walden, 2014; Bustamante, 2015; Belo et al., 2019; Corhay, Kung and Schmid, 2020; Dou et al., 2021*b*; Loualiche, 2021; Dou, Ji and Wu, 2021, 2022; Lin, Ying and Zhang, 2025). These models focus on all-equity firms, while we emphasize levered equity returns and credit spreads jointly determined by the dynamic interaction of endogenous competition and financial distress.

Finally, our paper is related to the burgeoning literature probing how financial characteristics influence firms' performance and decisions in the product market. In early seminal works, Titman (1984) and Maksimovic and Titman (1991) study how capital structure affects a firm's choice of product quality and the viability of the firm's product warranties. Brander and Lewis (1986) focus on the "limited liability" effect of short-term debt financing on product competition behavior. Bolton and Scharfstein (1990) show that financial constraints induce rational predation behavior. Allen (2000) shows that firms with greater debt have a higher probability of bankruptcy and liquidation, which is costly, and thus, higher leverage will be subsequently associated with less aggressive product market behavior. Phillips (1995), Chevalier and Scharfstein (1996), Hortaçsu et al. (2013), Koijen and Yogo (2015), Hoberg and Phillips (2016), Cookson (2017), Gilchrist et al. (2017), Hackbarth and Taub (2018), Banerjee et al. (2019), and Grieser and Liu (2019), among others, advance the empirical study of the product-market implications of financial frictions. Different from these existing works, our paper combines a dynamic Leland framework of long-term defaultable debt with dynamic strategic competition featuring collusive behavior.

2 Evidence on Industry Distress Anomaly

In this section, we provide evidence for the industry distress anomaly. In particular, we show that it is an industry-level phenomenon that is distinct from the distress anomaly at firm level. First, we show that more distressed industries exhibit lower expected equity returns despite higher credit spreads. Then, we show that, less than half of the industry distress anomaly can be explained by the firm-level distress spread, suggesting that the industry- and firm-level distress anomalies are likely driven by different economic mechanisms. Finally, we reshuffle firms to construct hypothetical industries with similar characteristics as the real industries. We show that the industry distress anomaly is no longer significant across these hypothetical industries, suggesting that the industry distress anomaly is tied to some mechanism within real industries, and the strength of the mechanism depends on certain industry characteristics.

2.1 Data and the Distress Measure

We obtain firm-level accounting data from Compustat and stock returns from the Center for Research in Security Prices (CRSP). Industry-level stock returns are the average firm-level stock returns weighted by market capitalization. As in Chen et al. (2018), our credit spread data combine the Mergent Fixed Income Securities Database (FISD) from 1973 to 2004 and

the Trade Reporting and Compliance Engine (TRACE) database from 2005 to 2018. We clean the Mergent FISD and TRACE data following Collin-Dufresne, Goldstein and Martin (2001) and Dick-Nielsen (2009). Following Blanco, Brennan and Marsh (2005), we construct credit spreads as the difference between the corporate bond yield and the rate of interest rate swaps, which is regarded as the best parsimonious proxy for the risk-free rate (Feldhütter and Lando, 2008). The interest rate swap data are from Bloomberg, and are available from 1988. The credit spread data span the period from 1988 to 2018 and cover a cross section of 400 to 750 firms. We obtain the spreads of credit default swaps (CDS) from Markit for the period from 2001 to 2018. Industry-level credit spreads and CDS spreads are the average firm-level credit spreads and CDS spreads weighted by the par value of bonds, respectively. For predictive analyses that involve both market and annual accounting data, we follow the practice of Fama and French (1993) and assume that accounting information becomes available at the end of June each year. For quarterly accounting data, we follow the practice of Campbell, Hilscher and Szilagyi (2008) and implement a 2-month lag (e.g., quarterly accounting data with the period end date of March 31 are matched with market data at the end of May).

Our analysis focuses on strategic competition among leading oligopolistic firms in an industry that produce close substitutes. Therefore, we use SIC4 codes to define industries following the literature.[2] We exclude all financial firms and utility firms (i.e., SIC codes 6,000 — 6,999 and 4,900 — 4,999, respectively). Following the literature (e.g., Frésard, 2010), we require that an industry-year pair has at least 10 firms to be included in our analysis.[3] This ensures that the industry-level variables are well behaved. On average, there are 123 industries in a year and 26.6 firms in an industry.

The firm distress measure for firm j in industry i and period t, denoted by $Distress_{ij,t}$, is constructed as the 12-month failure probability, following Campbell, Hilscher and Szilagyi (2008). The industry distress measure for industry i and period t, denoted by $Distress_{i,t}$, is the average firm distress measure $Distress_{ij,t}$ weighted by firms' sales.[4] To construct the firm-level distress spread, which excludes industry components, we construct an industry-adjusted firm distress measure, denoted by $Ind_Adj_Distress_{ij,t}$. The industry-adjusted firm distress measure is the firm's distress in excess of the average distress of firms within the same industry over the same period, and it is similar to the measure used by Moskowitz and Grinblatt (1999) in constructing "excess-industry" portfolios. Intuitively, the industry-

[2] E.g., Hou and Robinson (2006), Gomes, Kogan and Yogo (2009), Frésard (2010), Giroud and Mueller (2010), Giroud and Mueller (2011), Bustamante and Donangelo (2017), and Dou, Ji and Wu (2021, 2022).

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

[4] The empirical results are similar if we measure the industry distress based on the top six firms (ranked by sales) in each industry.

adjusted firm distress measure controls for the cross-industry variation in the degree of financial distress, and it captures each firm's distress relative to its peers in the same industry.

2.2 Portfolio Sorting Across Industries and Firms

We start with by providing a simple conceptual framework to illustrate the patterns captured by portfolio sorting based on the three measures, $Distress_{i,t}$, $Distress_{ij,t}$, and $Ind_Adj_Distress_{ij,t}$. To fix ideas, suppose there are M industries, denoted by $i = 1, ..., M$. In each industry i, there are $N_i \geq 2$ firms, denoted by $j = 1, ..., N_i$.

Let $D_{ij,t}$ denote the distress level of firm j in industry i in period t, which corresponds to our empirical measure of firm distress, $Distress_{ij,t}$. We note that $D_{ij,t}$ can be decomposed as follows:

$$D_{ij,t} = \nu_{i,t} + \varepsilon_{ij,t}, \tag{1}$$

where $\nu_{i,t}$ and $\varepsilon_{ij,t}$ capture the industry component and the idiosyncratic firm component, respectively. Suppose that $\nu_{i,t}$ and $\varepsilon_{ij,t}$ are independent and identically distributed across all industries and firms, with $\mathbb{E}[\nu_{i,t}] = 0$ and $\mathbb{E}[\varepsilon_{ij,t}|i] = 0$. The idiosyncratic firm component essentially captures the residual term of the industry distress. Sorting firms based on the firm distress $D_{ij,t}$ captures the cross section of firms that vary in both the industry and idiosyncratic firm components, $\nu_{i,t}$ and $\varepsilon_{ij,t}$. The relative importance of the two components is determined by their relative volatility.

The distress level of industry i in period t, denoted by $D_{i,t}$, is the sales-weighted average firms' distress, which corresponds to our empirical measure of industry distress, $Distress_{i,t}$. For simplicity, we assume that all firms have equal sales. Thus,

$$D_{i,t} = \frac{1}{N_i} \sum_{j=1}^{N_i} D_{ij,t} = \nu_{i,t} + \frac{1}{N_i} \sum_{j=1}^{N_i} \varepsilon_{ij,t}. \tag{2}$$

Comparing equations (1) and (2), it is clear that the industry component, $\nu_{i,t}$, is identical in $D_{ij,t}$ and $D_{i,t}$. However, the firm component, $\frac{1}{N_i} \sum_{j=1}^{N_i} \varepsilon_{ij,t}$, in $D_{i,t}$ is less important than that in $D_{ij,t}$ for $N_i \geq 2$, due to diversification. Thus, compared to sorting firms based on $D_{ij,t}$, sorting industries based on $D_{i,t}$ mainly captures the cross-section of industries that vary in the industry component $\nu_{i,t}$.

The industry-adjusted distress level of firm j in industry i and period t, denoted by $\widetilde{D}_{ij,t}$, is the firm's distress in excess of the average distress of firms within the same industry over

the same period,

$$\widetilde{D}_{ij,t} = D_{ij,t} - \frac{1}{N_i}\sum_{j=1}^{N_i} D_{ij,t} = \varepsilon_{ij,t} - \frac{1}{N_i}\sum_{j=1}^{N_i} \varepsilon_{ij,t}, \tag{3}$$

which captures our empirical measure of the industry-adjusted firm distress, $Ind_Adj_Distress_{ij,t}$. Comparing equations (2) and 3, it is clear that $\widetilde{D}_{ij,t}$ does not contain any industry component; instead, it includes own idiosyncratic firm component $\varepsilon_{ij,t}$ and an average idiosyncratic firm component, $-\frac{1}{N_i}\sum_{j=1}^{N_i} \varepsilon_{ij,t}$. Because $N_i \geq 2$, due to diversification, the latter is less important than the former. Thus, sorting firms based on $\widetilde{D}_{ij,t}$ mainly captures the cross section of firms that vary in the idiosyncratic firm component $\varepsilon_{ij,t}$.

2.3 Industry- and Firm-Level Distress Spreads

To show that the distress anomaly exists across industries, we sort all SIC4 industries into quintiles based on the industry distress measure, $Distress_{i,t}$. Panel A of Table 1 presents the results. The average equity excess returns of industries in quintile group Q5 (high $Distress_{i,t}$) are significantly lower than those in quintile group Q1 (low $Distress_{i,t}$). We construct the industry-level distress spread as the equity returns of the long-short portfolio of industries sorted on $Distress_{i,t}$, i.e., the equity returns of quintile group Q5 (high $Distress_{i,t}$) minus the equity returns of quintile group Q1 (low $Distress_{i,t}$). The average industry-level distress spread (Q5−Q1) is −5.625% and is significant both statistically and economically. This spread remains significant after controlling for the market, value, and size factors. These industry-level patterns are consistent with the financial distress anomaly documented at the firm level (e.g., Campbell, Hilscher and Szilagyi, 2008). In addition, industries with higher $Distress_{i,t}$ are associated with higher credit spreads and CDS spreads, which is in sharp contrast to the lower average equity excess returns associated with these industries.

In panel B of Table 1, we sort all firms into quintiles based on the industry-adjusted firm distress measure, $Ind_Adj_Distress_{ij,t}$. The firm-level distress spread is the equity returns of the long-short portfolio (Q5−Q1) of firms sorted on $Ind_Adj_Distress_{ij,t}$, which has a statistically significant average value of −8.507%. Thus, panels A and B jointly indicate that both the industry- and firm-level distress spreads are statistically significant, with comparable economic magnitudes. Complementary to these two panels, we sort all firms into quintiles based on the firm distress measure, $Distress_{ij,t}$, in panel C. This exercise follows the approach of Campbell, Hilscher and Szilagyi (2008), except for using a much longer sample period. It is shown that average equity excess returns of firms in quintile group Q5 (high $Distress_{ij,t}$) are 11.429% lower than those in quintile group Q1 (low $Distress_{ij,t}$). As illustrated in Section 2.2, this difference is attributed to the cross-firm variation in both the

Table 1: Industry- and firm-level distress spreads.

	Panel A: Portfolios of industries sorted on the industry distress measure					
$Distress_{i,t}$	Q1 (low)	Q2	Q3	Q4	Q5 (high)	Q5−Q1
Excess return	9.699***	10.487***	10.435***	9.207***	4.073*	−5.625***
	[5.34]	[5.37]	[6.19]	[5.45]	[1.85]	[−3.04]
CAPM alpha	1.203	1.605	0.836	−1.176	−6.962***	−8.165***
	[1.17]	[1.42]	[0.56]	[−0.63]	[−3.25]	[−3.90]
FF3 alpha	1.385*	1.676*	0.381	−1.675	−8.298***	−9.683***
	[1.96]	[1.89]	[0.34]	[−1.24]	[−5.23]	[−5.65]
Credit spread	0.992***	1.253***	1.430***	1.814***	3.338***	2.346***
	[9.40]	[7.08]	[7.47]	[7.72]	[7.95]	[7.33]
CDS spread	0.298***	0.409***	0.530***	0.812***	2.046***	1.748***
	[6.14]	[5.07]	[5.14]	[4.11]	[5.86]	[5.51]
	Panel B: Portfolios of firms sorted on the industry-adjusted firm distress measure					
$Ind_Adj_Distress_{ij,t}$	Q1 (low)	Q2	Q3	Q4	Q5 (high)	Q5−Q1
Excess return	9.203***	9.501***	8.512***	6.333**	0.696	−8.507**
	[4.25]	[4.07]	[4.18]	[2.01]	[0.16]	[−2.15]
CAPM alpha	−0.603	1.361	0.043	−5.868**	−13.849***	−13.245***
	[−0.44]	[1.58]	[0.06]	[−2.22]	[−3.47]	[−3.75]
FF3 alpha	0.281	2.270***	0.642	−5.577***	−14.668***	−14.950***
	[0.22]	[3.95]	[0.88]	[−2.79]	[−5.69]	[−6.12]
	Panel C: Portfolios of firms sorted on the firm distress measure					
$Distress_{ij,t}$	Q1 (low)	Q2	Q3	Q4	Q5 (high)	Q5−Q1
Excess return	9.844***	9.143***	6.607***	2.843	−1.585	−11.429***
	[4.55]	[5.39]	[2.71]	[0.84]	[−0.39]	[−2.77]
CAPM alpha	2.191***	0.219	−4.425**	−9.986***	−16.296***	−18.487***
	[2.99]	[0.24]	[−2.37]	[−3.24]	[−3.90]	[−4.21]
FF3 alpha	3.166***	0.954	−4.404**	−10.443***	−17.947***	−21.113***
	[5.57]	[0.98]	[−2.54]	[−4.13]	[−5.41]	[−6.10]

Note: Panel A reports the average equity excess returns, the alphas of CAPM and the Fama-French three-factor model, credit spreads, and CDS spreads of industry portfolios sorted on the industry distress measure ($Distress_{i,t}$). Panels B and C sort all firms based on the industry-adjusted firm distress measure ($Ind_Adj_Distress_{ij,t}$) and the firm distress measure ($Distress_{ij,t}$), respectively. In panel A, the number of observations is 42,385 except for the credit spread and CDS spread rows, where the number of observations is 12,963 and 2,499, respectively. In panels B and C, the number of observations is 1,126,119. All returns are in annualized percentage units. The sample is monthly and spans the period from 1976 to 2021, except for the credit spread and CDS spread rows, which span the period from 1988 to 2018 and from 2001 to 2018, respectively. *t*-statistics robust to heteroskedasticity and autocorrelation are reported in brackets. *, **, and *** indicate statistical significance at 10%, 5%, and 1%, respectively.

Table 2: The distress spread across industries is not explained by that across firms.

	(1)	(2)	(3)	(4)
Intercept	-3.037^{**}	-4.539^{***}	-6.247^{***}	-4.192^{***}
	$[-2.04]$	$[-2.82]$	$[-4.68]$	$[-3.19]$
$Firm_distress_spread_t$	0.304^{***}	0.274^{***}	0.230^{***}	0.089^{**}
	[11.45]	[13.91]	[3.87]	[2.15]
Mkt_t		0.149^{**}	0.177^{***}	0.143^{***}
		[2.55]	[3.27]	[3.23]
HML_t			0.249^{*}	0.099
			[1.83]	[0.81]
SMB_t			0.214	0.412^{***}
			[1.31]	[3.75]
MOM_t				-0.429^{***}
				$[-8.58]$
Observations	549	549	549	549
R-squared	0.296	0.318	0.357	0.498

Note: This table presents the results of regressing the industry-level distress spread on the firm-level distress spread (i.e., $Firm_distress_spread_t$), controlling for standard risk factors. All returns are in annualized percentage units. The sample is monthly and spans the period from 1976 to 2021. The number of observations for constructing the industry-level (firm-level) distress spread is 42,385 (1,126,119). t-statistics robust to heteroskedasticity and autocorrelation are reported in brackets. *, **, and *** indicate statistical significance at 10%, 5%, and 1%, respectively.

industry and idiosyncratic firm components.

Next, we show that the industry- and firm-level distress spreads are likely explained by different mechanisms. We regress the industry-level distress spread on the firm-level distress spread, controlling for standard risk factors. Table 2 presents the results. Column (1) shows that, after controlling for the firm-level distress spread, the estimated intercept is -3.037% and remains statistically significant. This indicates that the firm-level distress spread only explains less than half of the average industry-level distress spread, which is -5.625% as reported in panel A of Table 1. In columns (2) to (4), we gradually add the market, value, size, and momentum factors as controls. All four columns show that the industry-level distress spread loads positively on the firm-level distress spread. The estimated intercepts in all four regression specifications are statistically significant, indicating that the industry-level distress spread is not fully explained by the firm-level distress spread or standard risk factors in our sample. These empirical findings suggest that the industry- and firm-level distress anomalies are likely explained by different economic mechanisms.

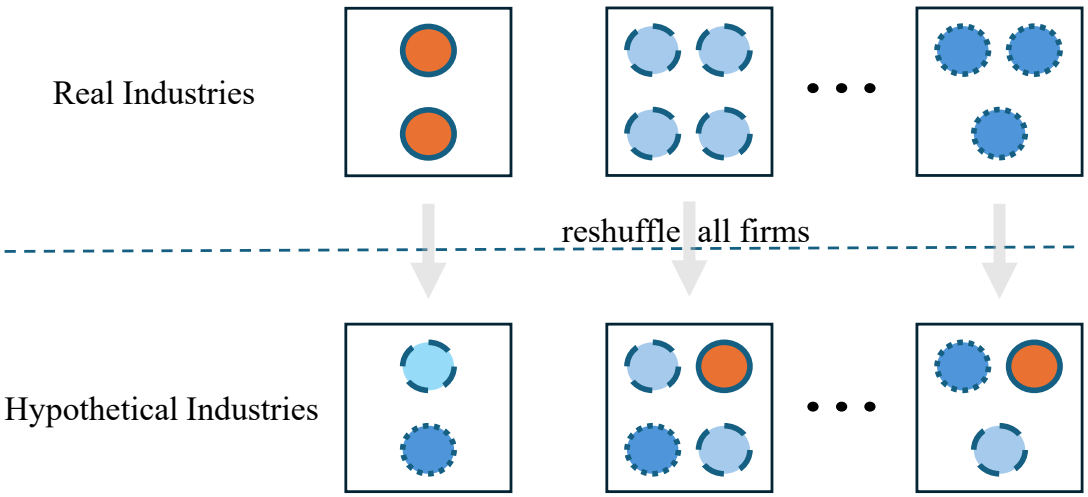


Figure 1: **An illustration for the construction of hypothetical industries.** Each square represents an industry; firms within the same real industry are represented by filled circles with identical color.

2.4 Absence of the Distress Spread Across Hypothetical Industries

In this subsection, we show that the distress spread across hypothetical industries is insignificant, and its magnitude is much smaller than that across real industries. This indicates that the industry-level distress spread is likely explained by some intrinsic characteristics and mechanisms at the industry level, rather than those at the firm level.

Conceptual Framework for Testing Hypothetical Industries. We first use our conceptual framework in Section 2.2 to illustrate the idea behind our tests based on hypothetical industries.

We construct hypothetical industries by randomly moving firms across industries. This method shares similarities with the "random" industry portfolios created by Moskowitz and Grinblatt (1999), which are used to assess whether momentum effects are truly attributed to industry components. Thus, as illustrated in Figure 1, a hypothetical industry i in period t may include firms belonging to different real industries. Let the mapping function $r(j)$ represent the actual industry of firm j, after the completion of random shuffling. Thus, the distress level of a hypothetical industry i in period t is given by

$$D^h_{i,t} = \frac{1}{N_i}\sum_{j=1}^{N_i} D_{r(j)j,t} = \frac{1}{N_i}\sum_{j=1}^{N_i} \nu_{r(j),t} + \frac{1}{N_i}\sum_{j=1}^{N_i} \varepsilon_{r(j)j,t}. \tag{4}$$

Comparing equations (2) and (4), it is obvious that the distress level of a real industry, $D_{i,t}$, and that of a hypothetical industry, $D^h_{i,t}$, have similar idiosyncratic firm components (i.e., the volatilities of $\frac{1}{N_i}\sum_{j=1}^{N_i}\varepsilon_{ij,t}$ and $\frac{1}{N_i}\sum_{j=1}^{N_i}\varepsilon_{r(j)j,t}$ are identical), but very different industry

components. The industry component is ν_i for the real industry i, but it is $\frac{1}{N_i}\sum_{j=1}^{N_i}\nu_{r(j),t}$ for the hypothetical industry i, which is determined by the average industry component of N_i randomly-selected industries. Due to diversification ($N_i \geq 2$), the industry component in $D^h_{i,t}$ is much less important than that in $D_{i,t}$.

This suggests that if the industry distress spread shown in panel A of Table 1 truly reflects the effect of a mechanism related to the industry component, $\nu_{i,t}$, rather than the idiosyncratic firm component, $\frac{1}{N_i}\sum_{j=1}^{N_i}\varepsilon_{ij,t}$, then we would observe a much weaker and insignificant distress spread across hypothetical industries. Conversely, if the industry distress spread spuriously reflects the effect of a mechanism related to the idiosyncratic firm component, $\frac{1}{N_i}\sum_{j=1}^{N_i}\varepsilon_{ij,t}$, rather than the industry component, $\nu_{i,t}$, then we would observe a similarly significant (if not stronger) distress spread across hypothetical industries. Therefore, by comparing the sorting results based on $D_{i,t}$ across real industries with those based on $D^h_{i,t}$ across hypothetical industries, we essentially test whether the industry distress spread is due to the cross-industry variation in the industry component, $\nu_{i,t}$, or the cross-industry variation in the within-industry average idiosyncratic firm component, $\frac{1}{N_i}\sum_{j=1}^{N_i}\varepsilon_{ij,t}$.

Results Based on Hypothetical Industries. To show robustness of our results, we use three methods to construct hypothetical industries in each month t. Method M1 serves as the benchmark with no controls. We randomly assign each firm into one of N industries, where N is the median number of real industries. Method M2 ensures that the number of firms of the hypothetical industries is identical to that of real industries. To this end, we randomly reshuffle firms' SIC4 codes in the cross section of firms. Method M3 further controls for industry-level distress. We sort all firms into quintiles based on the firm distress measure. Within each quintile, firms' SIC4 codes are randomly reshuffled in the cross section. Thus, method M3 ensures that the hypothetical industries not only have a similar number of firms as the real industries, but also consist of firms with similar levels of distress risk.[5]

Next, for each hypothetical industry, we construct the industry distress measure based on the average firm distress measure weighted by firms' sales, similar to what we do for real industries. We then perform portfolio sorting analysis similar to panel A of Table 1 on the distress levels of hypothetical industries. This allows us to obtain the distress spread (Q5−Q1) in the cross section of hypothetical industries.

For each method (M1, M2, and M3), the above procedure is repeated 2,000 times with independent randomization to construct 2,000 cross sections of hypothetical industries. Table 3 presents the summary statistics of the distribution of the hypothetical industry-level

[5]We also construct hypothetical industries that have similar market capitalization as real industries by double sorting all firms on their distress levels and market capitalization. All results remain robust.

Table 3: The distress spread across hypothetical industries.

	Mean	p1	p5	p10	p50	p90	p95	p99
M1	−0.70	−2.56	−1.98	−1.68	−0.70	0.30	0.60	1.10
M2	−1.28	−3.39	−2.82	−2.49	−1.30	−0.08	0.28	1.01
M3	−1.54	−3.77	−3.08	−2.75	−1.53	−0.40	−0.05	0.68

Note: This table reports the summary statistics of the distribution of the hypothetical industry-level distress spread (Q5−Q1) across the 2,000 independently simulated cross sections of hypothetical industries. In each cross section of hypothetical industries, the distress spread is computed in the same way as Q5−Q1 reported in panel A of Table 1. Rows M1, M2, and M3 represent the three different methods for constructing hypothetical industries. For each method, we report the mean, the 1st, 5th, 10th, 50th, 90th, 95th, and 99th percentiles of the distribution across the 2,000 simulations. All returns are in annualized percentage units.

distress spread (Q5−Q1) across the 2,000 cross sections of hypothetical industries. The three methods imply average distress spreads of −0.70%, −1.28%, and −1.54%, respectively, across the hypothetical industries, which are much less negative than the distress spread of −5.625% across real industries (see panel A of Table 1). Moreover, the distress spread corresponding to the 1st percentile of the distribution remains less negative than −5.625%, indicating that, in the absence of real industry structures, it is unlikely to observe a large distress spread as in the data. The distress spread of hypothetical industries is also statistically insignificant as the value corresponding to the 99th percentile of the distribution is positive. Complementary to these findings, we show that the differences in credit spreads and CDS spreads between Q1 and Q5 in the cross section of hypothetical industries are also significantly lower than those in real industries (see Table IA.IV in Online Appendix 2.4).

3 Model

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

3.1 Financial Distress

Financial Frictions. Firms are financed by long-term debt and equity. For tractability, we model long-term debt as a consol with perpetual coupon payments at rate b_i for firm i; further, we follow Leland (1994) and adopt a framework of static capital structure: the

coupon rate b_i is optimally chosen at the beginning upon the firm entering the market to maximize firm value given the tradeoff between tax shield benefits and distress costs.[6] The corporate tax rate is $\tau > 0$. A levered firm first uses its cash flows to make interest payments, then pays taxes, and finally distributes the rest to shareholders as dividends. The firm makes decisions to maximize its equity value. Shareholders have limited liability and the option to default on debt. When operating cash flows cannot cover interest expenses, the firm can issue equity to cover the shortfalls without paying any extra financing costs. When the equity value falls to zero, the firm will choose to file bankruptcy and exit. Upon exiting the market, the firm is sold as an intact business or is liquidated piecemeal, and its debtholders obtain a fraction ν of the asset value, with $\nu \in (0, 1)$.

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

$$H_{i,t} = (1 - \tau) \left(\Pi_{i,t} M_{i,t} - b_i \right), \tag{5}$$

where $\Pi_{i,t} M_{i,t}$ is the operating cash flow, $M_{i,t}$ is the firm's customer base,[7] and $\Pi_{i,t}$ is the firm's endogenous profitability per unit of customer base, which is determined in the Nash equilibrium of competition games. We assume that firm i's customer base $M_{i,t}$ evolves with the following jump-diffusion process:

$$\frac{\mathrm{d}M_{i,t}}{M_{i,t}} = g\mathrm{d}t + \varsigma \mathrm{d}Z_t + \sigma \mathrm{d}W_{i,t} - \mathrm{d}J_{i,t}, \tag{6}$$

where parameter g captures the growth rate of the customer base, the standard Brownian motion Z_t captures aggregate shocks, the standard Brownian motion $W_{i,t}$ captures idiosyncratic shocks to firm i's customer base, and the Poisson process $J_{i,t}$ with intensity ν captures idiosyncratic left-tail shocks to firm i's customer base. Upon the occurrence of a Poisson shock, firm i loses its entire customer base and exits the industry.[8] The shocks Z_t, $W_{i,t}$, and $J_{i,t}$ are mutually independent.

The firm's financial distress is determined not only by the cash flow level $\mathcal{E}_{i,t}$ but also

[6] Models with a dynamic capital structure (e.g., Goldstein, Ju and Leland, 2001; Hackbarth, Miao and Morellec, 2006; Bhamra, Kuehn and Strebulaev, 2010*b*; Chen, 2010) allow firms to optimally issue more debt when current cash flows surpass a threshold, which helps generate stationary default rates under a general-equilibrium setup. Adopting the static optimal capital structure makes the model more tractable, given the complexity of the current setup, and does not change the main insights or results of this paper.

[7] A firm's customer base helps stabilize the firm's capacity for demand flows by creating entry barriers and durable advantages over competitors. The customer base plays an essential role in determining the short-run demand for a firm's products (e.g., Bronnenberg, Dubé and Gentzkow, 2012; Gourio and Rudanko, 2014; Dou et al., 2021*b*; Dou, Ji and Wu, 2021, 2022).

[8] Our specification is close to that of Seo and Wachter (2018) and Collin-Dufresne, Junge and Trolle (2024), who calibrate a disastrous idiosyncratic left-tail shock which leads to almost certain default for a firm.

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

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

$$\frac{\mathrm{d}\Lambda_t}{\Lambda_t} = -r_f \mathrm{d}t - \gamma_t \mathrm{d}Z_t - \zeta \mathrm{d}Z_{\gamma,t}, \tag{7}$$

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

$$\mathrm{d}\gamma_t = -\varphi(\gamma_t - \overline{\gamma})\mathrm{d}t - \pi \mathrm{d}Z_{\gamma,t}, \quad \text{with} \quad \varphi, \overline{\gamma}, \pi > 0. \tag{8}$$

Our specification for the time-varying aggregate discount rate γ_t follows the literature on cross-sectional return predictability (e.g., Lettau and Wachter, 2007; Belo and Lin, 2012; Dou, Ji and Wu, 2021; Meeuwis et al., 2025). Similar to Meeuwis et al. (2025), we allow the discount-rate shock $Z_{\gamma,t}$ to be priced. We assume $\zeta > 0$ to capture the well-documented countercyclical market price of risk. The primitive economic mechanism driving the countercyclical market price of risk could be, for example, time-varying risk aversion, as in Campbell and Cochrane (1999).

Interpretation of the Shocks. The aggregate Brownian shock Z_t in equations (6) and (7) can be interpreted as the economy-wide or industry-wide demand shock. The shock ensures that variation in the discount rate γ_t affects the valuation of firms' cash flows, and thus can generate variation in industry competition intensity. In other words, the aggregate demand shock Z_t is needed for the discount-rate shock $Z_{\gamma,t}$ to affect valuation and competition

intensity. The discount rate γ_t is the only aggregate state variable. Economic downturns in our model are characterized by a high value of γ_t.

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

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

One interpretation of the idiosyncratic left-tail shock is that it captures exogenous displacement. Small market followers in an industry are constantly challenging and trying to displace market leaders, and they typically do so through distinctive innovation or rapid business expansion (e.g., Gârleanu, Panageas and Yu, 2012; Kogan, Papanikolaou and Stoffman, 2020; Kogan et al., 2021). A change in market leaders does not occur gradually over an extended period of time; rather, market leaders are displaced rapidly and disruptively (e.g., Christensen, 1997). For instance, Apple and Samsung displaced Nokia and Motorola as new market leaders in the mobile phone industry over a brief period of time.

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

To maintain tractability, we assume that a new firm enters the industry only after an incumbent firm exits so that the number of firms stays constant. This assumption is inspired by the "return process" of Luttmer (2007) and the "exit and reinjection" assumption in the models of Miao (2005) and Gabaix et al. (2016) for industry dynamics. The same assumption

is also commonly adopted in the IO literature on oligopolistic competition and predation (e.g., Besanko, Doraszelski and Kryukov, 2014) and is interpreted as the reorganization of the exiting firm. Essentially, the exit and reinjection assumption in our model implies that we always focus on the rivalry between the two top market leaders in the industry. In particular, upon incumbent firm i's exit, a new firm enters immediately with an initial customer base $M_{new} = \kappa M_{j,0} > 0$ and coupon rate b_{new}, where b_{new} is optimally chosen to maximize the new firm's value. The parameter $\kappa > 0$ captures the relative size of the new entrant and the initial size of the surviving incumbent, firm j. Upon entry, the dynamic game of Bertrand duopolistic competition, which we describe next in Section 3.3, is "reset" to a new one between the surviving incumbent firm and the new entrant.

3.2 Product Market Competition

The setup in Section 3.1 almost follows the standard model of Leland (1994), except for the endogenous profitability $\Pi_{i,t}$, which results from the strategic competition among firms. We explain the determination of $\Pi_{i,t}$ in this section.

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

$$C_t = \left[\sum_{i=1}^{2} \left(\frac{M_{i,t}}{M_t} \right)^{\frac{1}{\eta}} C_{i,t}^{\frac{\eta-1}{\eta}} \right]^{\frac{\eta}{\eta-1}}, \quad \text{with } M_t = \sum_{i=1}^{2} M_{i,t}, \tag{9}$$

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

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

$$C_{i,t} = \frac{M_{i,t}}{M_t} \left(\frac{P_{i,t}}{P_t} \right)^{-\eta} C_t, \tag{10}$$

where $P_t = \left[\sum_{j=1}^{2} \left(M_{i,t}/M_t \right) P_{i,t}^{1-\eta} \right]^{1/(1-\eta)}$ is the industry's price index. All else equal, the demand for firm i's goods $C_{i,t}$ increases with consumers' relative tastes $M_{i,t}/M_t$ in equilibrium. One can naturally think of consumers' tastes $M_{i,t}$ as firm i's customer base (or

customer capital) and M_t as the industry's total customer base (e.g., Gourio and Rudanko, 2014; Dou et al., 2021*b*); the share $M_{i,t}/M_t$ is the customer base share of firm i within the industry, whereby a larger $M_{i,t}/M_t$ implies that firm i's price $P_{i,t}$ has greater influence on the price index P_t. Furthermore, the demand for firm i's goods $C_{i,t}$ depends on its competitor j's price $P_{j,t}$ through the industry's price index P_t. This reflects the externality of firm j's pricing decisions. For example, holding firm i's price fixed, if firm j cuts its price $P_{j,t}$, the industry's price index P_t will drop, which will reduce the demand for firm i's goods $C_{i,t}$.

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

$$C_t = M_t P_t^{-\epsilon}, \tag{11}$$

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

Now, we characterize the profitability function. Firms' shareholders choose production, set profit margins, and make optimal decisions about defaulting to maximize their equity values. The marginal cost for a firm to produce a flow of goods is a constant $\omega > 0$. That is, when firm i produces goods at rate $Y_{i,t}$, its total costs of production are $\omega Y_{i,t} \mathrm{d}t$ over $[t, t + \mathrm{d}t)$. In equilibrium, the firm finds it optimal to choose $P_{i,t} > \omega$ and produce goods to exactly meet the demand, that is, $Y_{i,t} = C_{i,t}$, because production is costly and goods are immediately perishable. Let $\theta_{i,t} \equiv (P_{i,t} - \omega)/P_{i,t}$ and $\theta_t \equiv (P_t - \omega)/P_t$ represent the firm-level and industry-level profit margins. Denote by $\Pi_{i,t} = \Pi_i(\theta_{i,t}, \theta_{j,t})$ firm i's operating profits per unit of its customer base, which is given by

$$\Pi_i(\theta_{i,t}, \theta_{j,t}) \equiv (P_{i,t} - \omega)\, C_{i,t}/M_{i,t} = \omega^{1-\epsilon} \theta_{i,t} \left(1 - \theta_{i,t}\right)^{\eta-1} \left(1 - \theta_t\right)^{\epsilon-\eta}, \tag{12}$$

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

[9] This assumption is consistent with assumptions made in the literature (e.g., Atkeson and Burstein, 2008; Corhay, Kung and Schmid, 2020; Dou, Ji and Wu, 2021).

3.3 Nash Equilibrium

The two firms in an industry play a supergame (Friedman, 1971), in which the stage games of setting profit margins are continuously played and infinitely repeated with exogenous and endogenous state variables varying over time. There exists a non-collusive equilibrium, which is the repetition of the one-shot Nash equilibrium, and thus is Markov perfect. Meanwhile, multiple subgame-perfect collusive equilibria can also exist, in which profit-margin strategies are sustained by conditional punishment strategies.[10]

Formally, a subgame perfect Nash equilibrium for the supergame consists of a collection of profit-margin strategies that constitute a Nash equilibrium for every history of the game. We do not consider all such equilibria; instead, we focus on those that allow for collusive arrangements enforced by punishment schemes. All strategies depend on "payoff-relevant" states $x_t = \{M_{1,t}, M_{2,t}, \gamma_t\}$ in the state space $\mathcal{X}$, as in Maskin and Tirole (1988*a*,*b*), as well as a pair of indicator functions that track whether either firm has previously deviated from the collusive agreement, as in Fershtman and Pakes (2000, p. 212).[11]

Non-Collusive Equilibrium. The non-collusive equilibrium is characterized by a profit-margin-setting scheme $\Theta^N(\cdot) = (\theta_1^N(\cdot), \theta_2^N(\cdot))$, which is a pair of functions defined in state space $\mathcal{X}$, such that each firm i chooses profit margin $\theta_{i,t} \equiv \theta_i(x_t)$ to maximize its equity value $E_i^N(x_t)$, under the assumption that its competitor j will stick to the one-shot Nash-equilibrium profit margin $\theta_{j,t}^N \equiv \theta_j^N(x_t)$.

Denote by $\underline{M}_{i,t}^N \equiv \underline{M}_i^N(M_{j,t}, \gamma_t)$ firm i's endogenous default boundary with respect to $M_{i,t}$ in the non-collusive equilibrium; importantly, the endogenous default boundary of firm i depends on its rival's customer base $M_{j,t}$. Following the recursive formulation in dynamic games for characterizing the Nash equilibrium (e.g., Pakes and McGuire, 1994; Ericson and Pakes, 1995), we formulate the optimization problems, conditioning on $M_{i,t} > \underline{M}_{i,t}^N$ for $i \neq j \in \{1, 2\}$, as a pair of Hamilton-Jacobi-Bellman (HJB) equations:

$$0 = \max_{\theta_{i,t}} (1-\tau)[\Pi_i(\theta_{i,t}, \theta_{j,t}^N) M_{i,t} - b_i]\mathrm{d}t + \Lambda_t^{-1} \mathbb{E}_t \left[\mathrm{d}(\Lambda_t E_i^N(x_t))\right], \tag{13}$$

where $i \neq j \in \{1, 2\}$. The coupled HJB equations give solutions for the non-collusive profit margin, where $\theta_{i,t}^N \equiv \theta_i^N(x_t)$ for $i = 1, 2$.

At the default boundary $\underline{M}_{i,t}^N$, the equity value of firm i is equal to zero (i.e., the

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

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

value matching condition), and the optimality of the boundary implies the smooth pasting condition:

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

As $M_{i,t} \to +\infty$, firm i essentially becomes an industry monopoly, which sets an asymptotic boundary condition (see Online Appendix 1.1). The value matching and smooth pasting conditions in (14) ensure that the smooth-pasting conditions with respect $M_{j,t}$ and γ_t hold in equilibrium, i.e., $\frac{\partial}{\partial M_{j,t}} E_i^N(x_t)\Big|_{M_{i,t}=\underline{M}_{i,t}^N} = 0$ and $\frac{\partial}{\partial \gamma_t} E_i^N(x_t)\Big|_{M_{i,t}=\underline{M}_{i,t}^N} = 0$. We provide detailed proofs and discussions in Online Appendix 1.2.

Collusive Equilibrium. In the collusive equilibrium, firms tacitly collude with each other in setting higher profit margins, where any deviation would trigger a switch to the non-collusive equilibrium. The collusion is "tacit" in the sense that it can be enforced without relying on legal contracts. Each firm is deterred from breaking the collusion agreement because doing so could provoke the fiercest competition (i.e., the non-collusive equilibrium in our model).

Consider a generic collusive equilibrium in which the two firms follow a collusive profit-margin-setting scheme. Both firms can costlessly observe the other's profit margin, such that deviant behavior can be detected and punished. The assumption of perfect information follows the literature.[12] If one firm deviates from the collusive profit-margin-setting scheme, then with probability $\xi \mathrm{d}t$ over $[t, t+\mathrm{d}t)$, the other firm will implement a punishment strategy in which it will forever set the non-collusive profit margin. Entering the non-collusive equilibrium punishes the deviating firm because this equilibrium features the lowest profit margin.[13] We use an idiosyncratic Poisson process $N_{i,t}$ with intensity ξ to characterize whether a firm can successfully implement a punishment strategy after the competitor's deviation.[14] Thus, a higher ξ makes the threat of punishment more credible,

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

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

[14] One interpretation of $N_{i,t}$ is that, with probability $1-\xi \mathrm{d}t$ over $[t, t+\mathrm{d}t)$, the deviator can persuade its competitor not to enter the non-collusive equilibrium over $[t, t+\mathrm{d}t)$. Ex-post renegotiations can occur because the non-collusive equilibrium is not renegotiation-proof or "immune to collective rethinking" (Farrell and Maskin, 1989). The strategy we consider is essentially a probabilistic punishment strategy. This "inertia assumption" also solves the technical issue of continuous-time dynamic games about the indeterminacy of outcomes (e.g., Simon and Stinchcombe, 1989; Bergin and MacLeod, 1993).

which reduces any incentives to deviate and enables collusion at higher profit margins.

Let $E_i^C(x)$ denote firm i's equity value in the collusive equilibrium, and $E_i^D(x)$ denote firm i's equity value if it chooses to deviate from the collusion. The set of incentive-compatible collusion agreements, denoted by $\mathcal{C}$, consists of all continuous profit-margin-setting schemes $\Theta^C(\cdot) \equiv (\theta_1^C(\cdot), \theta_2^C(\cdot))$ such that the participation constraints (PC),

$$E_i^N(x) \leq E_i^C(x), \tag{15}$$

and the incentive compatibility (IC) constraints,

$$E_i^D(x) \leq E_i^C(x), \tag{16}$$

are satisfied for all $x \in \mathcal{X}$ and $i = 1, 2$.

Next, we describe how $E_i^C(x)$ and $E_i^D(x)$ are determined in equilibrium. Denote by $\underline{M}_{i,t}^C \equiv \underline{M}_i^C(M_{j,t}, \gamma_t)$ firm i's endogenous default boundary with respect to $M_{i,t}$ in the collusive equilibrium. Conditional on $M_{i,t} \geq \underline{M}_{i,t}^C$ for $i \neq j \in \{1, 2\}$, the value functions $E_i^C(x)$ satisfy the following coupled HJB equations:

$$0 = (1-\tau)[\Pi_i(\theta_{i,t}^C, \theta_{j,t}^C)M_{i,t} - b_i]\mathrm{d}t + \Lambda_t^{-1}\mathbb{E}_t\left[\mathrm{d}(\Lambda_t E_i^C(x_t))\right], \tag{17}$$

subject to the PC and IC constraints (15) and (16), where $i \neq j \in \{1, 2\}$. The variables $\theta_{i,t}^C \equiv \theta_i^C(x_t)$ are the collusive profit margins for $i = 1, 2$. The optimal default boundary $\underline{M}_{i,t}^C$ is endogenously determined by the following value matching and smooth pasting conditions:

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

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

Denote by $\underline{M}_{i,t}^D \equiv \underline{M}_i^D(M_{j,t}, \gamma_t)$ firm i's endogenous default boundary with respect to $M_{i,t}$ if firm i deviates from collusion and its rival j continues to follow the collusive profit-margin-setting scheme. Conditional on $M_{i,t} \geq \underline{M}_{i,t}^D$ for $i \neq j \in \{1, 2\}$, the value functions $E_i^D(x_t)$ satisfy the following coupled HJB equations:

$$0 = \max_{\theta_{i,t}}(1-\tau)[\Pi_i(\theta_{i,t}, \theta_{j,t}^C)M_{i,t} - b_i]\mathrm{d}t - \xi\left[E_i^D(x_t) - E_i^N(x_t)\right]\mathrm{d}t + \Lambda_t^{-1}\mathbb{E}_t\left[\mathrm{d}(\Lambda_t E_i^D(x_t))\right], \tag{19}$$

where $i \neq j \in \{1,2\}$. The optimal default boundary $\underline{M}_{i,t}^D$ is endogenously determined by the following value matching and smooth pasting conditions:

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

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

Two points are worth further discussion. First, the PC constraints (15) can become binding in the collusive equilibrium, triggering the two firms to switch to the non-collusive equilibrium. The endogenous switch captures the endogenous outbreak of price wars. We assume that once the two firms switch to the non-collusive equilibrium, they will stay there forever. Second, there exist infinitely many elements in $\mathcal{C}$ and hence infinitely many collusive equilibria. The equilibrium selection follows the method of Dou, Ji and Wu (2021) whereby the Pareto efficient equilibrium is selected.

Debt Value and Optimal Coupon Choice. We illustrate the debt value and optimal coupon choice in the collusive equilibrium. Those in the non-collusive equilibrium are determined similarly, based on the corresponding policy functions in the non-collusive equilibrium.

Debt value equals the sum of the present value of the cash flows that accrue to debtholders until the occurrence of endogenous default or exogenous displacement, whichever occurs first, plus the recovery value. We follow the literature on dynamic debt models and set the recovery value of endogenous default to be a fraction δ of the firm's unlevered asset value, which is the value of an all-equity firm. In the collusive equilibrium, the unlevered asset value $A_i^C(x_t)$ is similarly determined by equations (13) to (20) except we set $b_i = 0$ and remove the default boundary conditions (14), (18), and (20). Regarding exogenous displacement, when the idiosyncratic left-tail shock hits firm i over $[t, t+\mathrm{d}t)$ (i.e., $\mathrm{d}J_{i,t} = 1$), two outcomes are possible: with probability ϖ, the firm is wiped out with no debt recovery; and with probability $1-\varpi$, the firm is restructured by the new entrant firm, the old debt is retired at par value, and new debt is optimally issued.

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

$$\left[\varpi D_i^C(x_t) + (1-\varpi)(D_i^C(x_t) - D_i^C(x_{t_0}))\right] \nu \mathrm{d}t = b_i \mathrm{d}t + \Lambda_t^{-1} \mathbb{E}_t\left[\mathrm{d}(\Lambda_t D_i^C(x_t))\right], \tag{21}$$

with the following boundary conditions:

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

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

The left-hand side of equation (21) is the expected loss of debt due to the idiosyncratic left-tail shock, and the right-hand side is the expected gain of debtholders if the left-tail shock does not occur over $[t, t + \mathrm{d}t)$. The first condition in equation (22) is the recovery value to debtholders at the default boundary, and the second condition captures the asymptotic behavior of debt when the customer base $M_{i,t}$ approaches infinity, which is basically the value of a bond with a constant coupon rate b_i until the occurrence of the idiosyncratic left-tail shock at the rate ν, upon which the bond retires at the par value with probability $1 - \varpi$ or defaults with no debt recovery with probability ϖ.

At $t = 0$, the firms' initial coupon rates b_1 and b_2 are optimally determined in the Nash equilibrium. Specifically, each firm $i = 1, 2$ optimally chooses its coupon rate b_i to maximize the sum of equity and debt values, $E_i^C(x_0) + D_i^C(x_0)$, in the collusive equilibrium at $t = 0$, given its competitor's optimal choice of coupon rate b_j.

3.4 Illustration of Strategic Competition in Setting Profit Margins

To illustrate the strategic competition between the two firms within the same industry, Figure 2 plots the profit margins of firms i and j, respectively, as a function of firm i's customer base $M_{i,0}$, with firm j's customer base fixed at $M_{j,0} = 1$ at $t = 0$. Both firms have higher profit margins in the collusive equilibrium (the solid lines) than in the non-collusive equilibrium (the dotted lines). Moreover, firm i's default boundary (represented by the vertical lines) in the collusive equilibrium is lower than that in the non-collusive equilibrium (i.e., $\underline{M}_{i,0}^C < \underline{M}_{i,0}^N$). The solid line in panel A shows that firm i reduces its profit margin when it becomes more financially distressed (i.e., lower distance to default as $M_{i,0}$ decreases). Moreover, its financially strong competitor, firm j, also lowers its profit margin (the solid line in panel B) even though firm j's customer base $M_{j,0}$ remains unchanged.

The competitor firm j undercuts the profit margin knowing that the financially weak firm i will cut its profit margin to compete for customers (the solid line in panel A). Firm j's intention in setting a lower profit margin is to prevent its financially weak competitor from stealing demand. If firm j were to fix its profit margin, its financially weak competitor, firm i, will deviate from the collusive equilibrium by significantly undercutting the profit margin.

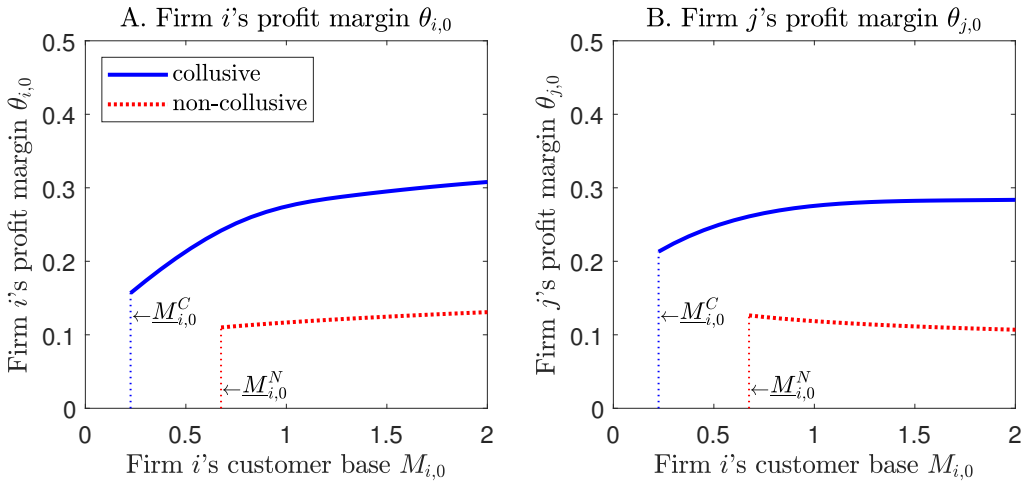


Figure 2: **Firms' profit-margin decisions as a function of customer base.** Panels A and B plot the profit margins $(\theta_{i,0}, \theta_{j,0})$ of firms i and j, respectively, as a function of firm i's customer base $M_{i,0}$ at $t = 0$, holding $\gamma_0 = \overline{\gamma}$ and $M_{j,0}$ unchanged at the initial level $M_{j,0} = 1$. The solid and dotted lines represent the collusive and non-collusive equilibrium. The vertical dotted lines represent the default boundaries of firm i in the corresponding cases. Parameters are set according to our calibration in Section 4.2.

To maintain tacit collusion and prevent firm i from deviating, firm j has to cut its own profit margin, which itself is an optimal response to the increased financial distress of firm i.

By contrast, in the non-collusive equilibrium, firm i's profit margin increases with its own customer base (the dotted line in panel A), and firm j's profit margin decreases with its competitor firm i's customer base (the dotted line in panel B). In other words, both firms' non-collusive profit margins increase with their own customer base share. This is a standard result in the literature: non-collusive profit margins (i.e., the one-shot Nash equilibrium of Bertrand competition) are solely determined by the short-run price elasticity of demand, which decreases with the firm's customer base share.

3.5 Profit Margins' Exposure to Discount-Rate Shocks

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

To illustrate this mechanism, we consider an industry with two identical firms such that $M_{i,0} = M_{j,0} = M_0/2$ constantly holds at $t = 0$. Panel A of Figure 3 plots the industry's profit margin as a function of firms' average customer base. The vertical lines show that firms' endogenous default boundary in the collusive equilibrium is lower than that in the non-collusive equilibrium. Therefore, given the same average customer base of firms, as industry equilibrium shifts from the collusion to non-collusion, firms' distance to default

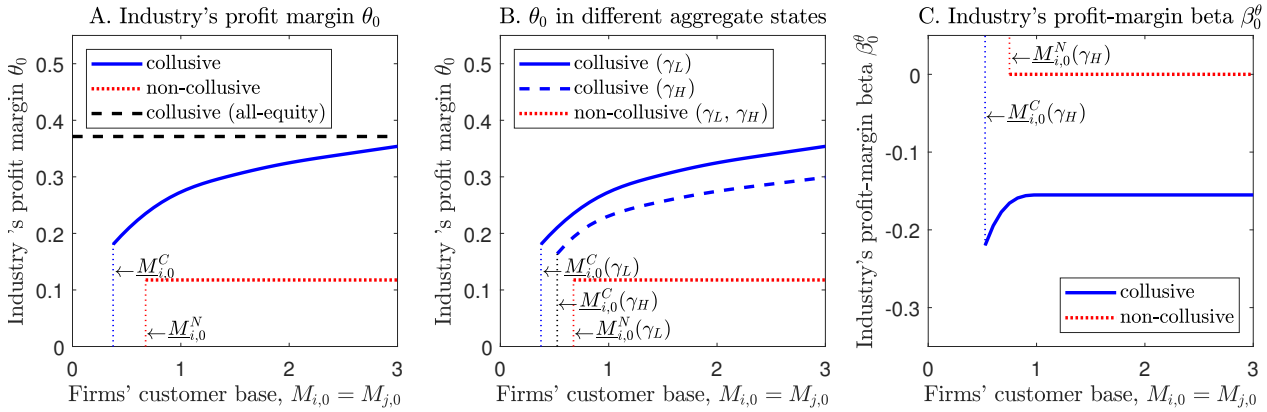


Figure 3: **Feedback loop between competition and financial distress.** We consider an industry with two identical firms such that $M_{i,0} = M_{j,0} = M_0/2$ constantly holds at $t = 0$. In panel A, the solid and dotted lines plot the industry's profit margin θ_0 in the collusive and non-collusive equilibrium. As a benchmark, the dashed line represents the industry's profit margin in the collusive equilibrium when both firms are wholly financed by equity. We set $\gamma_0 = \overline{\gamma}$ in panel A. Panel B plots the industry's profit margin θ_0 for different aggregate states γ_0. The solid and dashed lines represent a low $\gamma_0 \equiv \gamma_L$ and a high $\gamma_0 \equiv \gamma_H$ in the collusive equilibrium. The dotted line represents the non-collusive equilibrium. We set $\gamma_L = \overline{\gamma}$ and $\gamma_H = \overline{\gamma} + 2\text{std}(\gamma_t)$. Panel C plots the profit-margin beta to the discount rate defined in equation (23). The solid and dotted lines represent the collusive and non-collusive equilibrium respectively. In all panels, the vertical dotted lines represent firms' default boundaries in the corresponding cases. Parameters are set according to our calibration in Section 4.2.

decreases. This indicates that intensified competition leads to higher financial distress.

Moreover, zeroing in on the collusive equilibrium (the solid line) in panel A of Figure 3, we see that higher distress would intensify competition. Specifically, when firms' average customer base is lower, their distances to default decrease, implying that firms become more distressed. The solid line shows that, the industry's profit margin also endogenously decreases with firms' average customer base, reflecting increased competition intensity. Intuitively, the incentive to collude on higher profit margins depends on how much firms value future cash flows relative to their contemporaneous cash flows. By deviating from the collusive profit-margin-setting scheme, firms can obtain higher contemporaneous cash flows; however, firms run the risk of losing future cash flows because once the deviation is punished by the other firm, the non-collusive equilibrium will be implemented, which features low profit margins. When firms are closer to the default boundary, they are more likely to exit the market in the near future because of their higher probability of default. As a result, firms become effectively more impatient and care less about future cooperation, which motivates them to undercut their competitors' profit margins. Thus, to ensure that deviation does not occur in the collusive equilibrium (i.e., the IC constraints (16) are satisfied), the mutually agreed-upon profit margins must fall when firms are driven closer to the default boundary.[15]

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

Taken together, panel A of Figure 3 shows a positive feedback loop between competition and financial distress. By contrast, the non-collusive equilibrium (the dotted line) does not have a feedback loop, because the intensity of competition is only determined by the constant price elasticity of demand when the customer base share is fixed, and the distance to default has no effect on industry competition. In addition, the industry with all-equity firms does not have a feedback loop, which can be seen from the constant profit margin (the flat dashed line). Thus, the endogenous distressed competition mechanism is the key to generating the competition-distress feedback.

Amplification Effects on the Exposure to Discount-Rate Shocks. Due to the endogenous movement in firms' profit margins, industries' exposure to aggregate discount-rate shocks is significantly amplified by the competition-distress feedback mechanism. Intuitively, when the discount rate rises, future cash flows are discounted at a higher rate, reducing the firms' continuation value. The lower continuation value directly affects the strategic decisions of shareholders through two channels: first, it motivates shareholders to default early, effectively reducing firms' distances to default and increasing firms' distress levels; second, it reduces firms' capacity to collude because a lower continuation value increases firms' deviation incentives. This leads to more intensive competition within the industry, resulting in lower profit margins. Therefore, a higher discount rate directly increases both the financial distress level and competition intensity within the industry. Such direct effects are further amplified by the competition-distress feedback, increasing firms' exposure to aggregate discount-rate shocks.

To illustrate the impact of the discount rate on competition intensity, panel B of Figure 3 plots the industry's profit margin in the collusive equilibrium of the aggregate states with a low discount rate γ_L (the solid line) and a high discount rate γ_H (the dashed line). The industry's profit margin is lower when the discount rate is higher.[16] This is because a higher discount rate γ_H makes firms more impatient and focus more on short-term cash flows, thereby making firms care less about future cooperation. As a result, future punishment becomes less threatening and higher profit margins are more difficult to sustain. By contrast, in the non-collusive equilibrium, profit margins remain unchanged when the discount rate rises (the dotted line) because competition intensity is only determined by the constant price elasticity of demand, given fixed customer base shares.

for collusive behavior becomes weaker.

[16] 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 (i.e., the rate of time preference is closer to 1); instead, they may enter into a price war until only one firm in the industry is alive. This is not the case in our model because we allow new firms to enter the industry.

To illustrate how the exposure of profit margins to the discount rate varies with the distance to default, we calculate the industry-level profit-margin beta β_0^θ to the discount rate at $t = 0$, defined as the ratio of the industry's profit margin between the two aggregate states:

$$\beta_0^\theta \equiv \theta_0^C(\gamma_H)/\theta_0^C(\gamma_L) - 1. \tag{23}$$

The solid line in panel C of Figure 3 shows that the profit-margin beta becomes more negative when the industry becomes more financially distressed in the collusive equilibrium. In particular, when the industry is close to the default boundary, the profit-margin beta is -0.22, indicating that the industry's profit margin decreases by 22% in response to a two-standard-deviation increase in the discount rate γ_t. This is because the endogenously intensified competition is further amplified by the competition-distress feedback, dramatically amplifying the industry's exposure to the discount rate, especially when the industry is financially distressed. By contrast, the profit-margin beta is always zero in the non-collusive equilibrium (the dotted line).

3.6 Financial Distress Anomaly across Industries

We now discuss the asset pricing implications of the competition-distress feedback across industries with different intensities ν of idiosyncratic left-tail shocks. To fix ideas, we focus on the collusive equilibrium because, as discussed in Section 3.5, the competition-distress feedback does not exist in the non-collusive equilibrium.

Our model implies that the feedback effect is weaker in industries with higher ν. Intuitively, firms in such industries are more financially distressed and have higher exit rates because of their higher exposure to idiosyncratic left-tail shocks (i.e., a higher probability of exogenous replacement). The higher exit rate makes firms less concerned about future cooperation, thereby dampening their incentives to collude. As the competition-distress feedback effect arises from endogenous collusion, the feedback effect naturally diminishes when firms have weaker collusion incentives. A weaker competition-distress feedback further implies that industries with higher ν are less negatively exposed to aggregate discount-rate shocks. Because aggregate discount-rate shocks are negatively priced, investors demand lower expected excess returns for holding these industries' stocks. Taken together, the model implies that industries with higher ν are less profitable and more financially distressed due to the higher probabilities of default; meanwhile, these industries are less exposed to discount-rate shocks, leading to lower expected stock returns. Therefore, our model provides an explanation for the financial distress anomaly across industries.

As an illustration, we consider two industries with different levels of idiosyncratic left-tail

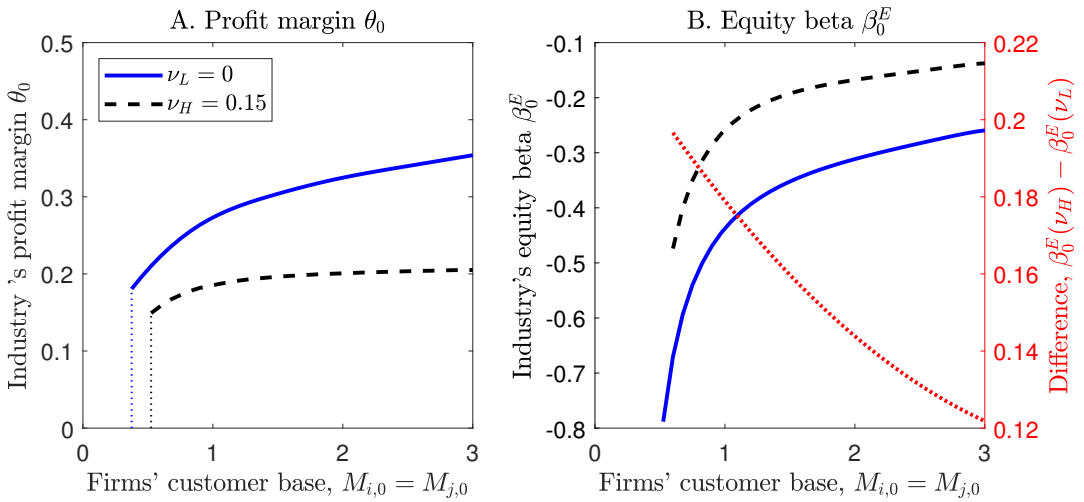


Figure 4: **Industry exposure to discount-rate shocks in the cross section.** We consider an industry with two identical firms such that $M_{i,0} = M_{j,0} = M_0/2$ constantly holds at $t = 0$. Panel A plots the profit margin θ_0 of industries with ν_L and ν_H as functions of firms' average customer base in the state of γ_L. The vertical dotted lines represent firms' default boundaries in the corresponding industries. Panel B plots the equity beta β_0^E (defined in equation (24)) of the two industries. The dotted line in panel B (corresponding to the right y-axis) plots the difference in the equity beta between the two industries. We set $\nu_L = 0$, $\nu_H = 0.15$, $\gamma_L = \overline{\gamma}$ and $\gamma_H = \overline{\gamma} + 2\text{std}(\gamma_t)$. Other parameters are set according to our calibration in Section 4.2.

risk, ν_L and ν_H, with $\nu_L < \nu_H$. We assume that firms in the same industry have an identical customer base. Panel A of Figure 4 shows that the industry with ν_H has a lower profit margin than the industry with ν_L because firms lack collusion incentives when idiosyncratic left-tail shocks occur at a higher rate.[17] Therefore, the industry with ν_H has a weaker competition-distress feedback than the industry with ν_L.

To compare the equity exposure of the two industries, we define the industry-level equity beta β_0^E to the discount rate at $t = 0$ as the value-weighted firm-level equity beta:

$$\beta_0^E = \sum_{i=1}^{2} w_{i,0}^E \beta_{i,0}^E, \text{ where } \beta_{i,0}^E = \frac{E_{i,0}^C(\gamma_H)}{E_{i,0}^C(\gamma_L)} - 1 \text{ and } w_{i,0}^E = \frac{E_{i,0}^C(\gamma_L)}{\sum_{j=1}^{2} E_{j,0}^C(\gamma_L)}, \tag{24}$$

for all $M_{i,0}, M_{j,0} > 0$. Panel B of Figure 4 shows that for both industries, the equity beta is more negative when the industry is closer to the default boundary, reflecting the competition-distress feedback effect. Importantly, the equity beta is much less negative in the industry with ν_H (the dashed line) because the within-industry competition-distress feedback is weaker owing to the weaker collusion incentive. Moreover, the dotted line (corresponding to the right y-axis) shows that the equity-beta gap between the two industries is wider

[17] As a side prediction, our model implies that more profitable industries have higher expected equity returns due to lower (i.e., more negative) exposure to discount-rate shocks. Relatedly, Kogan and Papanikolaou (2013) show that more profitable firms have higher expected equity returns due to lower exposure to investment-specific technology (IST) shocks.

when the distance to default is lower, indicating that the strength of the competition-distress feedback in each industry differs more when the two industries are closer to the default boundary, as this is the time when the competition-distress feedback becomes more relevant.

4 Quantitative Analysis

In this section, we conduct quantitative analysis. Subsection 4.1 describes the empirical measures. Subsection 4.2 calibrates the model's parameters. In Subsection 4.3, we study the model's implications on stock returns and credit spreads. Finally, in Subsection 4.4, we inspect the model's mechanism.

4.1 Empirical Measures

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

Measure of Default Event. We retrieve and merge the information on Chapter 7 and Chapter 11 bankruptcies filed by large, public, nonfinancial U.S. firms over the period from 1981 to 2014 using the databases from New Generation Research's Bankruptcydata.com, the UCLA LoPucki Bankruptcy Research Database, Public Access to Court Electronic Records (PACER), National Archives at various locations, and U.S. Bankruptcy Courts for various districts, following Ma, Tong and Wang (2020) and Dou et al. (2021*a*). Similar to Campbell, Hilscher and Szilagyi (2008), we define a default event as the first of the following events: Chapter 7 or Chapter 11 bankruptcy filing, delisting due to insolvency (delisting code 572), and a default or selective default rating by a rating agency. This expanded measure of failure (relative to measuring only bankruptcy filings) allows us to capture instances in which firms fail but reach an agreement with creditors before an actual bankruptcy filing, such as pre-court liquidation or pre-court reorganization (e.g., Gilson, John and Lang, 1990;

Gilson, 1997; Dou et al., 2021*a*).

Measure of Distance-to-Default. In the model, an industry's default risk is determined by both its idiosyncratic left-tail risk and its distance to the default boundary. The cross-industry heterogeneity in default risk is mainly captured by industries' different levels of idiosyncratic left-tail risk, whereas the time-series variation in default risk within an industry is mainly reflected by the time-varying distance to default. Thus, we also construct a distance-to-default measure following the Merton model for the purpose of testing the competition-distress feedback effect. Specifically, we use (i) the book value of a firm's debt, computed as short-term debt plus one half of long-term debt, (ii) the total value of a firm's assets, estimated by the sum of the firm's book value of debt and its market value of equity, (iii) the risk-free rate, and (iv) the volatility of the market value of a firm's assets, approximated by the volatility of its deleveraged equity returns. The distance-to-default measure for industry i and period t, denoted by $DD_{i,t}$, is the average firm-level distance-to-default measure of all firms in the same industry i weighted by their sales.

Measure of Ex-Ante Idiosyncratic Left-Tail Risk. We construct a measure of idiosyncratic left-tail risk in two steps. First, we construct a measure of the realized frequency of idiosyncratic left-tail shocks for each industry i and year t, denoted by $Idio_Tail_Freq_{i,t}$. Specifically, for each firm j in year t, we measure its cash flows by the firm's net income divided by its 1-year lagged total assets, and we further measure the firm's idiosyncratic cash flows by subtracting its industry-level cash flows, which are constructed by the average cash flows of all firms within the industry. We then construct the realized frequency of idiosyncratic left-tail shocks $Idio_Tail_Freq_{i,t}$ as the sales-weighted fraction of firms (within the industry) whose cash flows are below the 10th percentile cutoff of the distribution of firm-level cash flows across all firm-year observations. We further project the realized frequency of idiosyncratic left-tail shocks in year $t+1$ to industry characteristics in year t by estimating the following panel regression using industry-year observations between 1971 and 2021:

$$Idio_Tail_Freq_{i,t+1} = \alpha + \beta X_{i,t} + \epsilon_{i,t+1}, \tag{25}$$

where $X_{i,t}$ is a vector of industry-level variables, constructed as the sales-weighted average of the firm-level variables used by Campbell, Hilscher and Szilagyi (2008) in estimating firms' failure probability. We report the estimates in Online Appendix 2.1. We then construct an ex-ante measure, $\nu_{i,t}$, for the idiosyncratic left-tail risk of each industry i in month t based

Table 4: Parameter choice.

Panel A: Externally determined parameters

Parameter	Symbol	Value	Parameter	Symbol	Value
Risk-free rate	r_f	2%	Persistence of market price of risk	φ	0.13
Volatility of market price of risk	π	0.12	Within-industry elasticity	η	15
Industry price elasticity	ϵ	2	Corporate tax rate	τ	0.27
Mean growth rate of customer base	g	1.89%	Initial customer base	M_0	1
Customer base of new entrants	κ	0.35	Intensity of left-tail shocks	$[\underline{\nu}, \overline{\nu}]$	$[0, 0.15]$

Panel B: Internally calibrated parameters and targeted moments

Parameter	Symbol	Value	Moments	Data	Model
Bond recovery rate	δ	0.41	Average leverage ratio (Baa rated)	0.34	0.36
Volatility of idiosyncratic shocks	σ	25%	5-year default rate (Baa rated)	2.2%	2.9%
Default rate upon left-tail shocks	ϖ	0.14	Diff. in 5-year default rate (Q5−Q1)	5.1%	4.3%
Marginal cost of production	ω	0.17	Average net profitability	3.9%	3.9%
Punishment rate	ξ	0.09	Average gross profit margin	33.4%	27.1%
Average market price of risk for Z_t	$\overline{\gamma}$	0.15	Market equity premium	7.4%	7.0%
Volatility of aggregate shocks	ς	0.04	Market Sharpe ratio	0.40	0.39
Market price of risk for $Z_{\gamma,t}$	ζ	0.45	Credit spread (Baa-rated)	1.4%	1.5%

on the predictive component of (25), as follows:

$$\nu_{i,t} = \widehat{\alpha} + \widehat{\beta} X_{i,t}. \tag{26}$$

4.2 Calibration and Parameter Choices

Panel A of Table 4 presents the externally calibrated parameters. The real risk-free rate is $r_f = 2\%$. We set the persistence of the market price of risk to be $\varphi = 0.13$ as in Campbell and Cochrane (1999) and the volatility of the market price of risk $\pi = 0.12$ as in Lettau and Wachter (2007). The within-industry elasticity of substitution is set at $\eta = 15$ and the cross-industry price elasticity of demand at $\epsilon = 2$, which are broadly consistent with the calibration and estimation in the industrial organization and international trade literature (e.g., Harrigan, 1993; Head and Ries, 2001; Atkeson and Burstein, 2008). We set the corporate tax rate at $\tau = 27\%$ and the drift term under the physical measure at $g = 1.89\%$, as in He and Milbradt (2014) to match the growth rate of real cash flows. We assume that the two firms in the industry initially have the same customer base M_0 which is normalized to be 1. We set the initial customer base of new entrants to be a fraction $\kappa = 0.35$ of the initial customer base. We assume that the intensity of idiosyncratic left-tail shocks ν ranges from $\underline{\nu}$ to $\overline{\nu}$. We discretize $[\underline{\nu}, \overline{\nu}]$ into $N = 10$ grids with equal spacing so that $\nu_1 = \underline{\nu}$ and $\nu_N = \overline{\nu}$.

The mass of industries associated with each value of ν is the same. We normalize $\underline{\nu} = 0$ and set $\overline{\nu} = 0.15$ as in Dou, Ji and Wu (2021, 2022).

The remaining parameters are calibrated by matching the relevant moments summarized in panel B of Table 4. When constructing the model moments, we simulate a sample of 1,000 industries for 20 years starting from the initial customer base distribution. We then compute the model counterparts of the data. For each moment, the table reports the average value of 2,000 simulations. We set the ex-post bond recovery rate at $\delta = 0.41$ so that the model-implied average leverage ratio is 0.36, matching that of Baa-rated bonds in the data.[18] The volatility of idiosyncratic shocks is $\sigma = 25\%$, which generates a 5-year default rate of 2.9%. We set $\varpi = 0.14$ so that the difference in 5-year default rates across the quintile portfolios of industries sorted on financial distress (Q5−Q1) is 4.3%, comparable to the value in the data. The marginal cost of production is $\omega = 0.17$, determined to match the average net profitability. We set the punishment rate $\xi = 0.09$ so that the average gross profit margin is 27.1%. In the data, net profitability and gross profit margins are measured as in Dou, Ji and Wu (2021). We set $\zeta = 0.45$, $\overline{\gamma} = 0.15$, and $\varsigma = 4\%$ so that the market portfolio's equity premium is 7.0%, Sharpe ratio is 0.39, and credit spread is 1.5%. The model generates a high credit spread because both the risk premium and default boundaries are countercyclical in our model, the two ingredients that have been shown to be crucial to quantitatively match the credit spread in the data (Chen, Collin-Dufresne and Goldstein, 2008). Importantly, compared to the standard Leland-type models, the default boundaries exhibit greater countercyclicality in our model due to the strong endogenous negative covariance between profit margins and risk premium (see panel C of Figure 3) caused by the competition-distress feedback.

4.3 Financial Distress Anomaly across Industries

We now quantitatively examine the asset pricing implications of the competition-distress feedback mechanism. Specifically, we show that our model can quantitatively rationalize the financial distress anomaly across industries: more financially distressed industries have lower expected equity excess returns and higher credit spreads.

Panel A of Table 5 shows that in the data, the differences in expected equity excess returns and credit spreads between quintile portfolios of industries sorted on financial distress (Q5−Q1) are −5.63% and 2.35%, respectively. We perform the same portfolio sorting

[18]The calibrated recovery rate is also close to the rate estimated by Chen (2010) based on the mean recovery rate of Baa-rated bonds, as well as the average recovery rate of debt in bankruptcy for large, public, nonfinancial U.S. firms from 1996 to 2014 structurally estimated by Dou et al. (2021*a*). Collin-Dufresne, Goldstein and Yang (2012) and Seo and Wachter (2018) also use a 40% recovery rate in normal times to match CDX spreads.

analyses in our model. The model-implied difference in expected equity excess returns (Q5−Q1) is −4.35%, which is comparable to the magnitude in the data. As discussed in Section 3.6, the difference in the idiosyncratic left-tail risk is the primary force causing the difference in financial distress across industries. Thus, sorting industries by financial distress in the model captures the cross-industry variation in idiosyncratic left-tail risk. Industries with higher financial distress have a weaker competition-distress feedback effect. As a result, these industries have lower expected equity excess returns because equity returns are less negatively exposed to aggregate discount-rate shocks (see panel B of Figure 4).

The model-implied difference in credit spreads (Q5−Q1) is 1.81%, which is also comparable to the magnitude in the data. The model implies a positive difference in credit spreads because industries with higher idiosyncratic left-tail risk have a higher probability of default. This can be verified by looking at the 5-year default rate, which is 0.97% for Q1 and 4.94% for Q5. Similar patterns for default rates are also observed in the data. Therefore, the positive difference in credit spreads (Q5−Q1) is generated by the positive difference in default probabilities rather than the difference in credit risk premium. In fact, similar to the structural models following Merton (1974), the model-implied difference in credit risk premium (Q5−Q1) is negative, in line with the negative difference in expected equity excess returns (Q5−Q1). This implication is consistent with the empirical findings of Friewald, Wagner and Zechner (2014), who show that firms' excess equity returns are positively associated with their credit risk premia estimated from CDS spreads. Our model also implies that, compared with the industries in Q1, a larger proportion of the credit spreads of industries in Q5 is attributed to the higher default rates of these industries rather than the credit risk premia. This implication is consistent with the stylized fact documented by Huang and Huang (2012), that is, for firms with lower ratings (or higher credit spreads), expected default losses account for a larger fraction of their credit spreads than the credit risk premia.

In contrast to our model's implications, the canonical framework (e.g., Merton, 1974; Leland, 1994) cannot rationalize the financial distress anomaly. Specifically, we extend the standard model of Leland (1994) by incorporating the time-varying market price of risk (equations (7) and (8)).[19] This extended Leland framework implies higher expected returns and credit spreads for more financially distressed industries. This is because more financially distressed industries are closer to default and thus have higher financial leverage, which amplifies the exposure of both equity and debt to aggregate shocks. Unique to our model is that the competition-distress feedback mechanism, together with heterogeneous

[19]The time-varying market price of risk allows the canonical Leland framework to generate average levered equity excess returns and credit spreads consistent with the data (e.g., Chen, Collin-Dufresne and Goldstein, 2008; Bhamra, Kuehn and Strebulaev, 2010*b*; Chen, 2010).

Table 5: Industry portfolios in model and data.

	Data			Model		
	Panel A: Industry portfolios sorted on financial distress					
$Distress_{i,t}$	Q1 (low)	Q5 (high)	Q5−Q1	Q1 (low)	Q5 (high)	Q5−Q1
Equity excess return (%)	9.70	4.07	−5.63	9.09	4.74	−4.35
	[6.13, 13.27]	[−0.26, 8.41]	[−9.27, −1.99]			
Credit spread (%)	0.99	3.34	2.35	0.68	2.49	1.81
	[0.79, 1.20]	[2.51, 4.16]	[1.72, 2.98]			
5-year default rate (%)	0.53	5.66	5.13	0.97	4.94	3.97
	[0.26, 0.81]	[4.08, 7.25]	[3.60, 6.66]			
Leverage ratio (%)	22.57	33.47	10.90	24.51	40.36	15.85
	[20.57, 24.57]	[31.60, 35.34]	[9.12, 12.67]			
Gross profit margin (%)	40.88	29.07	−11.81	32.76	23.77	−8.99
	[35.79, 45.95]	[25.08, 33.06]	[−14.81, −8.81]			
	Panel B: Industry portfolios sorted on idiosyncratic left-tail risk					
$\nu_{i,t}$	Q1 (low)	Q5 (high)	Q5−Q1	Q1 (low)	Q5 (high)	Q5−Q1
Equity excess return (%)	9.95	3.89	−6.06	9.24	4.73	−4.51
	[6.22, 13.68]	[−1.09, 8.87]	[−10.40, −1.72]			
Credit spread (%)	1.19	3.10	1.91	0.73	2.61	1.88
	[0.94, 1.44]	[2.24, 3.96]	[1.22, 2.60]			
5-year default rate (%)	0.97	4.95	3.98	0.92	5.03	4.11
	[0.38, 1.56]	[3.62, 6.29]	[2.76, 5.22]			
Leverage ratio (%)	25.76	31.39	5.63	23.97	38.89	14.92
	[23.03, 28.50]	[29.46, 33.32]	[3.11, 8.14]			
Gross profit margin (%)	39.85	29.09	−10.76	33.14	23.45	−9.69
	[35.58, 44.12]	[25.52, 32.66]	[−12.66, −8.86]			

Note: In the data, the sample period is from 1976 to 2021. The industry-level default rate is the average default rate of the top six firms (ranked by sales) in the industry. Default event is defined in Section 4.1. The leverage ratio is total short-term debt plus total long-term debt divided by total assets. The 95% confidence intervals are reported in brackets. In the model, financial distress is measured by the expected 1-year default probability as in the data.

idiosyncratic left-tail risk, generates less negative exposure to the discount-rate shock and thus lower expected equity excess returns for the more financially distressed industries. In Online Appendix 1.3, we provide a decomposition of the risk premium and show that the cross-industry difference in expected equity excess returns is mainly due to the differential exposure to the discount-rate shock.

Further, we emphasize that introducing idiosyncratic left-tail risk alone to the canonical framework does not help explain the industry distress anomaly. This is simply because idiosyncratic left-tail risk is not priced, so it merely increases the default rate without affecting the risk premium in the absence of the competition-distress feedback. This

highlights the importance of the endogenous competition-distress feedback mechanism of our model. Idiosyncratic left-tail risk has cross-sectional asset pricing implications precisely because it affects the strength of the competition-distress feedback.

The model also implies that the more financially distressed industries (Q5) have higher leverage ratios than the less financially distressed industries (Q1) because the former optimally choose higher financial leverage ex-ante. In our model, industries with higher financial distress are associated with a higher intensity of idiosyncratic left-tail shocks. Firms in such industries face weaker competition-distress feedback. Since the competition-distress feedback is an additional source of financial distress costs for issuing debt, a weaker feedback effect implies lower distress costs and thus a higher optimal leverage ratio. Moreover, the model implies that the more financially distressed industries (Q5) have lower profit margins than the less financially distressed industries (Q1), and the difference in magnitude is similar to that in the data. Thus, the model rationalizes the negative profitability-leverage relationship across industries in the data.

Panel B of Table 5 further strengthens the empirical support for our mechanism by sorting industries based on their idiosyncratic left-tail risk in both the data and the model.[20] The patterns are similar to those in panel A of Table 5 because the cross-industry variation in financial distress is mainly determined by the cross-industry difference in idiosyncratic left-tail risk. By contrast, we examine the hypothetical industries constructed in Section 2.4 and show that the differences in expected equity excess returns across the quintile portfolios of hypothetical industries sorted on idiosyncratic left-tail risk are statistically insignificant (see panel C of Table IA.V in Online Appendix 2.4).

4.4 Inspecting the Model's Mechanism

In Table 6, we conduct various counterfactual experiments with the aim of examining the model's mechanism. Column (3) of Table 6 presents the model's implications in the non-collusive equilibrium. Because the endogenous competition-distress feedback is absent, firms choose a higher initial leverage, leading to a higher leverage ratio, compared with the collusive equilibrium. For the same reason, the equity premium and credit spread of the market portfolio decrease from 7.02% and 1.51% to 3.67% and 1.29%, respectively. More importantly, the difference in expected equity excess returns of portfolios sorted on financial distress (Q5−Q1) becomes positive with a small magnitude because the cross-industry difference in ν does not affect industries' profit margins or their exposure to the discount rate in the non-collusive equilibrium. The positive excess return difference (Q5−Q1)

[20] An expanded set of empirical results is provided in Table IA.III in Online Appendix 2.3.

Table 6: Inspecting the model's mechanism.

	(1) Data	(2) Model	(3) No collusion	(4) Same ν	(5) $\epsilon = 3$	(6) $\eta = 12$
Leverage ratio	0.34	0.36	0.45	0.40	0.38	0.37
Expected equity excess return (%)	7.36	7.02	3.67	4.38	6.28	6.45
Diff in excess return sorted on $Distress_{i,t}$ (%)	−5.63	−4.35	0.46	0.57	−3.12	−3.73
Diff in excess return sorted on $\nu_{i,t}$ (%)	−6.06	−4.51	−0.19	0.04	−3.29	−3.89
Credit spread (%)	1.38	1.51	1.29	1.36	1.32	1.41
Diff in credit spread sorted on $Distress_{i,t}$ (%)	2.35	1.81	1.43	0.54	1.67	1.76
Diff in credit spread sorted on $\nu_{i,t}$ (%)	1.91	1.88	1.46	0.02	1.69	1.80

reflects the higher financial leverage of more financially distressed industries (Q5). The comparison between collusive and non-collusive outcomes indicates that the competition-distress feedback mechanism is the key to explaining the industry distress anomaly in our model. However, the credit spread remains significantly different between the portfolios sorted on financial distress or idiosyncratic left-tail risk due to the cross-industry difference in default risk.

To illustrate the importance of the cross-industry difference in idiosyncratic left-tail risk, in column (4), we assume that all industries have the same intensity of idiosyncratic left-tail shocks, $\nu \equiv (\underline{\nu} + \overline{\nu})/2$. Not surprisingly, the model implies that both the equity premium and the credit spread are similar across industry portfolios sorted on idiosyncratic left-tail risk. The small and positive excess return difference (Q5−Q1) for industry portfolios sorted on financial distress reflects a pure leverage effect.

In column (5) of Table 6, we evaluate the model's quantitative implications for $\epsilon = 3$. The competition-distress feedback effect weakens as the cross-industry price elasticity of demand ϵ is larger, because a larger ϵ makes it more difficult to collude (Dou, Ji and Wu, 2021). As the feedback effect is weaker, the average equity premium and credit spread of the market portfolio decrease from 7.02% and 1.51% (column 2) to 6.28% and 1.32% (column 5), respectively. The model-implied difference in expected equity excess returns and credit spreads between industries with high and low financial distress (or idiosyncratic left-tail risk) also becomes less pronounced.

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

5 Empirical Support for the Model

We provide empirical evidence for the model in three steps. Subsection 5.1 provides evidence showing that the industry-level idiosyncratic left-tail risk is a fundamental industry characteristic that explains the industry distress anomaly. Subsection 5.2 provides evidence for the economic mechanism that explains the industry distress anomaly. Subsection 5.3 tests the competition-distress feedback mechanism.

5.1 Idiosyncratic Left-Tail Risk and Financial Distress Anomaly

In Subsection 5.1.1, we examine the relationship among industry-level idiosyncratic left-tail risk, financial distress, and profit margin. In Subsection 5.1.2, we show that the industry-level distress spread becomes statistically insignificant after controlling for the industry-level idiosyncratic left-tail risk.

5.1.1 Idiosyncratic Left-Tail Risk, Financial Distress, and Profit Margin

Our model predicts that the idiosyncratic left-tail risk is negatively associated with the profit margin due to the competition-distress feedback mechanism and positively associated with the level of financial distress across industries (see Figure 4 and Table 5). To empirically examine this relationship, we sort all SIC4 industries into quintiles based on the industry-level measure of idiosyncratic left-tail risk ($\nu_{i,t}$). The average financial distress and profit margins of quintile group Q5 (high $\nu_{i,t}$) minus those of quintile group Q1 (low $\nu_{i,t}$) are 0.11% and -11.57%, respectively. The differences are also statistically significant as the t-statistics robust to heteroskedasticity and autocorrelation are 8.36 and -6.70, respectively. Therefore, industries with high $\nu_{i,t}$ are indeed associated with higher financial distress and lower profit margins than those with low $\nu_{i,t}$.

Further, we conduct similar sorting analyses based on the hypothetical industries constructed in Section 2.4, where the idiosyncratic left-tail risk of each hypothetical industry is re-estimated following the same procedure in Section 4.1. Panel A of Table IA.V in Online Appendix 2.4 shows that the difference (Q5$-$Q1) in distress across hypothetical industries is no longer statistically significant, and its magnitude is much lower than that across real industries. This implies that, rather than a firm characteristic, the idiosyncratic left-tail risk is a fundamental industry characteristic that is correlated with industry-level distress across real industries. Thus, the variation in idiosyncratic left-tail risk captures the variation in financial distress across real industries, but not hypothetical industries. Moreover, panel B of Table IA.V in Online Appendix 2.4 shows that the difference (Q5$-$Q1)

in profit margins across hypothetical industries is no longer statistically significant, and its magnitude is much lower than that across real industries. This suggests that the mechanism that generates the negative relation between idiosyncratic left-tail risk and profit margins only exists in real industries, but not in hypothetical industries. As demonstrated by our model, this mechanism is the competition-distress feedback, which captures distressed firms' competition behavior within the same real industry, but not the same hypothetical industry. Intuitively, firms within the same hypothetical industry are not directly competing with each other in the product market. This explains the lack of statistically significant correlations between profit margins and idiosyncratic left-tail risk across hypothetical industries in the data.

5.1.2 Industry Distress Anoamly After Controlling For $\nu_{i,t}$

Building on the results presented in Table 5, we further investigate whether the industry-level distress spread significantly diminishes after controlling for the industry-level idiosyncratic left-tail risk.

We perform a double-sort analysis, where we first sort industries into quintiles based on the measure of idiosyncratic left-tail risk ($\nu_{i,t}$). Then, for industries within each quintile portfolio, we further sort them into quintiles based on the industry distress measure ($Distress_{i,t}$). Panel A of Table 7 reports the results. The magnitude of the differences (Q5$-$Q1) in expected equity excess returns and the alphas of CAPM and the Fama-French three-factor model are -2.326%, -2.848%, and -2.987%, respectively, which are statistically insignificant, as compared with -5.625%, -8.165%, and -9.683% in panel A of Table 1.

Panel B of Table 7 performs an additional test by sorting industries on an adjusted industry distress measure ($Distress_adjusted_{i,t}$) which controls for idiosyncratic left-tail risk $\nu_{i,t}$. Specifically, $Distress_adjusted_{i,t}$ is the residuals of regressing the industry distress measure ($Distress_{i,t}$) on the measure of idiosyncratic left-tail risk ($\nu_{i,t}$) and a constant term in the cross section of industries in each month t. It is evident that both the differences (Q5$-$Q1) in expected equity excess returns and the alphas of CAPM and the Fama-French three-factor model become statistically insignificant once we sort industries on $Distress_adjusted_{i,t}$.

Taken together, the empirical findings support our model's prediction that the cross-industry heterogeneity in financial distress is mainly captured by industries' different levels of idiosyncratic left-tail risk, which is a fundamental industry characteristic that explains the industry distress anomaly.

Table 7: Industry distress anomaly after controlling for idiosyncratic left-tail risk.

	Panel A: Double sort on industry distress and idiosyncratic left-tail risk					
$Distress_{i,t}$	Q1 (low)	Q2	Q3	Q4	Q5 (high)	Q5−Q1
Excess return	9.877***	8.504***	8.409***	9.858***	7.550***	−2.326
	[5.41]	[4.78]	[4.59]	[5.68]	[4.15]	[−1.38]
CAPM alpha	0.456	−0.873	−1.279	−0.144	−2.392	−2.848
	[0.27]	[−0.80]	[−0.87]	[−0.09]	[−1.62]	[−1.61]
FF3 alpha	0.070	−1.230	−1.583	−0.628	−2.918**	−2.987*
	[0.06]	[−1.60]	[−1.52]	[−0.58]	[−2.39]	[−1.69]
	Panel B: Industry portfolios sorted on adjusted industry distress					
$Distress_adjusted_{i,t}$	Q1 (low)	Q2	Q3	Q4	Q5 (high)	Q5−Q1
Excess return	8.526***	7.740***	9.743***	9.961***	7.791***	−0.735
	[4.56]	[3.79]	[5.89]	[6.89]	[4.00]	[−0.53]
CAPM alpha	−1.747	−2.221	0.335	1.014	−2.087	−0.339
	[−0.87]	[−1.71]	[0.25]	[0.81]	[−1.63]	[−0.27]
FF3 alpha	−2.766**	−2.574**	0.072	0.959	−2.481***	0.285
	[−2.24]	[−2.26]	[0.07]	[1.12]	[−2.93]	[0.26]

Note: This table studies the industry distress anomaly after controlling for idiosyncratic left-tail risk. In panel A, we perform a double-sort analysis. We first sort industries into quintiles based on $\nu_{i,t}$. Then, we further sort industries within each quintile portfolio into quintiles based on $Distress_{i,t}$. In panel B, we perform a single-sort analysis based on the adjusted industry distress measure ($Distress_adjusted_{i,t}$), which is computed as the residuals of regressing $Distress_{i,t}$ on $\nu_{i,t}$ and a constant term in the cross section of industries in each month t. All returns are in annualized percentage units. The sample is monthly and spans the period from 1976 to 2021. The number of observations is 42,385. t-statistics robust to heteroskedasticity and autocorrelation are reported in brackets. *, **, and *** indicate statistical significance at 10%, 5%, and 1%, respectively.

5.2 Economic Mechanism Behind the Industry Distress Anomaly

According to the model, the economic mechanism that generates the industry-level distress spread is the industries' differential exposure to discount-rate shocks (i.e., $Z_{\gamma,t}$). We now provide empirical tests for this mechanism. Specifically, in Subsection 5.2.1, we show that industries with higher financial distress or idiosyncratic left-tail risk are less negatively exposed to discount-rate shocks. In Subsection 5.2.2, we show that the industry-level discount-rate spread, i.e., the equity returns of the long-short portfolio of industries sorted on their expected loadings on discount-rate shocks, strongly comoves with the industry-level distress spread. Furthermore, the industry-level distress spread becomes statistically insignificant after controlling for the industry-level discount-rate spread. In Subsection 5.2.3, we show that the industry-level discount-rate spread and the industry-level distress spread have similar explanatory power for the cross-sectional equity returns of portfolios that vary in the level of distress risk.

Table 8: Equity beta to the discount rate.

	Panel A: Industry portfolios sorted on financial distress					
$Distress_{i,t}$	Q1 (low)	Q2	Q3	Q4	Q5 (high)	Q5−Q1
$\Delta Discount_rate_t$	-6.322^{***}	-0.325	-2.009	3.433	4.564	10.886^{**}
	[−2.68]	[−0.12]	[−0.76]	[0.92]	[1.34]	[2.45]
Mkt_t	0.904^{***}	1.125^{***}	1.188^{***}	1.283^{***}	1.474^{***}	0.570^{***}
	[11.65]	[15.03]	[29.25]	[16.34]	[18.53]	[4.65]
	Panel B: Industry portfolios sorted on idiosyncratic left-tail risk					
$\nu_{i,t}$	Q1 (low)	Q2	Q3	Q4	Q5 (high)	Q5−Q1
$\Delta Discount_rate_t$	-4.364^{**}	-3.322^{*}	-0.967	2.534	5.369	9.733^{**}
	[−2.03]	[−1.67]	[−0.40]	[0.81]	[1.28]	[2.00]
Mkt_t	0.956^{***}	1.042^{***}	1.192^{***}	1.321^{***}	1.460^{***}	0.504^{***}
	[14.98]	[26.24]	[21.39]	[21.93]	[14.38]	[4.32]

Note: We estimate the equity beta to the discount rate according to (27). Panels A and B focus on industry portfolios sorted on financial distress and idiosyncratic left-tail risk, respectively. The sample is quarterly and spans the period from 1976 to 2021. The number of observations is 13,943. t-statistics robust to heteroskedasticity and autocorrelation are reported in brackets. *, **, and *** indicate statistical significance at 10%, 5%, and 1%, respectively.

5.2.1 Equity Beta to the Discount Rate

Our model implies that industries with higher financial distress or idiosyncratic left-tail risk have lower expected equity excess returns because they are less negatively exposed to aggregate discount-rate shocks. We test this prediction by estimating the equity beta to the discount rate. Specifically, in each quintile group k of industries sorted on $Distress_{i,t}$, we run the following time-series regression:

$$R_{k,t} - R_{f,t} = \alpha_k + \beta_k \times \Delta Discount_rate_t + \gamma_k \times Mkt_t + \epsilon_{k,t}, \tag{27}$$

where $R_{k,t}$ is the equity return of quintile group k, $R_{f,t}$ is the risk-free rate, $\Delta Discount_rate_t$ is the discount-rate shock, and Mkt_t is the market's excess return over the risk-free rate.

Panel A of Table 8 shows that the expected equity excess returns of quintile portfolio Q1 (low distress) are significantly more negatively exposed to the discount rate compared to those of quintile group Q5 (high distress). Panel B of Table 8 shows that the results are similar if we sort industries based on the measure of idiosyncratic left-tail risk ($\nu_{i,t}$). By contrast, among the hypothetical industries constructed in Section 2.4, the differences in the equity beta to the discount rate across industry portfolios of low and high distress/idiosyncratic left-tail risk are much less pronounced than those reported in Table 8 (see Panel C of Table IA.IV and Panel D of IA.V in Online Appendix 2.4).

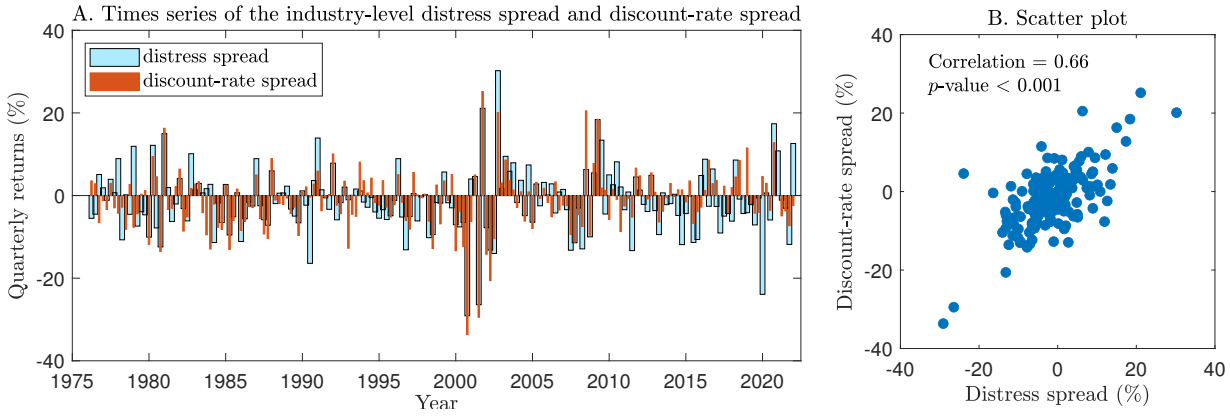


Figure 5: **Correlation between the industry-level distress spread and discount-rate spread.** Panel A plots the time series of the industry-level distress spread and discount-rate spread. Panel B is a scatter plot of the two spreads. We also regress the industry-level distress spread on the industry-level discount-rate spread and a constant term, according to (31). The estimated loading $\widehat{\beta}$ is 0.638 and statistically significant (with a t-statistic of 10.10); the estimated intercept $\widehat{\alpha}$ is -2.146% and statistically insignificant (with a t-statistic of -1.01).

5.2.2 The Industry-Level Distress Spread and Discount-Rate Spread

In this subsection, we show that the industry-level distress spread strongly comoves with the industry-level discount-rate spread. Moreover, the former becomes statistically insignificant after controlling for the latter. These results corroborate the model's economic mechanism, indicating that the industry-level distress spread is driven by variations in industries' exposure to discount-rate shocks.

Estimating the Expected Loading of Industry Returns on Discount-Rate Shocks. To construct the industry-level discount-rate spread, we first estimate the expected loadings of industry returns on discount-rate shocks. This is achieved in three steps. First, we estimate the realized loading of industry returns on discount-rate shocks using a moving-window regression. For each industry i in quarter t, we estimate the following regression over a four-quarter horizon from $\tau = t-3$ to $\tau = t$, consistent with the horizon used by Campbell, Hilscher and Szilagyi (2008) for the estimation of failure probability:

$$R_{i,\tau} - R_{f,\tau} = a_t + b_{i,t} \times \Delta Discount_rate_\tau + c_{i,t} \times Mkt_\tau + \varepsilon_{i,\tau}, \tag{28}$$

where $R_{i,\tau}$ and $R_{f,\tau}$ are the equity return of industry i and the risk-free rate in quarter τ, respectively; $\Delta Discount_rate_\tau$ and Mkt_τ are the discount-rate shock and the market's excess return over the risk-free rate in quarter τ, respectively. The estimated coefficient $\widehat{b}_{i,t}$ is the realized loading of industry i in quarter t (i.e., over the four-quarter horizon from $t-3$ to t).

Second, we relate the realized loading of industry returns on discount-rate shocks in

quarter $t+4$ to industry characteristics in quarter t by estimating the following panel regression using industry-quarter observations from 1975 to 2021:

$$\widehat{b}_{i,t+4} = \alpha + \beta X_{i,t} + \epsilon_{i,t+4}, \tag{29}$$

where $X_{i,t}$ is a vector of industry-level variables, constructed as the sales-weighted average of firm-level variables used by Fama and French (2015) in constructing the Fama-French five-factor model and those used by Campbell, Hilscher and Szilagyi (2008) in constructing firms' failure probability.[21]

Third, we construct the measure of the expected loading of industry returns on discount-rate shocks for industry i in month t as

$$Discount_loading_{i,t} = \widehat{\alpha} + \widehat{\beta} X_{i,t}. \tag{30}$$

Correlations of the Two Spreads. We construct the industry-level discount-rate spread as the equity returns of the long-short portfolio of industries sorted on $Discount_loading_{i,t}$, i.e., the equity returns of Q5 (high $Discount_loading_{i,t}$) minus the equity returns of Q1 (low $Discount_loading_{i,t}$).[22] Then, we relate this industry-level discount-rate spread to the industry-level distress spread constructed in Section 2.3. Figure 5 shows that the industry-level distress spread strongly comoves with the industry-level discount-rate spread, with a correlation coefficient of 0.66. This supports our model's prediction that more distressed industries are associated with higher loadings on discount-rate shocks (i.e., less negatively exposed to discount-rate shocks) and lower expected equity returns.

Next, we examine whether the industry-level discount-rate spread can explain the industry-level distress spread by running the following regression:

$$Industry_distress_spread_t = \alpha + \beta \times Industry_discount_rate_spread_t + \epsilon_t. \tag{31}$$

[21] Specifically, these firm-level variables are: net income over market value of total assets ($NIMTA$), total liabilities over market value of total assets ($TLMTA$), log of gross stock return in excess of the value-weighted S&P 500 return ($EXRET$), square root of the sum of squared firm stock returns over a 3-month period ($SIGMA$) annualized, log of equity market value over the total valuation of the S&P 500 index ($RSIZE$), stock of cash and short-term investments over the market value of total assets ($CASHMTA$), market-to-book ratio (MB), log of price per share winsorized above \$15 ($PRICE$), revenue minus cost of goods sold, minus selling, general, and administrative expenses, minus interest expense divided by book equity (OP), and the change in total assets from the last year to the current year divided by total assets (INV).

[22] We perform the portfolio sorting based on the predicted loading (i.e., $Discount_loading_{i,t}$ estimated in equation (30)) rather than the realized loading (i.e., $\widehat{b}_{i,t}$ estimated in equation (28)) of industry returns on discount-rate shocks. This is because the realized loading could be noisy as we use a 4-quarter moving window when estimating equation (30), following Campbell, Hilscher and Szilagyi (2008). We do not use a longer moving window in our estimation because in this case, the estimated loadings cannot capture the time-varying component in industries' exposure to discount-rate shocks very well.

The estimated loading $\widehat{\beta}$ is 0.638, positive and statistically significant (with a t-statistic of 10.10), further confirming the strong comovement of the two time series. Moreover, the estimated intercept $\widehat{\alpha}$ is -2.146% and statistically insignificant (with a t-statistic of -1.01). The magnitude of $\widehat{\alpha}$ is much smaller than the average industry-level distress spread (-5.625%) reported in panel A of Table 1. These results lend further support to our model's prediction that the industry-level distress spread is attributed to industries' differential loadings on discount-rate shocks.

5.2.3 Pricing Assets that Vary in Distress Risk

To provide further support for the economic mechanism that generates the industry-level distress spread, we show that the industry-level distress spread and discount-rate spread have similar explanatory power for the cross-sectional equity returns of portfolios that vary in the level of distress risk.

We consider a cross-section of 21 test assets that vary in the level of distress risk, including 5 industry portfolios sorted on industry-level distress, 10 stock portfolios sorted on firm-level distress, and 6 Treasury bond portfolios sorted on maturity. For each asset i, we estimate the factor loadings using the following time-series regression:

$$R_{i,t} - R_{f,t} = c_i + \sum_k \beta_{i,k} f_{k,t} + \varepsilon_{i,t}, \tag{32}$$

where $R_{i,t}$ is asset i's return, $R_{f,t}$ is the risk-free rate, and $f_{k,t}$ represents risk factor k. We then estimate the cross-sectional price of risk associated with the factors $f_{k,t}$ by running a cross-sectional regression of time-series average excess returns, $\mathbb{E}[R_{i,t} - R_{f,t}]$, on risk factor exposures estimated in equation (32) as follows,

$$\mathbb{E}[R_{i,t} - R_{f,t}] = \alpha + \sum_k \widehat{\beta}_{i,k} \lambda_k + \epsilon_i, \tag{33}$$

where the estimated $\widehat{\lambda}_k$ is the price of risk for factor k and $\widehat{\alpha}$ is the average cross-sectional pricing error or zero-beta rate.

Table 9 presents the prices of risk and test diagnostics across four linear factor models. As a benchmark, column (1) reports the results of CAPM, which clearly shows that the exposure to market risk cannot explain the spread in average returns across the test assets. The cross-sectional intercept is statistically significant and the factor price of risk is statistically insignificant. The pricing errors are also large, with a high total mean absolute pricing error (MAPE) of 3.499% and a low R-squared of 0.160.

Table 9: Pricing assets that vary in distress risk.

	(1)	(2)	(3)	(4)
		Panel A: Prices of risk		
Intercept	3.015***	0.492	0.398	0.508
$t-$FM	[4.07]	[0.98]	[0.79]	[1.01]
$t-$Shanken	[4.06]	[0.94]	[0.74]	[0.96]
Mkt_t	2.948	8.956***	9.277***	9.274***
$t-$FM	[1.08]	[3.73]	[3.87]	[3.86]
$t-$Shanken	[1.08]	[3.71]	[3.84]	[3.84]
$Industry_distress_spread_t$		−8.552***		
$t-$FM		[−3.20]		
$t-$Shanken		[−3.15]		
$Industry_discount_rate_spread_t$			−13.519***	
$t-$FM			[−3.61]	
$t-$Shanken			[−3.44]	
$Industry_tail_risk_spread_t$				−9.354***
$t-$FM				[−3.25]
$t-$Shanken				[−3.19]
		Panel B: Test diagnostics		
Total MAPE	3.499	1.357	1.439	1.363
Industry distress 5	3.632	1.333	1.514	1.311
Stock distress 10	4.209	2.118	2.230	2.122
Bond 6	2.204	0.108	0.059	0.140
R-squared	0.160	0.821	0.801	0.835

Note: This table presents pricing results for 21 test assets that vary in distress risk, including 10 stock portfolios sorted on firm-level distress, 5 industry portfolios sorted on industry-level distress, and 6 Treasury bond portfolios sorted on maturity. Each model is estimated using equation (33). Mkt_t is the market's excess return over the risk-free rate. $Industry_distress_spread_t$ and $Industry_discount_rate_spread_t$ are the industry-level distress spread and discount-rate spread, respectively. $Industry_tail_risk_spread_t$ is the returns of the long-short portfolio of industries sorted on the measure of idiosyncratic left-tail risk ($\nu_{i,t}$). Panel A reports the prices of risk with Fama-McBeth's and Shanken's t-statistics. Panel B reports test diagnostics. All returns are in annualized percentage units. The sample is monthly and spans the period from 1976 to 2021. The numbers of observations for constructing $Industry_distress_spread_t$, $Industry_discount_rate_spread_t$, and $Industry_tail_risk_spread_t$ are 42,385, 42,320, and 42,385, respectively. The 5 industry portfolios sorted on industry-level distress are constructed using 42,385 industry-month observations. The 10 stock portfolios sorted on firm-level distress are constructed using 1,129,119 stock-month observations. *, **, and *** indicate statistical significance at 10%, 5%, and 1%, respectively.

In column (2) of Table 9, we report the results of a two-factor model that includes the industry-level distress spread as an additional risk factor. The cross-sectional intercept is 0.492%, which is statistically insignificant and much lower than that in column (1). The price of risk for the industry-level distress spread is negative and statistically significant. The R-squared is 0.821 and the total MAPE is only 1.357%. In addition, we break down the MAPE by asset class and show that the MAPE for each cross-section is low: 1.333% for the 5 industry portfolios sorted on industry-level distress, 2.118% for the 10 stock portfolios sorted on firm-level distress, and 0.108% for the 6 Treasury bond portfolios sorted on maturity.

In column (3) of Table 9, we report the results of a two-factor model based on the market's excess return and the industry-level discount-rate spread. The price of risk for the industry-level discount-rate spread is negative and statistically significant. The R-squared and total MAPE are similar to those in column (2), suggesting that the industry-level distress spread and the industry-level discount-rate spread have similar explanatory power for the equity returns of these test portfolios that vary in the level of distress risk.

According to our model, the cross-industry heterogeneity in the exposure to discount-rate shocks is mainly captured by industries' differential exposure to idiosyncratic left-tail risk. Thus, as a robustness check, in column (4) of Table 9, we consider a two-factor model based on the market factor and the return of the long-short portfolio of industries sorted on the measure of idiosyncratic left-tail risk $\nu_{i,t}$, i.e., the equity returns of Q5 (high $\nu_{i,t}$) minus the equity returns of quintile group 1 (low $\nu_{i,t}$). We estimate that the price of risk for this long-short portfolio of industries sorted on $\nu_{i,t}$ is negative and statistically significant. The R-squared and total MAPE are similar to those in columns (2) and (3).

In Figure 6, we visualize our results by plotting the predicted versus realized average excess returns. Aside from the stock portfolio with the highest distress (i.e., stock 10), the test assets line up very close to the 45-degree line in the two-factor models presented in panels B to D. In contrast, panel A shows that CAPM has large pricing errors for these assets. Moreover, in Figure IA.2 in Online Appendix 2.3, we show that most test assets have statistically significant factor loadings, indicating that these factors are not weak factors.

5.3 Testing the Competition-Distress Feedback Mechanism

We now provide evidence supporting the competition-distress feedback mechanism. In Subsection 5.3.1, we test the feedback effects on industry-level profit margins and expected equity excess returns. In Subsection 5.3.2, we investigate the variation in the strength of the feedback effects across industries that differ in the distribution of market shares among top firms. In Subsection 5.3.3, we exploit exogenous variation in the competitiveness of market

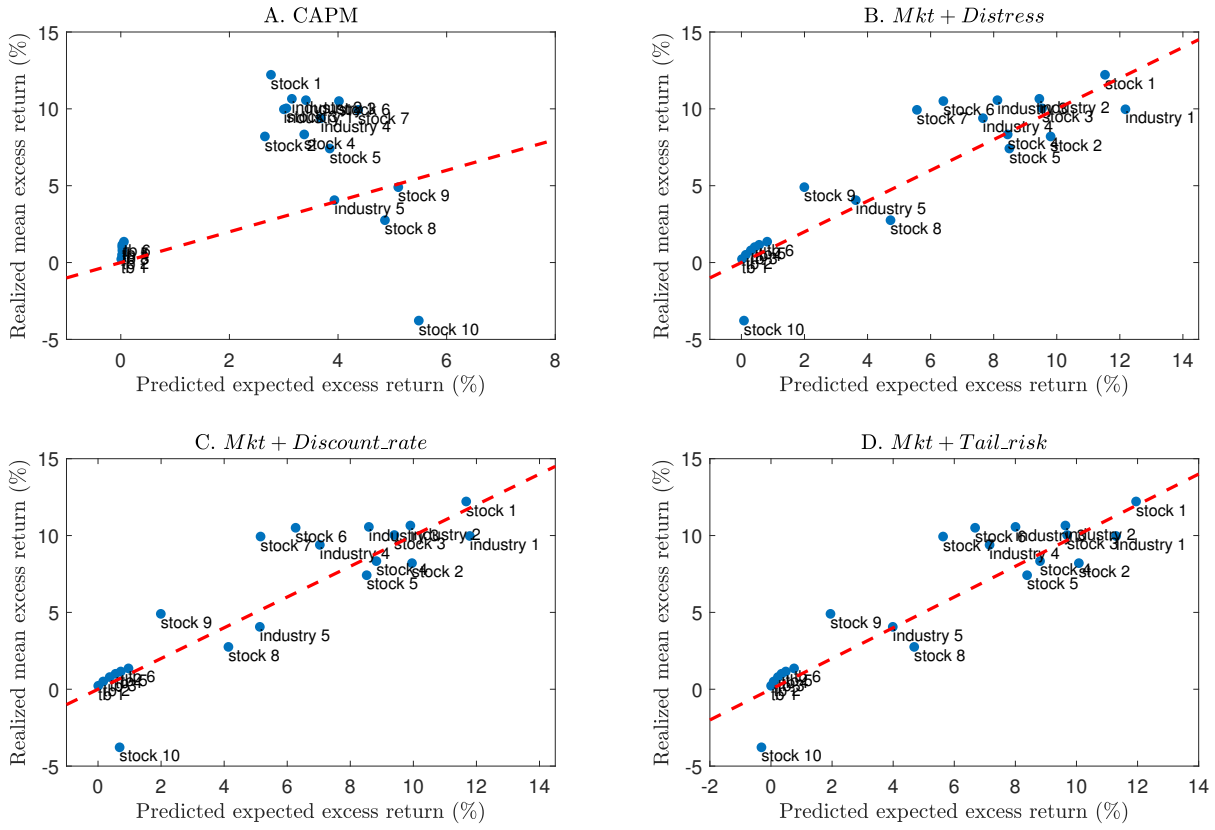


Figure 6: **Realized versus predicted mean excess returns.** This figure plots the realized mean excess returns of 21 test assets that vary in distress risk (including 10 stock portfolios sorted on firm-level distress, 5 industry portfolios sorted on industry-level distress, and 6 Treasury bond portfolios sorted on maturity) against the expected excess returns predicted by three linear factor models estimated using equation (33). The predicted expected excess returns are computed as $\sum_k \widehat{\beta}_{i,k}\widehat{\lambda}_k$ without including the estimated intercept $\widehat{\alpha}$. The sample spans the period from 1976 to 2021.

structure at the industry level to test the competition-distress feedback mechanism.

5.3.1 Feedback Effect on Profit Margins and Equity Returns

We first test the feedback effect on profit margins. Our model implies that industry-level profit margins load negatively on the discount rate, and more so in industries where firms are closer to their default boundaries (see panel C of Figure 3), because the strength of the competition-distress feedback effect increases as firms approach their default boundaries.

To test this implication, we sort industries into different groups based on the distance-to-default measure ($DD_{i,t}$). We then examine the profit-margin beta to the discount rate by

Table 10: Feedback effect on profit margins and equity returns.

	(1)	(2)	(3)	(4)
	Panel A: Feedback effect on profit margins			
	All firms in the industry		Top six firms in the industry	
$DD_{i,t}$	T3−T1	Q5−Q1	T3−T1	Q5−Q1
$\Delta Discount_rate_t$	0.370**	0.538**	0.382*	0.536**
	[2.03]	[2.17]	[1.91]	[2.13]
	Panel B: Feedback effect on equity returns			
$Profitability_{i,t}$	T1 (low)	T2	T3 (high)	T3−T1
Group 1 (low $DD_{i,t}$)	6.602*	6.747**	10.094***	3.492*
	[1.84]	[1.99]	[2.99]	[1.92]
Group 2	7.517***	9.820***	10.448***	2.930*
	[2.82]	[3.38]	[3.59]	[1.90]
Group 3 (high $DD_{i,t}$)	8.671***	9.225***	10.255***	1.585
	[3.56]	[3.67]	[4.34]	[1.29]

Note: Panel A reports the difference in the profit-margin beta to the discount rate across groups of industries sorted on the distance-to-default measure ($DD_{i,t}$). The regression specification is described in (34). In columns (1) and (2), we sort industries into terciles and quintiles, respectively, and report the difference in the profit-margin beta. In columns (3) and (4), we measure industry-level variables based on the top six firms (ranked by sales) in each industry. The sample spans the period from 1969 to 2021. The number of observations is 53. Panel B reports average gross profitability spreads in split samples by $DD_{i,t}$. We first sort industries into three groups based on their $DD_{i,t}$. In each group, we further sort industries into terciles based on their gross profitability, which is constructed as gross profits (revenue minus cost of goods sold) scaled by assets following the definition of Novy-Marx (2013). All returns are in annualized percentage units. The sample spans the period from 1975 to 2021. The number of observations is 558. t-statistics robust to heteroskedasticity and autocorrelation are reported in brackets. *, **, and *** indicate statistical significance at 10%, 5%, and 1%, respectively.

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

$$\Delta \ln(1 + PM_{k,t}) = \alpha_k + \beta_k \times \Delta Discount_rate_t + \epsilon_{k,t}, \tag{34}$$

where the dependent variable $\Delta \ln(1 + PM_{k,t}) \equiv \ln(1 + PM_{k,t}) - \ln(1 + PM_{k,t-1})$ is the year-on-year change in group-k's net profit margin measure $\ln(1 + PM_{k,t})$, which is the equal-weighted average of logged one plus the industry-level net profit margin of all industries in group k.[23]

Panel A of Table 10 presents the results. Column (1) shows that the profit-margin beta to the discount rate of tercile group T3 (high distance to default) minus that of tercile group

[23]To ensure that the industry-year observations of $\ln(1 + PM_{i,t})$ are well defined, we winsorize the net profit margin of industry i in year t at the first percentile so that it is above -1. We use $\ln(1 + PM_{i,t})$ because about 20% of the industry-year observations of $PM_{i,t}$ are negative, making the percentage change in net profit margins undefined.

T1 (low distance to default) is positive and statistically significant. This indicates that T1 is more negatively exposed to the discount rate, consistent with the prediction of our model. The result is robust if we sort industries into quintiles (column (2)) or focus on the top six firms (ranked by sales) in the industry when constructing the industry-level variables (columns (3) and (4)).

We further test the feedback effect on equity returns. As shown in Figure 4, the competition-distress feedback is stronger when industries are closer to the default boundary. As a result, the difference in the equity beta to the discount rate across industries with different gross profitability widens when the distance to default is lower. To test this prediction, we equally split all industries into three groups based on the distance-to-default measure ($DD_{i,t}$). Within each group, we sort industries into terciles based on their gross profitability. Panel B of Table 10 shows that the average industry-level gross profitability spread, i.e., the average equity return of tercile group T3 (high gross profitability) minus that of tercile group T1 (low gross profitability), is positive and statistically significant among industries in the group with low $DD_{i,t}$ (group 1). The average gross profitability spread is much smaller and statistically insignificant among industries in the group with high $DD_{i,t}$ (group 3).

5.3.2 Variation in Feedback Effects Across Industries

Our model suggests that the feedback effect on profit margins and equity returns is stronger in industries where market leaders (of different distress levels) have more evenly distributed market shares. This is because in such industries, market leaders have a greater motivation to engage in collusion.

To test this prediction, we construct an industry-level imbalance measure of market shares, which captures how evenly distributed market shares are among the market leaders of an industry. Specifically, we focus on the top six firms (ranked by sales) in each industry and split them into terciles based on the industry-level financial distress measure ($Distress_{i,t}$) in each year. T1 and T3 contain the two firms with the lowest and highest financial distress, respectively. The imbalance measure of market shares is defined as the absolute difference in the logged sales between T1 and T3.[24] A larger value of the imbalance measure means that the market share of T1 is more different from that of T3.

Based on the industry-level imbalance measure of market shares, we then equally split all industries into three groups in each year. We test the cross-industry variation in feedback

[24]For example, an industry with sales 5 for T1 and 1 for T3 is considered equally unbalanced as an industry with sales 1/5 for T1 and 1 for T3. Note that according to the model, the ratio of sales matters, but whether T1 or T3 has higher sales does not.

effects on profit margins by running the following regression for industries in each group:

$$\ln(1+PM_{i,t}^{(\mathrm{T1})}) = \sum_{k\in\{\mathrm{T1,\ T3}\}} \beta_k \times IdShock_{i,t}^{(k)} + \sum_{j=1}^{5} \gamma_j \times \ln(1+PM_{i,t-j}^{(\mathrm{T1})}) + \delta_t + \ell_i + \epsilon_{i,t}, \quad (35)$$

where the independent variable $IdShock_{i,t}^{(k)}$ is the idiosyncratic shock of tercile k =T1, T3 in industry i and year t, constructed using two methods M1 and M2 (see Online Appendix 2.2 for details). Our regression specification (35) controls for the idiosyncratic shocks to firms in T1 (i.e., $IdShock_{i,t}^{(\mathrm{T1})}$), the lagged profit margins of firms in T1 (i.e., $\sum_{j=1}^{5} \gamma_j \times \ln(1+PM_{i,t-j}^{(\mathrm{T1})})$), and the time and industry fixed effects. The coefficient β_{T3} captures the effect of idiosyncratic shocks to firms in T3 (financially distressed) on the profit margin of firms in T1 (financially healthy), which is informative about the strength of the feedback effect on profit margins.

Panel A of Table 11 presents the results. Column (1) shows that the coefficient β_{T3} is positive and statistically significant for the idiosyncratic shocks constructed by both methods, indicating that positive idiosyncratic shocks to T3 robustly increase the profit margin of T1. Columns (2) and (3) show that β_{T3} is significantly larger in the group of industries with more balanced market shares, which supports our model's prediction. The difference in the estimated coefficient β_{T3} (Group 3$-$1) is negative and statistically significant.

Next, we test the cross-industry variation in feedback effects on equity returns. Within each group of industries split by the industry-level imbalance measure of market shares, we sort industries into terciles based on the industry-level financial distress ($Distress_{i,t}$). Panel B of Table 11 shows that the average industry-level distress spread is negative and statistically significant among industries in the group with balanced market shares (group 1). The average distress spread is much less negative and statistically insignificant among industries in the group with imbalanced market shares (group 3). This supports our model's prediction that the competition-distress feedback is stronger in industries where market leaders have more evenly distributed market shares.

5.3.3 Impacts of Market Structure Changes

As shown in Figure 4 and Table 5, the asset-pricing implications of our model are generated by industries' differential exposure to aggregate discount-rate shocks owing to the differences in the strength of the competition-distress feedback across industries. The competition-distress feedback becomes weaker when industries' market structure becomes more competitive. In this section, we provide direct evidence supporting this mechanism.

Properly measuring market structure changes in our panel regressions is challenging. Endogeneity problems will arise if we use empirical proxies for the competitiveness of market

Table 11: Variation in feedback effects across industries.

	(1)	(2)	(3)	(4)
	Panel A: Feedback effect on profit margins across industries			
$MktShare_Imbalance_{i,t}$	All	Group 1 (balance)	Group 3 (imbalance)	Group 3−1
M1	0.021**	0.057***	0.016	−0.041**
	[2.47]	[4.89]	[0.91]	[−2.18]
M2	0.023**	0.062***	0.014	−0.048*
	[2.23]	[4.52]	[0.59]	[−1.93]
	Panel B: Feedback effect on equity returns across industries			
$Distress_{i,t}$	T1 (Low)	T2	T3 (high)	T3−T1
Group 1 (balance)	10.857***	9.815***	4.173**	−6.685***
	[6.34]	[4.75]	[2.28]	[−3.74]
Group 2	9.994***	9.685***	7.799***	−2.195
	[4.83]	[5.44]	[3.79]	[−1.03]
Group 3 (imbalance)	9.453***	11.613***	6.934***	−2.519
	[4.95]	[5.31]	[3.19]	[−1.48]

Note: Panel A tests the variation in feedback effects on profit margins across industries. The coefficient β_{T3} in specification (35) captures the effect of idiosyncratic shocks to firms in T3 (financially distressed) on the profit margin of firms in T1 (financially healthy). Column (1) presents the estimated β_{T3} based on the whole sample, and columns (2) to (4) present the estimated β_{T3} in split samples by the market-share imbalance measure. The sample spans the period from 1976 to 2021. The number of industry-year observations is 4,623 for M1 and 4,615 for M2. Panel B tests the variation in feedback effects on equity returns across industries. Within each group of industries split by the industry-level imbalance measure of market shares, we sort industries into terciles based on the industry-level financial distress ($Distress_{i,t}$), and reports the expected equity excess returns. All returns are in annualized percentage units. The sample is monthly and spans the period from 1976 to 2021. The number of observations is 40,708. *t*-statistics robust to heteroskedasticity and autocorrelation are reported in brackets. *, **, and *** indicate statistical significance at 10%, 5%, and 1%, respectively.

structure such as the Herfindahl-Hirschman index (HHI). Specifically, omitted variables that are correlated with both changes in HHI and the feedback effect could exist through channels other than the competitiveness of market structure. For instance, technology development can lead to both changes in HHI and changes in the sensitivity of industries' profit margins to the discount rate by altering the duration of firms' cash flows.

To address the endogeneity concern, we exploit exogenous variation in the competitiveness of market structure at the industry level. We follow the literature (Frésard, 2010; Valta, 2012; Frésard and Valta, 2016; Dou, Ji and Wu, 2021) and use unexpected large cuts in import tariffs to identify exogenous variation in market structures. The existing literature provides extensive evidence showing that tariff cuts substantially alter the competitive configuration of industries. For example, Bernard, Jensen and Schott (2006) show that import tariff cuts significantly increase competitive pressures from foreign rivals. Valta (2012) shows that tariff

Table 12: Impact of market structure changes on the competition-distress feedback effect.

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

Note: This table examines the impact of market structure changes on the competition-distress feedback effect. We run panel regressions according to specification (36), where the independent variable is the year-on-year change in the logged one plus the industry-level net profit margin (columns (1) and (2)) or the industry-level net profit margin (columns (3) and (4)). $Low_DD_{i,t-1}$ is an indicator variable that equals 1 if $DD_{i,t-1}$ is below the 25% quantile of the distance-to-default measure across all industries in year $t-1$. We measure market structure changes based on large import tariff cuts. Specifically, $Mkt_chg_{i,t}$ is an indicator variable that equals 1 if industry i experiences a large tariff cut in the last two years (t and $t-1$). A large tariff cut refers to a cut with a magnitude greater than three times the median tariff cut in this industry across the whole sample period (e.g., Frésard, 2010). To ensure that large tariff cuts indeed capture nontransitory changes in the competitive environment, following Frésard (2010), we exclude tariff cuts followed by equivalently large increases in tariffs over the subsequent two years. We obtain tariff data for manufacturing industries at the SIC4 level from 1974 to 2005 from Laurent Fresard's website (Frésard, 2010) and extend these data to 2017 based on the tariff data at the Harmonized System level obtained from Peter Schott's website (Schott, 2008). We control for industry fixed effects. The sample spans the period from 1976 to 2017. Standard errors are clustered at the industry level. We report t-statistics in brackets. *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels.

reductions are followed by a significant increase in imports.

To examine the impact of large tariff cuts on the strength of the competition-distress feedback mechanism, we run the following panel regression using industry-year observations in a difference-in-differences framework, in which we add a dummy variable for unexpected market structure changes (i.e., unexpected large tariff cuts), $Mkt_chg_{i,t}$, to the empirical

specification in panel A of Table 10:

$$\begin{aligned}\Delta \ln(1+PM_{i,t}) &= \beta_1 \times Mkt_chg_{i,t} \times Low_DD_{i,t-1} \times \Delta Discount_rate_t \\ &+ \beta_2 \times Low_DD_{i,t-1} \times \Delta Discount_rate_t + \beta_3 \times Mkt_chg_{i,t} \times \Delta Discount_rate_t \\ &+ \beta_4 \times \Delta Discount_rate_t + \beta_5 \times Mkt_chg_{i,t} \times Low_DD_{i,t-1} \\ &+ \beta_6 \times Low_DD_{i,t-1} + \beta_7 \times Mkt_chg_{i,t} + \ell_i + \epsilon_{i,t}. \end{aligned} \tag{36}$$

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

Column (1) of Table 12 presents the benchmark results without including the terms with $Mkt_chg_{i,t}$ in specification (36). The net profit margins of industries with a low distance to default are more negatively exposed to the discount rate, consistent with the implication of the competition-distress feedback. Column (2) of Table 12 reports the results for the full specification (36). The estimated coefficient $\hat{\beta}_1$ for the triple interaction term is positive and significant both statistically and economically, suggesting that industries with high and low distances to default display less difference in the sensitivity of net profit margins to the discount rate when their market structure becomes more competitive after large tariff cuts.[25] The results remain robust if we use changes in the industry-level net profit margin (i.e., $\Delta PM_{i,t}$) as the independent variable in columns (3) and (4).

6 Conclusion

This paper documents the industry distress anomaly and provides a risk-based explanation. In the data, we show that the distress anomaly is significant across both firms and industries. However, the industry-level distress spread cannot be fully explained by the firm-level distress spread, suggesting that the industry- and firm-level distress anomalies could be driven by different economic mechanisms. Moreover, the industry-level distress spread is no longer significant in hypothetical industries, suggesting that it is tied to some economic mechanism within real industries, with its strength depending on certain industry characteristics.

To provide a structural explanation for the industry distress anomaly, we develop a dynamic model of long-term defaultable debt that incorporates time-varying discount rates and a supergame of strategic rivalry. Our model shows that the competition-distress

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

feedback within industries amplifies industries' exposure to aggregate discount-rate shocks, more so for less distressed industries that feature a low level of idiosyncratic left-tail risk. As such, our model provides a novel mechanism that helps explain the puzzling cross-industry patterns of equity and bond returns, namely, the industry distress anomaly — more distressed industries exhibit lower expected equity returns despite having higher credit spreads.

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