Feedback and Contagion Through Distressed Competition

1 Notation

b_i: perpetual coupon payment at rate b_i (the coupon rate)
τ: the corporate tax rate
$E_{i,t}$: Firm i's earning flow after interest expenses and taxes over $[t, t+dt]$ is $E_{i,t} = (1-\tau)\,(\Pi_{i,t} M_{i,t} - b_i)$
$\Pi_{i,t} M_{i,t}$: the operating cash flow
$M_{i,t}$: the firm's customer base
$\Pi_{i,t}$: the firm's endogenous profitability per unit of customer base, which is determined in the Nash equilibrium of competition ganmes.
γ_t time-varying market price of risk (discount rate)

2 Model

2.1 Financial Distress

Financial Frictions

- Firms are financed by long-term debt and equity
- we model long-term debt as a consol with perpetual coupon payments at rate b_i for firm i.
- 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 and distress costs. 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.
- When operating cash flows cannot cover interest expenses, the firm can issue equity to cover the shortfalls without paying any extra financing costs.

Cash Flows

Firm i's earning flow after interest expenses and taxes over $[t, t + dt]$ is

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

- $\Pi_{i,t} M_{i,t}$ is the operating cash flow, $M_{i,t}$ is the firm's customer base, and $\Pi_{i,t}$ is the firm's endogenous profitability per unit of customer base, which is determined in the Nash equilibrium of competition games.

We assume that firm i's customer base $M_{i,t}$ evolves with the following jump-diffusion process:

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

- 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.
- The Poisson process $J_{i,t}$ with intensity λ captures left-tail idiosyncratic jumps in firm i's customer base.
- Upon the occurrence of a Poisson shock, firm i loses its entire customer base and exits the industry.

The firm's financial distress is determined not only by the cash flow level $E_{i,t}$ but also jump intensity λ.

Stochastic Discount Factor

Countercyclical risk premiums crucially allow Leland-type models to quantitatively reconcile jonit patterns of low leverage, high credit spread, and low default frequency.

we specify the stochastic discount factor (SDF) Λ_t as

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

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

γ_t evolves as follows:

$$\mathrm{d}\gamma_t = -\varphi\left(\gamma_t - \bar{\gamma}\right)\mathrm{d}t - \pi \mathrm{d}Z_{\gamma,t} \text{ with } \varphi, \bar{\gamma}, \pi > 0 \tag{4}$$

- Our specification for the time-varying aggregate discount rate $\gamma_t$follows the literature on cross-sectional return predictability.
- 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 time-varying risk aversion.

Interpretation of the shocks

- The aggregate Brownian shock Z_t 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.
- The idiosyncratic Brownian shocks,$W_{i,t}$ and $W_{2,t}$ can be interpreted as idiosyncratic demand shocks.
- The left-tail idiosyncratic Poisson shocks, $J_{1,t}$ and $J_{2,t}$ paly a crucial role in our theory and empirical results

Exit and Entry: Endogenous Default versus Exogenous Displacement In our model, a market leader can exit the industry in two ways, either endogenous 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 $M_{i,t}$.
- On the other hand, market leader i may go bankrupt and exit because of the occurence of the left-tail idiosyncratic jump shock (i.e., $dJ_{i,t} = 1$)

2.2 Product Market Competition

Demand System for Differentialed Products

The industry-level consumption C_t is determined by Dixit-Stiglitz constant-elasticity-of-substitution (CES) aggregator:

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

- $C_{i,t}$ 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 industry-level consumption C_t, the demand for firm i's goods $C_{i,t}$ can be obtained by solving a standard expenditure minimization problem:

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

All else equal, the demand for firm i's goods $C_{i,t}$ increases with consumers' relative tastes $M_{i,t}/M_t$ in equilibrium.

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.

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

- 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.

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

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

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

Endogenous Profitability and Externality

- Firms' shareholders choose production, set profit margins, and make optimal decisions about defaulting to maximize their equity value.

- The marginal cost for a firm to produce a 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 $\omega Y_{i,t}dt$ over $[t, t+dt]$.

- In equilibrium, the firm finds it optimal to choose $P_{i,t} > \omega$) and produce goods to exactly meet the demand, that is, $Y_{i,t} = C_{i,t}$.

Firm i's operating profits per unit its customer base are

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

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

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

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

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

Equation (10) shows that firm i's profitability $\Pi_i(\theta_{i,t}, \theta_{j,t})$ depends on its competitor j's profit margin $\theta_{j,t}$ through the industry's profit margin θ_t.

For example, holding firm i's profit margin fixed, if firm j cuts its profit margin $\theta_{j,t}$, the industry's profit margin θ_t will drop, which will reduce the demand for firm i's goods $C_{i,t}$.

2.3 Nash Equilibrium

- The two firms in an industry play a supergame, in which the stage games of setting profit margins are continuously played and infinitely repeated with exogenous and endogenous state variables varying over time.
- 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 $\mathscr{X}$, as well as a pair of indicator functions that track whether either firm has previously deviated from the collusive agreement.

Non-Collusive Equilibrium

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

Following the recursive formulation in dynamic games for characterizing the Nash equilibrium, we formulate optimization problems conditioning on no endogenous default at time t as a pair of Hamilton-Jacobi-Bellman (HJB) equations:

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

- left-hand side $\lambda V_i^N(x_t)dt$ is the expected loss of equtiy value due to the left-tail idiosyncratic jump shock, which occurs with intensity λ.
- The right-hand side is the expected gain of shareholders if the left-tail jump shock does not occur over $[t, t+dt]$.
- The coupled HJB equations give solutions for the non-collusive profit margin, where $\theta_{i,t}^N \equiv \theta_i^N(x_t)$ for $i = 1, 2$.

Denoted by $\underline{M}_{i,t}^N \equiv \underline{M}_i^N(M_{j,t}, \gamma_t)$ firm i's **endogenous default boundary** in the non-collusive equilibrium.

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

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

- As $M_{i,t} \to +\infty$, firm i essentially becomes an industry monopoly, which sets another boundary condition.

Collusive Equilibrium

- For the collusive equilibrium, firms tacitly collude with each other in setting higher profit margins, where any deviation would trigger a switch to the non-collusive equilibrium.
- If one firm deviates from the collusive profit-margin-setting scheme, then with probability ζdt over $[t, t+dt]$, the other firm will implement a punishment strategy in which it will forever set the non-collusive profit margin.
- We use an idiosyncratic Poisson process $N_{i,t}$ with intensity ζ to characterize whether a firm can successfully implement a punishment strategy after the competitor's deviation.

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

Participation constraints(PC)

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

Incentive compatibility (IC)

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

where $V_i^D(x)$ is firm i's equity value if it chooses to deviate from the collusion, and $V_i^C(x)$ is firm i's equity value in the collusive equilibrium.

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

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

The variables $\theta_{i,t}^C = \theta_i^C(x_t)$ are the collusive profit margins for $i = 1, 2$. The non-default region is characterized by $M_{i,t} > \underline{M}_{i,t}^C \equiv \underline{M}_i^C(M_{j,t}, \gamma_t)$ where $\underline{M}_{i,t}^C$ is firm i 's optimal default boundary in the collusive equilibrium, determined by the following value matching and smooth pasting conditions:

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

3 Quantitative Analysis

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

3.1 Data and Empirical Measures

- For each transaction, we calculate the credit spread by taking the difference between the bond yield and the treasury yield with corresponding maturity.

Measure of Financial Distress:

- The firm-level financial distress measure is constructed as the 12-month failure probability.
- In the model, an industry's default risk is determined by both its left-tail idiosyncratic jump risk and its distance to the default boundary.
- we also construct a distance-to-default measure following the Merton model for the purpose of testing the competition-distress feedback effect.

Measure of Default Event

- The empirical proxy for discount rates is based on the smoothed earnings-price ratio motivated by return predictability studies.
- In our regression analyses, the discount rate in motn t, denoted by $Discount\_rate_t$, is calculated by fitting a time-series regression of 12-month-ahead market return on the smoothed earning-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 residual of AR(1) time-series regressions, which are extracted at an annual frequency for the estimation of profit-margin betas and at a quarterly frequency for the estimation of equity and credit spread betas, aligning with the frequency of the beta-estimation regressions.

Measure of Left-Tail idiosyncratic Jump Risk

- First, we estimate the daily residuals of the Fama-French three-factor model for each stock using a 60-month rolling window.
- For each stock j, the realized left-tail idiosyncratic jump shock over a year, denoted by $IdTail\_shock_{j,t-11,t}$, is constructed using the 5th percentile value of the estimated daily residual distribution from the beginning of month $t-11$ to the end of month t at the firm level.
- Second, we construct a measure for ex-ante left-tail idiosyncratic jump risk for each stock j. In each month t, we run the following panel regression for all stocks in the subsample from the first month up to month t:

$$IdTail_shock_{j,s+1,s+12} = \alpha_t + \beta_t X_{j,s} + \epsilon_{j,s+12}, \quad s = 1, \cdots, t-12 \tag{19}$$

3.2 Calibration

We calibrate the intensity of left-tail idiosyncratic jump shocks to match the difference in stock returns and credit spreads across industries sorted on the financial distress measure $Distress_{i,t}$. In particular, we assume that the intensity of left-tail idiosyncratic jump shocks λ ranges from $\underline{\lambda}$ to $\overline{\lambda}$. We discribe $[\underline{\lambda}, \overline{\lambda}]$ into $N = 10$ grids with equal spacing so that $\lambda_1 = \underline{\lambda}$ and $\lambda_N = \overline{\lambda}$.

3.3 Financial Distress Anomaly across Industries

We show that our model can quantitatively rationalize the financial distress anomaly across industries: **more financially distressed industries have lower expected equity excess returns and higher credit spreads.**

In the data

- we sort all SIC4 industries into quintiles based on the industry-level financial distress measure $Distress_{i,t}$ and indeed find that more distressed industries have lower expected equity excess returns and higher credit spreads.
- sorting industries by financial distress in the model captures the cross-industry variation in left-tail idiosyncratic jump risk, thereby generating lower expected equity excess returns for the industries that are more financailly distressed.

3.4 Inspecting the Model's Mechanism

- the excess return difference (Q5-Q1) of portfolios sorted on financial distress or left-tail idiosyncratic jump risk becomes positive with small magnitude because the cross-industry difference in λ does not affect industries' profit margins or their exposure to the discount rate in the non-collusive equilibrium.

4 Empirical Tests

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

4.1 Left-Tail Idiosyncratic Jump Risk and Financial Distress Anomaly

Equity Returns and Credit Spreads in the Cross Section

- Appendix A shows that more financially distressed industries have lower CAPM alphas.
- Moreover, the results are similar if we sort industries on left-tail idiosyncratic jump risk.

Left-Tail idiosyncratic Jump risk, Profit Margin, and Financial Distress

- Our model predicts that the left-tail idiosyncratic jump risk is negatively associated with the profit margin and positively associated with the level of financial distress across industries.

Financial Distress Anomaly after Controlling for $IdTail_risk_{i,t}$

- In our model, the financial distress spread across industries can be explained by the heterogenous exposure to the left-tail idiosyncratic jump risk.
- $Distress\_adjusted_{i,t}$ **is the residuals of cross-sectionally regressing the financial distress measure ($Distress_{i,t}$)** on the left-tail idiosyncratic jump risk measure ($IdTail\_risk_{i,t}$) and a constant term.

4.2 Feedback and Contagion Effects on Profit Margins

Competition-Distress Feedback Effects

- Our model implies that industry-level profit margins load negatively on the discount rate and that the loadings are more negative in industries where firms are closer to their default boundaries.
- To test this implication, we sort industries into different groups based on the distance-to-default measure ($DD_{i,t}$).
- We then examine the profit-margin beta to the discount rate by running the following time-series regression using yearly observations for each group k:

$$\Delta \ln (1 + PM_{k,t}) = \alpha_k + \beta_k \times \Delta Discount\_rate_t + \epsilon_{k,t} \tag{20}$$

- the difference in the profit-margin beta to discount rate between the tertile groups of industries with high and low distances to default, respectively, is positive and statiscally significant.

Financial Contagion within Industries

- Our model predicts that adverse idiosyncratic shocks to a financially distressed market leader will motivate other market leaders within the same industry to cut their profit margins under a common market structure.
- To test this prediction, we split the top six firms in each industry into three groups based on the financial distress measure ($Distress_{i,t}$) in each year.
- Group L contains the two firms with the lowest financial distress; group H contains the two firms with the highest financial distress; and group M labels the middle group.

$$\ln\left(1+PM_{i,t}^{(L)}\right)=\sum_{j\in\{H,L\}}\beta_j\times\ \text{IdShock}\ _{i,t}^{(j)}+\sum_{j=1}^{5}\gamma_j\times\ln\left(1+PM_{i,t-j}^{(L)}\right)+\delta_t+\ell_i+\epsilon_{i,t} \quad (21)$$

where the independent variable $IdShock_{i,t}^{(}k)$ is the idiosyncratic shock of group $K = L, H$ in industry i and year t. We construct the group-level idiosyncratic shocks based on firm-level idiosyncratic shocks, which are constructed using two different methods for roubustness.

- Method $M1$ uses firms' sales grouth minus the cross-sectional average minus the cross-sectional average sales growth; and method $M2$ uses time-series regression residuals of firms' sales growth on the cross-sectional average sales growth.
- Our regression specification controls for the idiosyncratic shocks to firms in group L (i.e., $Idshock_{i,t}^{L}$), the lagged profit margins of firms in group L (i.e. $\sum_{j=1}^{5}\gamma_j\times\ln\left(1+PM_{i,t-j}^{(L)}\right)$), and the time and industry fixed effects.
- The coefficient β_H captures the effect of idiosyncratic shocks to firms in group H (financially distressed) on the profit margin of firms in group L (financially health), reflecting the contagion effect on profit margins.

Test: Our model further predicts that the within-industry contagion effect on profit margins is more pronounced in industries in which market leaders have more balanced market shares

- To test this prediction ,we split industries into three tertiles in each year based on an industry-level imbalance measure of market shares and run the same regression for industries in each tertile.
- The imbalance measure of market shares is defined as the absolute difference in the logged sales between group L and group H of the industry.

Test: our model predicts that the contagion effect on profit margins is more pronounced in industries with lower entry threat due to greater predatory incentive.

- We test this prediction by splitting industries into three tertiles in each year based on an industry-level entry threat measure, proxied by entry costs.
- we measure industry-level entry costs based on the median of the firm-level trailing 5-year average of the net total property, plant, and equipment for each industry in each year.

Financial Contagion across Industries

Test: Although our model focuses on the market leaders within the same industry, the financial contagion effect may well exist among market leaders in different industries, following the economic intuition.

- To test the cross-industry financial contagion effect, we construct a competition network of industries linked by common market leaders. Based on the competition network, we test whether idiosyncratic shocks to market leaders in one industry influence the profit margins of market leaders in another industry if the two industries share some common market leaders.

- In the first stage, we estimate the impact of idiosyncratic shocks of market leaders in industry i on the profit margin of the common market leader $c_{i,t}$ with industries i and j. The fitted value of the regression, $\widehat{\text{IdShoc}}\,k_{i,t}^{(c_{i,j})}$, captures the changes in the common market leader $c_{i,t}$'s profit margin attributad to idiosyncratic shocks to market leaders in industry i.

- In the second stage, we estimate the cross-industry financial contagion effect on profit margins by regressing logged one plus the profit margins by regressing logged one plus the profit margin of industry i excluding its common market leaders on $\widehat{\text{IdShoc}}\,k_{i,t}^{(c_{i,j})}$.

4.3 Feedback and Contagion Effects on Asset Prices

Competition-Distress Feedback Effects

Test: competition-distress feedback is stronger when industries are closer to the default boundary. **As as result, the difference in the equity beta to the discount rate across industries with different gross profitability becomes larger when the distance to default is lower.**

- To test this prediction, we equally split all industries into three groups based on the distance-to-default measure ($DD_{i,t}$). Within each group, we sort industries into three tertiles based on their gross profitability.

- Table 10 shows that **the return spread between industries with high and low gross profitability is positive and statistically significant among industries in the group with a low $DD_{i,t}$.**

Financial Contagion within industries

- **Test: Our model implies that the financial contagion effect among market leaders within the same industry is also reflected in firms' credit spreads**

- To test this prediction, we conduct regression analysis using specification except for using the group-level credit spreads on both sides:

$$Credit\_spread_{i,t}^{(L)} = \sum_{j\in\{H,L\}} \beta_j \times \text{ IdShock }_{i,t}^{(j)} + \sum_{j=1}^{5} \gamma_j \times Credit\_spread_{i,t-j}^{(L)} + \delta_t + \ell_i + \epsilon_{i,t} \quad (22)$$

- Table 11 shows that the contagion effect on credit spreads is negative, indicating that positive idiosyncratic shocks to group H (highly financial distressed) reduce the credit spreads of group L.

4.4 Testing the Endogenous Distressed Competition Mechanism

In this section, we provide direct evidence supporting the unique predictions of our model's endogenous distressed competition mechanism.

Test: we test whether the competition-distress feedback and financial contagion effects become weaker when the industries' market structure becomes more competitive.

Tariff cuts

- The existing literature provides extensive evidence showing that tariff cuts sustantially alter the competitive configuration of industries.
- Bernard (2006) show that import tariff cuts significantly increase competitive pressures from foreign rivals.
- Valta (2012) shows that tariff reductions are followed by a significant increase in imports.
- Intuitively, large tariff cuts can lead to a more competitive market structure because the reduction in trade barriers can increase **(i) the industry's price elasticity of demand ϵ because of the similar products and services provided by foreign rivals** and (ii) **the number of market leaders n because of the entry of foreign rivals as major players.**

Examination
First

- we first examine the impact of large tariff cuts on the sensitivity of profit margins to discount rates across industries with different values of the distance to default.
- We run the following panel regression using industry-year observations in a difference-in-differences framework, essentially by adding unpected market structure changes (i.e., unexpected large tariff cuts) dummy variable $mkt\_chg_{i,t}$ to the empirical specification.

$$
\begin{aligned}
&\Delta \ln \left(1+PM_{i,t}\right)=\beta_1 \times mkt\_ \operatorname{ch} g_{i,t} \times Low\_DD_{i,t-1} \times \Delta Discount\_rate_t \\
&+\beta_2 \times Low\_DD_{i,t-1} \times \Delta Discount\_rate_t+\beta_3 \times mkt_c chg_{i,t} \times \Delta Discount\_rate_t \\
&+\beta_4 \times \Delta Discount\_rate_t+\beta_5 \times mkt_5 \operatorname{chg}_{i,t} \times Low\_DD_{i,t-1} \\
&+\beta_6 \times Low\_DD_{i,t-1}+\beta_7 \times mkt\_ \operatorname{ch} g_{i,t}+\ell_i+\epsilon_{i,t}
\end{aligned} \tag{23}
$$

- 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.
- The estimated coefficient $\hat{\beta}_1$ for the triple interaction term is positive and significant both statistically and economically, **suggesting that industries with high and low distances to default display less difference in the sensitivity of profit margins to the discount rate when their market structure becomes less more competitive after large tariff cuts.**

Next

- Next, **we examine the impact of large tariff cuts on the financial contagion effect.** Specifically, we run the following panel regression using industry-year oberservations, essentially by adding the unexpected large tariff cut) to the regression specification.

$$
\begin{aligned}
\ln \left(1+PM_{i,t}^{(L)}\right)= & \beta_1 \times mkt\_chg_{i,t} \times Id \text{ Shoc } k_{i,t}^{(H)}+\beta_2 \times Id \text{ Shoc } k_{i,t}^{(H)}+\beta_3 \times mkt_c chg_{i,t} \\
& +\beta_4 \times \text{ IdShock }_{i,t}^{(L)}+\sum_{j=1}^5 \gamma_j \times \ln \left(1+PM_{i,t-j}^{(L)}\right)+\delta_t+\ell_i+\epsilon_{i,t} .
\end{aligned} \tag{24}
$$

- The estimated coefficient $\hat{\beta}_1$ for the interaction term is negative and significant both statistically and economically, **indicating that the financial contagion effect on profit margins becomes weaker after unexpected large tariff cuts**.

5 Conclusion

Our model has salient asset pricing implication

- first, our because the financial contagion, the credit risks of leading firms in an industry are jointly determined, whereby firm-specific shocks can significantly affect the credit spread of peer firms;
- second, competition-distress feedback amplifies firms' aggregate risk exposure, more so for industries with lower left-tail idiosyncratic jump risk, which helps explain the puzzling cross-sectional patterns of equity patterns of equity and bond returns, namely, the financial distress anomaly across industries.

Research in the future

- Equity issurance is costless in our model but costly in reality. The costless insurance of equity is a simplication widely adopted in standard credit risk models. **Do firms compete more aggressively when they become more liquidity constrained, but no yet more financially distressed?** we focus on frictions related to debt financing, but the equity financing friction should also be investigated.
- Also, our paper highlights an important source of cash flow risk – endogenous competition risk – that depends on idustries' market structures. **Extending the model to study the joint determination of optimal capital structure and risk management would be another potentially fruitful research area.**