Predation or Self-Defense?
Endogenous Competition and Financial Distress

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Abstract
Firms tend to compete on prices more when they are in financial distress. More intense competition can in turn reduce firms’ profit margins and push weaker firms further into distress. To study the quantitative effects of the feedback loop between industry competition and financial distress, we incorporate dynamic games of price competition into a model of long-term debt and strategic default. We show that this feedback mechanism endogenously generates stochastic volatility and jump risks in cash flows, and amplifies the risks of financial distress. Moreover, depending on the heterogeneity in customer bases and financial conditions across firms in an industry as well as across incumbent firms and new entrants, firms can exhibit a rich variety of strategic interactions, including predation, self-defense, and collaboration. Finally, we provide empirical support for our model’s main predictions.

Keywords: Competition-Distress Feedback, Industrial Organization, Credit Risk, Profit Margin, Customer Base, Dynamic Games

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1 Introduction

Product markets are often highly concentrated, and strategic competition among industry leaders plays a vital role in determining industry dynamics (see, e.g. Autor et al., 2017; Loecker and Eeckhout, 2017).\textsuperscript{1} It is well established that firms’ decisions in product markets affect their profit margins, financial conditions, and valuation.\textsuperscript{2} Our paper focuses on how strategic competition is endogenously affected by the macroeconomic conditions and the industry structure, specifically the distribution of customer base and financial conditions among the leading firms.

In our model, a firm’s incentive to collude with others in setting prices depends on its future perspective. Recessions are times with high discount rates and low persistent consumption growth, which shift firms attention from long-run cash flows to short-run cash flows. This induce firms to compete on prices more fiercely at such times. Increased competition lowers firms’ profit margins, which raises the default risk of levered firms, more so for those with higher leverage. The rising risk of financial distress has the similar effect as higher discount rate or lower expected growth in demand. It makes firms in poor financial conditions want to compete more aggressively to generate more profits now, and that induces other firms to lower prices as well, including those financially strong firms. Thus, defensive predatory pricing strategy emerges endogenously. As competition becomes more intense, the risks of financial distress rise further across firms. The result is a positive feedback loop between industry competition and financial distress, amplifying firms’ exposure to aggregate risk.

To study the quantitative effects of such feedbacks, we incorporate dynamic games of price competition into an equilibrium framework with time-varying macroeconomic conditions captured by pro-cyclical expected growth rate of aggregate demand. There is a continuum of industries and each industry features dynamic Bertrand duopoly with differentiated products and implicit price collusion (Tirole, 1988, Chapter 6). Consumers have deep habits (see

\textsuperscript{1}According to the U.S. Census data, the top four firms within each 4-digit SIC industry account for about 48% of the industry’s total revenue, and the top eight firms own over 60% market shares (see Dou, Ji and Wu, 2019, Online Appendix C).

\textsuperscript{2}For example, Corhay, Kung and Schmid (2017), Corhay (2017), and Dou, Ji and Wu (2019) analyze the implication of product market competition on equity returns and credit spreads.
Ravn, Schmitt-Grohe and Uribe, 2006) over firms’ products, and thus firms find it valuable to maintain their customer base. Firms’ cash flows are endogenously determined by their product prices and customer base. Shareholders issue consols and promises a perpetual coupon payment to debtholders. Asset prices are determined by a representative household with recursive preferences.

In our baseline model, duopolists can implicitly collude with each other on setting high product prices and obtaining high profit margins. Knowing that the competitor will honor the collusive price-setting agreement, a firm can boost up its short-run revenue by undercutting prices to attract more customers; however, deviating from the collusive price-setting scheme may reduce revenue in the long run if the price undercutting behavior is detected and punished by the competitor. Following the literature (see, 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 implicit collusive price levels depend on firms’ deviation incentives: a higher implicit collusive price can only be sustained by a lower deviation incentive, which is further shaped by firms’ trade-off between short-term and long-term cash flows.

Our baseline model yields three main implications. First, there exists a positive feedback loop between competition and financial distress. When firms become more financially distressed, default risk rises. The increased default risk makes competition more fierce because both firms find it more difficult to collude with each other. Intuitively, with rising default risk, the firm becomes effectively more impatient and values its cash flows in the short run more than those in the long run. This motivates the firm to undercut its competitor’s price, which intensifies price competition. The increased competition results in lower profit margins, further amplifying financial distress and default risk.

Second, predation behavior emerges endogenously as an equilibrium outcome of collusion. The model implies that the financially strong firm lowers its price when the financially weak

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3Even though explicit collusion is illegal in many countries including United States, Canada and most of the EU due to antitrust laws, but implicit collusion in the form of price leadership and tacit understandings still takes place. For example, Intel and AMD implicitly collude on prices of graphic cards and central processing units in the 2000s, though a price war was waged between the two companies recently in October 2018.
firm becomes more distressed. Such kind of pricing strategy echoes the idea of defensive predation termed by Fisher (2001). It is different from the usual (offensive) predation because the motivation of the financially strong firm to lower its price is to protect its customer base from being stolen by its competitor, not to drive its competitor out of the market. In other words, the financially strong firm should be treated as a defender but not a predator. Intuitively, when the financially weak firm becomes more distressed, its deviation incentive increases, motivating it to undercut the financially strong firm’s price to gain customer base. Anticipating such increased deviation incentive, the financially strong firm lowers its price to maintain collusion and prevent itself from being hurt by its financially weak competitor.

Third, the feedback loop between endogenous competition and financial distress further amplifies firms’ exposure to price war risk. Dou, Ji and Wu (2019) show that prices endogenously decline during economic downturns due to weakened market power and increased competition in the product market. With the feedback loop between competition and financial distress, the lower profit margins raise the default risk of levered firms, which further induce more fierce competition and lower profit margins, largely amplify both shareholders and debtholders’ exposure to price war risk and aggregate risk.

In our extended model, we augment the baseline model by adding one ingredient — imperfect monitoring. In particular, we assume that firms need to incur a non-pecuniary cost to monitor their competitors for potential deviation. Thus, whether firms collude with each other depends on whether the benefit from colluding on higher prices exceeds the monitoring cost. Owing to the feedback loop between competition and financial distress, the benefit from collusion is lower when default risk is higher. As a result, collusion is more likely to break up when firms are more financially distressed, which brings negative jump shocks to their cash flows, leading to higher default risk.

1.1 Related Literature

Our paper contributes to the large and growing literature on the structural model of corporate debt and default (see, e.g., Merton, 1974; Black and Cox, 1976; Fischer, Heinkel and Zechner, 1989; Leland, 1994; Leland and Toft, 1996; Anderson and Sundaresan, 1996; Goldstein, Ju and
Leland, 2001; DeMarzo and Sannikov, 2006; Hackbarth, Miao and Morellec, 2006; Broadie, Chernov and Sundaresan, 2007; DeMarzo and Fishman, 2007; Chen, 2010; Anderson and Carverhill, 2012; He and Milbradt, 2014; Corhay, 2017). Sundaresan (2013) provides a comprehensive review. Theoretically, our paper pushes forward the literature by developing a structural model of default incorporated with dynamic supergames, in which product market competition endogenously varies with macroeconomic conditions. Chen (2010) and Hackbarth, Miao and Morellec (2006) focus on the impact of macroeconomic conditions on firms’ financing policies and asset prices. In their models, cash flow dynamics exogenously vary with macroeconomic conditions. By contrast, we micro-found firms’ cash flows through endogenous time-varying product market competition and emphasize the endogenous linkage between firms’ cash flows and macroeconomic conditions. Like ours, Corhay (2017) also develops a model in which firms’ cash flows are determined by strategic competition in the product market. The key difference is that our model incorporates a dynamic Bertrand duopoly playing a price-setting supergame. Therefore, our model predicts that the degree of product market competition endogenously varies with macroeconomic conditions, providing an amplification mechanism on credit risks through procyclical profit margins and cash flows.

Our paper is related to the literature on the connection between product markets and financial decision making (see, e.g., Brander and Lewis, 1986; Maksimovic, 1988; Dumas, 1989; Gertner, Gibbons and Scharfstein, 1988; Bolton and Scharfstein, 1990; Chevalier and Scharfstein, 1996; Dasgupta and Titman, 1998; MacKay and Phillips, 2005; Miao, 2005; Banerjee, Dasgupta and Kim, 2008; Fresard, 2010; Valta, 2012; Phillips and Sertsios, 2013; Belo, Lin and Vitorino, 2014; Gourio and Rudanko, 2014; Leary and Roberts, 2014; Vitorino, 2014; Gilchrist et al., 2017; D’Acunto et al., 2018; Dou and Ji, 2018; Belo et al., 2018). In particular, our paper is closely related to the literature that links product market competition to firm risks (see, e.g., Hou and Robinson, 2006; Aguerrevere, 2009; Loualiche, 2016; Bustamante and Donangelo, 2017; Corhay, 2017; Corhay, Kung and Schmid, 2017). We contribute to this literature by showing that there is a positive feedback loop between financial leverage and product market competition. This feedback loop amplifies default risks and is also empirically relevant. For example, Valta (2012) finds that the cost of bank debt is
systematically higher for firms in competitive product markets. Fresard (2010) finds that large cash reserves allow firms to gain future market shares at the expense of their industry rivals. Phillips (1995) finds that following sharply increased financial leverage, the largest firms in the gypsum industry increased their market share at the expense of small firms and operating margins decrease.

2 The Baseline Model

2.1 Customer Base and Demands

Industry demand. Similar to the seminar works Pindyck (1993) and Caballero and Pindyck (1996), we focus on the industry equilibrium by starting with specifying the industry demand curve, rather than the demand curve facing an individual firm, and assume that it is isoelastic:

\[ C_t = M_t P_t^{-\epsilon}, \]

(1)

where \( M_t \) is an exogenous stochastic process that captures the total customer base in the industry, which is subject to economy-wide aggregate shocks and industry-and firm-specific shocks, and \( \epsilon \) is the industry elasticity of price.

Differentiated goods and firm-level demand. The demand for the industry final good \( C_t \) is a basket of firm-level composites, determined by a Dixit-Stiglitz CES aggregation. More precisely, the demand for the final consumption good \( C_t \) is determined through the aggregation of firm-level differentiated products,

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

(2)

where \( C_{i,t} \) is the demand for firm \( i \)'s products, parameter \( \eta > 1 \) captures the elasticity of substitution among products produced in the same industry, and \( M_{i,t}/M_t \) captures the consumer’s relative “taste” for firm \( i \)'s products.
Given firm \( i \)'s price \( P_{i,t} \) and industry demand \( C_t \), we obtain the firm-level demand \( C_{i,t} \) by solving a standard expenditure minimization problem. The firm-level demand curves are

\[
C_{i,t} = M_{i,t} P_t^{-\epsilon} \left( \frac{P_{i,t}}{P_t} \right)^{-\eta}, \quad \text{with} \quad P_t = \left[ \sum_{i=1}^{2} \left( \frac{M_{i,t}}{M_t} \right) P_{i,t} \right]^{1-\eta},
\]

where \( P_t \) is the price index for the final consumption good.

In equation (3), the demand for firm \( i \)'s goods \( C_{i,t} \) is linear in \( M_{i,t} \). According to (3), firm \( i \) will have more influence on the industry's price index \( P_t \) when the relative customer base \( M_{i,t}/M_t \) toward firm \( i \)'s goods is greater. In our duopoly industry, each firm internalizes both the effect of its own price and the effect of its competitor's price on the industry's price index, leading to rich strategic interaction. By contrast, in a standard monopolistic competition model with a continuum of firms, each firm is atomistic and has no influence on the industry's price index.

### 2.2 Endogenous Cash Flows and Default

The firm-level customer base \( M_{i,t} \) in equation (2) is persistent over time and can be interpreted as customer inertia and brand loyalty to firm \( i \)'s product (see Klemperer, 1995). From a firm's perspective, the consumer's taste determines its customer base (or customer capital) because it determines the demand for its products \( C_{i,t} \) (see, e.g., Gourio and Rudanko, 2014; Dou et al., 2018). We will make this connection clearer by deriving the firm's demand curve.

**Production and profits.** The marginal cost for a firm to produce a flow of goods is \( \omega \) with \( \omega > 0 \). When firm \( i \) produce goods at rate \( Y_{i,t} \), its total costs of production will be \( \omega Y_{i,t} dt \) over \([t, t + dt]\). In equilibrium, the firm finds it optimal to choose \( P_{i,t} > \omega \) and the market clears for each differentiated good \( Y_{i,t} = C_{i,t} \). The firm's operating profit is

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

Equation (4) shows that the (local) profit rate of firm \( i \) depends on its competitor \( \tilde{i} \)'s
product price $P_{i,t}$ through the industry’s price index $P_t$. This reflects the externality of firm $i$’s decisions. For example, holding firm $i$’s price fixed, if firm $\bar{i}$ cuts its price $P_{\bar{i},t}$, the price index $P_t$ will drop, which will reduce the demand for firm $i$’s goods $C_{i,t}$ (see equation (3)), and in turn firm $i$’s profit $\Pi_i(P_{i,t}, P_{\bar{i},t})$. This will motivate firm $i$ to lower its own price $P_{i,t}$ in order to defend its customer base, and thus the two firms’ pricing decisions exhibit strategic complementarity in equilibrium.

**Default.** The corporate tax rate is $\tau$. For tractability, we follow Leland (1994) by considering consols which promise perpetual coupon payments at rate $b_i$. Thus, firm $i$’s flow of earnings after interest expenses and taxes over $[t, t+dt]$ is $(1-\tau)\left[\Pi_i(P_{i,t}, P_{\bar{i},t}) - b_i\right]dt$.

When net profits are negative, firms’ shareholders can costlessly issue equity to cover the coupon payment. Shareholders have limited liability and can default. Thus, if the equity value falls to zero, shareholders will default.

To keep the model tractable, we maintain the duopoly market structure for the market leaders in each industry even after the occurrence of a market leader’s default. Suppose that firm $i$ defaults at $t$, we assume that debtholders would obtain a fraction $\nu$ of the firm’s unlevered asset value at $t$. A new firm $i$ with initial customer base $M_0 > 0$ and coupon rate $b_i$ will enter the market, where $b_i$ is optimally chosen to maximize its firm value.\(^4\)

**Evolution of customer base.** Firm $i$’s customer base evolves according to

\[
\frac{dM_{i,t}}{M_{i,t}} = g_t dt + \sigma_m dZ_{m,t} + \sigma_i dW_{i,t}, \tag{5}
\]

\[
dg_t = -\kappa(g_t - \bar{g}) dt + \sigma_g dZ_{g,t}, \tag{6}
\]

where $Z_{g,t}$ captures both aggregate and industry-specific shocks on the expected growth rate.

\(^4\)Except in the event of defaults, we do not allow firms’ entry or exit in order to keep the tractable duopoly market structure. In fact, most entries and exits in the data are associated with small firms (see, e.g., Haltiwanger, 2012; Tian, 2018), while our model focuses on the major players in an industry. Moreover, our model emphasizes the cyclicality of profit margins driven by firms’ endogenous time-varying collusion incentive, while the evidence on the cyclicality of business startups is mixed due to the existence of countervailing forces (see, e.g., Parker, 2009; Fairlie, 2013). The data do not suggest strong cyclical patterns in firms’ entry rates (see, e.g., Stangler and Kedrosky, 2010).
2.3 Heterogeneous Persistence of Market Leadership

The market leaders’ position is sticky. Market followers in an industry are constantly challenging and trying to replace the existing market leaders, and they typically do so through distinctive innovation or rapid business expansion. The change of market leaders does not occur gradually over an extended period of time; instead, market leaders are replaced rapidly and disruptively (see, e.g., Christensen, 1997). For example, Apple and Samsung replaced Nokia and Motorola and became the leaders in the mobile phone industry over a very short period of time.

We assume that the change of market leaders in the industry, as a disruption to the market structure, occurs with intensity $\lambda_t$. The economy comprises a continuum of industries, and thus the industry-specific change of market leaders is an idiosyncratic event to the representative agent. In such a change, the existing market leaders are replaced by new market leaders who used to be followers. Each of the new leaders has a customer base $M > 0$.

Significant heterogeneity exists in the persistence of market leaders’ position across industries. In our model, the variable $\lambda_t$ is the only industry characteristic that is ex-ante heterogeneous across industries. We assume that the value of $\lambda_t$ remains the same until the industry is hit by an idiosyncratic Poisson shock with rate $\chi$. Conditional on receiving the Poisson shock, a new characteristic is drawn randomly from the set $\{\lambda_1, \cdots, \lambda_N\}$ each with equal probability, where $0 \leq \lambda_1 < \cdots < \lambda_N$.

The assumption above technically ensures that the industry-level customer base $M_t$ is mean-reverting and stationary in the model. This modeling assumption is intended to be parsimonious to maintain tractability and keep the model focused.

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$^5$See, for example, Baldwin (1995), Geroski and Toker (1996), Caves (1998), Matraves and Rondi (2007), Sutton (2007), Bronnenberg, Dhar and Dubé (2009), and Ino and Matsumura (2012) for empirical evidence on the significant heterogeneity of $\lambda_{i,t}$.

$^6$How innovation and competition affect the aggregate growth has been a long-standing research question in the literature of development and economic growth, but it is not the focus of this paper.
2.4 Stochastic Discount Factor

The SDF evolves as follows:

\[
\frac{d\Lambda_t}{\Lambda_t} = -r_fd t - \gamma_t dZ_{m,t} - \zeta dZ_{g,t},
\]

\[(7)\]

where \(Z_{m,t}\) and \(Z_{g,t}\) are independent standard Brown motions, the equilibrium risk-free rate is \(r_f\), and the time-varying market prices of risk \(\eta_{m,t}\) follows

\[
d\gamma_t = -\varphi(\gamma_t - \bar{\gamma})dt + \nu_m \sqrt{\gamma_t}dZ_{m,t} + \nu_\gamma \sqrt{\gamma_t}dZ_{\gamma,t},
\]

\[(8)\]

where \(\nu_m < 0, \nu_\gamma > 0\), and \(Z_{\gamma,t}\) is the discount rate shock which is not priced.

2.5 Solving the Nash Equilibria

We now solve the dynamic games based on the equilibrium SDF specified in (7) and (8). There are two aggregate state variables, the discount rate \(\gamma_t\) and the expected consumption growth \(g_t\). To ease notations, we define \(s_t = (\gamma_t, g_t)\) to capture the aggregate state of the economy. Economic downturns in our model are characterized by those states with high \(\gamma_t\) and/or low \(g_t\).

Subgame Perfect Nash Equilibrium The two firms in an industry play a dynamic game (see Friedman, 1971), in which the stage games of setting profit margins are played continuously and repeated infinitely with exogenous and endogenous state variables varying over time. Formally, a subgame perfect Nash equilibrium for the dynamic game consists of a collection of profit-margin strategies that constitute a Nash equilibrium for every history of the game. We do not consider all such equilibria, only those which allow for collusive arrangements enforced by punishment schemes. All strategies are allowed to depend upon both “payoff-relevant” states \(x_t = \{M_{1,t}, M_{2,t}, s_t\}\) in state space \(X\), as in Maskin and Tirole (1988a, b), and a set of indicator functions that track whether any firm has previously deviated from a collusive profit-margin agreement, as in Fershtman and Pakes (2000, Page 212).\footnote{For notational simplicity, we omit the indicator states of historical deviations.}
In particular, there exists a non-collusive equilibrium, which is the repetition of the one-shot Nash equilibrium and thus is Markov perfect. Meanwhile, multiple subgame perfect collusive equilibria also exist in which profit-margin strategies are sustained by conditional punishment strategies.\(^8\)

Non-collusive equilibrium with endogenous default boundaries. The non-collusive equilibrium is characterized by profit-margin scheme \(\Theta^N(\cdot) = (\theta^N_1(\cdot), \theta^N_2(\cdot))\), 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 shareholder value \(V^N_{i,t} \equiv V^N_i(x_t)\), under the assumption that its competitor \(\bar{i}\) will set the one-shot Nash-equilibrium profit margin \(\theta^N_{\bar{i},t} \equiv \theta^N_{\bar{i}}(x_t)\). Following the recursive formulation in dynamic games for characterizing the Nash equilibrium (see, e.g., Pakes and McGuire, 1994; Ericson and Pakes, 1995; Maskin and Tirole, 2001), optimization problems can be formulated recursively by Hamilton-Jacobi-Bellman (HJB) equations:

\[
0 = \max_{\theta_{i,t}} \Lambda_t \left[ \Pi_t(\theta_{i,t}, \theta^N_{i,t}) M_{i,t} - \lambda_t V^N_i(x_t) \right] dt + \mathbb{E}_t \left[ \frac{d(\Lambda_t V^N_i(x_t))}{d(\theta_{i,t}, \theta^N_{i,t})} \right] \text{ if not disrupted. (9)}
\]

The solutions to the coupled HJB equations give the non-collusive-equilibrium profit margin \(\theta^N_{i,t} \equiv \theta^N_i(x_{i,t})\) with \(i = 1, 2\), which are chosen based on intertemporal tradeoff considerations because \(\theta^N_{i,t}\) determines the continuation value \(V^N_{i,t+dt}\) by altering the customer base \(M_{i,t+dt}\) according to equation (5).

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

\[
V^N_i(x_t) \bigg|_{M_{i,t}=M^N_{i,t}} = 0 \quad \text{and} \quad \frac{\partial}{\partial M_{i,t}} V^N_i(x_t) \bigg|_{M_{i,t}=M^N_{i,t}} = 0. \quad (10)
\]

\(^8\)In the industrial organization and macroeconomics literature, this equilibrium is called the collusive equilibrium or collusion (see, e.g., Green and Porter, 1984; Rotemberg and Saloner, 1986). Game theorists generally call it the equilibrium of repeated game (see Fudenberg and Tirole, 1991) in order to distinguish it from the one-shot Nash equilibrium (i.e., our non-collusive equilibrium).
The boundary condition at $M_{i,t} = +\infty$ is given by Appendix A.2.

**Collusive equilibrium with endogenous default boundaries.** In the collusive equilibrium, firms “tacitly” collude in setting higher profit margins, with any deviation triggering a switch to the non-collusive Nash equilibrium. The collusion is “tacit” in the sense that it can be enforced without relying on legal contracts. Each firm is deterred from breaking the collusion agreement because doing so could provoke fierce non-collusive competition.

Consider a generic collusive equilibrium in which the two firms follow a collusive profit-margin scheme. Both firms can costlessly observe the other’s profit margin, so that deviation can be detected and punished. The assumption of perfect information follows the literature.\(^9\) In particular, if one firm deviates from the collusive profit-margin scheme, then with probability $\xi dt$ over $[t, t + dt]$ the other firm will implement a punishment strategy in which it will forever set the non-collusive profit margin. Setting non-collusive profit margins is considered punishment for the deviating firm because the industry will switch from the collusive to the non-collusive equilibrium, which features the lowest profit margin.\(^10\) We use the idiosyncratic Poisson process $N_{i,t}$ to characterize whether a firm can successfully implement a punishment strategy. One interpretation of $N_{i,t}$ is that, with $1 - \xi dt$ probability over $[t, t + dt]$, the deviator can persuade its competitor not to enter the non-collusive Nash equilibrium over the period $[t, t + dt]$.\(^11\) Thus, the punishment intensity $\xi$ can be viewed as a parameter governing the credibility of the punishment for deviating behavior. A higher $\xi$ leads to a lower deviation incentive.

Formally, the set of incentive-compatible collusion agreements, denoted by $\mathcal{C}$, consists of all continuous profit-margin schemes $\Theta^C(\cdot) \equiv (\theta^C_1(\cdot), \theta^C_2(\cdot))$, such that the following participation

\(^9\)A few examples include Rotemberg and Saloner (1986), Haltiwanger and Harrington (1991), Staiger and Wolak (1992), and Bagwell and Staiger (1997).

\(^10\)We adopt the non-collusive equilibrium as the incentive-compatible punishment for deviation, which follows the literature (see, e.g., Green and Porter, 1984; Rotemberg and Saloner, 1986). We can extend the setup to allow for finite-period punishment. The quantitative results are not altered significantly provided that the punishment lasts long enough.

\(^11\)Ex-post renegotiations can occur because the non-collusive equilibrium is not renegotiation-proof or “immune to collective rethinking” (see Farrell and Maskin, 1989). The strategy we consider is essentially a probabilistic punishment strategy. This “inertia assumption” also solves the technical issue of continuous-time dynamic games about indeterminacy of outcomes (see, e.g., Simon and Stinchcombe, 1989; Bergin and MacLeod, 1993).
constraints (PC) and incentive compatibility (IC) constraints are satisfied:

\[
V_i^N(x) \leq V_i^C(x), \quad \text{for all } x \in \mathcal{X} \text{ and } i = 1, 2; \quad \text{(PC constraints)} \tag{11}
\]

\[
V_i^D(x) \leq V_i^C(x), \quad \text{for all } x \in \mathcal{X} \text{ and } i = 1, 2. \quad \text{(IC constraints)} \tag{12}
\]

Here, \(V_i^N(x)\) is the firm \(i\)’s shareholder value in the non-collusive equilibrium, \(V_i^D(x)\) is firm \(i\)’s shareholder value if it chooses to deviate from the collusion characterized by (15), and \(V_i^C(x)\) is firm \(i\)’s shareholder value in the collusive equilibrium, pinned down recursively according to

\[
0 = \Lambda_t \{(1 - \tau)[\Pi_i(\theta_{i,t}^C, \theta_{\bar{i},t}^C)M_{i,t} - b_i] - \lambda_i V_i^C(x_t)\} \, dt + \mathbb{E}_t \left[d(\Lambda_i V_i^C(x_t))|\theta_{i,t}, \theta_{\bar{i},t}\right], \tag{13}
\]

subject to the participation constraints (11) and incentive compatibility constraints (12), where \(\theta_{i,t}^C \equiv \theta_i^C(x_t)\) with \(i = 1, 2\) are the collusive profit margins. Obviously, the equilibrium recursive relation in (13) only holds true within the non-default region, characterized by \(M_{i,t} > M_{i,t}^C \equiv M_i^C(M_{i,t}, \theta_t)\) where \(M_i^C\) is firm \(i\)’s default boundary in the collusive equilibrium. The value matching and smooth pasting conditions for the optimal default boundary are

\[
V_i^C(x_t)\big|_{M_{i,t} = M_i^C} = 0 \quad \text{and} \quad \frac{\partial}{\partial M_{i,t}} V_i^C(x_t)\bigg|_{M_{i,t} = M_i^C} = 0, \quad \text{respectively.} \tag{14}
\]

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

**Equilibrium deviation values.** Firm \(i\)’s highest shareholder value if it chooses to deviate from the tacit collusion:

\[
0 = \max_{\theta_{i,t}} \Lambda_t \{(1 - \tau)[\Pi_i(\theta_{i,t}, \theta_{\bar{i},t})M_{i,t} - b_i] - \xi (V_i^D(x_t) - V_i^N(x_t)) - \lambda_i V_i^D(x_t)\} \, dt
\]

\[
+ \mathbb{E}_t \left[d(\Lambda_i V_i^D(x_t))|\theta_{i,t}, \theta_{\bar{i},t}\right]. \tag{15}
\]
The equilibrium recursive relation above in (15) only holds true within the non-default region, characterized by $M_{i,t} > M^D_{i,t} \equiv M^D_i(M_{i,t}, \theta_t)$ where $M^D_{i,t}$ is firm $i$’s default boundary if it chooses to deviate from the collusion. The value matching and smooth pasting conditions for the optimal default boundary are

$$V^D_i(x_t)\big|_{M_{i,t}=M^D_{i,t}} = 0 \quad \text{and} \quad \frac{\partial}{\partial M_{i,t}} V^D_i(x_t)\bigg|_{M_{i,t}=M^D_{i,t}} = 0,$$

respectively. (16)

**More discussion.** There are several points that worth mentioning. First, the IC constraints are never violated in the equilibrium, while the PC constraints can be occasionally violated (i.e., $V^N_i(x) > V^C_i(x)$) in the equilibrium. The latter property is a key difference of our model from the one in Dou, Ji and Wu (2019), who consider all equity firms. There the PC constraints for profit-margin collusion always hold since higher profit margin leads to higher shareholder value in the case of no credit risk or financial distress.

Second,

Third, there exist infinitely many elements in $\mathcal{C}$ and hence infinitely many collusive equilibria. We focus on a subset of $\mathcal{C}$, denoted by $\overline{\mathcal{C}}$, consisting of all profit-margin schemes $\Theta^C_i(\cdot)$ such that the IC constraints (??) are binding state by state, i.e., $V^D_{ij}(x) = V^C_{ij}(x)$ for all $x \in \mathcal{X}$ and $j = 1, 2$.\(^\text{12}\) It is obvious that the subset $\overline{\mathcal{C}}$ is nonempty since it contains the profit-margin scheme in the non-collusive Nash equilibrium. We further narrow our focus to the “Pareto-efficient frontier” of $\overline{\mathcal{C}}$, denoted by $\overline{\mathcal{C}}_p$, consisting of all pairs of $\Theta^C_i(\cdot)$ such that there does not exist another pair $\tilde{\Theta}^C_i(\cdot) \in \overline{\mathcal{C}}$ with $\tilde{\theta}_{ij}(x) \geq \theta_{ij}(x)$ for all $x \in \mathcal{X}$ and $j = 1, 2$, and with strict inequality holding for some $x$ and $j$.\(^\text{13}\) Our numerical algorithm follows a method similar to that of Abreu, Pearce and Stacchetti (1990).\(^\text{14}\) Deviation never occurs on the equilibrium path. Using the one-shot deviation principle (see Fudenberg and Tirole,

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\(^{12}\)Such equilibrium refinement in a general equilibrium framework is similar in spirit to ?, ?, and Opp, Parlour and Walden (2014).

\(^{13}\)It can be shown that the “Pareto-efficient frontier” is nonempty based on the fundamental theorem of the existence of Pareto-efficient allocations (see, e.g., Mas-Colell, Whinston and Green, 1995), as $\overline{\mathcal{C}}$ is nonempty and compact, and the order we are considering is complete, transitive, and continuous.

\(^{14}\)Alternative methods include Cronshaw and Luenberger (1994), Pakes and McGuire (1994), and Judd, Yeltekin and Conklin (2003), which contain similar ingredients to those of our solution method. Proving the uniqueness of the equilibrium under our selection criterion is beyond the scope of the paper. We use different initial points in our numerical algorithm and find robust convergence to the same equilibrium.
it is clear that the collusive equilibrium characterized above is a subgame perfect Nash equilibrium.

2.6 Bond Valuation and Issuance

In the collusive equilibrium, the unlevered asset value $A_{ij}^C(x_{i,t})$ is determined similarly except for setting $b_{ij} = 0$. The value of debt $D_{ij}^C(x_{i,t})$ in the non-default region (i.e., $m_{ij,t} > m_{ij}^C$) is given by

$$0 = \Lambda_t b_{ij} dt + \mathbb{E}_t \left[ d(\Lambda_t D_{ij}^C(x_{i,t})) \right]. \quad (17)$$

The boundary conditions are

$$D_{ij}^C(x_{i,t}) \Big|_{m_{ij,t}=m_{ij}^C} = \nu A_{ij}^C(x_{i,t}) \Big|_{m_{ij,t}=m_{ij}^C} \quad \text{and} \quad \lim_{m_{ij,t} \to +\infty} D_{ij}^C(x_{i,t}) = \pi b(\theta_t), \quad (18)$$

where $b(\theta_t)$ is given by Appendix A.2. The coupon rate of consol bond is determined when the firm is created with initial customer base $m_0$. Specifically, suppose that firm $ij$ defaults at $t$ and is replaced by a new firm $ij$. The new firm $ij$ optimally chooses $b_{ij}$ to maximize its firm value at $t$ by solving:

$$\max_{b_{ij}} V_{ij}^C(m_0, m_{ij,t}, b_{ij}, \pi_{ij}, \theta_t) + D_{ij}^C(m_0, m_{ij,t}, b_{ij}, \pi_{ij}, \theta_t). \quad (19)$$

As in standard Leland-type models, the coupon rate is determined to balance the tradeoff between the benefit from tax shields and the cost of financial distress (i.e., the parameter $\nu$). However, the coupon rate in our model also depends on the competitor’s status ($m_{ij,t}$ and $\pi_{ij}$), and thus the scaling property (see, e.g., Goldstein, Ju and Leland, 2001; Chen, 2010) does not apply.

2.7 Competition and Financial Distress

In this subsection, we illustrate the interaction between endogenous product market competition and financial distress. We present three main results. First, there is a positive

\footnote{The value of debt in the non-collusive equilibrium can be calculated similarly.}
feedback loop between competition and financial distress as increased competition leads to more financial distress, which in turn motivates firms to compete more fiercely. Second, there is endogenous defensive predation in the product market as when one firm becomes financially distressed, its competitor lowers product prices, which further increases the firm’s default risk. Third, the debtholders and equity holders of distressed firms are more exposed to aggregate risks. Importantly, the endogenous time-varying competition amplifies risk exposure.

**Feedback Loop.** In Panel A of Figure 1, we plot the firm’s expected one-year default rate (i.e., the probability of default within a year) in different equilibria to study how product market competition affects the firm’s financial distress. In general, the default rate is lower when the firm’s distance to default is higher (i.e., larger $m_{ij,t}$). For a given $m_{ij,t}$, the firm has a lower default rate in the collusive equilibrium (the blue solid line) than in the non-collusive equilibrium (the blue dashed line), because implicit collusion alleviates within-industry competition, allowing firms to set higher prices. We further make a comparison with a monopolistic industry (with a single firm) and a competitive industry (with a continuum of firms). Given the same coupon rate $b_{ij}$, Panel A shows that the firm has the lowest default rate in the monopolistic industry (the black dash-dotted) and the highest default rate in the competitive industry (the red dotted line). Taken together, Panel A indicates that financial distress is more likely to occur with increased competition because competition erodes firms’ profit margins and cash flows.

Panel B plots firm $ij$’s equilibrium price as a function its customer base $m_{ij,t}$ given its competitor’s customer base $m_{i\bar{j},t}$ fixed. Implicit collusion allows the firm to set a higher price in the collusive equilibrium for any customer base $m_{ij,t}$. Consistent with Panel A, the firm is less likely to default in the collusive equilibrium as $m_{ij}^C < m_{ij}^N$. Importantly, the difference between the collusive price (the blue solid line) and the non-collusive price (the black dashed line) is smaller when firm $ij$ is closer to the default boundary (i.e., smaller $m_{ij,t}$), suggesting that financial distress endogenously leads to more competition and lower equilibrium prices. Intuitively, the incentive to collude on higher prices depends on how much firms value future cash flows relative to their contemporaneous cash flows. By deviating from collusive
price-setting schemes, firms can obtain higher contemporaneous cash flows and expand their customer base in the short run; however, firms run into the risk of losing future cash flows because once the deviation is punished by the other firm, non-collusive equilibrium will be implemented. When firm $ij$ is closer to the default boundary, the probability of default increases and the firm is more likely to exit the market in the near future. As a result, firm $ij$ becomes effectively more impatient and values its cash flows in the short run more than those in the long run. This motivates firm $ij$ to undercut its competitor $\bar{j}$’s price, which intensifies price competition. If the two firms were to maintain the collusive equilibrium, the mutually agreed equilibrium prices must fall when firm $ij$ is more distressed to ensure that it does not deviate (i.e., the IC constraints are satisfied).

Our idea echoes and formalizes the important generic insight of Maskin and Tirole (1988a) and Fershtman and Pakes (2000): the tacit collusion among oligopolists arises in industries where each firm expects others to remain in the market for a long time; but if firms are more likely to exit the market in the future, the incentive for collusive behavior becomes weaker. Panel A and B jointly imply a positive feedback loop between price competition and financial distress. Such a feedback loop amplifies default risks because firms would find their profit margins lower exactly when they are more distressed.

**Defensive Predation.** The defensive predatory pricing strategy endogenously emerges in the collusive equilibrium. To fix ideas, consider two firms within the same industry, firm $ij$ is relatively more financially distressed in the sense that it is closer to the default boundary...
than its competitor $\bar{j}$. Given firm $j$’s customer base $m_{ij,t}$ fixed, Panels A and B of Figure 2 illustrate how the two firms would change their equilibrium prices when firm $ij$’s customer base $m_{ij,t}$ varies. In particular, the blue solid line in Panel A shows that firm $ij$’s price is lower when it is closer to the default boundary, due to the distress effect discussed above. The blue solid line in Panel B shows that the competitor $\bar{j}$, which is financially strong, also reduces its equilibrium price when firm $ij$ moves closer to the default boundary. In other words, the financially strong firm chooses to lower its price when the financially weak firm’s financial condition worsens.

Such kind of pricing strategy is termed as defensive predation by Franklin Fisher in his testimony for Microsoft (see Fisher, 2001). Defensive predation refers to the price undercutting strategy whose intention is to protect existing businesses from being snatched by competitors. It is different from the usual (offensive) predation whose intention is to create entry barriers or drive competitors out of the market for monopoly rents, although both strategies feature price undercutting.

In our model, the price undercutting behavior of the financially strong firm $\bar{j}$ is defensive because the intention of setting a lower price is to prevent the financially weak firm $ij$ from deviating the collusive pricing scheme. Intuitively, as firm $ij$ moves closer to the default boundary, its deviation incentive increases. If the financially strong firm $\bar{j}$ were to maintain its price fixed, the IC constraint for firm $ij$ would be violated. As a result, firm $ij$ would undercut firm $\bar{j}$’s price to steal $\bar{j}$’s customer base. Anticipating the increased deviation incentive, firm $\bar{j}$ lowers its price to restore the IC constraint and prevent itself from being hurt by firm $ij$.

Presumably we would not see defensive predation if firm $ij$’s deviation incentive does not increase much when it becomes more financial distressed. To further test the mechanism, we

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16 The concept of defensive predation is originally from zoology. One vivid example is from Tom Ryan about the threat of rattlesnake: “... large animals capable of killing him (the rattlesnake) are inclined to do so as a self-defense measure. A large, hoofed animal like a deer or horse has no interest in eating the rattlesnake, but will trample one if he crosses its path. The rattlesnake is capable of downing large prey like this, so the larger animal will stamp out the snake if he feels threatened.”

17 In a model without new entries, Wiseman (2017) shows that the financially strong firm sets lower prices to drive financially weak firms out of markets to enjoy monopoly rents, formalizing the idea of offensive predation.
solve the model under an alternative ownership structure in which the same shareholders own both firm $i,j$ and the new firm that replaces firm $i,j$ upon its default. Under this alternative specification, firm $i,j$’s shareholders would have less incentive to deviate compared to the baseline model, even when they are closer to the default boundary. This is because shareholders’ continuation value incorporates the potential punishment on the new firm. The black-dashed line in Panel A shows that firm $i,j$ sets a significantly higher price compared to our baseline model. Moreover, there is virtually no defensive predation under this alternative specification. The black-dashed line in Panel B shows that the competitor $\bar{j}$’s price barely decreases when firm $i,j$ becomes more financially distressed. As a result, the default boundary of firm $i,j$ also shifts to the left (the vertical black dotted line), implying lower default risks.

**Financial Distress and Risk Exposure.** The degree of competition in the product market also endogenously varies with the economy’s aggregate condition, captured by the state variable $\theta_t$. In our model, both a lower surplus consumption ratio $s_t$ and a lower persistent growth rate $g_t$ increase the marginal utility of consumption. In the data, the two are highly correlated. Therefore, we can think of recessions as those states with a lower surplus consumption ratio $s_t$ and a lower persistent growth rate $g_t$. As discussed by Dou, Ji and Wu (2019), the qualitative implications of changing $s_t$ and $g_t$ on firms’ collusion decisions are similar. Here, we focus on illustrating the qualitative implications of endogenous competition on firms’ exposure to aggregate risks $\theta_t$ without distinguishing the different quantitative impacts of $s_t$ and $g_t$. 

Figure 2: Illustration of defensive predation in the collusive equilibrium.
Figure 3: Financial distress, exposure to aggregate risks, and amplification.

Panel A of Figure 3 plots firm $ij$’s collusive price in the state $\theta_H$ with high surplus consumption ratio and persistent growth (the blue solid line) and the state $\theta_L$ with low surplus consumption ratio and persistent growth (the black dashed line), given firm $\bar{j}$’s customer base $m_{\bar{i}j}$ fixed. It is shown that when the economy falls into a recession, firms also compete more fiercely and set low collusive prices. The default boundary jumps from $m_{ij}^C = 0.05$ (the vertical blue line) to $m_{ij}^C = 0.1$ (the vertical black line). By contrast, in the non-collusive equilibrium, prices do not vary with macroeconomic conditions (the red dash-dotted line) and default boundaries remain almost unchanged.

Intuitively, higher collusive prices are more difficult to sustain when firms become effectively more impatient, which could be due to high discount rates, as reflected by lower $s_t$, or low persistent growth rates of aggregate consumption, as reflected by lower $g_t$. In both cases, future punishment becomes less threatening because firms care less about cash flows in the long run. As a result, collusive prices decline following negative aggregate shocks, generating endogenous price war risks. The price war risks during economic downturns are further amplified by the feedback loop between competition and financial distress, generating much larger amplification effects for the aggregate risk exposure of both equity holders and debtholders. In particular, the price war risks during economic downturns lower firms’ profit margins, which raises the default risk of levered firms. The rising risk of financial distress makes firms in poor financial conditions compete more aggressively, which further reduces profit margins and increases the risks of financial distress across firms.
We illustrate the exposure to aggregate risks by computing $\beta$s for debtholders and equity holders, defined by

$$
\beta_{ij,\text{debt}}(m_{ij,t}) = \frac{D^C_{ij}(m_{ij,t}, \theta_H)}{D^C_{ij}(m_{ij,t}, \theta_L)} - 1
$$

$$
\beta_{ij,\text{equity}}(m_{ij,t}) = \frac{V^C_{ij}(m_{ij,t}, \theta_H)}{V^C_{ij}(m_{ij,t}, \theta_L)} - 1
$$

The blue solid lines in Panels B and C show that both debtholders and equity holders are more exposed variations in the macroeconomic condition $\theta_t$ when the firm is closer to the default boundary, due to a standard leverage effect. To illustrate the amplification effect of time-varying competition incentives, the black dashed lines plot the exposure in a counterfactual economy where both firms’ prices are unchanged when the macroeconomic condition $\theta_t$ changes. It is shown that without price war risks, both debtholders and equity holders are less exposed to long-run growth shocks. When the firm is closer to the default boundary, the exposure to aggregate risks is amplified by as large as 100%.

3 Empirical Analyses

3.1 Data

In the empirical section, we take firm level accounting data from Compustat, stock return data from CRSP (used in the construction of the distress measure), credit spread data, consumption growth data, and the fluidity data from Hoberg, Phillips and Prabhala (2014). Finance and utility firms are excluded from the analysis, as some of the analyses involves leverage. Unless otherwise noted, at least 10 firms are required in each industry-year to ensure that the aggregate variables, such as industry-year level profit margin, are well-behaved. Throughout the section, the finance distress measure is as in Campbell, Hilscher and Szilagyi (2008). For the analyses below we will look at the “top firms” within an industry-year, as some of theory applies better to that context. Those top firms are firms with the highest sales. All industry-year aggregate variables—profit margin, distress, operating leverage, idiosyncratic shocks, fluidity—are weighted by sales. Across industries, weighting is always equal whether it
Table 1: Industry Distress and Profit Margin Loadings on Consumption Growth

<table>
<thead>
<tr>
<th></th>
<th>1 (Low Distress)</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5 (High Distress)</th>
<th>5 - 1</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\beta$</td>
<td>0.421**</td>
<td>0.284**</td>
<td>0.335*</td>
<td>0.219</td>
<td>-0.650</td>
<td>-1.071*</td>
</tr>
<tr>
<td></td>
<td>[2.34]</td>
<td>[2.12]</td>
<td>[1.96]</td>
<td>[0.98]</td>
<td>[-1.20]</td>
<td>[-1.92]</td>
</tr>
<tr>
<td>Obs</td>
<td>46</td>
<td>46</td>
<td>46</td>
<td>46</td>
<td>46</td>
<td>46</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.098</td>
<td>0.020</td>
<td>0.017</td>
<td>0.007</td>
<td>0.015</td>
<td>0.039</td>
</tr>
</tbody>
</table>

Note: This table reports results from the following annual time-series regressions: $\Delta PM_{i,t} = \alpha_i + \beta_i x_t + \epsilon_{i,t}$. Here, the cross section of industries are sorted into 5 bins based on industry level distress. $\Delta PM_{i,t} = PM_{i,t} - PM_{i,t-1}$, where $PM_{i,t}$ is the average profit margin among industries in bin $i$. $x_t$ is the shock to the 8 quarter average consumption growth rate, computed as the AR1 residuals. Each bin’s profit margin loadings on consumption growth shock, $\beta_i$, are reported in the table. Both profit margin and the consumption growth rate are in fractional unit, and the consumption growth rate is annualized. T-statistics robust to heteroskedasticity and autocorrelation are reported in square brackets.

is aggregation to the bin level or in regression. Variables involving bonds are always weighted by the bonds’ par value. When organizing the cross section of accounting data, we first map fiscal year to calendar year and when applicable, map to market data starting from the June of the next year. This follows the practice of Fama and French (1993).

### 3.2 Empirical Results

**Sensitivity to Consumption Growth Rates** We test our model’s prediction on industries’ loadings on the low frequency component of consumption growth, measured using the eight-quarter moving average of consumption growth rates. Table 1 reports the loadings of the change in industry profit margin on the shock to the consumption growth measure. The cross section of industries are sorted into five bins based on each industry’s aggregate distress level. Average profit margin and its change are then computed for each bin. The loading is then estimated for each bin using time series regressions. The table shows that industries with low distress level have higher loadings than those with high distress level. While this relationship is not monotonic with respect to the bin number, the downward trend from left to the right is clear. The difference in loadings between bin 5 and bin 1 is only marginally statistically significant. However, the economic scale of the difference is large. Both profit margin and the consumption growth rate are in fractional unit, and the consumption growth rate is annualized. The coefficient of 0.421 in column 1 means when 1% increase in annualized consumption growth rate shock corresponds to 0.421% increases in change of profit margin, for the most financially sound industries of the cross section.

Table 2 reports the loadings of firms’ credit spread on the consumption growth rate. Here,
Table 2: Industry Distress and Credit Spread Loadings on Consumption Growth

<table>
<thead>
<tr>
<th></th>
<th>1 (Low Distress)</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5 (High Distress)</th>
<th>5 - 1</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>3</td>
<td>2</td>
<td>1</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>β</strong></td>
<td>-0.181**</td>
<td>-0.165**</td>
<td>-0.312**</td>
<td>-0.278*</td>
<td>-0.387**</td>
<td>-0.206**</td>
</tr>
<tr>
<td></td>
<td>[-2.10]</td>
<td>[-2.20]</td>
<td>[-2.32]</td>
<td>[-1.79]</td>
<td>[-2.22]</td>
<td>[-2.00]</td>
</tr>
<tr>
<td><strong>Panel A: All firms</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>β</strong></td>
<td>-0.137*</td>
<td>-0.160</td>
<td>-0.166</td>
<td>-0.351*</td>
<td>-0.408**</td>
<td>-0.271**</td>
</tr>
<tr>
<td>Obs</td>
<td>181</td>
<td>181</td>
<td>181</td>
<td>181</td>
<td>181</td>
<td>181</td>
</tr>
</tbody>
</table>

Note: This table reports results from the following quarterly time-series regressions: \( \text{Spread}_{i,t} = \alpha_i + \beta_i x_t + \gamma_i \text{OL}_{i,t} + \epsilon_{i,t} \). Here, the cross section of industries are sorted into 5 bins based on industry level distress. \( \text{Spread}_{i,t} \) is the par value weighted average credit spread among firms within bin \( i \). \( x_t \) is the 8 quarter average consumption growth rate ending in quarter \( t \). \( \text{OL}_{i,t} \) is the par-value weighted operating leverage within bin \( i \), where operating leverage is operating cost divided by total asset, as in [Novy-Marx 2011]. Top 6 firms are determined by sales. Annual accounting data of year \( t \) are mapped to credit spread data from Q2 of year \( t+1 \) to Q1 of year \( t+2 \), as in [Fama French 1993]. Each bin’s credit spread loadings on consumption growth, \( \beta_i \), are reported in the table. Credit spread and consumption growth are both in annualized fractional unit. T-statistics robust to heteroskedasticity and autocorrelation are reported in square brackets.

the cross section of firms are sorted into five bins based on the aggregate distress level of their industries. Average credit spread is then computed for each bin, and each bin’s loading on the consumption growth rate is estimated using a time series regression. Overall, the table shows that credit spread have negative loadings on the consumption growth rate, which means that bond prices are on average pro-cyclical. This credit spread loadings then become more negative as the distress level increases. The difference in loadings for bin 1 and 5 is statistically significant. Credit spread and consumption growth are both in annualized fractional unit. The coefficient of -0.181 means that 1% increase in annualized consumption growth rate corresponds to 0.181% decrease in credit spread for firms in the most financially sound industries.

**Spillover effect among top firms** Table 3 tests our model’s prediction on the spillover effect among the industry leaders. The model predicts that idiosyncratic shocks to the distressed firms within an industry will spillover to the financially healthy firms. Additionally, the model predicts that this spillover effect to be larger on industries where the distressed and healthy firms are of comparable sizes. To see the spillover effect, in each year we split the top firms of each industries into 3 bins based on the firms’ distress level, where bin 1 contains the financially healthy firms and bin 3 contains the distressed. We then compute the contemporaneous idiosyncratic shock to each bin. Three methods of computing the idiosyncratic shocks are tried, and the details of their construction are described in Appendix.
Table 3: Spillover Effect among Top Firms and Heterogeneity across Industries

<table>
<thead>
<tr>
<th>Method 1</th>
<th>All</th>
<th>1 (Comparable)</th>
<th>2</th>
<th>3 (Different)</th>
<th>3-1</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>0.035***</td>
<td>0.061***</td>
<td>0.029*</td>
<td>0.022***</td>
<td>0.039**</td>
</tr>
<tr>
<td>[3.61]</td>
<td>[4.02]</td>
<td>[1.96]</td>
<td>[2.03]</td>
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</tr>
<tr>
<td>Method 2</td>
<td>0.037***</td>
<td>0.064***</td>
<td>0.032*</td>
<td>0.021</td>
<td>0.043**</td>
</tr>
<tr>
<td>[3.45]</td>
<td>[5.02]</td>
<td>[1.94]</td>
<td>[1.19]</td>
<td>[2.05]</td>
<td></td>
</tr>
<tr>
<td>Method 3</td>
<td>0.035***</td>
<td>0.061***</td>
<td>0.034**</td>
<td>0.014</td>
<td>0.047***</td>
</tr>
<tr>
<td>[3.48]</td>
<td>[4.61]</td>
<td>[2.12]</td>
<td>[0.89]</td>
<td>[2.08]</td>
<td></td>
</tr>
</tbody>
</table>

Note: This table reports results from the following industry-annual level panel regressions: \( PM_{1i,t} = \alpha + \beta_3 Shock_{3i,t} + \beta_1 Shock_{1i,t} + \sum_{j=1}^{5} \gamma_j PM_{1i,t-j} + \sum_t \delta_t FE_t + \sum_i \rho_i FE_i + \epsilon_{i,t} \). Here, each industry-year is sorted into 3 groups according to the firm’s distress level, where group 1 is the least distressed, and group 3 is the most distressed. \( PM_{1i,t} \) is the profit margin of group 1 of industry \( i \) in year \( t \). \( Shock_{3i,t} \) and \( Shock_{1i,t} \) are the aggregated idiosyncratic shocks to group 3 and group 1 of industry \( i \) in year \( t \), where the idiosyncratic shocks are computed using 3 methods: 1) firm’s sales growth subtracting the cross-sectional average sales growth, 2) time series regression residual of firm’s sales growth on the cross-sectional average sales growth, and 3) time series regression residual of firm’s sales growth on the first PC extracted from a panel of industry level sales growth. \( FE_t \) and \( FE_i \) are time and industry fixed effect. Each bin’s spillover coefficient, \( \beta_3 \), are reported in the first column (ALL). The rest of the columns are the coefficients on the subsamples of the panel split according to the relative size of group 1 and group 3: the first sub-sample includes industries where group 1 and 3 are of the most comparable sizes, while sub-sample 3 contains those where they are the most unbalanced. Results in this table use only the top 6 firms. Idiosyncratic shocks and profit margin are both in fractional unit. T-statistics computed with Driscoll-Kraay standard errors with 5 lags are reported in square brackets.

C.1. We then run the following industry-annual level panel regression:

\[
PM_{1i,t} = \alpha + \beta_3 Shock_{3i,t} + \beta_1 Shock_{1i,t} + \sum_{j=1}^{5} \gamma_j PM_{1i,t-j} + \sum_t \delta_t FE_t + \sum_i \rho_i FE_i + \epsilon_{i,t} \quad (22)
\]

The coefficient \( \beta_3 \) capture effect of bin 3 shock on the profit margin of bin 1, hence measures the spillover effect. Notice group 1’s own idiosyncratic shock, group 1’s past profit margins, the time fixed effects, and the industry fixed effects are controlled for in this regression.

The first column, titled “ALL”, of table 3 shows that the spillover effect is strong and robust to the choice of the specific idiosyncratic risk measure. Both idiosyncratic the shocks and the profit margins are in fractional units. A coefficient of 0.035 means a 100% increase in idiosyncratic shock to the distressed firms’ sales (note all idiosyncratic shocks are sales-based) corresponds to a 3.5% increase in profit margins of the financially sound firms in the same industry-year. In addition to this unconditional spillover effect, the model makes an unique prediction that such spillover effect should be larger when the size of distressed and the healthy are the more comparable, and smaller when the sizes are more unbalanced. To test this prediction, we split the aforementioned panel regression into 3 subsamples based on the absolute value of the log size ratio of bin 1 over bin 3. When bin 1 and bin 3 are of equal size, the absolute value will achieve the theoretical minimum of zero. When bin 1 contains
much larger or smaller firms than those in bin 3, this absolute value will be larger.

Column 2-4 of table 3 report the spillover coefficients for the 3 subsamples. As we can see, the spillover effect is the largest in subsample 1 where the firm sizes are the most comparable, and the smallest when the firm sizes are least comparable. The difference between the coefficient in subsample 1 and 3 are statistically significant. This is consistent with the model’s prediction.

**Volatility and Industry Concentration** In this section we test the model’s prediction that more concentrated industries should see lower volatility in credit spread and profit margin in the future. We measure each industry’s concentration level with the Herfindahl-Hirschman Index. As a crude way to make sure that this measure behaves well, we require at least 6 firms in each industry-year. To measure a firm’s credit spread volatility, we take its monthly credit spread and compute its volatility within the next 12-month. Table 4 regresses each firm’s forward one year credit spread volatility on the firm’s industry’s HHI index, while controlling for the industry’s distress, operating leverage, the firm’s past credit spread volatility, in addition the time and industry fixed effect. The first row of the table shows that firms in more concentrated industries, measured using higher HHI value, sees higher credit spread volatility in the next 12 months. Here both credit spread volatility and HHI are in fractional units. A coefficient of -0.133 means a 0.15 (about the standard deviation of the HHI measure) increase in HHI corresponds to a 2.00% decrease in credit spread volatility.

Table 5 tests a similar prediction on profit margin volatility. For each firm, we compute its quarterly profit margin, and then winsorize at the 5th and 95th percentile values on the panel. This winsorization step is necessary as firm level profit margin can attain very extreme values. We then compute each firm’s profit margin volatility over the next four quarters, and regress it on the industry’s HHI. Controls are similar to those found in table 4. Here, we find that more concentrated industries see lower volatility in profit margin over the next four quarters, consistent with the model’s prediction. Here both profit margin volatility and HHI are in fractional units. A coefficient of -0.030 means a 0.15 (about the standard deviation of the HHI measure) increase in HHI corresponds to a 0.45% decrease in profit margin volatility.
Table 4: Credit Spread Volatility and Heterogeneity across Industries

<table>
<thead>
<tr>
<th></th>
<th>All Firms</th>
<th></th>
<th>Top 6</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Vol_{i,t+1}</td>
<td></td>
<td>Vol_{i,t+1}</td>
<td></td>
</tr>
<tr>
<td>HHI_{i,t}</td>
<td>-0.133**</td>
<td></td>
<td>-0.176***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>[-2.40]</td>
<td></td>
<td>[-3.13]</td>
<td></td>
</tr>
<tr>
<td>Vol_{i,t}</td>
<td>0.364***</td>
<td></td>
<td>0.409***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>[14.89]</td>
<td></td>
<td>[16.84]</td>
<td></td>
</tr>
<tr>
<td>Distress_{i,t}</td>
<td>6.074</td>
<td>4.736</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>[1.62]</td>
<td>0.65</td>
<td></td>
<td></td>
</tr>
<tr>
<td>OL_{i,t}</td>
<td>-0.004</td>
<td>-0.032</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>[-0.28]</td>
<td>[-1.53]</td>
<td></td>
<td></td>
</tr>
<tr>
<td>N</td>
<td>6621</td>
<td>9153</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.439</td>
<td>0.427</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Note: This table reports results from the following firm-annual level panel regressions: $Vol_{i,t+1} = \alpha + \beta_1 HHI_{i,t} + \beta_2 Vol_{i,t} + \beta_3 Distress_{i,t} + \beta_4 OL_{i,t} + \sum_t \delta_t FE_t + \sum_i \rho_i FE_i + \epsilon_{i,t}$. Here, $Vol_{i,t+1}$ the volatility of the monthly credit spread for firm $i$ over year $t+1$. $HHI_{i,t}$, $Distress_{i,t}$, and $OL_{i,t}$ are the Herfindahl-Hirschman Index, the average distress level, and the average operating leverage of the industry of firm $i$ in year $t$. $FE_t$ and $FE_i$ are time and industry fixed effect. The computation of the HHI index requires at least 6 firms in each industry-year. Average within an industry is weighted by sales. The regression is weighted by the bond’s par value. The spread on which we compute the volatility are in annualized, percentage unit. All other variables are in fractional unit. T-statistics computed with Driscoll-Kraay standard errors with 5 lags are reported in square brackets.

Predictive Relationship among Industry Profit Margin, Distress, and Fluidity

Table 6 shows the predictive relationship among profit margin, distress, and competition, as measured by fluidity. The first two columns show that when the industry is distressed this year, it is likely to have lower profit margin in the next year. The next two columns show that when the profit margin of the industry is low, it is likely to have high level distress in the next year. The last two columns show that when the current competition level in the industry is high, the industry is likely to be more distressed in the next year. These results confirm the basic channels of the model. Here, profit margin and distress are in fractional unit, while fluidity are in the original unit as in HPP (2014). The coefficient of -4.274 in the first column means that a 1% increase in distress this year corresponds to a 4.274% decrease in the profit margin of the industry in the next year. The standard deviation of the fluidity measure is about 0.65 and that for the aggregate distress measure is about 0.00044. Hence, a coefficient of 0.0004 in the 5th column means a 1 standard deviation increase fluidity corresponds to 0.65 standard deviation increase in distress level the next year.
### Table 5: Profit Margin Volatility and Heterogeneity across Industries

<table>
<thead>
<tr>
<th></th>
<th>All Firms</th>
<th>Top 6</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$PMVol_{i,t}$</td>
<td>$PMVol_{i,t}$</td>
</tr>
<tr>
<td></td>
<td>$HHI_{i,t}$</td>
<td>$HHI_{i,t}$</td>
</tr>
<tr>
<td></td>
<td>-0.030***</td>
<td>-0.016***</td>
</tr>
<tr>
<td></td>
<td>[-3.50]</td>
<td>[-2.61]</td>
</tr>
<tr>
<td></td>
<td>0.259***</td>
<td>0.180***</td>
</tr>
<tr>
<td></td>
<td>[7.73]</td>
<td>[4.41]</td>
</tr>
<tr>
<td></td>
<td>4.300***</td>
<td>3.671***</td>
</tr>
<tr>
<td></td>
<td>[3.92]</td>
<td>[3.44]</td>
</tr>
<tr>
<td></td>
<td>-0.006</td>
<td>-0.011***</td>
</tr>
<tr>
<td></td>
<td>[-1.55]</td>
<td>[-4.23]</td>
</tr>
<tr>
<td></td>
<td>173,015</td>
<td>46,202</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.168</td>
<td>0.167</td>
</tr>
</tbody>
</table>

Note: This table reports results from the following firm-annual level panel regressions: $PMVol_{i,t+1} = \alpha + \beta_1 HHI_{i,t} + \beta_2 PMVol_{i,t} + \beta_3 Distress_{i,t} + \beta_4 OL_{i,t} + \sum_t \delta_t FE_t + \sum_i \rho_i FE_i + \epsilon_{i,t}$. Here, $Vol_{i,t}$ the volatility of the quarterly winsorized profit margin for firm $i$ over year $t+1$. $HHI_{i,t}$, $Distress_{i,t}$, and $OL_{i,t}$ are the Herfindahl-Hirschman Index, the average distress level, and the average operating leverage of the industry of firm $i$ in year $t$. $FE_t$ and $FE_i$ are time and industry fixed effect. The computation of the HHI index requires at least 6 firms in each industry-year. Average within an industry is weighted by sales. The regression is weighted by the firm’s sale in year $t$. The spread on which we compute the volatility are in annualized, percentage unit. All other variables are in fractional unit. T-statistics computed with Driscoll-Kraay standard errors with 5 lags are reported in square brackets.

### Table 6: Predictive Relationship among Industry Profit Margin, Distress, and Fluidity

<table>
<thead>
<tr>
<th></th>
<th>All Firms</th>
<th>Top 6</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$PM_{i,t}$</td>
<td>$PM_{i,t}$</td>
</tr>
<tr>
<td></td>
<td>$Distress_{i,t}$</td>
<td>$Distress_{i,t}$</td>
</tr>
<tr>
<td></td>
<td>$Fluidity_{i,t}$</td>
<td>$Fluidity_{i,t}$</td>
</tr>
<tr>
<td></td>
<td>4.271**</td>
<td>2.569*</td>
</tr>
<tr>
<td></td>
<td>[-2.13]</td>
<td>[-1.97]</td>
</tr>
<tr>
<td></td>
<td>-0.003***</td>
<td>-0.003***</td>
</tr>
<tr>
<td></td>
<td>[-3.31]</td>
<td>[-2.99]</td>
</tr>
<tr>
<td></td>
<td>0.0004***</td>
<td>0.0003***</td>
</tr>
<tr>
<td></td>
<td>[3.72]</td>
<td>[4.28]</td>
</tr>
<tr>
<td>$N$</td>
<td>4,754</td>
<td>4,754</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.208</td>
<td>0.246</td>
</tr>
</tbody>
</table>

Note: This table reports results from the following industry-annual level panel regressions: $PM_{i,t+1} = \alpha + \beta_1 Distress_{i,t} + \sum_t \delta_t FE_t + \sum_i \rho_i FE_i + \epsilon_{i,t}$. $Distress_{i,t}$ and $Fluidity_{i,t}$ are the average profit margin, the average distress, and the average fluidity of the industry of firm $i$ in year $t$. $FE_t$ and $FE_i$ are time and industry fixed effect. Average within an industry is weighted by sales. All variables are in fractional unit, except for the fluidity, which is taken from Hoberg, Phillips and Prabhala (2014). Instead of 10 firms, 5 are required for an industry-year to be included in the regressions involving fluidity. This is because the fluidity measure has coverage for only a fraction of the sample and the cutoff of 10 will greatly cut our sample size. All other variables are in fractional unit. T-statistics computed with Driscoll-Kraay standard errors with 5 lags are reported in square brackets.

### 4 Quantitative Analyses

#### 4.1 Calibration

We calibrate the model monthly. Some parameters are determined using external information without simulating the model (see Panel A of Table 7). The remaining parameters are calibrated internally from moment matching (see Panel B of Table 7).
### Externally Determined Parameters

For comparison with the classic habit model, we follow Campbell and Cochrane (1999) and choose $g = 0.0189/12$, $\sigma_c = 0.015/\sqrt{12}$, $\phi = 1 - 0.87^{1/12}$. Because of the amplification effect from price war risks, we choose a lower risk aversion $\gamma = 1.3$ to ensure the risk premium is in line with data. We set the lower bound of monthly consumption growth to be $\varsigma = -0.01/12$. We set $\kappa = 0.025$ and $\sigma_g = 0.012/\sqrt{12}$ so that the implied persistence and predictable component of consumption growth are consistent with the calibration of Bansal, Kiku and Yaron (2012). These parameter values ensure that the model-implied consumption process is consistent with the data (see Panel A of Table 8). The within-industry elasticity of substitution is set at $\eta = 15$ and the between-industry elasticity of substitution at $\epsilon = 2$, which are broadly consistent with the values of Atkeson and Burstein (2008). We choose a low depreciation rate $\delta = 0.1/12$ to capture a sticky customer base (see, e.g., Gourio and Rudanko, 2014; Gilchrist et al., 2017). We set the corporate tax rate $\tau = 27\%$ and the idiosyncratic volatility of cash flows $\sigma_M = 0.072$ following He and Milbradt (2014). We set the bond recovery rate at $\nu = 0.41$ based on the mean recovery rate of Baa-rated bonds estimated by Chen (2010).

### Internally Calibrated Parameters

The remaining parameters are calibrated by matching relevant moments in Panel B of Table 8. We run 2,000 independent parallel simulations. Within each simulation, we generate a sample of 500 industries for 150 years according to

---

**Table 7: Calibration and parameter choice.**

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Symbol</th>
<th>Value</th>
<th>Parameter</th>
<th>Symbol</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Panel A: Externally Determined Parameters</strong></td>
<td></td>
<td></td>
<td><strong>Panel B: Internally Calibrated Parameters</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Risk aversion</td>
<td>$\gamma$</td>
<td>1.3</td>
<td>Baseline volatility of growth</td>
<td>$\sigma_c$</td>
<td>0.015/\sqrt{12}</td>
</tr>
<tr>
<td>Persistence of surplus ratio</td>
<td>$\phi$</td>
<td>$1 - 0.87^{1/12}$</td>
<td>Mean consumption growth</td>
<td>$g$</td>
<td>0.0189/12</td>
</tr>
<tr>
<td>Lower bound of growth</td>
<td>$\varsigma$</td>
<td>$-0.01/12$</td>
<td>Persistence of growth</td>
<td>$\kappa$</td>
<td>0.025</td>
</tr>
<tr>
<td>Volatility of persistent growth</td>
<td>$\sigma_g$</td>
<td>0.012/\sqrt{12}</td>
<td>Between-industry elasticity</td>
<td>$\epsilon$</td>
<td>2</td>
</tr>
<tr>
<td>Customer base volatility</td>
<td>$\sigma_M$</td>
<td>0.072</td>
<td>Within-industry elasticity</td>
<td>$\eta$</td>
<td>15</td>
</tr>
<tr>
<td>Corporate tax rate</td>
<td>$\tau$</td>
<td>0.27</td>
<td>Bond recovery rate</td>
<td>$\nu$</td>
<td>0.41</td>
</tr>
<tr>
<td>Customer base depreciation rate</td>
<td>$\delta$</td>
<td>0.1/\sqrt{12}</td>
<td>Persistence of displacement rate</td>
<td>$\chi$</td>
<td>0.0002</td>
</tr>
</tbody>
</table>
Table 8: Moments in the data and model.

<table>
<thead>
<tr>
<th>Moments</th>
<th>Data</th>
<th>Model</th>
<th>Moments</th>
<th>Data</th>
<th>Model</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Panel A: Moments related to consumptions growth</strong></td>
<td></td>
<td></td>
<td>Average consumption growth (%)</td>
<td>1.89</td>
<td>1.90</td>
</tr>
<tr>
<td></td>
<td>[1.51, 2.26]</td>
<td>[1.36, 2.46]</td>
<td>Consumption growth volatility (%)</td>
<td>1.21</td>
<td>1.46</td>
</tr>
<tr>
<td>AR(1) of consumption growth</td>
<td>0.46</td>
<td>0.40</td>
<td>Consumption variance ratio (2)</td>
<td>1.47</td>
<td>1.40</td>
</tr>
<tr>
<td></td>
<td>[0.18, 0.70]</td>
<td>[0.20, 0.59]</td>
<td></td>
<td>[1.10, 1.86]</td>
<td>[1.19, 1.60]</td>
</tr>
<tr>
<td>AR(4) of consumption growth</td>
<td>0.11</td>
<td>0.06</td>
<td>Consumption variance ratio (4)</td>
<td>1.89</td>
<td>1.79</td>
</tr>
<tr>
<td></td>
<td>[−0.20, 0.27]</td>
<td>[−0.18, 0.30]</td>
<td></td>
<td>[0.85, 3.15]</td>
<td>[1.22, 2.41]</td>
</tr>
<tr>
<td>AR(6) of consumption growth</td>
<td>0.05</td>
<td>0.01</td>
<td>Consumption variance ratio (6)</td>
<td>2.21</td>
<td>2.00</td>
</tr>
<tr>
<td></td>
<td>[−0.35, 0.14]</td>
<td>[−0.23, 0.25]</td>
<td></td>
<td>[0.88, 4.00]</td>
<td>[1.11, 2.99]</td>
</tr>
<tr>
<td><strong>Panel B: Other moments</strong></td>
<td></td>
<td></td>
<td>Average real risk-free rate (%)</td>
<td>0.68</td>
<td>0.68</td>
</tr>
<tr>
<td></td>
<td>[−0.21, 1.65]</td>
<td>[0.68, 0.68]</td>
<td>Average net profitability (%)</td>
<td>3.92</td>
<td>3.58</td>
</tr>
<tr>
<td></td>
<td>[−0.21, 1.65]</td>
<td>[0.68, 0.68]</td>
<td>Volatility of real net profits’ growth rates (%)</td>
<td>2.79, 5.09</td>
<td>3.08, 3.99</td>
</tr>
<tr>
<td></td>
<td>0.082</td>
<td>0.085</td>
<td></td>
<td>16.22</td>
<td>12.15</td>
</tr>
<tr>
<td>to profit margins</td>
<td>[0.016, 0.123]</td>
<td>[0.079, 0.090]</td>
<td></td>
<td>[11.11, 19.88]</td>
<td>[9.19, 15.06]</td>
</tr>
<tr>
<td></td>
<td>31.39</td>
<td>26.50</td>
<td>10-yr default probability (%)</td>
<td>4.9</td>
<td>5.2</td>
</tr>
<tr>
<td></td>
<td>[29.98, 33.00]</td>
<td>[21.50, 30.09]</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

the solved policy functions; the first 80 years are dropped as burn-in, and thus we keep a 70-year simulated panel, putting our sample within the ballpark range. We then compute the model-implied moments and adjust parameters until these moments are in line with their values in the data.

We set the subjective discount factor $\beta = 0.0091$ to match the average real risk-free rate between 1948-2017. The marginal cost of production $\omega = 62$ is determined to match the average net profitability. We set the punishment rate $\xi = 0.0075$ to match the average gross profit margin of all industries. The price monitoring effort $\nu$ determines the frequency of full-blown price war. We calibrate $\nu = 0.0011$ to match the volatility of the growth rates of real net profits of all industries. The growth of customer base parameter $\alpha = 0.09$ is set according to match the regression coefficient in Appendix Table C.1, implying that a 1% increase in gross profit margin increases industries’ log asset growth rate by about 0.08%. We set the initial customer base $m_0$ to match the 10-year cumulative default probability of Baa-rated firms.
5 Conclusion

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


He, Zhiguo, and Konstantin Milbradt. 2014. “Endogenous Liquidity and Defaultable Bonds.” Econo-
metrica, 82(4): 1443–1508.


Appendix

A  Model Solutions

A.1  Highest Deviation Value in The Extended Model

Firm $j$’s deviation value $V^D_{ij,t}(x_{ij,t})$ is given by the following HJB equations:

$$0 = \begin{cases} 
\max_{P_{ij,t}} \Lambda_t (1 - \tau) \left[ \Pi_{ij}(P_{ij,t}, P^C_{ij,t}) - b_{ij} \right] dt + \mathbb{E}_t \left[ \frac{d}{dt} \left( \Lambda_t V^D_{ij,t} \right) \right] P_{ij,t} \left| P_{ij,t}, P^C_{ij,t} \right] + \Lambda_t \left( V^N_{ij,t} - V^D_{ij,t} \right) \xi dt, & \text{if } \Gamma_{ij,t} \geq h \text{ for all } j, (III) \\
\max_{P_{ij,t}} \Lambda_t \Pi_{ij}(P_{ij,t}, P^N_{ij,t}) M_{ij,t} dt + \mathbb{E}_t \left[ \frac{d}{dt} \left( \Lambda_t V^D_{ij,t} \right) \right] P_{ij,t} \left| P_{ij,t}, P^N_{ij,t} \right], & \text{otherwise, (IV)}
\end{cases}$$

where $P^N_{ij,t} \equiv P^N_{ij}(x_{i,t})$ with $j = 1, 2$ are the non-collusive prices that solve the maximization problems in (IV), and $V^N_{ij,t} \equiv V^N_{ij}(x_{i,t})$ with $j = 1, 2$ are firm values in the non-collusive equilibrium.

A.2  Boundary Condition at $m_{ij,t} = +\infty$

When $m_{ij,t} = +\infty$, firm $ij$ is essentially a monopoly in industry $i$ with negligible default rate because $m_{ij,t}/m^*_j = +\infty$ for any given $m^*_j$. Thus, the boundary condition of firm $ij$’s shareholder value at $m_{ij,t} = +\infty$ should satisfy:

$$\frac{\partial}{\partial m_{ij,t}} V^N_{ij}(x_{i,t}) \bigg|_{m_{ij,t}=+\infty} = \frac{\partial}{\partial m_{i,t}} U(m_{i,t}, \theta_t) \bigg|_{m_{i,t}=+\infty}, \quad (23)$$

where $U(m_{i,t}, \theta_t)$ is the shareholder value of an unlevered monopoly industry $i$ which has a single firm with customer base $m_{i,t}$. In this monopoly industry, the demand curve facing the single firm is

$$C_{i,t} = P^{-\epsilon}_{i,t} m_{i,t}, \quad (24)$$

and the evolution of the single firm’s customer base $m_{i,t}$ is

$$\frac{dm_{i,t}}{m_{i,t}} = \frac{dM_{i,t}}{M_{i,t}} + \frac{dC_{i,t}}{C_{i,t}} = \alpha \frac{P_{ij,t} - \omega}{P_{ij,t}} dt + (g_t - \delta) dt + \sigma dZ_{i,t} + \sigma c dZ_{c,t}. \quad (25)$$

Thus, the HJB equation that determines $U_i(m_{i,t}, \theta_t)$ can be written as

$$0 = \max_{P_{i,t}} \Lambda_t (1 - \tau) (P_{i,t} - \omega) P^{-\epsilon}_{i,t} m_{i,t} dt + \mathbb{E}_t \left[ d(\Lambda_t U_i(m_{i,t}, \theta_t)) \right]. \quad (26)$$

The boundary condition of firm $ij$’s debt value at $m_{ij,t} = +\infty$ is the value of a default-free consol bond, which has value $\pi b(\theta_t)$, with $b(\theta_t)$ given by

$$b(\theta_t) = \mathbb{E}_t \left[ \int_t^\infty \frac{A_s}{\Lambda_t} ds \right]. \quad (27)$$

34
A.3 Monopolistic and Competitive Industries

Although our model focuses on duopoly industries with two firms competing for customer base, we can also analyze the implications in monopolistic and competitive industries using a similar framework.

**Monopolistic Industry.** Consider a monopolistic industry with a single firm $ij$. The demand for firm $ij$’s good is obtained by setting $P_{i,t} = P_{ij,t}$ in equation (28):

$$C_{ij,t} = P_{ij,t}^{-\epsilon} m_{ij,t}. \quad (28)$$

Thus, in the monopolistic industry, the firm’s price elasticity of demand is determined by the between-industry elasticity of substitution $\epsilon$. The firm’s operating profit is given by

$$b_{ij}(P_{ij,t}) = (P_{ij,t} - \omega) P_{ij,t}^{-\epsilon} m_{ij,t}. \quad (29)$$

When $z = 0$, the optimal price chosen by the firm is $P_{ij,t} = \frac{\epsilon}{\epsilon - 1} \omega$, which implies that the equilibrium operating profit is

$$b_{ij}^* = \left( \frac{\epsilon}{\epsilon - 1} - 1 \right) \omega \left( \frac{\epsilon \omega}{\epsilon - 1} \right)^{-\epsilon} m_{ij,t}. \quad (30)$$

**Competitive Industry.** Consider a competitive industry with a continuum of firms. The demand for each firm’s good is determined by

$$C_{ij,t} = \left( \frac{P_{ij,t}}{P_{i,t}} \right)^{-\eta} P_{i,t}^{-\epsilon} m_{ij,t}, \quad (31)$$

where $P_{i,t}$ is

$$P_{i,t} = \left[ \int_{j \in \mathcal{F}} \left( \frac{m_{ij,t}}{m_{i,t}} \right)^{\eta} P_{ij,t}^{1-\eta} \text{d}j \right]^{\frac{1}{1-\eta}}. \quad (32)$$

The key difference between the price index (31) of a duopoly industry and the price index (32) of a competitive industry is that for the latter, each firm is atomistic and takes the price index $P_{i,t}$ as exogenously given when choosing $P_{ij,t}$.

When $z = 0$, the optimal price chosen by any firm $ij$ is $P_{ij,t} = \frac{\eta}{\eta - 1} \omega$. Thus, the competitive industry’s price index is $P_{i,t} = \frac{\eta}{\eta - 1} \omega$. In equilibrium, firm $ij$’s operating profit is

$$b_{ij}^* = \left( \frac{\eta}{\eta - 1} - 1 \right) \omega \left( \frac{\eta \omega}{\eta - 1} \right)^{-\epsilon} m_{ij,t}. \quad (33)$$

B Numerical Algorithm

TBA
C Supplementary Empirical Results

C.1 Construction of Industry-Level Shocks

Method 1:

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

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

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

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

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

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

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

Method 2:

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

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

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

Method 3:

(i) Aggregate the winsorized firm-year level sales growth to industry-year level.

(ii) Over the 50 year of 1968 to 2017, drop those industries with less than 45 non-missing sales growth measures.

(iii) For the remaining industry-year, replace missing sales growth with the cross sectional average sales growth among the available industry-year sales growths.

(iv) Extract the first principal component from the panel of industry-year level sales growth.

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

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

C.2 Industry Asset Growth and Gross Profitability
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<tbody>
<tr>
<td>$\ln(\text{asset}<em>{i,t+1}/\text{asset}</em>{i,t})$</td>
<td>0.057***</td>
<td>0.063***</td>
<td>0.066***</td>
<td>0.065***</td>
<td>0.064***</td>
<td>0.068***</td>
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<td>$\ln(\text{number of firms})_{i,t}$</td>
<td>0.024***</td>
<td>0.018***</td>
<td>0.030***</td>
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<td>[3.867]</td>
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<tr>
<td>$\ln(\text{sales})_{i,t}$</td>
<td>−0.032***</td>
<td>−0.024***</td>
<td>−0.055***</td>
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<td>0.059</td>
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<td>0.096</td>
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</table>

Note: This table shows the relation between asset growth rate and gross profitability. Standard errors are clustered at both the industry and year levels. The sample spans from 1950 to 2017. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.