Equilibrium Asset Pricing with Price War Risks

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Abstract

We develop a general-equilibrium asset pricing model incorporating dynamic supergames of price competition. Price war risks can rise endogenously due to declines in long-run consumption growth, because firms become effectively more impatient for cash flows and their incentives to undercut prices are stronger. The triggered price war risks amplify the initial shocks in long-run growth by narrowing profit margins and discouraging customer base development. In the industries with higher capacities of radical innovation, incentives of price undercutting are less responsive to persistent growth shocks, and thus firms are more immune to price war risks and thus long-run risks. Exploiting detailed patent, product price, brand-perception survey, and Factiva news data, we find evidence for price war risks, which are significantly priced. Our results shed new light on how long-run risks are priced in time series and cross section through the forward-looking industry competition.

Keywords: Profit margins, Long-run risks, Oligopoly, Innovation similarity, Deep habits, Forward-looking competition, Self-fulfilling Regime Switching. (**JEL**: G1, G3, O3, L1)

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1 Introduction

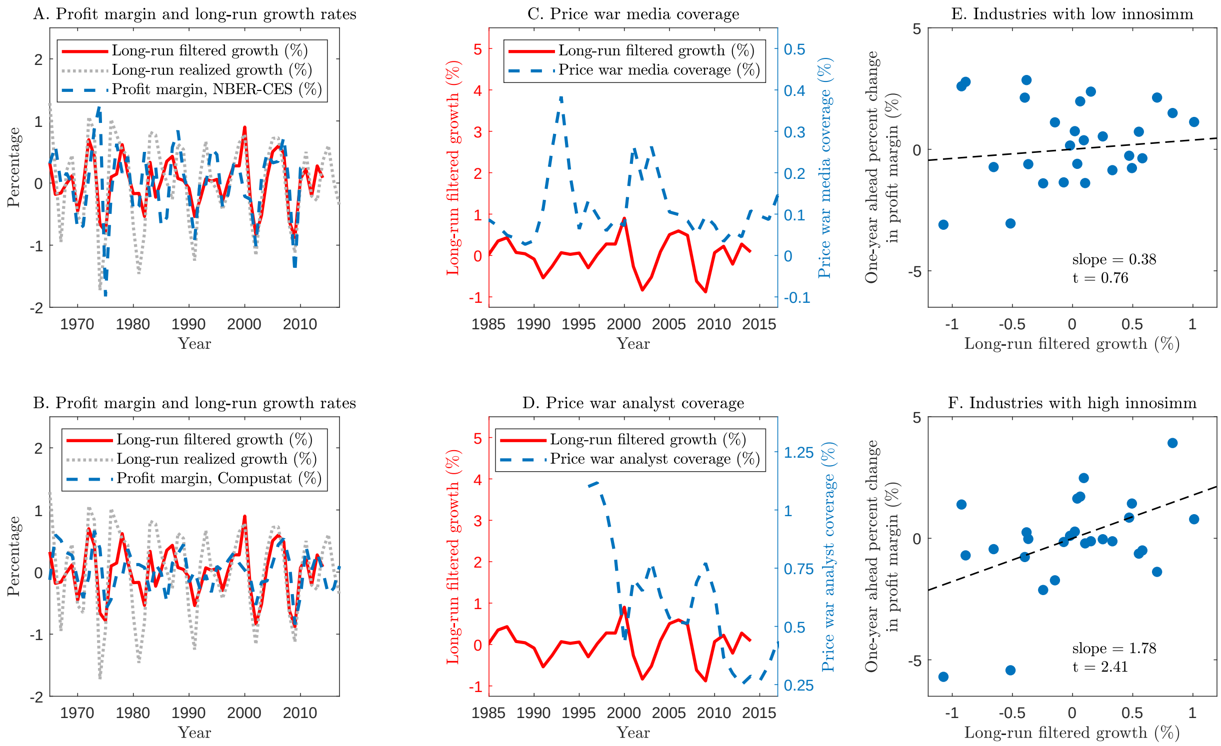
A price war refers to the situation in which rival firms fiercely undercut prices to gain market shares. Price war risks are vital and concern investors, partly because product markets are highly concentrated, featuring rich strategic competition among leading firms (see, e.g. Autor et al., 2017; Loecker and Eeckhout, 2017).[1] According to the U.S. Census data, the top four firms within each 4-digit SIC industry account for about 48% of the industry's total revenue (see Appendix Figure C.6), and the top eight firms own over 60% market shares. However, little is known about how price war risks systematically affect asset prices. This paper is the first to study endogenous price war risks and its asset pricing implications.

We document three stylized facts that motivate our study. First, there is a significant co-movement between aggregate profit margins of firms and long-run consumption growth rates (Panel A and B of Figure 1).[2] This comovement cannot be explained by the sales composition changes across industries because we plot the average profit margins across industries in Panel A and B. Second, price war coverage in the media and analyst reports spikes up during periods with low long-run consumption growth rates (Panel C and D). These two stylized facts together suggest that there is a systematic component in price war risks. Third, the pattern that long-run consumption growth predicts one-year-head profit margins is more pronounced in industries with low capacities of radical innovation (Panels E and F). These empirical findings raise three relevant questions. What fundamentally drives price war risks at the aggregate level? How are the heterogeneous exposure to price war risks determined across industries? To what extent can the equity premium be attributed to firms' exposure to price war risks?

Our paper takes the first step to answer these three questions. First, we develop a model which implies that persistent consumption growth shocks (as in Bansal and

[1] There has been extensive and constant media coverage on the implications of price war risks on stock returns. We list a few of headline quotes in Appendix A.

[2] We focus on the co-movement between long-run consumption growth rates and profit margins, instead of product markups, because profit margins are directly related to price war risks. Our stylized fact is consistent with the literature, which suggests that profit margins are strongly procyclical (see, e.g. Machin and Van Reenen, 1993; Hall, 2012; Anderson, Rebelo and Wong, 2018). Although markups and profit margins are related, the empirical evidence on the cyclicality of markups is mixed, primarily because measuring markups is challenging (Blanchard, 2009; Anderson, Rebelo and Wong, 2018). For example, Domowitz, Hubbard and Petersen (1986), Nekarda and Ramey (2011, 2013), Hall (2014), and Braun and Raddatz (2016) find that markups are procyclical. Bils (1987) and Chevalier and Scharfstein (1996) find markups are countercyclical.



Note: Panel A and Panel B plot the yearly time series of aggregate profit margins (simple average across 4-digit SIC industries) and long-run growth rates of consumption, filtered by an HP filter with the smoothing parameter equal to 6.25 (Ravn and Uhlig, 2002). Panel C and Panel D plot the price war media coverage and analyst coverage. Panels E and F plot long-run growth rates (annualized based on filtered consumption growth in the last quarter of the year) against the one-year ahead percent change in Compustat-based profit margins in industries with low (i.e. bottom tertile) and high (i.e. top tertile) values of innosimm. Innosimm is a measure of industry-level innovation similarity (Jaffe, 1986; Bloom, Schankerman and Van Reenen, 2013, see Section 4.1 for its construction). An industry has a low capacity of radical or distinctive innovation if rival firms conduct similar innovation (i.e. high values of innosimm). Long-run growth rates of consumption in year t are measured by: (1) the average realized consumption growth in year t and year $t-1$, and (2) the consumption growth filtered by a Bayesian mixed-frequency approach as in Schorfheide, Song and Yaron (2018). Two measures of profit margins are constructed using Compustat and NBER-CES Manufacturing Industry Database. We follow Anderson, Rebelo and Wong (2018) to construct Compustat-based profit margins. Specifically, in each 4-digit SIC industry i and year t, profit margins are computed as $(\text{Sales}_{i,t} - \text{COGS}_{i,t})/\text{Sales}_{i,t}$, where $\text{Sales}_{i,t}$ and $\text{COGS}_{i,t}$ are industry i's total sales and costs of goods sold based on firms in Compustat. Following Domowitz, Hubbard and Petersen (1986) and Allayannis and Ihrig (2001), we compute NBER-CES-based profit margins as $(\text{Value of shipments}_{i,t} + \Delta\text{Inventory}_{i,t} - \text{Payroll}_{i,t} - \text{Cost of material}_{i,t})/(\text{Value of shipments}_{i,t} + \Delta\text{Inventory}_{i,t})$. We measure price war media coverage and analyst coverage using textual analysis. We follow Baker, Bloom and Davis (2016) and quantify the prevalence of price wars using the targeted search approach, which is a simplest but at the same time the most powerful approach in textual analysis (see, Loughran and McDonald, 2016). Specifically, the price war media coverage (in percent) is the number of articles that contain the term "price war" or "price wars" normalized by the number of articles published in the Wall Street Journal, the New York Times, and the Financial Times. We consider articles covering the US region, obtained from the Dow Jones Factiva. The price war analyst coverage (in percent) is the number of analyst reports that contain the term "price war" or "price wars" normalized by the number of analyst reports. We consider analyst reports covering the US region, obtained from Thomson ONE Investext. Following Huang, Zang and Zheng (2014), we plot the price war analyst coverage after 1996, because the coverage for the full text of analyst reports is limited before 1996. We list a few of examples of analyst reports in Appendix B.

Figure 1: Profit margins, price wars, and long-run growth rates.

Yaron, 2004) can drive price war risks. Second, in the model and the data, we show that firms' exposure to price war risks and thus long-run risks are higher if they are in the industry with a lower capacity of radical innovation. Our results shed new light on how long-run risks are priced in the cross section (see, e.g. Bansal, Dittmar and Lundblad, 2005; Hansen, Heaton and Li, 2008; Bansal, Dittmar and Kiku, 2009; Malloy, Moskowitz and Vissing-Jørgensen, 2009; Koijen et al., 2010; Constantinides and Ghosh, 2011; Ai, Croce and Li, 2013; Kung and Schmid, 2015; Bansal, Kiku and Yaron, 2016; Dittmar and Lundblad, 2017). Third, we use the calibrated model to quantify the impact of price war risks. The model implies that about $30\% - 40\%$ of the equity premium explained by long-run risks is attributed to price war risks.

Theoretically, what is a price war? A full-blown price war is a non-collusive price competition, which serves as an enforcement device to sustain implicit collusion on prices (see, e.g. Friedman, 1971; Green and Porter, 1984; Porter, 1985; Abreu, Pearce and Stacchetti, 1986; Athey, Bagwell and Sanchirico, 2004; Sannikov and Skrzypacz, 2007). More broadly, a price war can also be a collusive price competition in which prices drop due to self-fulfilling declines in market power, not just initial demand declines (see, e.g. Rotemberg and Saloner, 1986; Lambson, 1987; Haltiwanger and Harrington, 1991). As profit margins are narrowed sufficiently, a full-blown price war will be triggered in the equilibrium, featuring a regime shift from a collusive competition equilibrium to a non-collusive competition equilibrium. Thus, price war risks are also inherently related to the jump risks from the collusion regime to the non-collusion regime.

We study price war risks by developing a general-equilibrium asset pricing model incorporating dynamic supergames of price competition among firms. Our baseline model deviates from the standard long-run-risk model (Bansal and Yaron, 2004) mainly in two aspects: (1) consumers have deep habits (see Ravn, Schmitt-Grohe and Uribe, 2006) over firms' products, and thus firms need to maintain their customer base; and (2) there are a continuum of industries and each industry features dynamic Bertrand oligopoly with differentiated products and implicit price collusion (Tirole, 1988, Chapter 6).[3]

In our baseline model, oligopolies can implicitly collude with each other on setting high product prices and obtaining high profit margins.[4] Given the implicit collusive prices, a firm can boost up its short-run revenue by secretly undercutting prices to attract

[3]Tirole (1988, Chapter 6) builds oligopoly models with Bertrand price competition and obtains similar price war implications as in the models of Cournot quantity competition (Green and Porter, 1984; Rotemberg and Saloner, 1986).

[4]Even 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.

more customers; however, deviating from collusive prices may reduce revenue in the long run if the price undercutting behavior is detected and punished by the firm's peers. 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' tradeoff between short-term and long-term cash flows. In other words, higher collusive prices are more difficult to sustain when the long-run growth rate is lower, because future punishment becomes less threatening when firms expect a persistent decline in aggregate consumption demand. As a result, collusive prices decline following negative long-run-growth shocks, increasing the risk of entering a full-blown price war. With large negative long-run-growth shocks, collusive prices decline significantly, making the benefit of collusion exceed its cost. As a result, firms optimally abandon collusion and the industry falls into the non-collusive equilibrium—a full-blown price war occurs. Importantly, price wars amplify the initial shocks in long-run growth by further narrowing down profit margins and discouraging customer base development.

Our theory sheds new light on industries' heterogeneous exposure to price war risks and thus long-run risks. In the model and the data, we show that firms in the industries with higher capacities of radical innovation (e.g. Jaffe, 1986; Christensen, 1997; Manso, 2011; Kelly et al., 2018) are more immune to price war risks. The capacity of radical innovation is a fundamental, persistent, and predictable industry characteristic. Intuitively, a successful radical innovation produces products sufficiently distinctive from existing products, allowing firms to disrupt the market and rapidly grab substantial market shares. A prominent recent example is from Apple, a company that disrupted the mobile phone market by cobbling together an amazing touch screen with user-friendly interface. Thus, in the industries with higher capacities of radical innovation, the market structure is more likely to experience dramatic changes and become highly concentrated in the future. This implies that firms in such industries would find it more difficult to implicitly collude with each other, because they all rationally expect that the product market is likely to be monopolized in the future, rendering future punishment on price undercutting less threatening. As a result, these industries feature low implicit collusive prices regardless of long-run growth rates, generating much less variation in product prices over long-run growth fluctuations. By contrast, in the industries with lower capacities of radical innovation, the market structure is relatively stable, making a costly future punishment more credible. As a result, firms have stronger incentives for implicit price collusion, and rationally focus on maintaining existing customer base and profit margins. However, because firms collude on higher prices in these industries, the equilibrium collusive prices become more sensitive to the fluctuations in firms' collusion incentives, which are fundamentally driven by long-run-risk shocks. Hence, these industries are more exposed to price war risks and long-run risks.

Our model has the following main implications. First, profit margins are more sensitive to long-run-risk shocks during periods with low long-run consumption growth rates. Second, in the industries where the capacity of radical innovation is lower, profit margins are higher and more sensitive to long-run consumption growth shocks. Third, in these industries, the exposure to long-run risks and (risk-adjusted) expected excess returns are higher.

We test these predictions using detailed data on patents and product prices. We first construct an innovation similarity measure based on U.S. patenting activities from 1976 to 2017 to capture the capacity of radical or distinctive innovation across industries. In light of previous studies (e.g. Jaffe, 1986; Bloom, Schankerman and Van Reenen, 2013), our innovation similarity measure is constructed based on the technology classifications of firms' patents within industries. An industry is associated with a higher innovation similarity measure, if the patents produced by firms within the industry have more similar technology classifications. Thus, intuitively, an industry with a higher innovation similarity measure should have a lower capacity of radical or distinctive innovation.

Consistent with our theory, we find that the aggregate profit margins co-move positively with long-run-risk shocks. Moreover, the sensitivity of aggregate profit margins with respect to long-run risk shocks is higher in recessions. In the cross section, we show that profit margins of the industries with lower capacities of radical innovation are more exposed to long-run-risk shocks. We further examine the sensitivity of product prices to long-run-risk shocks by exploiting a dataset that contains detailed product-level data. We find that product prices are more exposed to price war risks in industries with lower capacities of radical innovation. In particular, our event-type study shows that these industries were more likely to engage in price wars in response to the Lehman crash in September of 2008, a time period in which the U.S. economy experienced a prominent negative long-run-risk shock according to the estimation of Schorfheide, Song and Yaron (2018). Finally, we test the asset pricing implications of our model. We find that industries' capacities of radical innovation are priced in the cross section of industry returns. In particular, industries with lower capacities of radical innovation are associated with higher (risk-adjusted) expected excess returns. The stock returns and dividend growth of these industries are more exposed to long-run risks.

Related Literature. Our paper contributes to the literature on long-run risks (see, e.g. Bansal and Yaron, 2004; Bansal, Dittmar and Lundblad, 2005; Hansen, Heaton and Li, 2008; Malloy, Moskowitz and Vissing-Jørgensen, 2009; Ai, 2010; Chen, 2010; Koijen et al., 2010; Constantinides and Ghosh, 2011; Bansal, Kiku and Yaron, 2012; Gârleanu, Panageas and Yu, 2012; Croce, 2014; Kung and Schmid, 2015; Bansal, Kiku and Yaron, 2016; Dittmar and Lundblad, 2017; Schorfheide, Song and Yaron, 2018). Our main contribution is to show that price war risks can endogenously arise from long-run risks, generating a novel amplification mechanism. Moreover, we shed new light on the cross-sectional implication of long-run risks based on industries' capacities of radical innovation.

Our paper contributes to the burgeoning literature on the intersection between industrial organization, marketing and finance (see, e.g. Phillips, 1995; Kovenock and Phillips, 1997; Allen and Phillips, 2000; Hou and Robinson, 2006; Carlin, 2009; Aguerrevere, 2009; Hoberg and Phillips, 2010; Hackbarth and Miao, 2012; Carlson et al., 2014; Hackbarth, Mathews and Robinson, 2014; Hoberg, Phillips and Prabhala, 2014; Bustamante, 2015; Weber, 2015; Hoberg and Phillips, 2016; Loualiche, 2016; Bustamante and Donangelo, 2017; Corhay, 2017; Corhay, Kung and Schmid, 2017; Andrei and Carlin, 2018; D'Acunto et al., 2018; Dong, Massa and Zaldokas, 2018; Yang, 2018; Dou and Ji, 2018; Dou et al., 2018; Hackbarth and Taub, 2018; Roussanov, Ruan and Wei, 2018).[5] In a closely related paper, Corhay, Kung and Schmid (2017) develop a novel general equilibrium production-based asset pricing model to understand the endogenous relation between markups and stock returns in the presence of firms' static strategic competition. Their model implies that industries with higher markups are associated with higher expected returns. Our model yields a similar implication through firms' dynamic strategic competition. We show that industries with lower capacities of radical innovation have higher equilibrium product prices and are more exposed to price war risks and long-run risks. Theoretically, our paper pushes forward the literature by developing a general-equilibrium model

[5]There is also a strand of the literature that studies the asset pricing implications of imperfect competition in the market micro-structure setting (see, e.g. Christie and Schultz, 1994; Biais, Martimort and Rochet, 2000; Liu and Wang, 2018).

incorporated with dynamic supergames, in which price war risks arise endogenously and industry competition is endogenously connected to fundamental long-run risks in consumption growth.

Our paper is also related to a growing literature that studies the implications of innovation on asset prices (see, e.g. Li, 2011; Gârleanu, Kogan and Panageas, 2012; Gârleanu, Panageas and Yu, 2012; Hirshleifer, Hsu and Li, 2013; Kung and Schmid, 2015; Kumar and Li, 2016; Hirshleifer, Hsu and Li, 2017; Kogan et al., 2017; Corhay, Kung and Schmid, 2017; Dou, 2017; Fitzgerald et al., 2017; Kogan, Papanikolaou and Stoffman, 2018; Kogan et al., 2018). One of the key results from Corhay, Kung and Schmid (2017) is that the extensive and intensive margins of innovation endogenously drive volatility risks and long-run risks, deepening our understanding of the economic origins of the fluctuations in risk premia. Our model abstracts away from the growth effect of innovation and focus on the strategic customer base stealing effect of innovation. We contribute to this literature by showing that industries with higher capacities of radical innovation are less exposed to price war risks and associated with lower (risk-adjusted) expected excess returns. Importantly, we emphasize that the capacity of radical innovation provides forward-looking information on the degree of competition in the product market, complementing the traditional static measures of competition such as Herfindahl-Hirschman Index (HHI) and the product similarity measure.

Our paper also contributes to the macroeconomics and industrial organization literature on implicit collusion and price wars in dynamic oligopoly industries (see Stigler, 1964; Green and Porter, 1984; Rotemberg and Saloner, 1986; Haltiwanger and Harrington, 1991; Rotemberg and Woodford, 1991; Staiger and Wolak, 1992; Bagwell and Staiger, 1997; Athey, Bagwell and Sanchirico, 2004; Opp, Parlour and Walden, 2014). We make several contributions to this literature. First, we analyze the asset pricing implications of price war risks. Second, we show that, in the model and the data, the exposure to price war risks varies across industries with different capacities of radical innovation.

Finally, our paper lies in the cross-sectional asset pricing literature (see, e.g. Cochrane, 1991; Berk, Green and Naik, 1999; Gomes, Kogan and Zhang, 2003; Pastor and Stambaugh, 2003; Ait-Sahalia, Parker and Yogo, 2004; Lustig and Van Nieuwerburgh, 2005; Nagel, 2005; Yogo, 2006; Campbell, Hilscher and Szilagyi, 2008; Livdan, Sapriza and Zhang, 2009; Gomes and Schmid, 2010; Garlappi and Yan, 2011; Belo and Lin, 2012; Ai and Kiku, 2013; Kogan and Papanikolaou, 2013; Belo, Lin and Bazdresch, 2014; Donangelo, 2014; Kogan and Papanikolaou, 2014; Hackbarth and Johnson, 2015; Herskovic et al., 2016; Tsai and

Wachter, 2016; Koijen, Lustig and Nieuwerburgh, 2017; Kozak, Nagel and Santosh, 2017; Ai et al., 2018; Belo, Lin and Yang, 2018; Gomes and Schmid, 2018; Gu, Hackbarth and Johnson, 2018). A comprehensive survey is provided by Nagel (2013). We show that the exposure to price war risks varies across industries with different capacities of radical innovation. Our paper is particularly related to the works investigating the cross-sectional stock return implications of firms' fundamental characteristics through intangible capital (see, e.g. Ai, Croce and Li, 2013; Eisfeldt and Papanikolaou, 2013; Belo, Lin and Vitorino, 2014; Dou et al., 2018).

2 The Baseline Model

The economy contains a continuum of industries indexed by $i \in \mathcal{I} \equiv [0, 1]$. Each industry i is a duopoly, consisting of two all-equity firms that are indexed by $j \in \mathcal{F} \equiv \{1, 2\}$. We label a generic firm by ij and its competitor in industry i by $i\bar{j}$. All firms are owned by a continuum of atomistic homogeneous households. Firms produce differentiated goods and set prices strategically to maximize shareholder value.

2.1 Preferences

Households are homogeneous and have stochastic differential utility of Duffie and Epstein (1992*a*,*b*), defined recursively as follows:

$$U_0 = \mathbb{E}_0 \left[\int_0^\infty f(C_t, U_t) \mathrm{d}t \right], \tag{2.1}$$

where

$$f(C_t, U_t) = \beta U_t \frac{1-\gamma}{1-1/\psi} \left[\frac{C_t^{1-1/\psi}}{[(1-\gamma)U_t]^{\frac{1-1/\psi}{1-\gamma}}} - 1 \right]. \tag{2.2}$$

This preference is a continuous-time version of the recursive preferences proposed by Kreps and Porteus (1978), Epstein and Zin (1989), and Weil (1990). The felicity function $f(C_t, U_t)$ is an aggregator over current consumption rate C_t of the final consumption good and future utility level U_t. The coefficient β is the rate parameter of time preference, γ is the relative risk aversion parameter for one-period consumption, and ψ is the parameter of elasticity of intertemporal substitution (EIS) for deterministic consumption paths.

The final consumption good C_t is obtained through a two-layer aggregation. Following the functional form of *relative deep habits* developed by Ravn, Schmitt-Grohe and Uribe (2006)[6], industry i's composite is determined by the aggregation of firm-level differentiated goods

$$C_{i,t} = \left[\sum_{j \in \mathcal{F}} \left(\frac{M_{ij,t}}{M_{i,t}} \right)^{\frac{1}{\eta}} C_{ij,t}^{\frac{\eta-1}{\eta}} \right]^{\frac{\eta}{\eta-1}}, \tag{2.3}$$

where the parameter $\eta > 1$ captures the elasticity of substitution among the goods produced in the same industry. $M_{ij,t}/M_{i,t}$ captures the relative deep habits of firm j in industry i, where $M_{i,t}$ is defined as $M_{i,t} = \sum_{j \in \mathcal{F}} M_{ij,t}$.

Further, the demand for the final consumption good C_t is determined by the aggregation of industry composites

$$C_t = \left(\int_0^1 M_{i,t}^{\frac{1}{\epsilon}} C_{i,t}^{\frac{\epsilon-1}{\epsilon}} \mathrm{d}i \right)^{\frac{\epsilon}{\epsilon-1}}, \tag{2.4}$$

where the parameter $\epsilon > 1$ captures the elasticity of substitution among industry composites. Consistent with the literature (see, e.g. Atkeson and Burstein, 2008; Corhay, Kung and Schmid, 2017), we assume that $\eta \geq \epsilon > 1$, meaning that products within the same industry are more similar to each other and thus the within-industry elasticity of substitution is higher than the between-industry elasticity of substitution. For example, the elasticity of substitution between Apple iPhone and Samsung Galaxy is higher than the elasticity of substitution between Apple iPhone and Dell Desktop.

2.2 Customer Base and Its Dynamics

A firm's customer base determines the demand for the firm's goods, and it exists due to consumers' habits in consumption. Below, we make the connection between customer base and habits clear by deriving the firm's demand curve.

[6]The specification of relative deep habits is inspired by the habit formation of Abel (1990), which features *catching up with the Joneses*. The habit formation arises endogenously from the pecuniary externality of the competition over scarce resources (DeMarzo, Kaniel and Kremer, 2007, 2008). The key difference between the formation of relative deep habits and the formation of habits is that with relative deep habits, agents form habits over individual varieties of goods as opposed to over a composite consumption good.

Demand Curves. Let $P_{i,t}$ denote the price of industry i's composite. Given $P_{i,t}$ and C_t, solving a standard expenditure minimization problem gives the demand for industry i's composite:

$$C_{i,t} = \left(\frac{P_{i,t}}{P_t}\right)^{-\epsilon} C_t M_{i,t}, \tag{2.5}$$

where P_t is the price index for the final consumption good, given by

$$P_t = \left(\int_0^1 M_{i,t} P_{i,t}^{1-\epsilon} \mathrm{d}i\right)^{\frac{1}{1-\epsilon}}. \tag{2.6}$$

Without loss of generality, we normalize $P_t \equiv 1$ so that the final consumption good is the numeraire. Next, given $C_{i,t}$, the demand for firm j's good is:

$$C_{ij,t} = \left(\frac{P_{ij,t}}{P_{i,t}}\right)^{-\eta} P_{i,t}^{-\epsilon} C_t M_{ij,t}, \quad \text{with } j = 1, 2. \tag{2.7}$$

where $P_{i,t}$ is given by

$$P_{i,t} = \left[\sum_{j \in \mathcal{F}} \left(\frac{M_{ij,t}}{M_{i,t}}\right) P_{ij,t}^{1-\eta}\right]^{\frac{1}{1-\eta}}. \tag{2.8}$$

In equation (2.7), the demand for firm j's goods increases with $M_{ij,t}$. Thus, we can think of $M_{ij,t}$ as capturing firm j's customer base in industry i and $M_{i,t}$ as capturing industry i's total customer base. Moreover, according to equation (2.8), firm j has more influence on the industry's price index $P_{i,t}$ when there are higher relative deep habits $M_{ij,t}/M_{i,t}$ toward firm j's goods. Thus, in our model, firm j would naturally have the incentive to accumulate the customer base $M_{ij,t}$ in order to increase demand and gain market power.

Effective Short-Run Price Elasticity. The effective price elasticity of firm j in industry i is

$$\begin{aligned}
\frac{\partial \ln C_{ij,t}}{\partial \ln P_{ij,t}} &= \underbrace{s_{ij,t} \frac{\partial \ln C_{i,t}}{\partial \ln P_{i,t}}}_{\text{between-industry}} + \underbrace{(1 - s_{ij,t}) \frac{\partial \ln(C_{ij,t}/C_{i,t})}{\partial \ln(P_{ij,t}/P_{i,t})}}_{\text{within-industry}} \\
&= s_{ij,t}\epsilon + (1 - s_{ij,t})\eta
\end{aligned} \tag{2.9}$$

where $s_{ij,t}$ is the *revenue market share* of firm j in industry i

$$s_{ij,t} = \frac{P_{ij,t}C_{ij,t}}{P_{i,t}C_{i,t}} = \left(\frac{P_{ij,t}}{P_{i,t}}\right)^{1-\eta} \frac{M_{ij,t}}{M_{i,t}}. \tag{2.10}$$

Thus, equation (2.9) shows that the short-run price elasticity of demand is given by the average of the within-industry elasticity of substitution η and the between-industry elasticity of substitution ϵ weighted by the firm's revenue shares. Depending on the revenue market share $s_{ij,t}$, firm j's short-run price elasticity of demand lies in $[\epsilon, \eta]$. On the one hand, when firm j's revenue market share $s_{ij,t}$ is small, within-industry competition becomes more relevant and thus firm j's price elasticity of demand depends more on η. In the extreme case with $s_{ij,t} = 0$, firm j becomes atomistic and takes the industry price index $P_{i,t}$ as given. As a result, firm j's short-run price elasticity of demand is entirely determined by the within-industry elasticity of substitution η. On the other hand, when firm j's revenue market share $s_{ij,t}$ is large, between-industry competition becomes more relevant and thus firm j's short-run price elasticity of demand depends more on ϵ. In the extreme case with $s_{ij,t} = 1$, firm j becomes the monopoly in industry i and its short-run price elasticity of demand is entirely determined by the between-industry elasticity of substitution ϵ.

The key reason why between-industry competition matters for the firm's price elasticity of demand is that each firm's price has a non-negligible effect on the industry's price index in the duopoly industry. The magnitude of this effect is determined by the firm's revenue market share $s_{ij,t}$. Thus, when setting prices, each firm internalizes the effect of its own price on the industry's price index, which in turn determines the demand for the industry's goods given the between-industry elasticity of substitution ϵ. If there exists a continuum of firms in each industry, as in standard monopolistic competition models, then each firm is atomistic and has no influence on the industry's price index. As a result, between-industry competition would have no impact on firms' price elasticities of demand.

Thus, although each industry only has two firms, the modeling of endogenous customer base allows us to simultaneously capture the pricing behavior resembling a price taker (as in a model with monopolistic competition) and the pricing behavior resembling an industry-level monopoly. As we show in Section 3, this tractable framework also allows us to analyze how collusion incentive would endogenously change due to the change in market structure caused by radical innovation. In Appendix E.1, we further discuss the role of the two elasticities in determining equilibrium prices.

Dynamics of Customer Bases. There are uncountable cases about how firms attract consumers through price undercutting or discount offering. A temporary cut in prices can have a persistent effect on increasing the firm's demand because consumers have switching costs. Attracted by lower prices, new customers buy the firm's products, feel satisfied and become loyal to the firm. Due to switching costs, these consumers become the firm's customers and keep buying the firm's products in the future. To capture this idea, following Phelps and Winter (1970) and Ravn, Schmitt-Grohe and Uribe (2006), we model the evolution of firm j's customer base as

$$\mathrm{d}M_{ij,t} = -\rho M_{ij,t}\mathrm{d}t + z\frac{C_{ij,t}}{C_t}\mathrm{d}t, \tag{2.11}$$

where the parameter $z \geq 0$ determines the speed of customer base accumulation. Intuitively, a lower price $P_{ij,t}$ increases the contemporaneous demand flow rate $C_{ij,t}$, allowing the firm to accumulate a larger customer base over $[t, t + \mathrm{d}t]$. The parameter $\rho > 0$ captures customer base depreciation due to economy-wide reasons such as the mortality of consumers.

The firm's pricing decision crucially depends on the value of z and its customer base $M_{ij,t}$. To elaborate, if $z = 0$, the firm's pricing decision is static, chosen to maximize contemporaneous profits. If $z > 0$, the firm's pricing decision becomes dynamic, facing the tradeoff between increasing contemporaneous profits through setting higher prices to exploit existing customer base $M_{ij,t}$ and increasing future profits through setting lower prices to accumulate more customer base (Chevalier and Scharfstein, 1996; Gilchrist et al., 2017). Consistent with the empirical evidence, the slow-moving customer base $M_{ij,t}$ implies that the long-run price elasticity of demand is higher than the short-run elasticity (see, e.g. Rotemberg and Woodford, 1991).

2.3 Consumption Risks for the Long Run

We directly model the dynamics of aggregate consumption demand C_t. Thus, in fact, we incorporate product market frictions into a Lucas-tree model (Lucas, 1978) with homogeneous agents and complete financial markets. Many extensions of the basic homogeneous-agent complete-market Lucas-tree models have been developed in the literature. For example, Longstaff and Piazzesi (2004), Bansal and Yaron (2004), Santos and Veronesi (2006), and Wachter (2013) consider leveraged dividends and implicitly incorporate labor market frictions in the Lucas-tree model; Cochrane, Longstaff and Santa-Clara (2007), Menzly, Santos and Veronesi (2004) and Santos and Veronesi (2006, 2010), Martin (2013), and Tsai and Wachter (2016) consider a multi-asset (or multi-sector) Lucas-tree economy. We consider a Lucas-tree economy with multiple sectors whose shares are endogenously determined in the equilibrium.[7] Specifically, we assume that C_t evolves according to

$$\frac{\mathrm{d}C_t}{C_t} = \theta_t \mathrm{d}t + \sigma_c \mathrm{d}Z_{c,t}, \tag{2.12}$$

where

$$\mathrm{d}\theta_t = \kappa(\overline{\theta} - \theta_t)\mathrm{d}t + \varphi_\theta \sigma_c \mathrm{d}Z_{\theta,t}. \tag{2.13}$$

The consumption growth rate contains a persistent predictable component θ_t, which determines the conditional expectation of consumption growth (see, e.g. Kandel and Stambaugh, 1991, for early empirical evidence). The parameter $\overline{\theta}$ captures the average long-run consumption growth rate. The parameter κ determines the persistence of the expected growth rate process. The parameter φ_θ determines the exposure to long-run risks. $\mathrm{d}Z_{c,t}$ and $\mathrm{d}Z_{\theta,t}$ are independent standard Brownian motions. Compared to other models with long-run risks, the key feature of our model is that firm-level demand is endogenous and depends on strategic competition.

Stochastic Discount Factors. The state-price density Λ_t is

$$\Lambda_t = \exp\left[\int_0^t f_U(C_s, U_s)\mathrm{d}s\right] f_C(C_t, U_t). \tag{2.14}$$

The market price of risk evolves according to

$$\frac{\mathrm{d}\Lambda_t}{\Lambda_t} = -r\mathrm{d}t - \gamma\sigma_c \mathrm{d}Z_{c,t} - \frac{\gamma - 1/\psi}{h+\eta}\mathrm{d}Z_{\theta,t}, \tag{2.15}$$

[7] The heterogenous-agent complete-market Lucas-tree models have also been developed and widely used in asset pricing literature. For example, Chan and Kogan (2002) introduced heterogeneous risk aversions in the Lucas-tree model, Xiong and Yan (2010) introduced information frictions to the Lucas-tree model, Albuquerue and Wang (2015) and Kaniel and Kondor (2013) introduces agency problems into a (productive) Lucas-tree economy, and Wang (2003), Lustig and Van Nieuwerburgh (2005), Chien and Lustig (2009), and Chien, Cole and Lustig (2011) introduced market-incompleteness into a Lucas-tree economy.

where r is the interest rate and h is the long-run deterministic steady-state consumption-wealth ratio determined in general equilibrium (see Section 2.6).

2.4 Firm Production and Cash Flows

Firms produce differentiated goods using a linear technology. Over $[t, t + \mathrm{d}t]$, firm j produces a flow of goods $Y_{ij,t}\mathrm{d}t$ with costs $\omega Y_{ij,t}\mathrm{d}t$, where ω is the per unit cost of production, paid to households. In equilibrium, the firm finds it optimal to choose $P_{ij,t} > \omega$ and the market clears for each differentiated good:

$$Y_{ij,t} = C_{ij,t}. \tag{2.16}$$

Thus, firm j's operating profit over $[t, t + \mathrm{d}t]$ is given by

$$\mathrm{d}E_{ij,t} = \left(P_{ij,t} - \omega\right) C_{ij,t}\mathrm{d}t. \tag{2.17}$$

All the operating profits are paid out as dividends (or equity financing if $\mathrm{d}E_{ij,t} < 0$).

2.5 Price Setting Supergames

The two firms in the same industry play a dynamic game, in which the stage games of setting prices are played continuously and infinitely repeated.[8] There exist a non-collusive equilibrium and multiple collusive equilibria sustained by conditional punishment strategies. Below, we first illustrate the non-collusive equilibrium. Then we define and characterize the collusive equilibrium that yields higher profits for both firms.

Non-Collusive Equilibrium. Substituting equation (2.7) into equation (2.17), we obtain

$$\frac{\mathrm{d}E_{ij,t}}{M_{ij,t}} = \Pi_{ij}(P_{i1,t}, P_{i2,t})\mathrm{d}t, \tag{2.18}$$

[8] We do not model dynamic entries and exits because most entries and exits in the data are associated with small firms while our model focuses on the main players in a market (Tian, 2018). Loualiche (2016) and Corhay, Kung and Schmid (2017) develop novel models to show that the exposure of firms to entry risk affects firms' profit margins, which in turn determines expected stock returns. Our model emphasizes a different point, i.e. profit margins could be affected by firms' endogenous time-varying collusion incentive.

where $\Pi_{ij}(P_{i1,t}, P_{i2,t})$ is the conditional expected profit rate defined by

$$\Pi_{ij}(P_{i1,t}, P_{i2,t}) \equiv \left(P_{ij,t} - \omega\right) \left(\frac{P_{ij,t}}{P_{i,t}}\right)^{-\eta} P_{i,t}^{-\epsilon} C_t. \tag{2.19}$$

Equation (2.19) shows that the (local) conditional expected profit rate of firm j depends on its peer firm $\bar{j}$'s product price $P_{i\bar{j},t}$ through the industry's price index $P_{i,t}$. This reflects the externality of firm $\bar{j}$'s decisions. For example, if firm $\bar{j}$ sets a low price $P_{i\bar{j},t}$, the price index $P_{i,t}$ will drop, and thus the demand for firm j's goods $C_{ij,t}$ will decrease. This will motivate firm j to set a lower price $P_{ij,t}$, and thus the two firms' pricing decisions exhibit strategic complementarity in equilibrium.

In the non-collusive equilibrium, firm j chooses product price $P_{ij,t}$ to maximize shareholder value $V_{ij}^{N}(M_{i1,t}, M_{i2,t}, C_t, \theta_t)$, conditional on its peer firm $\bar{j}$ setting the equilibrium price $P_{i\bar{j},t}^{N}$. Following the standard recursive formulation in dynamic games with Markov Perfect Nash equilibrium (see, e.g. Pakes and McGuire, 1994; Ericson and Pakes, 1995; Maskin and Tirole, 2001), the optimization problems can be formulated recursively by HJB equations:

$$0 = \max_{P_{i1,t}} \Lambda_t \Pi_{i1}(P_{i1,t}, P_{i2,t}^{N}) M_{ij,t} \mathrm{d}t + \mathbb{E}_t \left[\mathrm{d}(\Lambda_t V_{i1}^{N}(M_{i1,t}, M_{i2,t}, C_t, \theta_t))\right], \tag{2.20}$$

$$0 = \max_{P_{i2,t}} \Lambda_t \Pi_{i2}(P_{i1,t}^{N}, P_{i2,t}) M_{ij,t} \mathrm{d}t + \mathbb{E}_t \left[\mathrm{d}(\Lambda_t V_{i2}^{N}(M_{i1,t}, M_{i2,t}, C_t, \theta_t))\right]. \tag{2.21}$$

The non-collusive equilibrium prices $P_{ij}^{N}(M_{i1,t}, M_{i2,t}, C_t, \theta_t)$ (with $j = 1, 2$) are determined by the coupled HJB equations (2.20). The Nash equilibrium considered here is non-collusive, because it does not depend on historical information (i.e. not using conditional punishment strategies based on the two firms' historical decisions). In the non-collusive equilibrium, firms set prices independently taking the best actions of the other firms as given.

Collusive Equilibrium. In the collusive equilibrium, firms collectively set higher prices to gain higher profit margins and values.[9]

[9] In the industrial organization and macroeconomics literature, this equilibrium is called 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 (Fudenberg and Tirole, 1991) in order to distinguish its nature from the static equilibrium (i.e. our non-collusive equilibrium).

Consider a generic collusive equilibrium in which firms follow the collusive pricing schedule $P_{ij}^C(M_{i1,t}, M_{i2,t}, C_t, \theta_t)$ (with $j = 1, 2$).[10] The two firms apply non-collusive price competition as punishment strategies to ensure the collusive price schedule is sustained in equilibrium.

In particular, in the collusive equilibrium, each firm has to incur a flow cost of $\overline{\omega}\mathrm{d}t$ over $[t, t + \mathrm{d}t]$ to monitor the other firm's price. If one firm deviates from the collusive equilibrium, the peer firm will implement a punishment strategy with probability $\phi\mathrm{d}t$ over $[t, t + \mathrm{d}t]$ by setting the non-collusive price in future.[11] The Poisson process for successfully implementing a punishment strategy is firm-specific, denoted by $N_{ij,t}$. We assume that punishment may not always be implemented upon deviation to capture the possibility that the two firms can negotiate with each other in order to avoid entering non-collusive price competition.

Whether firms monitor each other is common knowledge. Thus if either firm chooses not to monitor, both firms would set the non-collusive prices $P_{ij}^N(M_{i1,t}, M_{i2,t}, C_t, \theta_t)$, or in other words, both firms have to pay the monitoring costs $\overline{\omega}\mathrm{d}t$ in order to sustain the collusive pricing schedule $P_{ij}^C(M_{i1,t}, M_{i2,t}, C_t, \theta_t)$ as an equilibrium outcome.[12] Firm j's value in the collusive equilibrium, denoted by $V_{ij}^C(M_{i1,t}, M_{i2,t}, C_t, \theta_t)$, is determined by

$$\begin{aligned} 0 = \max \Big\{ &\Lambda_t \Pi_{ij}(P_{i1}^C, P_{i2}^C) M_{ij,t}\mathrm{d}t - \overline{\omega}\mathrm{d}t + \mathbb{E}_t \left[\mathrm{d}(\Lambda_t V_{ij}^C(M_{i1,t}, M_{i2,t}, C_t, \theta_t)) \right], \\ &\Lambda_t \Pi_{ij}(P_{i1}^N, P_{i2}^N) M_{ij,t}\mathrm{d}t + \mathbb{E}_t \left[\mathrm{d}(\Lambda_t V_{ij}^C(M_{i1,t}, M_{i2,t}, C_t, \theta_t)) \right] \Big\} \quad \text{with } j = 1, 2. \end{aligned} \tag{2.22}$$

The collusive equilibrium is sub-game perfect if conditional on monitoring, there is no deviation from $P_{ij}^C(M_{i1,t}, M_{i2,t}, C_t, \theta_t)$. Formally, denote $V_{ij}^D(M_{i1,t}, M_{i2,t}, C_t, \theta_t)$ as firm j's

[10] Fershtman and Pakes (2000) require all firms to adopt the same collusive price to maintain tractability. Our collusive pricing schedule is more general because it allows firms to set different prices based on their customer base and aggregate conditions.

[11] Setting the non-collusive price is considered as a punishment strategy because the industry will switch to the non-collusive equilibrium, which has sub-game perfection. Specifically, conditional on the peer firm's price being non-collusive, the deviating firm would also set the non-collusive price, because setting the non-collusive price is the best response to the peer firm's non-collusive price. We adopt the non-collusive equilibrium as the incentive-compatible punishment for deviation to follow the literature (see, e.g. Green and Porter, 1984; Rotemberg and Saloner, 1986).

[12] Intuitively, because monitoring is common knowledge, if firm j does not pay the monitoring cost. Firm $\bar{j}$ knows and will rationally deviate from collusive pricing. Firm j knows that firm $\bar{j}$ knows that firm j does not pay the monitoring cost. Thus firm j can perfectly infer that firm $\bar{j}$ will deviate. As a result, firm j will also deviate conditional on firm $\bar{j}$'s deviation, and so on. This will completely rule out any collusive equilibrium, making the non-collusive equilibrium a unique one.

value for one-shot deviation conditional on monitoring,[13] the HJB equations are:

$$
\begin{aligned}
0 = & \max_{P_{i1,t}} \Lambda_t \Pi_{i1}(P_{i1,t}, P_{i2}^C) M_{i1,t} \mathrm{d}t - \overline{\omega} \mathrm{d}t + \mathbb{E}_t \left[\mathrm{d}(\Lambda_t V_{i1}^D(M_{i1,t}, M_{i2,t}, C_t, \theta_t)) \right] \\
& + \Lambda_t \left[V_{i1}^N(M_{i1,t}, M_{i2,t}, C_t, \theta_t) - V_{i1}^D(M_{i1,t}, M_{i2,t}, C_t, \theta_t) \right] \mathrm{d}N_{i1,t}, \qquad (2.23) \\
0 = & \max_{P_{i2,t}} \Lambda_t \Pi_{i2}(P_{i1}^C, P_{i2,t}) M_{i2,t} \mathrm{d}t - \overline{\omega} \mathrm{d}t + \mathbb{E}_t \left[\mathrm{d}(\Lambda_t V_{i2}^D(M_{i1,t}, M_{i2,t}, C_t, \theta_t)) \right] \\
& + \Lambda_t \left[V_{i2}^N(M_{i1,t}, M_{i2,t}, C_t, \theta_t) - V_{i2}^D(M_{i1,t}, M_{i2,t}, C_t, \theta_t) \right] \mathrm{d}N_{i2,t}, \qquad (2.24)
\end{aligned}
$$

The incentive compatibility (IC) constraints that ensure non-deviation are given by:

$$
V_{ij}^D(M_{i1,t}, M_{i2,t}, C_t, \theta_t) \leq V_{ij}^C(M_{i1,t}, M_{i2,t}, C_t, \theta_t), \tag{2.25}
$$

for $j = 1, 2$ and all monitoring states. In fact, there exist infinitely many collusive pricing schedules $P_{ij}^C(M_{i1,t}, M_{i2,t}, C_t, \theta_t)$ that satisfy the IC constraints, and hence infinitely many collusive equilibria. Because firms maximize profits in general equilibrium, it is reasonable for them to collude on prices as high as possible.[14] We thus focus on the highest collusive pricing schedule, under which the IC constraints are binding for all monitoring states, i.e. $P_{ij}^C(M_{i1,t}, M_{i2,t}, C_t, \theta_t)$ are determined such that

$$
V_{ij}^D(M_{i1,t}, M_{i2,t}, C_t, \theta_t) = V_{ij}^C(M_{i1,t}, M_{i2,t}, C_t, \theta_t). \tag{2.26}
$$

2.6 General Equilibrium Conditions

In equilibrium, the value function of the representative household is

$$
U_t = \exp\left(A_0 + A_1 \theta_t\right) \frac{W_t^{1-\gamma}}{1-\gamma}, \tag{2.27}
$$

[13]The one-shot deviation principle indicates that focusing on no one-shot-deviation is necessary and sufficient to attain a sub-game perfect equilibrium (see Fudenberg and Tirole, 1991).

[14]There are two reasons why we focus on the highest collusive pricing schedule. First, non-binding IC constraints imply that there is room to further increase both firms' values by increasing collusive prices. Given that firms collude with each other to maximize their values, it is a bit unreasonable to rule out a better collusion. Second, considering the highest collusive price allows us to conduct more disciplined comparative statics in the presence of multiple equilibria. In other words, focusing on the highest collusive price ensures that we always pick up the same equilibrium when we compare across different industries.

where A_0 is a deterministic function of model parameters, and A_1 is equal to

$$A_1 = \frac{\psi^{-1}(1-\gamma)}{h+\kappa}, \quad \text{with} \quad h = \exp\left(\overline{\ln C - \ln W}\right). \tag{2.28}$$

The equilibrium wealth-consumption ratio is

$$\frac{W_t}{C_t} = \rho^{-\psi} \exp\left[\frac{1-\psi}{1-\gamma}A_0 + \left(\frac{1-\psi^{-1}}{h+\kappa}\right)\theta_t\right]. \tag{2.29}$$

In equilibrium, the long-run deterministic steady-state consumption-wealth ratio is:

$$\ln(h) = \overline{\ln C - \ln W} = \psi \ln(\rho) - \frac{1-\psi}{1-\gamma}A_0 - \frac{1-\psi^{-1}}{h+\kappa}\bar{\theta}. \tag{2.30}$$

2.7 Price Wars and Long-Run Growth Rates

In this subsection, we illustrate price war risks in collusive equilibrium.[15] We show that price war risks endogenously arise from long-run risks and as a result, price war risks amplify industries' exposure to long-run risks. Moreover, our model implies that profit margins respond more to negative long-run-risk shocks and less to positive long-run-risk shocks. The sensitivity of profit margins to long-run-risk shocks is higher during periods with low long-run consumption growth rates.

Price War Risks Arise from Long-Run-Risk Shocks. In our model, price war risks endogenously arise from long-run risks. When the long-run consumption growth rate θ_t declines, profit margins decline due to endogenous declines in collusive prices P_{ij}^C. With significant declines in long-run consumption growth rate, a full-blown price war occurs.

Intuitively, the incentive to collude on higher prices depends on the extent to which the two firms value future revenue relative to its current revenue. By deviating from the collusive price, firms can attain higher contemporaneous revenue and accumulate more customer base in the short run. However, firms run into the risk of losing future revenue because once the deviation is detected by the other firm, the non-collusive equilibrium will be implemented as a punishment strategy. During periods with low long-run growth rates, firms expect a relative reduction in aggregate future consumption and the later punishment looks less costly. This makes firms more impatient for cash

[15] The equilibrium property of our model is discussed in Appendix D.

flows and attain stronger incentives to undercut peers' prices.[16] Therefore, a decline in long-run consumption growth intensifies the degree of collusive price competition, reducing equilibrium product prices, which is broadly regarded as a price war (see, e.g. Rotemberg and Saloner, 1986; Lambson, 1987; Haltiwanger and Harrington, 1991).

When long-run consumption growth declines significantly, firms optimally choose not to collude with each other because the costs paid to monitor peers' prices exceed the potential gains from collusion. When this happens, the industry enters into a full-blown price war, in which both firms set the non-collusive prices P_{ij}^N (see, e.g. Friedman, 1971; Green and Porter, 1984; Porter, 1985; Abreu, Pearce and Stacchetti, 1986). Thus, in our model, a full-blown price war is a regime shift from the collusive competition equilibrium to the non-collusive competition equilibrium. A moderate decline in long-run consumption growth reduces equilibrium product prices and profit margins, increasing the risk of entering a full-blown price war.

Importantly, the decrease in profit margins after negative long-run risk shocks is owing to intensified competition and reduced market power rather than declines in aggregate demand. To elaborate, in Panel A of Figure 2, we plot the supply and demand curves for firm j's good in industry i in collusive equilibrium. Fixing firm j's customer base M_{ij}, the supply curve (blue solid line) is flat because firm j agrees to sell its product at the collusive price P_{ij}^C irrespective of the level of its contemporaneous demand. The demand curve (black dashed line) is downward sloping, given by equation (2.7). The initial equilibrium is given by point O_0.

A negative shock to long-run growth rate θ reduces collusion incentive and intensifies collusive competition, shifting the supply curve downward (the blue dotted line). If the demand curve were unchanged, the new equilibrium would feature a much lower price and a much higher demand for firm j's goods (point O'). However, the demand curve also shifts downward (black dash-dotted line) because the industry's price index P_i endogenously declines due to intensified collusive competition. As a result, the new equilibrium is given by point O_1, featuring a price war with a much lower equilibrium price and a slightly higher equilibrium demand for firm j's goods. As illustrated in Figure 3, we emphasize that the price war driven by negative long-run risk shocks to

[16]The intuition is related to the Folk Theorem in game theory. The Folk Theorem says that provided players are sufficiently patient, not only can repeated interaction allow many sub-game perfect outcomes, but actually sub-game perfection can allow virtually any outcome in the sense of average payoffs. The effective discount rate is approximately given by $r - \theta_t$. Thus, the periods with low θ_t feature high discount rates and more impatience.

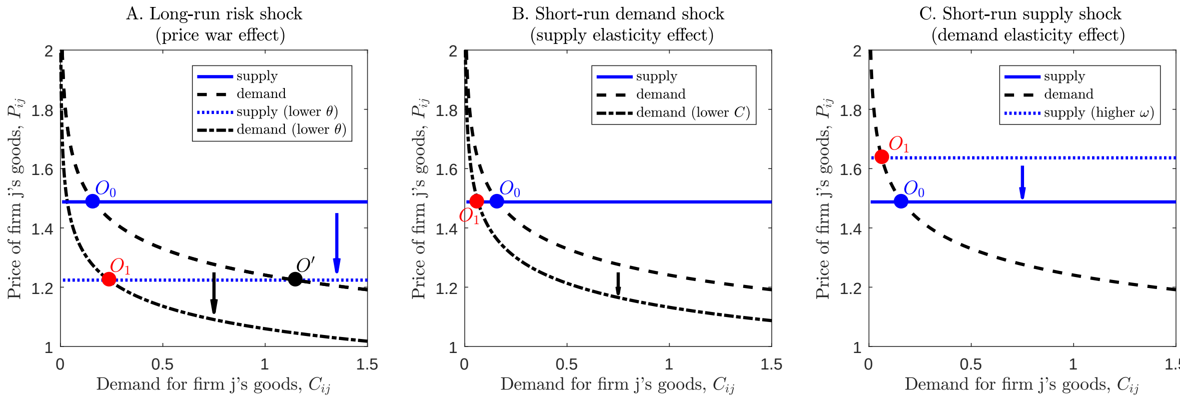


Figure 2: The impact of demand and supply shocks on equilibrium prices and quantities.

consumption is initially caused by the downward shift in the supply curve owing to the self-fulfilling declines in market power and collusion incentive. The shift in the supply curve further induces a shift in the demand curve due to the endogenous response in the industry's price index.

By contrast, Panel B shows that a negative short-run demand shock (i.e. lower C) only generates a downward shift in the demand curve, without affecting the supply curve. As a result, the change in equilibrium price and demand purely depends on the price elasticity of supply. Given a flat supply curve (infinite price elasticity of supply), firm j's price in the new equilibrium (point O_1) is exactly the same as the initial equilibrium price (point O_0).[17] Panel C shows that a negative short-run supply shock (i.e. higher ω) only generates an upward shift in the supply curve, without affecting the demand curve. As a result, the change in equilibrium demand and supply purely depends on the price elasticity of demand. As the demand curve is downward sloping, the new equilibrium (point O_1) has a higher price and a lower demand for firm j's goods.

Thus, the price war caused by negative long-run risk shocks involves shifts in both the demand and the supply curves owing to intensified competition and declined market power. Price war risks are generated by long-run risks and are fundamentally different from the risks associated with short-run demand or supply shocks.

[17] If the marginal cost of production increases with output, the supply curve would be upward sloping. Then, a negative short-run demand shock would result in a lower equilibrium price and a lower equilibrium demand for firm j's good. This is the standard negative effect of demand shocks on equilibrium price in models with decreasing-return-to-scale production technology. We intentionally assume constant marginal cost of production ω (as in textbook New Keynesian models) to eliminate this effect and cleanly present the price war effect.

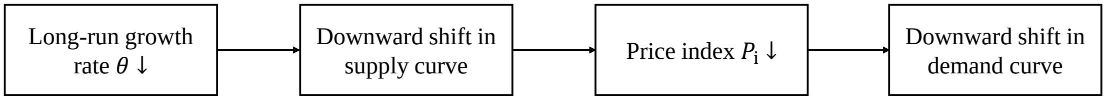


Figure 3: An illustration of how negative long-run risk shocks result in a price war.

Price War Risks and the Exposure to Long-Run Risks. We now illustrate price war risks numerically in Figure 4. By exploiting linearity on $M_{i,t}C_t$, we reduce the model to two state variables: $M_{i1,t}/M_{i,t}$ and θ_t. We solve the normalized firm value $v^N_{ij}(M_{i1,t}/M_{i,t}, \theta_t)$ in non-collusive equilibrium and $v^C_{ij}(M_{i1,t}/M_{i,t}, \theta_t)$ in collusive equilibrium.

Panel A and B plot firm 1's equilibrium price in periods with different long-run growth rates. The blue solid line plots the firm's price during periods with high long-run growth rates (i.e. θ_h). In Panel A, we consider a moderate decrease in the long-run growth rate to $\theta_m < \theta_h$, and it shows that the firm's equilibrium prices are lower. The industry features narrowed profit margins for both firms and a price war occurs. Panel B shows that when the long-run growth rate further drops to $\theta_l < \theta_m$, the two firms choose not to collude with each other, and the equilibrium prices are significantly lower and equal to non-collusive prices. The industry enters into a full-blown price war.

The endogenous movement in equilibrium prices induced by changes in long-run growth rates generates a large variation in firms' expected future cash flows. Thus, our model offers a novel explanation for Larrain and Yogo (2008)'s finding that the value of corporate assets is mostly driven by changes in expected future cash flows, instead of changes in discount rates.

Panel C illustrates the magnitude of price war risks by plotting the difference in collusive prices between periods with high and low long-run growth rates. It is shown that price war risks display an inverted U-shape, and the risks are the largest when the two firms have comparable customer base shares (i.e. $M_{i1}/M_i \approx 0.5$). Intuitively, collusion allows both firms to set higher prices to enjoy higher profit margins than what they would have in the non-collusive equilibrium. However, the collusive pricing schedule has to be chosen such that both firms have no incentive to deviate given their current customer base shares. When firm 1 is dominating the market (i.e. with high M_{i1}/M_i), forming a collusive equilibrium would be less appealing from firm 1's perspective as it already has high market power, which allows it to set a high price in the non-collusive equilibrium any way (see the red dash-dotted line in Panel A). On the other hand, when

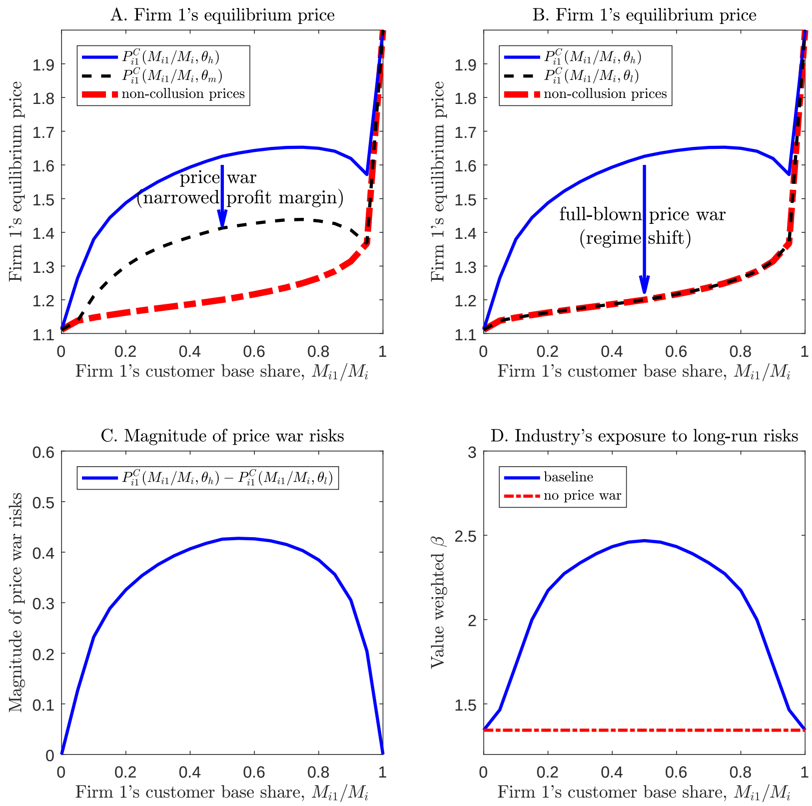


Figure 4: Price war risks and the industry's exposure to long-run risks.

firm 1 has low customer base share M_{i1}/M_i, forming a collusive equilibrium would be less appealing from firm 2's perspective, who already has high market power to set a high price in the non-collusive equilibrium. In other words, when one firm dominates the other firm in customer base share, there is not much incentive to form a collusion in the industry; and as a result, there is not much variation in collusive prices when long-run growth rates change.

We emphasize that long-run consumption risks play an essential role in driving substantial price war risks in equilibrium. A moderate temporary shock to the level of aggregate consumption demand has little impact on the potential losses caused by the punishment, and hence, it has little impact on the deviation incentive. Therefore, moderate temporary shocks cannot drive substantial price war risks in equilibrium. Only persistent shocks in long-run growth can significantly change the severity of punishment

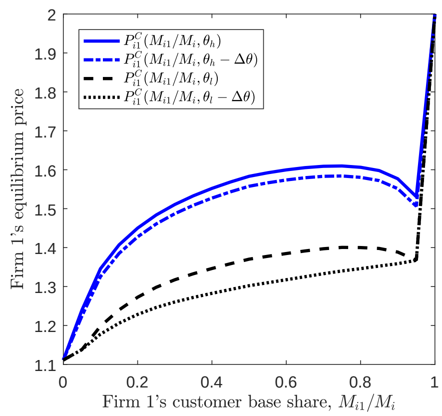


Figure 5: Profit Margin Sensitivity to Long-Run Risk Shocks.

and thus firms' effective discount rates. In Appendix E.2, we show that the magnitude of price war risks declines when the growth shocks become less persistent. Specifically, price war risks become negligible when there are only moderate temporary shocks in consumption growth.

The time-varying collusion incentive amplifies the effect of long-run risks because during periods with low long-run consumption growth, firms not only face low demand but also low profit margins. To illustrate this amplification mechanism, we calculate the industry-level beta $\beta_i(M_{i1}/M_i)$ as value-weighted firm-level betas $\beta_{ij}(M_{ij}/M_i)$

$$\beta_i(M_{i1}/M_i) = \sum_{j=1,2} \frac{v_{ij}^C(M_{i1}/M_i, \theta_r)}{v_{i1}^C(M_{i1}/M_i, \theta_r) + v_{i2}^C(M_{i1}/M_i, \theta_r)} \beta_{ij}(M_{ij}/M_i), \tag{2.31}$$

where $\beta_{ij}(M_{ij}/M_i) = \frac{v_{ij}^C(M_{i1}/M_i, \theta_b)}{v_{ij}^C(M_{i1}/M_i, \theta_r)} - 1$.

Panel D shows that the industry's beta displays an inverted U-shape (see the blue solid line) due to the inverted-U price war risks. As a benchmark, the red dash-dotted line plots the industry's beta in the absence of price war risks (i.e. when collusive prices do not change with long-run growth rates). When the two firms have comparable customer base shares, price war risks significantly amplify the industry's exposure to long-run risks.

Profit Margin Sensitivity to Long-Run Risk Shocks. Our model implies that profit margins are more sensitive to long-run-risk shocks during periods with low long-run growth rates. Intuitively, in periods with low long-run growth rates, firms are more likely to abandon collusion and enter a full-blown price war if long-run growth rates further drop. As a result, firms' collusion incentive becomes more sensitive to long-run growth rates, increasing the profit margin sensitivity and the exposure to price war risks.

To see this, in Figure 5, we plot firm 1's equilibrium prices in periods with high (blue solid line) and low long-run growth rates (black dashed line). It is shown that a negative long-run-risk shock of magnitude $\Delta\theta$ reduces the firm's equilibrium prices more in the latter case (black dotted line), indicating that profit margins are more sensitive to long-run-risk shocks in periods with low long-run growth rates.

In our model, the mechanism that generates countercyclical profit margin sensitivity crucially depends the potential regime shift from the collusive competition equilibrium to the non-collusive competition equilibrium, or a full-blown price war. As we discussed above, this regime shift is a direct outcome of dynamic strategic competition, in which firms can adopt conditional punishment pricing strategies to sustain implicit collusion. Our mechanism is different from Corhay, Kung and Schmid (2017), who emphasize that the role of entry risks in generating countercyclical markup sensitivity.

3 The Model with Innovation

In this section, we extend the baseline model by allowing firms to conduct innovation. There are two main reasons why we emphasize innovation activities. First, product innovation is an important channel through which firms develop customer base, on top of strategic pricing. We show that whether firms collude with each other crucially depends on the extent to which they have the ability to conduct radical innovation, which determines the future market structure (i.e. the distribution of customer base). Second, introducing innovation yields new cross-sectional predictions and expands the scope of testing our asset pricing theory of price war risks. Our model predicts that industries with lower capacities of radical innovation are more exposed to price war risks, and thus long-run risks.

3.1 Modeling Innovation

Firms conduct innovation, which succeeds independently across firms at a constant rate μ. A successful innovation allows the innovating firm to snatch a fraction $\tau_{ij,t}$ of the peer firm's customer base, where $\tau_{ij,t}$ takes two values,

$$\tau_{ij,t} = \begin{cases} \tau_\iota, & \text{with probability } \lambda_{i,t}, \\ \tau_d, & \text{with probability } 1 - \lambda_{i,t}. \end{cases} \tag{3.1}$$

We assume $0 \approx \tau_\iota << \tau_d \approx 1$ to parsimoniously capture two different types of innovation. The event of snatching a small fraction τ_ι of customer base captures a successful incremental innovation which produce innovative outputs similar to existing ones. Incremental innovation adds value to customers through incrementally introducing new features to existing products. For example, Motorola has launched a series of Motorola Razr since 2004, based on constant improvement of previous generations. The event of snatching a large fraction τ_d of customer base captures a radical innovation that creates newer and distinctive technology to surpass the old and disrupt existing companies. There are quite a few examples of radical innovation, one of the more prominent being Apple's iPhone disruption of the mobile phone market.

In our model, the evolution of aggregate consumption C_t is exogenously specified by equation (2.12). However, in principle, firms' innovation can also drive the growth of aggregate consumption. For example, Corhay, Kung and Schmid (2017) develop a novel general equilibrium production-based asset pricing model with both extensive and intensive margins of innovation, which endogenously drive volatility risks and long-run risks. Different from Corhay, Kung and Schmid (2017), we emphasize that the strategic customer-base stealing effect of innovation yields implications on industries' exposure to price war risks.

The innovation similarity $\lambda_{i,t}$ is the only industry characteristic that is ex-ante heterogeneous across industries, evolving idiosyncratically according to a Markov chain on $\lambda = \{\lambda_1 < ... < \lambda_N\}$ (see Section 5.1), where $\lambda_1 > 0$ and $\lambda_N \leq 1$. A higher $\lambda_{i,t}$ implies that firms in industry i are more likely to conduct incremental innovation at time t, which produces products similar to existing products. On other other hand, a lower $\lambda_{i,t}$ captures the industry with a higher capacity of radical innovation at time t. In Section 4.1, We use patent data to construct an innovation similarity measure for the industry characteristic $\lambda_{i,t}$ in our model.

With innovation, the dynamics of customer base (2.11) is modified as

$$\mathrm{d}M_{ij,t} = -\rho M_{ij,t}\mathrm{d}t + z\frac{C_{ij,t}}{C_t}\mathrm{d}t + \tau_{ij,t}M_{i\bar{j},t}\mathrm{d}I_{ij,t} - \tau_{i\bar{j},t}M_{ij,t}\mathrm{d}I_{i\bar{j},t} \tag{3.2}$$

where $I_{ij,t}$ and $I_{i\bar{j},t}$ are independent Poisson processes capturing the success of firm j and $\bar{j}$'s innovation.

3.2 Price War Risks Across Industries

We now study the implication of innovation characteristics on the industry's exposure to price war risks. To fix ideas, consider two industries different in their innovation similarity λ_i.

Panel A of Figure 6 plots the equilibrium collusive prices in the two industries during periods with high and low long-run growth rates, respectively. It shows that although firms in both industries collude on higher prices during periods with high long-run growth rates, collusive prices are much lower in the industry with a high capacity of radical innovation (low λ_i). As we discuss in section 2.7, the incentive to collude exhibits an inverted-U shape and becomes the smallest in concentrated industries (i.e. one firm's customer base share is much larger than the other's). The industry with a high capacity of radical innovation is more likely to be concentrated in future because one firm can steal its competitor's customer base and almost monopolize the industry upon the success of radical innovation. Thus, even if the two firms have comparable customer base shares today, the possibility of having a successful radical innovation in future still largely dampens the incentive to collude, resulting in low collusive prices.

Panel B confirms the above intuition by showing that the industry with a high capacity of radical innovation has more dispersed market shares in future. In particular, we consider two firms currently having equal market shares (measured by the firm's sales over the industry's total sales) in each industry. We simulate the industry dynamics for 10 years and calculate the dispersion of market shares, measured by the standard deviation of the two firms' market shares in year 10. Panel B plots the simulated probability density function of the dispersion of market shares across 10,000 simulations for each industry. The industry with a high capacity of radical innovation has a more right skewed distribution (red bars) than the industry with a low capacity of radical innovation (blue bars). This pattern also holds for the steady-state distribution of market shares.

Not only the levels are lower, collusive prices are also less responsive to persistent growth shocks in the industry with a high capacity of radical innovation. Panel A shows that when the economy switches between periods with high and low long-run growth rates, the change in collusive prices in the industry with a high capacity of radical

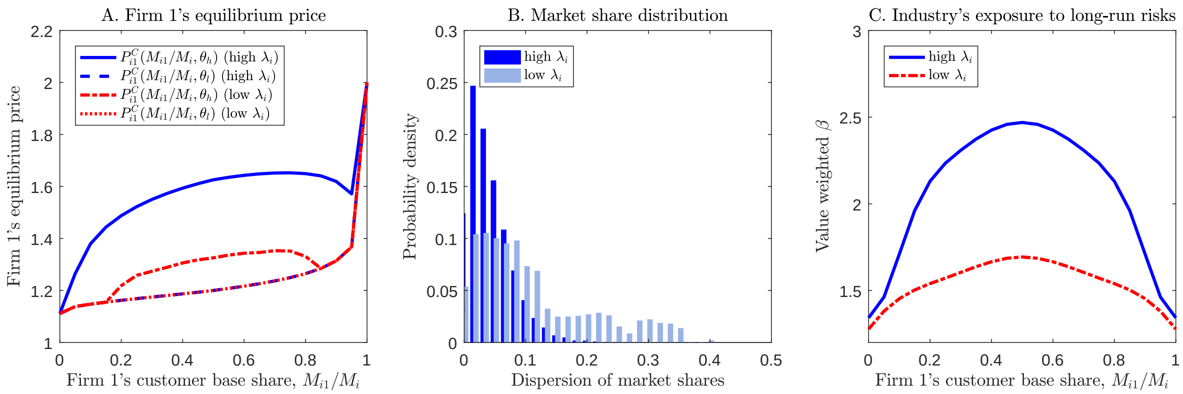


Figure 6: Comparing collusive prices, the dispersion of market shares, and the exposure to long-run risks across industries with different capacities of radical innovation.

innovation (the difference between the red dash-dotted line and the red dotted line) is much smaller compared to that in the industry with a low capacity of radical innovation (the difference between the blue solid line and the blue dashed line). This implies that firms in the industry with a high capacity of radical innovation face smaller price war risks simply because collusion is difficult to form in the first place.

In Panel C, we compare the two industries' exposure to long-run risks for different levels of industry concentration, as reflected by firm 1's customer base share. Conditional on the same level of concentration, firms in the industry with a high capacity of radical innovation are less exposed to long-run risks. The industry-level value-weighted beta exhibits an inverted U-shape in both industries. The difference in beta across the two industries is large when the two firms within the same industry have comparable customer base shares ($M_{i1}/M_i = 0.5$). Thus our model implies that the industries with low capacities of radical innovation tend to be riskier as price decreases more when the long-run consumption growth rate declines.

3.3 Main Predictions of the Model

We summarize the main predictions of the model as follows:

(1). The profit margin sensitivity is higher during periods with low long-run growth rates (see Figure 5).

(2). Industries with lower capacities of radical innovation are more exposed to price war risks (see Panel A of Figure 6). Specifically, in these industries, profit margins are higher and decrease more after negative long-run-risk shocks.

(3). Industries with lower capacities of radical innovation are more exposed to long-run risks (see Panel B of Figure 6). Thus, these industries are associated with higher expected returns and higher risk-adjusted returns.

4 Empirical Analyses

In this section, we empirically test the main predictions of our model. We first use patent data to construct an innovation similarity measure for the industry characteristic $\lambda_{i,t}$ in our model. We then test the mechanism of our model by examining the time-series and cross-sectional property of profit margins. We find that aggregate profit margins co-move positively with long-run-risk shocks and such co-movement is more significant for negative long-run-risk shocks and in recessions. In the cross-section, we find that industries with higher innovation similarity (i.e. industries with lower capacities of radical innovation) have profit margins that are more exposed to long-run risks. We further exploit detailed product prices data and find that industries with higher innovation similarity are more exposed to price war risks. The product prices of these industries decrease more in response to negative long-run-risk shocks. In particular, these industries were more likely to engage in price wars after the Lehman crash in 2008. Finally, we test the asset pricing implications of our model. We find that industries with higher innovation similarity have higher average excess returns and risk-adjusted returns. The stock returns and dividend growth of these industries are more exposed to long-run risks.

4.1 Data and the Innovation Similarity Measure

In this subsection, we first introduce the patent data and explain the method we use to construct the innovation similarity measure. We then provide external validate tests for our innovation similarity measure and contrast it with the product similarity measure developed by Hoberg and Phillips (2016).

Patent Data and Our Merged Sample. We obtain the patent issuance data from PatentView, a patent data visualization and analysis platform. PatentView contains detailed and up-to-date information on granted patents from 1976 onward. Its coverage of recent patenting activities is more comprehensive than the NBER patent data (Hall, Jaffe and Trajtenberg, 2001) and the patent data assembled by Kogan et al. (2017).[18] Patent assignees in PatentView are disambiguated and their locations and patenting activities are longitudinally tracked. PatentView categorizes patent assignees into different groups, such as corporations, individuals, and government agencies. It also provides detailed information of individual patents, including their grant dates and technology classifications.

We match patent assignees in PatentView to U.S. public firms in CRSP/Compustat, and to U.S. private firms and foreign firms in Capital IQ.[19] Private firms are included in our sample because they play an important role in industry competition (see, e.g. Ali, Klasa and Yeung, 2008). We drop patents granted to individuals and government agencies. We use a fuzzy name-matching algorithm to obtain a pool of potential matches from CRSP/Compustat and Capital IQ for each patent assignee in PatentView. We then manually screen these potential matches to identify the exact matches based on patent assignees' names and addresses. In Appendix C.2, we detail our matching procedure. In total, we match 2,235,201 patents to 10,139 U.S. public firms, 132,100 patents to 3,080 U.S. private firms, 241,582 patents to 300 foreign public firms, and 35,597 patents to 285 foreign private firms. The merged sample covers 13,804 firms in 752 4-digit SIC industries from 1976 to 2017.[20]

Innovation Similarity Measure. We construct our innovation similarity measure (denoted as "innosimm") for the industry-level innovation similarity based on the technology classifications of an industry's patents. In light of previous studies (see, e.g. Jaffe, 1986; Bloom, Schankerman and Van Reenen, 2013), we measure the cosine similarity of two patents within the same industry based on their technology classification vectors.[21]

[18]The PatentView data contain all patents granted by the U.S. Patent and Trademark Office (USPTO) from 1976 to 2017, while the NBER data and the data used by Kogan et al. (2017) only cover patents granted up to 2006 and 2010, respectively.

[19]Capital IQ is one of the most comprehensive data that include private firms and foreign firms.

[20]We use 4-digit SIC codes in Compustat and Capital IQ to identify the industries of patent assignees. Both Compustat and Capital IQ are developed and maintained by S&P Global and the SIC industry classifications in these two datasets are consistent with each other. We verify the consistency by comparing the SIC codes for U.S. public firms covered by both Compustat and Capital IQ. We find that the SIC codes of these firms are virtually identical across the two data sources.

[21]PatentView provides both the Cooperative Patent Classification (CPC) and the U.S. Patent Classification (USPC), the two major classification systems for U.S. patents. We use CPC for our analyses because USPC

Specifically, the similarity between two patents, a and b, is defined by:

$$\text{similarity}\ (a, b) = \frac{\mathbf{A} \cdot \mathbf{B}}{\|\mathbf{A}\|\ \|\mathbf{B}\|}, \tag{4.1}$$

where **A** and **B** are the technology vectors of patent a and patent b. If the two patents share exactly the same technology classifications, the cosine similarity attains the maximum value, 1. If the two patents are mutually exclusive in their technology classifications, the cosine similarity reaches the minimum value, 0. Because patent technology classifications are assigned according to the technical features of patents, the cosine similarity measure captures how similar the patents are in terms of their technological positions. Based on the pairwise cosine similarity of patents, we take the following steps to construct the industry-level innovation similarity measure.

First, we construct the patent-level similarity measure to capture to what extent a patent is differentiated from other patents recently developed by peer firms. In particular, for a patent granted to firm i in year t, the patent-level similarity measure is the average of the pairwise cosine similarity (defined by equation 4.1) between this patent and the other patents granted to firm i's peer firms in the same 4-digit SIC industry from year $t-5$ to year $t-1$.

Next, we aggregate patent-level similarity measures to obtain industry-level similarity measures. For example, a 4-digit SIC industry's similarity measure in year t is the average of patent-level similarity measures associated with all the patents granted to firms in the industry in year t. Because firms are not granted with patents every year, we further average the industry-level similarity measures over time to filter noise and better capture firms' ability in generating differentiated innovation. In particular, our innosimm measure in industry i and year t (i.e. innosimm_{it}) is constructed as the time-series average of industry i's similarity measures from year $t-9$ to year t.

Panel A of Figure 7 presents the time-series of several industries' innosimm measure. In the "Search, Detection, Navigation, Guidance, Aeronautical, and Nautical Systems and Instruments" industry, the innosimm measure is low throughout our sample period, suggesting that firms in this industry seem to be able to consistently generate radical innovation. The innosimm measure keeps increasing for the "Drilling Oil and Gas Wells"

is not available after 2015. Our results are robust to the classification based on USPC for data prior to 2015. There are 653 unique CPC classes (four-digit level) in PatentView. The technology classification vector for a patent consists of 653 indicator variables that represent the patent's CPC classes.

industry, while it peaks in early 2000s for the "Rubber and Plastics Footwear" industry.

Validation of the Innosimm Measure. We perform two external validation tests for our innosimm measure. In the first validation test, we examine the relation between innosimm and the brand perception of consumers. If a higher innosimm captures a lower capacity of radical innovation in an industry, we expect that fewer consumers would consider the brands of high-innosimm industries as distinctive. We test this hypothesis by examining the relation between innosimm and the relative change in brand distinctiveness over time, measured using the BAV consumer survey data.[22] We standardize innosimm using its unconditional mean and the standard deviation of all industries' innosimm across all time to ease the interpretation of coefficients in our regression analyses. Column (1) of Table 1 shows that innosimm is negatively correlated with the two-year percent change in the industry-level brand distinctiveness, suggesting that industries with higher innosimm are associated with lower brand distinctiveness in future.

Our innosimm measure is conceptually different from the product similarity measure (denoted as "prodsimm") constructed by Hoberg and Phillips (2016). Innosimm captures to what extent firms in an industry can differentiate their products from peers' through innovation. Thus, it is a forward-looking measure that captures the (potential) similarity/distinctiveness of firms' businesses in the future. Product similarity, on the other hand, is derived from text analyses based on firms' current product description (Hoberg and Phillips, 2016). Therefore, it reflects the similarity of products produced by different firms as of today, rather than the potential similarity/distinctiveness of firms' products in the future. In other words, product similarity contains littile information, if at all, about firms' innovation activities, which are the necessary inputs for making products distinctive in the future. The conceptual difference between the two measures is formally confirmed by column (2) of Table 1, which shows that innosimm is unrelated with prodsimm.[23] In Section 4.4 and 4.3, we further show that the prodsimm is neither

[22]The BAV database is regarded as the world's most comprehensive database of consumers' perception of brands (see, e.g. Gerzema and Lebar, 2008; Keller, 2008; Mizik and Jacobson, 2008; Aaker, 2012; Lovett, Peres and Shachar, 2014; Tavassoli, Sorescu and Chandy, 2014). The BAV brand perception survey consists of more than 870,000 respondents in total, and it is constructed to represent the U.S. population according to gender, ethnicity, age, income group, and geographic location. See Dou et al. (2018) for the details of the survey.

[23]The correlation between innosimm and prodsimm is low. The Pearson correlation coefficient, the Spearman's rank correlation coefficient, and the Kendall's τ_A and τ_B coefficients between the two variables are 0.06, 0.02, 0.04, and 0.04, respectively.

priced in the cross section nor related to industries' price war risks.

Table 1: Validation of the innosimm measure (yearly analysis).

	(1)	(2)	(3)	(4)
	Percent changes from year t to year $t+2$ (%)			
	Brand distinctiveness	Prodsimm	The dispersion of market shares (%)	
Innosimm$_t$	-0.69^{***}	0.10	-1.26^{***}	-1.61^{***}
	[−3.06]	[0.04]	[−2.60]	[−3.26]
Year FE	Yes	Yes	No	Yes
Observations	2466	5906	8967	8967
R-squared	0.298	0.002	0.008	0.033

Note: This table shows the relation of our innosimm measure with measures of brand distinctiveness, product similarity, and the dispersion of market shares at the 4-digit SIC industry level. In column (1) , the dependent variable is the two-year percent change in brand distinctiveness. The percent change is computed as $100\times$(brand distinctiveness$_{t+2}$ $-$ brand distinctiveness$_t$) /brand distinctiveness$_t$. At the brand level, brand distinctiveness is the fraction of consumers who consider a brand to be distinctive. We first aggregate the brand-level distinctiveness measure to the firm level, and then further aggregate it to the 4-digit SIC industry level. Prodsimm (i.e. product similarity measure) comes from Hoberg and Phillips (2016), and it is derived from text analyses based on the business description in 10-K filings. We download the product similarity measure from the Hoberg and Phillips Data Library, and aggregate it to the 4-digit SIC industry level. The dispersion of market shares (in percent) is defined as the standard deviation of all firms' market shares (measured by sales) within the 4-digit SIC industry. The sample in column (1) spans from 1993 to 2017, and the sample in column (2) spans from 1996 to 2015. The sample in columns (3)–(4) spans from 1988 to 2017. We include t-statistics in brackets. Standard errors are clustered by the 4-digit SIC industry and year. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels.

In the second validation test, we examine the relation between innosimm and dispersion of market shares. As explained in Section 3.2, we expect that firms in the industries with lower capacities of radical innovation are more likely have comparable market shares. If our innosimm measure captures industries' (lack of) capacities in generating radical innovation, we expect that high-innosimm industries to have lower dispersion of market shares. This is indeed what we find in the data. As shown by columns (3) and (4) of Table 1, innosimm is negatively associated with the dispersion of market shares.

4.2 Sensitivity of Profit Margins to Long-Run Risks

We test our model's mechanism in this subsection. We present several sets of empirical results supporting the predictions of our model. First, aggregate profit margins co-move positively with long-run risks. Profit margins are more (less) sensitive to long-run-risk shocks during recessions (expansions). Second, firms in high-innosimm industries have higher profit margins. Finally, profit margins are more exposed to long-run risks in high-innosimm industries.

Table 2: Sensitivity of aggregate profit margins to long-run risks (yearly analysis).

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$\ln\left(\frac{\text{Aggregate profit margins}_t}{\text{Aggregate profit margins}_{t-1}}\right)$							
Measures of LRR	Filtered consumption growth				Realized consumption growth			
Data sources of profit margins	Compustat		NBER-CES		Compustat		NBER-CES	
LRR_t	0.53**		0.76*		0.35**		0.49*	
	[2.43]		[1.89]		[2.38]		[1.84]	
LRR_t × indicator for expansions		−0.20		−0.97		0.06		−0.41
		[−1.08]		[−1.56]		[0.28]		[−0.74]
LRR_t × indicator for recessions		1.15***		2.01***		0.74**		1.46***
		[5.47]		[4.43]		[2.37]		[3.02]
Constant	0.00**	0.01***	0.01***	0.01***	0.00*	0.01**	0.01**	0.01***
	[2.64]	[4.25]	[2.77]	[3.89]	[1.92]	[2.07]	[2.47]	[2.81]
Observations	51	51	47	47	53	53	47	47
R-squared	0.115	0.288	0.064	0.268	0.080	0.142	0.042	0.155

Note: This table shows the sensitivity of aggregate profit margins to long-run risks. The aggrergate profit margin in year t is the simple average across all industries' profit margins in year t. We compute industry-level profit margins based on Compustat and NBER-CES data as explained in Figure 1. The sample of the Compustat data ends at 2017, while the sample of the NBER-CES data ends at 2011. Long-run risks are measured by the annualized filtered consumption growth in the last quarter of year t (columns 1–4), and by the average of the realized consumption growth rates in year t and year $t-1$ (columns 5–8). Expansions and recessions are defined based on the NBER Business Cycles. The sample spans from 1965 to 2015 in columns (1)–(2), and spans from 1965 to 2017 in columns (5)–(6). In columns (3)–(4) and columns (7)–(8), the sample spans from 1965 to 2011. We include t-statistics in parentheses. Standard errors are computed using the Newey-West estimator allowing for serial correlation in returns. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels.

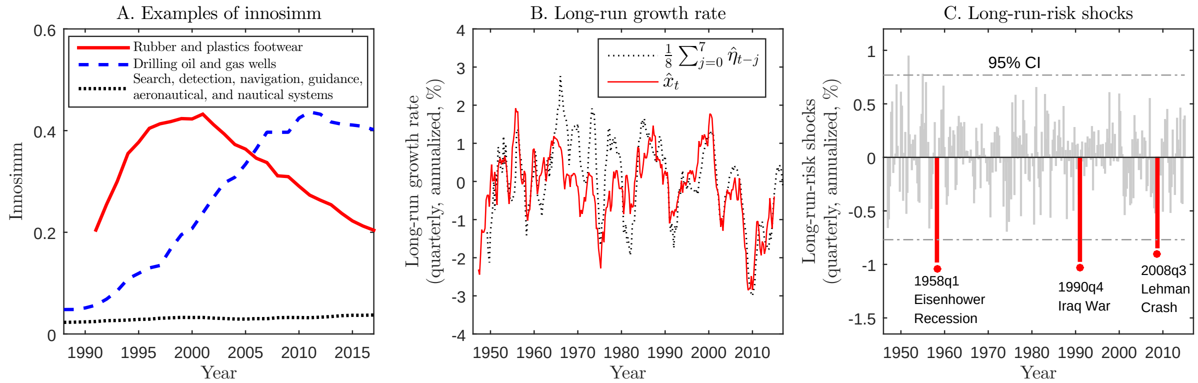
4.2.1 Time-Series Variation of Profit Margins

We first examine how aggregate profit margins are associated with long-run risks. We construct two measures of aggregate profit margins based on Compustat and NBER-CES Manufacturing Industry Database. Both data have their own advantages. The Compustat data cover public firms from all industries, while the NBER-CES data cover both public firms and private firms in the manufacturing sector. We measure long-run-risk shocks using the consumption growth filtered by a Bayesian mixed-frequency approach consumption growth as in Schorfheide, Song and Yaron (2018) (see Panel B of Figure 7).[24]

We find that aggregate profit margins co-move positively with long-run risks (columns 1 and 3 in Table 2). This finding is consistent with previous studies (see, e.g. Machin and Van Reenen, 1993; Hall, 2012; Anderson, Rebelo and Wong, 2018) that show profit margins are strongly procyclical. We further show that profit margins are more sensitive

[24]We are grateful to Amir Yaron for sharing data on the filtered consumption growth. The time series of the filtered consumption growth ends at 2015.

to long-run-risk shocks during recessions (columns 2 and 4). These findings are consistent with the predictions of our model.



Note: Panel A plots the innosimm for three industries: rubber and plastics footwear (SIC 3021); drilling oil and gas wells (SIC 1381); and search, detection, navigation, guidance, aeronautical, and nautical systems and instruments (SIC 3812). Panel B plots the annualized long-run growth rate. The red solid line represents filtered consumption growth as in Schorfheide, Song and Yaron (2018). The black dotted line represents 8-quarter cumulative realized consumption growth. Panel C plots the long-run-risk shocks in the post-war period (from 1947q1 to 2015q4). We construct long-run-risk shocks from the residuals of the AR(1) model for the quarterly time series of filtered consumption growth in Schorfheide, Song and Yaron (2018). Gray dashed lines represent the 95% CI of long-run-risk shocks. Red bars highlight the three prominent negative shocks in 1958q1, 1990q4, and 2008q3, which represent the Eisenhower recession, the Iraq war, and the Lehman crash.

Figure 7: Examples of innosimm, consumption growth, and long-run-risk shocks.

4.2.2 Cross-Sectional Variation of Profit Margins

Next, we examine cross-sectional variation of profit margins. Our model implies that, all else equal, firms in high-innosimm industries endogenously have higher profit margins. In Table 3, we show that industry-level profit margins are positively associated with innosimm. This relation is robust for the measures of profit margins constructed from both the Compustat and NBER-CES data. The coefficient of innosimm is economically significant and comparable across the two measures of profit margins. According to the regressions with year fixed effects (columns 2 and 4), a one standard deviation increase in innosimm is associated with a 2.47-percentage-point increase in the Compustat-based profit margins and an 3.19-percentage-point increase in the NBER-CES-based profit margin.

Our model further predicts that profit margins are more exposed to long-run risks in high-innosimm industries. Consistent with the model, Table 4 shows that the one-year ahead changes in industry-level profit margins are more positively correlated with long-run risks in high-innosimm industries (columns 1 and 5). One potential alternative

Table 3: Profit margins across industries with different innosimm (yearly analysis).

	(1)	(2)	(3)	(4)
	Industry-level profit margins, Compustat (%)		Industry-level profit margins, NBER-CES (%)	
Innosimm_t	2.57***	2.47**	3.29***	3.19***
	[4.31]	[4.08]	[3.65]	[3.51]
Year FE	No	Yes	No	Yes
Observations	9212	9212	2787	2787
R-squared	0.017	0.019	0.063	0.072

Note: This table shows the relation of the innovation similarity with industry-level profit margins. In columns (1) and (2), the dependent variables are the industry-level Compustat-based profit margins. In columns (3) and (4), the dependent variables are the industry-level NBER-CES-based profit margins. Profit margins are computed as in Figure 1. The sample spans from 1988 to 2017 in columns (1)–(2), and spans from 1988 to 2011 in columns (3)–(4). Standard errors are clustered by the 4-digit SIC industry and year. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels.

explanation for this cross-sectional pattern is that innosimm may be correlated with other industry characteristics such as income elasticity of demand and durability of firms' output. It is possible that these industry characteristics, rather than innosimm, drive the heterogeneous sensitivity of profit margins to long-run risks. To rule out this possibility, we control for the interaction between long-run-risk shocks and these industry characteristics. We find that the coefficient of the interaction term between long-run-risk shocks and innosimm remain positive and statistically significant (columns 2–4 and columns 6–8).[25]

4.3 Sensitivity of Product Prices to Long-Run Risks

The key mechanism of our model is that high-innosimm industries collude on higher product prices in good times, and their prices drop more in bad times due to endogenous price wars. We test this mechanism in this subsection. In particular, we study the changes of product prices using comprehensive product-level data. This data allow us to hold the products (and thus their attributes) constant in examining the pricing behavior across industries with different innosimm. Our findings suggest that high-innosimm industries

[25]Table 4 implies that the profit margins are less sensitive to long-run-risk shocks in luxury industries and durable industries. The finding for luxury industries is consistent with the marketing literature (see, e.g. Keller, 2008), which suggests that luxury goods producers tend to have stable and high product prices to maintain their brand image and the perception of scarcity. The finding for durable industries is consistent with the fact that the CPI index of durable goods is less volatile than that of non-durable goods (CPI indexes are available from St. Louis Fed's website). Yogo (2006) shows that the consumption of durable goods is more procyclical than non-durable goods, and Ait-Sahalia, Parker and Yogo (2004) show that luxury consumption is more procyclical than basic consumption. Different from these two papers, we focus on the profit margins instead of consumption demand.

Table 4: Sensitivity of profit margins to long-run risks across industries with different innosimm (yearly analysis).

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
				$\ln\left(\frac{\text{Profit margins}_{t+1}}{\text{Profit margins}_t}\right)$				
Measures of LRR	Filtered consumption growth				Realized consumption growth			
$\text{LRR}_t \times \text{innosimm}_t$	0.28**	0.28*	0.31*	0.29**	0.23**	0.21*	0.23*	0.24**
	[2.22]	[1.75]	[1.89]	[2.35]	[2.32]	[1.71]	[1.87]	[2.46]
$\text{LRR}_t \times \text{income elasticity of demand}_t$		−0.37***				−0.31**		
		[−2.81]				[−2.61]		
$\text{LRR}_t \times \text{luxury industries}_t$			−0.77**				−0.55*	
			[−2.63]				[−1.83]	
$\text{LRR}_t \times \text{durable industries}_t$				−0.89**				−0.79**
				[−2.59]				[−2.26]
$\text{income elasticity of demand}_t$		−0.00				−0.00		
		[−1.01]				[−0.76]		
$\text{luxury industries}_t$			−0.00				0.00	
			[−0.23]				[0.02]	
$\text{durable industries}_t$				−0.01**				−0.00
				[−2.33]				[−0.96]
LRR_t	0.20	0.57	0.50	0.28	0.37	0.69	0.59	0.45
	[0.47]	[1.10]	[0.89]	[0.71]	[1.07]	[1.61]	[1.29]	[1.37]
innosimm_t	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	[1.25]	[1.36]	[1.44]	[1.36]	[1.14]	[1.22]	[1.29]	[1.22]
Observations	8848	6979	6979	8848	9163	7234	7234	9163
R-squared	0.001	0.002	0.002	0.001	0.002	0.003	0.002	0.002

Note: This table shows the sensitivity of industry-level profit margins to long-run risks. Profit margins are computed based on Compustat data as explained in Figure 1. Long-run risks are measured by the annualized filtered consumption growth in the last quarter of year t (columns 1–4), and by the average of the realized consumption growth rates in year t and year $t-1$ (columns 5–8). We estimate the income elasticity of demand based on the representative consumer's income and expenditures on different products (see Appendix C.4 for details). We define luxury industries as the industries with income elasticity of demand larger than one. The durability of firms' output comes from Gomes, Kogan and Yogo (2009). The sample spans from 1988 to 2015 in columns (1)–(4), and spans from 1988 to 2017 in columns (5)–(8). We include t-statistics in parentheses. Standard errors are clustered by the 4-digit SIC industry and year. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels.

are more exposed to price war risks. Firms in the high-innosimm industries have product prices that decrease more in response to negative long-run-risk shocks and they are more likely to engage in price wars in the periods after the Lehman crash.

4.3.1 The Nielsen Data for Product Prices

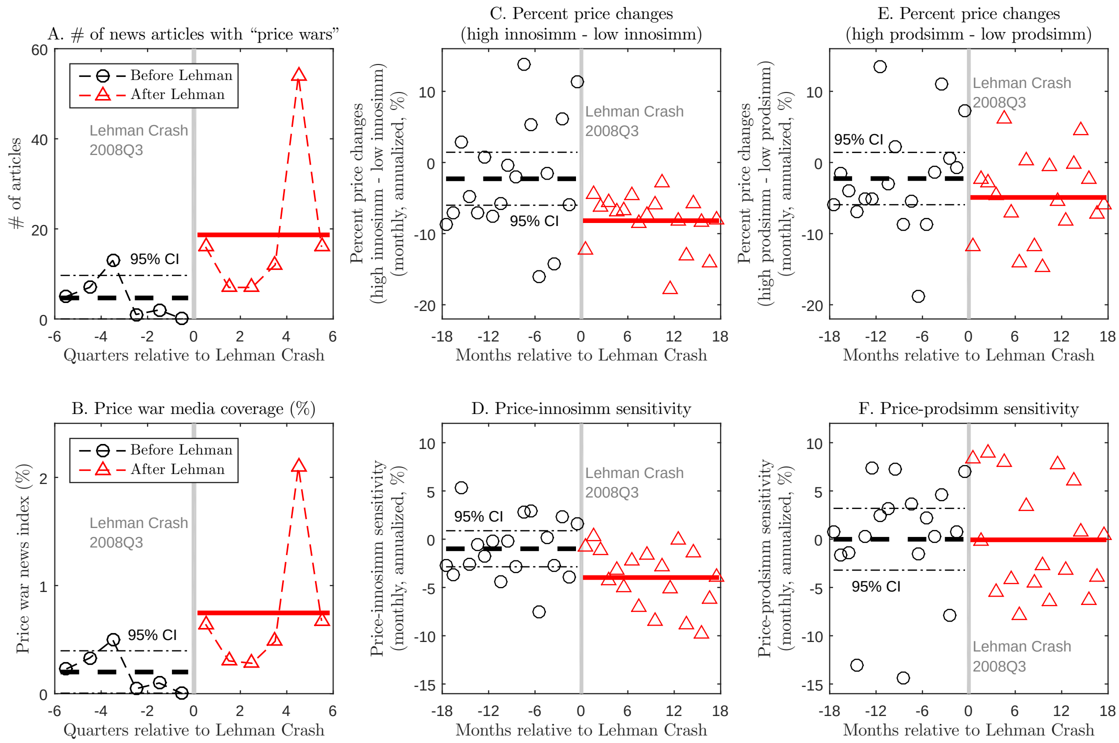
We use the Nielsen Retail Measurement Services scanner data to measure product price changes.[26] The Nielsen data record prices and quantities of every unique product that had any sales in the $42,928$ stores of more than 90 retail chains in the U.S. market from January 2006 to December 2016. In total, the Nielsen data consist of more than 3.5 million unique products identified by the Universal Product Codes (UPCs), and the data represent 53% of all sales in grocery stores, 55% in drug stores, 32% in mass merchandisers, 2% in convenience stores, and 1% in liquor stores (see, e.g. Argente, Lee and Moreira, 2018). We use the product-firm links provided by GS1, the official source of UPCs in the U.S., to match products in the Nielsen data to firms in CRSP/Compustat and Capital IQ. In Appendix C.3, we detail the matching procedure. Our merged data cover the product prices of 472 4-digit SIC industries.

4.3.2 Product Prices around the Lehman Crash

To begin, we examine the changes in media coverage about price war around the Lehman crash, the period during which the U.S. economy experienced a prominent negative long-run-risk shock (see Panel C of Figure 7). Because the Nielsen data mainly cover consumer goods sold by retailers and wholesalers, we focus on media coverage of the consumer goods sector and the retail/wholesale sector. Panel A of Figure 8 shows that, after the Lehman crash, the number of articles covering price wars increased dramatically. This pattern remains robust when we normalize the number of articles covering price wars using the total number of news articles (see Panel B of Figure 8).

Next, we examine the changes in product prices around the Lenman crash. We sort all industries into tertiles based on innosimm. Table 5 quantifies the changes in product prices among high-innosimm industries (Tertile 3) relative to low-innosimm industries (Tertile 1) around the Lehman crash. In particular, we restrict the sample to industries in Tertile 1 and Tertile 3, and create a Tertile-3 indicator for the latter group. We also create a post-Lehman indicator that equals one for observations in Oct. 2008 and thereafter. We then regress the percent change in product prices on the Tertile-3 indicator, the

[26] We obtain the Nielsen data from the Kilts Center for Marketing at the University of Chicago Booth School of Business (https://www.chicagobooth.edu/research/kilts/datasets/nielsen). The data have been widely used in the macroeconomics literature (see, e.g. Aguiar and Hurst, 2007; Broda and Weinstein, 2010; Hottman, Redding and Weinstein, 2016; Argente, Lee and Moreira, 2018; Jaravel, 2018).



Note: Panel A plots the number of articles (quarterly) that contain the term "price war" or "price wars" published in the Wall Street Journal, the New York Times, and the Financial Times around the Lehman crash. We require that the articles cover the US region and cover either the consumer goods sector or the retail/wholesale sector. The black dashed and red solid lines represent the mean number of articles before and after the Lehman crash. Panel B plots the price war media coverage (in percent), which is the number of articles that contain the term "price war" or "price wars" normalized by the number of articles published in the Wall Street Journal, the New York Times, and the Financial Times. We apply the same region/industry filters as those in Panel A. Panel C plots the difference in the percent change in product prices between high-innosimm (i.e. Tertile 3) and low-innosimm (i.e. Tertile 1) industries around the Lehman crash. The percent change in product prices is annualized from monthly data. The gray vertical bar represents the Lehman crash. The black circles and red triangles represent the difference in annualized monthly percent price changes between high-innosimm and low-innosimm industries in the 18 months before and after the Lehman crash. The black dashed and red solid lines represent the mean values of the differences before and after the Lehman crash. Panel D shows the price-innosimm sensitivity around the Lehman crash. The black circles and red triangles represent the monthly estimates of the price-innosimm sensitivity in the 18 months before and after the Lehman crash. The black dashed lines and red solid lines represent the mean values of the price-innosimm sensitivity before and after the Lehman crash. Panel E plots the difference in the percent change in product prices between high-prodsimm (i.e. Tertile 3) and low-prodsimm (i.e. Tertile 1) industries. Panel F shows the price-prodsimm sensitivity. We estimate confidence intervals using the bootstrapping method. Specifically, for each panel, we construct 1,000,000 time series by randomly drawing (with replacement) from a sample pool that contains observations both before and after the Lehman crash. We then estimate the 95% CI (dotted dashed lines) for the difference between the mean values before and after the Lehman crash. The differences between the mean values before and after the Lehman crash are statistically significant (insignificant) if the red solid lines are outside (within) the 95% CI.

Figure 8: Changes of price war news index and product prices around the Lehman crash.

post-Lehman-crash indicator, and an interaction term between these two indicators. The coefficient of the interaction term is negative and statistically significant across different regression specifications, suggesting that product prices in high-innosimm industries reduce significantly relative to those in low-innosimm industries after the Lehman crash.

The difference in product prices is economically significant. According to the regression without industry fixed effects (column 1 of Table 5), product prices decrease by 4.98% in high-innosimm industries after the Lehman crash, relative to those of low-innosimm industries.

Panel C of Figure 8 visualizes the difference in average product prices between low-innosimm and high-innosimm industries in the 36-month period around the Lehman crash. The plot clearly shows that product prices in high-innosimm industries reduced more relative to those of low-innosimm industries after the Lehman crash. The above findings support our model's prediction that high-innosimm industries are more likely to engage in price wars following negative long-run-risk shocks.

Table 5: Product prices around the Lehman crash (monthly analysis).

	(1)	(2)	(3)	(4)
	Percent change in product prices (monthly, annualized, %)			
Similarity measure	Innosimm		Prodsimm	
Tertile-3 similarity$_{t-1}$ × post Lehman crash$_t$	-4.98^{***}	-5.12^{**}	-2.02	-1.48
	[-2.85]	[-2.64]	[-1.33]	[-0.78]
Tertile-3 similarity$_{t-1}$	-2.32	-4.73	-2.25	-3.17
	[-1.05]	[-0.93]	[-1.07]	[-1.58]
Post Lehman crash$_t$	0.40	1.03	-0.82	-0.74
	[0.19]	[0.50]	[-0.59]	[-0.44]
Industry FE	No	Yes	No	Yes
Observations	5106	5106	4809	4809
R-squared	0.003	0.053	0.001	0.041

Note: This table shows the changes in product prices around the Lehman crash. The dependent variable is the annualized monthly percent change in product prices of 4-digit SIC industries. Product prices are obtained from the Nielsen Data. To compute the monthly percent change in product prices for 4-digit SIC industries, we first compute the transaction-value weighted price for each product across all stores in each month. We then calculate the monthly percent change in prices for each product. Finally, we compute the value-weighted percent change in product prices for each 4-digit SIC industry based on the transaction values of the industry's products. In columns (1) and (2), the similarity measure is innosimm. In columns (3) and (4), the similarity measure is prodsimm. We consider the 36-month period around the Lehman crash. In Appendix F.1, we perform the analysis by considering the 24-month period around the Lehman crash and find similar results. We include t-statistics in parentheses. Standard errors are clustered by the 4-digit SIC industry and month. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels.

We continue to extend our analysis to all industries. According to the theory, the Lehman crash brings about product price changes in all industries, but with different magnitudes presumably depending on the industry's innosimm. To understand how the percent change in product prices varies with industry-level innosimm, or what we call the price-innosimm sensitivity, we regress the percent change in product prices on innosimm, the post-Lehman indicator, and an interaction term between innosimm and

Table 6: Price-similarity sensitivity around the Lehman crash (monthly analysis).

	(1)	(2)	(3)	(4)
	Percent change in product prices (monthly, annualized, %)			
Similarity measure	Innosimm		Prodsimm	
$\text{Similarity}_{t-1} \times \text{post Lehman crash}_t$	-3.04^{***}	-2.84^{***}	-0.07	-0.35
	[-3.19]	[-2.79]	[-0.20]	[-1.15]
Similarity_{t-1}	-1.00	-2.05	-0.01	-5.90^{***}
	[-1.32]	[-1.45]	[-0.01]	[-3.95]
Post Lehman crash_t	-1.61	-1.64	-2.25^{*}	-2.35^{*}
	[-1.44]	[-1.47]	[-1.80]	[-1.87]
Industry FE	No	Yes	No	Yes
Observations	7641	7641	7192	7192
R-squared	0.004	0.040	0.001	0.039

Note: This table shows the price-similarity sensitivity around the Lehman crash. The dependent variable is the annualized monthly percent change in product prices of 4-digit SIC industries. We consider the 36-month period around the Lehman crash. In Appendix F.1, we perform the analysis by considering the 24-month period around the Lehman crash and find similar results. We include t-statistics in parentheses. Standard errors are clustered by the 4-digit SIC industry and month. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels.

the post-Lehman indicator. The regression results are presented in columns (1) and (2) of Table 7. The change in price-innosimm sensitivity owing to the Lehman crash is given by the coefficient on the interaction term. Table 7 shows that the coefficient of the interaction term is negative, indicating that high-innosimm industries are more affected by the Lehman crash and their product prices decrease relatively more compared to low-innosimm industries, which again suggests that high-innosimm industries are more likely to engage in price wars following negative long-run-risk shocks. Panel D of Figure 8 visualizes the monthly price-innosimm sensitivity. It is evident that the price-innosimm sensitivity reduces significantly after the Lehman crash.

We also examine the product prices around the Lehman crash for industries with different prodsimm. We find that product prices do not move differently for high-prodsimm industries and low-prodsimm industries (Panel E of Figure 8, columns 3 and 4 in Table 5). Moreover, we observe little change in price-prodsimm sensitivity following the Lehman crash (Panel F of Figure 8, columns 3 and 4 in Table 6). These findings suggest that, unlike innosimm, prodsimm does not appear to be related to the price war risks that endogenously arise from long-run risks.

4.3.3 Sensitivity of Product Prices to Long-Run Risks Across Industries

Having conducted an event-type study by focusing on the time period around the Lehman crash, we now extend our analysis to the whole time series covered by the Nielsen data from 2006 to 2016. Specifically, we regress the percent change in product prices on innosimm, long-run growth rate, and the interaction term between innosimm and the long-run growth rate. Table 7 shows that the coefficient of the interaction term is positive and statistically significant. This result remain robust when we control for various industry characteristics such as the income elasticity of demand and durability of industry's outputs. The above findings suggest that the product prices of high-innosimm industries are more sensitive to long-run risks and hence these industries are more exposed to price war risks.

4.4 Asset Pricing Tests

We now test the asset pricing implications of our model. We find that high-innosimm industries have higher average excess returns and risk-adjusted returns. The spreads between high-innosimm industries and low-innosimm industries (denoted as innosimm spreads) remain robust after controlling for various related measures. Moreover, the innosimm spreads become much weaker among the industries that experience antitrust enforcement in recent years. Finally, we show that the stock returns and dividend growth of the high-innosimm industries are more exposed to long-run risks.

4.4.1 Innosimm Spreads Across Industries

We examine whether innosimm is priced in the cross section. Panel A of Table 8 presents the value-weighted average excess returns and alphas for the 4-digit SIC industry portfolios sorted on innosimm. It shows that the portfolio consisting of high-innosimm industries (i.e. Q5) exhibits significantly higher average excess returns and alphas. The annualized spread in average excess returns between Q1 and Q5 is 3.41% and the annualized spreads in alphas are 5.22% and 4.75% for the Fama-French three-factor model and the Carhart four-factor model. We also perform the same analysis for prodsimm. We find that prodsimm is not priced in the cross section. The return difference between the high-prodsimm portfolio and the low-prodsimm portfolio is statistically insignificant (see Panel B of Table 8).

Table 7: Price-innosimm sensitivity and long-run growth rate (quarterly analysis).

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	One-year ahead percent change in product prices ($\sum_{j=1}^{4} price\_gr_{t+j}$)							
Measures of LRR	Filtered consumption growth				Realized consumption growth			
$\text{LRR}_t \times \text{innosimm}_t$	1.17**	1.13*	1.17**	1.16**	0.80**	0.75*	0.81**	0.79**
	[2.37]	[2.24]	[2.34]	[2.35]	[2.36]	[2.15]	[2.33]	[2.28]
$\text{LRR}_t \times$ income elasticity of demand_t		−0.36				−0.77***		
		[−0.75]				[−5.69]		
$\text{LRR}_t \times$ luxury industries_t			−0.52				−0.91***	
			[−1.56]				[−3.92]	
$\text{LRR}_t \times$ durable industries_t				−1.27*				0.52
				[−2.14]				[0.51]
income elasticity of demand_t		0.01				−0.00		
		[0.52]				[−0.68]		
luxury industries_t			−0.00				−0.01	
			[−0.22]				[−0.94]	
durable industries_t				−0.10***				−0.05**
				[−5.29]				[−2.71]
LRR_t	−0.20	0.26	0.07	−0.02	0.11	1.07**	0.58	0.07
	[−0.13]	[0.17]	[0.05]	[−0.02]	[0.23]	[3.07]	[1.20]	[0.15]
Innosimm_t	0.00	0.00	0.00	0.00	−0.00	−0.00	−0.00	−0.00
	[0.17]	[0.18]	[0.17]	[0.17]	[−0.24]	[−0.21]	[−0.13]	[−0.25]
Observations	7338	7338	7338	7338	8208	8208	8208	8208
R-squared	0.002	0.003	0.002	0.006	0.004	0.006	0.005	0.010

Note: This table shows the sensitivity of percent changes in product prices to consumption growth across the 4-digit SIC industries with different innosimm. The dependent variable is the industry-level annualized percent change in product prices from quarter $t+1$ to quarter $t+4$. Long-run risks are measured by annualized filtered consumption growth in quarter t in columns (1)–(4), and by the average realized consumption growth from quarter $t-7$ to t (annualized). We estimate the income elasticity of demand based on the representative consumer's income and expenditures on different products (see Appendix C.4 for details). We define luxury industries as the industries with income elasticity of demand larger than one. The durability of firms' output comes from Gomes, Kogan and Yogo (2009). The sample period of columns is from 2006 to 2016. We include t-statistics in parentheses. Standard errors are clustered by the 4-digit SIC industry and year. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels.

4.4.2 Double-Sort Analyses

Profit margins. We have shown that profit margins of high-innosimm industries are more exposed to long-run risks. According to our theory, innosimm is priced in the cross section because it captures the sensitivity of profit margins to long-run risks. Previous studies have shown that profitability is strongly related to asset returns (see, e.g. Novy-Marx, 2013; Fama and French, 2015; Hou, Xue and Zhang, 2015). Since innosimm is positively related to profit margins (see Table 3), it is possible that innosimm is priced

Table 8: The average excess returns and alphas of portfolios sorted on innovation similarity and product similarity (monthly analysis).

	1 (Low)	2	3	4	5 (High)	$5-1$
			Panel A: Portfolios sorted on innosimm			
			Average excess returns			
$\mathbb{E}[R]-r_f$ (%)	6.13^{***}	8.37^{***}	7.35^{***}	8.62^{***}	9.54^{***}	3.41^{***}
	[2.74]	[3.73]	[3.01]	[4.42]	[3.17]	[2.71]
			Fama-French three-factor model (Fama and French, 1993)			
α (%)	-2.51^{**}	0.07	-1.34	1.08	2.71^{**}	5.22^{***}
	[-2.48]	[0.10]	[-0.69]	[1.21]	[2.49]	[3.54]
			Carhart four-factor model (Carhart, 1997)			
α (%)	-2.47^{***}	0.09	-1.25	1.43	2.28^{***}	4.75^{***}
	[-2.70]	[0.18]	[-0.78]	[1.50]	[2.63]	[4.01]
			Panel B: Portfolios sorted on prodsimm			
			Average excess returns			
$\mathbb{E}[R]-r_f$ (%)	4.94^{**}	6.44^{**}	8.07^{**}	6.25^{*}	6.19^{*}	1.25
	[2.29]	[2.05]	[2.59]	[1.77]	[1.91]	[0.42]
			Fama-French three-factor model (Fama and French, 1993)			
α (%)	-0.89	0.03	2.21^{**}	0.08	0.82	1.70
	[-0.48]	[0.01]	[2.53]	[0.06]	[0.86]	[0.64]
			Carhart four-factor model (Carhart, 1997)			
α (%)	-0.57	0.42	2.19^{**}	0.69	0.70	1.26
	[-0.36]	[0.20]	[2.43]	[0.68]	[0.75]	[0.53]

Note: This table shows the value-weighted average excess returns and alphas for the 4-digit SIC industry portfolios sorted on innosimm. In June of year t, we sort the 4-digit SIC industries into five quintiles based on this industry's innosimm in year $t-1$. Once the portfolios are formed, their monthly returns are tracked from July of year t to June of year $t+1$. The sample period is from July 1988 to June 2018. We exclude financial firms and utility firms from the analysis. We include t-statistics in parentheses. Standard errors are computed using the Newey-West estimator allowing for serial correlation in returns. We annualize average excess returns and alphas by multiplying by 12. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels.

via its correlation with the level of profit margins instead of via the sensitivity of profit margins to long-run risks. We present two sets of evidence that argue against this alternative explanation. First, the innosimm spreads documented in Table 8 are robust when we control for the profitability factor using the Fama-French five-factor model (Fama and French, 2015) and the Hou-Xue-Zhang q factor model (Hou, Xue and Zhang, 2015). The annualized spreads in alphas between the high-innosimm industries (Q5) and the low-innosimm industries (Q1) are 9.24% and 8.88%, while the t-statistics are 4.11 and 6.38, for these two models. Second, the innosimm spreads remain robust after we double sort on the profit margins (see Table 9). These findings suggest that innosimm and profitability are priced for different underlying economic mechanisms, which is not surprising given that profitability is affected by many other factors besides its sensitivity to long-run risks.

Other related variables. Besides the level of profitability, we also conduct a number of double-sort analyses for other related variables. innosimm spreads are robust after controlling for prodsimm, innovation originality, asset growth rate, income elasticity of demand, and the durability of firms' outputs (see Table 9).

Table 9: Double-sort analyses (monthly analysis).

Double-sort variables	Excess returns (%)	Fama-French three-factor alpha (%)	Carhart four-factor alpha (%)
Profit margins	2.53***	4.43**	4.14***
	[2.80]	[5.00]	[4.42]
Prodsimm	2.15*	3.81***	3.72***
	[1.92]	[4.27]	[4.81]
Innovation originality	2.83***	4.31***	3.70***
	[3.36]	[3.27]	[3.59]
Asset growth rate	3.37***	4.91**	4.54***
	[2.60]	[3.75]	[4.12]
Income elasticity of demand	3.76***	5.45***	4.78***
	[2.98]	[3.20]	[3.29]
Durability of firms' outputs	3.66**	3.96**	3.69**
	[2.27]	[2.07]	[2.48]

Note: This table shows the average excess returns and alphas from double-sort analyses. In the double-sort analyses, we first sort the 4-digit SIC industries into three groups based on measures of profit margins, product similarity, innovation originality or durability of firms' outputs in June of year t. We then sort firms within each group into five quintiles based on innosimm in year $t-1$. Once the portfolios are formed, their monthly returns are tracked from July of year t to June of year $t+1$. Industry-level profit margins are computed based on Compustat data as explained in Figure 1. Prodsimm is the product similarity measure as in (Hoberg and Phillips, 2016), which is derived from text analysis based on the business deription in 10-K filings. Innovation originality is constructed following Hirshleifer, Hsu and Li (2017) to capture the patents' originality. In particular, we count the number of unique technology classes contained in a patent's citations/reference list. We then obtain the industry-level innovation originality measure by averaging the number of classes across all patents in a 4-digit SIC industry every year. Asset growth rate is the growth rate of the total asset. We obtain the industry-level asset growth rate by averaging the firm-level asset growth rate in a 4-digit SIC industry every year. We estimate the industry-level income elasticity of demand based on the representative consumer's income and expenditures on different products (see Appendix C.4 for details). The durability of firms' output comes from Gomes, Kogan and Yogo (2009), who classify each SIC industry into six categories (durables, non-durables, services, private domestic investment, government, and net exports) based on its contributions to final demand. We exclude financial firms and utility firms from the analysis. We include t-statistics in parentheses. Standard errors are computed using the Newey-West estimator allowing for serial correlation in returns. We annualize average excess returns and alphas by multiplying by 12. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels.

4.4.3 The Impact of Antitrust Enforcement

We now test whether innosimm spreads are related to the difference in industries' collusion incentive (see Appendix E.3 for model implications). We exploit the variation in collusion incentive due to antitrust enforcement, which punishes collusive behavior and thus dampens firms' incentive to collude.

To examine the impact of antitrust enforcement on innosimm spreads, we split all industries in each year into two groups based on whether they have experienced any antitrust enforcement in the past ten years.[27] As shown in Table 10, the innosimm spreads are much smaller in the industries that have recently experienced antitrust enforcement, suggesting that innosimm spreads are driven by heterogeneous collusion incentive across industries with different innosimm as illustrated by our model.

Table 10: Antitrust enforcement and innosimm spreads (monthly analysis).

Excess returns (%)	Fama-French three-factor alpha (%)	Carhart four-factor alpha (%)
Panel A: Industries with antitrust enforcement in the past 10 years		
−0.81	0.59	−0.44
[−0.33]	[0.24]	[−0.21]
Panel B: Industries without antitrust enforcement in the past 10 years		
3.27**	5.44**	5.54***
[2.01]	[2.91]	[3.00]

Note: This table presents the average excess returns and alphas (both in percent) of the value-weighted long-short 4-digit SIC industry portfolio sorted on innosimm in the sub-samples with (Panel A) and without (Panel B) antitrust enforcement in past ten years. We exclude financial firms and utility firms from the analysis. We include t-statistics in parentheses. Standard errors are computed using the Newey-West estimator allowing for serial correlation in returns. We annualize the average excess returns and the alphas by multiplying by 12. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels.

4.4.4 The Exposure of Stock Returns and Dividend Growth to Long-Run Risks

Finally, we show that the stock returns and dividend growth of high-innosimm industries have higher exposure to long-run risks. We first examine the exposure of stock returns to long-run risks. We sort all industries into quintile portfolios based on innosimm, and regress the cumulative portfolio returns of each portfolio on long-run risks, following Dittmar and Lundblad (2017). We use two measures of long-run risks in our analyses: the cumulative realized consumption growth as in Dittmar and Lundblad (2017), and the filtered consumption growth as in Schorfheide, Song and Yaron (2018). Table 11 tabulates the coefficients of long-run risks across the quintile portfolios sorted on innosimm (denoted as LRR beta). The LRR beta for the long-short portfolio is positive and statistically significant, suggesting that the stock returns of high-innosimm industries are more exposed to long-run risks.

[27] The antitrust enforcement cases are hand collected from the websites of the U.S. Department of Justice (DOJ) and the Federal Trade Commission (FTC). DOJ provides 4-digit SIC codes for the firms in some of the cases. For the rest of DOJ cases and all FTC cases, we match the firms involved in antitrust enforcement to CRSP/Compustat and Capital IQ, from which we collect the 4-digit SIC codes of these firms.

Table 11: Long-run-risk exposure of portfolios sorted on innosimm (quarterly analysis).

Portfolios sorted on innosimm	1 (Low)	2	3	4	5 (High)	$5-1$
Panel A: Long-run risks measured by 8-quarter cumulative realized consumption growth						
LRR betas	1.78	6.55***	3.48***	5.51***	5.24***	3.46**
	[1.58]	[5.09]	[3.12]	[3.73]	[4.03]	[2.09]
Panel B: Long-run risks measured by 8-quarter cumulative filtered consumption growth						
LRR betas	−0.05	4.45***	−0.62	3.57**	4.69**	4.75**
	[−0.05]	[3.16]	[−0.52]	[2.57]	[2.41]	[2.61]

Note: This table shows the exposure to long-run risks for industry portfolios sorted on innosimm. In June of year t, we sort industries into five quintiles based on innosimm in year $t-1$. Once the portfolios are formed, their monthly returns are tracked from July of year t to June of year $t+1$. In Panel A, following Dittmar and Lundblad (2017), we regress the 8-quarter cumulative portfolio returns on the 8-quarter cumulative realized consumption growth: $\prod_{j=0}^{7} R_{i,\tau-j} = \alpha_i + \beta_i \sum_{j=0}^{7} \hat{\eta}_{\tau-j} + e_{i,\tau}$, where $\hat{\eta}_\tau$ is the consumption growth shock, measured by the difference between the log consumption growth in quarter τ and the unconditional mean of log consumption growth over 1947–2018. We measure consumption using per-capita real personal consumption expenditures on non-durable goods and services. $R_{i,\tau}$ is the gross real return of the industry portfolio i in quarter τ. Consumption and returns are deflated to real terms using the personal consumption expenditure deflator from the U.S. Bureau of Economic Analysis (BEA). The analysis is conducted at quarterly frequency for the sample period from 1988 to 2018. In Panel B, we replace realized cumulative consumption growth ($\sum_{j=0}^{7} \hat{\eta}_{\tau-j}$) in the above regression with cumulative filtered consumption growth ($\sum_{j=0}^{7} \hat{x}_{\tau-j}$) as in Schorfheide, Song and Yaron (2018). The sample period in Panel B is from 1988 to 2015 because data on the filtered consumption growth end in 2015. We exclude financial firms and utility firms from the analysis. We include t-statistics in parentheses. Standard errors are computed using the Newey-West estimator allowing for serial correlation in returns. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels.

We further examine the exposure of real dividend growth to long-run risks for the long-short portfolio sorted on innosimm. We construct real dividend growth rate following previous literature (see, e.g. Campbell and Shiller, 1988; Bansal, Dittmar and Lundblad, 2005; Hansen, Heaton and Li, 2005, 2008; Bansal, Kiku and Yaron, 2016). We detail the construction method in Appendix C.5. Importantly we account for stock entries and exits when computing a portfolio's dividend growth rate. Table 12 shows that the dividend growth of high-innosimm industries is also more exposed to long-run risks.

5 Quantitative Analyses

In this section, we conduct quantitative analyses. We calibrate the extended model's parameters and examine whether our model can replicate the main asset pricing patterns from the data.

5.1 Calibration

We solve the model numerically (see Appendix G). The model's parameters are calibrated based on both existing estimates and micro data (see Table 13) without referring to asset

Table 12: Long-run-risk exposure of real dividend growth for the long-short industry portfolio sorted on innosimm ($Q5 - Q1$) (quarterly analysis).

Spreads of dividend growth (annualized, %)	2.09
	[0.48]
Exposure to LRR measured by realized consumption growth	7.68***
	[4.75]
Exposure to LRR measured by filtered consumption growth	6.23***
	[4.72]

Note: This table shows the exposure of real dividend growth to long-run risks for the long-short industry portfolios sorted on innosimm. We measure long-run risks using both realized consumption growth and filtered consumption growth as in Schorfheide, Song and Yaron (2018). For the first LRR measure, we regress the 4-quarter cumulative dividend growth of the long-short innosimm portfolios on the lagged 8-quarter cumulative realized consumption growth (annualized): $\sum_{j=1}^{4}(D_{Q_5,t+j} - D_{Q_1,t+j}) = \alpha + \beta \sum_{j=0}^{7} \hat{\eta}_{t-j}/2 + e_t$, where $\hat{\eta}_t$ is the realized consumption growth shock. For the second LRR measure, we replace the 8-quarter realized cumulative consumption growth in the above regression ($\sum_{j=0}^{7} \hat{\eta}_{t-j}/2$) with annualized quarterly filtered consumption growth. We exclude financial firms and utility firms from the analysis. We include t-statistics in parentheses. Standard errors are computed using the Newey-West estimator allowing for serial correlation in returns. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels.

pricing information, and we examine whether the calibrated model can quantitatively explain the observed asset pricing patterns.

The process of aggregate consumption is calibrated following Bansal and Yaron (2004). We set the persistence of expected growth rate to be $\kappa = 0.49$, so that the auto-correlation of annual consumption growth rates is 0.49. We set $\bar{\theta} = 0.018$ and $\sigma_c = 0.029$ so that the average annual consumption growth rate is 1.8% and its standard deviation is about 2.9%. Following Bansal and Yaron (2004), we set $\varphi_\theta = 0.044$, indicating that the predictable variation in consumption growth is 4.4%. Following the standard practice, we set the subjective discount factor $\beta = 0.976$, the risk aversion parameter $\gamma = 10$, and the intertemporal elasticity of substitution $\psi = 1.5$.

We set the within-industry elasticity of substitution $\eta = 10$ and the across-industry elasticity of substitution to be $\epsilon = 2$, broadly consistent with the values of Atkeson and Burstein (2008). The unit flow cost of production ω is normalized to be one. The success rate of innovation is set to be $\mu = 0.4$. We set the customer base depreciation rate to be $\rho = 0.15$, within the range of 15%-25% estimated by Gourio and Rudanko (2014). We choose a low $z = 0.05$ to capture sticky customer base (Gourio and Rudanko, 2014; Gilchrist et al., 2017).

We allow the industry characteristic $\lambda_{i,t}$ to take 11 values, i.e. $\lambda_{i,t} \in \{0.9, 0.91, 0.92, ..., 1\}$. The characteristic $\lambda_{i,t}$ remains the same unless it is hit by a Poisson shock with rate ε. Conditional on receiving the Poisson shock, a new characteristic is randomly drawn with

Table 13: Calibration and parameter choice.

Parameters	Symbol	Value	Parameters	Symbol	Value
Average long-run consumption growth rate	$\bar{\theta}$	0.018	Persistence of expected growth rate	κ	0.49
Exposure to long-run growth risks	φ_θ	0.044	Volatility of consumption growth	σ_c	0.029
Customer base adjustment friction	χ	0.3	Cost of production	ω	1
Customer base accumulation rate	z	0.05	Customer base depreciation rate	ρ	0.15
Across-industry elasticity of substitution	ϵ	2	Within-industry elasticity of substitution	η	10
Customer base stealing (incremental)	τ_ι	0.15	Customer base stealing (radical)	τ_d	0.90
Punishment rate	ϕ	0.15	Risk aversion	γ	10
Inter-temporal elasticity of substitution	ψ	1.5	Subjective discount factor	β	0.976
Persistence of industry characteristics	ε	0.03	Innovation success rate	μ	0.4

equal probabilities of each value. Across all industries, incremental innovation occurs every 6 months and radical innovation occurs every 10 years on average. We set $\varepsilon = 0.05$ to make $\lambda_{i,t}$ a persistent industry characteristic. The within-industry customer base stealing due to incremental and radical innovation are set to be $\tau_\iota = 0.15$ and $\tau_d = 0.90$. The punishment rate is set to be $\phi = 0.15$, implying that the difference in price changes between Tertile 1 and Tertile 3 innosimm portfolios is about 1% for a one-percent change in long-run consumption growth rates, roughly consistent with Table 7.

5.2 Quantitative Results

Now we check whether our model can quantitatively replicate the main asset pricing patterns presented in Table 8. In each year t, we sort the simulated firms into five quintiles based on their $\lambda_{i,t}$ at the beginning of the year. We then compute the value-weighted average excess return of each quintile's portfolio. Table 14 shows that the model-implied difference in the annualized average excess returns between Q1 and Q5 is about 3.28%. These numbers are quantitatively consistent with the findings in Table 8. If we simulate the model without price war risks (by focusing on constant collusive prices), the average risk premium decreases by about 33%, and the model-implied spread is largely reduced to 0.43%.

6 Conclusion

In this paper, we explore the the implication of price war risks. We develop a general-equilibrium asset pricing model incorporating dynamic supergames of price competition

Table 14: Average excess returns of portfolios in data and model.

$\mathbb{E}[R] - r_f$	Data	Model	
		Baseline	No price war risks
Quintile 1 (%)	6.13	4.02	3.63
Quintile 5 (%)	9.54	7.30	4.06
Q5 – Q1 (%)	3.41	3.28	0.43

among firms. In our model, price wars can arise endogenously from declines in long-run consumption growth, since firms become effectively more impatient for cash flows and their incentives to undercut prices become stronger. The exposure to price war risks reflect predictable and persistent heterogeneous industry characteristics. Firms in industries with higher capacities of radical innovation are more immune to price war risks due to the higher likelihood of creative destruction and market disruption. Exploring detailed patent and product price data, we found evidence for the existence of price war risks. Moreover, that endogenous price war risks are priced in the cross section.

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Appendix

A Headline Quotes for Price Wars and Stock Returns

We cite a few recent media headlines on how price wars can depress firms' stock returns.

- "Best Buy Co. shares plunged 11% Tuesday, after the electronics chain warned investors about price war fears." – *The Wall Street Journal* on November 20th of 2013.
- "Target shares dive as it shifts to cut-price strategy." – *Financial Times* on February 28th of 2017.
- "Price war eats into the profits of pharmaceutical wholesalers and manufacturers alike and erases billions of dollars of the market value in recent days" – *The Wall Street Journal* on August 5th of 2017.
- "Airline stocks plunge on price war fears." – *Financial Times* on January 24th of 2018.
- "Investors Purge Infinera Stock on Price War Concerns, Ignore Q1 Results." – *SDxCentral* on May 10th of 2018.
- "A fierce price war between consumer goods giants hit Unilever shares hard." – *The Wall Street Journal* on July 19th of 2018.
- "Coffee price war takes jolt out of Dunkin' results." – *Financial Times* on September 27th of 2018.

B Analyst Report Coverage on Price Wars

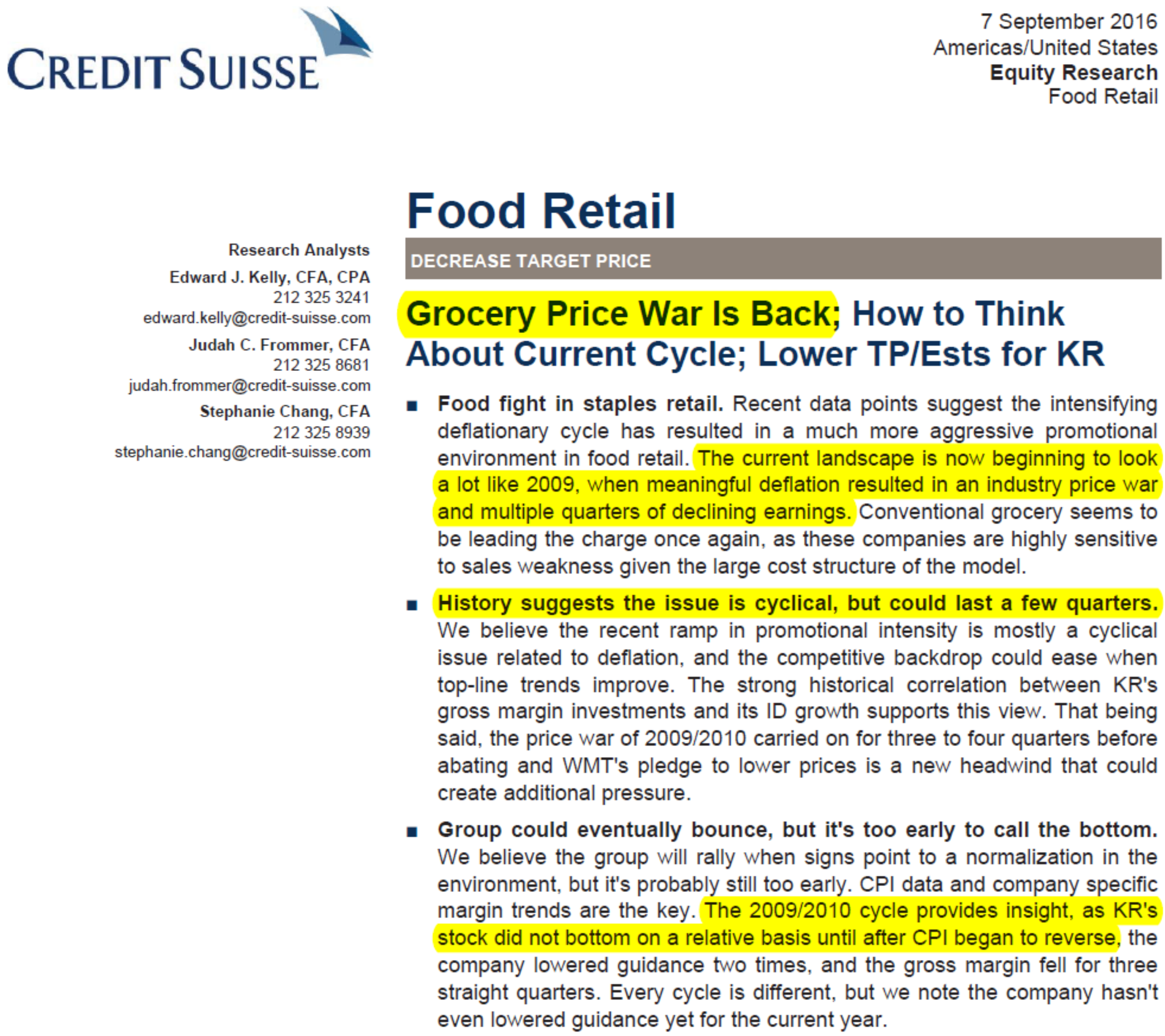
We cite a few analyst reports that provide coverage and comments on price wars.

- Figure B.1 shows Credit Suisse's coverage on the food retail industry.
- Figure B.2 shows MF Global's coverage on Apple Inc.
- Figure B.3 shows Salomon Smith Barney's coverage on Compaq.
- Figure B.4 shows Indigo Equity Research's coverage on AT&T.
- Figure B.5 shows Cowen's coverage on Dick's Sporting Goods.

C Data

C.1 Industry Concentration Ratio

We use the U.S. Census concentration ratio data from 1987, 1992, 1997, 2002, 2007, and 2012 to compute the time-series maximal and mean revenue shares for the top 4 firms (CR4) and top 8 firms (CR8) in each 4-digit SIC industry. The concentration ratios are at the 6-digit NAICS level after 1997. We follow Ali, Klasa



7 September 2016
Americas/United States
Equity Research
Food Retail

Food Retail

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DECREASE TARGET PRICE

Grocery Price War Is Back; How to Think About Current Cycle; Lower TP/Ests for KR

- **Food fight in staples retail.** Recent data points suggest the intensifying deflationary cycle has resulted in a much more aggressive promotional environment in food retail. The current landscape is now beginning to look a lot like 2009, when meaningful deflation resulted in an industry price war and multiple quarters of declining earnings. Conventional grocery seems to be leading the charge once again, as these companies are highly sensitive to sales weakness given the large cost structure of the model.
- **History suggests the issue is cyclical, but could last a few quarters.** We believe the recent ramp in promotional intensity is mostly a cyclical issue related to deflation, and the competitive backdrop could ease when top-line trends improve. The strong historical correlation between KR's gross margin investments and its ID growth supports this view. That being said, the price war of 2009/2010 carried on for three to four quarters before abating and WMT's pledge to lower prices is a new headwind that could create additional pressure.
- **Group could eventually bounce, but it's too early to call the bottom.** We believe the group will rally when signs point to a normalization in the environment, but it's probably still too early. CPI data and company specific margin trends are the key. The 2009/2010 cycle provides insight, as KR's stock did not bottom on a relative basis until after CPI began to reverse, the company lowered guidance two times, and the gross margin fell for three straight quarters. Every cycle is different, but we note the company hasn't even lowered guidance yet for the current year.

Figure B.1: Credit Suisse's coverage on the food retail industry.

and Yeung (2008) and convert the ratios to 4-digit SIC levels. Figure C.6 plots the histogram of the max CR4 (Panel A1), max CR8 (Panel B1), mean CR4 (Panel A2), and mean CR8 (Panel B2) in all 4-digit SIC industries. Red vertical lines represent the cross-sectional mean values.

Technology | **MF Global**

Communications | Per Lindberg, +44 (0)20 7144 4264, plindberg@mfglobal.com | **20th October 2009**

Apple [AAPL US]

All-time heights

Sell

Results review (Q4 '09)

Current Price	US$ 200
Target Price	US$ 90

iPhones – in preparation for price wars

The situation today is markedly different from that of a year ago. In July 2008, the 3G version of the iPhone took the market by storm. Its features, form-factor and fashion were absolutely unique – affording immense pricing powers (even though Apple relinquished on initial demands to make a cut of service revenues). Most importantly, at the time Apple ten-folded its customer base, from a handful to ca 70 operators (targeted by end of 2008). At this juncture, Apple confronts a number of *"me-too"* competitors – many of whom taking advantage of Google's spiraling interests in this space (see further remarks below). In spite of the robust start to the 3GS campaign (or perhaps because of it), we are not inclined to increase our forecasts for the current period, for which we look for 7.0-7.5m units shipped, up slightly year-on-year. We stand by our thesis that it appears increasingly clear that Apple, especially in this economic climate and phase of the competitive cycle, must make the iPhone considerably more affordable for end-user and operators alike. We anticipate significant price concessions in the imminent future. It should help to broaden the take-up of the iPhone and hence allow the company to deliver on its market share objectives. On this basis, we look for shipments of 42m units in 2010, 56m in 2011 and 62m in 2012, 3x that of 2009.

Figure B.2: MF Global's coverage on Apple Inc.

SALOMON SMITH BARNEY

Target Price Change ☑
Estimate Change ☑

Compaq Computer (CPQ)#

CPQ: PRICE WAR ROLLS ON - REITERATE 3H RATING WITH $24 TARGET

3H *(Neutral, High Risk)*
Mkt Cap: **$35,352.8 mil.**

April 24, 2001

PCS

Richard Gardner
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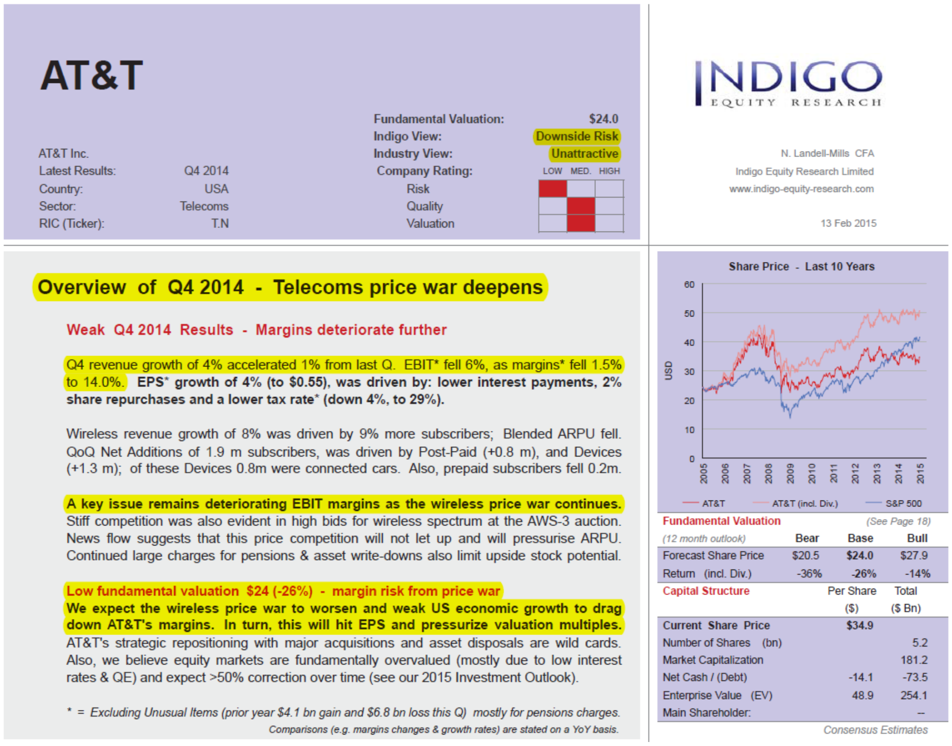
SUMMARY

- Compaq reported 1Q01 results yesterday after the close. Revenue of $9.2B (-3% yoy) was slightly below our estimate of $9.3B, but in line with revised guidance of $9.0-9.2B. Diluted EPS of $0.12 (excluding one time charges), were one penny below consensus but within revised guidance of $0.12-0.14.
- Consumer demand remains weak worldwide and price pressure is intense in PCs and Intel-based servers. Mgmt also cited price pressure in enterprise storage and even business critical server (Alpha and Himalaya).
- The company now plans to reduce headcount by 7,000 employees worldwide versus prior guidance of 5,000. These reductions come from closure of manufacturing plants, the combination of the commercial and consumer PC divisions and cuts in administrative areas. Mgmt hopes to reduce op ex by $500M annually.
- 2Q revenue is now expected to decline to $9.0B and earnings are expected to

>decline to $0.05 (versus prior consensus of $0.17). The downward revision reflects mgmt's intent to 1) reduce PC and Intel-based server inventories by $500M, 2) price more aggressively, and 3) spend more on demand generation in core markets to defend mkt share against Dell and IBM.

United States

Figure B.3: Salomon Smith Barney's coverage on Compaq.



AT&T

AT&T Inc.		Fundamental Valuation:	$24.0
		Indigo View:	Downside Risk
		Industry View:	Unattractive
Latest Results:	Q4 2014	Company Rating:	LOW MED. HIGH
Country:	USA	Risk	
Sector:	Telecoms	Quality	
RIC (Ticker):	T.N	Valuation	

INDIGO EQUITY RESEARCH

N. Landell-Mills CFA
Indigo Equity Research Limited
www.indigo-equity-research.com

13 Feb 2015

Overview of Q4 2014 - Telecoms price war deepens

Weak Q4 2014 Results - Margins deteriorate further

Q4 revenue growth of 4% accelerated 1% from last Q. EBIT* fell 6%, as margins* fell 1.5% to 14.0%. **EPS* growth of 4% (to $0.55), was driven by: lower interest payments, 2% share repurchases and a lower tax rate* (down 4%, to 29%).**

Wireless revenue growth of 8% was driven by 9% more subscribers; Blended ARPU fell. QoQ Net Additions of 1.9 m subscribers, was driven by Post-Paid (+0.8 m), and Devices (+1.3 m); of these Devices 0.8m were connected cars. Also, prepaid subscribers fell 0.2m.

A key issue remains deteriorating EBIT margins as the wireless price war continues. Stiff competition was also evident in high bids for wireless spectrum at the AWS-3 auction. News flow suggests that this price competition will not let up and will pressurise ARPU. Continued large charges for pensions & asset write-downs also limit upside stock potential.

Low fundamental valuation $24 (-26%) - margin risk from price war
We expect the wireless price war to worsen and weak US economic growth to drag down AT&T's margins. In turn, this will hit EPS and pressurize valuation multiples. AT&T's strategic repositioning with major acquisitions and asset disposals are wild cards. Also, we believe equity markets are fundamentally overvalued (mostly due to low interest rates & QE) and expect >50% correction over time (see our 2015 Investment Outlook).

** = Excluding Unusual Items (prior year $4.1 bn gain and $6.8 bn loss this Q) mostly for pensions charges.*
Comparisons (e.g. margins changes & growth rates) are stated on a YoY basis.

Fundamental Valuation	(See Page 18)		
(12 month outlook)	Bear	Base	Bull
Forecast Share Price	$20.5	**$24.0**	$27.9
Return (incl. Div.)	-36%	-26%	-14%

Capital Structure	Per Share ($)	Total ($ Bn)
Current Share Price	**$34.9**	
Number of Shares (bn)		5.2
Market Capitalization		181.2
Net Cash / (Debt)	-14.1	-73.5
Enterprise Value (EV)	48.9	254.1
Main Shareholder:		--

Consensus Estimates

Figure B.4: Indigo Equity Research's coverage on AT&T.

COWEN

Retail & Consumer Brands

Dick's Sporting Goods

Equity Research

August 24, 2017

Price: $26.53 (08/23/2017)
Price Target: $28.00 (Prior $31.00)

MARKET PERFORM (2)
FROM OUTPERFORM (1)

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Rating Change

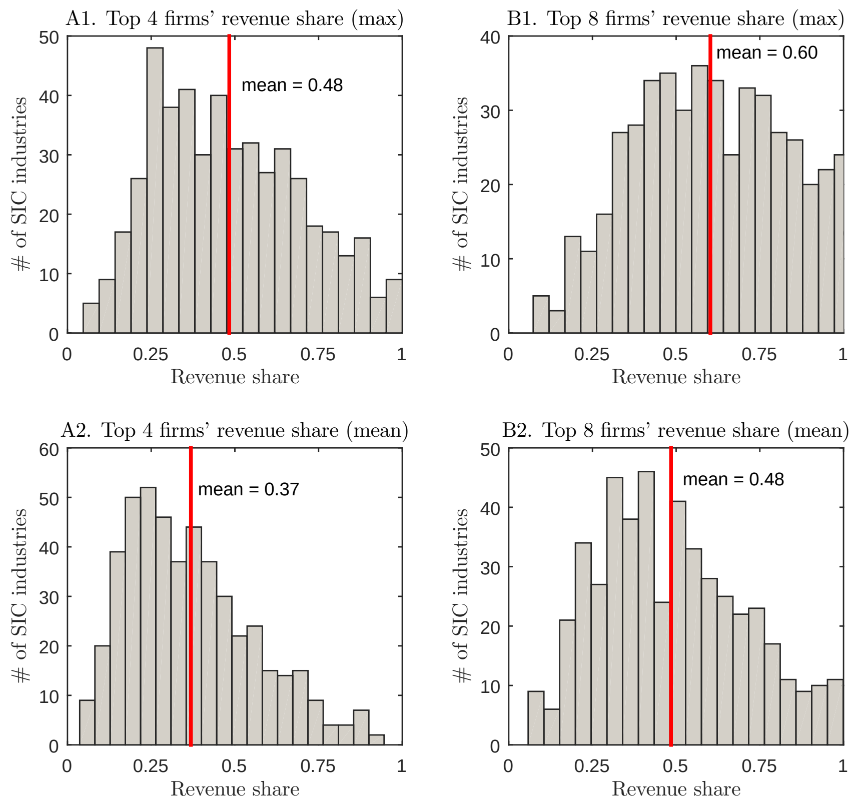
Downgrade - "Price War" Will Push Margins And Cash Flow Lower

The Cowen Insight

We overestimated DKS ability to achieve guidance and maintain profitability in the face of structural (digital competition) and cyclical (athletic cycle) headwinds. Consensus estimates for '18 assume the current environment improves dramatically despite "price war" declaration and lower ASPs on UAA, Nike and Adidas apparel markdowns, merch margin pressure, shipping cost pressure.

Nike, Adidas And Under Armour Direct To Consumer Efforts Expand

Figure B.5: Cowen's coverage on Dick's Sporting Goods.



Note: This figure plots the histogram of the top 4 and top 8 firms' total revenue share in 4-digit SIC industries. We use the U.S. Census concentration ratio data from 1987, 1992, 1997, 2002, 2007, and 2012 to compute the time-series maximal and mean revenue shares for the top 4 firms (CR4) and top 8 firms (CR8) in each 4-digit SIC industry. The concentration ratios are at the 6-digit NAICS level after 1997. We follow Ali, Klasa and Yeung (2008) and convert the ratios to 4-digit SIC levels. We plot the histogram of the max CR4 (Panel A1), max CR8 (Panel B1), mean CR4 (Panel A2), and mean CR8 (Panel B2) in all 4-digit SIC industries. Red vertical lines represent the cross-sectional mean values.

Figure C.6: Top 4 and top 8 firms' revenue share in 4-digit SIC industries.

C.2 Match PatentView with CRSP/Compustat/Capital IQ

In this Appendix, we detail the matching procedure for the data from PatentView, CRSP/Compustat, and Capital IQ.[28] We first drop patent assignees that are classified as individuals and government agencies by PatentView, because these assignees are not associated with any particular industry. We then clean assignee names in PatentView and firm names in CRSP/Compustat and Capital IQ following the approach of Hall, Jaffe and Trajtenberg (2001). To elaborate, we remove punctuations and clean special characters. We then transform the names into upper cases and standardize them. For example, "INDUSTRY" is standardized to be "IND"; and "RESEARCH" is standardized to be "RES"; and corporate form words (e.g. "LLC" and "CORP") are dropped, etc.

[28]The PatentView data are available at `http://www.patentsview.org/download/`.

Match PatentView with CRSP/Compustat. We match patent assignees in PatentView with firms in CRSP/Compustat based on standardized names. We use the fuzzy name matching algorithm (*matchit* command in Stata), which generates the matching scores (Jaccard index) for all name pairs between patent assignees in PatentView and firms in CRSP/Compustat.[29] We obtain a pool of potential matches based on two criteria: (1) we require the matching score to be higher than 0.6; (2) we require the first three letters of patent assignees to be the same as those of firms in CRSP/Compustat.[30] We then go through all potential matches to manually identify exact matches.[31]

As pointed out by Lerner and Seru (2017), one major challenge for linking patent data to CRSP/Compustat is that some patent assignees are subsidiaries of firms in CRSP/Compustat. For these assignees, we cannot directly match them with CRSP/Compustat based on firm names. To deal with this challenge, the NBER patent data (Hall, Jaffe and Trajtenberg, 2001) use the 1989 edition of the Who Owns Whom directory (now known as the D&B WorldBase®- Who Owns Whom) to match subsidiaries to parent companies. Kogan et al. (2017) purged the matches identified by the NBER patent data, and extended the matching between patent data and CRSP/Compustat to 2010. For those patent assignees who are subsidiaries of firms in CRSP/Compustat, we augment our matches by incorporating the data of Kogan et al. (2017) for patents granted before 2010. For patents granted after 2010, we use the subsidiary-parent link table from the 2017 snapshot of the Orbis data to match subsidiaries in PatentView to their parent firms in CRSP/Compustat.

Match PatentView with Capital IQ. We match the remaining patent assignees in PatentView with firms in Capital IQ following the same matching procedure. To keep the workload manageable, we drop firms in Capital IQ whose assets are worth less than $100 million (in 2017 dollars). Because we focus on the U.S. product market, we also drop foreign firms whose asset values are below the 90th percentile of the asset value distribution among firms in the CRSP/Compustat sample in each year, respectively. This is because small foreign firms are less likely to have a material impact on the competition environment of the U.S. product market. We match PatentView to Capital IQ directly using the information on subsidiaries provided by Capital IQ.

C.3 Match Nielsen with CRSP/Compustat/Capital IQ

We follow previous studies (see, e.g. Hottman, Redding and Weinstein, 2016; Argente, Lee and Moreira, 2018; Jaravel, 2018) to find the companies that own the products in the Nielsen data using the product-firm link table in the "GS1 US Data Hub | Company" data, which is provided by GS1 – the official source of

[29]Jaccard index measures the similarity between finite sample sets, and is defined as the size of the intersection divided by the size of the union of the sample sets. Jaccard index ranges between 0 and 1, reflecting none to perfect similarity.

[30]These two matching criteria are sufficiently conservative to ensure that exact matches are included in the pool of potential matches. For example, among all the exact matches in the first quarter of 2016, 98% of them satisfy the two matching criteria and are included in our pool of potential matches.

[31]We rely on assignee names in PatentView and firm names in CRSP/Compustat to identify matches. In addition, we use location information in both datasets to facilitate the matching process.

UPCs in the U.S.[32] We match 95.3% of the products in the Nielsen data with firms in the GS1 data. Our matching rate is the same as those reported by Argente, Lee and Moreira (2018) and Jaravel (2018). We further match the companies in the GS1 data to CRSP/Compustat and Capital IQ to find their SIC industry codes. The matching procedures are the same as patent matching. Our merged data cover products in 472 SIC industries.

C.4 Income Elasticity of Demand

We estimate the income elasticity of demand at the 4-digit SIC industry level using the Consumer Expenditure Surveys from the Bureau of Labor Statistics (BLS) and the Nielsen data. We first obtain the representative consumer's income and annual expenditures on various products (such as bread, ice cream, etc.) from the All CU Prepublication Means, Variances, and Percent reporting Tables. We calculate the income elasticity of demand (i.e. the percentage change in expenditure divided by the percentage change in income) for each product category. Next, we merge the product-category level income elasticity data from the BLS survey with the Nielsen data based on product descriptions, which allows us to link product categories to SIC industries. Finally, we compute the income elasticity of demand at the 4-digit SIC industry level by averaging the elasticities across all product categories in the same industries. Because the product-level Consumer Expenditure Surveys data are only available from 2013 to 2017, we make the assumption that the industry-level income elasticity of demand is a constant overtime.

C.5 Construct Dividend Growth

We follow previous studies (see, e.g. Campbell and Shiller, 1988; Bansal, Dittmar and Lundblad, 2005; Hansen, Heaton and Li, 2005, 2008; Bansal, Kiku and Yaron, 2016) to contrust dividend growth rates of portfolios.

Denote V_{0t} as the market value of all firms in a given portfolio. Denote the value of this portfolio at date $t+1$ to be V_{t+1}. The aggregate dividends for data $t+1$ for this portfolio is D_{t+1}. The total return on the portfolio between t and $t+1$ is:

$$R_{t+1} = \frac{V_{t+1} + D_{t+1}}{V_{0t}} = h_{t+1} + d_{t+1}. \tag{C.1}$$

where h_{t+1} is the price appreciation, which represents the ratio of the value at time $t+1$ to time t (i.e., $\frac{V_{t+1}}{V_{0t}}$), while d_{t+1} is the dividend yield, which represents the total dividends paid by at time $t+1$ divied by portfolio value at time t (i.e., $\frac{D_{t+1}}{V_{0t}}$).

Holding the portfolio composition constant (i.e., no exits and entries), the real dividend growth rate is:

$$\frac{D_{t+1}/PCE_{t+1}}{D_t/PCE_t} = \frac{d_{t+1}V_{0t}}{d_t V_{0(t-1)}} \frac{PCE_t}{PCE_{t+1}} = \frac{d_{t+1}h_t}{d_t} \frac{PCE_t}{PCE_{t+1}} = \frac{(R_{t+1} - h_{t+1})h_t}{R_t - h_t} \frac{PCE_t}{PCE_{t+1}}, \tag{C.2}$$

[32] The "GS1 US Data Hub | Company" data provide the company names, company addresses, and the UPC prefixes owned by the companies. More information about the "GS1 US Data Hub | Company" is available at: https://www.gs1us.org/tools/gs1-us-data-hub/company.

where PCE is the personal consumption expenditure deflator from the U.S. BEA.

Because stocks move in and out of portfolios, we account for the entries and exits following the literature (see, e.g. Hansen, Heaton and Li, 2005, 2008; Bansal, Kiku and Yaron, 2016) by adding an adjustment term. Specifically, the real dividend growth rate for a portfolio is:

$$\frac{V_t}{V_{0t}} \frac{D_{t+1}/PCE_{t+1}}{D_t/PCE_t}, \tag{C.3}$$

where V_t is exit value of the portfolio at time t (i.e., the time t market value of firms in the portfolio formed at time $t-1$), and V_{0t} is the market value of firms in the new position we initiate at time t. Plug equation C.2 into C.3, the real dividend growth rate for a portfolio is:

$$\frac{V_t}{V_{0t}} \frac{D_{t+1}/PCE_{t+1}}{D_t/PCE_t} = \frac{V_t}{V_{0t}} \frac{(R_{t+1}-h_{t+1})h_t}{R_t - h_t} \frac{PCE_t}{PCE_{t+1}}. \tag{C.4}$$

We calculate portfolio R_t and h_t by computing the value-weighted RET and $RETX$ (both from CRSP) across firms within the portfolio. Since share repurchases are prevelant in our sample period, we follow Bansal, Dittmar and Lundblad (2005) and adjust the capital gain series for a given firm as following:

$$RETX^*_{t+1} = RETX_{t+1} \min\left[\left(\frac{n_{t+1}}{n_t}\right), 1\right], \tag{C.5}$$

where n_t is the number of shares after adjusting for splits, stock dividends, etc using the CRSP share adjustment factor.

D Illustration of Equilibrium Concepts

Our model is based on a general equilibrium framework with a continuum of industries. Within each industry, we formulate the two firms' dynamic competition using stochastic game-theoretic models. In this Appendix, we illustrate the dynamic game-theoretic equilibrium within an industry in our baseline model. We start by illustrating the non-collusive equilibrium in Section D.1. We highlight that the strategic complementarity embedded in the non-collusive equilibrium is a crucial force that generates price wars during periods with low long-run consumption growth. In Section D.2, we illustrate the collusive equilibrium that naturally arises from the dynamic repeated interaction between the two firms. The collusive equilibrium is a sub-game perfect equilibrium that is endogenously sustained by using the non-collusive equilibrium as punishment. In Section D.3, we illustrate the IC constraints and the determination of collusive prices in the collusive equilibrium.

D.1 Non-Collusive Equilibrium

In the non-collusive equilibrium, the two firms simultaneously set prices, taking the other firm's price as given. Thus, the equilibrium prices are determined by the intersection of the two firms' optimal price as a function of the other firm's price. Denote $\widehat{P}^N_{i1}(M_{i1}/M_i; P_{i2})$ as firm 1's optimal price as a function of

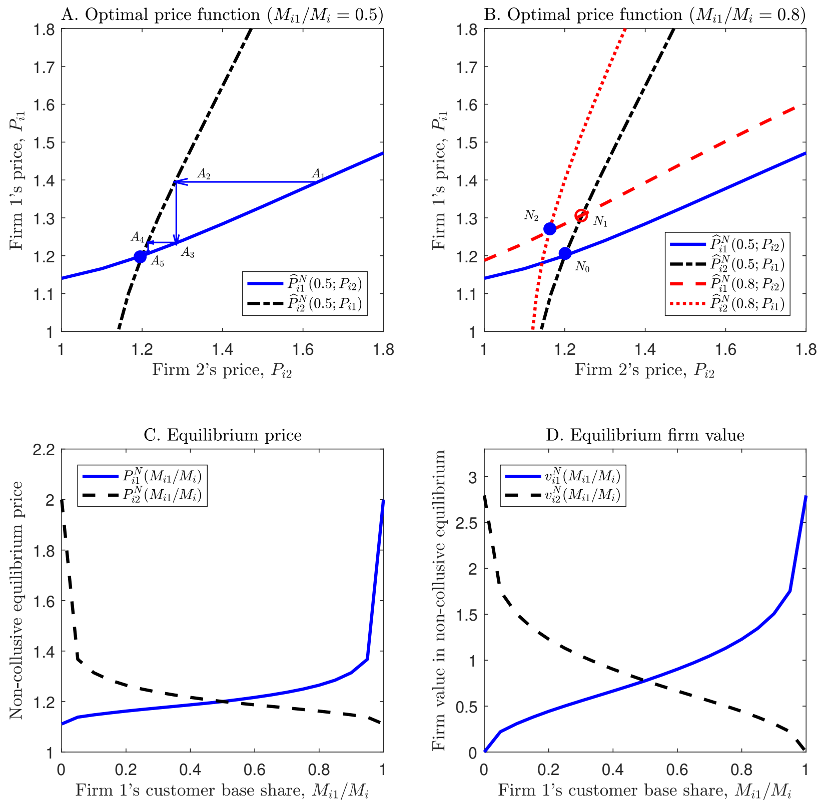


Figure D.7: Prices and firm values in the non-collusive equilibrium.

its customer base share M_{i1}/M_i and firm 2's price P_{i2}. Similarly, we denote $\widehat{P}^N_{i2}(M_{i1}/M_i; P_{i1})$ as firm 2's optimal price as a function of firm 1's customer base share M_{i1}/M_i and price P_{i1}.

In Panel A of Figure D.7, the blue solid line plots firm 1's optimal price as a function of firm 2's price P_{i2}, when the two firms have equal customer base shares (i.e. $M_{i1}/M_i = 0.5$). The black dash-dotted line plots firm 2's optimal price as a function of firm 1's price P_{i1} for the same customer base share. The intersection of the two curves (the blue filled circle) determines the equilibrium prices, i.e. $P^N_{i1}(0.5)$ and $P^N_{i2}(0.5)$:

$$P^N_{i1}(0.5) = \widehat{P}^N_{i1}(0.5; P^N_{i2}(0.5)) \quad \text{and} \quad P^N_{i2}(0.5) = \widehat{P}^N_{i2}(0.5; P^N_{i1}(0.5)). \tag{D.1}$$

The two firms set exactly the same prices when they have the same customer base shares. Both curves are upward sloping, indicating that there exists strategic complementarity in setting prices in the non-collusive equilibrium: both firms tend to set lower prices when the other firm's price is lower. This is because when the other firm's price is lower, the price elasticity of demand endogenously increases, motivating the firm to lower its own price. Because of such strategic complementarity, the non-collusive equilibrium features low prices and hence low profit margins for both firms. To see it clearly, suppose firm

2 sets $P_{i2} = 1.6$, then firm 1's best response is to set $P_{i1} = 1.4$ (A_1). Given that firm 1's price is lower than firm 2's, firm 2 will further lower its price to $P_{i2} = 1.28$ (A_2). But then firm 2's price is lower than firm 1's, which triggers firm 1 to lower its price to $P_{i1} = 1.23$ (A_3), and so on, until the prices reach equilibrium values. Such price adjustments happen instantaneously in rational expectation equilibrium.[33]

In Panel B, we investigate how firms change prices when their customer base shares change. The blue solid line and black dash-dotted line represent the same benchmark case (i.e. $M_{i1}/M_i = 0.5$) as in Panel A. The red dashed and red dotted lines refer to the prices set by the two firms when firm 1's customer base share M_{i1}/M_i increases from 0.5 to 0.8 (thus firm 2's customer base share decreases from 0.5 to 0.2 accordingly). It is shown that firm 1's optimal price function shifts upward and firm 2's optimal price function shifts to the left, implying that both firms tend to set higher prices when their own customer base shares increase. Intuitively, there are two main reasons. First, when the customer base share is higher, setting low prices to further compete for customer base is relatively more costly compared to setting high prices to profit from inertial customers. Second, the firm's influence on the equilibrium price index increases with its customer base share (see equation 2.8). Therefore, a higher customer base share increases the firm's market power and lowers the price elasticity of demand, resulting in higher prices.

Panel B also clearly illustrates the implication of strategic pricing. In the benchmark equilibrium (N_0), the prices are P_{i1,N_0} and P_{i2,N_0}. A higher customer base share M_{i1}/M_i shifts the equilibrium to N_2, and the new equilibrium prices satisfy $P_{i1,N_2} > P_{i1,N_0}$ and $P_{i2,N_2} < P_{i2,N_0}$. However, if firm 2 were to hold its price decisions unchanged (at the black-dashed line), the new equilibrium would be N_1, with $P_{i1,N_1} > P_{i1,N_2}$, indicating that firm 1 would raise its price more in response to the increase in its customer base share M_{i1}/M_i. Therefore, firm 1's price is less responsive precisely because it anticipates that firm 2 would lower its price P_{i2} (as captured by the red dotted line). Such strategic concerns result in a smaller increase in firm 1's price P_{i1}, which helps prevent too much loss in its customer base share M_{i1}/M_i.

Panel C shows that when firm 1's customer base share increases, firm 1 sets higher prices (blue solid line) and firm 2 sets lower prices (black dashed line) symmetrically in equilibrium. This is because firm 1 gains market power whereas firm 2 loses market power (see equation 2.8). Moreover, both firms have higher values when their customer base shares increase (see Panel D).

D.2 Collusive Equilibrium

We now turn to the illustration of the collusive equilibrium. In the collusive equilibrium, both firms set prices according to the collusive pricing schedule $P_{ij}(M_{i1}/M_i, \theta_t)$.

In Panel A of Figure D.8, we compare the firm's prices in the collusive equilibrium and the non-collusive equilibrium. As the two firms are symmetric, we only focus on illustrating firm 1's price. The black dashed line plots firm 1's price in the non-collusive equilibrium (as in Panel C of Figure D.7). The blue solid line plots firm 1's price in the collusive equilibrium. It is shown that due to collusion, firm 1 sets higher prices than what it would set in the non-collusive equilibrium. When firm 1's customer base share increases from 0 to 0.8, firm 1's collusive price increases because of the increasing market power. However, firm

[33]The dynamics of price adjustment is related to the old tradition that used Tâtonnement or Cobweb dynamics to capture the off-equilibrium adjustment of prices in Walrasian economies.

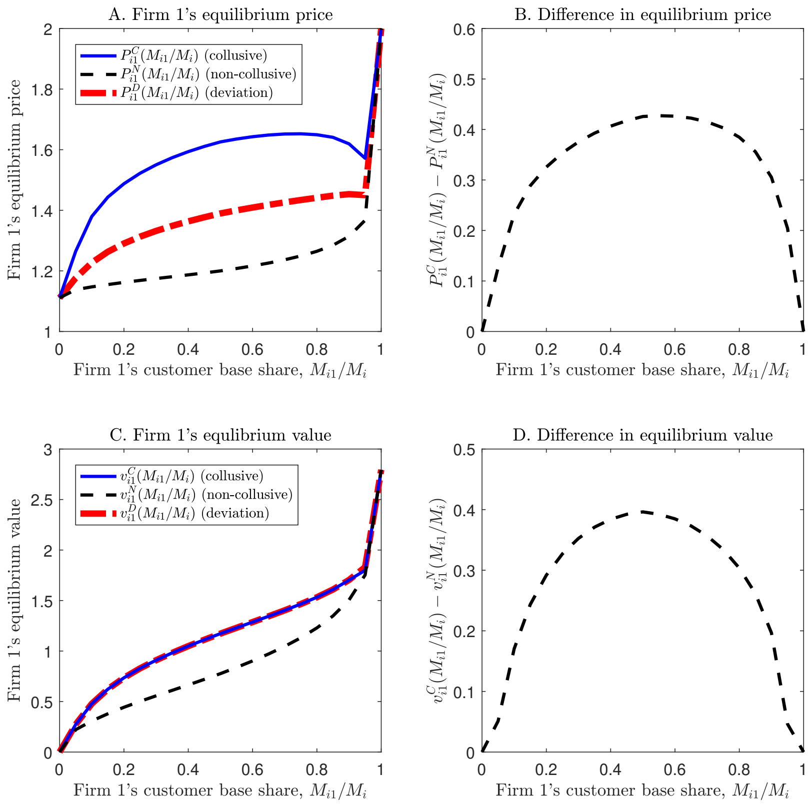


Figure D.8: Comparing prices and firm values in the collusive and non-collusive equilibria.

1's colusive price starts to decrease when its customer base share further increases from 0.8 to 1. This is because when the customer base share becomes more unevenly distributed between firm 1 and firm 2, the two firms are more likely to enter into a full-blown price war when long-run growth rates decline (see Figure 4). The increased risk of entering into a full-blown price war significantly dampens the initial collusion incentive and depresses collusive prices.

Interestingly, Panel B shows that the ability to collude on higher prices, as reflected by the difference between the collusive price and the non-collusive price exhibits an inverted-U shape. The increase in prices due to collusion is the largest when the two firms have comparable customer base shares (i.e. $M_{i1}/M_i \approx 0.5$). Intuitively, collusion allows both firms to set higher prices to enjoy higher profit margins than what they would have in the non-collusive equilibrium. However, the collusive pricing schedule has to be chosen such that both firms have no incentive to deviate given their current customer base shares. When firm 1 is dominating the market (i.e. with high M_{i1}/M_i), forming a collusive equilibrium would be less appealing from firm 1's perspective as it already has high market power, which allows it to set a high price in the non-collusive equilibrium any way (see the black dashed line). On the other hand, when firm 1 has low customer base share M_{i1}/M_i, forming a collusive equilibrium would be less appealing from firm

2's perspective which already has high market power to set a high price in the non-collusive equilibrium. Thus, it is easier to collude on relatively higher prices when firm 1 and firm 2 have comparable customer base shares.

The above intuition is more clearly seen in two extreme cases. When firm 1's customer base share $M_{i1}/M_i \approx 1$, Panel A shows that it sets a price close to $\frac{\epsilon}{\epsilon-1}\omega = 2$. This is the price that firm 1 would choose facing a price elasticity of demand ϵ. In this case, firm 1 essentially acts almost as a monopoly in industry i and sets prices to compete with firms in other industries. Thus, the constant across-industry price elasticity of demand is what determines firm 1's optimal price in both the collusive and the non-collusive equilibria. By contrast, when firm 1's customer base share $M_{i1}/M_i \approx 0$, Panel A shows that it sets a price close to $\frac{\eta}{\eta-1}\omega = 1.11$. This is the price that firm 1 would choose facing a price elasticity of demand η. In this case, firm 1 essentially acts almost as a price taker in industry i because it has little market power to influence the industry's price index. Thus, the constant within-industry price elasticity of demand is what determines firm 1's optimal price in both the collusive and the non-collusive equilibria.

Panel C compares firm 1's value in the collusive and the non-collusive equilibria. Colluding on higher prices increases firm 1's profit margins, leading to higher firm values. Not surprisingly, due to the inverted-U collusive prices, the difference in firm values displays a similar inverted-U shape (Panel D) when the customer base share M_{i1}/M_i varies.

D.3 Determination of Collusive Prices

In this section, we clarify how the collusive prices are determined in equilibrium. In Panel A of Figure D.8, the red line plots the optimal price that firm 1 would choose conditional on its deviation from the collusive pricing schedule.[34] It shows that the optimal deviation price is always lower than the collusive price. This is intuitive because firms collude on higher prices relative to what they would set in the non-collusive equilibrium, and thus both firms have the incentive to undercut the other firms in order to increase both contemporaneous demand and gain more customer base. Whether firm 1 would deviate depends on what deviation value firm 1 would obtain by setting the optimal deviation price. Intuitively, there are countervailing forces that determine the gains from deviation. If deviation is not detected by firm 2, then firm 1 would gain by stealing customer base from firm 2 through lower prices. However, if deviation is detected by firm 2, then firm 1 will be punished by switching to the non-collusive equilibrium which features low prices and low profit margins.

Whether the collusive equilibrium can be sustained depends on the level of collusive prices. A higher collusive price increases the profits from deviation and is more difficult to be sustained in equilibrium. The collusive prices we choose are the highest prices subject to the IC constraints that both firms have no incentive to deviate in the collusive equilibrium. In Panel C of Figure D.8, the red dash-dotted line plots the deviation value that firm 1 would obtain by setting the optimal deviation price (the red dash-dotted

[34]Here, we follow the standard game theory by considering one-shot deviation. That is, we consider what the deviation price that firm 1 would choose conditional on firm 2 not deviating from the collusive equilibrium. The one-shot deviation property ensures that no profitable one-shot deviations for every player is a necessary and sufficient condition for a strategy profile of a finite extensive-form game to form a sub-game perfect equilibrium.

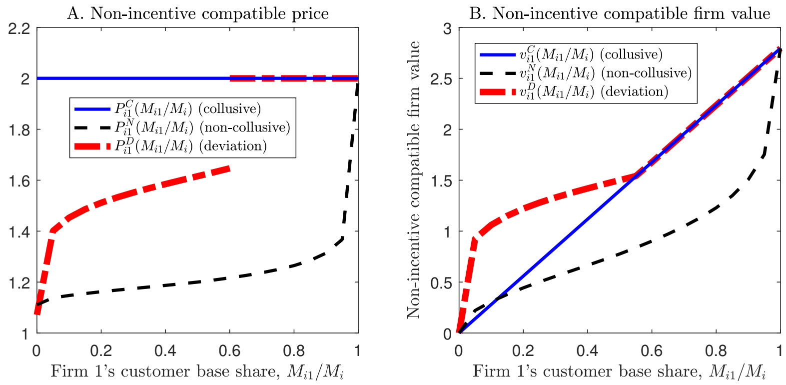


Figure D.9: An illustration of non-incentive compatible collusive prices.

line in Panel A). It is shown that firm 1's deviation value is exactly the same as firm 1's value in the collusive equilibrium, indicating that firm 1 is indifferent between setting the collusive price or deviating from the collusive equilibrium. In other words, firm 1's IC constraints are binding. Because the collusive and deviation values are equal for any customer base share, firm 2 is also indifferent about collusion and deviation.

The IC constraints are violated, if firms choose collusive prices higher than the blue solid line in Panel A. We illustrate this in Figure D.9. To obtain a stark comparison, we assume that the collusive price is set equal to $\frac{\epsilon}{\epsilon-1}\omega = 2$ (as shown by the blue solid line in Panel A), which is the price that maximizes the contemporaneous demand if the two firms can perfectly collude with each other and act like a monopoly.

The red dash-dotted line indicates that when firm 1's customer base share M_{i1}/M_i is lower than 0.6, it would set a significantly lower price to steal firm 2's customer base share. As a result, firm 1's deviation value is strictly larger than its collusion value (see the red dash-dotted line in Panel B) when $M_{i1}/M_i < 0.6$, indicating that the IC constraint is violated. Thus, requiring the two firms to collude on a higher price like what is considered here does not form a sub-game perfect equilibrium because one of the firms (or both firms) will deviate by setting a lower price.

E Discussions on Model Ingredients

In this Appendix, we discuss the role played by within- and between- elasticities, long-run risks, and antitrust enforcement on our model's implications.

E.1 Discussions on Elasticities

The parameter η and ϵ capture the elasticity of substitution of goods produced within the same industry and the elasticity of substitution of goods produced in different industries. In this section, we discuss the role of the two elasticities on collusion incentives and prices. To fix ideas, we shut down the price channel for customer base accumulation by setting $z = 0$.

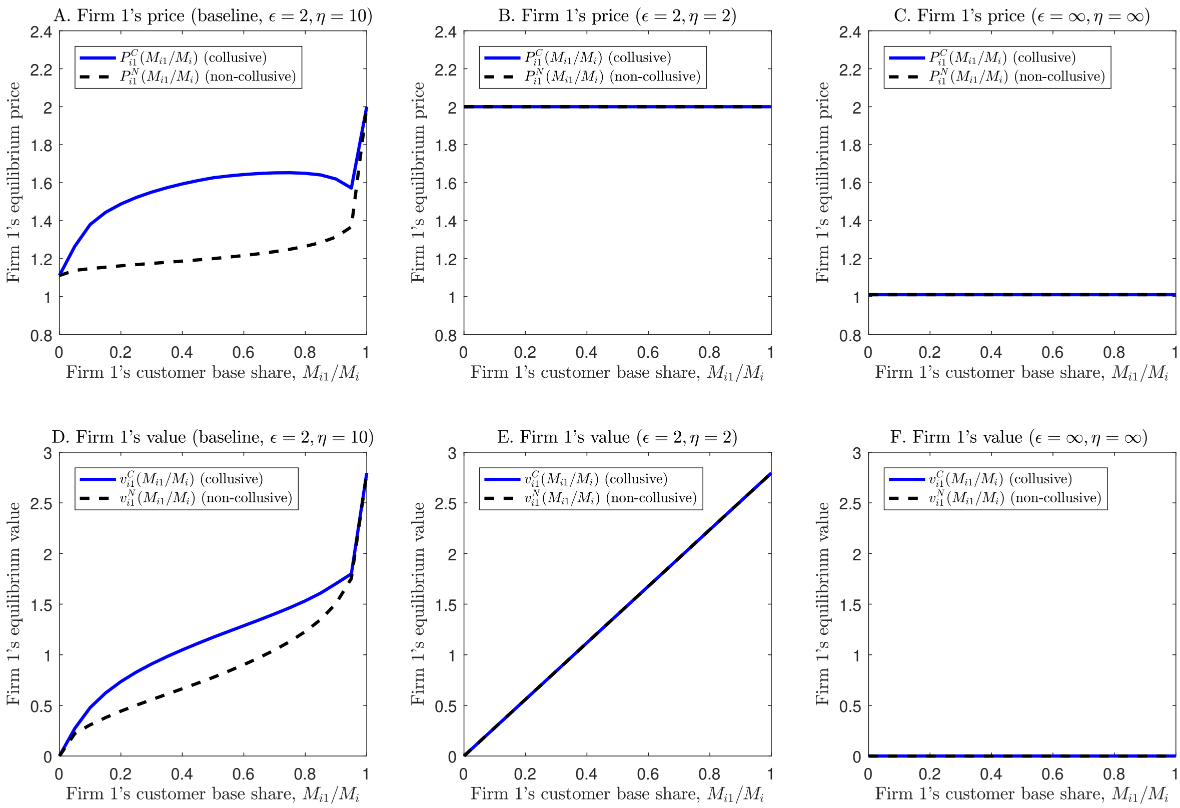


Figure E.10: The role of price elasticities of demand on collusive prices.

In our baseline calibration, we set $\eta > \epsilon$ to be consistent with empirical estimates. As we vary η and ϵ, the model can capture different degrees of within- and between-industry competition. As we show in equation (2.9), the price elasticity of demand for firm 1 depends on both the within-industry elasticity η and the between-industry elasticity ϵ because firm 1 simultaneously faces within-industry competition from firm 2 as well as the between-industry competition from firms in other industries.

With $\eta > \epsilon$, within-industry competition is more fierce than between-industry competition due to the higher elasticity of substitution among goods produced in the same industry. Thus, essentially the within-industry elasticity η gives the upper bound of competition, and hence determines the lower bound of prices; whereas the between-industry elasticity ϵ gives the lower bound of competition, and hence determines the upper bound of prices.

In particular, the highest level of competition is obtained by firm 1 when it becomes atomic in industry i (i.e. $M_{i1}/M_i = 0$). In this case, firm 1 would set the lower-bound price $\frac{\eta}{\eta-1}\omega$, determined by the within-industry elasticity η. However, when firm 1 is atomic, firm 2 is essentially the monopoly in industry i, facing the minimal level of competition due to the absence of within-industry competition. Thus, firm 2 would set the upper-bound price $\frac{\epsilon}{\epsilon-1}\omega$, determined by the between-industry elasticity ϵ. Because firm

2 already sets its price equal to the upper bound, there is no incentive for firm 2 to collude with firm 1, although firm 1 wants to collude due to its low price.

Thus, the two firms have the incentive to collude with each other only when neither firm is the monopoly in industry i. In this case, collusion benefits both firms by alleviating within-industry competition so that prices become higher, more reflecting the between-industry elasticity ϵ. Therefore, the existence of collusion incentive crucially depends on the assumption that $\eta > \epsilon$. If $\eta = \epsilon$, the level of competition does not change with the customer base share. And the firm would always set the upper bound price $\frac{\epsilon}{\epsilon-1}\omega$, determined by the between-industry elasticity ϵ.

Specifically, if we set $\eta = 2\ (= \epsilon)$, Panel B of Figure E.10 shows that firm 1 always sets its price equal to $\frac{\epsilon}{\epsilon-1}\omega = 2$. In this case, achieving the collusive equilibrium does not further increase the two firms' prices because they already set the upper bound price consistent with what is implied by between-industry competition.[35] Firm 1's value increases linearly with its customer base share M_{i1}/M_i (see Panel E). In Panels C and F, we further increase $\eta = \epsilon = \infty$ to mimic an economy with perfect competition. The infinite elasticity results in zero profit margins. Both firms set their prices equal to the marginal costs (see Panel C) and attain zero values (see Panel F) in equilibrium regardless of their customer base shares.

E.2 Discussions on Long-Run Risks

We emphasize that long-run risks play a crucial role in generating price war risks. In our model, firms collude more during periods with high long-run growth rates precisely because they know that the growth rate of consumption is persistent. In Figure E.11, we compare the baseline calibration with a 0.49 auto-correlation of annual consumption growth rates to an economy with a 0.049 auto-correlation of annual consumption growth rates, featuring less persistent expected growth rate component. Panel A shows that, in the economy with less persistent expected growth rate component, there is almost no change in collusive prices between periods with high and low long-run growth rates, and this is true regardless of the capacity of radical innovation (see the red dash-dotted line and the red dotted line). Moreover, Panel B shows that the industry's exposure to long-run risks is much smaller in the economy with less persistent expected growth rate component. Importantly, there is virtually no difference in the exposure to long-run risks across the two industries. Thus, the model suggests that the persistence of expected growth rate component is crucial in generating both the high magnitude of price war risks and the variation in the exposure to long-run risks across industries with different capacities of radical innovation.

Intuitively, with long-run risks in consumption, what determines the collusion incentive is not only the current level of aggregate consumption, but also the expected change in aggregate consumption in the future. Firms that expect a relative increase in aggregate consumption are able to sustain higher collusive prices now because none of the firms want to deviate and be punished later by their competitors in periods with higher aggregate consumption. On the contrary, during bad times, firms expect a relative decrease in aggregate consumption and the later punishment looks less costly. Consequently, declines in long-run

[35] In fact, when the two elasticities are the same ($\eta = \epsilon$), the two layers of CES aggregation collapses to a single between-industry CES aggregation, and within-industry competition would not matter for price setting.

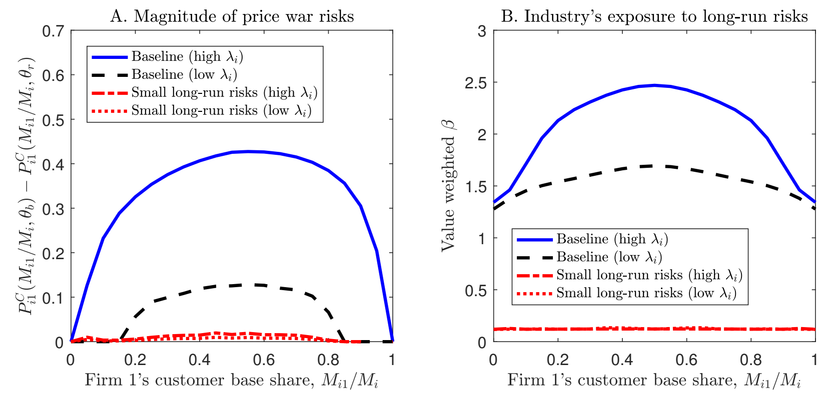


Figure E.11: Illustrating the importance of long-run risks in generating price war risks.

consumption growth generate price wars, amplifying firms' exposure to long-run risks.

E.3 Discussions on Antitrust Enforcement

Our model predicts that antitrust enforcement reduces price war risks. Intuitively, with stronger laws against collusion, it is more difficult for firms to conduct collusive pricing, resulting in lower collusive prices and less variation in collusive prices with long-run growth rates. In our model, the parameter ϕ controls the ability for firms to collude with each other. A smaller ϕ makes it harder to implement higher collusive prices, which is equivalent to the effect of implementing more stringent antitrust enforcement. In the extreme case with $\phi = 0$, there is no way to implement the punishment strategy, and as a result, there is no way to sustain an incentive compatible collusive equilibrium.

In Figure E.12, we compare our baseline calibration with $\phi = 0.15$ to an economy with $\phi = 0.05$. The magnitude of price war risks is significantly lower in the latter economy (see Panel A). As a result, the industry's exposure to long-run risks is much smaller when collusion is more difficult to implement. Across the two industries, our model implies that antitrust enforcement has larger effects in the industry with no radical innovation, as this is the industry with the highest collusion incentive to begin with.

F Supplementary Empirical Results

F.1 Product Prices in the 24-month Period Around the Lehman Crash

In the main text, we have analyzed the changes of product prices in the 36-month period around the Lehman crash. Here, we show that our findings remain robust for a narrower time window (i.e., 24-month period around the Lehman crash). Specifically, after the Lehman crash, the product prices of high-innosimm industries drop significantly relative to those of the low-innosimm industries (see Table F.1), and the price-similarity sensitivity reduces significantly (see Table F.2).

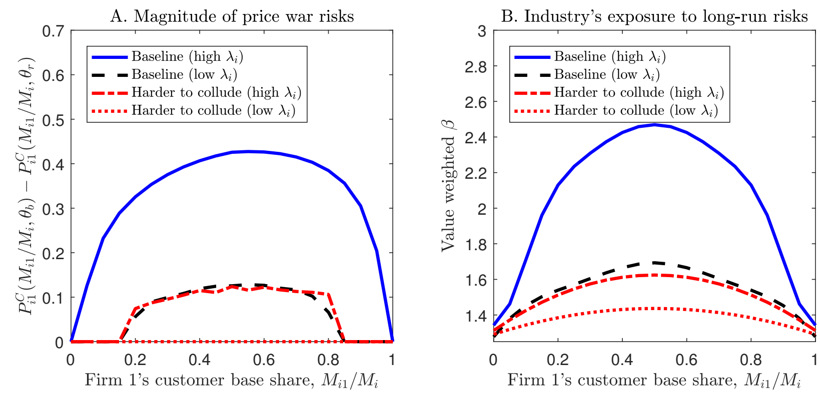


Figure E.12: Antitrust enforcement, price war risks, and the exposure to long-run risks.

Table F.1: Product prices around the Lehman crash (monthly analysis).

	(1)	(2)
	Percent change in product prices (monthly, annualized, %)	
Tertile-3 innosimm$_{t-1}$ × post Lehman crash$_t$	-6.04^{***}	-6.64^{***}
	[−3.14]	[−3.23]
Tertile-3 innosimm$_{t-1}$	−1.44	−5.79
	[−0.57]	[−0.99]
post Lehman crash$_t$	1.50	2.62
	[0.58]	[1.08]
Industry FE	No	Yes
Observations	3398	3398
R-squared	0.003	0.055

Note: This table shows the changes in product prices around the Lehman crash. The dependent variable is the annualized monthly percent change in product prices of 4-digit SIC industries. Product prices are obtained from the Nielsen Data. To compute the monthly percent change in product prices for 4-digit SIC industries, we first compute the transaction-value weighted price for each product across all stores in each month. We then calculate the monthly percent change in prices for each product. Finally, we compute the value-weighted percent change in product prices for each 4-digit SIC industry based on the transaction values of the industry's products. We consider we consider the 24-month period around the Lehman crash. We include t-statistics in parentheses. Standard errors are clustered by the 4-digit SIC industry and year. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels.

G Numerical Algorithm

In this section, we detail the numerical algorithm that solves the model. We solve the model in risk-neutral measure. By Girsanov's theorem, we have

$$\mathrm{d}Z_{c,t} = -\lambda_c \mathrm{d}t + \mathrm{d}\tilde{Z}_{c,t}, \tag{G.1}$$

$$\mathrm{d}Z_{\theta,t} = -\lambda_\theta \mathrm{d}t + \mathrm{d}\tilde{Z}_{\theta,t}. \tag{G.2}$$

Table F.2: Price-innosimm sensitivity around the Lehman crash (monthly analysis).

	(1)	(2)
	Percent change in product prices (monthly, annualized, %)	
$\text{innosimm}_{t-1} \times \text{post Lehman crash}_t$	-2.52^{**}	-2.32^{**}
	[−2.52]	[−2.27]
innosimm_{t-1}	−1.02	-3.02^{*}
	[−1.35]	[−2.02]
$\text{post Lehman crash}_t$	−2.09	−1.92
	[−1.49]	[−1.36]
Industry FE	No	Yes
Observations	5086	5086
R-squared	0.003	0.043

Note: This table shows the price-innosimm sensitivity around the Lehman crash. The dependent variable is the annualized monthly percent change in product prices of 4-digit SIC industries. We consider we consider the 24-month period around the Lehman crash. We include t-statistics in parentheses. Standard errors are clustered by the 4-digit SIC industry and year. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels.

Under the risk-neutral measure, the dynamics of aggregate conditions are

$$\frac{\mathrm{d}C_t}{C_t} = \theta_t \mathrm{d}t + \sigma_c \mathrm{d}\tilde{Z}_{c,t}, \tag{G.3}$$

$$\mathrm{d}\theta_t = \kappa \left(\overline{\theta}^Q - \theta_t \right) \mathrm{d}t + \varphi_\theta \sigma_c \mathrm{d}\tilde{Z}_{\theta,t}, \tag{G.4}$$

where

$$\overline{\theta}^Q = \overline{\theta} - \lambda_c \sigma_c - \kappa^{-1} \lambda_\theta \varphi_\theta \sigma_c. \tag{G.5}$$

To give an overview, our algorithm proceeds in the following steps:

(1). We solve for the non-collusive equilibrium. This requires us to solve the Markov-Perfect equilibrium of the dynamic game played by two firms. The simultaneous-move dynamic game requires us to solve the intersection of the two firms' best response (i.e. optimal price) functions, which themselves are optimal solutions to coupled PDEs.

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

(3). After solving the baseline model, we solve the extended model with endogenous cash holdings by repeating steps (1) and (2). The extended model is more challenging because it involves solving PDEs with free boundaries (due to endogenous payout boundaries). We employ the piecewise multilinear interpolation method of Weiser and Zarantonello (1988) to obtain accurate interpolants in a 3-dimensional space.

Note that standard methods for solving PDEs with free boundaries (e.g. finite difference or finite element) can easily lead to non-convergence of value functions. To mitigate such problems and obtain accurate solutions, we solve the continuous-time game using a discrete-time dynamic programming method. In Appendix G.1, we present the discretized recursive formulation for the baseline model, including firms' problems in non-collusive equilibrium, collusive equilibrium, and deviation. In Appendix G.2, we discuss how we discretize the stochastic processes, time grids, and state variables in the model. Finally, in Appendix G.3, we discuss the details on implementing our numerical algorithms, including finding the equilibrium prices in the non-collusive equilibrium and solving the optimal collusive prices.

G.1 The Baseline Model

Because firm 1 and firm 2 are symmetric, one firm's value and policy functions are obtained directly given the other firm's value and policy functions. In this section, we illustrate firm 1's problem in our baseline model. We first illustrate the non-collusive equilibrium and then we illustrate the collusive equilibrium.

G.1.1 Non-Collusive Equilibrium

Below, we present the recursive formulation for the firm's value in the non-collusive equilibrium. Then we exploit linearity to simplify the problem and present the recursive formulation for the normalized firm value. Finally, we present the conditions that determine the non-collusive (Nash) equilibrium.

Recursive Formulation for The Non-Collusive Firm Value. The industry's state is characterized by four state variables, firm 1's customer base $M_{i1,t}$, firm 2's customer base $M_{i2,t}$, the aggregate consumption C_t, and the long-run growth rate θ_t. Denote the value functions in the non-collusive equilibrium as $V_{ij}^N(M_{i1,t}, M_{i2,t}, C_t, \theta_t)$ for $j = 1, 2$.

To characterize the equilibrium value functions, it is more convenient to introduce two off-equilibrium value functions. Let $\widehat{V}_{ij}^N(M_{i1,t}, M_{i2,t}, C_t, \theta_t; P_{ik,t})$ be firm $j(= 1, 2)$'s value when its peer firm k's price is set at any (off-equilibrium) value $P_{ik,t}$.

Firm 1 solves the following problem:

$$\widehat{V}_{i1}^N(M_{i1,t}, M_{i2,t}, C_t, \theta_t; P_{i2,t}) = \max_{P_{i1,t}} (P_{i1,t} - \omega) \left(\frac{P_{i1,t}}{P_{i,t}}\right)^{-\eta} P_{i,t}^{-\epsilon} C_t M_{i1,t} \Delta t + \mathbb{E}_t \left[\frac{\Lambda_{t+\Delta t}}{\Lambda_t} V_{i1}^N(M_{i1,t+\Delta t}, M_{i2,t+\Delta t}, C_{t+\Delta t}, \theta_{t+\Delta t})\right], \tag{G.6}$$

subject to the evolution of state variables. (1). The evolution of the customer base is

$$M_{ij,t+\Delta t} = M_{ij,t} + \left[z \left(\frac{C_{ij,t}}{C_t}\right)^{\alpha} M_{ij,t}^{1-\alpha} - \rho M_{ij,t}\right] \Delta t, \qquad \text{for } j = 1, 2, \tag{G.7}$$

where firm-level demand is given by

$$C_{ij,t} = \left(\frac{P_{ij,t}}{P_{i,t}}\right)^{-\eta} P_{i,t}^{-\epsilon} C_t M_{ij,t}, \qquad \text{for } j = 1, 2, \tag{G.8}$$

and the industry's price index

$$P_{i,t} = \left(\frac{M_{i1,t}}{M_{i,t}} P_{i1,t}^{1-\eta} + \frac{M_{i2,t}}{M_{i,t}} P_{i2,t}^{1-\eta}\right)^{\frac{1}{1-\eta}}. \tag{G.9}$$

(2). The evolution of aggregate consumption C_t is

$$C_{t+\Delta t} = (1 + \theta_t \Delta t + \sigma \Delta Z_{c,t}) C_t. \tag{G.10}$$

(3). The long-run growth rate θ_t evolves according to the discrete Markov chain specified in Appendix G.2.

Recursive Formulation for The (Normalized) Non-Collusive Firm Value. Exploiting the linearity, we normalize the firm's value by $M_{i,t}C_t$. Firm 1's customer base share is $m_{i1,t} = M_{i1,t}/M_{i,t}$; firm 2's customer base share is $m_{i2,t} = M_{i2,t}/M_{i,t} = 1 - m_{i1,t}$. Define

$$v_{ij}^N(m_{i1,t}, \theta_t) = \frac{V_{ij}^N(M_{i1,t}, M_{i2,t}, C_t, \theta_t)}{M_{i,t}C_t} \tag{G.11}$$

$$\widehat{v}_{ij}^N(m_{i1,t}, \theta_t; P_{ik,t}) = \frac{\widehat{V}_{ij}^N(M_{i1,t}, M_{i2,t}, C_t, \theta_t; P_{ik,t})}{M_{i,t}C_t} \tag{G.12}$$

Firm 1 solves the following normalized problem:

$$\begin{aligned}\widehat{v}_{i1}^N(m_{i1,t}, \theta_t; P_{i2,t}) = &\max_{P_{i1,t}} (P_{i1,t} - \omega) \left(\frac{P_{i1,t}}{P_{i,t}}\right)^{-\eta} P_{i,t}^{-\epsilon} m_{i1,t} \Delta t \\ &+ \mathbb{E}_t \left[\frac{\Lambda_{t+\Delta t}}{\Lambda_t} \frac{M_{i,t+\Delta t}}{M_{i,t}} (1 + \theta_t \Delta t + \sigma \Delta Z_{c,t}) v_{i1}^N(m_{i1,t+\Delta t}, \theta_{t+\Delta t})\right],\end{aligned} \tag{G.13}$$

subject to the evolution of state variables. (1). The evolution of firm 1's customer base share is

$$m_{i1,t+\Delta t} \frac{M_{i,t+\Delta t}}{M_{i,t}} = m_{i1,t} + \left[z \left(\frac{P_{i1,t}}{P_{i,t}}\right)^{-\eta\alpha} P_{i,t}^{-\epsilon\alpha} - \rho\right] m_{i1,t} \Delta t, \tag{G.14}$$

where the industry's price index is given by

$$P_{i,t} = \left[m_{i1,t} P_{i1,t}^{1-\eta} + (1 - m_{i1,t}) P_{i2,t}^{1-\eta}\right]^{\frac{1}{1-\eta}}. \tag{G.15}$$

(2). The evolution of the industry's customer base is

$$\frac{M_{i,t+\Delta t}}{M_{i,t}} = 1 + \left[z\left(\frac{P_{i1,t}}{P_{i,t}}\right)^{-\eta\alpha} P_{i,t}^{-\epsilon\alpha} - \rho\right] m_{i1,t}\Delta t + \left[z\left(\frac{P_{i2,t}}{P_{i,t}}\right)^{-\eta\alpha} P_{i,t}^{-\epsilon\alpha} - \rho\right] (1 - m_{i1,t})\Delta t. \tag{G.16}$$

(3). The long-run growth rate θ_t evolves according to the discrete Markov chain specified in Appendix G.2.

Non-Collusive (Nash) Equilibrium. Denote the equilibrium price functions as $P_{ij}^N(m_{i1,t}, \theta_t)$ and the off-equilibrium price functions as $\widehat{P}_{ij}^N(m_{i1,t}, \theta_t; P_{ik,t})$. Exploiting the symmetry between firm 1 and firm 2, we can obtain firm 2's off-equilibrium value and policy functions as

$$\widehat{v}_{i1}^N(m_{i1,t}, \theta_t; P_{i2,t}) = \widehat{v}_{i2}^N(1 - m_{i1,t}, \theta_t; P_{i1,t}), \tag{G.17}$$
$$\widehat{P}_{i1}^N(m_{i1,t}, \theta_t; P_{i2,t}) = \widehat{P}_{i2}^N(1 - m_{i1,t}, \theta_t; P_{i1,t}). \tag{G.18}$$

Given $j = 1, 2$'s price P_{ij}, firm k optimally sets the price P_{ik}. The non-collusive (Nash) equilibrium is derived from the fixed point—each firm's price is optimal given the other firm's optimal price:

$$P_{i1}^N(m_{i1,t}, \theta_t) = \widehat{P}_{i1}^N(m_{i1,t}, \theta_t; P_{i2}^N(m_{i1,t}, \theta_t)), \tag{G.19}$$
$$P_{i2}^N(m_{i1,t}, \theta_t) = \widehat{P}_{i2}^N(m_{i1,t}, \theta_t; P_{i1}^N(m_{i1,t}, \theta_t)). \tag{G.20}$$

The equilibrium value functions are given by

$$v_{i1}^N(m_{i1,t}, \theta_t) = \widehat{v}_{i1}^N(m_{i1,t}, \theta_t; P_{i2}^N(m_{i1,t}, \theta_t)), \tag{G.21}$$
$$v_{i2}^N(m_{i1,t}, \theta_t) = \widehat{v}_{i2}^N(m_{i1,t}, \theta_t; P_{i1}^N(m_{i1,t}, \theta_t)). \tag{G.22}$$

After solving the equilibrium value and policy functions above, we can verify that the following conditions are satisfied due to symmetry,

$$v_{i1}^N(m_{i1,t}, \theta_t) = v_{i2}^N(1 - m_{i1,t}, \theta_t), \tag{G.23}$$
$$P_{i1}^N(m_{i1,t}, \theta_t) = P_{i2}^N(1 - m_{i1,t}, \theta_t). \tag{G.24}$$

G.1.2 Collusive Equilibrium

Below, we present the recursive formulation for the firm's value in the collusive equilibrium. Then we present the recursive formulation for the firm's value when the firm deviates from the collusive equilibrium. Finally, we present the incentive compatibility constraints and the conditions that determine the optimal collusive prices.

Recursive Formulation for The Collusive Firm Value. In the collusive equilibrium, we can still exploit the linearity property and solve firms' values as a function of customer base shares. Specifically, denote $\widehat{v}_{ij}^C(m_{i1,t}, \theta_t; \widehat{P}_{ij}^C)$ as firm j's value in the collusive equilibrium with collusive prices $\widehat{P}_{ij}^C(m_{i1,t}, \theta_t)$. Note that because the two firms in the same industry are symmetric, the collusive prices satisfy $\widehat{P}_{i1}^{C}(m_{i1,t},\theta_t) = \widehat{P}_{i2}^{C}(1-m_{i1,t},\theta_t)$.

Firm 1 solves the following normalized problem:

$$\widehat{v}_{i1}^{C}(m_{i1,t},\theta_t;\widehat{P}_{ij}^{C}) = \left(\widehat{P}_{i1}^{C}(m_{i1,t},\theta_t)-\omega\right)\left(\frac{\widehat{P}_{i1}^{C}(m_{i1,t},\theta_t)}{P_{i,t}}\right)^{-\eta} P_{i,t}^{-\epsilon} m_{ij,t}\Delta t$$
$$+\mathbb{E}_t\left[\frac{\Lambda_{t+\Delta t}}{\Lambda_t}\frac{M_{i,t+\Delta t}}{M_{i,t}}(1+\theta_t\Delta t+\sigma\Delta Z_{c,t})\widehat{v}_{i1}^{C}(m_{i1,t+\Delta t},\theta_{t+\Delta t};\widehat{P}_{ij}^{C})\right], \tag{G.25}$$

subject to the evolution of state variables. (1). The evolution of firm 1's customer base share is

$$m_{i1,t+\Delta t}\frac{M_{i,t+\Delta t}}{M_{i,t}} = m_{i1,t} + \left[z\left(\frac{\widehat{P}_{i1}^{C}(m_{i1,t},\theta_t)}{P_{i,t}}\right)^{-\eta\alpha} P_{i,t}^{-\epsilon\alpha}-\rho\right] m_{i1,t}\Delta t, \tag{G.26}$$

where the industry's price index is given by

$$P_{i,t} = \left[m_{i1,t}\widehat{P}_{i1}^{C}(m_{i1,t},\theta_t)^{1-\eta} + (1-m_{i1,t})\widehat{P}_{i2}^{C}(m_{i1,t},\theta_t)^{1-\eta}\right]^{\frac{1}{1-\eta}}. \tag{G.27}$$

(2). The evolution of the industry's customer base is

$$\frac{M_{i,t+\Delta t}}{M_{i,t}} = 1 + \left[z\left(\frac{\widehat{P}_{i1}^{C}(m_{i1,t},\theta_t)}{P_{i,t}}\right)^{-\eta\alpha} P_{i,t}^{-\epsilon\alpha}-\rho\right] m_{i1,t}\Delta t + \left[z\left(\frac{\widehat{P}_{i2}^{C}(m_{i1,t},\theta_t)}{P_{i,t}}\right)^{-\eta\alpha} P_{i,t}^{-\epsilon\alpha}-\rho\right](1-m_{i1,t})\Delta t. \tag{G.28}$$

(3). The long-run growth rate θ_t evolves according to the discrete Markov chain specified in Appendix G.2.

Recursive Formulation for The Deviation Value. The deviation value is obtained by assuming that firm j optimally sets its price conditional on firm k following the collusive pricing rule $\widehat{P}_{ik}^{C}(m_{i1,t},\theta_t)$. We exploit the linearity property and solve firms' deviation values as a function of customer base shares. Denote $\widehat{v}_{ij}^{D}(m_{i1,t},\theta_t;\widehat{P}_{ij}^{C})$ as firm j's deviation value.

Firm 1 solves the following normalized problem:

$$\widehat{v}_{i1}^{D}(m_{i1,t},\theta_t;\widehat{P}_{ij}^{C}) = \max_{P_{i1,t}}\,(P_{i1,t}-\omega)\left(\frac{P_{i1,t}}{P_{i,t}}\right)^{-\eta} P_{i,t}^{-\epsilon} m_{ij,t}\Delta t$$
$$+\mathbb{E}_t\left[\frac{\Lambda_{t+\Delta t}}{\Lambda_t}\frac{M_{i,t+\Delta t}}{M_{i,t}}(1+\theta_t\Delta t+\sigma\Delta Z_{c,t})\left[(1-\phi\Delta t)\widehat{v}_{i1}^{D}(m_{i1,t+\Delta t},\theta_{t+\Delta t};\widehat{P}_{ij}^{C})+\phi\Delta t v_{i1}^{N}(m_{i1,t+\Delta t},\theta_{t+\Delta t})\right]\right], \tag{G.29}$$

subject to the evolution of state variables. (1). The evolution of firm 1's customer base share is

$$m_{i1,t+\Delta t}\frac{M_{i,t+\Delta t}}{M_{i,t}} = m_{i1,t} + \left[z\left(\frac{P_{i1,t}}{P_{i,t}}\right)^{-\eta\alpha} P_{i,t}^{-\epsilon\alpha}-\rho\right] m_{i1,t}\Delta t, \tag{G.30}$$

where the industry's price index is given by

$$P_{i,t} = \left[m_{i1,t} P_{i1,t}^{1-\eta} + (1 - m_{i1,t}) \widehat{P}_{i2}^{C}(m_{i1,t}, \theta_t)^{1-\eta} \right]^{\frac{1}{1-\eta}}. \tag{G.31}$$

(2). The evolution of the industry's customer base is

$$\frac{M_{i,t+\Delta t}}{M_{i,t}} = 1 + \left[z \left(\frac{P_{i1,t}}{P_{i,t}} \right)^{-\eta\alpha} P_{i,t}^{-\epsilon\alpha} - \rho \right] m_{i1,t} \Delta t + \left[z \left(\frac{\widehat{P}_{i2}^{C}(m_{i1,t}, \theta_t)}{P_{i,t}} \right)^{-\eta\alpha} P_{i,t}^{-\epsilon\alpha} - \rho \right] (1 - m_{i1,t}) \Delta t. \tag{G.32}$$

(3). The long-run growth rate θ_t evolves according to the discrete Markov chain specified in Appendix G.2.

Incentive Compatibility Constraints and Optimal Collusive Prices. The collusive equilibrium is a sub-game perfect equilibria if and only if the collusive prices $\widehat{P}_{ij}^{C}(m_{i1,t}, \theta_t)$ satisfy the following incentive compatibility constraints:

$$\widehat{v}_{ij}^{C}(m_{i1,t}, \theta_t; \widehat{P}_{ij}^{C}) \geq \widehat{v}_{ij}^{D}(m_{i1,t}, \theta_t; \widehat{P}_{ij}^{C}), \tag{G.33}$$

for all $m_{i1,t} \in [0, 1]$, θ_t, and $j = 1, 2$.

There exist infinitely many sub-game perfect collusive equilibrium. We focus on the collusive equilibrium with the highest collusive prices (denoted by $P_{ij}^{C}(m_{i1,t}, \theta_t)$), which are obtained when all incentive compatibility constraints are binding, i.e.

$$\widehat{v}_{ij}^{C}(m_{i1,t}, \theta_t; P_{ij}^{C}) = \widehat{v}_{ij}^{D}(m_{i1,t}, \theta_t; P_{ij}^{C}), \tag{G.34}$$

for all $m_{i1,t} \in [0, 1]$, θ_t, and $j = 1, 2$. We denote $v_{ij}^{C}(m_{i1,t}, , \theta_t)$ as firm j's value in the collusive equilibrium with collusive prices $P_{ij}^{C}(m_{i1,t}, \theta_t)$. Thus, by definition

$$v_{ij}^{C}(m_{i1,t}, \theta_t) = \widehat{v}_{ij}^{C}(m_{i1,t}, \theta_t; P_{ij}^{C}). \tag{G.35}$$

G.2 Discretization

We discretize the unpredictable consumption growth shocks $dZ_{c,t}$ based on n_c grids spanning from $-3\sigma_c$ and $3\sigma_c$ using the method of Tauchen (1986). We use the method of Rouwenhorst (1995) to approximate the persistent AR(1) process of long-run risks θ_t using n_θ discrete states. The time line is discretized into intervals with length Δt.

We use collocation methods to solve each firm's problem. Let $S_m \times S_\theta$ be the grid of collocation nodes for a firm's equilibrium value, and $S_m \times S_\theta \times S_p$ be the grid of collocation notes for a firm's off-equilibrium value. We have $S_m = \{m_1, m_2, ..., m_{n_m}\}$, $S_\theta = \{\theta_1, \theta_2, ..., \theta_{n_\theta}\}$, $S_p = \{p_1, p_2, ..., p_{n_p}\}$.

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

G.3 Implementation

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

Selection of Grids We set $n_c = 11$, $n_m = 21$, $\Delta t = 1/24$, $n_p = 11$. The gird for long-run risks S_θ is determined by applying the method of Rouwenhorst (1995). The grid for unpredictable consumption growth shocks S_c is determined by applying the method of Tauchen (1986). The grid of customer base share S_m is discretized into 21 nodes from 10^{-7} to $1 - 10^{-7}$ with equal spaces. We do not set S_m from 0 to 1 to avoid the indeterminacy of optimal price with $m = 0$. The time interval Δt is set to be $1/24$. A higher Δt implies faster convergence for the same number of iterations but lower accuracy. We checked that the solution is accurate enough for $\Delta t = 1/24$, further reducing Δt would not improve the accuracy much. With $\Delta = 1/24$, 5000 times iterations allow us to achieve convergence in value functions. The industry characteristic grid is discretized into 11 nodes from 0 to 1 with equal spaces. The price grid is discretized into 11 nodes from 1 to 2 with equal spaces. The upper bound is chosen according to $\epsilon/(\epsilon - 1) \times \omega = 2$, which is the highest price a firm will set.

Calculating Iterations and Searching For the Nash Equilibrium. Given the value functions from the previous iteration, we use the golden section search method to find the equilibrium prices. The computational complexity of this algorithm is at the order of $\log(n)$, much faster and more accurate than a simple grid search.

Searching for the equilibrium price is very challenging because we have to solve a fixed-point problem (equations G.19-G.22) that involves both firms' simultaneous prices decisions. Our solution technique is to iteratively solve the following three steps.

First, given $v^N_{i1}(m_{i1}, \theta)$, we solve for the off-equilibrium value $\widehat{v}^N_{i1}(m_{i1}, \theta; P_{i2})$ and the off-equilibrium policy function $\widehat{P}^N_{i1}(m_{i1}, \theta; P_{i2})$. Exploiting symmetry, we obtain $\widehat{v}^N_{i2}(m_{i1}, \theta; P_{i1})$ and $\widehat{P}^N_{i2}(m_{i1}, \theta; P_{i1})$. Second, for each $(m_{i1}, \theta) \in S_m \times S_\theta$, we use a nonlinear solver knitro to solve equations (G.19-G.20) and obtain the equilibrium prices $P^N_{i1}(m_{i1}, \theta)$, $P^N_{i2}(m_{i1}, \theta)$. Third, we solve equations (G.21-G.22) and obtain equilibrium value functions $v^N_{i1}(m_{i1}, \theta)$ and $v^N_{i2}(m_{i1}, \theta)$.

Searching For Collusive Prices. We modify the golden section search method to find the highest collusive prices $P^C(m_{i1}, \theta)$ by iterations. Within each iteration, we solve firms' collusion value and deviation value using standard recursive methods given $\widehat{P}^C_{ij}(m_{i1}, \theta)$.

There are two key differences between our method and a standard golden section search method. First, to increase efficiency, we guess and update the collusive pricing schedule $\widehat{P}^C_{ij}(m_{i1}, \theta)$ simultaneously for all $(m_{i1}, \theta) \in S_m \times S_\theta$, instead of doing it one by one for each state. A natural problem introduced by the simultaneous updating is that there might be overshooting. For example, if for some particular state

(m^*, θ^*), we updated a collusive price $\widehat{P}_{ij}^{C}(m^*, \theta^*)$ too high in the previous iteration, the collusive price for some other states $(m, \theta) \neq (m^*, \theta^*)$ might be affected in this iteration and never achieve a binding incentive compatibility constraint. Eventually, this may lead to non-convergence.

We solve this problem by gradually updating the collusive prices. In particular, in each round of iteration, we first compute the updated collusive pricing schedule $\widehat{P}_{ij}^{C'}(m_{i1}, \theta)$ implied by the golden section search method. Then, instead of changing the upper search bound or lower search bound to $\widehat{P}_{ij}^{C'}(m_{i1}, \theta)$ directly, we change it to $(1 - adj) \times \widehat{P}_{ij}^{C}(m_{i1}, \theta) + adj \times \widehat{P}_{ij}^{C'}(m_{i1}, \theta)$, a weighted average of the current collusive price $\widehat{P}_{ij}^{C}(m_{i1}, \theta)$ and the updated collusive price $\widehat{P}_{ij}^{C'}(m_{i1}, \theta)$. For our baseline model, we set $adj = 0.15$ to ensure perfect convergence.