Competition, Profitability, and Risk Premia

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Abstract

We build a general equilibrium model with dynamic strategic competition to reconcile competition intensity, profitability, and returns. Product market competition endogenously intensifies as discount rates rise and expected consumption growth declines, because firms compete more aggressively for current cash flows by undercutting each other as the present value of future cooperation decreases. The intensified competition amplifies the impact of the aggregate shocks driving discount rates and expected consumption growth. In industries with a lower turnover rate of market leaders, firms' profit margins are higher and more exposed to discount rate and expected growth fluctuations, thereby generating the gross profitability premium.

Keywords: Product market friction, Habit, Competition intensity, Gross profitability premium, Time-varying risk premium. (**JEL**: G12, L13, O33, C73)

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1 Introduction

Product market competition intensifies when rival firms undercut profit margins aggressively to gain market shares. The degree of competition fluctuates dramatically over time, and the risk of an industry entering a period of intensified competition concerns investors. This is partly because product markets are highly concentrated and the market leadership is highly persistent, featuring rich strategic product market competition among leading firms.[1]

This paper studies endogenous competition on profit margins in product markets and its asset pricing implications. Our contribution is mainly theoretical and quantitative. More precisely, we incorporate dynamic games of strategic competition among firms into a habit-formation framework (see Campbell and Cochrane, 1999) with a predictable component of expected consumption growth as in Campbell (1999, Section 4.3) and Santos and Veronesi (2006, 2010).[2] In the model, competition in product markets endogenously intensifies as the discount rate rises and/or expected consumption growth declines, because firms become effectively more impatient for cash flows and their incentives to undercut profit margins grow stronger. In both the model and data, a rise in accumulated consumption growth is associated with a decline in the discount rate and a rise in expected consumption growth.[3] Thus, the competition intensity, and hence the profit margin, comoves positively with accumulated consumption growth. Further, in industries with a lower turnover rate of market leadership, firms' profit margins are higher and more exposed to shocks to the discount rate and expected consumption growth, and therefore they comove more positively with accumulated consumption growth. This sheds new light on the relation between gross profitability and stock returns – the gross profitability premium (see Novy-Marx, 2013).

As a theoretical contribution, our model highlights endogenous cash flows driven by the strategic considerations of agents for stock valuation, while the bulk of asset pricing research related to stock valuation has been focusing on non-strategic mechanisms; there are a few exceptions (see, e.g., Pástor and Veronesi, 2012; Opp, Parlour and Walden,

[1] According to U.S. Census data, the top four and eight firms within each four-digit SIC industry account for more than 48% and 60% of that industry's total revenue, respectively. For further evidence, see, e.g., Autor et al. (2017), Loecker and Eeckhout (2017), and Grullon, Larkin and Michaely (2019) for a high concentration of product markets, and Geroski and Toker (1996), Matraves and Rondi (2007), Sutton (2007), and Bronnenberg, Dhar and Dubé (2009) for leadership persistence.

[2] This assumption of a small persistent predictable component of consumption growth is also consistent with the long-run risk literature (see, e.g., Bansal and Yaron, 2004; Hansen, Heaton and Li, 2008).

[3] Similar empirical measures of accumulated consumption growth are referred to as the ultimate consumption risk in Parker and Julliard (2005), and the low-frequency consumption risk in Bansal, Dittmar and Lundblad (2005); Dittmar and Lundblad (2017).

2014; Corhay, Kung and Schmid, 2017; Pástor and Veronesi, 2019). Specifically, consistent with the data, profit margins fluctuate substantially in our model, and are endogenously driven by time-varying competition intensity. Competition is more likely to intensify as economic conditions weaken, in which the discount rate is higher and/or expected consumption growth is lower. By narrowing profit margins in bad times, endogenously intensified competition amplifies adverse aggregate shocks and enlarges the market risk premium. We refer to the additional component of the risk premium due to the variation in competition intensity in product markets as the *competition risk premium*.

Our model deviates from the model of Campbell and Cochrane (1999) mainly in three aspects. First, households have persistent tastes for firms' differentiated products (similar in spirit to the deep habits specification of Ravn, Schmitt-Grohé and Uribe, 2006; van Binsbergen, 2016). Such persistent tastes for each single differentiated good can be viewed as customer base from a firm's perspective, and the firm finds it valuable to maintain its customer base.

Second, there is a continuum of industries, and each industry contains a few leading firms with many market followers with measure zero. Effectively, each industry features a dynamic Bertrand oligopoly with differentiated products and tacit collusion on profit margins.[4] Oligopolists can collude tacitly with each other to obtain high profit margins.[5] Knowing that competitors will honor the collusive profit-margin agreement, a firm can boost its short-run revenue by undercutting profit margins to attract more customers; however, deviating from the collusive profit-margin scheme may reduce revenue in the long run if the competitors find out and punish the firm by ceasing cooperation.[6] Importantly, the tacit collusive profit margins depend on firms' deviation incentives: a higher implicit collusive profit margin can only be sustained by a lower deviation incentive, which is further shaped by firms' tradeoff between short- and long-term cash flows. In other words, higher collusive profit margins are more difficult to sustain when the discount rate is higher and/or expected consumption growth is lower, because future punishment becomes less threatening when firms discount future cash flows to a greater

[4]Tirole (1988, Chapter 6) builds oligopoly models with Bertrand competition and obtains collusion implications similar to those of models with Cournot competition.

[5]Collusion is pervasive among leading competitors in industries. John Connor's Private International Cartels Dataset (see Connor, 2016) shows that during 1990-2016, 953 cartels were convicted of price fixing and 296 suspected cartels were under investigation. The estimated cartel overcharges since 1990 exceed $1.5 trillion. The majority of the corporate cartelists were from Europe or North America. More importantly, besides explicit collusion, firms also engage, even more pervasively, in tacit collusion. For example, Bourveau, She and Zaldokas (2019) show that firms can use corporate disclosure to facilitate tacit coordination. For another example, institutional cross-ownership can facilitate firms in tacitly colluding and better collaborating with each other in product markets (see, e.g., He and Huang, 2017).

[6]Following the literature (see Green and Porter, 1984; Brock and Scheinkman, 1985; Rotemberg and Saloner, 1986), we adopt the non-collusive Nash equilibrium as punishment for deviation.

extent and/or expect a persistent decline in aggregate demand. In short, a rise in the discount rate and/or a decline in expected consumption growth intensifies competition by suppressing the present value of future cooperation.

Third, we assume that market leadership is sticky. The change of market leaders in an industry, as a disruption to the market structure, occurs with certain intensity, which captures a fundamental industry characteristic. In such a change, an existing market leader is displaced by a new market leader who used to be a market follower. The persistence of market leadership, or the turnover rate of market leaders, is the only ex-ante heterogeneity across industries emphasized by our model.[7]

As a major cross-industry implication, the model suggests that industries with a higher turnover rate of market leaders are more immune to endogenous fluctuations in competition intensity and thus these industries have lower average returns. Intuitively, in such industries, market leaders are more likely to be replaced by market followers, and thus they would find it more difficult to collude with each other on profit margins in product markets. This is because all market leaders rationally expect to be displaced not far in the future, so the punishment for deviation becomes less threatening. The lack of collusion incentives in these industries results in low collusive profit margins, which are also less responsive to fluctuations in the discount rate and expected consumption growth. By contrast, in industries with a lower turnover rate of market leaders, the existing market structure is more stable, making the punishment for deviation in the future more threatening. As a result, it is easier for firms to collude and obtain higher profit margins. Thus, in these industries, profit margins are higher and more sensitive to fluctuations in the discount rate and expected consumption growth.

The within-industry implications on stock returns also follow directly from the mechanism above. The firm with a larger share of the customer base has greater market power than its competitors, and thus its profit margin is higher. When the discount rate rises and/or expected consumption growth declines, the profit margins of all firms in the industry drop, but the drop is greater in percentage terms for smaller firms because of the "leverage effect". As a result, the firm with higher gross profitability is less exposed to aggregate shocks and thus has lower expected excess returns, opposite to the cross-industry pattern.

Why do we need habit persistence and a predictable component of consumption? They generate substantial fluctuations in the discount rate and expected consumption growth. The demand level, demand growth, and discount rate are argued to be major

[7] In reality, firms can also compete strategically on innovation. Our model focuses on the time-varying intensity of competition on profit margins in product markets, by assuming that the change of market leaders caused by radical innovation in an industry occurs exogenously.

forces that drive endogenous competition.[8] However, the effect of demand level is shown to be negligible in a realistic quantitative framework. Therefore, we focus on the demand growth and discount rate, which connect the discount rate and expected consumption growth to accumulated consumption growth, defined as $\hat{g}_t \equiv \sum_{j=0}^{K} \phi^j \Delta c_{t-j} / \sum_{j=0}^{K} \phi^j$ with $\Delta c_t \equiv \ln(C_t) - \ln(C_{t-1})$, C_t being the aggregate consumption and ϕ being a constant less than but close to unity.[9] In other words, due to the habit persistence and growth persistence, accumulated consumption growth can serve as an approximation simultaneously for the discount rate and expected consumption growth. The approximation for the discount rate (i.e., the surplus consumption ratio) follows the ideas of the works involving habit persistence (see, e.g., Parker and Julliard, 2005; Santos and Veronesi, 2010), and the approximation for expected consumption growth follows those involving low-frequency consumption risk (see, e.g., Bansal, Dittmar and Lundblad, 2005; Dittmar and Lundblad, 2017). Both are intuitively suggested by our model. Specifically, a lower accumulated consumption growth $\hat{g}_t$ is associated with a lower surplus consumption ratio (i.e., a higher discount rate) or a lower expected consumption growth.

While our contribution is mainly theoretical, we empirically test the main predictions of our model and find strong evidence that supports the theoretical implications in Section 4. We show that profit margins and profitability comove with accumulated consumption growth and that such a comovement is more pronounced in profitable industries. We show that more profitable industries are less likely to experience market leader changes. Next, we show that gross profitability is positively priced both within and across industries. Consistent with our model, the cross-industry profitability spreads load positively on the accumulated consumption growth and concentrates in the industries that have not recently faced antitrust charges. After controlling for the exposure to accumulated consumption growth, the magnitudes of both the cross-industry and firm-level gross profitability premia decrease substantially and become statistically insignificant.

To directly test the economic mechanism of our model, we also construct an approximation for the likelihood of market leadership changes. Specifically, we use patent data to construct a measure that captures the innovation similarity among industries. In light of previous studies (see, e.g., Jaffe, 1986; Bloom, Schankerman and Van Reenen,

[8] For example, Rotemberg and Saloner (1986) and Green and Porter (1984) argue for the effect of the demand level in the current period on the incentive to deviate. Haltiwanger and Harrington (1991) and Bagwell and Staiger (1997) emphasize the effect of expected demand growth on the incentive to deviate. Opp, Parlour and Walden (2014) qualitatively study the effect of the discount rate on the incentive to deviate.

[9] Similar weighted average cash flow measures have also been constructed based on aggregate dividends, which are referred to as the discount N-year sum of dividend growth in Cohen, Polk and Vuolteenaho (2009), the accumulated consumption growth in Santos and Veronesi (2010), and the slow-moving exponentially weighted average of past dividend growth in Nagel and Xu (2018).

2013), a higher innovation similarity predicts a lower likelihood of radical innovation in the industry and hence a lower likelihood of market structure disruption. Using the innovation similarity measure, as well as other industry characteristic measures, we construct estimates for the turnover rate of market leaders based on a logistic regression, which is referred to as the *disruption rate measure*. The gross profitability is significantly negatively correlated with the disruption rate measure in the cross section and they share similar asset pricing implications as predicted by the model. These findings are consistent with the theoretical implications of the model that the market leadership turnover rate at the industry level serves as a fundamental industry characteristic justifying the cross-industry gross profitability premium through the channel of endogenous product market competition.

Finally, in Section 5, we extend the baseline model to a full quantitative model to evaluate the quantitative capacity of the mechanism. In particular, we augment the baseline model by incorporating collusion costs and allowing for multiple market leaders (more than two). We assume that firms incur a non-pecuniary cost to maintain collusion. Under large adverse shocks to the discount rate and/or expected consumption growth, collusive profit margins decline significantly, and the benefit of collusion exceeds collusion costs. As a result, firms optimally abandon collusion, and the industry falls into a non-collusive equilibrium — which is when competition is the most severe. Importantly, an endogenous switch from the collusive to the non-collusive equilibrium generates a significant downward jump in profit margins and amplifies the impact of shocks to the discount rate and expected consumption growth.[10] Moreover, the probability of jumping into a non-collusive equilibrium (i.e., the most severe competition) endogenously varies over time and is driven by fluctuations in discount rates and expected consumption growth. Further, we extend the baseline model from a duopoly to an oligopoly of three market leaders. We find that the quantitative results are similar, because the endogenous jumps from collusive to non-collusive equilibria take place more frequently in the oligopolistic setting and the lower profit margins reinforce the "leverage effect" in percentage terms, even though collusive profit margins respond less dramatically to the aggregate shocks to the discount rate and expected consumption growth.

Related Literature. Our paper contributes to the burgeoning literature on the intersection between industrial organization, marketing, and finance. In this literature, the earlier contributions focus on the interaction of competition and contracting, including Fersht-

[10]The endogenous equilibrium switching driven by fundamental shocks is similar in spirit to that of Tsyvinski, Mukherji and Hellwig (2006), Angeletos, Hellwig and Pavan (2007), Bebchuk and Goldstein (2011), and Goldstein, Dow and Guembel (2017), among others.

man and Judd (1987), Bolton and Scharfstein (1990), and Aggarwal and Samwick (1999), among others. Recently, more studies have emerged on the interaction of competition and asset pricing (see, e.g., Hou and Robinson, 2006; Carlin, 2009; Aguerrevere, 2009; Opp, Parlour and Walden, 2014; Bustamante, 2015; Koijen and Yogo, 2015; Loualiche, 2016; Bustamante and Donangelo, 2017; Corhay, 2017; Corhay, Kung and Schmid, 2017; Andrei and Carlin, 2018).[11] Corhay, Kung and Schmid (2017) develop a general-equilibrium production-based asset pricing model to understand the endogenous relation between markups and stock returns amid strategic competition among firms. They focus on one-shot non-collusive Nash equilibria, while we consider collusive Nash equilibria. Different from theirs, our model yields the gross profitability premium, especially across industries. Opp, Parlour and Walden (2014) investigate how competition endogenously intensifies as the discount rate rises. They show that the endogenous dispersion of profit margins across industries can cause welfare losses and raise investors' pricing kernel. Our paper is different in three ways: (i) their model focuses on identical firms producing homogeneous goods within an industry, whereas we allow firms to be different and to produce differentiated goods within an industry, generating within-industry heterogeneity in profit margins and returns; (ii) their model focuses on industries differing in terms of the number of firms they contain, whereas we emphasize industries with different turnover rates of market leaders, a source of heterogeneity that allows us to capture industry-specific strategic behavior, thereby generating heterogeneous levels and variability of profit margins, as well as the cross-industry gross profitability premium; and (iii) their model is qualitative, whereas ours is quantitative.

Our paper also contributes to the literature on the relation between corporate profitability and stock returns (see, e.g., Fama and French, 2006; Novy-Marx, 2013; Hou, Xue and Zhang, 2015; Ball et al., 2015, 2016; Deng, 2018). Fama and French (2006) find that earnings have explanatory power for stock returns. Novy-Marx (2013) documents the gross profitability premium, indicating that firms with higher gross profitability are associated with higher expected returns. Despite mounting empirical evidence, the literature has provided limited theoretical explanations for the profitability premium. One notable exception is Kogan and Papanikolaou (2013), who highlight the role of the

[11] The strand of literature on the intersection of industrial organization and corporate finance has also been growing (see, e.g., Phillips, 1995; Kovenock and Phillips, 1997; Allen and Phillips, 2000; Aghion et al., 2005; Morellec and Zhdanov, 2005, 2008; Hoberg and Phillips, 2010*a*; Hackbarth and Miao, 2012; Phillips and Zhdanov, 2013; Carlson et al., 2014; Hackbarth, Mathews and Robinson, 2014; Hoberg, Phillips and Prabhala, 2014; Hoberg and Phillips, 2016; Azar, Schmalz and Tecu, 2018; Dong, Massa and Zaldokas, 2018; Yang, 2018; Dou and Ji, 2018; Hackbarth and Taub, 2018; Roussanov, Ruan and Wei, 2018). Another strand of literature 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; Atkeson, Eisfeldt and Weill, 2015; Liu and Wang, 2018).

investment-specific technology (IST) shock as a risk factor priced in the cross section. The IST shock can help explain the within-industry gross profitability premium, but not the cross-industry gross profitability premium. Our model complements their mechanism by offering a risk-based rationale for the gross profitability premium (see Novy-Marx, 2013) through the mechanism of endogenous competition, especially for the cross-industry gross profitability premium.

More broadly, an increasing number of works are incorporating strategic considerations into asset pricing and portfolio choice models to help explain challenging asset pricing and trading patterns. For example, Pástor and Veronesi (2012, 2013) develop models with learning to study the asset pricing implications of political uncertainty. In their model, the average firm profitability is determined by the prevailing government policy. Economic downturns drive policy changes, which in turn affect firms' profitability. Pástor and Veronesi (2012) solve the games played by firms (and the government) and analyze price dynamics in Nash equilibrium. In a recent paper, Pástor and Veronesi (2019) provide an explanation for the "presidential puzzle" by developing a model with endogenous election outcomes driven by voters' time-varying risk aversion. Agents play a simultaneous-move game in deciding which party to elect. In the Nash equilibrium, each agent maximizes the expected utility while taking the choices of all other agents as given. In the mutual fund literature, Bretona, Hugonnier and Masmoudi (2010) study the strategic interactions of managers of different funds through a Nash game where investors are non-strategic. Hugonnier and Kaniel (2010) and Kaniel, Tompaidis and Zhou (2019) highlight the strategic moves between managers and investors by studying a Stackelberg stochastic differential game in which the leader (i.e., the manager) moves first and then the followers (i.e., the investors) move next.

Finally, our paper is situated in the vast literature on cross-sectional asset pricing (see, e.g., Cochrane, 1991; Berk, Green and Naik, 1999; Gomes, Kogan and Zhang, 2003; Pástor and Stambaugh, 2003; Belo and Lin, 2012; Ai and Kiku, 2013; Belo, Lin and Bazdresch, 2014; Hackbarth and Johnson, 2015; Dou, 2017; Koijen, Lustig and Van Nieuwerburgh, 2017). Nagel (2013) provides a comprehensive survey.

2 Motivating Facts

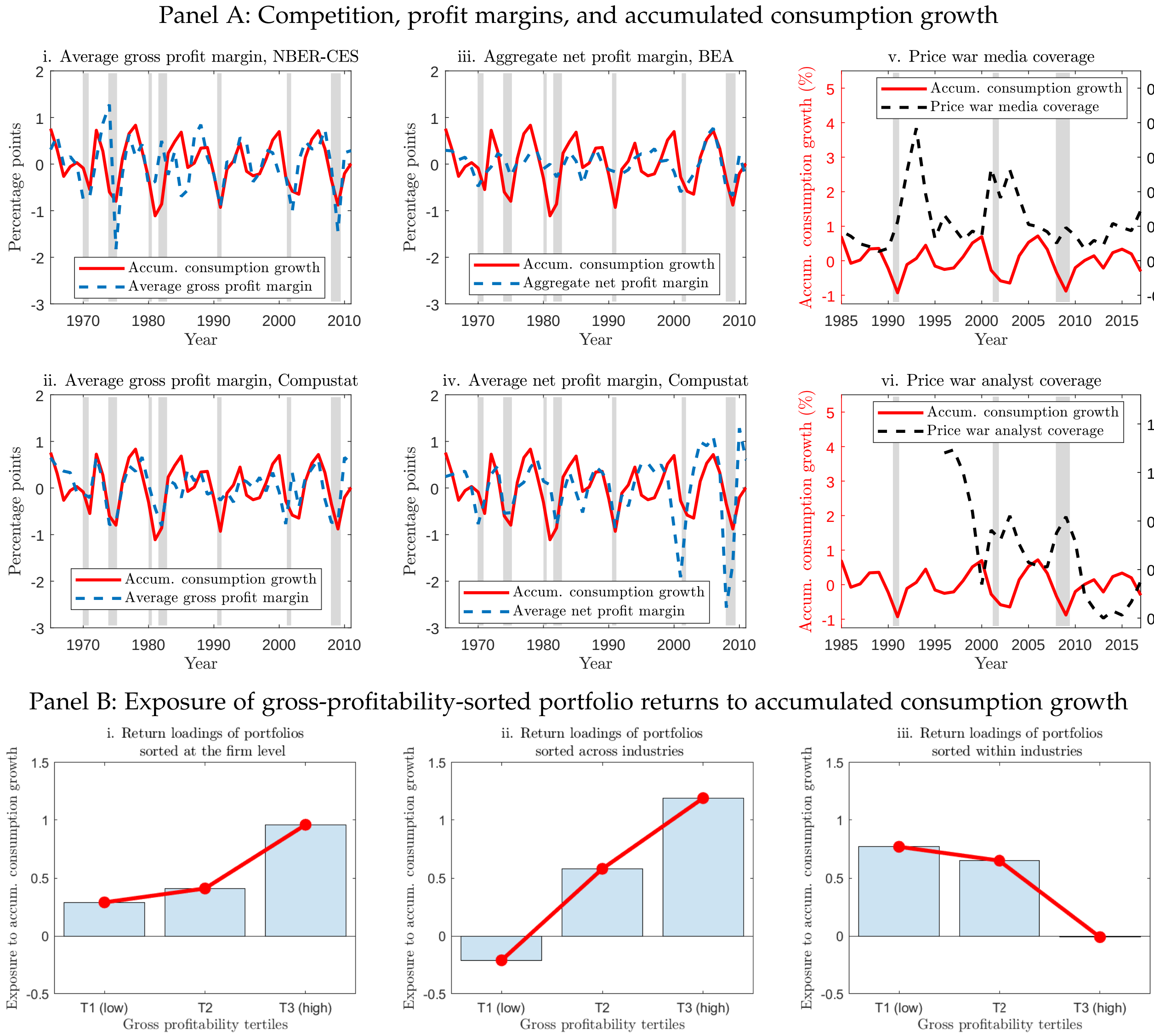
We document two motivating facts about competition, profitability, and stock returns in Figure 1. The first is a time-series pattern. The average profit margin over industries, reflecting the average competition intensity in product markets, positively comoves with accumulated consumption growth (see panels A.i – A.iv).[12] Moreover, as a prominent form of intensified competition in product markets, price wars present a severe concern for investors, and their coverage by media and analyst reports is strongly countercyclical with respect to accumulated consumption growth (see panels A.v – A.vi). This provides direct evidence on the pro-cyclical patterns of competing firms' collusion incentives from investors' perspective. These patterns suggest that certain primitive economic forces exist that drive both competition intensity and accumulated consumption growth.

The second is a cross-sectional pattern. Firms' gross profitability is positively associated with their stock return betas on accumulated consumption growth (see panel B.i). This suggests that accumulated consumption growth has the potential to rationalize the gross profitability premium since it carries a positive market price of risk. However, panels B.ii and B.iii suggest that the mechanism behind the gross profitability premium might be more subtle than one would expect: the cross- and within-industry gross profitability premia can be caused by vastly different economic mechanisms. In particular, panel B.ii shows that a higher gross profitability is associated with higher stock return betas on accumulated consumption growth across industries, while panel B.iii shows that the pattern is the opposite within industries. Therefore, accumulated consumption growth can justify the cross-industry gross profitability premium, but not the within-industry one. As an important complement, Kogan and Papanikolaou (2013)'s displacement risk channel mainly rationalizes the within-industry gross profitability premium.[13]

To rationalize the time-series and cross-sectional patterns in Figure 1, we develop a general-equilibrium model with dynamic strategic competition in the following section.

[12] The average profit margin is the simple average of industries' profit margins as in Machin and Van Reenen (1993), so the comovement is not because of a composition effect from time-varying industry size. We focus on the comovement between accumulated consumption growth and profit margins, instead of product markups, because profit margins are related directly to competition intensity. Our stylized fact is consistent with the literature, which suggests that profit margins are strongly pro-cyclical (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 (see 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 pro-cyclical, whereas Bils (1987) and Chevalier and Scharfstein (1996) find markups to be countercyclical.

[13] When the economy is hit by positive IST shocks, the large and mature firms with a higher profitability tend to be displaced by the young and growing firms with a lower profitability, which generates the gross profitability premium in the cross section within an industry. This channel mainly works within industries since it is difficult for one industry to displace another after innovation shocks.



Note: Panel A shows the strong comovement between the degree of competition and accumulated consumption growth. Panels A.i – A.iv plot the yearly time series of average profit margins and accumulated consumption growth, using the Hodrick-Prescott (HP) filter with a smoothing parameter of 6.25 (see Ravn and Uhlig, 2002). Panels A.v and A.vi plot the media and analyst coverage of price wars, respectively. Grey areas represent the National Bureau of Economic Research (NBER) recession periods. The accumulated consumption growth in quarter t is measured by the weighted average of past 12-quarter consumption growth: $\hat{g}_t \equiv \sum_{j=0}^{11} \phi^j \Delta c_{t-j} / \sum_{j=0}^{11} \phi^j$ with $\Delta c_t \equiv \ln(C_t) - \ln(C_{t-1})$ where consumption C_t is measured as per-capita real personal consumption expenditures on non-durable goods and services. We set the coefficient $\phi = 0.966$ to be consistent with the yearly persistence coefficient of the surplus consumption ratio (0.87) in Campbell and Cochrane (1999). Following Parker and Julliard (2005), we compute the weighted average for the past 12 quarters. We take the $\hat{g}_t$ in the last quarter of each year and multiply it by four to represent accumulated consumption growth at the yearly frequency. We plot accumulated consumption growth and profit margins at the yearly frequency in panel A because profit margins exhibit strong seasonality at the quarterly frequency. See Appendix A for detailed explanations of the construction of profit margins and the coverage of price wars. The implications of competition intensity fluctuations on stock returns and profit margins have been extensively covered by the media and analysts. To show that the time-varying degree of industry competition presents a serious concern for investors, we give a few headline quotes, a few examples of analyst reports, and a case study in Online Appendix A. Panel B shows the exposure of portfolio returns sorted on gross profitability to the accumulated consumption growth. Panel B.i plots the return loadings of portfolios constructed by sorting all firms on gross profitability, which is first studied by Novy-Marx (2013); panel B.ii plots the return loadings of portfolios constructed by sorting all industries on gross profitability; and panel B.iii plots the return loadings of portfolios constructed by sorting firms within the same industry on gross profitability. The loadings on the accumulated consumption growth shock are estimated in Table 4. The differences in the loadings between the high (T3) and low (T1) gross profitability portfolios are statistically significant for panels B.i – B.iii (see Table 4).

Figure 1: Motivating empirical facts.

3 The Baseline Model

To generate time-varying predictable expected returns and discount rates, we appeal to the concept of habit persistence (see, e.g., Campbell and Cochrane, 1999, 2000), which connects past consumption growth to the current discount rate (the "discount rate channel" for endogenous competition). Further, to generate the predictable persistent component of consumption growth, which connects past consumption growth to expected future consumption growth (the "cash flow channel" for endogenous competition), we incorporate a predictable component of expected consumption growth under a habit-formation framework as in Campbell (1999, Section 4.3), Santos and Veronesi (2006, 2010), and Lettau and Wachter (2007). We quantify the importance of both channels.

3.1 Preferences

Differentiated Goods. The corporate sector comprises a continuum of industries indexed by $i \in \mathcal{I} \equiv [0,1]$, owned by households. Each industry i has two market leaders, indexed by $j \in \{1,2\}$, and many followers with measure zero;[14] so each industry is essentially a duopoly. We label a generic firm by ij, referring to firm j in industry i, and its competitor by $i\bar{j}$. Firms produce differentiated perishable goods and set their profit margins strategically to maximize shareholder value.

Preferences for Differentiated Goods. Households are atomistic and homogeneous, and they have access to complete financial markets. There exists a representative agent whose preference for the final goods is characterized by

$$U_0 = \mathbb{E}_0 \left[\int_0^\infty u_t(C_t, H_t) \mathrm{d}t \right], \tag{3.1}$$

with $u_t(C_t, H_t)$ being the instantaneous utility function given by

$$u_t(C_t, H_t) = e^{-\beta t} \frac{(C_t - H_t)^{1-\gamma}}{1-\gamma}, \tag{3.2}$$

where the variable H_t denotes an external habit level, γ denotes the agent's risk aversion, and β denotes the subjective discount rate.

Households' preferences fall into the class of external habit-formation utilities. More precisely, similar to Menzly, Santos and Veronesi (2004) and Santos and Veronesi (2006,

[14] In Online Appendix D, we extend the model to allow for a nonzero measure of followers and microfound their competition with leaders. Doing so does not change the main implications of interest in this paper.

2010), our specification is a continuous-time analog of the preferences adopted by Campbell and Cochrane (1999).[15] The external habit level H_t depends upon the past aggregate consumption. That is, households derive utility from their consumption relative to the past aggregate consumption path. The external habit level H_t captures a subsistence level of consumption or social externality.

The final consumption good C_t is determined by a two-layer aggregation. First, the demand for C_t is determined through the aggregation of industry composites

$$C_t = \left(\int_0^1 M_{i,t}^{\frac{1}{\epsilon}} C_{i,t}^{\frac{\epsilon-1}{\epsilon}} \mathrm{d}i \right)^{\frac{\epsilon}{\epsilon-1}}, \tag{3.3}$$

where $C_{i,t}$ is the demand for industry i's composite and parameter $\epsilon > 1$ captures the elasticity of substitution among industry composites. The weight coefficient $M_{i,t}$ captures households' "tastes" for industry i's composite. A higher $M_{i,t}$ reflects a higher utility gain from consuming industry i's composite.[16]

Further, industry i's composite $C_{i,t}$ is determined by aggregating firm-level differentiated products

$$C_{i,t} = \left[\sum_{j=1}^{2} \left(\frac{M_{ij,t}}{M_{i,t}} \right)^{\frac{1}{\eta}} C_{ij,t}^{\frac{\eta-1}{\eta}} \right]^{\frac{\eta}{\eta-1}}, \text{ with } M_{i,t} = \sum_{j=1}^{2} M_{ij,t}, \tag{3.4}$$

where C_{ij} is the demand for firm j's product in industry i and parameter $\eta > 1$ captures the elasticity of substitution among products in the same industry. $M_{ij,t}/M_{i,t}$ captures the households' "tastes" for firm j's products.

Consistent with the literature (see, e.g., Atkeson and Burstein, 2008; Corhay, Kung and Schmid, 2017), we assume $\eta \geq \epsilon > 1$, meaning that products within the same industry are more substitutable. For example, the elasticity of substitution between the Apple iPhone and the Samsung Galaxy is much higher than that between a cell phone and coffee.

3.2 Customer Base, Demand Curves, and Profit Margins

The taste coefficient $M_{ij,t}$ in equation (3.4) is persistent over time, which can be interpreted as customers' tendency to keep buying product ij due to either brand loyalty or customer

[15] Another specification of the external habit formation is the relative habit formation of Abel (1990), which features *catching up with the Joneses*. The relative habit formation can arise endogenously from the pecuniary externality of the competition for scarce resources (see Demarzo, Kaniel and Kremer, 2004; DeMarzo, Kaniel and Kremer, 2007, 2008).

[16] According to the assumption in Section 3.3, the industry-level customer base $M_{i,t}$ for every $i \in \mathcal{I}$ is mean-reverting and stationary.

inertia (see Klemperer, 1995). From a firm's perspective, the households' tastes (brand loyalty or customer inertia) $M_{ij,t}$ can be viewed implicitly as its customer base (or customer capital), as $M_{ij,t}$ determines the demand for its products $C_{ij,t}$ given prices (see, e.g., Gourio and Rudanko, 2014; Dou et al., 2019).

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

$$C_{i,t} = M_{i,t} \left(\frac{P_{i,t}}{P_t} \right)^{-\epsilon} C_t, \quad \text{with } P_t = \left(\int_0^1 M_{i,t} P_{i,t}^{1-\epsilon} \mathrm{d}i \right)^{\frac{1}{1-\epsilon}}, \tag{3.5}$$

where P_t is the price index for the final consumption good. 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 goods is

$$C_{ij,t} = \frac{M_{ij,t}}{M_{i,t}} \left(\frac{P_{ij,t}}{P_{i,t}} \right)^{-\eta} C_{i,t}, \quad \text{with } P_{i,t} = \left[\sum_{j=1}^{2} \left(\frac{M_{ij,t}}{M_{i,t}} \right) P_{ij,t}^{1-\eta} \right]^{\frac{1}{1-\eta}}. \tag{3.6}$$

In equation (3.6), the demand for firm j's goods increases with $M_{ij,t}$. Thus, it is natural to think of $M_{ij,t}$ as firm j's customer base and $M_{i,t}$ as industry i's total customer base. Moreover, equation (3.6) implies that firm j has a larger influence on the price index $P_{i,t}$ when its share of the customer base $M_{ij,t}/M_{i,t}$ is higher. Thus, firm j has the incentive to accumulate $M_{ij,t}$ to increase demand and gain market power.

Endogenous Price Elasticity of Duopolists. The short-run price elasticity of demand for product j, taking into account the externality, is

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

where $\mu_{ij,t}$ is the *(revenue) market share* of firm j in industry i and is defined as follows:

$$\mu_{ij,t} = \frac{P_{ij,t}C_{ij,t}}{P_{i,t}C_{i,t}} = \left(\frac{P_{ij,t}}{P_{i,t}} \right)^{1-\eta} \frac{M_{ij,t}}{M_{i,t}}. \tag{3.7}$$

Equation (3.7) shows that the short-run price elasticity of demand is given by the average of η and ϵ, weighted by the firm's market share. Depending on $\mu_{ij,t}$, firm j's short-run price elasticity of demand lies in $[\epsilon, \eta]$. On the one hand, when firm j's market share $\mu_{ij,t}$ becomes smaller, within-industry competition becomes more relevant, so firm j's price elasticity of demand depends more heavily on η. In the extreme case of $\mu_{ij,t} = 0$, firm j becomes atomistic and takes the industry price index $P_{i,t}$ as given. As a result, firm j's price elasticity of demand is exactly η. On the other hand, when $\mu_{ij,t}$ becomes larger, cross-industry competition becomes more relevant and thus firm j's price elasticity of demand depends more strongly on ϵ. In the extreme case of $\mu_{ij,t} = 1$, firm j monopolizes in industry i and its price elasticity of demand is exactly ϵ.

Each firm's price has a non-negligible effect on the price index of the duopoly industry. The magnitude of this effect is determined by $\mu_{ij,t}$. Thus, when setting prices, each firm internalizes the effect of its own price on $P_{i,t}$, which in turn determines the demand for the industry's goods. If a continuum of firms exist in each industry as in standard monopolistic competition models, each firm would be atomistic and would have no influence over $P_{i,t}$, and cross-industry competition would have no impact on the firm's price elasticity of demand.

Profit Margins. The marginal cost for a firm to produce a flow of goods is ω with $\omega > 0$. That is, the firm incurs cost with intensity $\omega Y_{ij,t}$ in producing a flow of goods with intensity $Y_{ij,t}$ over $[t, t + \mathrm{d}t]$. Given the demand $C_{ij,t}$ and price $P_{ij,t}$, firm j's optimal profits over $[t, t + \mathrm{d}t]$ are

$$\text{Earnings}_{ij,t} = \max_{Y_{ij,t} \geq 0} (P_{ij,t} - \omega) Y_{ij,t}, \text{ subject to the demand constraint } Y_{ij,t} \leq C_{ij,t}. \quad (3.8)$$

Similar to Gourio and Rudanko (2014), Corhay, Kung and Schmid (2017), and Dou et al. (2019), the demand constraint (3.8) is imposed since the firm would never produce more than the demand $C_{ij,t}$ due to costly production of the immediately perishable goods. Therefore, the firm finds it optimal to choose $P_{ij,t} > \omega$ and produce up to $C_{ij,t}$ in equilibrium, and the optimal net profits (3.8) can be written as

$$\text{Earnings}_{ij,t} = \left(P_{ij,t} - \omega\right) C_{ij,t}, \text{ with } P_{ij,t} > \omega. \quad (3.9)$$

All net profits are paid out as dividends, as the model has no financial friction. The gross profitability is

$$GP_{ij,t} \equiv \underbrace{\frac{(P_{ij,t} - \omega) C_{ij,t}}{M_{ij,t}}}_{\text{gross profitability}} = \underbrace{\frac{P_{ij,t} - \omega}{P_{ij,t}}}_{\text{profit margin}} \times \underbrace{\frac{P_{ij,t} C_{ij,t}}{M_{ij,t}}}_{\text{asset turnover}} . \quad (3.10)$$

The net profitability in the model is $NP_{ij,t} = GP_{ij,t} - \delta$, where δ is the depreciation rate of customer capital $M_{ij,t}$. The gross profitability captures the economic gain from a firm's assets, which concerns investors. It can be decomposed into two parts: the profit margin and asset turnover. The profit margin is how much of net sales firms manage to keep as profits, and the asset turnover is the pace at which firms sell products. The former reflects the price-cost relation shaped by the degree of competition. The firm-level and industry-level profit margins are denoted by

$$\theta_{ij,t} \equiv \frac{P_{ij,t} - \omega}{P_{ij,t}} \text{ and } \theta_{i,t} \equiv \frac{P_{i,t} - \omega}{P_{i,t}}, \text{ respectively.} \tag{3.11}$$

It directly follows from equation (3.6) that the relation between industry-level profit margin $\theta_{i,t}$ and firm-level profit margin $\theta_{ij,t}$ is

$$1 - \theta_{i,t} = \left[\sum_{j=1}^{2} \left(\frac{M_{ij,t}}{M_{i,t}} \right) (1 - \theta_{ij,t})^{\eta-1} \right]^{\frac{1}{\eta-1}}. \tag{3.12}$$

The profit margin, rather than the marginal price, is examined in this paper for the following reasons.[17] First, we focus on asset pricing and thus it is the profit margin, not the price tag, that matters here. Second, the purpose of competition and even price wars is not merely to reduce competitors' prices, but to destroy their profit margins. Third, accurate and detailed data of retail prices and firms' marginal costs for a broad set of industries are not available. Fourth, even if high quality price and cost data were available, the implicit discounts, coupons, rebates, and gifts are not easily observable to economists. Last but not the least, price levels cannot be meaningfully compared across industries, but profit margins can.

Evolution of Customer Base. We model the evolution of firm j's customer base as

$$\mathrm{d}M_{ij,t} = (\alpha\theta_{i,t} - \delta) M_{ij,t}\mathrm{d}t + \sigma_M M_{ij,t}\mathrm{d}Z_{ij,t}, \tag{3.13}$$

where parameter $\alpha \geq 0$ determines the speed of customer base accumulation through advertising efforts, and the standard Brownian motion $Z_{ij,t}$ captures idiosyncratic shocks to firms' customer base due to, e.g., changes in households' tastes. Firms' advertising campaigns introduce their brands to more people and attract more customers (see, e.g., Bagwell, 2007). We assume that advertising efforts increase with the industry's profit

[17] Focusing on profit margins differentiates our paper from those focusing on nominal prices (see, e.g., Weber, 2015).

margin $\theta_{i,t}$. This parsimonious assumption captures the fact that profit margins have a statistically and economically significant causal effect on driving marketing efforts (see, e.g., Comanor and Wilson, 1967; Strickland and Weiss, 1976; Martin, 1979). The evidence that supports this assumption can be found in Appendix Table B.1.[18]

Strategic Complementarity. Substituting equation (3.6) into equation (3.9) gives

$$\text{Earnings}_{ij,t} = \Pi_{ij}(\theta_{ij,t}, \theta_{i\bar{j},t}) M_{ij,t}, \tag{3.14}$$

where $\Pi_{ij}(\theta_{ij,t}, \theta_{i\bar{j},t})$ is the gross profitability calculated as follows:

$$\Pi_{ij}(\theta_{ij,t}, \theta_{i\bar{j},t}) = \omega^{1-\epsilon}\theta_{ij,t}(1-\theta_{ij,t})^{\eta-1}(1-\theta_{i,t})^{\epsilon-\eta}C_t. \tag{3.15}$$

Equation (3.15) shows that $\Pi_{ij}(\theta_{ij,t}, \theta_{i\bar{j},t})$ depends on competitor $\bar{j}$'s profit margin $\theta_{i\bar{j},t}$ through the industry-level profit margin $\theta_{i,t}$, which reflects the direct externality of firm $\bar{j}$'s decisions. For example, if firm $\bar{j}$ sets a lower profit margin $\theta_{i\bar{j},t}$, the industry-level profit margin $\theta_{i,t}$ will also drop, increasing the degree of competition. This will motivate firm j to set a lower profit margin $\theta_{ij,t}$, so the two firms' profit margin decisions exhibit strategic complementarity as follows:

$$\frac{\partial^2 \Pi_{ij}(\theta_{ij,t}, \theta_{i\bar{j},t})}{\partial\theta_{ij,t}\partial\theta_{i\bar{j},t}} > 0, \quad \text{for all } i \in \mathcal{I}, \text{ and } j \neq \bar{j}. \tag{3.16}$$

3.3 Heterogeneous Persistence of Market Leadership

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

We assume that the change of market leaders in industry $i \in \mathcal{I}$, as a disruption to the market structure, occurs with intensity $\lambda_{i,t}$. The economy comprises a continuum of industries, and thus the industry-specific change of market leaders is an idiosyncratic event to the representative agent. In such a change, the existing market leaders are

[18] As a simplifying technical assumption that captures empirical regularities, Pástor and Veronesi (2003, 2009) also assume that the growth rate of firms is positively associated with their profitability.

replaced by new market leaders who used to be followers. Each of the new leaders has a customer base $\overline{M} > 0$.

Significant heterogeneity exists in the persistence of market leaders' position across industries.[19] In our model, the variable $\lambda_{i,t}$ is the only industry characteristic that is ex-ante heterogeneous across industries. We assume that the value of $\lambda_{i,t}$ remains the same until the industry is hit by an idiosyncratic Poisson shock with rate χ. Conditional on receiving the Poisson shock, a new characteristic is drawn randomly from the set $\{\lambda_1, \cdots, \lambda_N\}$ each with equal probability, where $0 \leq \lambda_1 < \cdots < \lambda_N$.

The assumption above technically ensures that the industry-level customer base $M_{i,t}$ for each $i \in \mathcal{I}$ is mean-reverting and stationary in the model. This modeling assumption is intended to be parsimonious to maintain tractability and keep the model focused.[20]

3.4 Aggregate Demand and Discount Rates

Endowment and Consumption. Suppose the per-capita endowment in final goods is E_t and let $e_t = \ln(E_t)$, which evolves as follows:

$$\mathrm{d}e_t = g_t \mathrm{d}t + \sigma_e \mathrm{d}Z_{e,t}, \tag{3.17}$$

$$\mathrm{d}g_t = -\kappa(g_t - \overline{g})\mathrm{d}t + \sigma_g \sqrt{g_t - \varsigma}\,\mathrm{d}Z_{g,t}, \tag{3.18}$$

where $Z_{e,t}$ and $Z_{g,t}$ are two independent standard Brownian motions, and ς is the lower bound for g_t.

The equilibrium outcome in a laissez-faire market economy is that consumption equals endowment, $C_t = E_t$, since the private marginal utility under the preference specification of (3.1) – (3.2) is strictly positive. As in Campbell and Cochrane (1999), we assume that consumption growth has constant volatility. Moreover, following Campbell (1999, Section 4.3), Santos and Veronesi (2006, 2010), and Lettau and Wachter (2007), we assume that expected consumption has a predictable component in a habit-formation framework. We make this assumption for three reasons. First, this assumption is consistent with the long-run-risk literature, which emphasizes that a small component of consumption growth is persistent and predictable[21] (see, e.g., Kandel and Stambaugh, 1991; Bansal and Yaron,

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

[20] How innovation and competition affect the aggregate growth has been a long-standing research question in the literature of development and economic growth, but it is not the focus of this paper.

[21] We show that our calibrated model generates implications on the persistence of consumption growth consistent with the empirical moments emphasized by Beeler and Campbell (2012). Like Santos and Veronesi (2010), we also regress future consumption growth on $\ln(W_t/C_t)$ in simulated data and find a

2004; Hansen, Heaton and Li, 2008; Bansal, Kiku and Yaron, 2012; Müller and Watson, 2018). Second, as emphasized in the macroeconomics literature (see, e.g., Haltiwanger and Harrington, 1991; Bagwell and Staiger, 1997; Galeotti and Schiantarelli, 1998; Nekarda and Ramey, 2013), the growth of demand and output can affect the degree of competition among firms. Modeling the small component of persistent consumption growth allows us to incorporate such a "cash flow channel" for endogenous fluctuations in the degree of competition. Third, in our model the time variation of expected consumption growth overthrows the theoretical validity of the CAPM, both conditionally and unconditionally.

External Habits. The habit level H_t depends on the past consumption process. The effect of habit persistence on risk aversion can be conveniently summarized by the surplus consumption ratio $S_t \equiv (C_t - H_t)/C_t$, defined as the gap in percentage between consumption and habit. Following the idea of Campbell and Cochrane (1999, 2000), Menzly, Santos and Veronesi (2004), and Santos and Veronesi (2006, 2010), among others, we postulate the evolution of $s_t \equiv \ln(S_t)$ to preserve tractability. More precisely, we assume that[22]

$$\mathrm{d}s_t = -\phi(s_t - \bar{s})\mathrm{d}t + \lambda(s_t)\left(\mathrm{d}c_t - \mathbb{E}_t\left[\mathrm{d}c_t\right]\right) + \pi\left(\mathrm{d}g_t - \mathbb{E}_t\left[\mathrm{d}g_t\right]\right), \tag{3.19}$$

where $\lambda(s_t)$ describes how the habit level is formed from past aggregate consumption calculated as follows:

$$\lambda(s_t) = \begin{cases} \overline{S}^{-1}\sqrt{1 - 2(s_t - \bar{s})} - 1, & \text{when } s_t \leq \hat{s}, \\ 0, & \text{when } s_t > \hat{s}. \end{cases} \tag{3.20}$$

$\overline{S}$ is the steady state of S_t with $\overline{S} = \sigma_c\sqrt{\gamma/\phi}$, pinned down by the three conditions imposed by Campbell and Cochrane (1999), and $\bar{s} = \ln(\overline{S})$.

The specification of $\pi = \sqrt{2/(\gamma\sigma_g^2)}$ is chosen to ensure a constant equilibrium interest rate. The sensitivity function $\lambda(s_t) = 0$ if and only if $s_t \geq \hat{s} \equiv \bar{s} + \left(1 - e^{2\bar{s}}\right)/2$. In our specification, the correlation between s_t and contemporaneous consumption growth is not necessarily perfectly negatively as in Campbell and Cochrane (1999). Specifically, the evidence on a negative correlation between persistent expected growth and discount rates (e.g., Chen, 2010) suggests that $\pi > 0$ in (3.19). In this sense, our specification is similar

very small R-squared, equal to 0.13% and 0.3% for the three- and four-year horizons, respectively.

[22] Obviously, the assumption does not lead to linear habit formation specified by Constantinides (1990) and Detemple and Zapatero (1991): $H_t = \phi\int_{-\infty}^{t} e^{-\phi(t-\tau)}C_\tau \mathrm{d}\tau$. However, Li (2015) shows that linear habit persistence has similar quantitative implications to the nonlinear habit persistence proposed by Campbell and Cochrane (1999).

in spirit to Brandt and Wang (2003) who allow for s_t to be correlated with other business cycle variables such as inflation, and to Lettau and Wachter (2007) and Bekaert, Engstrom and Xing (2009) who allow for shocks to preferences.

Stochastic Discount Factor (SDF). The equilibrium stochastic discount factor is

$$\Lambda_t = e^{-\beta t}(C_t - H_t)^{-\gamma} = e^{-\beta t} S_t^{-\gamma} C_t^{-\gamma}. \tag{3.21}$$

Thus, appealing to Ito's lemma, we can derive Λ_t's dynamics as follows:

$$\frac{\mathrm{d}\Lambda_t}{\Lambda_t} = -r_{f,t}\mathrm{d}t - \eta_{e,t}\mathrm{d}Z_{e,t} - \eta_{g,t}\mathrm{d}Z_{g,t}, \tag{3.22}$$

with the equilibrium risk-free rate being

$$r_{f,t} = \beta + \gamma\varsigma - \frac{\gamma\phi}{2}, \tag{3.23}$$

and the equilibrium market prices of risk for $Z_{e,t}$ and $Z_{g,t}$ being

$$\eta_{e,t} = \gamma\sigma_e[1 + \lambda(s_t)] \ \text{ and } \ \eta_{g,t} = \gamma\sigma_g\pi\sqrt{g_t - \varsigma}, \text{ respectively.} \tag{3.24}$$

The market price of risk for $Z_{e,t}$ has the same functional form as in the nonlinear external habit-formation model Campbell and Cochrane (1999). Further, similar to the long-run risk model (see Bansal and Yaron, 2004), the market price of risk for $Z_{g,t}$ is positive and sizeable.

3.5 Solving the Nash Equilibria

We now solve the dynamic games based on the equilibrium SDF derived in (3.21) – (3.24).

Subgame Perfect Nash Equilibria. The two firms in the same industry play a dynamic game (see Friedman, 1971), in which the stage games of setting profit margins are played continuously and repeated infinitely with exogenous and endogenous state variables varying over time. Formally, a subgame perfect Nash equilibrium for the dynamic game consists of a collection of profit-margin strategies that constitute a Nash equilibrium for every history of the game. We do not consider all such equilibria, only those which allow for collusive arrangements enforced by punishment schemes. All strategies are allowed to depend upon both "payoff-relevant" physical states $x_{i,t} = \{M_{i1,t}, M_{i2,t}, C_t, g_t, s_t\}$ in state space $\mathcal{X}$, as in Maskin and Tirole (1988*a*,*b*), and a set of indicator functions that track whether any firm has previously deviated from a collusive profit-margin agreement, as in Fershtman and Pakes (2000, Page 212).[23]

In particular, there exists a non-collusive equilibrium, which is the repetition of the one-shot Nash equilibrium and thus is Markov perfect. Meanwhile, multiple subgame perfect collusive equilibria also exist in which profit-margin strategies are sustained by conditional punishment strategies.[24]

Non-collusive Equilibria. The non-collusive equilibrium is characterized by profit-margin scheme $\Theta_i^N(\cdot) = (\theta_{i1}^N(\cdot), \theta_{i2}^N(\cdot))$, which is a pair of functions defined in state space $\mathcal{X}$, such that each firm j chooses profit margin $\theta_{ij,t} \equiv \theta_{ij}(x_{i,t})$ to maximize shareholder value $V_{ij,t}^N \equiv V_{ij}^N(x_{i,t})$, under the assumption that its competitor $\bar{j}$ will set the one-shot Nash-equilibrium profit margin $\theta_{i\bar{j},t}^N \equiv \theta_{i\bar{j}}^N(x_{i,t})$. Following the recursive formulation in dynamic games for characterizing the Nash equilibrium (see, e.g., Pakes and McGuire, 1994; Ericson and Pakes, 1995; Maskin and Tirole, 2001), optimization problems can be formulated recursively by Hamilton-Jacobi-Bellman (HJB) equations:

$$0 = \max_{\theta_{ij,t}} \Lambda_t \left[\Pi_{ij}(\theta_{ij,t}, \theta_{i\bar{j},t}^N) M_{ij,t} - \lambda_{i,t} V_{ij,t}^N\right] \mathrm{d}t + \underbrace{\mathbb{E}_t \left[\mathrm{d}(\Lambda_t V_{ij,t}^N) \middle| \theta_{ij,t}, \theta_{i\bar{j},t}^N\right]}_{\text{if not disrupted}}. \tag{3.25}$$

The solutions to the coupled HJB equations give the non-collusive-equilibrium profit margin $\theta_{ij,t}^N$ with $j = 1, 2$, which are chosen based on intertemporal tradeoff considerations because $\theta_{ij,t}^N$ determines the continuation value $V_{ij,t+\mathrm{d}t}^N$ by altering the customer base $M_{ij,t+\mathrm{d}t}$ according to equation (3.13).

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

Consider a generic collusive equilibrium in which the two firms follow a collusive profit-margin scheme. Both firms can costlessly observe the other's profit margin, so that deviation can be detected and punished. The assumption of perfect information follows

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

[24] In the industrial organization and macroeconomics literature, this equilibrium is called the collusive equilibrium or collusion (see, e.g., Green and Porter, 1984; Rotemberg and Saloner, 1986). Game theorists generally call it the equilibrium of repeated game (see Fudenberg and Tirole, 1991) in order to distinguish it from the one-shot Nash equilibrium (i.e., our non-collusive equilibrium).

the literature.[25] In particular, if one firm deviates from the collusive profit-margin scheme, then with probability $\xi \mathrm{d}t$ over $[t, t + \mathrm{d}t]$ the other firm will implement a punishment strategy in which it will forever set the non-collusive profit margin. Setting non-collusive profit margins is considered punishment for the deviating firm because the industry will switch from the collusive to the non-collusive equilibrium, which features the lowest profit margin.[26] We use the idiosyncratic Poisson process $N_{ij,t}$ to characterize whether a firm can successfully implement a punishment strategy. One interpretation of $N_{ij,t}$ is that, with $1 - \xi \mathrm{d}t$ probability, the deviator can persuade its competitor not to enter the non-collusive Nash equilibrium over the period $[t, t + \mathrm{d}t]$.[27] Thus, the punishment intensity ξ can be viewed as a parameter governing the credibility of the punishment for deviating behavior. A higher ξ leads to a lower deviation incentive and thus sustains collusion better.

Formally, the set of incentive-compatible collusion agreements, denoted by $\mathcal{C}$, consists of all continuous profit-margin schemes $\Theta_i^C(\cdot) \equiv (\theta_{i1}^C(\cdot), \theta_{i2}^C(\cdot))$, such that the following incentive compatibility (IC) constraints are satisfied:

$$V_{ij}^D(x) \leq V_{ij}^C(x), \quad \text{for all } x \in \mathcal{X} \text{ and } j = 1, 2. \tag{3.26}$$

Here, $V_{ij,t}^C \equiv V_{ij}^C(x_{i,t})$ is firm j's value in the collusive equilibrium, pinned down recursively according to

$$0 = \Lambda_t \left[\Pi_{ij}(\theta_{ij,t}^C, \theta_{i\bar{j},t}^C) M_{ij,t} - \lambda_{i,t} V_{ij,t}^C \right] \mathrm{d}t + \underbrace{\mathbb{E}_t \left[\mathrm{d}(\Lambda_t V_{ij,t}^C) \middle| \theta_{ij,t}^C, \theta_{i\bar{j},t}^C \right]}_{\text{if not disrupted}}, \tag{3.27}$$

where $\theta_{ij,t}^C \equiv \theta_{ij}^C(x_{i,t})$ with $j = 1, 2$ are the collusive profit margins.

Further, $V_{ij,t}^D \equiv V_{ij}^D(x_{i,t})$ is firm j's highest shareholder value if it deviates from the implicit collusion:

$$0 = \max_{\theta_{ij,t}} \Lambda_t \left[\Pi_{ij}(\theta_{ij,t}, \theta_{i\bar{j},t}^C) M_{ij,t} - \xi \left(V_{ij,t}^D - V_{ij,t}^N \right) - \lambda_{i,t} V_{ij,t}^D \right] \mathrm{d}t + \underbrace{\mathbb{E}_t \left[\mathrm{d}(\Lambda_t V_{ij,t}^D) \middle| \theta_{ij,t}, \theta_{i\bar{j},t}^C \right]}_{\text{if not punished}}.$$

[25] A few examples include Rotemberg and Saloner (1986), Haltiwanger and Harrington (1991), Staiger and Wolak (1992), and Bagwell and Staiger (1997).

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

[27] Ex-post renegotiations can occur because the non-collusive equilibrium is not renegotiation-proof or "immune to collective rethinking" (see Farrell and Maskin, 1989). The strategy we consider is essentially a probabilistic punishment strategy.

In fact, there exist infinitely many elements in $\mathcal{C}$ and hence infinitely many collusive equilibria. We focus on a subset of $\mathcal{C}$, denoted by $\overline{\mathcal{C}}$, consisting of all profit-margin schemes $\Theta_i^C(\cdot)$ such that the IC constraints (3.26) are binding state by state, i.e., $V_{ij}^D(x) = V_{ij}^C(x)$ for all $x \in \mathcal{X}$ and $j = 1, 2$.[28] It is obvious that the subset $\overline{\mathcal{C}}$ is nonempty since it contains the profit-margin scheme in the non-collusive Nash equilibrium. We further narrow our focus to the "Pareto-efficient frontier" of $\overline{\mathcal{C}}$, denoted by $\overline{\mathcal{C}}_p$, consisting of all pairs of $\Theta_i^C(\cdot)$ such that there does not exist another pair $\widetilde{\Theta}_i^C(\cdot) \in \overline{\mathcal{C}}$ with $\widetilde{\theta}_{ij}(x) \geq \theta_{ij}(x)$ for all $x \in \mathcal{X}$ and $j = 1, 2$, and with strict inequality holding for some x and j.[29] Our numerical algorithm follows a method similar to that of Abreu, Pearce and Stacchetti (1990).[30] Deviation never occurs on the equilibrium path. Using the one-shot deviation principle (see Fudenberg and Tirole, 1991), it is clear that the collusive equilibrium characterized above is a subgame perfect Nash equilibrium.

State Variables. By exploiting the model's homogeneity in $M_{i,t}C_t$ for the firms in each industry $i \in \mathcal{I}$, we can reduce the model to three state variables, $M_{i1,t}/M_{i,t}$, s_t, and g_t when characterizing industry i's equilibrium. In particular, the value function of firm j in industry i can be represented by $V_{ij}^C(M_{i1,t}, M_{i2,t}, C_t, s_t, g_t) \equiv v_{ij}^C(M_{i1,t}/M_{i,t}, s_t, g_t)M_{i,t}C_t$. We solve normalized firm values $v_{ij}^C(M_{i1,t}/M_{i,t}, s_t, g_t)$ and profit margins $\theta_{ij}^C(M_{i1,t}/M_{i,t}, s_t, g_t)$ in the collusive equilibrium numerically.[31]

3.6 Key Mechanism: Endogenous Competition

In this subsection, we illustrate the key mechanism of the model. The degree of product market competition is endogenous, because the present value of future revenue from tacit cooperation endogenously responds to fluctuations in equilibrium discount rates and expected consumption growth. In turn, the endogenous competition generates its own asset pricing implications since the endogenous variation in profit margins further amplifies industries' exposure to the aggregate shocks driving discount rates and expected consumption growth, resulting in both higher risk premia and higher conditional stock

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

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

[30]Alternative methods include Cronshaw and Luenberger (1994), Pakes and McGuire (1994), and Judd, Yeltekin and Conklin (2003), which contain similar ingredients to those of our solution method. Proving the uniqueness of the equilibrium under our selection criterion is beyond the scope of the paper. We use different initial points in our numerical algorithm and find robust convergence to the same equilibrium.

[31]See Online Appendix H for more discussion.

return volatility.

More precisely, when the discount rate rises (i.e., when s_t decreases in the model) or when expected consumption growth declines (i.e., when g_t decreases in the model), industry competition endogenously intensifies and profit margins shrink. Intuitively, the incentive to collude on higher profit margins depends on the extent to which firms value their future revenues from cooperation relative to their contemporaneous revenue. By deviating from collusive profit-margin schemes, firms can obtain higher contemporaneous revenue than they otherwise would in the short run; however, in the long run, they run the risk of losing future revenue from tacit cooperation since the industry will be stuck in the non-collusive equilibrium once the deviation is punished by their competitors.

For example, as the discount rate increases, firms become effectively more impatient because they discount future cash flows more aggressively in determining their present values. As a result, firms would be less concerned about possible future punishment for deviating from the collusive profit-margin scheme, which makes it more difficult to collude right now, and thus equilibrium profit margins decline. The equilibrium profit-margin undercutting behavior reflects intensified product market competition. We refer to the channel through which the discount rate fluctuation endogenously affects industry competition as the "discount rate channel."

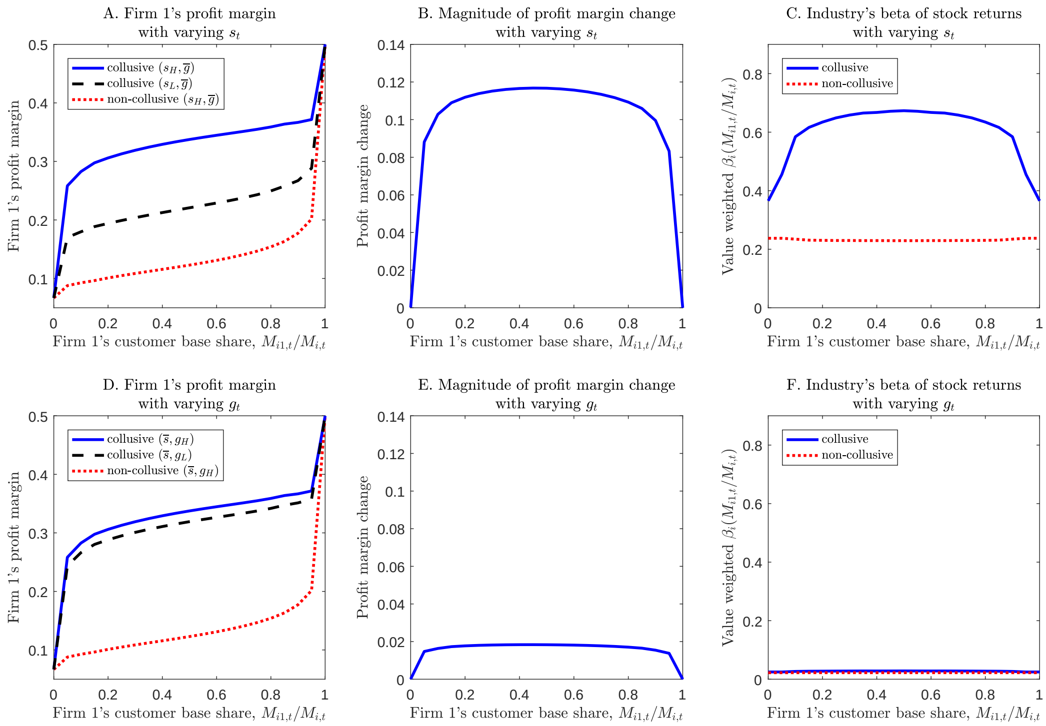
For another example, as expected consumption growth declines, firms also become effectively more impatient because they expect lower future cash flows anyway. As a result, firms care less about possible future punishment for deviating from the collusive profit-margin scheme, leading to a decline in equilibrium profit margins. We refer to the channel through which the fluctuation in expected consumption growth endogenously affects industry competition as the "cash flow channel."

In sum, when s_t or g_t decreases, the future punishment for deviation becomes less costly from firms' perspective, which gives them a stronger incentive to deviate from the collusive profit-margin scheme and undercut their competitors' profit margins.[32]

Profit Margin Fluctuations and Amplification: The Discount Rate Channel. To illustrate endogenous competition, we plot firms' profit margins and stock returns' exposure to aggregate shocks that drive the discount rate and expected consumption growth.

Panel A of Figure 2 plots firm 1's equilibrium profit margins for different discount rates (i.e., $s_t = s_L$ or s_H with $s_L < s_H$) holding $g_t = \overline{g}$ fixed. The blue solid and red dotted

[32]The intuition is related to the folk theorem. In particular, Fudenberg and Maskin (1986)'s version of the folk theorem asserts that provided players are sufficiently patient, repeated interaction can allow many subgame perfect outcomes, but more importantly subgame perfection can allow virtually any outcome in the sense of average payoffs. The effective discount rate is given approximately by $r_t - g_t$. Thus, the periods of a higher discount rate r_t and/or a lower consumption growth g_t feature less patient firms.



Note: This figure is based on an industry with $\lambda_{i,t} = 2\%$ using the calibrated parameter values in Table 8. In panels A – C, we choose $s_H = \bar{s}$ and s_L is two standard deviations below s_H according to the (steady-state) stationary distribution of s_t. In panels D – F, we choose $g_H = \bar{g}$ and g_L is two standard deviations below g_H according to the (steady-state) stationary distribution of g_t.

Figure 2: Profit margins and industry-level exposure to the aggregate shocks.

lines represent profit margins when the discount rate is low (i.e., s_t is high where $s_t = s_H$) in the collusive and non-collusive equilibria, respectively. Firm 1's profit margin increases with its share of the customer base $M_{i1,t}/M_{i,t}$ due to lower price elasticity of demand (see equation 3.7). Importantly, firm 1's profit margin in the collusive equilibrium falls sharply following an increase in the discount rate (i.e., the profit margin shifts downward from the blue solid line to the black dashed line, when s_t drops from s_H to s_L in the model).

Panel B illustrates the magnitude of the change in profit margins by plotting the difference in profit margins between the cases of high and low discount rates. The change in profit margins displays an inverted U shape, and is the largest when the two firms have comparable shares of the customer base (i.e., $M_{i1,t}/M_{i,t} = 0.5$). Intuitively, in an almost monopolistic industry, firms have weak collusion incentives because the difference between collusive and non-collusive profit margins (i.e., the gap between the blue solid line and red dotted line in panel A) is tiny. As a result, profit margins do not vary much with discount rates.[33]

[33]More discussion is presented in Online Appendix E.2.

The endogenous time-varying collusion incentive amplifies the effect of discount rate shocks: when discount rates rise, firm values decline not only because of the direct discounting effect, but also because of the narrowed profit margins caused by intensified industry competition. To illustrate this amplification effect, we calculate the industry-level beta $\beta_{i,t}$ as the value-weighted firm-level beta $\beta_{ij,t}$:

$$\beta_{i,t} = \sum_{j=1}^{2} w_{ij,t}\beta_{ij,t}, \text{ where } \beta_{ij,t} = \frac{v^C_{ij,t}(s_H)}{v^C_{ij,t}(s_L)} - 1 \text{ and } w_{ij,t} = \frac{v^C_{ij,t}(s_L)}{\sum_{j'=1}^{2} v^C_{ij',t}(s_L)}, \tag{3.28}$$

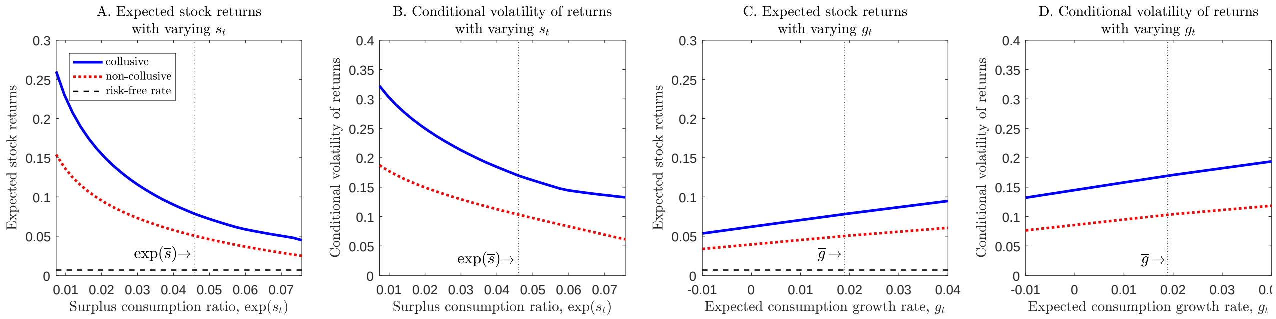
for all $M_{i1,t}/M_{i,t} \in (0,1)$ with $g_t = \overline{g}$ kept fixed.

Panel C shows that the industry's beta of stock returns displays an inverted U shape (the blue solid line), because the change in profit margins exhibits an inverted U shape (see panel B). As a benchmark, the red dotted line plots the industry's beta of stock returns in the non-collusive equilibrium where profit margins barely vary with discount rates. When the two firms have comparable customer base shares, the industry's exposure to discount rate shocks is significantly amplified owing to the large endogenous variation in profit margins.

Profit Margin Fluctuations and Amplification: The Cash Flow Channel. Panels D – F illustrate the profit margins for different levels of expected consumption growth (i.e., $g_t = g_L$ or g_H with $g_L < g_H$) and industry exposure to aggregate shocks to expected consumption growth. When expected consumption growth declines, profit margins in the collusive equilibrium drop (i.e., the profit margin declines from that shown by the blue solid line to that indicated by the black dashed line, when g_t drops from g_H to g_L in the model). However, the magnitude of the change in profit margins (panel E), the exposure of the industry's value to shocks to expected consumption growth (panel F), and the amplification effect (panel F) are much smaller than those in panels A – C, which suggests that the "discount rate channel" is much stronger than the "cash flow channel" in generating endogenous fluctuations in competition intensity and profit margins. In Section 5.3 below, we quantify the contribution of these two channels in generating risk premia, profit margin, and volatility based on our calibrated model.

Conditional Expected Returns and Volatility In Figure 3, we illustrate the model's implication on conditional expected stock returns and the volatility of stock returns.

In panels A and B, we plot conditional expected returns and volatility when the discount rate (i.e., the log surplus consumption ratio s_t) varies along the x-axis. Like Campbell and Cochrane (1999), both conditional expected returns and volatility increase



Note: This figure is plotted based on an industry with $\lambda_{i,t} = 2\%$ using the calibrated parameter values in Table 8.

Figure 3: Expected returns and conditional volatility of returns.

with the discount rate. Further, both are higher in the collusive equilibrium (the blue solid line) than in the non-collusive equilibrium (the red dotted line) due to the amplification effect of endogenous competition.

In panels C and D, we plot conditional expected stock returns and volatility for different levels of expected consumption growth g_t. Consistent with the habit model of Santos and Veronesi (2010), an increase in g_t results in lower prices, higher conditional expected returns, and higher volatility.[34] Again, both conditional expected returns and volatility are higher in the collusive equilibrium due to endogenous competition.

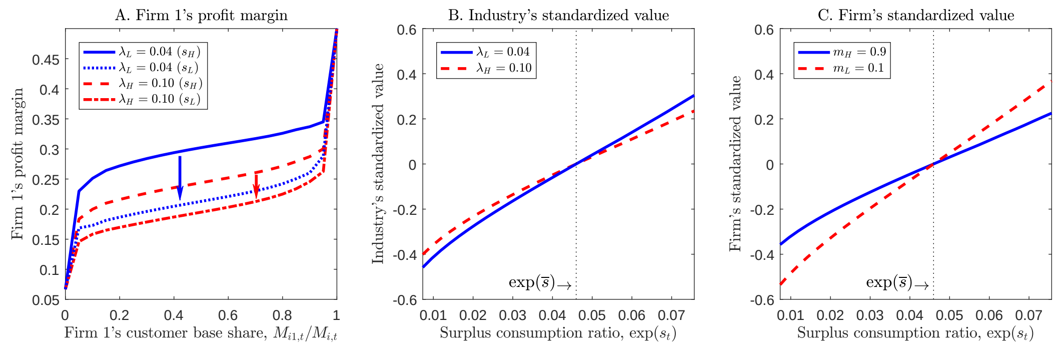
3.7 Cross-Sectional Implications

Industries facing a lower chance of market leadership turnover are associated with higher profit margins. These industries are more exposed to changes in discount rates and expected consumption growth, and thus have higher expected returns.

To fix ideas, consider two industries differing in turnover rates of market leadership $\lambda_{i,t}$ (i.e., $\lambda_{i,t} = \lambda_L, \lambda_H$ with $\lambda_L < \lambda_H$). Panel A of Figure 4 plots firm 1's profit margin in the two industries. Profit margins are much lower in the industry with a higher rate λ_H regardless of how the customer base is divided between the two firms.[35] More importantly, profit margins drop more substantially in the industry with a lower rate λ_L

[34] It follows from standard economic reasoning that a low elasticity of intertemporal substitution implies a taste for consumption smoothing. An increase in expected consumption growth yields a stronger desire for current consumption, and hence lower savings. Because stocks are less desirable now for the representative household, it would have little desire to hold the stocks unless prices drop, resulting in a decrease in the price-dividend ratio, an increase in expected return, and thus conditional volatility.

[35] Moreover, when $M_{i1}/M_{i,t} \to 0$, firm 1's profit margin in both industries converges to the profit margin determined by the within-industry elasticity of substitution η, as we have shown in equation (3.7). When $M_{i1}/M_{i,t} \to 1$, firm 1's profit margin in both industries converges to the profit margin determined by the cross-industry elasticity of substitution ϵ. The limits of profit margins are almost the same in the two industries because all firms face exactly the same η and ϵ.



Note: This figure is plotted using the calibrated parameter values in Table 8. In panels A and B, we choose $\lambda_H = 0.1$, $\lambda_L = 0.04$. In panel A, $s_H = \bar{s}$ and s_L is two standard deviations below s_H. In panel B, the industry comprises two firms with equal share of the customer base (i.e., $M_{i1,t}/M_{i,t} = 0.5$). Panels B and C plot the standardized market value to ease comparison of the sensitivity of market value to the aggregate state variable s_t; The standardized market value of industry i is defined as $V_i^C(s_t)/V_i^C(\bar{s}) - 1$ and the standardized market value of firm j in industry i is defined as $V_{ij}^C(s_t)/V_{ij}^C(\bar{s}) - 1$.

Figure 4: Implication of market structure disruption.

in response to a decline in s_t from s_H to s_L. In other words, the cash flows of firms in such industries are more exposed to discount rate shocks.[36]

Intuitively, a higher rate of market structure disruption has a similar effect to that of a higher discount rate or a lower expected consumption growth. It motivates firms to compete more aggressively to generate more profits now rather than in the future, which dampens the collusion incentive, resulting in both lower levels and lower sensitivity of profit margins to aggregate shocks. Our idea echoes the important generic insight of Maskin and Tirole (1988*a*) and Fershtman and Pakes (2000): oligopolists tacitly collude in industries where all firms expect all other firms to remain in the market for a long time.

Panel B illustrates the exposure to discount rate shocks by plotting the standardized market values of the two industries as a function of the discount rate (i.e., s_t). In the collusive equilibrium, the market value of the industry with λ_L is more sensitive to discount rates than that of the industry with λ_H. Thus, industries with lower rates of market structure disruption are associated with higher profitability and more exposed to discount rate shocks (and expected consumption growth shocks).

Panel C illustrates the exposure to discount rate shocks within an industry by plotting the standardized market values of the two market leaders as a function of the discount rate. The panel shows that the market value of the firm with a larger customer base share m_H is less sensitive to discount rates. Thus, within an industry, firms with larger customer base shares are associated with higher profitability (see panel A of Figure 2) and less exposed to discount rate shocks (and expected consumption growth shocks). The intuition is straightforward: The firm with a larger customer base share has greater

[36]The cash flows of firms in such industries are also more exposed to expected consumption growth shocks, the illustration of which is omitted from the figure.

market power than its competitor, and thus its profit margin is higher. When the discount rate rises and/or expected consumption growth declines, the profit margins of all firms in the industry drop, but the drop is greater in percentage terms for smaller firms because of the "leverage effect".

4 Empirical Analyses

In this section, we empirically test the main predictions of our model. In Section 4.1, we show that the measure of accumulated consumption growth is informative about the discount rate and expected consumption growth. Section 4.2 shows that profit margins and profitability comove with accumulated consumption growth and that such comovement is more pronounced in more profitable industries. Section 4.3 examines the gross profitability premium (see Novy-Marx, 2013), and we show that a large fraction of the premium can be explained by industries' heterogeneous exposure to accumulated consumption growth. Finally, in Section 4.4, we construct a measure for the turnover rate of market leaders and directly test the mechanism of our model.

4.1 Accumulated Consumption Growth

Our model is built on habit persistence and a predictable component of expected consumption growth, which implies that accumulated consumption growth can approximate both the discount rate and expected consumption growth at the same time. The approximation for the discount rate (i.e., the surplus consumption ratio) follows the ideas of the works involving habit persistence (see, e.g., Parker and Julliard, 2005; Santos and Veronesi, 2010), and the approximation for expected consumption growth follows those involving low-frequency consumption risk (see, e.g., Bansal, Dittmar and Lundblad, 2005; Dittmar and Lundblad, 2017). To be more precise, a lower accumulated consumption growth is associated with a lower surplus consumption ratio (i.e., a higher discount rate) and a lower expected consumption growth.

We further verify that accumulated consumption growth is tightly connected to the discount rate and expected future consumption growth in the data. Panel A of Table 1 shows that accumulated consumption growth positively predicts future consumption growth. Panel B shows the market excess return predictability using accumulated consumption growth, which verifies the negative relation between accumulated consumption growth and risk premium. Panel C directly shows the negative contemporaneous relation between accumulated consumption growth and risk premium based on various risk premium measures.

Table 1: Accumulated consumption growth, future consumption, and risk premium.

Panel A: Predictability of the future consumption growth using accumulated consumption growth

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
				Cumulative consumption growth$_{t+1,t+\Delta t}$			
Δt quarters	4	8	12	16	20	24	28
$\hat{g}_t$	0.34**	0.54*	0.70	0.84	0.94	0.99	0.93
	[2.16]	[1.79]	[1.61]	[1.60]	[1.61]	[1.49]	[1.18]
Constant	0.01***	0.03***	0.04***	0.06***	0.08***	0.10***	0.12***
	[3.55]	[4.12]	[4.47]	[4.92]	[5.32]	[5.52]	[5.64]
Observations	270	266	262	258	254	250	246
R-squared	0.058	0.056	0.056	0.055	0.049	0.041	0.029

Panel B: Predictability of the market excess return using accumulated consumption growth

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
				Cumulative market excess returns$_{t+1,t+\Delta t}$			
Δt quarters	4	8	12	16	20	24	28
$\hat{g}_t$	−4.59***	−7.66***	−10.90***	−15.29***	−19.37***	−20.74***	−22.20***
	[−2.84]	[−3.12]	[−4.01]	[−5.23]	[−6.10]	[−5.51]	[−5.04]
Constant	0.16***	0.29***	0.43***	0.58***	0.74***	0.83***	0.92***
	[5.34]	[7.06]	[9.57]	[11.46]	[10.43]	[10.57]	[11.59]
Observations	270	266	262	258	254	250	246
R-squared	0.068	0.105	0.164	0.261	0.312	0.313	0.321

Panel C: Accumulated consumption growth and risk premium

	(1)	(2)	(3)	(4)	(5)
	GOS equity premium$_t$	GZ spread$_t$	Aaa-10y spread$_t$	Baa-10y spread$_t$	Baa-Aaa spread$_t$
$\hat{g}_t$	−2.28***	−0.37***	−0.31***	−0.50***	−0.18***
	[−6.18]	[−3.03]	[−7.39]	[−7.68]	[−3.89]
Constant	0.10***	0.02***	0.02***	0.03***	0.01***
	[11.71]	[9.38]	[16.51]	[20.55]	[12.07]
Observations	182	174	224	224	272
R-squared	0.328	0.142	0.294	0.387	0.146

Note: Panel A and panel B show the predictability of the future consumption growth and market return, respectively, using accumulated consumption growth. The dependend variable are the cumulative log consumption growth and cumulative market excess returns from quarter $t+1$ to $t+\Delta t$, with Δt ranging from 4 to 28 quarters. The independent variable is accumulated consumption growth, which is the weighted average of past 12-quarter consumption growth: $\hat{g}_t \equiv \sum_{j=0}^{11} \phi^j \Delta c_{t-j} / \sum_{j=0}^{11} \phi^j$ with $\Delta c_t \equiv \ln(C_t) - \ln(C_{t-1})$. We set the coefficient $\phi = 0.966$ to be consistent with the yearly persistence coefficient of the surplus consumption ratio (0.87) in Campbell and Cochrane (1999). The sample of panels A and B spans the period from 1950 to 2017. Panel C shows the relation between accumulated consumption growth and risk premium measures. We perform the analysis at the quarterly frequency. GOS equity premium is the annualized market risk premium estimated by Gagliardini, Ossola and Scaillet (2016), who develop a sophisticated econometric methodology to infer the path of risk premia from large cross-sectional equity data sets. Data on the GOS equity premium span the period from 1964 to 2009. GZ spread is the excess bond premium introduced by Gilchrist and Zakrajšek (2012). Data on GZ spread span the period from 1973 to 2016. Aaa-10y spread is Moody's seasoned Aaa corporate bond yield relative to the yield on 10-year treasury constant maturity. Baa-10y spread is Moody's seasoned Baa corporate bond yield relative to the yield on 10-year treasury constant maturity. Data on Aaa-10y spread and Baa-10y spread span the period from 1962 to 2017. Baa-Aaa spread is Moody's seasoned Baa corporate bond yield relative to the yield on Moody's seasoned Aaa corporate bond. Data on Baa-Aaa spread span the period from 1950 to 2017. 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, respectively.

4.2 Profit Margins and Accumulated Consumption Growth

We examine the comovement of profit margins and accumulated consumption growth at the aggregate level and in the cross section of different industries.

Time-series Comovement. Our model implies that profit margins comove with discount rates and expected consumption growth, and hence accumulated consumption growth (see panels A and D of Figure 2). To test this prediction, we regress the year-on-year changes in the average profit margin and profitability on the AR(1) residual of accumulated consumption growth.[37] Panel A of Table 2 shows that when accumulated consumption growth increases, both the average profit margin and profitability increase significantly. This result is robust to different measures of profit margins and profitability.[38] Our finding is consistent with previous studies (see, e.g., Machin and Van Reenen, 1993; Hall, 2012; Anderson, Rebelo and Wong, 2018) showing that profit margins (especially net profit margins) are pro-cyclical.

Cross-industry Heterogeneity. Our model implies that the positive comovement between profit margins and accumulated consumption growth is more pronounced in profitable industries (see panel A of Figure 4). To test this implication, we split industries into tertiles based on their gross profitability and examine the sensitivity of net profit margins and net profitability to accumulated consumption growth shocks $(\mathbb{E}_t - \mathbb{E}_{t-1})\hat{g}_t$. We focus on net profit margins and net profitability because they directly reflect firms' net cash flows used for pricing stocks in our model. Panel B of Table 2 shows that profit margins and profitability are more pro-cyclical with respect to accumulated consumption growth in more profitable industries. These industries also have more volatile cash flows (see columns 1 – 4 in panel C).

Profitability and Market Leader Turnovers. Our model implies that more profitable industries are associated with a lower turnover rate of market leaders (see panel A of Figure 4). To test this implication, we construct a set of indicator variables that equal one if the market leaders (top two firms ranked by sales in a given industry) in year t are different from those in year $t + \Delta t$, with Δt ranging from 3 to 10 years.[39] Our results from

[37]We perform our analysis at the yearly frequency instead of the quarterly frequency because profits exhibit strong seasonality in the data. The average profit margin and profitability are the simple averages across four-digit SIC industries. See Appendix A for detailed explanations of the industry classifications.

[38]We use Compustat, NBER-CES, and BEA data to compute profit margins and profitability. These datasets have different advantages as discussed in Appendix A.

[39]We consider both public firms and private firms in defining industry leaders (see Appendix A for details). Results are qualitatively similar if we examine the turnover of the top firm or the top four firms.

Table 2: Profit margins, profitability, and accumulated consumption growth.

Panel A: Average profit margin and profitability comove with accumulated consumption growth

	(1)	(2)	(3)	(4)	(5)	(6)
	ΔAverage profit margin$_t$				ΔAverage profitability$_t$	
Data source	Gross Compustat	Gross NBER-CES	Net Compustat	Net BEA	Gross Compustat	Net Compustat
$(\mathbb{E}_t - \mathbb{E}_{t-1})\hat{g}_t$	0.35***	0.41***	0.28**	0.18**	0.59**	0.37**
	[2.70]	[2.90]	[2.06]	[2.40]	[2.13]	[2.51]
Observations	53	47	53	53	53	53
R-squared	0.130	0.085	0.012	0.075	0.091	0.050

Panel B: Cross-sectional heterogeneity across industries with different levels of gross profitability

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	ΔAverage profit margin$_t$ (net, Compustat)				ΔAverage profitability$_t$ (net, Compustat)			
Gross profitability tertiles	T1 (low)	T2	T3 (high)	T3 − T1	T1 (low)	T2	T3 (high)	T3 − T1
$(\mathbb{E}_t - \mathbb{E}_{t-1})\hat{g}_t$	−0.56	0.37***	0.30***	0.85**	0.14	0.46***	0.48**	0.34**
	[−1.45]	[2.77]	[3.26]	[2.23]	[0.70]	[3.51]	[2.67]	[2.12]
Observations	53	53	53	53	53	53	53	53
R-squared	0.003	0.041	0.058	0.008	0.003	0.063	0.074	0.021

Panel C: Gross profitability, volatility of net profitability, and turnovers of market leaders

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$\ln(\sigma_{NP,i}^{t\to t+\Delta t})$				$\mathbb{1}_{turnover,i}^{t\to t+\Delta t}$			
Δt years	3	4	5	10	3	4	5	10
Gross profitability$_{i,t}$ (standardized)	0.10***	0.10***	0.10***	0.10***	−0.02***	−0.02***	−0.02***	−0.02***
	[7.76]	[8.90]	[8.78]	[8.32]	[−4.51]	[−4.41]	[−4.28]	[−3.03]
ln(number of firms)$_{i,t}$	0.01	0.01	−0.00	−0.04***	0.19***	0.21***	0.21***	0.22***
	[0.62]	[0.45]	[−0.20]	[−3.21]	[27.15]	[30.75]	[27.01]	[12.55]
ln(sales)$_{i,t}$	−0.18***	−0.18***	−0.17***	−0.15***	−0.02***	−0.03***	−0.03***	−0.03***
	[−17.94]	[−25.30]	[−24.64]	[−24.50]	[−5.22]	[−5.31]	[−5.27]	[−4.71]
Average obs./year	355	349	338	312	378	372	367	345
Average R-squared	0.136	0.151	0.163	0.194	0.163	0.175	0.178	0.178

Note: Panel A examines the sensitivity of the average profit margin and profitability to accumulated consumption growth shocks. Industry-level profit margins and profitability are constructed according to Appendix A. $(\mathbb{E}_t - \mathbb{E}_{t-1})\hat{g}_t$ is the AR(1) shock of yearly accumulated consumption growth. The construction of yearly accumulated consumption growth is explained in Figure 1. The sample of this panel spans the period from 1965 to 2017, except for column (2), whose sample spans the period from 1965 to 2011 due to availability of the NBER-CES data. We include t-statistics in the brackets. Standard errors are computed using the Newey-West estimator allowing for serial correlation. Panel B presents the results of the time-series regressions in industry tertile portfolios sorted on the lagged gross profitability. Panel C reports the slope coefficients and test statistics in brackets from Fama-MacBeth regressions. Columns (1) – (4) report results from Fama-MacBeth regressions of the log volatility of net profitability from year t to $t+\Delta t$ (denoted by $\ln(\sigma_{NP,i}^{t\to t+\Delta t})$) on gross profitability, controlling for the log number of firms and log sales. Columns (5) – (8) report results from Fama-MacBeth regressions that regress the indicator variable for market leader turnovers (denoted by $\mathbb{1}_{turnover,i}^{t\to t+\Delta t}$) on the same set of independent variables. We standardize gross profitability using its unconditional mean and standard deviation of all industry-year observations to ease the interpretation of the regression coefficients. We omit the coefficients for the constant terms in all panels for brevity. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Fama-MacBeth regressions indicate that market leaders are significantly less likely to be displaced in industries with higher gross profitability (see columns 5 – 8 in panel B of Table 2).[40]

Our inference remains unchanged if we instead define the turnover indicator as one if there is a change of market leaders in any year from year t to year $t+\Delta t$.

[40]Our inference remains unchanged with and without controlling for the amount of sales and number of firms in the industries. We replicate the Fama-MacBeth regressions using the panel regression approach for

4.3 Profitability Spreads and Accumulated Consumption Growth

Previous studies have shown that both gross profitability (see Novy-Marx, 2013) and net profitability (see Hou, Xue and Zhang, 2015) are priced at the firm level. We test our model's asset pricing implications using gross profitability as a profitability measure in this subsection and we demonstrate robustness using net profitability in Appendix B. In particular, we highlight the difference between the cross-industry, within-industry, and firm-level gross profitability spreads in terms of their exposure to accumulated consumption growth and IST shocks.[41]

4.3.1 Gross Profitability Premium

Excess returns. Our model predicts that industries with a higher profitability are more exposed to fluctuations in discount rates and expected consumption growth, and hence accumulated consumption growth. As a result, industries with a higher profitability have higher expected stock returns. We test these predictions by sorting industries into tertiles and examining their returns. Panel A of Table 3 presents the value-weighted average excess returns and CAPM alphas for the industry portfolios sorted on gross profitability. The panel shows that the portfolio consisting of industries with a high gross profitability (i.e., T3) exhibits significantly higher average excess returns and CAPM alphas. The difference in the average annualized excess returns (i.e., T3 − T1) is 3.06% and the difference in CAPM alphas is 2.32%.

Our model implies that the cross-industry premium is related to firms' collusion incentive, and thus the premium is lower across industries in which it is more difficult for firms to collude. To test this prediction, we exploit the cross-industry heterogeneity in antitrust enforcement. Intuitively, antitrust enforcement punishes collusive behavior, dampening firms' incentive to collude.[42]

We split all industries into two groups in each year based on whether they recently have faced antitrust charges.[43] Our findings suggest that the cross-industry gross profitability premium is statistically significant for industries that have not faced antitrust charges in the past 10 years (see panel B), but becomes weaker and insignificant for industries that

robustness checks. The results are qualitatively similar (see Appendix Table B.9).

[41]The firm-level spread is the return difference among firms sorted on gross profitability, which is first studied by Novy-Marx (2013). The cross-industry spread is the return difference among industries sorted on gross profitability. The within-industry spread is the return difference among gross-profitability-sorted firms within the same industry.

[42]Levenstein and Suslow (2011) find that the probability of cartel breakup increases significantly after the expansion of antitrust enforcement efforts.

[43]The antitrust enforcement cases are hand collected from the websites of the U.S. Department of Justice (DOJ) and the Federal Trade Commission (FTC). See Appendix A for detailed explanations.

Table 3: Gross profitability premia.

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Excess returns (%)				CAPM alphas (%)			
T1 (low)	T2	T3 (high)	T3 − T1	T1 (low)	T2	T3 (high)	T3 − T1
Panel A: Cross-industry gross profitability premium							
6.74***	7.99***	9.79***	3.06***	−0.13	−0.43	2.19***	2.32**
[4.82]	[5.21]	[5.11]	[2.73]	[−0.24]	[−0.52]	[3.39]	[2.10]
Panel B: Cross-industry gross profitability premium (no antitrust charges)							
7.69***	7.37***	10.80***	3.11***	1.19*	−0.76	3.23***	2.04**
[4.58]	[5.01]	[8.53]	[2.71]	[1.66]	[−1.18]	[3.10]	[2.33]
Panel C: Cross-industry gross profitability premium (with antitrust charges)							
7.42***	7.99***	9.40***	1.97	1.41	0.96	3.09**	1.69
[6.88]	[4.66]	[3.59]	[0.70]	[0.98]	[0.98]	[2.01]	[0.60]
Panel D: Within-industry gross profitability premium							
6.38***	8.33***	9.10***	2.72**	−2.29**	0.21	1.82**	4.11***
[2.67]	[3.75]	[4.66]	[2.41]	[−2.33]	[0.22]	[2.43]	[3.76]
Panel E: Firm-level gross profitability premium							
5.96***	7.58***	9.24***	3.28***	−1.94***	−0.11	2.02***	3.95***
[2.87]	[3.85]	[4.75]	[2.67]	[−2.89]	[−0.24]	[2.80]	[3.13]

Note: Panel A shows the value-weighted average excess returns and CAPM alphas for the industry portfolios sorted on gross profitability. In June of year t, we sort industries into three tertiles based on their gross profitability 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 panels B and C, we split industries into two sub-samples based on whether they have faced antitrust charges in the past 10 years, and we perform the same sorting analysis as in panel A. The two sub-samples have comparable sample size. In panel D, we sort individual firms within each industry (with at least six firms) into tertiles based on their one-year-lagged gross profitability. In panel E, we sort all firms into tertiles based on their one-year-lagged gross profitability. The sample period is from July 1951 to June 2018. We exclude financial firms and utility firms from the analysis. We include t-statistics in brackets. Standard errors are computed using the Newey-West estimator allowing for serial correlation in returns. We annualize average excess returns and alphas by multiplying them by 12. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

have faced such charges (see panel C).

Although our model emphasizes the heterogeneous variations in competition intensity across industries, for completeness, we also investigate the within-industry gross profitability premium in the data. Panel D shows that the difference in the average annualized excess returns is 2.72% and the difference in CAPM alphas is 4.11%. The magnitudes of both within- and cross-industry profitability premia are comparable to the magnitude of the firm-level premium (see panel E) studied by Novy-Marx (2013).

Exposure to accumulated consumption growth. Our model predicts that more profitable industries are more exposed to accumulated consumption growth (see panel B of Figure 4) and thus the cross-industry profitability spread loads positively on accumulated consumption growth. Consistent with this prediction, Table 4 (columns 1 – 3) shows that the exposure to accumulated consumption growth increases monotonically across industry portfolios sorted on gross profitability, and the loading of the cross-industry

Table 4: Exposure of gross profitability spreads to accumulated consumption growth.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Accumulated portfolio excess returns$_t$											
GP tertiles	T1 (low)	T2	T3 (high)	T3 − T1	T1 (low)	T2	T3 (high)	T3 − T1	T1 (low)	T2	T3 (high)	T3 − T1
	Cross-industry spread				Within-industry spread				Firm-level spread			
$\hat{g}_t$	1.00	1.90**	2.57***	1.57***	2.25***	2.01***	1.36*	−0.90*	1.57	1.73*	2.29**	0.72**
	[1.34]	[2.53]	[3.11]	[3.05]	[2.61]	[2.62]	[1.69]	[−1.89]	[1.17]	[1.97]	[2.10]	[2.04]
Observations	257	257	257	257	257	257	257	257	257	257	257	257
R-squared	0.012	0.040	0.056	0.043	0.040	0.039	0.019	0.019	0.026	0.035	0.052	0.010

Note: This table shows the heterogeneous exposure to accumulated consumption growth for portfolios sorted on gross profitability. The dependent variable is a weighted average of past 12-quarter portfolio excess returns: $\sum_{j=0}^{11}\phi^j(r_{p,t-j}-r_{f,t-j})/\sum_{j=0}^{11}\phi^j$. The independent variable is accumulated consumption growth $\hat{g}_t$. Portfolio sorting is performed at the quarterly frequency according to the procedure explained in Table 3. The sample spans the period from 1951 to 2018. We exclude financial firms and utility firms from the analysis. We include t-statistics in brackets. Standard errors are computed using the Newey-West estimator allowing for serial correlation in returns. We omit the coefficients for the constant terms for brevity. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

gross profitability spread on $\hat{g}_t$ is significantly positive (see column 4).

Although the mechanism of our model is more suitable for explaining the exposure of cross-industry gross profitability spread, the model also predicts that within a given industry, more profitable firms are less exposed to accumulated consumption growth (see panel C of Figure 4). To test this prediction, we sort firms within each industry based on their gross profitability. Consistent with our model, columns (5) – (7) of Table 4 show that exposure to accumulated consumption growth decreases monotonically across firm portfolios sorted on gross profitability.

We further examine how the firm-level gross profitability premium studied by Novy-Marx (2013) is exposed to accumulated consumption growth. From a theoretical perspective, the loading of firm-level spread is ambiguous because cross-industry and within-industry profitability spreads have opposite loadings, as discussed above. In the data, we find that the firm-level profitability spread loads positively on the accumulated consumption growth (see column 12 of Table 4), meaning that the loading of cross-industry spread dominates.

The above findings remain robust after controlling for market returns (Appendix Table B.2), suggesting that the heterogeneous loadings on accumulated consumption growth are unlikely explained by their heterogeneous market exposure.

4.3.2 Explaining the Gross Profitability Premium

Our analysis in Table 4 shows that both cross-industry and firm-level gross profitability spreads load positively on accumulated consumption growth. This seems to suggest that the heterogeneous exposure to accumulated consumption growth, as emphasized

Table 5: Explaining the firm-level gross profitability premium.

Panel A: Exposure to the $\beta_{\hat{g}}$ spread				
	(1)	(2)	(3)	(4)
	Firm-level gross profitability spread$_t$(%)			
Intercept (%)	0.25***	0.29***	0.15	0.19
	[2.81]	[2.61]	[1.08]	[1.17]
MktRf$_t$(%)		−0.08		−0.07
		[−1.13]		[−1.13]
$\beta_{\hat{g}}$ spread$_t$(%)			0.35**	0.34*
			[2.20]	[1.91]
Observations	702	702	702	702
R-squared	0.000	0.017	0.070	0.083

Panel B: Explaining the firm-level gross profitability premium		
	(1)	(2)
	Excess returns	CAPM alpha
Annualized premium (%)	2.97***	3.49***
	[2.81]	[2.61]
Annualized premium after controlling for $\beta_{\hat{g}}$ spread (%)	1.75	2.24
	[1.08]	[1.17]
Fraction of firm-level premium explained by $\beta_{\hat{g}}$ spread (%)	41.1	35.8

Note: Panel A shows the results of the time-series regression of monthly firm-level gross profitability spread on market excess returns and the $\beta_{\hat{g}}$ spread. Panel B shows that firm-level gross profitability premium can be partially explained by the exposure to accumulated consumption growth. The sample spans the period from 1960 to 2018. The magnitude of the annualized firm-level gross profitability premium is slightly different from that in Table 3 because the analysis here requires the availability of the $\beta_{\hat{g}}$ spread. We exclude financial firms and utility firms from the analysis. We include t-statistics in brackets. 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, respectively.

by our model, has the potential to explain both the cross-industry and firm-level gross profitability premia. In this subsection, we investigate whether this is the case in the data.

We start by constructing a tradable long-short portfolio mimicking the fluctuations in accumulated consumption growth. In particular, we form a set of anomaly portfolios based on the deciles of each of the following five characteristics: investment, momentum, accruals, net share issues, and earnings-to-price ratio. Building on Bansal, Dittmar and Lundblad (2005) and Dittmar and Lundblad (2017), for each portfolio p, we estimate its beta on accumulated consumption growth, denoted by $\beta_{\hat{g},p}$, by regressing the 12-quarter accumulated portfolio excess returns on accumulated consumption growth using a 30-year rolling window:[44]

$$\sum_{j=0}^{11} \phi^j (r_{p,t-j} - r_{f,t-j}) = a_p + \beta_{\hat{g},p}\hat{g}_t + \varepsilon_{p,t}, \tag{4.1}$$

where we set the quarterly persistence coefficient $\phi = 0.966$, consistent with the construction of accumulated consumption growth $\hat{g}_t$. As in Dittmar and Lundblad (2017), our estimated $\beta_{\hat{g},p}$ is positively priced in the cross section of portfolios: the Fama-MacBeth regression of portfolio excess returns on $\beta_{\hat{g},p}$ gives a positive coefficient with a t-statistic of 2.89 (p-value = 0.004). We then sort all portfolios into deciles each quarter based on the estimated $\beta_{\hat{g},p}$. We define the $\beta_{\hat{g}}$ spread as the equal-weighted returns of the long-short portfolio (Decile 10 − Decile 1) sorted on $\beta_{\hat{g},p}$.

Next, we regress the gross profitability spreads on the $\beta_{\hat{g}}$ spread. As shown in panel

[44] For earlier years of the sample, we require at least 10 years of data for estimation.

A of Table 5, the firm-level gross profitability spread loads positively on the $\beta_{\hat{g}}$ spread, confirming our findings in panel C of Table 4. Importantly, after controlling for the $\beta_{\hat{g}}$ spread, the firm-level gross profitability premium reduces by a sizable amount and becomes statistically insignificant (see panel B of Table 5).

According to our model, the firm-level explanatory power of accumulated consumption growth for the gross profitability premium stems from the cross-industry explanatory power. Indeed, Appendix Table B.3 shows that the cross-industry gross profitability premium is also largely explained by the heterogeneous exposure to accumulated consumption growth.

4.3.3 Discussions on Alternative Mechanisms.

Predation Behavior. Our model emphasizes a mechanism of endogenous competition due to time-varying collusion incentives among firms in an industry. However, in principle, firms do not necessarily have to collude with each other if they can drive their competitors out of the market and enjoy the monopoly rent. Intuitively, competitors may undercut each other's profit margins more aggressively in hopes of driving others out and monopolizing the industry, when the discount rate declines and/or the expected growth rises. However, such a mechanism can disappear or be substantially weakened once there is a new entry. Wiseman (2017) formalizes this intuition in a game-theoretic model and shows that with a sufficiently high entry barrier (infinitely high in his baseline model), sufficiently patient firms exhibit predation behavior, which contradicts the collusion behavior predicted by the folk theorems. In other words, such an anti-folk-theorem force is not robust or prevalent: it only shows up when the entry barrier is very high and firms are extremely patient. We show that the folk-theorem force dominates in the data for most of the industries.

Inspired by the analysis of Wiseman (2017), we hypothesize that our model's prediction would be stronger and more relevant in industries with lower entry costs. To test this conjecture, we perform split sample analyses based on two measures of entry costs: the Herfindahl-Hirschman Index (HHI) and a measure quantifying the difference in property, plant, and equipment (PP&E) between market leaders and followers. The first measure reflects the idea that concentrated industries are intrinsically associated with higher entry costs. Because private firms play an important role in industry competition (see, e.g., Ali, Klasa and Yeung, 2008), we measure industry concentration using the fitted HHI measure from Hoberg and Phillips (2010*b*), who take both public firms and private firms into consideration. The second measure reflects the idea that as the gap in PP&E gap widens, potential challengers among the market followers need to incur higher setup costs to

Table 6: Gross profitability premia in industries with different entry costs.

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Excess returns (%)				CAPM alphas (%)		
T1 (low)	T2	T3 (high)	T3 − T1	T1 (low)	T2	T3 (high)	T3 − T1
Panel A: Cross-industry gross profitability premium (bottom 70% of fitted HHI)							
5.76***	8.06***	9.98***	4.22*	−2.62**	−1.40*	2.41**	5.02***
[5.01]	[6.84]	[4.86]	[1.90]	[−2.54]	[−1.84]	[2.57]	[2.72]
Panel B: Cross-industry gross profitability premium (top 30% of fitted HHI)							
8.59***	6.08**	6.66***	−1.92	3.06	−1.14	−0.59	−3.64
[4.87]	[2.13]	[2.65]	[−0.80]	[1.61]	[−0.53]	[−0.34]	[−1.52]
Panel C: Cross-industry gross profitability premium (bottom 70% of the gap in PP&E)							
6.84***	8.43***	11.13***	4.29**	−2.16	−0.98	2.80**	4.97**
[4.47]	[4.69]	[6.41]	[2.16]	[−1.62]	[−0.68]	[2.25]	[2.34]
Panel D: Cross-industry gross profitability premium (top 30% of the gap in PP&E)							
6.22***	7.47**	9.41***	3.20*	−0.28	−0.50	2.34*	2.61
[3.25]	[4.11]	[3.76]	[1.79]	[−0.23]	[−0.58]	[2.28]	[1.30]

Note: This table shows the value-weighted average excess returns and CAPM alphas for the industry portfolios sorted on gross profitability in industries with different entry costs. The sample period of panels A and B is from July 1976 to June 2007 due to data availability of the fitted HHI measure. The sample period of panels C and D is from July 1951 to June 2018. We exclude financial firms and utility firms from the analysis. We include t-statistics in brackets. Standard errors are computed using the Newey-West estimator allowing for serial correlation in returns. We annualize average excess returns and alphas by multiplying them by 12. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

compete with and displace the existing market leaders (see, e.g., Sutton, 1991; Karuna, 2007), which also coincides with the higher costs of entering the market leaders club.

We find that the cross-industry gross profitability premium is indeed more pronounced in industries with lower entry costs (see Table 6), and the gross-industry gross profitability spread is also more exposed to accumulated consumption growth in these low-entry-cost industries (see Table 7 and Appendix Table B.4).

Exposure to IST Shocks. Existing studies have offered limited theoretical explanations for the gross profitability premium. One notable exception is Kogan and Papanikolaou (2013), who argue that firms with a higher profitability are less exposed to IST shocks and their average stock returns are higher.

Following Kogan and Papanikolaou (2013, 2014), we use the difference between the stock returns of investment-good producers and consumption-good producers (i.e., IMC) as a return-based measure of IST shocks. We regress the gross profitability spread on IMC, with and without controlling for market excess returns. Consistent with Kogan and Papanikolaou (2013), we find that the firm-level gross profitability spread loads negatively on IMC, suggesting that the heterogeneous exposure to IST shocks can partially explain the firm-level gross profitability premium (see panel C of Appendix Table B.5). We find

Table 7: Exposure to accumulated consumption growth in different industries.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Accumulated portfolio excess returns$_t$							
Gross profitability tertiles	T1 (low)	T2	T3 (high)	T3 − T1	T1 (low)	T2	T3 (high)	T3 − T1
	Panel A: Subsamples sorted on the fitted HHI							
	Bottom 70% of the fitted HHI				Top 30% of the fitted HHI			
$\hat{g}_t$	2.31*	3.09**	4.96***	2.64**	1.88	2.43	2.04	0.16
	[1.73]	[2.32]	[3.88]	[2.40]	[1.65]	[1.53]	[1.44]	[0.11]
Observations	113	113	113	113	113	113	113	113
R-squared	0.021	0.050	0.111	0.042	0.052	0.032	0.026	0.000
	Panel B: Subsamples sorted on the gap in PP&E							
	Bottom 70% of the gap in PP&E				Top 30% of the gap in PP&E			
$\hat{g}_t$	0.46	1.90**	2.31**	1.85**	0.55	2.41**	1.80	1.25
	[0.43]	[1.99]	[2.31]	[2.24]	[0.44]	[1.97]	[1.27]	[1.30]
Observations	257	257	257	257	257	257	257	257
R-squared	0.001	0.027	0.039	0.022	0.003	0.050	0.028	0.021

Note: This table shows the heterogeneous exposure to accumulated consumption growth for industry portfolios sorted on gross profitability in industries with different entry costs. The analysis is performed at the quarterly level. The sample period of panel A is from 1979 to 2007 due to data availability of the fitted HHI measure. The sample period of panel B is from 1954 to 2018. We include t-statistics in brackets. Standard errors are computed using the Newey-West estimator allowing for serial correlation in returns. We exclude financial firms and utility firms from the analysis. We omit the coefficients for the constant terms for brevity. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

that the within-industry gross profitability spread loads negatively on IMC (see panel B), while the cross-industry gross profitability spread has insignificant loading on IMC (see panel A). These results suggest that the exposure to IST shocks is unlikely to explain the cross-industry premium. Intuitively, the channel of displacement risk mainly works within industries since it is difficult for one industry to displace another after innovation shocks. Our paper proposes a novel mechanism based on endogenous competition to rationalize the cross-industry profitability premium, which essentially complements the mechanism of displacement risk in Kogan and Papanikolaou (2013).

4.4 Measuring the Turnover Rate of Market Leadership

Our model emphasizes that it is the heterogeneity in the turnover rate of market leadership across industries that generates heterogeneous industry-level competition risk, which in turn rationalizes the cross-industry gross profitability premium. To directly test this fundamental mechanism, in this section, we construct an industry-level measure for the market leadership turnover, referred to as the *disruption rate measure*. We show that in industries with a lower disruption rate, profit margins and profitability are higher and more exposed to accumulated consumption growth. The disruption rate measure shares highly similar asset pricing implications with gross profitability.

4.4.1 Construction of the Disruption Rate Measure

Following the approach of estimating the probability of corporate events (see, e.g., Shumway, 2001; Campbell, Hilscher and Szilagyi, 2008), we estimate the disruption rate of the market structure using a logistic model. Specifically, we assume that the marginal probability of a change in market leadership follows a logistic distribution given by

$$\mathbb{P}(\mathbb{1}_{turnover,i}^{t\rightarrow t+2} = 1) = \frac{1}{1 + \exp(-\alpha - \beta x_{i,t})}, \tag{4.2}$$

where $\mathbb{1}_{turnover,i}^{t\rightarrow t+2}$ is an indicator that equals one if the market leaders of industry i in year $t + 2$ are different from those in year t, and $x_{i,t}$ is a column vector of explanatory variables known at the end of year t.[45] The disruption rate measure, denoted by $\hat{\lambda}_t$, is the predicted probability of changes of market leaders: $\hat{\lambda}_t = 1/\left[1 + \exp(-\hat{\alpha} - \hat{\beta} x_{i,t})\right]$ with estimators $\hat{\alpha}$ and $\hat{\beta}$.

Following the industrial organization literature (see, e.g., Geroski and Toker, 1996; Sutton, 2007; Kato and Honjo, 2009), we use the industry asset growth rate, industry advertising intensity (i.e., advertising expenses scaled by revenue) and industry R&D intensity (i.e., R&D expenses scaled by revenue) as explanatory variables. In addition, we include an innovation similarity measure, because market leaders are displaced typically through the distinctive innovation of followers (see, e.g., Christensen, 1997). Firms in industries with lower innovation similarity are more likely to create products that are drastically different from their peers' and thus these industries have a higher probability of experiencing market leader changes. In light of previous studies (see, e.g., Jaffe, 1986; Bloom, Schankerman and Van Reenen, 2013), we construct the industry-level innovation similarity measure based on the technology classifications of an industry's patents (see Appendix A for details).[46] Our disruption rate measure is estimated using equation (4.2) based on the industry panel from 1988 to 2017.[47]

[45]Results are similar if we use $\mathbb{1}_{turnover,i}^{t\rightarrow t+1}$ or $\mathbb{1}_{turnover,i}^{t\rightarrow t+3}$.

[46]The innovation similarity measure is similar in spirit to other recently developed similarity measures based on patent citations (see, e.g., Cohen, Gurun and Kominers, 2018; Fitzgerald et al., 2019) or patent descriptions (see, e.g., Bowen, Frésard and Hoberg, 2018; Kelly et al., 2018).

[47]The coefficients in the row vector β for the industry asset growth rate, industry advertising intensity, industry R&D intensity, and innovation similarity are 0.001 (p-value = 0.043), -0.085 (p-value = 0.945), 0.035 (p-value = 0.311), and -0.062 (p-value = 0.033), respectively. The estimation starts from 1988 due to availability of the innovation similarity measure. The coefficients are similar if we use other sample periods (i.e., 1988 to 2007 or 1988 to 2010).

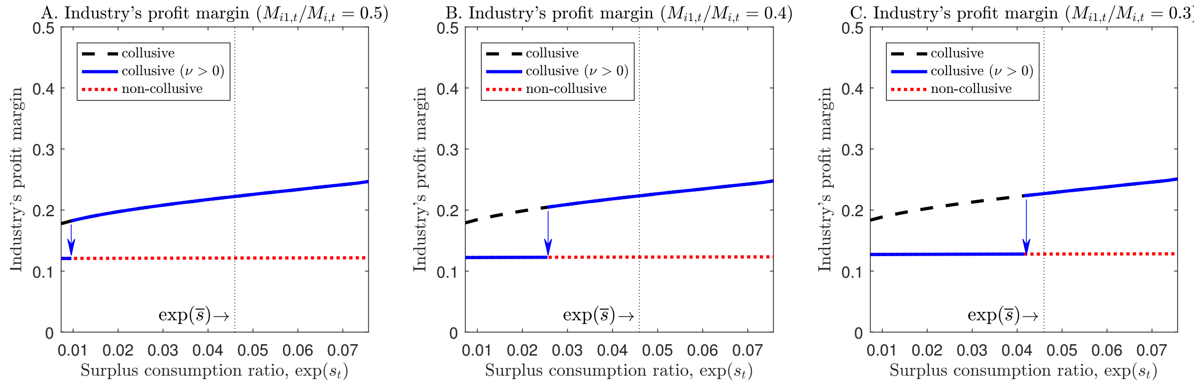
4.4.2 Testing the Model Mechanism

Our model implies that industries with a lower turnover rate of market leadership are associated with higher and more volatile profitability, which are also more exposed to accumulated consumption growth. Our empirical findings based on the disruption rate measure constructed in (4.2) support these predictions. Columns (1) – (5) in panel A of Appendix Table B.6 show that the disruption rate measure is negatively related to both profit margins and profitability. The relationship is both statistically and economically significant. For example, a one-standard-deviation decrease in the disruption rate measure is associated with a 3.08-percentage-point (0.45-percentage-point) increase in Compustat-based gross (net) profit margins, which is roughly one-sixth (one-twelfth) of the interquartile range of the corresponding profit margins. Columns (6) – (9) in panel A show that the disruption rate measure is negatively related to the volatility of net profitability, as our model implies. In panel B, we split industries into three tertiles based on the disruption rate measure. It is shown that both profit margins and profitability comove more positively with accumulated consumption growth in industries with a lower disruption rate, as our model predicts.

We further test the asset pricing implications of the disruption rate measure. Panel A of Appendix Table B.7 shows that industries with a higher disruption rate have lower expected stock returns. The differences in average excess returns and CAPM alphas between the industries with a high disruption rate (i.e., T3) and those with a low disruption rate (i.e., T1) are larger in the subgroup of industries that have not recently faced antitrust charges (see panels B and C), suggesting that the cross-industry gross profitability premium is closely related to industries' heterogeneous collusion incentives. Panel D shows that the portfolio spread sorted based on the disruption rate measure loads negatively on accumulated consumption growth, a finding that is robust regardless of whether or not we control for the market returns. Appendix Table B.8 shows that the cross-industry gross profitability premium can be partially explained by the disruption rate measure. After double sorting on the disruption rate measure, the cross-industry gross profitability premium is reduced by a sizable fraction and becomes statistically insignificant.

5 Quantitative Analyses

We first extend the baseline model with endogenous jumps as a result of collusion costs in Subsection 5.1. Then, in Subsection 5.2, we calibrate the model's parameters and examine whether the model can replicate the main findings on stock returns and



Note: This figure is plotted using the calibrated parameter values in Table 8. We consider $s_t = \overline{s}$ and an industry with $\lambda_{i,t} = 14\%$. The blue solid line represents the case of $\nu = 0.009$ according to our calibration.

Figure 5: Collusion costs and the endogenous jump risk.

corporate profitability from the data. Finally, we discuss the quantitative importance of various channels and model ingredients in Subsection 5.3.

5.1 Incorporating Endogenous Jumps

We extend our baseline model by incorporating endogenous jumps to amplify quantitative implications of the main mechanism in the cross section of different industries.

In the baseline model, firms can costlessly cooperate with their competitors on the collusive profit-margin scheme. As a result, the collusive profit-margin scheme is always maintained in equilibrium, and profit margins vary continuously with state variables s_t and g_t. In this section, we introduce collusion costs to generate endogenous shifts from the collusive regime to the non-collusive regime. One example of collusion costs is the monitoring costs (see, e.g., Green and Porter, 1984).

Cooperating with a competitor in setting profit margins over $[t, t + \mathrm{d}t]$ requires a firm's shareholders to make an effort with intensity ν per unit of customer base. The effort ν can be viewed as a non-pecuniary collusion cost. The fact that firms make an effort to cooperate with each other is common knowledge. So if either firm chooses not to cooperate with the other, both firms would set non-collusive profit margins. When deciding whether or not to cooperate, both firms must weigh the benefit of cooperation against the disutility of making an effort. If the benefit is lower than the cost for either firm, both firms will abandon collusion temporarily and enter into non-collusive competition.

As a numerical illustration, panel A of Figure 5 shows that when the two firms have equal shares of the customer base (i.e., $M_{i1,t}/M_{i,t} = 0.5$), the industry's profit margin jumps downward when the surplus consumption ratio drops below 0.01. Panels B and C show that when shares of the customer base become less evenly distributed, the negative

Table 8: Calibration and parameter choice.

Parameter	Symbol	Value	Parameter	Symbol	Value
Panel A: Externally Determined Parameters					
Risk aversion	γ	1.3	Conditional volatility of growth*	σ_e	0.015
Persistence of surplus ratio*	ϕ	0.13	Average consumption growth*	g	0.0189
Lower bound of growth*	ς	-0.01	Persistence of expected growth*	κ	0.262
Volatility of expected growth*	σ_g	0.012	Cross-industry elasticity	ϵ	2
Customer base volatility*	σ_M	0.01	Within-industry elasticity	η	15
Customer base depreciation rate*	δ	0.1	Range of turnover rate*	$\underline{\lambda}$, $\overline{\lambda}$	0, 0.18
Panel B: Internally Calibrated Parameters					
Subjective discount factor*	ρ	0.11	Punishment rate*	ξ	0.09
Marginal cost of production*	ω	62	Collusion cost*	ν	0.009
Growth of customer base*	α	0.09	Persistence of turnover rate*	χ	0.006

* Annualized values, e.g., $1-(1-\phi)^{12}$, 12ς, $\sqrt{12}\sigma_g$, $\sqrt{12}\sigma_M$, 12δ, $\sqrt{12}\sigma_e$, $12g$, $1-(1-\kappa)^{12}$, $12\overline{\lambda}$, 12ρ, 12ω, 12α, $1-(1-\xi)^{12}$, 12ν, $1-(1-\chi)^{12}$.

jumps in profit margins occur at higher surplus consumption ratios due to lower collusion benefits.

5.2 Calibration and Parameter Choice

Some parameters are determined from external information without simulating the model (see panel A of Table 8). Other parameters are calibrated internally from moment matching (see panel B of Table 8).

Externally Determined Parameters. We follow Campbell and Cochrane (1999) and choose $g = 0.0189$, $\sigma_e = 0.015$, $\phi = 0.13$. Because of the amplification effect from endogenous competition, we choose a lower risk aversion $\gamma = 1.3$ to ensure the risk premium is in line with the data. We set the lower bound of monthly consumption growth $\varsigma = -0.01$. We set $\kappa = 0.262$ and $\sigma_g = 0.012$ so that the implied persistence and predictable component of consumption growth are consistent with the calibration of Bansal, Kiku and Yaron (2012). These parameter values ensure that the model-implied consumption process is consistent with the data (see panel A of Table 9).

The within-industry elasticity of substitution is set at $\eta = 15$ and the cross-industry elasticity of substitution at $\epsilon = 2$, which are broadly consistent with Atkeson and Burstein (2008). We choose a low depreciation rate $\delta = 0.1$ and a low volatility $\sigma_M = 0.01$ to capture a sticky customer base (see, e.g., Gourio and Rudanko, 2014; Gilchrist et al., 2017). We assume that the industry-level rate of market structure disruption $\lambda_{i,t}$ is bounded between $\underline{\lambda}$ and $\overline{\lambda}$. We discretize $[\underline{\lambda}, \overline{\lambda}]$ into $N = 10$ grids with equal spacing, so that $\lambda_1 = \underline{\lambda}$ and $\lambda_N = \overline{\lambda}$. We set $\underline{\lambda} = 0$ and $\overline{\lambda} = 0.18$, so that market leaders in an average industry are displaced about every 11 years.

Internally Calibrated Parameters. The remaining parameters are calibrated by matching relevant moments in panel B of Table 9.

We set the subjective discount factor $\rho = 0.11$ to match the average real risk-free rate between 1948-2017. The marginal cost of production $\omega = 62$ is determined to match the average net profitability. We set the punishment rate $\xi = 0.09$ to match the average gross profit margin of all industries. We calibrate $\nu = 0.009$ to make the volatility of the growth rates of real net profits of all industries close to the data. The parameter $\alpha = 0.09$ is set to match the regression coefficient in Appendix Table B.1, implying that a 1% increase in gross profit margins increases industries' log asset growth rate by about 0.082%. The parameter χ is set at 0.006 so that the one-year autocorrelation of $\lambda_{i,t}$ in our model is consistent with the one-year autocorrelation of the disruption rate measure.

5.3 Quantitative Results

Table 10 (columns 1 and 2) shows that our model can quantitatively replicate the main asset pricing and corporate cash flow patterns. The model-implied equity premium, volatility of market excess returns, and Sharpe ratio are roughly in line with the data (columns 1 and 2). The model-implied gross profitability premium is about 3.83%, which is also roughly consistent with the 3.06% seen in the data. The gross profitability spread (T3 $-$ T1) is also positively exposed to accumulated consumption growth (sensitivity $= 1.49$), which is roughly consistent with the data (sensitivity $= 1.57$).

To quantify the relative importance of the discount rate channel and the cash flow channel, we consider a counterfactual economy in which expected consumption growth is fixed at $g_t \equiv \overline{g}$ (see column 3). Compared with the result of the full model (column 2), column 3 shows that the volatility of the growth rates of real net profits drops from 11.15% to 10.55%, the equity premium drops from 7.18% to 6.83%, and the volatility of market excess returns decreases from 17.79% to 16.28%. The implied gross profitability premium decreases from 3.83% to 3.56%. These results suggest that the cash flow channel roughly accounts for about 5% of the gross profitability premium and equity premium in the full model (column 2), which renders it much less important than the discount rate channel.

Next, we evaluate the quantitative implication of jump risks in profit margins caused by positive collusion costs. In column (4) we consider an economy without collusion costs (i.e., $\nu \equiv 0$) for all industries. Comparing columns (2) and (4), in the absence of collusion costs, the model implies a higher average net profitability and gross margins

Table 9: Moments in the data and model.

Moments	Data	Model	Moments	Data	Model
Panel A: Moments related to consumption growth					
Average consumption growth (%)	1.89	1.90	Consumption growth volatility (%)	1.21	1.46
	[1.51, 2.26]	[1.36, 2.46]		[1.00, 1.39]	[1.21, 1.74]
AC(1) of consumption growth	0.46	0.40	VR(2) of consumption growth	1.47	1.40
	[0.18, 0.70]	[0.20, 0.59]		[1.10, 1.86]	[1.19, 1.60]
AC(4) of consumption growth	0.11	0.06	VR(4) of consumption growth	1.89	1.79
	[−0.20, 0.27]	[−0.18, 0.30]		[0.85, 3.15]	[1.22, 2.41]
AC(6) of consumption growth	0.05	0.01	VR(6) of consumption growth	2.21	2.00
	[−0.35, 0.14]	[−0.23, 0.25]		[0.88, 4.00]	[1.11, 2.99]
Panel B: Other moments					
Average real risk-free rate (%)	0.68	0.68	Average net profitability (%)	3.92	3.58
	[−0.21, 1.65]	[0.68, 0.68]		[2.79, 5.09]	[3.08, 3.99]
Sensitivity of asset growth	0.082	0.085	Volatility of growth rates of	16.22	12.15
to profit margins	[0.016, 0.123]	[0.079, 0.090]	real net profits (%)	[11.11, 19.88]	[9.19, 15.06]
Average gross profit margin (%)	31.39	26.50	AC(1) of disruption rate $\lambda_{i,t}$	0.977	0.975
	[29.98, 33.00]	[21.50, 30.09]		[0.972, 0.981]	[0.969, 0.980]

Note: The consumption data are constructed based on U.S. Bureau of Economic Analysis (BEA) data and cover the post-war period from 1948 to 2017. Moments in panel A are computed following Beeler and Campbell (2012). We identify the same consumption data moments as those reported by Beeler and Campbell (2012) using their sample period (1948 – 2008). AC(k) of consumption growth refer to the autocorrelation of consumption growth with a k-year lag. VR(k) of consumption growth refer to the variance ratio of consumption growth with a k-year horizon. The average net profitability and average gross profit margin are computed based on Compustat data as explained in Table 2. Volatility of the growth rates of real net profits is the volatility of the growth rates of the real average industry net profits. We construct the above Compustat-based moments using the data from 1950 to 2017. Real risk-free interest rate is the average of the difference between the annual returns of one-month Treasury bills from CRSP and the rate of change in CPI from 1948 to 2018. The sensitivity of asset growth to profit margins is estimated from column (8) of Appendix Table B.1. When constructing the one-year autocorrelation of the disruption rate measure, we sort all industry-year observations into $N = 10$ bins based on the value of the disruption rate measure, consistent with the discretization of $\lambda_{i,t}$ in our model. The one-year autocorrelation is calculated based on the bin index. We bootstrap the data moments with 1000 replications and report the 2.5th and 97.5th percentiles of the bootstrapped distribution in brackets. When constructing the model moments, we simulate a sample of 500 industries for 150 years with an 80-year burn-in period. We then compute the model-implied moments similar to the data. For each moment, the table reports the average value of 2,000 simulations and the 2.5th and 97.5th estimated percentiles of the simulated distribution in brackets.

because firms can always costlessly collude with each other. Moreover, the volatility of the growth rates of real net profits decreases sharply from 11.15% to 6.97%, resulting in lower equity premium and volatility of market returns. The gross profitability premium decreases from 3.83% to 2.65% once we remove collusion costs.

In column (5), we set $\alpha = 0$ so that firms cannot accumulate customer base through advertising efforts. The average net profitability and gross profit margins decrease because firms have less incentive to collude in setting higher profit margins. Advertising efforts amplify the volatility of the growth rates of net profits because firms can grow faster during periods with lower discount rates and/or higher expected consumption growth. Thus, the growth rates of real net profits become less volatile when we set $\alpha = 0$, which in turn results in a lower equity premium and volatility of market excess returns. Moreover, the gross profitability premium decreases from 3.83% to 2.39%.

Table 10: Model mechanisms and asset pricing implications.

	(1) Data	(2) Full model collusive	(3) Model-based counterfactuals $g_t \equiv \bar{g}$	(4) $\nu = 0$	(5) $\alpha = 0$	(6) non-collusive	(7) Three firms collusive
Average net profitability (%)	3.92	3.76	3.57	3.81	3.45	2.08	2.45
	[2.79, 5.09]	[3.36, 4.08]	[3.09, 3.98]	[3.51, 4.08]	[3.19, 3.73]	[2.07, 2.09]	[2.28, 2.62]
Average gross profit margin (%)	31.39	27.87	26.44	28.27	20.07	12.21	18.97
	[29.98, 33.00]	[23.63, 31.33]	[21.51, 30.52]	[24.70, 31.16]	[17.96, 23.85]	[12.17, 12.25]	[17.15, 20.50]
Volatility of growth rates of real net profits (%)	16.22	11.15	10.55	6.97	10.47	1.88	9.91
	[11.11, 19.88]	[8.19, 14.06]	[7.34, 13.57]	[5.69, 8.31]	[7.66, 12.90]	[1.60, 2.17]	[8.84, 11.05]
Equity premium ($\mathbb{E}(r - r_f)$, %)	6.68	7.18	6.83	6.33	6.42	4.17	6.91
	[2.34, 10.88]	[5.62, 9.15]	[5.47, 8.64]	[5.10, 8.12]	[5.36, 7.58]	[3.10, 5.76]	[5.76, 8.57]
Volatility of market excess returns ($\sigma(r - r_f)$, %)	16.89	17.79	16.28	15.36	15.50	10.06	16.24
	[13.21, 19.39]	[12.58, 24.88]	[11.61, 21.71]	[11.26, 21.63]	[11.74, 22.39]	[6.26, 14.98]	[12.13, 21.42]
Sharpe ratio ($\mathbb{E}(r - r_f)/\sigma(r - r_f)$)	0.40	0.41	0.42	0.41	0.41	0.41	0.42
	[0.13, 0.77]	[0.31, 0.53]	[0.31, 0.56]	[0.31, 0.54]	[0.31, 0.55]	[0.30, 0.53]	[0.32, 0.54]
Gross profitability T1 ($\mathbb{E}(R_{T1} - R_f)$, %)	6.74	7.27	7.09	6.73	7.08	4.58	7.03
	[3.69, 7.22]	[6.01, 8.62]	[5.94, 8.55]	[5.31, 9.06]	[6.25, 8.09]	[3.31, 6.45]	[4.14, 7.79]
Gross profitability T3 ($\mathbb{E}(R_{T3} - R_f)$, %)	9.79	11.10	10.65	9.38	9.47	4.65	10.52
	[7.68, 10.47]	[8.17, 16.00]	[6.54, 14.97]	[7.46, 12.59]	[7.69, 13.41]	[3.39, 6.48]	[6.26, 14.27]
Gross profitability premium (T3 – T1, $\mathbb{E}(R_{T3} - R_{T1})$, %)	3.06	3.83	3.56	2.65	2.39	0.07	3.49
	[1.37, 5.88]	[0.92, 8.37]	[0.75, 8.16]	[2.14, 3.57]	[2.07, 3.10]	[0.01, 0.12]	[0.64, 8.11]
T3 – T1 spread's exposure to accum. consumption growth	1.57	1.49	1.41	1.03	0.92	0.05	1.39
	[0.50, 2.59]	[0.53, 2.92]	[0.46, 2.85]	[0.77, 1.35]	[0.63, 1.21]	[0.02, 0.09]	[0.43, 2.81]

Note: R represents simple returns and r represents log returns. When constructing the model moments, we simulate a sample of 500 industries for 150 years with an 80-year burn-in period. We then compute the model-implied moments similar to the data. For each moment, the table reports the average value of 2,000 simulations and the 2.5th and 97.5th estimated percentiles of the simulated distribution (in brackets).

To evaluate the importance of endogenous competition, we simulate a counterfactual in which firms are not allowed to collude with each other. That is, the two firms in the same industry adopt the non-collusive scheme, and both set profit margins taking the other's profit margin as given. As shown in column (6), the average net profitability and gross profit margin are much lower than those in column (2). The volatility of the growth rates of real net profits is 1.88%, merely reflecting shocks to aggregate consumption. The equity premium drops from 7.18% to 4.17%, indicating that about 40% of the equity premium is attributed to the competition risk premium. The volatility of market excess returns decreases from 17.79% to 10.06%. The model-implied gross profitability premium is largely reduced from 3.83% to 0.07%. Overall, by comparing the implications of our full model with those of the non-collusive model, we have shown that endogenous competition significantly contributes to the equity premium and stock return volatility, and it is also the key to explaining our cross-sectional asset pricing patterns in the data.

An Extension with Three Market Leaders For tractability and transparency, the baseline model in Section 3 and the full model in column (2) of Table 10 focus on the duopoly structure by emphasizing the endogenous strategic competition between two market leaders in an industry. The computational complexity increases exponentially with the number of firms because each firm's decisions are solved based on every other firm's profit margin, share of customer base, and collusion decisions. Thus, solving a generic $n-$firm model is NP hard.[48] In reality, an industry may have more than two market leaders. Because the difficulty of maintaining a collusive equilibrium increases with the number of firms, the endogenous competition mechanism emphasized by our model would have a smaller effect once we consider more firms in an industry.

As a robustness check, we further extend the model with endogenous jumps (column 2) by allowing three market leaders in an industry (column 7). Based on the same parameter values, column (7) reports that the average net profitability and gross profit margins significantly decrease as compared to column (2). However, our simulation results imply that the percentage change in net profits does not decrease much because of the low level of net profits, even though the level change in net profits in response to aggregate shocks decreases significantly. This can be seen from the small decrease from 11.15% to 9.91% in the volatility of the growth rates of real net profits. Since what matters for asset pricing is the time-varying net profits, this suggests that increasing the number of firms should not have a large dampening effect on the model-implied gross profitability premium, even though it indeed becomes significantly more difficult to collude. In addition, due to the lower net profitability, the cost of collusion is more likely to outweigh the benefit, which makes the endogenous downward jumps more frequent, further amplifying the gross profitability premium. As a result, increasing the number of firms from two to three only generates a moderate reduction from 3.83% to 3.49% in the gross profitability premium. Of course, further increasing the number of firms will likely further reduce the gross profitability premium implied by the model; however, the marginal impact of increasing the number of firms is likely diminishing, and due to tractability reasons, we cannot exhaust all such cases for robustness checks.

6 Conclusion

This paper investigates the origin of systematic endogenous fluctuations in the degree of industry competition and its asset pricing implications. We develop a general-equilibrium

[48] Our baseline model is solved in C++ with parallelization of 48 CPU cores. Even with parallel computation, we can at most tackle models that are solvable in polynomial time, because the speed of computation increases only linearly with the number of CPU cores.

asset pricing model incorporating dynamic games of competition among firms. In our model, industry competition endogenously intensifies as the discount rate rises and/or expected consumption growth declines, because firms become effectively more impatient for cash flows and their incentives to undercut profit margins grow stronger. The exposure to the aggregate shocks driving discount rates and expected consumption growth through the channel of endogenous competition reflects predictable and persistent heterogeneous industry characteristics. Industries with a higher turnover rate of market leadership are more immune to the fluctuations in profit margins driven by the discount rate and expected shocks. Our theoretical and empirical studies shed new light on the relation between gross profitability and stock returns – the gross profitability premium.

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Appendix

A Supplementary Information for Empirical Analyses.

Profit Margins and Profitability. We construct two measures of gross profit margins based on the NBER-CES Manufacturing Industry Database and Compustat, and two measures of net profit margins based on the U.S. Bureau of Economic Analysis (BEA) data and Compustat. These datasets have different advantages. Compustat covers public firms from all industries. The NBER-CES database covers both public firms and private firms in the manufacturing sector. BEA corporate profits data provide the time series for the aggregate profits of the entire corporate sector. Following Domowitz, Hubbard and Petersen (1986) and Allayannis and Ihrig (2001), we construct the NBER-CES-based profit margin for industry i at year t as $(\text{Value of shipments}_{i,t} + \Delta\text{Inventory}_{i,t} - \text{Payroll}_{i,t} - \text{Cost of material}_{i,t})/(\text{Value of shipments}_{i,t} + \Delta\text{Inventory}_{i,t})$. Following Anderson, Rebelo and Wong (2018), we construct the Compustat-based profit margin for industry i at year t as $(\text{Sales}_{i,t} - \text{COGS}_{i,t})/\text{Sales}_{i,t}$. We measure the BEA-based aggregate net profit margin as the profits after tax for the nonfinancial corporate business scaled by the GDP in the nonfinancial sector. We construct the Compustat-based net profit margin for industry i at year t as $\text{IB}_{i,t}/\text{Sales}_{i,t}$, where IB represents income before extraordinary items.

We construct industry-level gross profitability as gross profits (revenues minus cost of goods sold) scaled by assets. We construct net profitability as income before extraordinary items scaled by assets. The industry-level revenue, cost of goods sold, assets, and income before extraordinary items are the sum of the corresponding firm-level measures (Compustat items REVT, COGS, AT, and IB respectively) across firms in the industries.

Media and Analyst Coverage of Price Wars. We measure the media and analyst coverage of price wars using textual analysis following recent literature (see, e.g. Loughran and McDonald, 2011; Baker, Bloom and Davis, 2016; Manela and Moreira, 2017). Specifically, we follow Baker, Bloom and Davis (2016) and quantify the prevalence of price wars by searching for targeted phrases, which is "one of the simplest but at the same time the most powerful approaches" in textual analysis (see Loughran and McDonald, 2016). The price war media coverage is the number of articles that contain the term "price war" 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 U.S. region obtained from Dow Jones Factiva. The price war analyst coverage is the number of analyst reports that contain the term "price war" normalized by the number of analyst reports. We consider analyst reports covering the U.S. region obtained from Thomson ONE Investext. Following Huang, Zang and Zheng (2014), we plot the price war analyst coverage after 1996, because the data coverage for the full text of analyst reports is limited before 1996.

Industry Classification. We use four-digit SIC codes in Compustat to define industries. We use SIC codes from Compustat instead of historical SIC codes from CRSP because previous studies concluded that Compustat-based SIC codes are in general more accurate (see, e.g., Guenther and Rosman, 1994; Kahle and Walkling, 1996; Bhojraj, Lee and Oler, 2003). Earlier studies also point out that the four-digit SIC codes in Compustat often end with a 0 or 9, which could represent a broader three-digit industry definition. To address this problem, we follow Bustamante and Donangelo (2017) and replace the SIC code of firms whose SIC ends with a 0 or 9 with the SIC code of the main segment in the Compustat segment data. We then remove those firms whose four-digit SIC still ends with a 0 after this adjustment. We also eliminate conglomerate firms from the sample because they operate in multiple industries. To accomplish this, we follow Gopalan and Xie (2011) and Bustamante and Donangelo (2017) and define conglomerates as those firms that have more than three segments as reported by the Compustat segment data. We apply the above data filtering procedure for all industry-level analyses of our paper.

Turnovers of Market Leaders. We define the turnover indicator based on the market leaders in snapshot year t and snapshot year $t + \Delta t$. We use sales information from both Compustat and Capital IQ to define market leaders in a given industry. Capital IQ is one of the most comprehensive datasets covering private firms. By considering both public firms and private firms, we avoid errors in defining changes of market leaders due to IPOs of private firms or privatization of public firms. In addition, we use the SDC data to identify mergers and acquisitions (M&As). If neither the acquirer nor the target is a market leader prior to the M&A while the merged firm becomes a leader after the M&A, we define the turnover indicator as one. Similarity, if either the acquirer or the target is a market leader prior to the M&A but the merged firm is no longer a market leader, we also define the turnover indicator as one. Finally, if either the acquirer or the target prior to the M&A is a market leader and the merged firm remains a market leader after the M&A, then it is not a change of market leaders. Results are qualitatively similar if we exclude market leader changes that involve M&As.

Antitrust Enforcement Cases. The U.S. Department of Justice (DOJ) provides four-digit SIC codes for the firms in some cases. For the remaining DOJ cases and all Federal Trade Commission (FTC) cases, we match the firms involved in antitrust enforcement to Compustat and Capital IQ, from which we collect their four-digit SIC codes. Both Compustat and Capital IQ are developed and maintained by S&P Global, and the SIC codes in these two datasets are consistent with each other.

Patent Data and Innovation Similarity Measure. We obtain the patent issuance data from PatentsView, a patent data visualization and analysis platform. PatentsView contains detailed and up-to-date information on granted patents from 1976 onward. It covers recent patenting activities more comprehensively than the NBER patent data (see Hall, Jaffe and Trajtenberg, 2001) and the patent data assembled by Kogan et al. (2017) combined.[49] Patent assignees in PatentsView are disambiguated and their locations and patenting activities are tracked longitudinally. PatentsView categorizes patent assignees into groups such as corporations, individuals, and government agencies. The platform also provides detailed information about individual patents, including their grant dates and technology classifications.

We match patent assignees in PatentsView to U.S. public firms in CRSP/Compustat, and to U.S. private firms and large foreign firms in Capital IQ. We include private firms in the construction of the innovation similarity measure 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 PatentsView. We then manually screen these potential matches to identify the exact matches based on patent assignees' names and addresses. In Online Appendix B.2, we detail our matching procedure. In total, we match 2,235,201 patents to 10,139 US public firms, 132,100 patents to 3,080 U.S.

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

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 523 four-digit SIC industries from 1976 to 2017.

We define the cosine similarity between two patents, a and b, as follows:

$$\text{similarity}\,(a, b) = \frac{\mathbf{A} \cdot \mathbf{B}}{\|\mathbf{A}\|\;\|\mathbf{B}\|}, \tag{A.1}$$

where $\mathbf{A}$ and $\mathbf{B}$ are the technology vectors of patent a and patent b.[50] 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, their cosine similarity takes 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 the extent to which 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 A.1) between this patent and the other patents granted to firm i's peer firms in the same four-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 four-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 not all industries are granted patents every year, we further average the industry-level similarity measures over time (from year $t-9$ to year t) to filter out noise and better capture firms' ability to generate differentiated innovation. Finally, we standardize the innovation similarity measure using its unconditional mean and the standard deviation of all industries across the entire period from 1976 to 2017.

An industry in which firms have more similar patents has a higher innovation similarity measure. Let us provide a few concrete examples for the innovation similarity measure. In the industry of "Search, Detection, Navigation, Guidance, Aeronautical, and Nautical Systems and Instruments", innovation similarity is low throughout our sample period, suggesting that firms in this industry are able to consistently generate new innovations. On the other hand, in the industry of "Dolls and Stuffed Toys", innovation similarity is high throughout our sample period, suggesting that firms in this industry do not differ much in their innovations.

B Supplementary Empirical Results

Profitability and Marketing Expenditure. Columns (1) – (4) of Table B.1 show the relation between gross profitability and investment in total asset. We focus on the investment in both physical asset and intangible asset. We measure the investment in physical asset using capital expenditure and that in

[50] PatentsView provides both the Cooperative Patent Classification (CPC) and the U.S. Patent Classification (USPC), the two major classification systems for U.S. patents. As in Kelly et al. (2018), we use CPC for our analyses because USPC is no longer 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 PatentsView. The technology classification vector for a patent consists of 653 indicator variables that represent the patent's CPC classes.

intangible asset using the summation of R&D expenses and SG&A. We include SG&A because it captures firms' investment in organization capital (see, e.g., Eisfeldt and Papanikolaou, 2013) and customer capital (see, e.g., Gourio and Rudanko, 2014; Gilchrist et al., 2017). We find that more profitable industries are associated with higher investment rates. Columns (5) – (6) of Table B.1 show that more profitable industries incur higher marketing expenses in the future, suggesting that higher profit margin can lead to more marketing efforts, a finding that is consistent with previous studies (see, e.g., Comanor and Wilson, 1967; Strickland and Weiss, 1976; Martin, 1979). In addition, consistent with our model, we find that more profitable industries also have higher asset growth rates (see columns 7 – 8 of Table B.1).

Alternative Regression Methods. Table B.9 replicates the Fama-MacBeth regressions in the main text using the panel regression approach. We include year fixed effects in the regression and focus on the cross-sectional variations. The panel regression approach generates similar results to those from the Fama-MacBeth regressions.

Net Profitability Premium. Besides gross profitability, previous studies have also examined the asset pricing implications of other measures of profitability. In particular, return on equity (ROE, measured as income before extraordinary items scaled by book equity) has been shown to be positively priced (see Hou, Xue and Zhang, 2015). We replicate the main tests in our empirical analysis using the ROE measure. The results are very similar to those presented in the main text. Table B.10 shows that the average profit margin and profitability comove more positively with accumulated consumption growth in industries with a higher ROE. Table B.11 shows that, besides being priced at the firm level, ROE is also positively priced both within and across industries. The cross-industry ROE premium is more pronounced in the sub-sample that excludes the industries with high HHI. Table B.12 shows that the cross-industry ROE spread loads positively on accumulated consumption growth, while the within-industry ROE spread loads on accumulated consumption growth with the opposite sign. Moreover, the firm-level ROE spread also loads positively on accumulated consumption growth, suggesting that the cross-industry variation plays a more important role in determining the exposure to accumulated consumption growth of the stock portfolios sorted on the firms' ROE. Finally, Table B.13 shows that, unlike the within-industry and firm-level ROE spreads, the cross-industry ROE spread does not load on IMC, suggesting that the cross-industry ROE premium is unlikely explained by industries' heterogeneous exposure to the IST shocks.

Table B.1: Investment, asset growth, and gross profitability.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$\frac{\text{Gross investment}_{i,t+1}}{(\text{Asset}_{i,t+1}+\text{Asset}_{i,t})/2}$		$\frac{\text{Net investment}_{i,t+1}}{(\text{Asset}_{i,t+1}+\text{Asset}_{i,t})/2}$		$\frac{\text{Marketing expenditure}_{i,t+1}}{(\text{Asset}_{i,t+1}+\text{Asset}_{i,t})/2}$		$\ln(\frac{\text{Asset}_{i,t+1}}{\text{Asset}_{i,t}})$	
Gross profitability$_{i,t}$	0.044*	0.026**	0.041*	0.023**	0.007*	0.003*	0.068***	0.082***
	[1.838]	[2.433]	[1.797]	[2.160]	[1.701]	[1.739]	[3.969]	[5.775]
ln(number of firms)$_{i,t}$	−0.008	0.003	−0.007	0.003	−0.002*	0.002**	0.018***	0.024***
	[−1.095]	[0.498]	[−1.011]	[0.574]	[−1.793]	[−2.183]	[3.970]	[3.645]
ln(sales)$_{i,t}$	−0.008**	−0.019***	−0.008**	−0.016***	0.001	0.000	−0.024***	−0.074***
	[−2.120]	[−5.227]	[−2.103]	[−4.676]	[1.509]	[0.426]	[−7.110]	[−10.612]
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	No	Yes	No	Yes	No	Yes	No	Yes
Observations	23385	23385	23385	23385	23385	23385	23873	23873
R-squared	0.072	0.647	0.063	0.641	0.062	0.508	0.059	0.096

Note: This table shows the relation between gross profitability and investment in total asset (columns 1 – 4), marketing expenditure (columns 5 – 6), and asset growth rate (columns 7 – 8). Gross investment in total asset includes capital expenditure (Compustat item CAPX), selling, general and administrative expenses (SG&A), and R&D expenses (Compustat item XRD). Net investment in total asset is the gross investment minus depreciation and amortization (Compustat item DP) minus sales of property (Compustat item SPPE). Note that Compustat almost always adds the SG&A and R&D together in the item XSGA. Following Peters and Taylor (2017), we use the item XSGA to represent the total expenses of SG&A and R&D except when the item XRD exceeds the Compustat item XSGA but is less than cost of goods sold (Compustat item COGS), in which case we use the Compustat item XSGA to represent SG&A only. Marketing expenditure is measured by advertising expenses (Compustat item XAD). In columns (1) - (6), we normalize investment and marketing expenditure by average asset following Bloom (2009). Data span the period from 1950 to 2017. Standard errors are clustered at both the industry and year levels. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table B.2: Exposure of gross profitability spreads to accumulated consumption growth, controlling for accumulated market excess returns.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
					Accumulated portfolio excess returns$_t$							
GP tertiles	T1 (low)	T2	T3 (high)	T3 − T1	T1 (low)	T2	T3 (high)	T3 − T1	T1 (low)	T2	T3 (high)	T3 − T1
	Cross-industry spread				Within-industry spread				Firm-level spread			
$\hat{g}_t$	−0.21	0.58*	1.19***	1.40***	0.77**	0.65	−0.01	−0.78*	0.29	0.41	0.96*	0.67**
	[−0.65]	[1.88]	[2.68]	[2.68]	[2.38]	[1.60]	[−0.04]	[−1.69]	[0.52]	[1.25]	[1.83]	[2.37]
Accum. market	0.86***	0.94***	0.99***	0.12*	1.05***	0.96***	0.97***	−0.08	0.91***	0.93***	0.95***	0.04
excess returns$_t$	[15.07]	[21.68]	[23.26]	[1.73]	[14.71]	[17.08]	[27.93]	[−1.10]	[7.61]	[19.20]	[16.10]	[0.25]
Observations	257	257	257	257	257	257	257	257	257	257	257	257
R-squared	0.724	0.827	0.732	0.065	0.761	0.778	0.830	0.031	0.733	0.880	0.777	0.012

Note: This table shows the heterogeneous exposure to accumulated consumption growth for portfolios sorted on gross profitability. The dependent variable is a weighted average of past 12-quarter portfolio excess returns: $\sum_{j=0}^{11}\phi^j(r_{p,t-j}-r_{f,t-j})/\sum_{j=0}^{11}\phi^j$. The independent variables are accumulated consumption growth $\hat{g}_t$ and accumulated market excess returns ($\sum_{j=0}^{11}\phi^j(r_{mkt,t-j}-r_{f,t-j})/\sum_{j=0}^{11}\phi^j$). Portfolio sorting is performed at the quarterly frequency according to the procedures explained in Table 3. The sample spans the period from 1951 to 2018. We exclude financial firms and utility firms from the analysis. We include t-statistics in brackets. Standard errors are computed using the Newey-West estimator allowing for serial correlation in returns. We omit the coefficients for the constant terms for brevity. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table B.3: Explaining the cross-industry gross profitability premium.

Panel A: Exposure to the $\beta_{\hat{g}}$ spread

	(1)	(2)	(3)	(4)
	Cross-industry gross profitability spread$_t$ (%)			
Intercept (%)	0.22***	0.17**	0.12	0.06
	[2.73]	[2.00]	[0.81]	[0.43]
MktRf$_t$ (%)		0.09		0.11*
		[1.27]		[1.72]
$\beta_{\hat{g}}$ spread$_t$ (%)			0.36*	0.37**
			[1.78]	[2.06]
Observations	702	702	702	702
R-squared	0.000	0.017	0.057	0.078

Panel B: Explaining the cross-industry gross profitability premium

	(1)	(2)
	Excess returns	CAPM alpha
Annualized premium (%)	2.69***	2.10**
	[2.73]	[2.00]
Annualized premium after controlling for $\beta_{\hat{g}}$ spread (%)	1.43	0.72
	[0.81]	[0.43]
Fraction of cross-industry premium explained by $\beta_{\hat{g}}$ spread (%)	46.8	65.7

Note: Panel A shows the results of the time-series regression of monthly cross-industry gross profitability spread on market excess returns and the $\beta_{\hat{g}}$ spread. Panel B shows that the cross-industry gross profitability premium can be partially explained by heterogeneous exposure to accumulated consumption growth. The magnitude of the annualized cross-industry gross profitability premium is slightly different from that in Table 3 because the analysis here requires the availability of the $\beta_{\hat{g}}$ spread. The sample of this table spans the period from 1960 to 2018. We exclude financial firms and utility firms from the analysis. We include t-statistics in brackets. 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, respectively.

Table B.4: Exposure to accumulated consumption growth in different industries, controlling for accumulated market excess returns.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Accumulated portfolio excess returns$_t$							
Gross profitability tertiles	T1 (low)	T2	T3 (high)	T3 − T1	T1 (low)	T2	T3 (high)	T3 − T1
Panel A: Subsamples sorted on the fitted HHI								
	Bottom 70% of the fitted HHI				Top 30% of the fitted HHI			
$\hat{g}_t$	−2.13**	−0.71	0.76	2.89**	0.70	−0.57	−1.13	−1.83
	[−2.21]	[−0.77]	[0.99]	[2.33]	[0.66]	[−0.41]	[−1.10]	[−1.36]
Accumulated market excess returns$_t$	1.23***	1.05***	1.16***	−0.07	0.33***	0.83***	0.88***	0.55***
	[11.71]	[12.97]	[20.08]	[−0.59]	[4.15]	[6.55]	[12.39]	[5.47]
Observations	113	113	113	113	113	113	113	113
R-squared	0.650	0.674	0.773	0.045	0.221	0.439	0.558	0.242
Panel B: Subsamples sorted on the gap in PP&E								
	Bottom 70% of the gap in PP&E				Top 30% of the gap in PP&E			
$\hat{g}_t$	−1.08	0.43	1.30	2.38***	−0.54	1.01*	0.37	0.91
	[−1.59]	[0.68]	[1.59]	[2.99]	[−0.70]	[1.87]	[0.54]	[0.98]
Accumulated market excess returns$_t$	1.09***	1.04***	0.71***	−0.38*	0.77***	1.00***	1.02***	0.24**
	[13.66]	[13.24]	[4.45]	[−1.78]	[8.84]	[10.91]	[20.94]	[2.25]
Observations	257	257	257	257	257	257	257	257
R-squared	0.605	0.705	0.347	0.098	0.563	0.749	0.748	0.085

Note: This table shows the heterogeneous exposure to accumulated consumption growth for industry portfolios sorted on gross profitability in industries with different entry costs, controlling for accumulated market excess returns. The analysis is performed at the quarterly level. The sample period of panel A is from 1979 to 2007 due to data availability of the fitted HHI measure. The sample period of panel C is from 1954 to 2018. We include t-statistics in brackets. Standard errors are computed using the Newey-West estimator allowing for serial correlation in returns. We exclude financial firms and utility firms from the analysis. We omit the coefficients for the constant terms for brevity. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table B.5: Exposure of gross profitability spreads to IST shocks.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Portfolio excess returns$_t$							
Gross profitability tertiles	T1 (low)	T2	T3 (high)	T3 − T1	T1 (low)	T2	T3 (high)	T3 − T1
Panel A: Exposure of the cross-industry gross profitability spread								
IMC$_t$	0.62***	0.93***	0.64***	0.02	0.08***	0.32***	0.03	−0.06
	[11.74]	[16.32]	[11.86]	[0.38]	[2.89]	[6.32]	[0.65]	[−1.09]
MktRf$_t$					0.89***	1.01***	1.01***	0.12***
					[48.49]	[43.18]	[41.50]	[3.56]
Observations	804	804	804	804	804	804	804	804
R-squared	0.246	0.370	0.206	0.000	0.841	0.878	0.814	0.022
Panel B: Exposure of the within-industry gross profitability spread								
IMC$_t$	0.94***	0.85***	0.63***	−0.31***	0.31***	0.25***	0.06	−0.26***
	[16.52]	[15.04]	[13.21]	[−9.27]	[7.17]	[5.38]	[1.45]	[−7.46]
MktRf$_t$					1.05***	1.00***	0.96***	−0.09***
					[50.37]	[41.30]	[50.45]	[−3.99]
Observations	804	804	804	804	804	804	804	804
R-squared	0.356	0.328	0.232	0.168	0.870	0.851	0.856	0.183
Panel C: Exposure of the firm-level gross profitability spread								
IMC$_t$	0.70***	0.70***	0.57***	−0.13**	0.08***	0.10***	−0.02	−0.10***
	[9.82]	[7.94]	[6.41]	[−2.31]	[4.30]	[8.69]	[−1.00]	[−2.77]
MktRf$_t$					1.03***	1.00***	0.98***	−0.05
					[30.19]	[30.71]	[52.75]	[−1.02]
Observations	804	804	804	804	804	804	804	804
R-squared	0.256	0.281	0.196	0.026	0.911	0.944	0.870	0.031

Note: This table shows the exposure to IST shocks for portfolios sorted on gross profitability. The analysis is performed at the monthly level. The dependent variable is the monthly excess returns of the portfolios sorted on gross profitability. The independent variables are the monthly market excess returns and the monthly IMC returns. IMC is a measure of IST shocks based on stock returns (see Kogan and Papanikolaou, 2013, 2014). To construct the IMC portfolio, we classify industries as investment-good producers and consumption-good producers according to the NIPA Input-Output Tables, following the procedure described in Gomes, Kogan and Yogo (2009) and Papanikolaou (2011). The sample spans the period from July 1951 to June 2018. We exclude financial firms and utility firms from the analysis. We include t-statistics in brackets. Standard errors are computed using the Newey-West estimator allowing for serial correlation in returns. We omit the coefficients for the constant terms for brevity. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table B.6: Disruption rate measure and profitability.

Panel A: Disruption rate measure and profitability

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Profit margin$_{i,t}$ (%)			Profitability$_{i,t}$ (%)		$\ln(\sigma_{NP,i}^{t\to t+\Delta t})$			
	Gross	Gross	Net	Gross	Net	$\Delta t = 3$ y	$\Delta t = 4$ y	$\Delta t = 5$ y	$\Delta t = 10$ y
Data source	Compustat	NBER-CES	Compustat	Compustat	Compustat	Compustat	Compustat	Compustat	Compustat
$\hat{\lambda}_{i,t}$ (standardized)	-3.08^{***}	-4.06^{***}	-0.45^{**}	-2.80^{***}	-0.40^{**}	-0.08^{***}	-0.08^{***}	-0.09^{***}	-0.11^{***}
	[−8.11]	[−13.03]	[−2.12]	[−3.50]	[−2.63]	[−3.89]	[−4.62]	[−5.65]	[−4.96]
ln(number of firms)$_{i,t}$	7.34^{***}	3.39^{***}	-1.51^{***}	-1.31^{**}	-1.27^{***}	0.04	0.04	0.04	0.03^{*}
	[25.70]	[15.51]	[−3.86]	[−2.26]	[−5.85]	[1.10]	[1.21]	[1.28]	[1.97]
ln(sales)$_{i,t}$	-2.63^{***}	-0.29^{*}	2.30^{***}	−0.29	1.25^{***}	-0.20^{***}	-0.20^{***}	-0.19^{***}	-0.15^{***}
	[−18.40]	[−2.05]	[8.74]	[−0.96]	[12.40]	[−11.81]	[−14.05]	[−15.76]	[−16.18]
Average obs./year	176	103	176	176	176	169	168	166	157
Average R-squared	0.193	0.205	0.120	0.052	0.119	0.139	0.159	0.160	0.132

Panel B: Disruption rate measure and heterogeneous sensitivity of profitability to accumulated consumption growth

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	ΔAverage profit margin$_t$ (net, Compustat)				ΔAverage profitability$_t$ (net, Compustat)			
$\hat{\lambda}$ tertiles	T1 (low)	T2	T3 (high)	T3 − T1	T1 (low)	T2	T3 (high)	T3 − T1
$(\mathbb{E}_t - \mathbb{E}_{t-1})\hat{g}_t$	0.59^{**}	0.73^{**}	−0.31	-0.90^{**}	0.76^{***}	0.82^{***}	0.14	-0.62^{***}
	[2.29]	[2.39]	[−0.80]	[−2.24]	[3.35]	[2.92]	[0.62]	[−3.92]
Observations	29	29	29	29	29	29	29	29
R-squared	0.031	0.028	0.007	0.082	0.063	0.067	0.003	0.090

Note: Columns (1) – (5) of panel A report results from Fama-MacBeth regressions of profit margins and profitability on the disruption rate measure ($\hat{\lambda}$), the natural log of the number of firms in the industries, and the natural log of the industry sales. Columns (6) – (9) of panel A report results from Fama-MacBeth regressions of the natural log of volatility of net industry profitability from year t to $t + \Delta t$ on the same set of independent variables. Panel B shows the sensitivity of the average profit margin and average profitability to accumulated consumption growth in industry tertile portfolios sorted on the lagged disruption rate measure. We standardize the disruption rate measure using its unconditional mean and unconditional standard deviation of the full sample. $(\mathbb{E}_t - \mathbb{E}_{t-1})\hat{g}_t$ is the AR(1) shock of yearly accumulated consumption growth. The construction of yearly accumulated consumption growth is explained in Figure 1. The construction of the disruption rate measure is explained in Section 4.4.1. Other variables are explained in Table 2. Standard errors in panel B are computed using the Newey-West estimator allowing for serial correlation. The sample in column (2) of panel A spans the period from 1988 to 2011 due to availability of the NBER-CES data. The sample in the rest of the table spans the period from 1988 to 2017. We omit the coefficients for the constant terms for brevity. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table B.7: Long-short portfolio spread based on the disruption rate measure and its exposure to accumulated consumption growth.

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Excess returns (%)				CAPM alphas (%)		
T1 (low)	T2	T3 (high)	T3 − T1	T1 (low)	T2	T3 (high)	T3 − T1
Panel A: Cross-industry disruption rate measure premium							
10.89***	9.06***	6.30***	−4.59***	1.64**	0.04	−0.69	−2.33**
[5.51]	[6.10]	[3.91]	[−3.82]	[2.25]	[0.05]	[−0.86]	[−2.17]
Panel B: Cross-industry disruption rate measure premium (no antitrust charges)							
12.24***	9.11***	5.99***	−6.25***	2.25	1.02	−2.58***	−4.83***
[9.46]	[4.53]	[5.73]	[−4.44]	[1.58]	[0.65]	[−2.79]	[−3.45]
Panel C: Cross-industry disruption rate measure premium (with antitrust charges)							
11.87***	7.77**	9.45***	−2.42	2.82	−1.89	3.12***	0.30
[3.21]	[2.52]	[3.18]	[−0.89]	[1.36]	[−1.06]	[2.71]	[0.12]

Panel D: Exposure to accumulated consumption growth

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
					Accumulated portfolio excess returns$_t$			
$\hat{\lambda}$ tertiles	T1 (low)	T2	T3 (high)	T3 − T1	T1 (low)	T2	T3 (high)	T3 − T1
$\hat{g}_t$	6.46***	2.22*	1.09	−5.37***	2.79*	−1.10*	−1.68**	−4.46**
	[3.62]	[1.67]	[0.86]	[−2.63]	[1.81]	[−1.84]	[−2.57]	[−2.16]
Accumulated market excess returns$_t$					1.13***	1.02***	0.86***	−0.28**
					[11.35]	[13.91]	[19.57]	[−2.44]
Observations	109	109	109	109	109	109	109	109
R-squared	0.172	0.035	0.011	0.197	0.743	0.837	0.755	0.254

Note: Panel A shows the value-weighted average excess returns and CAPM alphas for industry portfolios sorted on the disruption rate measure. In panels B and C, we split industries into two sub-samples based on whether they have faced antitrust charges in the past 10 years. We then sort industries into tertiles based on the lagged disruption rate measure. We annualize average excess returns and alphas by multiplying them by 12. The sample in panels A, B, and C spans the period from July 1988 to June 2018. Panel D shows the heterogeneous exposure to accumulated consumption growth for industry portfolios sorted on the disruption rate measure. The analysis is performed at the quarterly level. The variables are explained in Table 4. The sample of panel D spans the period from 1991 to 2017. We omit the coefficient for the constant term for brevity. 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, respectively.

Table B.8: Gross profitability premium is partially explained by the disruption rate measure.

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Excess returns (%)				CAPM alphas (%)			
T1 (low)	T2	T3 (high)	T3 − T1	T1 (low)	T2	T3 (high)	T3 − T1
Panel A: Cross-industry gross profitability premium (conditional on the availability of the disruption rate measure)							
7.69***	9.16***	10.44***	2.75**	−0.18	−0.60	2.38**	2.56***
[5.53]	[5.53]	[5.83]	[2.24]	[−0.22]	[−0.54]	[2.86]	[2.63]
Panel B: Cross-industry gross profitability premium (double-sorted on the disruption rate measure)							
7.55***	10.47***	9.62***	2.07	−0.37	0.85	1.29**	1.66
[5.13]	[7.52]	[5.46]	[1.25]	[−0.46]	[0.85]	[2.09]	[1.62]
Panel C: Explaining the cross-industry gross profitability premium							
Reduction in premium (excess returns, %):			24.7	Reduction in premium (CAPM alphas, %):			35.2

Note: Panel A shows the value-weighted average excess returns and CAPM alphas for industry portfolios sorted on gross profitability conditional on the availability of the disruption rate measure. Panels B shows the excess returns and CAPM alphas for gross profitability tertiles double-sorted on the disruption rate measure. We first sort industries into three groups based on the disruption rate measure. We then sort industries within each group into tertiles based on their gross profitability. Panel C shows the amount of reduction in gross profitability premium after the double sort. We annualize average excess returns and alphas by multiplying them by 12. The sample of this table spans the period from July 1988 to June 2018. We exclude financial firms and utility firms from the analysis. We include t-statistics in brackets. 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, respectively.

Table B.9: Replicating the Fama-MacBeth regressions using the panel regression approach.

Panel A: Gross profitability, volatility of net profitability, and turnovers of industry leaders

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$\ln(\sigma_{NP,i}^{t\to t+\Delta t})$				$\mathbb{1}_{turnover,i}^{t\to t+\Delta t}$			
Δt years	3	4	5	10	3	4	5	10
Gross profitability$_{i,t}$	0.07***	0.08***	0.08***	0.07***	−0.02***	−0.02***	−0.02***	−0.02***
(standardized)	[3.10]	[3.39]	[3.34]	[3.01]	[−3.32]	[−2.91]	[−2.72]	[−2.10]
ln(number of firms)$_{i,t}$	0.05*	0.04	0.02	−0.02	0.20***	0.21***	0.21***	0.19***
	[1.73]	[1.23]	[0.77]	[−0.69]	[19.86]	[20.04]	[19.90]	[17.95]
ln(sales)$_{i,t}$	−0.20***	−0.19***	−0.18***	−0.16***	−0.02***	−0.02***	−0.02***	−0.02***
	[−13.73]	[−13.00]	[−12.13]	[−9.92]	[−4.62]	[−4.74]	[−4.58]	[−3.44]
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	23400	22673	21612	18415	24974	24208	23501	20362
R-squared	0.219	0.243	0.261	0.299	0.211	0.222	0.226	0.209

Panel B: Disruption rate measure and profitability

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Profit margin$_{i,t}$ (%)			Profitability$_{i,t}$ (%)		$\ln(\sigma_{NP,i}^{t\to t+\Delta t})$			
	Gross	Gross	Net	Gross	Net	$\Delta t = 3$ y	$\Delta t = 4$ y	$\Delta t = 5$ y	$\Delta t = 10$ y
Data source	Compustat	NBER-CES	Compustat	Compustat	Compustat	Compustat	Compustat	Compustat	Compustat
$\hat{\lambda}_{i,t}$ (standardized)	−2.08**	−2.26*	−0.32*	−1.23***	−0.20*	−0.07***	−0.06***	−0.08***	−0.10***
	[−2.43]	[−1.81]	[−1.71]	[−3.00]	[−1.82]	[−3.48]	[−3.65]	[−4.34]	[−4.79]
ln(number of firms)$_{i,t}$	7.29***	3.34***	−1.57***	−1.49***	−1.32***	0.05**	0.05***	0.04***	0.03**
	[8.30]	[11.20]	[−6.87]	[−3.62]	[−7.78]	[2.57]	[2.83]	[2.74]	[2.10]
ln(sales)$_{i,t}$	−2.54***	−0.15	2.41***	−0.22	1.27***	−0.20***	−0.19***	−0.19***	−0.16***
	[−4.93]	[−0.76]	[10.97]	[−1.02]	[15.67]	[−19.04]	[−20.27]	[−19.88]	[−16.36]
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5274	2480	5269	5274	5269	4739	4540	4309	3307
R-squared	0.183	0.169	0.121	0.030	0.133	0.154	0.180	0.183	0.148

Note: We replicate the Fama-MacBeth regressions in the main text of our paper using the panel regression approach. We control for time fixed effects in our analysis. Panel A of this table replicates the analysis in panel C of Table 2. Panel B of this table replicates the analysis in panel A of Table B.6. We include t-statistics in brackets. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table B.10: Sensitivity of profitability and profit margins to accumulated consumption growth across industries with different levels of ROE.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	ΔAverage profit margin$_t$ (net, Compustat)				ΔAverage profitability$_t$ (net, Compustat)			
ROE tertiles	T1 (low)	T2	T3 (high)	T3 − T1	T1 (low)	T2	T3 (high)	T3 − T1
$(\mathbb{E}_t - \mathbb{E}_{t-1})\hat{g}_t$	−0.36	0.40***	0.29**	0.65**	0.11	0.42***	0.59***	0.48**
	[−1.27]	[3.01]	[2.52]	[2.13]	[0.52]	[3.50]	[5.76]	[2.48]
Observations	53	53	53	53	53	53	53	53
R-squared	0.002	0.062	0.045	0.007	0.001	0.094	0.153	0.016

Note: This table shows the sensitivity of the average profit margin and average profitability to accumulated consumption growth across industry portfolios sorted on ROE. $(\mathbb{E}_t - \mathbb{E}_{t-1})\hat{g}_t$ is the AR(1) shock of yearly accumulated consumption growth. The construction of yearly accumulated consumption growth is explained in Figure 1. The sample of this table spans the period from 1965 to 2017. Standard errors are computed using the Newey-West estimator allowing for serial correlation. We omit the coefficient for the constant term for brevity. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table B.11: ROE premia.

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Excess returns (%)				CAPM alphas (%)		
T1 (low)	T2	T3 (high)	T3 − T1	T1 (low)	T2	T3 (high)	T3 − T1
			Panel A: Cross-industry ROE premium				
6.22***	8.08***	10.01***	3.79***	−1.63**	1.03*	2.09***	3.72***
[3.74]	[4.33]	[5.83]	[3.79]	[−2.53]	[1.83]	[4.26]	[4.00]
			Panel B: Cross-industry ROE premium (bottom 70% of fitted HHI)				
6.23***	8.51***	10.23***	4.00**	−2.42***	0.11	1.58	4.00**
[4.05]	[7.13]	[4.31]	[2.28]	[−3.92]	[0.11]	[1.04]	[2.45]
			Panel C: Cross-industry ROE premium (top 30% of fitted HHI)				
6.66***	6.69***	6.41***	−0.24	0.06	0.12	−0.42	−0.48
[5.32]	[5.83]	[6.32]	[−0.16]	[0.05]	[0.17]	[−0.56]	[−0.33]
			Panel D: Within-industry ROE premium				
6.41**	7.37***	8.57***	2.16	−2.33*	−0.48	0.81	3.14**
[2.47]	[3.36]	[4.16]	[1.61]	[−1.73]	[−0.46]	[1.17]	[2.29]
			Panel E: Firm-level ROE premium				
5.82***	7.98***	7.84***	2.03*	−3.10**	0.40	0.41	3.51**
[4.13]	[4.95]	[4.70]	[1.75]	[−2.16]	[0.83]	[1.05]	[2.42]

Note: This table shows the value-weighted average excess returns and CAPM alphas for portfolios sorted on ROE. We include t-statistics in brackets. Standard errors are computed using the Newey-West estimator allowing for serial correlation in returns. We annualize average excess returns and alphas by multiplying them by 12. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table B.12: Exposure of ROE spreads to accumulated consumption growth.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Accumulated portfolio excess returns$_t$							
ROE tertiles	T1 (low)	T2	T3 (high)	T3 − T1	T1 (low)	T2	T3 (high)	T3 − T1
	Panel A: Exposure of the cross-industry ROE spread							
$\hat{g}_t$	1.89***	0.83	2.45***	0.56*	0.39	−0.47	1.29***	0.90**
	[3.26]	[1.37]	[4.84]	[1.91]	[1.20]	[−1.61]	[4.00]	[2.34]
Accumulated market excess returns$_t$					1.07***	0.92***	0.82***	−0.25***
					[20.77]	[29.41]	[25.07]	[−3.93]
Observations	257	257	257	257	257	257	257	257
R-squared	0.031	0.008	0.076	0.008	0.826	0.852	0.777	0.134
	Panel B: Exposure of the within-industry ROE spread							
$\hat{g}_t$	3.64***	1.60**	1.55**	−2.08***	2.34***	0.29	0.14	−2.20***
	[3.54]	[2.04]	[1.99]	[−3.53]	[4.80]	[0.97]	[0.37]	[−3.76]
Accumulated market excess returns$_t$					0.92***	0.93***	1.01***	0.09
					[10.19]	[15.14]	[28.58]	[0.99]
Observations	257	257	257	257	257	257	257	257
R-squared	0.104	0.026	0.023	0.071	0.647	0.746	0.823	0.081
	Panel C: Exposure of the firm-level ROE spread							
$\hat{g}_t$	1.39	1.44	2.20**	0.81*	−0.05	0.19	0.89*	0.93**
	[1.09]	[1.21]	[2.28]	[1.73]	[−0.14]	[0.36]	[1.99]	[2.02]
Accumulated market excess returns$_t$					1.02***	0.88***	0.93***	−0.09
					[4.74]	[25.82]	[19.03]	[−0.38]
Observations	257	257	257	257	257	257	257	257
R-squared	0.014	0.027	0.055	0.011	0.635	0.853	0.874	0.022

Note: This table shows the heterogeneous exposure to accumulated consumption growth for portfolios sorted on ROE. The analysis is performed at the quarterly level. We exclude financial firms and utility firms from the analysis. T-statistics are shown in brackets. Standard errors are computed using the Newey-West estimator allowing for serial correlation in returns. We omit the coefficients for the constant terms for brevity. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table B.13: Exposure of ROE spreads to IST shocks.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Portfolio excess returns$_t$							
ROE tertiles	T1 (low)	T2	T3 (high)	T3 − T1	T1 (low)	T2	T3 (high)	T3 − T1
	Panel A: Exposure of the cross-industry ROE spread							
IMC$_t$	0.77***	0.63***	0.81***	0.04	0.17***	0.07*	0.21***	0.04
	[14.65]	[13.05]	[14.54]	[1.15]	[4.68]	[1.80]	[5.91]	[1.12]
MktRf$_t$					0.99***	0.92***	0.98***	−0.01
					[48.68]	[47.61]	[50.20]	[−0.28]
Observations	804	804	804	804	804	804	804	804
R-squared	0.295	0.249	0.320	0.003	0.872	0.876	0.877	0.003
	Panel B: Exposure of the within-industry ROE spread							
IMC$_t$	1.04***	0.86***	0.71***	−0.33***	0.44***	0.29***	0.11***	−0.33***
	[17.04]	[14.59]	[14.06]	[−7.78]	[7.43]	[4.56]	[3.37]	[−6.79]
MktRf$_t$					1.01***	0.94***	1.00***	−0.00
					[29.22]	[32.87]	[60.51]	[−0.07]
Observations	804	804	804	804	804	804	804	804
R-squared	0.385	0.342	0.268	0.147	0.805	0.822	0.895	0.147
	Panel C: Exposure of the firm-level ROE spread							
IMC$_t$	1.02***	0.69***	0.61***	−0.41***	0.39***	0.10***	0.01	−0.38***
	[15.00]	[8.36]	[5.93]	[−4.16]	[5.69]	[3.77]	[0.35]	[−4.54]
MktRf$_t$					1.05***	0.98***	1.00***	−0.05
					[22.78]	[60.24]	[45.96]	[−0.77]
Observations	804	804	804	804	804	804	804	804
R-squared	0.376	0.277	0.229	0.195	0.841	0.937	0.948	0.199

Note: This table shows the exposure to IST shocks for portfolios sorted on ROE. The analysis is performed at the monthly level. We exclude financial firms and utility firms from the analysis. We include t-statistics in brackets. Standard errors are computed using the Newey-West estimator allowing for serial correlation in returns. We omit the coefficients for the constant terms for brevity. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.