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Competition, profitability, and discount rates☆

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ABSTRACT

We build an asset-pricing model with dynamic strategic competition to explain the strong joint fluctuations in aggregate discount rates, competition intensity, profitability, and asset prices. Product market competition endogenously intensifies as discount rates rise, because firms compete more aggressively for current cash flows by undercutting each other as the value of future cooperation decreases. In industries with a lower turnover rate of market leaders, firms' profit margins tend to be higher yet more exposed to discount-rate fluctuations, thereby generating the gross profitability premium. We exploit large tariff cuts to identify exogenous variation in market structure to test the core mechanism directly.

1. Introduction

Product markets are highly concentrated and market leadership is persistent, leading to strategic competition

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among market leaders.[1] When rival firms undercut profit margins aggressively to gain revenue and market share, the industry competition intensifies. The competition intensity, as reflected in profit margins, fluctuates dramatically over time and concerns investors. However, these important facts emphasized in the industrial organization literature have been largely overlooked in asset pricing research.

The goal of this paper is to fill this gap by showing that fluctuations in discount rates play an important role in generating endogenous fluctuations in competition intensity. Discount rates (or risk premia) vary dramatically over time (e.g., Rozeff, 1984; Fama and French, 1988; Campbell and Shiller, 1988; Cochrane, 2011; Lustig and Verdelhan, 2012). We show that high discount rates depress firms' profit margins by intensifying industry competition. Further, we also show that the sensitivity of competition intensity to aggregate discount-rate shocks is highly heterogeneous across industries. Specifically, the impact of discount rates on competition intensity is greater for industries in which market leadership is more persistent. The endogenous competition mechanism can in turn explain various important asset pricing patterns, including the industry-level gross profitability premium (see Novy-Marx, 2013).

The repeated-game paradigm, particularly the collusion model and folk theorem (Fudenberg and Maskin, 1986), has become a dominant theoretical framework in the industrial organization (IO) literature for investigating strategic competition.[2] This paradigm allows for a rich set of dynamic competition strategies such as tacit collusion, which can describe the product-market behavior of market leaders realistically. However, the role of discount rates emphasized in the asset pricing literature has been overlooked in existing IO research.

In this article, we propose the first elements of a tractable dynamic framework to tackle this challenge. In a nutshell, our model incorporates repeated games with collusive equilibrium into an otherwise standard industry equilibrium framework with time-varying discount rates. The industry features a dynamic Bertrand oligopoly with differentiated products. Oligopolists can collude tacitly with each other to obtain high profit margins. Knowing that competitors will honor the collusive profit-margin agreement, a firm can boost its short-run revenue by deviating from the collusive scheme and undercutting profit margins to attract more customers. However, such betrayal of trust comes at a price, as revenue is reduced in the long run because the competitors will eventually find out and punish the firm's deviation behavior by ceasing cooperation in the future. 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. Therefore, higher collusive profit margins are more difficult to sustain when the discount rate is higher because future punishment becomes less threatening when firms discount future cash flows to a greater extent. In short, a rise in the discount rate intensifies competition and thus narrows profit margins by diminishing the present value of future cooperation.

Further, our model implies that the impact of discount rates on competition intensity is greater in industries with more persistent market leadership. The turnover rate of market leadership is a fundamental industry characteristic and is the only ex-ante heterogeneity across industries in our model. Upon an exogenous leadership turnover, existing market leaders are displaced by new market leaders who used to be market followers themselves. Intuitively, in the industries where market leaders are more likely to be replaced by market followers in the near future, the punishment for deviation behavior becomes less threatening. Thus, market leaders in such industries find it more difficult to collude. The lack of collusion incentives results in low collusive profit margins, which are also less responsive to fluctuations in discount rates. By contrast, in industries with a lower turnover rate of market leaders, the existing market leaders' position is more persistent, making the punishment for deviation behavior in the future more threatening. As a result, firms in such industries can collude more easily and obtain higher profit margins, which are also more sensitive to fluctuations in discount rates.

Our model improves the understanding of how fluctuations in discount rates are priced in the cross section, a central question in asset pricing research. The seminal work of Campbell and Vuolteenaho (2004) finds that cash-flow shocks, rather than discount-rate shocks, play a crucial role in explaining the value premium and the size premium.[3] In the literature, a long-standing question is as follows: In which cross sections, if any, do discount rates play a crucial role in explaining the return predictability? Our model suggests an answer based on imperfect industry competition. Through the endogenous competition channel, industries' exposure to discount-rate shocks is simultaneously reflected in two cross sections: Firms are more exposed to discount-rate shocks and their expected stock returns are higher (i) if their gross profitability is higher and (ii) if their market leadership persistence is higher. Based on the endogenous betas with respect to discount-rate shocks, our model offers an explanation for the cross-industry gross profitability premium: more profitable industries have higher expected returns.

Not only do we make contributions in theory, but we also provide strong supporting evidence and empirically test the main predictions of our model. We measure

[1] According to U.S. Census data, the top four and eight firms within each four-digit SIC (Standard Industrial Classification) industry account for more than 48% and 60% of that industry's total revenue, respectively. For further evidence, see, e.g., Autor et al. (2020), De Loecker et al. (2020), and Grullon et al. (2019) for a high concentration of product markets, and Geroski and Toker (1996), Matraves and Rondi (2007), Sutton (2007), and Bronnenberg et al. (2009) for leadership persistence.

[2] Examples include Green and Porter (1984), Brock and Scheinkman (1985), Rotemberg and Saloner (1986), Haltiwanger and Harrington (1991), Bagwell and Staiger (1997), Fershtman and Pakes (2000), Athey et al. (2004), Athey and Bagwell (2008), Green et al. (2015), Wiseman (2017), and Byrne and de Roos (2019).

[3] This empirical finding is also supported by Lettau and Wachter (2007), Bansal et al. (2005), Parker and Julliard (2005), Hansen et al. (2008), Cohen et al. (2009), Campbell et al. (2010), Santos and Veronesi (2010), and Dittmar and Lundblad (2017).

discount-rate variation using off-the-shelf proxies, in particular, the smoothed earnings-price ratio proposed by Campbell and Shiller (1988, 1998). To directly test the economic mechanism of our model, we construct a proxy for the likelihood of market leadership turnover. Specifically, we use patent data to construct a measure that captures the innovation similarity among industries. In light of previous studies (e.g., Jaffe, 1986; Bloom et al., 2013), a higher innovation similarity predicts a lower likelihood of radical innovation in the industry, and thus a lower likelihood of market leadership turnovers. Using the innovation similarity measure, as well as other industry characteristics, we construct an estimate of the turnover rate of market leaders based on a logistic regression, which is referred to as the *leadership turnover measure*.

We conduct our empirical analysis in three steps. First, we study the relation between discount rates, profitability, and stock returns. We show that profitability comoves negatively with discount rates and that such comovement is more pronounced in more profitable industries. We also show that the cross-industry gross profitability spread (high minus low) is significantly positive and loads negatively on discount-rate shocks.

Second, we examine the model-implied connection between an industry's profitability and market leadership turnover rate in the cross section. We empirically show that more profitable industries are indeed less likely to experience market leader changes. The leadership turnover measure is priced in the cross section of industries. Similar to the cross-industry gross profitability spread, the long-short return spread sorted on the leadership turnover measure also loads significantly on discount-rate shocks. Moreover, we show that the cross-industry gross profitability premium decreases substantially and becomes statistically insignificant after controlling for the leadership turnover measure. The above findings support the key theoretical implications of our model: 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.

Third, we directly test the core competition mechanism. Specifically, our model focuses on the gap in the sensitivity of profitability to discount-rate shocks between the more and less profitable industries (or between the industries with high and low leadership persistence). According to the model (see Section 3.8), this gap is less pronounced when industries' *market structure becomes more competitive*, which occurs when the industry-level price elasticity of demand (denoted by ϵ) is higher or when the number of market leaders within the industry (denoted by n) is greater. We exploit two empirical settings to test this hypothesis and find strong supporting evidence. In the first setting, we follow the literature (Frésard, 2010; Valta, 2012; Frésard and Valta, 2016) and use unexpected large cuts in import tariffs to identify exogenous variation in market structure. Intuitively, large tariff cuts render the industry market structure more competitive because the softening of trade barriers can increase the industry's price elasticity of demand ϵ and the number of market leaders within the industry n. In the second setting, we focus on large increases in the cross-industry product similarity measure, constructed based on the firm-level pairwise similarity scores (e.g., Hoberg and Phillips, 2010a; 2016). A large increase in an industry's cross-industry product similarity indicates that the products of this industry become more similar to those of other industries, leading to a higher industry-level price elasticity of demand ϵ and thus a more competitive market structure. Consistent with the implications of our model, we find that the gap in the sensitivity of profitability to discount-rate shocks between the more and less profitable industries (or between the industries with high and low leadership persistence) diminishes following large tariff cuts or large increases in cross-industry product similarity.

At the end of this paper, we conduct quantitative analysis. Shown in Appendix A, we evaluate the quantitative capacity of the mechanism based on an extended model that incorporates collusion costs and multiple (i.e. more than two) market leaders in the industry. In particular, firms incur a nonpecuniary cost to maintain collusion. We show that they optimally abandon collusion when the cost exceeds the benefit after large drops in the discount rate. As a result, the industry falls into the noncollusive equilibrium, which occurs when competition is the fiercest. The endogenous switch from the collusive to the noncollusive equilibrium generates a significant downward jump in profit margins, amplifying the impact of discount-rate shocks.[4] Moreover, such equilibrium switching is more likely when the discount rate rises. We further show that the oligopoly industry with three market leaders has lower collusive profit margins than the duopoly industry because firms find it more difficult to collude when there are more market leaders. The asset pricing implications of the endogenous competition mechanism in the duopoly industry and the oligopoly industry are quantitatively similar. This is because the endogenous jumps from collusive to noncollusive equilibria take place more frequently in the oligopoly industry and the lower collusive profit margins reinforce the leverage effect in percentage terms, even though collusive profit margins respond less dramatically to discount-rate shocks.

Related literature. Our paper contributes to the burgeoning literature situated at the intersection of IO, marketing, and finance. In this literature, earlier contributions focus on the interaction of competition and contracting, including Fershtman and Judd (1987), Bolton and Scharfstein (1990), and Aggarwal and Samwick (1999), among others. Recently, more studies have emerged on the interaction of competition, asset pricing, and industry dynamics (e.g., Hou and Robinson, 2006; Novy-Marx, 2007; Carlin, 2009; Aguerrevere, 2009; Carlson et al., 2014; Opp et al., 2014; Bustamante, 2015; Koijen and Yogo, 2015; Bustamante and Donangelo, 2017; Corhay, 2017; Andrei and Carlin, 2018; Chen et al., 2019; Corhay et al., 2020;

[4] In our model, the endogenous equilibrium switching is driven by fundamental shocks. By contrast, the endogenous equilibrium switching can also be caused by self-fulfilling beliefs (e.g., Tsyvinski et al., 2006; Angeletos et al., 2007; Bebchuk and Goldstein, 2011; Goldstein et al., 2017).

Dou et al., 2020a).[5] In a recent effort, Corhay et al. (2020) 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 noncollusive Nash equilibria, while we consider collusive Nash equilibria. Different from theirs, our model yields the gross profitability premium, especially across industries. Opp et al. (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; (ii) their model focuses on industries with different numbers of firms, 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 heterogenous variability of profit margins, as well as the cross-industry gross profitability premium; and (iii) their model is qualitative, whereas ours is quantitative. Another strand of literature studies the asset pricing implications of imperfect competition in the market microstructure setting (e.g., Christie and Schultz, 1994; Biais et al., 2000; Atkeson et al., 2015).

Our paper also contributes to the literature on the relation between corporate profitability and stock returns (e.g., Fama and French, 2006; Novy-Marx, 2013; Hou et al., 2015; Ball et al., 2015; 2016; Deng, 2018). Fama and French (2006) find that earnings have explanatory power for stock returns. Novy-Marx (2013) shows 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 the work of Kogan and Papanikolaou (2013), who highlight the role of the investment-specific technology (IST) shock as a systematic 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, especially the cross-industry one, arising from the endogenous competition mechanism.

Our model proposes a novel and robust channel through which discount-rate fluctuations have IO implications. As stressed by Cochrane (1991), discount-rate variations have important applications in understanding core questions in other fields, such as portfolio theory, corporate finance, and macroeconomics. For example, Dou and Verdelhan (2017) show that discount-rate fluctuations are the dominant force driving international capital flows; Haddad et al. (2017) show that discount-rate variations affect buyout activities; Gourio (2012) shows that the discount-rate shock is a major underlying force that drives business cycles; Mukoyama (2009), Hall (2017), Kilic and Wachter (2018), and Mitra and Xu (2020) argue that discount-rate variations explain large fluctuations in unemployment.[6] However, little is known about how discount-rate fluctuations apply to IO research. We contribute to this research agenda by showing that discount-rate fluctuations are important to understanding fluctuations in competition intensity, a core IO question.

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, Garlappi (2004) analyzes the impact of competition on the risk premia of R&D ventures engaged in a multiple-stage patent race with technical and market uncertainty. Pástor and Veronesi (2012, 2013) develop models with learning to study the asset pricing implications of political uncertainty and firms' profitability. In addition, 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 (2020) 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 mutual fund literature, Hugonnier and Kaniel (2010) and Kaniel et al. (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 the followers (i.e., the investors) move next. Our model highlights endogenous cash flows driven by the strategic considerations of agents. Specifically, consistent with the data, profit margins fluctuate substantially and are endogenously driven by time-varying competition intensity in our model. Competition intensifies as the discount rate rises in bad times. 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 as the *competition risk premium*.

Finally, our paper is also situated in the vast literature on continuous-time asset pricing theory (e.g., Cochrane, 1991; Berk et al., 1999; Gomes et al., 2003; Menzly et al., 2004; Santos and Veronesi, 2006; Kogan et al., 2009; Pástor and Veronesi, 2009; Papanikolaou, 2011; Gârleanu et al., 2012; Ai and Kiku, 2013; Eisfeldt and Papanikolaou, 2013; Hackbarth and Johnson, 2015; Dou, 2017; Kogan et al., 2017; Dou et al., 2019). In particular, similar to the work of Papanikolaou (2011) and Dou et al. (2019), our

[5] The strand of literature located at the intersection of IO and corporate finance has also been growing (e.g., Phillips, 1995; Kovenock and Phillips, 1997; Allen and Phillips, 2000; Aghion et al., 2005; Morellec and Zhdanov, 2005; 2008; Hoberg and Phillips, 2010a; Hackbarth and Miao, 2012; Phillips and Zhdanov, 2013; Hackbarth et al., 2014; Hoberg et al., 2014; Hoberg and Phillips, 2016; Azar et al., 2018; Hackbarth and Taub, 2018; Dou and Ji, 2020; Roussanov et al., 2020).

[6] There has been growing interest in the relation between discount-rate shocks and labor market dynamics (e.g., Borovička and Borovičková, 2018; Kehoe et al., 2019; Martellini et al., 2019).

economic mechanism implies that firm exposure to an aggregate shock is simultaneously reflected in two different cross sections associated with different firm characteristics. Such overidentification makes the model more quantitatively disciplined and improves the power and validity of the asset pricing test by checking whether the return spread from one cross section can explain the return predictability from the other cross section.

2. Motivating facts

We present two motivating facts about competition, profitability, and stock returns. The first motivating fact is a time-series pattern as illustrated in Fig. 1. The average profit margin over industries, reflecting the average competition intensity in product markets, negatively comoves with discount rates (see panels A and B).[7] Moreover, as a prominent form of intensified competition in product markets, price wars present a severe concern for investors, and their coverage by the media and analysts is strongly countercyclical, positively comoving with discount rates (see panels C and D). The time series of the coverage by media and analyst reports are constructed based on textual analysis. This motivating fact provides direct evidence on the procyclical patterns of competing firms' collusion incentives from investors' perspective: the competition is high when the discount rate is high. The implications of competition intensity fluctuations for 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.

The second motivating fact is a cross-sectional pattern as illustrated in Fig. 2. Firms with higher gross profitability have stock returns that are more negatively exposed to discount-rate shocks (see panel A). This suggests that the exposure to discount-rate shocks has the potential to rationalize the gross profitability premium because these shocks carry a negative market price of risk. However, panels B and C of Fig. 2 suggest that the mechanism behind the gross profitability premium (Novy-Marx, 2013) might be more subtle than one would expect: the cross- and within-industry gross profitability premia can be caused by different economic mechanisms. In particular, panel B shows that industries with higher gross profitability have stock returns that load more negatively on discount-rate shocks, while panel C shows that this pattern is not robust within industries. Therefore, the exposure to discount-rate shocks can potentially justify the cross-industry gross profitability premium, but not the within-industry one. As an important complement, the displacement risk channel proposed by Kogan and Papanikolaou (2013) mainly rationalizes the within-industry gross profitability premium.[8]

To better understand the economic mechanism behind the cross-industry return pattern (panel B), we look at the exposure of industry-level cash flows to discount-rate shocks. Panel D shows that industries with higher gross profitability have profitability that loads more negatively on discount-rate shocks, consistent with the pattern of industry-level stock returns.

3. The baseline model

To rationalize the time-series and cross-sectional patterns in Figs. 1 and 2, we develop an industry-equilibrium model with dynamic games and time-varying market prices of risk to generate endogenous time-varying competition intensity in the product market of n oligopolies. For simplification, we assume that the industry has two market leaders indexed by $i \in \{1, 2\}$, so it is essentially a duopoly (i.e., $n = 2$). We label a generic leading firm by i and its competitor by j. Firms produce differentiated perishable goods and set their profit margins strategically to maximize shareholder value.

3.1. Customer base and demand

Demand system for differentiated products. Firms within the same industry produce differentiated products. To model product differentiation, we assume that consumers derive utility from purchasing a basket of differentiated goods with imperfect substitution. Specifically, we denote the industry-level consumption index by C_t, consisting of a basket of firm-level composites $C_{i,t}$. More precisely, the industry-level consumption index C_t is determined by a Dixit-Stiglitz constant-elasticity-of-substitution (CES) aggregation:

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

where $C_{i,t}$ is the amount of firm i's products purchased by consumers, and the parameter $\eta > 1$ captures the elasticity of substitution among goods produced by different firms in the same industry. The greater the industry-level consumption index C_t is, the more utility consumers derive from it. Intuitively, the weight $M_{i,t}/M_t$ captures consumers' relative "taste" for firm i's products; in other words, the greater the

[7] The average profit margin is the simple average of industries' profit margins as in Machin and Van Reenen (1993), so the comovement does not arise from a composition effect from time-varying industry size. We focus on the comovement between discount rates 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 procyclical (e.g., Machin and Van Reenen, 1993; Hall, 2012; Anderson et al., 2018). Although markups and profit margins are related, the empirical evidence on the cyclicality of markups is mixed, primarily because measuring markups is challenging (e.g., Blanchard, 2009; Anderson et al., 2018). For example, Domowitz et al. (1986), Nekarda and Ramey (2011, 2020), Hall (2014), and Braun and Raddatz (2016) find that markups are procyclical, whereas Bils (1987) and Chevalier and Scharfstein (1996) find them to be countercyclical.

[8] When the economy is hit by positive IST shocks, large and mature firms, which are usually more profitable, tend to be displaced by small and young firms, which are usually less profitable. This generates the gross profitability premium in the cross section within an industry. Intuitively, this channel mainly works within industries (see Table 11) since it is extremely difficult for one industry to displace another due to moderate innovation shocks.

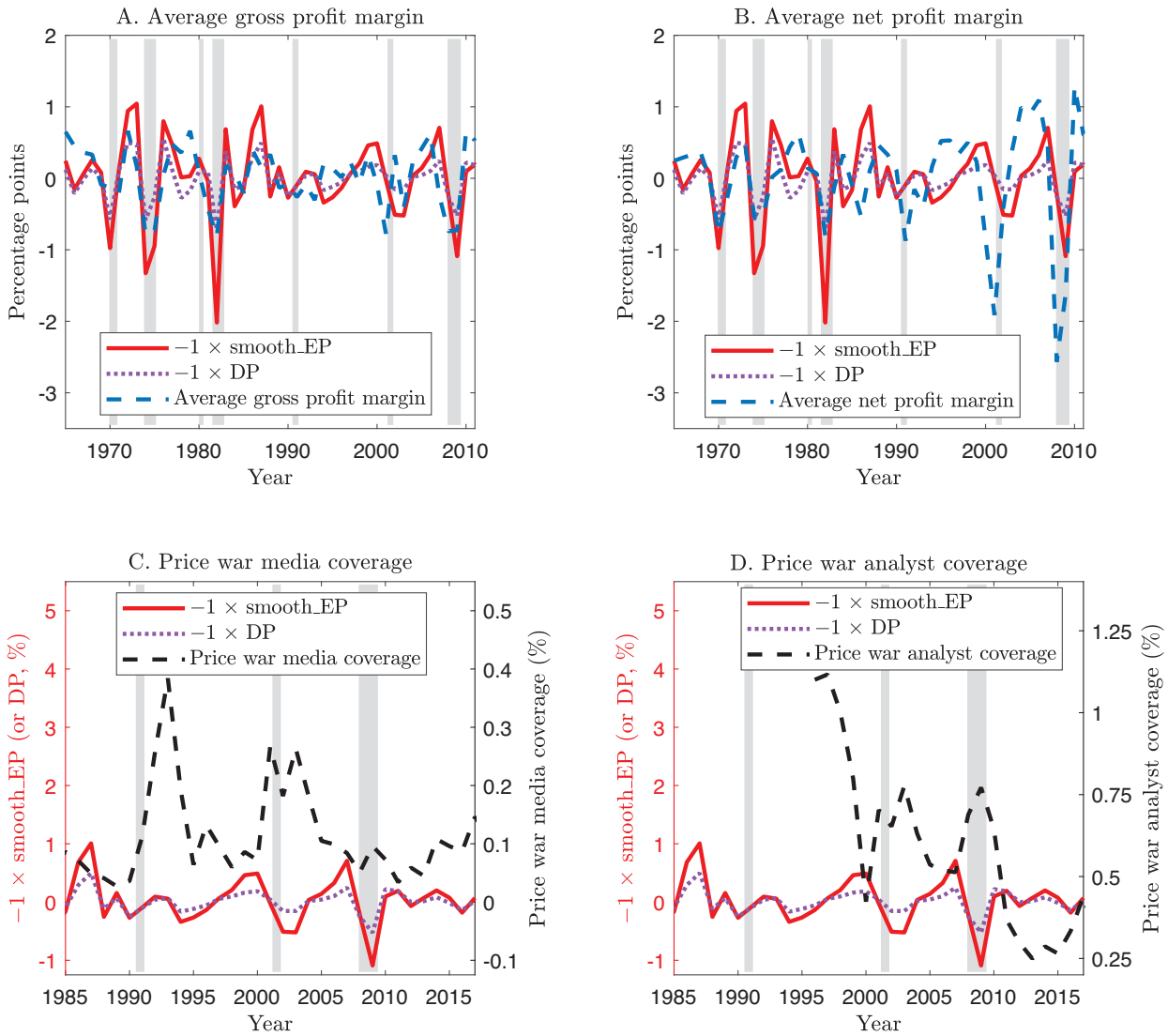

Fig. 1. Competition, profit margins, and discount rates.
This figure shows the strong comovement between competition intensity and discount rate. Panels A and B plot the yearly time series of average profit margins and discount rates using the Hodrick-Prescott (HP) filter with a smoothing parameter of 6.25 (see Ravn and Uhlig, 2002). Panels C and D plot the media and analyst coverage of price wars, respectively. Grey areas represent the National Bureau of Economic Research (NBER) recession periods. We use the smoothed earnings-price ratio (denoted by smooth_EP) proposed in the work of Campbell and Shiller (1988, 1998) as an empirical proxy for discount rates. Because the discount-rate measure is countercyclical, we multiply the smoothed earnings-price ratio by −1, so that high (low) values of the red solid line in the plot represent good (bad) times. We also plot the dividend-price ratio (denoted by DP) as an alternative measure of discount rates. We plot profit margins and discount rates at the yearly frequency in panel A because profit margins exhibit strong seasonality at the quarterly frequency. Yearly valuation ratios (i.e., smooth_EP and DP) are the average values of the monthly valuation ratios in each year. See Appendix B for detailed explanations of the construction of profit margins and the coverage of price wars.

weight $M_{i,t}/M_t$ is, the higher the utility consumers derive from consuming a unit of firm i's products, all other things being equal.

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

$$C_{i,t} = \frac{M_{i,t}}{M_t}\left(\frac{P_{i,t}}{P_t}\right)^{-\eta} C_t, \quad \text{with industry price index}$$

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

In Eq. (2), the demand for firm i's goods increases with $M_{i,t}$, all else unchanged. From a firm's perspective, it is natural to think of consumers' taste $M_{i,t}$ as firm i's customer base (or customer capital) and M_t as the industry's total customer base (e.g., Gourio and Rudanko, 2014; Dou et al., 2019). The share $M_{i,t}/M_t$ can be interpreted as the customer base share of firm i. Moreover, Eq. (2) implies that firm i has a greater influence on the price index P_t

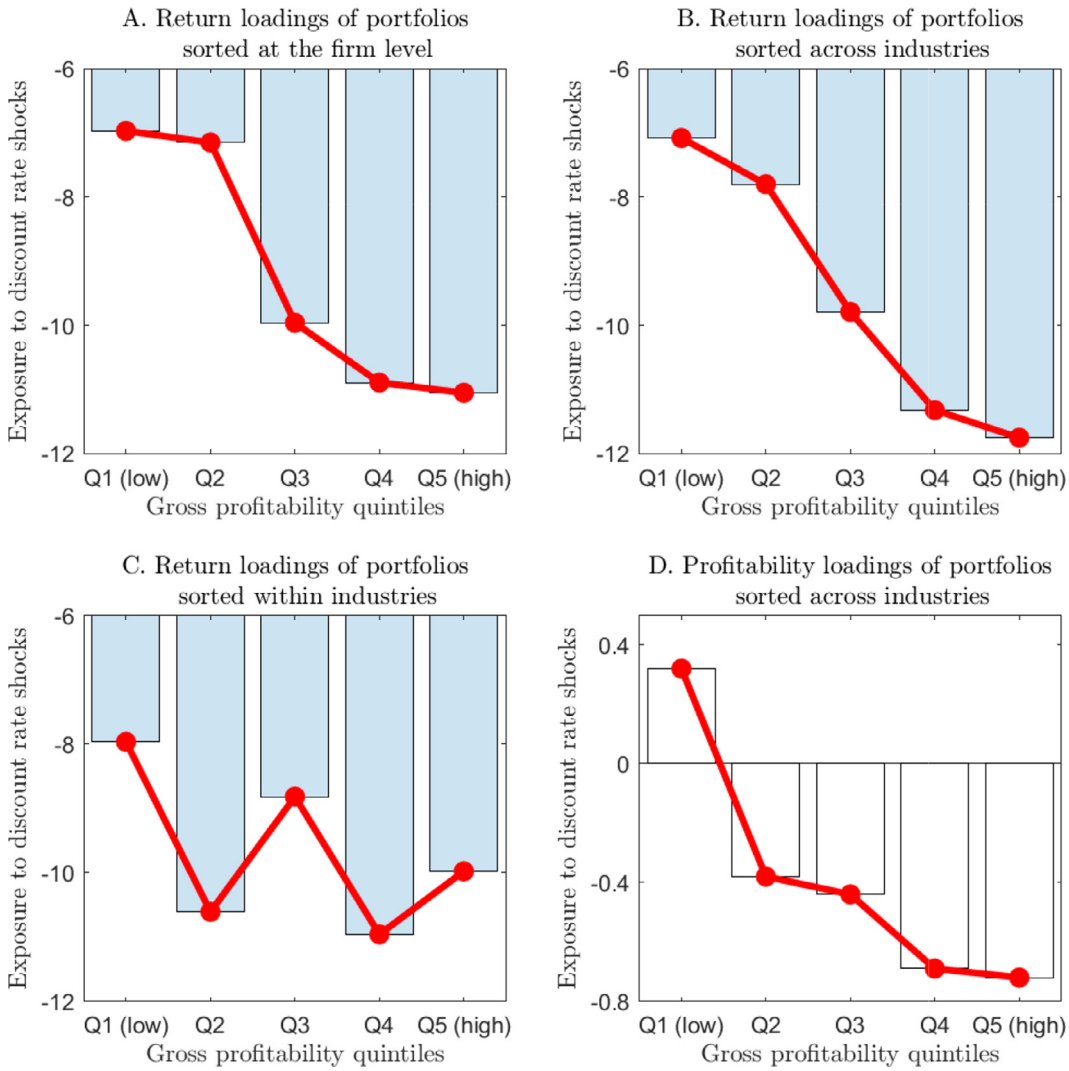

Fig. 2. Loadings on discount-rate shocks across gross-profitability-sorted portfolios.
This figure shows the exposure of profitability and portfolio returns to discount-rate shocks across gross-profitability-sorted portfolios. Panel A plots the return loadings on discount-rate shocks of firm portfolios constructed by sorting all firms on gross profitability. Panel B plots the return loadings on discount-rate shocks of industry portfolios constructed by sorting all industries on industry-level gross profitability. Panel C plots the return loadings on discount-rate shocks of firm portfolios constructed by sorting firms within the same industry on gross profitability. The return loadings in panels A–C are estimated in Table 3. Panel D plots the profitability loadings on discount-rate shocks of industry portfolios constructed by all industries on industry-level gross profitability. The profitability loadings in panel D are estimated in Table 1. The differences in the loadings between the high (Q5) and low (Q1) gross profitability portfolios are statistically significant for panels A, B, and D, but insignificant for panel C (see Tables 1 and 3).

when it possesses a larger share of the customer base, $M_{i,t}/M_t$. Thus, firm i has the incentive to accumulate $M_{i,t}$ to increase demand and gain market power.

Consumers would naturally like to purchase more products C_t to gain higher utility, but doing so incurs a cost that is dependent on the price index P_t for the basket of goods. To capture such a tradeoff, we follow the seminal work on industry dynamics by Hopenhayn (1992), Pindyck (1993), and Caballero and Pindyck (1996), postulating an industry-level demand curve $C_t = \mathscr{D}(P_t)$ as a function of the industry's price index P_t. Specifically, we assume an isoelastic industry demand curve:

$$C_t = M_t P_t^{-\epsilon}, \tag{3}$$

where M_t, as defined in Eq. (1), is an endogenous stochastic process that captures the total customer base of the industry. The coefficient $\epsilon > 1$ captures the industry's price elasticity of demand. A common microfoundation for such an isoelastic industry demand curve is that a continuum of industries exist in the economy producing differentiated industry-level baskets of goods, with the elasticity of substitution across industries being ϵ and the preference weight for an industry's goods equal to its customer base M_t.[9]

[9] The CES utility function that embodies aggregate preference for diversity over differentiated products can be further microfounded by the

Consistent with the literature (e.g., Atkeson and Burstein, 2008; Corhay et al., 2020), we assume that $\eta \geq \epsilon > 1$, 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 a cup of coffee.

In sum, by combining Eqs. (2) and (3), the demand system for differentiated products in our model is fully characterized as follows:

$$C_{i,t} = M_{i,t}\left(\frac{P_{i,t}}{P_t}\right)^{-\eta} P_t^{-\epsilon}, \quad \text{with } P_t = \left[\sum_{j=1}^{2}\left(\frac{M_{i,t}}{M_t}\right)P_{i,t}^{1-\eta}\right]^{\frac{1}{1-\eta}}, \tag{4}$$

which is a standard CES demand system.

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

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

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

$$\mu_{i,t} = \frac{P_{i,t}C_{i,t}}{P_t C_t} = \left(\frac{P_{i,t}}{P_t}\right)^{1-\eta}\frac{M_{i,t}}{M_t}. \tag{5}$$

Eq. (5) 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. On the one hand, when the market share $\mu_{i,t}$ shrinks, within-industry competition becomes more relevant for firm i, so its price elasticity of demand depends more heavily on η. In the extreme case where $\mu_{i,t} = 0$, firm i becomes atomistic and takes the industry price index P_t as given. As a result, firm i's price elasticity of demand is exactly η. On the other hand, when $\mu_{i,t}$ grows, cross-industry competition becomes more relevant for firm i and thus its price elasticity of demand depends more strongly on ϵ. In the extreme case where $\mu_{i,t} = 1$, firm i monopolizes the industry, and its price elasticity of demand is exactly ϵ.

Each firm's price has a nonnegligible effect on the price index of the duopoly industry. Thus, when setting prices, each firm internalizes the effect of its own price on P_t, which in turn determines the total demand for the industry's products. If a continuum of firms exist in the industry as in standard monopolistic competition models, each firm would be atomistic and would have no influence over P_t, and cross-industry competition would have no impact on the firm's price elasticity of demand.

3.2. Evolution of customer base

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

We assume that a change in market leaders in an industry (i.e., leadership turnover) occurs exogenously with intensity λ. We use the Poisson process N_t to characterize the exogenous occurrence of leadership turnover in the industry. The economy comprises a continuum of industries, and thus the industry-specific change in market leaders (i.e., $dN_t = 1$) is an idiosyncratic event to the representative investor. Upon such a change ($dN_t = 1$), the existing market leaders are replaced by new market leaders who used to be followers themselves. Each of the new leaders has the same initial customer base $\overline{M} > 0$. This parsimonious assumption technically ensures that the industry-level customer base M_t is mean-reverting and stationary in the model.[10]

The persistence of the position of market leaders is significantly heterogeneous across industries.[11] In this paper, we focus on the ex-ante heterogeneity in market leadership persistence λ as a crucial and fundamental industry characteristic across industries.

Deep habits and demand shocks. Firms can attract consumers by undercutting profit margins, using strategies such as lowering prices, offering discounts, or increasing marketing expenses. An increase in contemporaneous demand $C_{i,t}$ can boost the firm's demand in the long term due to consumption inertia, information frictions, and switching costs. To capture this idea, following Phelps and Winter (1970) and Ravn et al. (2006), we model the evolution of firm i's customer base, conditioned on $dN_t = 0$ (i.e., leadership turnover does not take place over $[t, t+dt]$), as follows:

$$dM_{i,t}/M_{i,t} = \left[\alpha(C_{i,t}/M_{i,t})^h - \rho\right]dt + \varsigma dZ_t + \sigma_M dW_{i,t}. \tag{6}$$

In Eq. (6), the term $\alpha\left(C_{i,t}/M_{i,t}\right)^h dt$ captures the endogenous accumulation of customer base. Intuitively, by setting a lower price $P_{i,t}$, firm i increases the contemporaneous demand flow rate $C_{i,t}$ according to Eq. (4), thereby allowing it to accumulate a larger customer base over $[t, t+dt]$. The parameter $\alpha > 0$ captures the speed of accumulation. A greater α indicates that customer base accumulation is more sensitive to contemporaneous demand $C_{i,t}$. The parameter $h \in [0, 1]$ captures the relative importance of contemporaneous demand in accumulating customer base.

characteristics (or address) model and the discrete choice theory (e.g., Anderson et al., 1989).

[10] How innovation and competition affect 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.

[11] See, e.g., Baldwin (1995), Geroski and Toker (1996), Caves (1998), Matraves and Rondi (2007), Sutton (2007), Bronnenberg et al. (2009), and Ino and Matsumura (2012) for empirical evidence on the significant heterogeneity of λ.

Next, we summarize the role of the endogenous drift term $\alpha\left(C_{i,t}/M_{i,t}\right)^h \mathrm{d}t$ in the evolution equation. First, it generates consumption inertia. Second, setting a lower profit margin leads to not only higher contemporaneous demand $C_{i,t}$, but also a larger future customer base and demand on average. It essentially means that the long-run price elasticity of demand is higher than the short-run elasticity, consistent with the empirical evidence (e.g., Rotemberg and Woodford, 1991). Third, according to Eq. (5), the firm with a smaller customer base $M_{i,t}$ in the industry faces a higher price elasticity of demand, and thus sets a lower price. The lower price induces a higher demand per unit of customer base $C_{i,t}/M_{i,t}$ according to Eq. (2), allowing the firm to accumulate a customer base faster than the other firm in the industry. Thus, the endogenous drift term $\alpha\left(C_{i,t}/M_{i,t}\right)^h \mathrm{d}t$ ensures that the two firms will not be too different from each other in terms of customer base in the stationary equilibrium. Last but not least, the endogenous drift term can generate different growth rates for different industries. We assume that the new market leaders' customer base is "reset" to a constant level of $\overline{M} > 0$ when market leadership changes. Therefore, we emphasize that no industry would grow so much relative to others as to dominate the economy in the long run, and thus the distinction between industries would not become blurred in the long run.

The constant term ρ in Eq. (6) captures customer base depreciation due to industry-level reasons such as mortality. The standard Brownian motion Z_t captures economy-wide aggregate shocks, and $W_{i,t}$ idiosyncratic shocks, to firm i's customer base. These shocks are mutually independent and shift the demand system of consumers. The aggregate shock Z_t can be interpreted as the aggregate demand shock, while $W_{1,t}$ and $W_{2,t}$ can be interpreted as idiosyncratic demand (or "taste") shocks. We introduce the aggregate shock mainly to ensure that aggregate discount-rate fluctuations matter for valuation of firms' cash flows and generate time-varying industry competition intensity. Moreover, we introduce the idiosyncratic shocks mainly to generate a nondegenerate cross-sectional distribution of customer base in the stationary equilibrium.

The preference for differentiated goods, combining Eqs. (1) and (6), is similar to the *relative deep habits* preference (e.g., Ravn et al., 2006; Binsbergen, 2016). The specification of relative deep habits is inspired by the habit formation of Abel (1990), which features *catching up with the Joneses*. The defining feature of relative deep habits is that agents form habits over (or loyalties to) individual varieties of goods as opposed to a composite consumption good. The coefficient α captures the strength of deep habits. When $\alpha = 0$, the deep habit channel collapses. For small values of α, as suggested by the empirical results of Gilchrist et al. (2017), the firm-level customer base $M_{i,t}$ is persistent over time, which can be interpreted as consumer inertia and brand loyalty to firm i's product (Klemperer, 1995).

3.3. Production and profit margins

Firms produce differentiated goods using capital, rented at a competitive rental rate $\omega \equiv r + \delta$. The risk-free rate is r, and the capital depreciation rate is δ.[12] Each firm uses an AK production technology. Over $[t, t + \mathrm{d}t]$, firm i produces a flow of goods with intensity

$$Y_{i,t} = AK_{i,t}, \tag{7}$$

where $K_{i,t}$ is the amount of capital rented by firm i at t. The rental cost is $\omega K_{i,t}\mathrm{d}t$ over $[t, t + \mathrm{d}t]$. Given productivity level A, the marginal cost of producing one unit of goods is ω/A. Without loss of generality, we normalize $A \equiv 1$. Thus, the firm incurs cost with intensity $\omega Y_{i,t}$ in producing a flow of goods with intensity $Y_{i,t}$ over $[t, t + \mathrm{d}t]$. Given the demand $C_{i,t}$ and price $P_{i,t}$, firm i's optimal profits over $[t, t + \mathrm{d}t]$ are

$$\text{Earnings}_{i,t} = \max_{Y_{i,t} \geq 0} (P_{i,t} - \omega) Y_{i,t}, \quad \text{subject to the demand constraint } Y_{i,t} \leq C_{i,t}. \tag{8}$$

Similar to Gourio and Rudanko (2014), Dou et al. (2019), and Corhay et al. (2020), we impose the demand constraint (8) because the firm would never produce more than the demand $C_{i,t}$ given the costly production of immediately perishable goods. Therefore, the firm finds it optimal to choose $P_{i,t} > \omega$ and produce up to $Y_{i,t} = C_{i,t}$ in equilibrium. The optimal net profits (8) can be written as

$$\text{Earnings}_{i,t} = (P_{i,t} - \omega) C_{i,t}, \text{ with } P_{i,t} > \omega. \tag{9}$$

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

$$GP_{i,t} \equiv \underbrace{\frac{(P_{i,t} - \omega) C_{i,t}}{K_{i,t}}}_{\text{gross profitability}} = \underbrace{\frac{P_{i,t} - \omega}{P_{i,t}}}_{\text{profit margin}} \times \underbrace{\frac{P_{i,t} C_{i,t}}{K_{i,t}}}_{\text{asset turnover}}. \tag{10}$$

The gross profitability captures the economic gain from a firm's assets, which concerns investors. It can be decomposed into two parts: profit margin and asset turnover. The profit margin is the amount of net sales that firms manage to retain as profits, while 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

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

The relation between θ_t and $\theta_{i,t}$ directly follows from Eq. (2) and is

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

The profit margin, rather than the marginal price, is examined in this paper for the following reasons.[13] First, we are concerned with asset pricing, and thus it is the profit

[12] Similar modeling approaches have been adopted in the macroeconomics literature (e.g., Jorgenson, 1963; Hall and Jorgenson, 1969; Buera and Shin, 2013; Moll, 2014) and in the corporate theory literature (e.g., Rampini and Viswanathan, 2013).

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

margin, rather than the nominal price tag, that matters here. Second, the purpose of competition and even price wars is not 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 they 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.

Strategic complementarity. Substituting Eq. (2) into Eq. (9) gives

$$\text{Earnings}_{i,t} = \Pi_i(\theta_{i,t}, \theta_{j,t})M_{i,t}, \tag{13}$$

where $\Pi_i(\theta_{i,t}, \theta_{j,t})$ describes the profits per unit of customer base, given by

$$\Pi_i(\theta_{i,t}, \theta_{j,t}) = \omega^{1-\epsilon}\theta_{i,t}(1-\theta_{i,t})^{\eta-1}(1-\theta_t)^{\epsilon-\eta}. \tag{14}$$

Eq. (14) shows that $\Pi_i(\theta_{i,t}, \theta_{j,t})$ depends on competitor j's profit margin $\theta_{j,t}$ through the industry-level profit margin θ_t, which reflects the direct externality of firm j's decisions. For example, if firm j sets a lower profit margin $\theta_{j,t}$, the industry-level profit margin θ_t will also drop, increasing the degree of competition. This will in turn motivate firm i to set a lower profit margin $\theta_{i,t}$, so the two firms' profit margin decisions exhibit strategic complementarity as follows:

$$\frac{\partial^2 \Pi_i(\theta_{i,t}, \theta_{j,t})}{\partial\theta_{i,t}\partial\theta_{j,t}} > 0. \tag{15}$$

3.4. Stochastic discount factor

We directly specify the stochastic discount factor (SDF) Λ_t, which evolves as follows:

$$\frac{\mathrm{d}\Lambda_t}{\Lambda_t} = -r_f\mathrm{d}t - \gamma_t\mathrm{d}Z_t - \zeta\,\mathrm{d}Z_{\gamma,t}, \tag{16}$$

where Z_t and $Z_{\gamma,t}$ are independent standard Brownian motions, and r_f is the equilibrium risk-free rate. Following the literature on cross-sectional return predictability (e.g., Zhang, 2005; Lettau and Wachter, 2007; Belo and Lin, 2012; Kogan and Papanikolaou, 2014), we directly specify the evolution of the time-varying discount rate γ_t:

$$\mathrm{d}\gamma_t = -\varphi(\gamma_t - \overline{\gamma})\mathrm{d}t - \pi\,\mathrm{d}Z_{\gamma,t} \quad \text{with} \quad \varphi, \overline{\gamma}, \pi > 0. \tag{17}$$

We assume $\zeta > 0$ to capture the well-documented countercyclical market price of risk whose primitive economic mechanism can be, for example, time-varying risk aversion, as shown by Campbell and Cochrane (1999) and Chan and Kogan (2002).[14]

It is worth pointing out that the shock of the industry's market leaders being displaced is not priced in the SDF because the economy comprises a continuum of industries; thus, any industry-specific change in market leaders is an idiosyncratic event to the fully diversified representative investor.

[14] It is also a common approach to directly model discount-rate variations in optimal portfolio choice problems (e.g., Koijen et al., 2009; Moreira and Muir, 2019).

3.5. Solutions of the 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 both 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 that allow for collusive arrangements enforced by punishment schemes. All strategies are allowed to depend upon both "payoff-relevant" physical states $x_t = \{M_{1,t}, M_{2,t}, \gamma_t\}$ in state space $\mathscr{X}$, as in Maskin and Tirole (1988a,b), and a set of indicator functions that track whether any firm has previously deviated from a collusive profit-margin agreement, as in Fershtman and Pakes (2000, p.212).[15]

In particular, there exists a noncollusive equilibrium, which repeats 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.[16]

Noncollusive equilibria. The noncollusive equilibrium is characterized by profit-margin scheme $\Theta^N(\cdot) = (\theta_1^N(\cdot), \theta_2^N(\cdot))$, which is a pair of functions defined in state space $\mathscr{X}$ such that each firm i chooses profit margin $\theta_{i,t} \equiv \theta_i(x_t)$ to maximize shareholder value $V_{i,t}^N \equiv V_i^N(x_t)$ under the assumption that its competitor j will set the one-shot Nash-equilibrium profit margin $\theta_{j,t}^N \equiv \theta_j^N(x_t)$. The superscript N stands for the noncollusive equilibrium. Following the recursive formulation in dynamic games for characterizing the Nash equilibrium (e.g., Pakes and McGuire, 1994; Ericson and Pakes, 1995; Maskin and Tirole, 2001), optimization problems can be formulated recursively using Hamilton-Jacobi-Bellman (HJB) equations:

$$0 = \max_{\theta_{i,t}} \underbrace{\Lambda_t\left[\Pi_i(\theta_{i,t}, \theta_{j,t}^N)M_{i,t} - \lambda V_{i,t}^N\right]\mathrm{d}t}_{\text{earnings and displacement loss}} + \underbrace{\mathbb{E}_t\left[\mathrm{d}(\Lambda_t V_{i,t}^N)|\theta_{i,t}, \theta_{j,t}^N\right]}_{\text{if not displaced}}. \tag{18}$$

The term $\Pi_i(\theta_{i,t}, \theta_{j,t}^N)M_{i,t}$ describes the earnings of firm i if it chooses profit margin $\theta_{i,t}$. The term $\lambda V_{i,t}^N$ is the expected loss due to possible displacement of firm i's market leadership. The term $\mathbb{E}_t\left[\mathrm{d}(\Lambda_t V_{i,t}^N)|\theta_{i,t}, \theta_{j,t}^N\right]$ is the expected valuation change if the market leadership does not change over $[t, t+\mathrm{d}t]$. The solutions to the coupled HJB equations in Eq. (18) give the noncollusive-equilibrium profit margin $\theta_{i,t}^N$ with $i = 1, 2$, which are chosen based on intertemporal

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

[16] In the IO and macroeconomics literature (e.g., Green and Porter, 1984; Rotemberg and Saloner, 1986), it is officially referred to as the collusive equilibrium or collusion. In game theory literature (see Fudenberg and Tirole, 1991), it is often referred to as the equilibrium of repeated game to be distinguished from the one-shot Nash equilibrium (i.e., our noncollusive equilibrium).

tradeoff considerations because $\theta^N_{i,t}$ determines the continuation value $V^N_{i,t+\mathrm{d}t}$ by altering the customer base $M_{i,t+\mathrm{d}t}$ (see Eq. (6)).

Collusive equilibria. In the collusive equilibrium, firms "tacitly" collude in setting higher profit margins, with any deviation triggering a switch to the noncollusive Nash equilibrium. The collusion is tacit in the sense that firms will comply without having to rely on legal contracts. Each firm is deterred from breaking the tacit collusion agreement because doing so could provoke fierce noncollusive competition.

Consider a generic collusive equilibrium in which the two firms follow a collusive profit-margin scheme. Both firms can costlessly observe the other's profit margin so that deviation can be detected and punished. The assumption of perfect information follows the literature.[17] 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 noncollusive profit margin. Setting noncollusive profit margins is considered as a punishment on the deviating firm because the industry will switch from the collusive to the noncollusive equilibrium, which features the lowest profit margin.[18] We use the idiosyncratic Poisson process $N_{i,t}$ to characterize whether a firm can successfully implement a punishment strategy. One interpretation of $N_{i,t}$ is that, with $1-\xi\,\mathrm{d}t$ probability, the deviator can persuade its competitor not to enter the noncollusive Nash equilibrium over the period $[t, t+\mathrm{d}t]$.[19] 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.

Formally, the set of incentive-compatible collusion agreements, denoted by $\mathscr{C}$, consists of all continuous profit-margin schemes $\Theta^C(\cdot) \equiv (\theta^C_1(\cdot), \theta^C_2(\cdot))$, such that the following incentive compatibility (IC) constraints are satisfied:

$$V^D_i(x) \le V^C_i(x), \quad \text{for all } x \in \mathscr{X} \text{ and } i = 1, 2. \tag{19}$$

Here, $V^C_{i,t} \equiv V^C_i(x_t)$ is firm i's value in the collusive equilibrium, pinned down recursively according to

$$0 = \underbrace{\Lambda_t\left[\Pi_i(\theta^C_{i,t}, \theta^C_{j,t})M_{i,t} - \lambda V^C_{i,t}\right]\mathrm{d}t}_{\text{earnings and displacement loss}} + \underbrace{\mathbb{E}_t\left[\mathrm{d}(\Lambda_t V^C_{i,t})|\theta^C_{i,t}, \theta^C_{j,t}\right]}_{\text{if not displaced}}, \tag{20}$$

where $\theta^C_{i,t} \equiv \theta^C_i(x_t)$ with $i = 1, 2$ are the collusive profit margins.

Further, $V^D_{i,t} \equiv V^D_i(x_t)$ is firm i's highest shareholder value if it deviates from the implicit collusion:

$$0 = \max_{\theta_{i,t}} \underbrace{\Lambda_t\left[\Pi_i(\theta_{i,t}, \theta^C_{j,t})M_{i,t} - \xi\left(V^D_{i,t} - V^N_{i,t}\right) - \lambda V^D_{i,t}\right]\mathrm{d}t}_{\text{earnings, displacement loss, and punishment loss}} + \underbrace{\mathbb{E}_t\left[\mathrm{d}(\Lambda_t V^D_{i,t})|\theta_{i,t}, \theta^C_{j,t}\right]}_{\text{if not displaced or punished}}. \tag{21}$$

The term $\Pi_i(\theta_{i,t}, \theta^C_{j,t})M_{i,t}$ describes the earnings that firm i gains by setting profit margin $\theta_{i,t}$. The term $\lambda V^D_{i,t}$ is the expected loss due to possible displacement of firm i's market leadership. The term $\xi\left(V^D_{i,t} - V^N_{i,t}\right)$ is the expected loss due to possible punishment for firm i's deviation behavior. The term $\mathbb{E}_t\left[\mathrm{d}(\Lambda_t V^D_{i,t})|\theta_{i,t}, \theta^N_{j,t}\right]$ is the expected valuation change if the market leadership does not change or the deviator is not punished over $[t, t+\mathrm{d}t]$.

In fact, there exist infinitely many elements in $\mathscr{C}$ and hence infinitely many collusive equilibria. We focus on a subset of $\mathscr{C}$, denoted by $\overline{\mathscr{C}}$, consisting of all profit-margin schemes $\Theta^C(\cdot)$ such that the IC constraints (19) are binding state by state, i.e., $V^D_i(x) = V^C_i(x)$ for all $x \in \mathscr{X}$ and $i = 1, 2$.[20] It is obvious that the subset $\overline{\mathscr{C}}$ is nonempty since it contains the profit-margin scheme in the noncollusive Nash equilibrium. We further narrow our focus to the "Pareto-efficient frontier" of $\overline{\mathscr{C}}$, denoted by $\overline{\mathscr{C}}_p$, consisting of all pairs of $\Theta^C(\cdot)$ such that there does not exist another pair $\widetilde{\Theta}^C(\cdot) \in \overline{\mathscr{C}}$ with $\widetilde{\theta}_i(x) \ge \theta_i(x)$ for all $x \in \mathscr{X}$ and $i = 1, 2$, and with strict inequality holding for some x and i.[21] Our numerical algorithm follows a method similar to that of Abreu et al. (1990).[22] 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.

Discussions on collusive equilibria: Evidence on (tacit) collusion. We focus on collusive equilibria, implying that the main assumption of our theory is that market leaders (tacitly) collude within industries. In the data, there is plenty of evidence that market leaders compete highly strategically through (tacit) collusion because product markets are highly concentrated and market leadership is highly persistent. In fact, collusion is pervasive among leading competitors in industries. John Connor's Private International Cartels data set (Connor, 2016) shows that from 1990 to 2016, 953 cartels were convicted of price fixing and 296

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

[18] We adopt the noncollusive equilibrium as the incentive-compatible punishment for deviation, which follows the literature (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.

[19] Ex-post renegotiations can occur because the noncollusive equilibrium is not renegotiation-proof or "immune to collective rethinking" (Farrell and Maskin, 1989). The strategy we consider is essentially a probabilistic punishment strategy. This "inertia assumption" also solves the technical issue of continuous-time dynamic games about the indeterminacy of outcomes (e.g., Simon and Stinchcombe, 1989; Bergin and MacLeod, 1993).

[20] Such equilibrium refinement in a general or industry equilibrium framework is similar in spirit to the works of Abreu (1988), Alvarez and Jermann (2000, 2001), and Opp et al. (2014).

[21] 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 et al., 1995), as $\overline{\mathscr{C}}$ is nonempty and compact, and the order we are considering is complete, transitive, and continuous.

[22] Alternative methods include those advanced by Cronshaw and Luenberger (1994), Pakes and McGuire (1994), and Judd et al. (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.

were suspected of it and being investigated. The estimated cartel overcharges during the period exceeded $1.5 trillion. The majority of the corporate cartelists came from Europe or North America. More importantly, besides explicit collusion, firms also engage in tacit collusion even more pervasively. For example, Bourveau et al. (2020) show that firms can use corporate disclosure to facilitate tacit coordination. He and Huang (2017) show that institutional cross-ownership can facilitate tacit collusion and collaboration among firms in product markets. González et al. (2019) show that managers have incentives to fix prices, as they enjoy greater job security and higher compensation. Managers also actively use concealment strategies to limit detection of cartel membership. Byrne and de Roos (2019) provide evidence on how collusive agreements are initiated. Based on a unique data set that contains the universe of station-level prices for an urban retail-gasoline market, they find that market leaders use price experiments to test rivals' willingness to collude and signal their intentions, leading to price coordination and widened profit margins.

Discussions on model ingredients: State variables and shocks. By exploiting the model's homogeneity in M_t, we can reduce the model to two state variables, $M_{1,t}/M_{i,t}$ and γ_t, when characterizing the industry's equilibrium. In particular, the value function of firm i can be represented by $V_i^C(M_{1,t}, M_{2,t}, \gamma_t) \equiv v_i^C(M_{1,t}/M_t, \gamma_t)M_t$. We solve the normalized value of firms $v_i^C(M_{1,t}/M_t, \gamma_t)$ and their normalized profit margins $\theta_i^C(M_{1,t}/M_t, \gamma_t)$ in the collusive equilibrium numerically.[23]

The state variables $(M_{1,t}/M_t, \gamma_t)$ are driven by two aggregate shocks Z_t and $Z_{\gamma,t}$, and three idiosyncratic shocks $W_{1,t}$, $W_{2,t}$, and N_t. Recall that Z_t in Eqs. (6) and (16) can be interpreted as the aggregate demand shock, and $Z_{\gamma,t}$ in Eq. (16) as the aggregate discount-rate shock. They are crucial to our core endogenous competition mechanism for the following reasons: (i) the aggregate demand shock Z_t shows up in both the customer-base Eq. (6) and the SDF Eq. (16) to ensure that the variation in discount rates γ_t affects the present value of future cooperation among competitors; and (ii) the aggregate discount-rate shock $Z_{\gamma,t}$ carries a negative market price of risk ζ in Eq. (16) and generates cross-sectional asset pricing implications. The idiosyncratic shocks are not crucial to the core mechanism; however, they are needed to ensure stationary and nondegenerate industry dynamics in the long run. In particular, the idiosyncratic demand (or "taste") shocks $W_{1,t}$ and $W_{2,t}$ in (6) ensure a nondegenerate stationary distribution of $M_{1,t}/M_t$ in equilibrium, and the idiosyncratic leadership turnover shock N_t guarantees that no industry would grow so much relative to others as to dominate the economy in the long run, and thus the distinction between industries would not become blurred in the long run.

3.6. Endogenous competition

In this subsection, we illustrate the core competition 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 aggregate discount rates γ_t. In turn, the endogenous competition generates endogenous variation in profit margins, which amplifies the industry's exposure to discount-rate shocks, resulting in both higher risk premia and stock return volatility.

More precisely, when the discount rate rises (i.e., higher γ_t), 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. In the long run, however, they run the risk of losing future revenue from tacit cooperation since the industry will be stuck in the noncollusive equilibrium once the deviation is detected and punished by their competitors. A higher discount rate in effect makes firms 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.[24] Undercutting profit margins in equilibrium reflects intensified product market competition.

Profit margin fluctuations and amplification. To illustrate endogenous competition, we plot firms' profit margins and stock returns' exposure to aggregate shocks that drive the discount rate.

Panel A of Fig. 3 plots firm i's equilibrium profit margins for two different discount rates (i.e., $\gamma_t = \gamma_L$ or γ_H with $\gamma_L < \gamma_H$). The blue solid and red dotted lines represent profit margins when the discount rate is low (i.e., $\gamma_t = \gamma_L$) in the collusive and noncollusive equilibria, respectively. Firm i's profit margin increases with its share of the customer base $M_{i,t}/M_t$ because of lower price elasticity of demand (see Eq. (5)). Importantly, firm i's profit margin in the collusive equilibrium plunges 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 γ_t increases from γ_L to γ_H in the model).

Panel B illustrates the increase in profit margins when γ_t decreases from γ_H to γ_L in the model. The change displays an inverted U shape and peaks when the two firms have comparable shares of the customer base (i.e., $M_{i,t}/M_t = 0.5$). Intuitively, in an almost monopolistic industry, firms have weak collusion incentives because the difference between collusive and noncollusive profit margins (i.e., the gap between the blue solid line and the red dotted line in panel A) is tiny. As a result, profit margins do not vary much with discount rates.[25]

[23] See Online Appendix H for more discussion.

[24] 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.

[25] More discussion is presented in Online Appendix D.2.

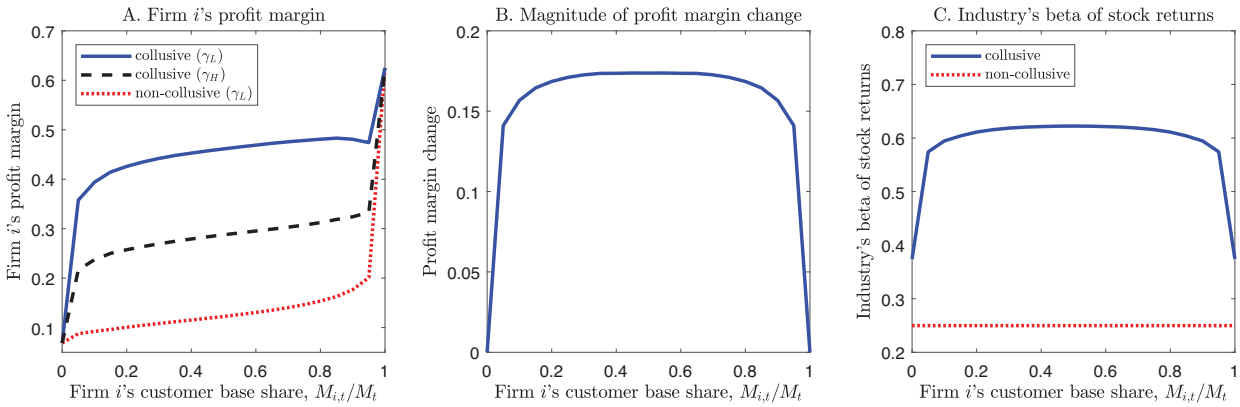

Fig. 3. Profit margins and industry-level exposure to discount-rate shocks.
Panel A plots firm i's profit margin as a function of its customer base. Panel B plots the increase in firm i's profit margin when the discount rate decreases from γ_H to γ_L. Panel C plots the industry's beta of stock returns defined in Eq. (22). We choose $\lambda = 0$, $\gamma_L = \overline{\gamma}$, and γ_H is two standard deviations above γ_L according to the stationary distribution of γ_t. Other parameters are set according to the calibration in Appendix Table A.1.

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

$$\beta_t = \sum_{i=1}^{2} w_{i,t}\beta_{i,t}, \text{ where } \beta_{i,t} = \frac{v^C_{i,t}(\gamma_L)}{v^C_{i,t}(\gamma_H)} - 1 \text{ and}$$
$$w_{i,t} = \frac{v^C_{i,t}(\gamma_H)}{\sum_{j=1}^{2} v^C_{j,t}(\gamma_H)}, \tag{22}$$

for all $M_{i,t}/M_t \in (0, 1)$.

Panel C highlights the amplification effect of the endogenous competition. The panel shows that the industry's beta of stock returns displays an inverted U shape (the blue solid line), because the change in profit margins does (see panel B). As a benchmark, the red dotted line plots the industry's beta of stock returns in the noncollusive 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. Such an amplification of the exposure to discount-rate shocks leads to higher excess returns: the competition risk premium.

3.7. Cross-sectional implications

Our model implies that market leaders tend to collude on higher profit margins when they are less likely to be displaced by followers. As a result, the industries with higher market leadership persistence are associated with higher profit margins and more exposed to aggregate discount-rate shocks, and thus compensate investors with higher expected returns.

To fix ideas, consider two industries differing in turnover rate of market leadership, and denote the two different turnover rates by λ_H and λ_L with $\lambda_L < \lambda_H$. Panel A of Fig. 4 plots firm i'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.[26] This implies that high-λ industries have low average gross profitability since the customer base share fluctuates around 0.5 due to mean reversion (see Eq. (6) and the discussions there). More importantly, profit margins drop *more* substantially in the industry with *lower* leadership turnover rate (i.e., $\lambda = \lambda_L$) in response to an increase in γ_t from γ_L to γ_H. In other words, profit margins in such industries are more exposed to discount-rate shocks. Our model has the same implications on asset turnover $P_{i,t}C_{i,t}/K_{i,t}$.[27]

Intuitively, a higher rate of market leadership turnover has a similar effect to that of a higher discount rate. 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 discount-rate shocks. Our idea echoes the important generic insight of Maskin and Tirole (1988a) 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 industries' exposure to discount-rate shocks by plotting the standardized market value of the two industries as a function of the discount rate γ_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 a lower rate of

[26] Moreover, when $M_{i,t}/M_t \to 0$, firm i's profit margin in both industries converges to the profit margin determined by the within-industry elasticity of substitution η, as we will show later in Eq. (5). When $M_{i,t}/M_t \to 1$, firm i'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.

[27] Eq. (10) shows that asset turnover is equal to $P_{i,t}$ given that in equilibrium $C_{i,t} = K_{i,t}$. Thus, asset turnover in our model is perfectly positively correlated with profit margin $\theta_{i,t}$ defined in Eq. (11).

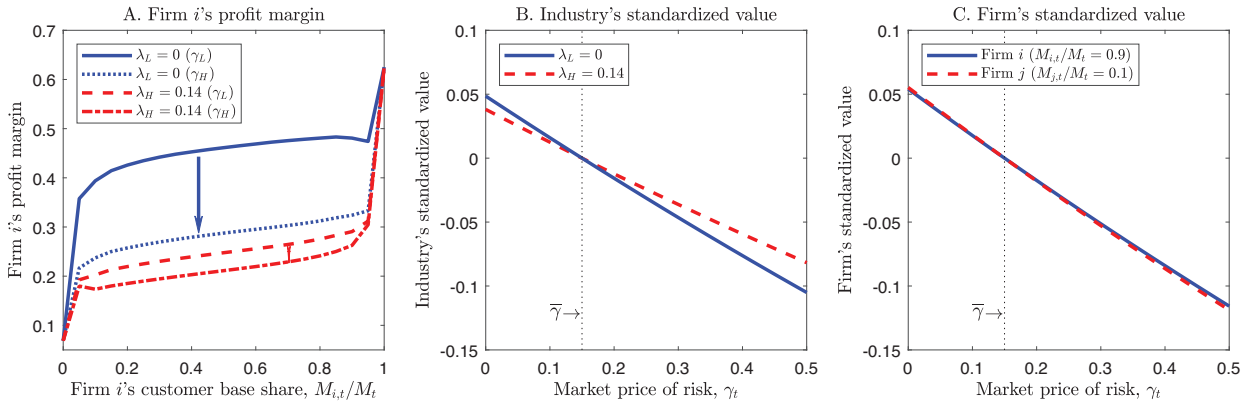

Fig. 4. Impact of market leadership turnover rate.
Panel A plots firm i's profit margin as a function of its customer base. We choose $\lambda_L = 0$, $\lambda_H = 0.14$, $\gamma_L = \overline{\gamma}$, and γ_H is two standard deviations above γ_L according to the stationary distribution of γ_t. Panel B plots the standardized market value of the industry, defined as $V^C(\gamma_t)/V^C(\overline{\gamma}) - 1$, to illustrate the sensitivity of the industry's market value to the discount rate γ_t. Here, the industry comprises two firms possessing equal shares of the customer base (i.e., $M_{i,t}/M_t = 0.5$). Panel C plots the standardized market value of firm i, defined as $V_i^C(\gamma_t)/V_i^C(\overline{\gamma}) - 1$, to illustrate the sensitivity of firm i's market value to the discount rate γ_t. Here, the industry has $\lambda = 0$. Other parameters are set according to the calibration in Appendix Table A.1.

market leadership turnover are more profitable and more exposed to discount-rate shocks.

Panel C illustrates the exposure to discount-rate shocks of firms within the same industry by plotting the standardized market value of the two firms as a function of the discount rate. The two firms have different customer base shares. The panel shows that the two firms are exposed to discount-rate shocks roughly to the same extent, indicating that our mechanism of endogenous competition does not provide any strong within-industry predictions.

3.8. The core competition mechanism and market structure

In this subsection, we shed further light on the core competition mechanism by analyzing the difference in the sensitivity of profit margins to discount rates between industries with low (λ_L) and high (λ_H) turnover rates of market leadership *under various market structures*. As in many other studies in the literature, the competitiveness of a market structure is characterized by the industry's price elasticity of demand ϵ and the number of market leaders n in our model.

Consider a decrease in the discount rate from γ_H to γ_L with $\gamma_L < \gamma_H$. We measure the sensitivity of profit margins to discount rates using the industry-level profit-margin beta β_t^θ, defined by the ratio of industry-level profit margins between the two aggregate states $\beta_t^\theta = \theta_t^C(\gamma_L)/\theta_t^C(\gamma_H) - 1$. Panel A of Fig. 5 plots the profit-margin beta under our baseline duopoly market structure with $\epsilon = 1.6$ and $n = 2$ for the two industries whose market leadership changes at different rates. Consistent with panel A of Fig. 4, the profit-margin beta is much higher in the industry with a low turnover rate λ_L.

Panel B considers a more competitive market structure by setting the industry's price elasticity of demand to $\epsilon = 3$, keeping the number of market leaders $n = 2$ unchanged. The industry with a low turnover rate λ_L still has a higher profit-margin beta than the industry with a high turnover rate λ_H. However, the difference in profit-margin betas between the two industries narrows significantly relative to that in panel A. In panel C, we consider a more competitive market structure by setting the number of market leaders to $n = 3$, keeping the industry's price elasticity of demand ϵ unchanged. Relative to the baseline case in panel A, again we find that the difference in profit-margin betas diminishes when the market structure becomes more competitive.

Taken together, Fig. 5 implies that when the industry market structure becomes more competitive, the difference in the sensitivity of profitability to discount-rate shocks between industries with low and high market leadership persistence (i.e., high and low λ, respectively) subsides. Intuitively, with a more competitive market structure, the market leaders within the same industry have less incentive to collude, irrespective of their market leadership persistence. As a result, profit-margin betas become less different across industries with different levels of leadership persistence (i.e., different values of λ).

4. Empirical analyses

In this section, we empirically test the main predictions of our model. Section 4.1 describes the data and the discount rate measure. We also construct a leadership turnover measure by estimating a logistic regression model. We then conduct our empirical tests in three steps. In Section 4.2, we first provide empirical evidence to support our model's main implications for risk premium and profitability, as discussed in Section 2. We show that profitability comoves negatively with discount rates and that such comovement is more pronounced in more profitable industries. The cross-industry gross profitability spread loads significantly on discount-rate shocks. In Section 4.3, we push one step further in terms of testing the theoretical implications for the turnover rate of the industry's market leaders and the joint cross-sectional asset pricing implications. We show that the leadership turnover measure is correlated negatively with profitability as

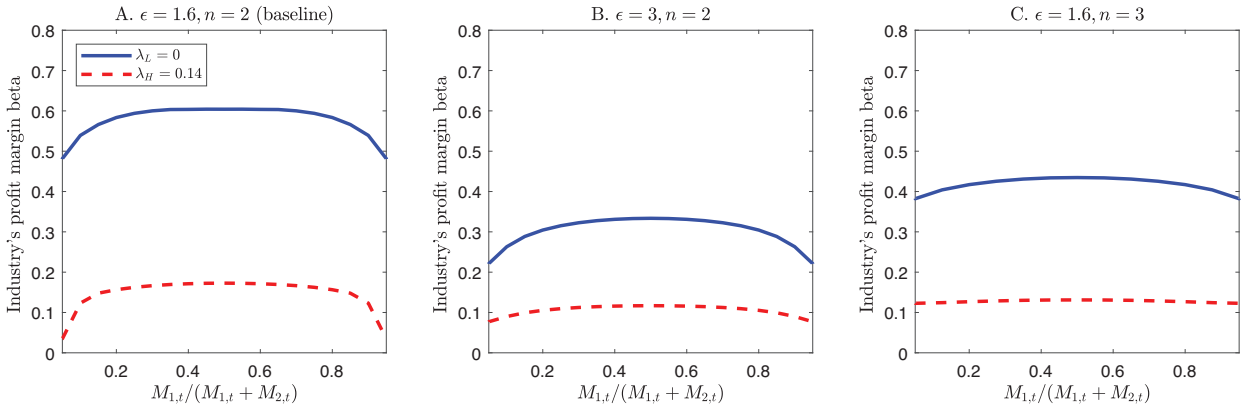

Fig. 5. Implications of ϵ and n for industry competition.
The blue solid and red dashed lines in each panel plot the profit-margin beta in industries with λ_L and λ_H, respectively. In panel A, we consider the market structure with $\epsilon = 1.6$ and $n = 2$ according to our baseline calibration in Appendix Table A.1. All other parameters are set according to the calibration in Appendix Table A.1. In panel B, we set $\epsilon = 3$ and $n = 2$; and in panel C, we set $\epsilon = 1.6$ and $n = 3$. For expository purposes, we fix firm 3's customer base share at 1/3, i.e., $M_{3,t}/(M_{1,t} + M_{2,t} + M_{3,t}) = 1/3$ in panel C. In all three panels, the x-axis represents $M_{1,t}/(M_{1,t} + M_{2,t})$, which is firm 1's share of the total customer base owned by firms 1 and 2. The stationary distribution of $M_{1,t}/(M_{1,t} + M_{2,t})$ is around 0.5.

predicted by the model. Moreover, the measure is priced in the cross section of industries, and the return spread of industry portfolios sorted on this measure can explain the cross-industry gross profitability premium. In Section 4.4, we push another step further to directly test the unique predictions of our core competition mechanism. We explore the impact of the variation in the industry market structure on firms' endogenous competition behavior by examining the changes in the sensitivity of profitability to discount rates. The empirical evidence strongly supports our core competition mechanism.

4.1. Data and empirical measures

In this subsection, we introduce our data, the empirical measures of aggregate discount rates, and the market leadership turnover measure.

Data. We construct profitability, profit margins, and asset turnover using Compustat, and the time series of the media coverage and analyst coverage on price war using Dow Jones Factiva and Thomson ONE Investext (see Appendix B for details).

Because our model focuses on the strategic competition among a few oligopolistic firms whose products are close substitutes, we follow the literature (e.g., Hou and Robinson, 2006; Gomes et al., 2009; Frésard, 2010; Giroud and Mueller, 2010; 2011; Bustamante and Donangelo, 2017) and use four-digit SIC codes (SIC4) to define industries. The Compustat Segment data are used to improve the precision of industry classifications (see Appendix B). On average, there are 403 industries in a year and 7.69 firms in an industry. For robustness, we also consider alternative industry classifications including three-digit SIC codes (SIC3) and the text-based fixed industry classification codes (FIC) of Hoberg and Phillips (2010a, 2016), obtained from the Hoberg-Phillips Data Library.

Stock returns are from CRSP. We exclude financial and utility firms from the analysis, and use CRSP delisting returns to adjust for stock delists. We construct measures of discount rates using the data from Robert Shiller's website. We construct the leadership turnover measure using the data from Compustat, Capital IQ, SDC M&A Database, and PatentsView. PatentsView contains detailed and up-to-date information on patents granted from 1976 onward (see Appendix B for more details).

When directly testing the unique predictions of our core competition mechanism in Section 4.4.1, we use the import tariff data from the websites of Peter Schott and Laurent Fresard and the product similarity data (Hoberg and Phillips, 2010a; 2016) from the Hoberg-Phillips Data Library.

Measures of discount rates. Various financial ratios such as the earnings-price ratio and the dividend-price ratio are classic measures of discount rates (e.g., Cochrane, 2011; Hall, 2017; Moreira and Muir, 2017; 2019). These ratios have been shown to predict future stock returns (e.g., Campbell and Shiller, 1988; Fama and French, 1988; Hodrick, 1992; Lewellen, 2004; Campbell and Yogo, 2006; Campbell and Thompson, 2008; Ferreira and Santa-Clara, 2011). Moreover, the variation in these financial ratios is mainly driven by the fluctuation in discount rates (e.g., Cochrane, 2011).

In this paper, we use the smoothed earnings-price ratio proposed by Campbell and Shiller (1988, 1998) as an empirical proxy for discount rates.[28] The smoothed earnings-price ratio is the reciprocal of the cyclically adjusted price-earnings ratio (CAPE). Campbell and Shiller argue that the smoothed earnings-price ratio has better forecasting power than the current earnings-price ratio because aggregate corporate earnings contain short-run cyclical noise. Moreover, in an influential paper, Campbell and Thompson (2008) show that the smoothed earnings-price ratio has better predictive power for stock returns than many other financial ratios.

[28] The results of our paper remain robust if we use the dividend-price ratio to measure discount rates (see Fig. 1 for a plot of both ratios).

Leadership turnover measure. We construct an industry-level measure of market leadership turnover, referred to as the *leadership turnover measure*. We define market leaders as the top two firms ranked by sales in a given industry. We consider both public firms and private firms in defining industry leaders (see Appendix B for details). Results are qualitatively similar if we define market leaders as the top one firm or the top four firms in a given industry. Similar to estimating the probability of corporate events (e.g., Shumway, 2001; Campbell et al., 2008), we estimate the leadership turnover rate using a logistic regression model. Specifically, we assume that the marginal probability of market leadership turnover follows a logistic regression model given by

$$\mathbb{P}(\mathbb{1}^{t\to t+2}_{turnover,i} = 1) = \frac{1}{1+\exp(-b_0 - b_1 x_{i,t})}, \tag{23}$$

where $\mathbb{1}^{t\to t+2}_{turnover,i}$ 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 whose values are known at the end of year t. Results are similar if we use $\mathbb{1}^{t\to t+1}_{turnover,i}$ or $\mathbb{1}^{t\to t+3}_{turnover,i}$. The leadership turnover measure, denoted by $\hat{\lambda}_t$, is the predicted probability that new market leaders will emerge: $\hat{\lambda}_t = 1/\left[1+\exp(-\hat{b}_0 - \hat{b}_1 x_{i,t})\right]$ with estimators $\hat{b}_0$ and $\hat{b}_1$.

Following the industrial organization literature (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 when followers generate distinctive innovation (e.g., Christensen, 1997). Firms in industries with lower innovation similarity are more likely to create products that are drastically different from their peers' products and thus these industries have a higher probability of experiencing market leader changes. In light of previous studies (e.g., Jaffe, 1986; Bloom et al., 2013), we construct the industry-level innovation similarity measure based on the technology classifications of an industry's patents (see Appendix B).[29] Our leadership turnover measure is estimated using Eq. (23) based on the industry panel from 1988 to 2017.[30]

4.2. Profitability and stock returns

In this subsection, we test the model's predictions on the relation between discount rates, profitability, and stock returns.[31] In particular, we first show that profitability comoves negatively with discount rates and that this comovement is more pronounced in industries with higher gross profitability. We then show that the cross-industry gross profitability spread (high minus low) is significantly positive on average and loads negatively on discount-rate shocks.

4.2.1. Exposure of profitability to discount rates

We examine the comovement of profitability and discount rates at the aggregate level and in the cross section of different industries.

Time-series comovement. Our model implies that profitability comoves negatively with discount rates (see panel A of Fig. 3). To test this prediction, we regress the year-on-year changes in the average profitability on the changes in the smoothed earnings-price ratio. The average profitability is the simple average of profitability across SIC4 industries. Columns (1)–(2) in panel A of Table 1 show that when discount rates rise, both the average gross profitability and net profitability drop significantly. By decomposing profitability into asset turnover and profit margins, columns (3)–(5) in panel A further show that both asset turnover and profit margins comove negatively with discount rates, as predicted by the model. The coefficients in panel A of Table 1 are economically significant. For example, a one-standard-deviation increase in the changes in the smoothed earnings-price ratio is associated with a 0.14-standard-deviation reduction in the changes of the average gross profitability and a 0.42-standard-deviation reduction in the changes of the average gross profit margin. Because recessions are characterized by high discount rates, our findings are consistent with the existing evidence showing that profit margins are procyclical (e.g., Machin and Van Reenen, 1993; Hall, 2012; Anderson et al., 2018).

Cross-industry heterogeneity. Our model also implies that the negative comovement between profitability and discount rates is more pronounced in more profitable industries (see panel A of Fig. 4). To test this implication, we split industries into quintiles based on their gross profitability and examine the sensitivity of net profitability to discount rates. We focus on net profitability because it reflects firms' net cash flows, which are directly related to asset prices (i.e., firm values) in our model. Columns (1)–(6) in panel B of Table 1 show that net profitability indeed comoves more negatively with discount rates in more profitable industries. According to column (6) in panel B, the difference in the sensitivity of net profitability to discount rates between the most profitable (Q5) and least profitable (Q1) industries is -1.03, which is almost four times the sensitivity of average net profitability to discount rates in the whole sample (see column 2 of panel A). We find similar cross-industry heterogeneity in the sensitivity of

[29] The innovation similarity measure is similar in spirit to other recently developed similarity measures based on patent citations (e.g., Cohen et al., 2019; Fitzgerald et al., 2019) or patent descriptions (e.g., Bowen et al., 2018; Kelly et al., 2020).

[30] The coefficients in the row vector $\hat{b}_1$ 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 because data for the innovation similarity measure are available only after 1987. The coefficients are similar if we use other sample periods (e.g., 1988–2007 or 1988–2010).

[31] Novy-Marx (2013) shows that the gross profitability spreads can be attributed to both asset turnover (sales scaled by asset) and gross margins (gross profits scaled by sales). In particular, he finds that it is the high asset turnover that primarily drives the high average returns of profitable firms. In Appendix C, we replicate the main tests of this section using asset turnover as the sorting variable and obtain highly similar results.

Table 1
Comovement between profitability and discount rates.

Panel A: Time series comovement

	(1) ΔAverage gross profitability$_t$	(2) ΔAverage net profitability$_t$	(3) ΔAverage asset turnover$_t$	(4) ΔAverage gross profit margin$_t$	(5) ΔAverage net profit margin$_t$
ΔSmooth_EP$_t$	−1.31***	−0.27**	−2.36*	−0.32***	−0.29**
	[−2.78]	[−2.34]	[−1.87]	[−5.73]	[−2.14]
Observations	64	64	64	64	64
R-squared	0.021	0.068	0.006	0.228	0.039

Panel B: Cross-sectional heterogeneity across SIC4 industries with different levels of gross profitability

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	ΔAverage net profitability$_t$						ΔAverage asset turnover$_t$					
GP quintiles	Q1 (low)	Q2	Q3	Q4	Q5 (high)	5 - 1	Q1 (low)	Q2	Q3	Q4	Q5 (high)	5 - 1
ΔSmooth_EP$_t$	0.32	−0.38*	−0.44*	−0.69***	−0.72**	−1.03***	3.18	−0.78	−3.07*	−4.03**	−7.15**	−10.33***
	[1.17]	[−1.71]	[−1.86]	[−3.13]	[−2.31]	[−2.76]	[1.28]	[−0.21]	[−1.86]	[−2.31]	[−2.24]	[−3.17]
Observations	64	64	64	64	64	64	64	64	64	64	64	64
R-squared	0.018	0.021	0.032	0.068	0.025	0.048	0.011	0.001	0.009	0.009	0.018	0.038

Panel A examines the sensitivity of the average profitability, asset turnover, and profit margin to discount rates. Industry-level profit margins, asset turnover, and profitability are constructed according to Appendix B. ΔSmooth_EP$_t$ is the year-on-year difference in the average level of the monthly smoothed earnings-price ratio. The sample of this panel spans the period from 1954 to 2017. Standard errors are computed using the Newey-West estimator, allowing for serial correlation in the data. Panel B presents the results of the time-series regressions in industry quintile portfolios sorted on the one-year-lagged gross profitability. We omit the coefficients for the constant terms in both panels for brevity. We include *t*-statistics in the brackets. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

asset turnover to discount rates (see columns 7–12 in panel B).

Our results are robust to alternative industry definitions. First, based on the industries defined by SIC3, we find similar results, that profitability comoves more negatively with discount rates in more profitable industries (see panel A of Appendix Table C.4). Second, we check whether our results are robust to the FIC codes (Hoberg and Phillips, 2010a; 2016). Panel B of Appendix Table C.4 shows that the sensitivity of profitability to discount rates is more negative in more profitable FIC industries. However, as FIC codes are only available after 1996, the result is not statistically significant due to the short sample period. To mitigate this problem, we assume that the FIC codes of all firms before 1996 are the same as those in 1996. Panel C of Appendix Table C.4 shows that the cross-sectional difference in the sensitivity of profitability to discount rates is statistically significant, and that its magnitude is comparable to the one from SIC4 industries in panel B of Table 1.

4.2.2. Exposure of gross profitability spreads to discount rates

In this subsection, we show that gross profitability spreads (high minus low) are significantly positive at the cross-industry, within-industry and cross-firm levels.[32] More importantly, we highlight their difference in terms of their exposure to discount rates. For brevity, hereafter we referred to the gross profitability spread as the GP spread.

Gross profitability premia. Because our model emphasizes the heterogeneous variations in competition intensity across industries, we primarily focus on the cross-industry GP spread in the data. Specifically, our model predicts that industries with higher profitability are more exposed to fluctuations in discount rates and thus have higher expected stock returns. To test this prediction, we sort all SIC4 industries into quintiles and examine their returns. Panel A of Table 2 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., Q5) exhibits significantly higher average excess returns and CAPM alphas. The difference in the average annualized excess returns (i.e., Q5 - Q1) is 5.06% and the difference in CAPM alphas is 3.98%. The above results are robust to alternative industry definitions. The cross-industry GP spreads are significantly positive with SIC3 and FIC (see Internet Table C.5).

For completeness, we also investigate the within-industry GP spread in the data. Panel B shows that the difference in the average annualized excess returns is 4.19% and the difference in CAPM alphas is 5.86%, across the quintile portfolios sorted on the gross profitability of firms within each industry. The within- and cross-industry GP spreads are comparable to the firm-level GP spread (see panel C) studied by Novy-Marx (2013).

Heterogeneous exposure of GP spreads to discount-rate shocks.

Our model specifically predicts that more profitable industries are exposed to discount-rate shocks to a greater degree (see panel B of Fig. 4) and thus the cross-industry GP spread should load negatively on discount-rate shocks. Consistent with this prediction, panel A of Table 3 (see columns 1–5) shows that the exposure to accumulated discount-rate shocks is negative and decreases (i.e., becomes more negative) monotonically across industry port-

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

Table 2
Gross profitability premia.

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
		Excess returns (%)						CAPM alphas (%)			
Q1 (low)	Q2	Q3	Q4	Q5 (high)	5 - 1	Q1 (low)	Q2	Q3	Q4	Q5 (high)	5 - 1
					Panel A: Cross-industry GP spread						
5.20***	8.88***	9.05***	9.37***	10.26***	5.06***	−1.23	1.08	0.05	1.22	2.75***	3.98**
[2.81]	[4.06]	[3.55]	[4.10]	[4.70]	[3.28]	[−1.38]	[1.04]	[0.04]	[1.21]	[2.60]	[2.56]
					Panel B: Within-industry GP spread						
5.11**	7.97***	7.89***	8.62***	9.30***	4.19***	−3.69***	−0.54	−0.27	0.92	2.17***	5.86***
[2.04]	[3.35]	[3.54]	[4.01]	[4.82]	[3.00]	[−3.23]	[−0.51]	[−0.29]	[0.97]	[2.76]	[4.27]
					Panel C: Firm-level GP spread						
5.67***	7.21***	7.60***	7.38***	9.90***	4.23***	−2.47***	−0.37	−0.16	−0.40	2.92***	5.40***
[2.59]	[3.56]	[3.73]	[3.58]	[5.14]	[3.10]	[−3.10]	[−0.48]	[−0.28]	[−0.57]	[3.52]	[3.92]

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 quintiles 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 panel B, we sort individual firms within each industry (with at least five firms) into quintiles based on their one-year-lagged gross profitability. In panel C, we sort all firms into quintiles 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. Newey-West standard errors are estimated with one lag. We annualize average excess returns and alphas by multiplying them by 12. We include t-statistics in brackets. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 3
Exposure of GP spreads to discount rates.

	(1)	(2)	(3)	(4)	(5)	(6)
			Accumulated portfolio excess returns$_t$			
GP quintiles	Q1 (low)	Q2	Q3	Q4	Q5 (high)	5 - 1
			Panel A: Cross-industry GP spread			
Accumulated smooth_EPshocks$_t$	−7.08***	−7.80***	−9.79***	−11.32***	−11.75***	−4.67**
	[−3.76]	[−4.61]	[−3.33]	[−4.98]	[−5.91]	[−2.34]
Observations	769	769	769	769	769	769
R-squared	0.258	0.340	0.348	0.493	0.573	0.108
			Panel B: Within-industry GP spread			
Accumulated smooth_EPshocks$_t$	−7.97***	−10.61***	−8.82***	−10.96***	−9.98***	−2.01
	[−3.49]	[−4.45]	[−4.79]	[−4.93]	[−5.47]	[−1.59]
Observations	769	769	769	769	769	769
R-squared	0.229	0.377	0.392	0.469	0.510	0.036
			Panel C: Firm-level GP spread			
Accumulated smooth_EPshocks$_t$	−6.97***	−7.15***	−9.96***	−10.89***	−11.05***	−4.08**
	[−2.80]	[−3.64]	[−5.19]	[−5.34]	[−6.77]	[−2.12]
Observations	769	769	769	769	769	769
R-squared	0.196	0.284	0.496	0.536	0.586	0.112

This table shows the heterogeneous exposure to discount rates for portfolios sorted on gross profitability. The dependent variable is the summation of portfolio excess returns for the past 36 months: $\sum_{j=0}^{35}(r_{p,t-j}-r_{f,t-j})$. The independent variable is the summation of shocks to the smoothed earnings-price ratio for the past 36 months. The monthly shocks are estimated using an AR(1) model. Gross profitability portfolios are rebalanced at the yearly frequency according to the procedure explained in Table 2. We omit the coefficients for the constant terms for brevity. The sample spans the period from 1954 to 2018. We exclude financial firms and utility firms from the analysis. Newey-West standard errors are estimated with 36 lags. We include t-statistics in brackets. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

folios sorted on gross profitability. Moreover, the loading of the cross-industry GP spread on accumulated discount-rate shocks is significantly negative (see column 6). This loading is also economically significant. A one-standard-deviation increase in the accumulated discount-rate shocks is associated with a 0.33-standard-deviation reduction in the accumulated cross-industry GP spread. We replicate the above analysis using SIC3 and FIC and find similar patterns (see Internet Table C.6).

In contrast to the cross-industry GP spread, the within-industry GP spread has an insignificant loading on accumulated discount-rate shocks (see panel B of Table 3). However, the firm-level GP spread studied by Novy-Marx (2013) loads significantly negatively on accumulated discount-rate shocks (see panel C of Table 3), suggesting that the cross-industry variation seems to play a more important role than the within-industry variation in driving the sensitivity of firm-level GP spread to discount rates.

4.3. Empirical tests on the implications of market leadership turnover

Our model emphasizes the tight connection between the industry's profitability and market leadership turnover rate in the cross section. Specifically, it is precisely the heterogeneity in the market leadership turnover rate across industries that generates heterogeneous industry-level competition risk, which in turn rationalizes the cross-

Table 4
Profitability and market leader turnovers.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Panel A: Profitability, market leader turnovers, and the volatility of cash flows							
	$\mathbb{1}^{t\to t+\Delta t}_{turnover,i}$				$\ln(\sigma^{t\to t+\Delta t}_{NP,i})$			
	$\Delta t=3$	$\Delta t=4$	$\Delta t=5$	$\Delta t=10$	$\Delta t=3$	$\Delta t=4$	$\Delta t=5$	$\Delta t=10$
$GP_{i,t}$ (standardized)	−0.02***	−0.02***	−0.02***	−0.02***	0.10***	0.10***	0.10***	0.10***
	[−4.51]	[−4.41]	[−4.28]	[−3.03]	[7.76]	[8.90]	[8.78]	[8.32]
$\ln(\text{number of firms})_{i,t}$	0.19***	0.21***	0.21***	0.22***	0.01	0.01	−0.00	−0.04***
	[27.15]	[30.75]	[27.01]	[12.55]	[0.62]	[0.45]	[−0.20]	[−3.21]
$\ln(\text{sales})_{i,t}$	−0.02***	−0.03***	−0.03***	−0.03***	−0.18***	−0.18***	−0.17***	−0.15***
	[−5.22]	[−5.31]	[−5.27]	[−4.71]	[−17.94]	[−25.30]	[−24.64]	[−24.50]
Average obs./year	378	372	367	345	355	349	338	312
Average R-squared	0.163	0.175	0.178	0.178	0.136	0.151	0.163	0.194
	Panel B: Leadership turnover measure, profitability, and the volatility of cash flows							
	$\text{Profitability}_{i,t}$ (%)		$\text{Profit margin}_{i,t}$ (%)		$\ln(\sigma^{t\to t+\Delta t}_{NP,i})$			
	Gross	Net	Gross	Net	$\Delta t=3$	$\Delta t=4$	$\Delta t=5$	$\Delta t=10$
$\hat{\lambda}_{i,t}$ (standardized)	−2.80***	−0.40**	−3.08***	−0.45**	−0.08***	−0.08***	−0.09***	−0.11***
	[−3.50]	[−2.63]	[−8.11]	[−2.12]	[−3.89]	[−4.62]	[−5.65]	[−4.96]
$\ln(\text{number of firms})_{i,t}$	−1.31**	−1.27***	7.34***	−1.51***	0.04	0.04	0.04	0.03*
	[−2.26]	[−5.85]	[25.70]	[−3.86]	[1.10]	[1.21]	[1.28]	[1.97]
$\ln(\text{sales})_{i,t}$	−0.29	1.25***	−2.63***	2.30***	−0.20***	−0.20***	−0.19***	−0.15***
	[−0.96]	[12.40]	[−18.40]	[8.74]	[−11.81]	[−14.05]	[−15.76]	[−16.18]
Average obs./year	176	176	176	176	169	168	166	157
Average R-squared	0.052	0.119	0.193	0.120	0.139	0.159	0.160	0.132

This table reports the slope coefficients and test statistics in brackets from Fama-MacBeth regressions. Columns (1)–(4) of panel A report results from Fama-MacBeth regressions that regress the indicator variable for market leader turnovers (denoted by $\mathbb{1}^{t\to t+\Delta t}_{turnover,i}$) on gross profitability, controlling for the log number of firms and log sales. Columns (5)–(8) of panel A report results from Fama-MacBeth regressions of the log volatility of net profitability from year t to $t+\Delta t$ on the same set of independent variables. The sample of panel A spans the period from 1954 to 2017. Columns (1)–(4) of panel B report the results from Fama-MacBeth regressions of profit margins and profitability on the leadership turnover measure ($\hat{\lambda}$), the natural log of the number of firms in the industries, and the natural log of the industry sales. Columns (5) – (8) of panel B report the results from Fama-MacBeth regressions of the natural log of the volatility of net industry profitability from year t to $t+\Delta t$ (denoted by $\ln(\sigma^{t\to t+\Delta t}_{NP,i})$) on the same set of independent variables. The sample of panel B spans the period from 1988 to 2017. We standardize gross profitability in panel A and the leadership turnover measure in panel B using their unconditional mean and unconditional standard deviation of the full sample. The construction of the leadership turnover measure is explained in Section 4.1. Industry-level profitability and profit margins are constructed according to Appendix B. We omit the coefficients for the constant terms for brevity. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

industry gross profitability premium. In this subsection, we test the implications above using our leadership turnover measure constructed in Section 4.1. We show that industries with a lower value of the leadership turnover measure have higher profit margins and higher profitability, which in turn, predicts a lower turnover rate of market leaders. We show that the leadership turnover measure is priced in the cross section of industries. Further, we also show that the cross-industry GP spread comoves closely with the leadership turnover spread (hereafter LT spread), defined as the return spread of industry portfolios sorted on the leadership turnover measure. The reason is that industries' exposure to discount-rate shocks is jointly reflected in the two cross sections of industries sorted by gross profitability and the leadership turnover rate, as predicted by the model.

Leadership turnover rate and profitability. Our model implies that more profitable industries experience market leader turnovers less often (see panel A of Fig. 4). To test this implication, we construct a set of indicator variables that equal one if the market leaders in year t are different from those in year $t+\Delta t$, with Δt ranging from three to ten years. Our results from Fama-MacBeth regressions indicate that market leaders are significantly less likely to be displaced in industries with higher gross profitability (see columns (1)–(4) in panel A of Table 4).[33] In addition, our model predicts that more profitable industries should have more volatile cash flows. To test this prediction, we examine the relation between gross profitability and the volatility of net profitability in columns (5)–(8) in panel B of Table 4. Consistent with our model, we find that cash flows are indeed more volatile in more profitable industries.

Additionally, we find similar results based on the leadership turnover measure. Columns (1)–(4) in panel B of Table 4 show that the leadership turnover measure is negatively related to both profitability and profit margins. The relation is both statistically and economically significant. For example, a one-standard-deviation decrease in the leadership turnover measure is associated with a 3.08-percentage-point (0.45-percentage-point) increase in gross (net) profit margins, which is roughly one-sixth (one-twelfth) of their interquartile range. Columns (5)–(8) in panel B show that the leadership turnover measure is negatively related to the volatility of net profitability.

[33] 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 robustness checks. The results are qualitatively similar (see Appendix Table C.7).

Table 5
Leadership turnover (LT) spread and discount rates.

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Panel A: Excess returns and CAPM alphas across industry portfolios sorted on the leadership turnover measure											
		Excess returns (%)						CAPM alphas (%)			
Q1 (low)	Q2	Q3	Q4	Q5 (high)	5 - 1	Q1 (low)	Q2	Q3	Q4	Q5 (high)	5 - 1
11.44***	10.02***	8.73***	7.78***	4.97***	−6.48***	2.43**	−0.14	−0.08	0.37	−1.78	−4.21**
[3.85]	[3.65]	[3.31]	[3.19]	[2.91]	[−2.98]	[2.33]	[−0.11]	[−0.03]	[−0.32]	[−1.60]	[−2.26]

	(1)	(2)	(3)	(4)	(5)	(6)
Panel B: Heterogeneous exposure to discount rates across industries sorted on the leadership turnover measure						
			Accumulated portfolio excess returns$_t$			
$\hat{\lambda}$ quintiles	Q1 (low)	Q2	Q3	Q4	Q5 (high)	5 - 1
Accumulated smooth_EPshocks$_t$	−29.42***	−26.99***	−23.22***	−21.45***	−17.92***	11.50**
	[−5.72]	[−4.79]	[−3.94]	[−4.01]	[−7.16]	[2.15]
Observations	325	325	325	325	325	325
R-squared	0.727	0.685	0.470	0.578	0.480	0.150

Panel A shows the value-weighted average excess returns and CAPM alphas for industry portfolios sorted on the leadership turnover measure. In June of year t, we sort industries into quintiles based on their leadership turnover measure in year $t-1$. Once the portfolios are formed, their monthly returns are tracked from July of year t to June of year $t+1$. We annualize average excess returns and alphas by multiplying them by 12. Newey-West standard errors are estimated with one lag. We exclude financial firms and utility firms from the analysis. Panel B shows the heterogeneous exposure to discount rates for industry portfolios sorted on the leadership turnover measure. The dependent variable is the summation of portfolio excess returns for the past 36 months: $\sum_{j=0}^{35}(r_{p,t-j}-r_{f,t-j})$. The independent variable is the summation of shocks to the smoothed earnings-price ratio for the past 36 months. The monthly shocks are estimated using an AR(1) model. Newey-West standard errors are estimated with 36 lags. We omit the coefficient for the constant term for brevity. The sample spans the period from 1988 to 2017. We include t-statistics in brackets. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Leadership turnover (LT) spread and discount rates. We further test the asset pricing implications of the leadership turnover rate. Panel A of Table 5 shows that industries whose leadership changes more often have lower expected stock returns. The difference in the average annualized excess returns (i.e., Q5 - Q1) is −6.48% and the difference in CAPM alphas is −4.21%, comparable to the equity premium and the value premium. We also examine the exposure of the LT spread to discount rates. Panel B shows that the LT spread loads positively on discount rates. The loading is also economically large. A one-standard-deviation increase in the accumulated discount-rate shocks is associated with a 0.39-standard-deviation increase in the accumulated LT spread.

Cross-equation restrictions imposed by two cross sections. Our model implies that industries' heterogeneous exposure to discount-rate shocks is simultaneously reflected by two industry characteristics: the gross profitability and the leadership turnover rate. We provide further evidence supporting this idea in Fig. 6 and Table 6.

Fig. 6 displays the time series and scatterplot of these two return spreads. Obviously, the two spreads are highly correlated: the yearly correlation between the GP spread and LT spread is −0.47 with a p-value of 0.009. If the leadership turnover rate and gross profitability are indeed two industry characteristics that capture the same fundamental mechanism, we would expect the LT spread to be able to explain a significant fraction of, if not all, the cross-industry GP spread. We look to the data for evidence.

Because the leadership turnover measure is only available after 1988, we extend the sample period back to 1953 using the mimicking portfolio approach. Specifically, we construct a mimicking portfolio for the LT spread by projecting the spread onto a set of portfolio returns that contains information about time-varying risk premia. Specifically, we run the following regression for the sample period from 1988 to 2018, during which the leadership turnover measure is available:

$$\text{LT spread}_t = a_0 + a_1 X_t + \varepsilon_t. \tag{24}$$

Vector X_t contains the base assets. Following the asset pricing literature, we choose a rich set of base assets in hopes of making the projection space as complete as possible.[34] These base assets include: the returns of the quintile portfolios sorted on the discount-rate beta,[35] the excess returns of the 2×3 Fama-French benchmark portfolios sorted on size (small and big) and book-to-market (low, medium, and high) in excess of the risk-free rate, the momentum factor (MOM_t), the difference between the ten-year and the one-year treasury bond yield ($TERM_t$), the difference between the Baa corporate bond yield and the ten-year treasury bond yield (DEF_t), the returns of the Fama-French five-industry portfolios, and the risk-free rate.

The choice of the above base assets follows the literature. In particular, the returns of the quintile portfolios sorted on the discount-rate beta follow the same idea as Ang et al. (2006), and the excess returns of the 2×3 Fama-French benchmark portfolios and the momentum factor are employed by Adrian et al. (2014). $TERM_t$ and DEF_t are employed by Eckbo et al. (2000), and they are intentionally included in our base assets to track fluctuations in the discount rate.[36] According to Campbell and Yogo (2006) and Ang and Bekaert (2007), the risk-free rate predicts future

[34] See, e.g., Chen et al. (1986), Breeden et al. (1989), Ferson and Harvey (1991), Eckbo et al. (2000), Lamont (2001), Ang et al. (2006), and Adrian et al. (2014).

[35] The estimation of discount-rate betas and the post-formation counterparts are detailed in Online Appendix C.

[36] It is well-documented that yields on short- and long-term treasury and corporate bonds have predictive power for subsequent stock returns

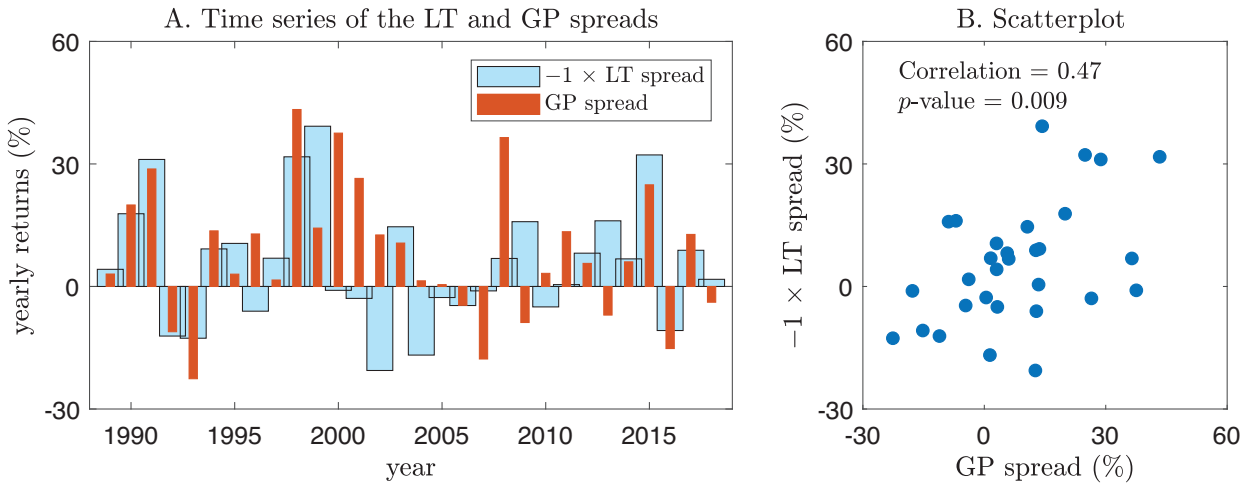

Fig. 6. Comovement between the LT and GP spreads.
Panels A and B illustrate the relation between the LT spread and the cross-industry GP spread. We multiply the LT spread by −1 because the LT and GP spreads load in opposite directions on discount-rate shocks.

Table 6
Explaining the cross-industry gross profitability premium.

	(1)	(2)	(3)	(4)
	Panel A: Exposure to the LT spread			
	Cross-industry GP spread$_t$ (%)			
Intercept	0.43***	0.35***	0.01	−0.01
	[3.28]	[2.62]	[0.06]	[−0.07]
MktRf$_t$		0.14***		0.12***
		[3.86]		[3.23]
The LT spread mimicking portfolio$_t$			−0.21***	−0.19***
			[−3.60]	[−3.07]
Observations	783	783	783	783
R-squared	0.000	0.030	0.042	0.063

	(1)	(2)
	Panel B: Explaining the cross-industry GP premium	
	Excess return	CAPM alpha
	5.18***	4.17***
	[3.28]	[2.62]
After controlling for the LT spread	0.12	−0.15
	[0.06]	[−0.07]

Panel A shows the results of the time-series regression of monthly spreads of gross profitability on market excess returns and the returns of the mimicking portfolio for the LT spread. The dependent variable is the cross-industry GP spread. Panel B tabulates the annualized GP spreads before and after controlling for the returns of the LT spread mimicking portfolio. The sample of this table spans the period from 1953 to 2018. The excess return and CAPM alpha are slightly different from those reported in Table 2 due to different sample periods. We exclude financial firms and utility firms from the analysis. We include *t*-statistics in brackets. Newey-West standard errors are estimated with one lag. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

equity excess returns, and thus we include it in our base assets to better capture changes in the discount rate. The industry portfolios are chosen following Lamont (2001)'s recommendation.[37]

After obtaining the estimate $\hat{a}_1$, we compute the returns of the LT spread mimicking portfolio for the sample period from 1953 to 2018 as follows:

$$\text{LT spread mimicking portfolio}_t = \hat{a}_1 X_t. \tag{25}$$

We present the in-sample and out-of-sample validation of the above mimicking portfolio in Appendix C.

Next, we regress the cross-industry GP spread on the returns of the LT spread mimicking portfolio. As shown in panel A of Table 6, the cross-industry GP spread loads significantly on this portfolio. After controlling for the LT spread, the GP spread reduces from 5.18% to 0.12% and becomes statistically insignificant (see panel B of Table 6). The CAPM alpha also drops to virtually zero. Because the LT spread directly reflects the heterogeneous exposure to discount-rate shocks through the competition mechanism in the model, these findings suggest that the cross-industry gross profitability premium is likely explained by the same endogenous competition mechanism.

4.4. Empirical tests on the core competition mechanism

In this subsection, we first provide evidence supporting the unique predictions of our core competition mechanism. Next, we discuss an anti-folk-theorem force and show that this force plays a limited role in the majority of industries. Finally, we show that the exposure to IST shocks can help explain the within-industry gross profitability premium as shown by Kogan and Papanikolaou (2013), but not the cross-industry one. This highlights the distinct nature between the two premia.

(e.g., Fama and Schwert, 1977; Keim and Stambaugh, 1986; Campbell, 1987; Fama and French, 1989) and are pried in the cross section of stock returns (e.g., Fama and French, 1993; Hodrick and Zhang, 2001).

[37] Our results remain robust if we exclude the 2 × 3 Fama-French benchmark portfolios or the momentum factor, or both for that matter, from the base assets.

Table 7
Impact of market structure changes on profitability in the cross section of industries sorted by gross profitability.

	(1)	(2)	(3)	(4)	(5)	(6)
	ΔNet profitability$_{i,t}$					
Market structure changes	n/a		Large tariff cut		Large similarity increase	
Mkt_chg$_{i,t}$ × high GP$_{i,t-1}$ × Δsmooth_EP$_t$			1.18**	1.19**	2.55**	3.64**
			[2.35]	[2.28]	[2.43]	[2.38]
High GP$_{i,t-1}$ × Δsmooth_EP$_t$	−0.69**	−0.70**	−1.23*	−1.29*	−2.34*	−2.63**
	[−2.36]	[−2.36]	[−1.84]	[−1.81]	[−1.89]	[−2.45]
Mkt_chg$_{i,t}$ × Δsmooth_EP$_t$			−0.40	−0.39	−0.48	−0.75
			[−0.88]	[−0.67]	[−0.63]	[−0.82]
ΔSmooth_EP$_t$	−0.14	−0.11	−0.14	−0.18	0.40	0.36
	[−0.74]	[−0.56]	[−0.38]	[−0.45]	[0.28]	[0.24]
Mkt_chg$_{i,t}$ × highGP$_{i,t-1}$			−0.01	−0.01	−0.01	−0.00
			[−0.85]	[−1.12]	[−1.27]	[−0.24]
High GP$_{i,t-1}$	−0.00	−0.00	−0.01	−0.01	−0.01	−0.00
	[−1.38]	[−0.66]	[−0.96]	[−0.87]	[−1.27]	[−0.24]
Mkt_chg$_{i,t}$			0.01	0.01	−0.03**	−0.03**
			[0.78]	[1.15]	[−2.30]	[−2.22]
Industry FE	No	Yes	No	Yes	No	Yes
Observations	20,848	20,848	8,286	8,286	8,436	8,436
R-squared	0.001	0.009	0.001	0.011	0.001	0.018

This table examines the impact of market structure changes on the sensitivity of net profitability to discount rates across industries with different levels of gross profitability. The independent variable is the year-on-year change in the industry-level net profitability. High GP$_{i,t-1}$ is an indicator variable that equals one if the one-year-lagged gross profitability of industry i is above the median gross profitability across all industries. The sample in columns (1) and (2) spans the period from 1954 to 2017. In columns (3) and (4), we measure market structure changes based on import tariff. Specifically, mkt_chg$_{i,t}$ is an indicator variable that equals one if an industry experiences a large tariff cut in the last two years (t and $t-1$). A large tariff cut refers to the tariff cut whose magnitude is greater than three times the median tariff cut in this industry across the whole sample period (e.g., Frésard, 2010). To ensure that large tariff cuts indeed capture nontransitory changes in the competitive environment, following Frésard (2010), we exclude tariff cuts that are followed by equivalently large increases in tariffs over the subsequent two years. We download the tariff data for manufacturing industries at the SIC4 industry level from 1974 to 2005 from Laurent Fresard's website. We extend the data to 2017 based on the tariff data at the Harmonized System level, which are downloaded from Peter Schott's website. In columns (5) and (6), we measure market structure changes based on product similarity (Hoberg and Phillips, 2010a; 2016). The pairwise product similarity scores are downloaded from the Hoberg and Phillips Data Library and cover the period from 1996 to 2017. For each firm at a given year, we compute the cross-industry product similarity at the firm level by summing up the pairwise similarity scores between the firm and other firms outside its SIC4 industry. We then compute an industry's cross-industry product similarity by averaging the firm-level values across firms in the industry. Mkt_chg$_{i,t}$ in columns (5) and (6) is an indicator variable that equals one if an industry experiences a large increase in the cross-industry product similarity in the last two years (t and $t-1$). A large increase in the cross-industry product similarity is one where the increase is greater than three times the median similarity increase in this industry. Standard errors are clustered at the industry level. We include t-statistics in brackets. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

4.4.1. Evidence for the competition mechanism

Our core competition mechanism generates an endogenous differential response of firms' competition intensity, as reflected in profit margins, to aggregate discount-rate shocks between industries featuring low and high market leadership persistence, which rationalizes the joint patterns of profitability and stock returns. To check whether the observed differential sensitivity of profit margins to fluctuation in discount rates is mainly driven by the endogenous competition mechanism, a direct test is to examine how such differential sensitivity would change if the industry market structure shifts to a more competitive one. As shown in Section 3.8, such differential sensitivity is weaker if the industry market structure becomes more competitive (i.e., if the industry's price elasticity of demand ϵ or the number of market leaders n increases). In this subsection, we directly test the unique predictions of our core competition mechanism described above.

We start by running our baseline regression in columns (1) and (2) of Table 7, in which we examine the heterogeneous sensitivities of net profitability to discount rates across industries with different gross profitability. Specifically, we run the following regression:

$$\begin{aligned}\Delta\text{net profitability}_{i,t} = {} & \beta_2 \times \text{high GP}_{i,t-1} \times \Delta\text{smooth\_EP}_t \\ & + \beta_4 \times \Delta\text{smooth\_EP}_t \\ & + \beta_6 \times \text{high GP}_{i,t-1} + a_i + \varepsilon_{i,t},\end{aligned} \tag{26}$$

where high GP$_{i,t-1}$ is the indicator variable for high-profitability industries, and it equals one for industry i and year $t-1$ if and only if industry i's profitability is above the median in year $t-1$; otherwise, it equals zero. The variable Δsmooth_EP$_t$ is the change in the smoothed earnings-price ratio from year $t-1$ to t, and the variable a_i represents industry fixed effects. The coefficient of the interaction term β_2 captures the difference in the sensitivity of net profitability to discount rates between industries with high and low profitability. As shown in columns (1)–(2) of Table 7, the estimated coefficient $\hat{\beta}_2$ is negative and statistically significant, suggesting that the profitability of more profitable industries comoves more negatively with discount rates. This finding is consistent with the theoretical results in panel B of Table 1.

Next, we move one step further to study how our baseline regression results, i.e., the difference in the sensitivity of profitability to discount rates between industries with high and low profitability, would change when industries' market structure becomes more competitive. Specifically, we add the variable for market structure changes, $\text{mkt\_chg}_{i,t}$, and its 0]/nteraction terms with high $\text{GP}_{i,t-1}$ and $\Delta\text{smooth\_EP}_t$ into specification (26), and we run the following panel regression:

$$\begin{aligned}\Delta\text{net profitability}_{i,t} &= \beta_1 \times \text{mkt\_chg}_{i,t} \times \text{high GP}_{i,t-1} \times \Delta\text{smooth\_EP}_t \\ &\quad + \beta_2 \times \text{high GP}_{i,t-1} \times \Delta\text{smooth\_EP}_t \\ &\quad + \beta_3 \times \text{mkt\_chg}_{i,t} \times \Delta\text{smooth\_EP}_t \\ &\quad + \beta_4 \times \Delta\text{smooth\_EP}_t + \beta_5 \times \text{mkt\_chg}_{i,t} \times \text{highGP}_{i,t-1} \\ &\quad + \beta_6 \times \text{highGP}_{i,t-1} + \beta_7 \times \text{mkt\_chg}_{i,t} + a_i + \varepsilon_{i,t}. \quad (27)\end{aligned}$$

Properly measuring $\text{mkt\_chg}_{i,t}$ in specification (27) is challenging. Endogeneity problems will arise if we use empirical proxies for the competitiveness of market structure such as the Herfindahl-Hirschman Index (HHI). In particular, there could exist some omitted variables that are correlated with both the changes in the HHI and the sensitivity of industries' net profitability to discount rates through channels other than the competitiveness of market structure. For example, technology development can lead to changes in the HHI. At the same time, it can also change the sensitivity of industries' net profitability to discount rates by altering the duration of firms' cash flows.

To address the endogeneity concern, we follow the literature (Frésard, 2010; Valta, 2012; Frésard and Valta, 2016) and use unexpected large cuts in import tariffs to identify exogenous variation in market structure.[38] The vast literature on barriers to trade suggests that globalization and trade openness substantially alter the competitive configuration of industries (see Tybout (2003) for a survey). For example, Bernard et al. (2006) show that tariff cuts significantly intensify the competitive pressures from foreign rivals. Valta (2012) shows that import tariff cuts are followed by a significant increase in imports. Thus, tariff reductions bring real changes to the competitiveness of industry market structure. Intuitively, large tariff cuts can lead to a more competitive market structure, because the reduction in trade barriers can increase (i) the industry's price elasticity of demand ϵ due to the similar products and services provided by foreign rivals and (ii) the number of market leaders n due to the entry of foreign rivals as major players.

In columns (3)–(4) of Table 7, we use a difference-in-differences (DID) approach to implement regression specification (27) by focusing on market structure changes caused by large tariff cuts.[39] The variable $\text{mkt\_chg}_{i,t}$ is an indicator variable that captures whether industries experience large tariff cuts. Specifically, $\text{mkt\_chg}_{i,t}$ is equal to one for industry i and year t if and only if industry i experiences large tariff cuts in year t; otherwise, it equals zero. The coefficient β_2 captures the difference in the sensitivity of net profitability to discount rates across industries with high and low profitability in the absence of large tariff cuts. The coefficient β_1 captures the changes in this cross-industry sensitivity difference caused by large tariff cuts.[40] As shown in columns (3)–(4) of Table 7, the estimated coefficient $\hat{\beta}_1$ is positive and statistically significant, suggesting that high- and low-profitability industries display less difference in the exposure to discount rates when the market structure shifts to a more competitive one.[41] The magnitude of $\hat{\beta}_1$ is economically large.

Besides exploring market structure changes caused by large tariff cuts, we also explore an additional source of variation of market structure directly implied by our model. In our model, an industry's market structure becomes more competitive when the industry price elasticity of demand ϵ is higher (see panel B of Fig. 5), which is the case when the products of the industry become more similar to those of other industries. Thus, as a robustness test, we use large increases in cross-industry product similarity to measure market structure changes. We construct the cross-industry product similarity in two steps. We first compute the similarity score of a firm by summing up its pairwise similarity scores with all firms in other industries (Hoberg and Phillips, 2010a; 2016).[42] We then average the similarity scores over all firms in the industry to obtain a measure of cross-industry product similarity. We present the results based on the cross-industry product similarity in columns (5)–(6) of Table 7. The indicator variable $\text{mkt\_chg}_{i,t}$ equals one for industry i and year t if and only if industry i experiences a large increase in cross-industry product similarity in year t; otherwise, it equals zero. The results are consistent with those based on tariff cuts, which provides additional evidence to support our model.

[38] Many other papers in the literature use tariff cuts as shocks to the competitiveness of industry market structure to address endogeneity concerns (e.g., Xu, 2012; Flammer, 2015; Huang et al., 2017; Dasgupta et al., 2018). There are also papers exploiting other exogenous shocks. For example, Zingales (1998) uses the deregulation in the trucking industry. Khanna and Tice (2000) exploit the entry of Walmart in local markets.

[39] The tariff cuts essentially work as an instrumental variable for the competitiveness of market structure in our analysis. Empirically, there are two standard methods to implement the instrumental variable test. The first method is to run two-stage least squares (2SLS) regressions. To apply this method, the key independent variable for which the instrumental variable instruments needs to be measurable. If the key independent variable is not easily measurable, the difference-in-differences approach can serve as an alternative, which has been widely used in the literature. For example, recent studies use the difference-in-differences approach to examine the causal impact of information asymmetry, a variable that is hard to measure empirically, on asset prices (Kelly and Ljungqvist, 2012), voluntary disclosure (Balakrishnan et al., 2014), and information acquisition of sophisticated investors (Chen et al., 2020).

[40] Although our regression specification (27) resembles a triple difference-in-differences setup, our goal is not to show which industries respond more to tariff cuts. Instead, our goal is to examine the impact of tariff cuts on the difference in the sensitivity of net profitability to discount rates between industries with high and low profitability.

[41] A positive $\hat{\beta}_1$ means that the difference in discount-rate exposure narrows because high-profitability industries are more negatively exposed to discount rates than low-profitability industries in the absence of large tariff cuts.

[42] Pairwise similarity between firms i and j in year t is the cosine similarity between the two word vectors of the product descriptions of firms i and j's 10-K in year t.

Table 8
Impact of market structure changes on profitability in the cross section of industries sorted by market leadership turnover rate.

	(1)	(2)	(3)	(4)	(5)	(6)
	ΔNet profitability$_{i,t}$					
Market structure changes	n/a		large tariff cut		large similarity increase	
Mkt_chg$_{i,t}$ × low $\hat{\lambda}_{i,t-1}$ × Δsmooth_EP$_t$			5.58**	5.43**	2.09**	1.93**
			[2.15]	[2.43]	[2.49]	[2.22]
Low $\hat{\lambda}_{i,t-1}$ × Δsmooth_EP$_t$	−0.99**	−1.05**	−4.29*	−4.48*	−1.96**	−2.01**
	[−2.18]	[−2.32]	[−1.89]	[−1.92]	[−2.21]	[2.43]
Mkt_chg$_{i,t}$ × Δsmooth_EP$_t$			−2.23	−2.91	−1.42	−1.06
			[−0.91]	[−1.07]	[−0.86]	[−0.72]
ΔSmooth_EP$_t$	0.19	0.11	1.67	1.74	0.41	0.35
	[0.28]	[0.32]	[0.87]	[0.90]	[0.44]	[0.37]
Mkt_chg$_{i,t}$ × low $\hat{\lambda}_{i,t-1}$			−0.00	−0.01	0.02	0.02
			[−0.31]	[−0.40]	[1.30]	[1.22]
Low $\hat{\lambda}_{i,t-1}$	−0.00	−0.01	−0.00	−0.01	−0.00	−0.01
	[−0.75]	[−1.00]	[−0.24]	[−0.71]	[−1.09]	[−0.57]
Mkt_chg$_{i,t}$			0.01	0.01	−0.02	−0.02
			[1.00]	[1.05]	[−1.19]	[−1.16]
Industry FE	No	Yes	No	Yes	No	Yes
Observation	4,849	4,849	2,153	2,153	3,673	3,673
R-squared	0.001	0.018	0.003	0.016	0.004	0.012

This table examines the impact of market structure changes on the sensitivity of net profitability to discount rates across industries with different values of the leadership turnover measure. The independent variable is the year-on-year change in the industry-level net profitability. Low $\hat{\lambda}_{i,t-1}$ is an indicator variable that equals one if the one-year-lagged leadership turnover measure of industry i is below the median leadership turnover across all industries. Other variables are explained in Table 7. The sample in columns (1)–(4) spans the period from 1988 to 2017. The sample in columns (5)–(6) spans the period from 1996 to 2017. We include t-statistics in brackets. Standard errors are clustered at the industry level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Compared to the tariff cut shocks, exploring the variation in the cross-industry product similarity has its own advantages and disadvantages in our setting. There are two main advantages. The product similarity measure covers a broader cross section than what is covered by tariff cut shocks. On average, there are 384 SIC4 industries per year in the product similarity sample compared to 188 SIC4 industries per year in the tariff cut sample. More importantly, as we have mentioned earlier, the variation in the cross-industry product similarity can be directly mapped to our model as the variation in the industry's price elasticity of demand. There are two main weaknesses. First, the variation in the cross-industry product similarity could suffer from omitted variables problems. For example, technology changes could simultaneously drive changes in both the cross-industry product similarity and the sensitivity of industries' net profitability to discount rates.[43] Second, the cross-industry product similarity measure is constructed based on the pair-wise product similarity data, which are only available after 1996, making the sample period relatively short.

Finally, we examine the impact of market structure on the sensitivity of net profitability to discount rates across industries with different rates of leadership turnover. Specifically, we replace the indicator variable for high-profitability industries with the one for low-leadership-turnover industries in panel regression specifications (26) and (27). Table 8 presents the results. Consistent with our model, industries with low and high leadership turnover rates exhibit a smaller difference in the sensitivity of net profitability to discount rates when their market structure becomes more competitive. The estimated coefficient on the triple interaction term $\hat{\beta}_1$ is positive and significant both statistically and economically.

4.4.2. Discussions on the anti-folk-theorem force

Our model emphasizes a mechanism of endogenous competition due to time-varying collusion incentives among firms in an industry. In particular, we highlight the folk-theorem force: collusion incentives are lower when discount rates are higher. But in principle, firms could predate competitors and undercut profit margins more aggressively to drive them out of the market and enjoy the monopoly rent when discount rates are lower. Intuitively, competition can intensify when the aggregate discount rate decreases, because the financially stronger firm has incentives to undercut prices more aggressively to drive its financially distressed competitors out for monopolistic rents in the future. This channel is often referred to as the *anti-folk-theorem channel* (e.g., Kawakami and Yoshihiro, 1997; Wiseman, 2017; Chen et al., 2019).

However, such a mechanism can disappear or be substantially weakened if the entry cost is not too high or if competing market leaders are not too imbalanced in terms of the amount of financial distress they are each experiencing. This intuition is formalized by the theoretical study of Wiseman (2017) and the quantitative investigation of Chen et al. (2019).

[43] For example, recent development in smart phone technology has made cell phones more similar to personal computers.

Table 9
Cross-industry GP spreads in industry subsamples with different entry costs.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Panel A: Industry subsamples with different levels of fitted HHI											
Industry subsamples:	Bottom 70% of the fitted HHI						Top 30% of the fitted HHI					
GP quintiles	Q1	Q2	Q3	Q4	Q5	5 - 1	Q1	Q2	Q3	Q4	Q5	5 - 1
Excess returns (%)	5.47	7.52*	8.37*	10.45***	13.21***	7.73***	6.27**	8.40**	6.10*	8.04**	7.42**	1.16
	[1.58]	[1.92]	[1.83]	[2.96]	[3.82]	[2.83]	[2.03]	[2.35]	[1.71]	[2.09]	[2.15]	[0.41]
	Panel B: Industry subsamples with different fixed-costs-to-profits ratios											
Industry subsamples:	Bottom 70% of the fixed-costs-to-profits ratio						Top 30% of the fixed-costs-to-profits ratio					
GP quintiles	Q1	Q2	Q3	Q4	Q5	5 - 1	Q1	Q2	Q3	Q4	Q5	5 - 1
Excess returns (%)	5.88***	8.96***	7.50***	8.52***	10.16***	4.29***	9.79***	8.66***	8.92***	10.53***	8.43***	−1.36
	[3.30]	[4.30]	[3.34]	[3.50]	[4.56]	[2.61]	[2.85]	[2.73]	[3.27]	[4.22]	[3.62]	[−0.48]

This table shows the value-weighted average excess returns for the industry portfolios sorted on gross profitability among industries with different entry costs. In panel A, industries' entry costs are measured using the fitted HHI measure from Hoberg and Phillips (2010b). In panel B, industries' entry costs are measured using the fixed-costs-to-profits ratio. We proxy for fixed costs using SG&A expenses following the literature (e.g., Gilchrist and Himmelberg, 1998; Gorodnichenko and Weber, 2016; Gilchrist et al., 2017). The sample period of panel A is from July 1976 to June 2007, during which the fitted HHI measure is available. The sample period of panel B is from July 1951 to June 2018. We exclude financial firms and utility firms from the analysis. We annualize average excess returns and alphas by multiplying them by 12. Newey-West standard errors are estimated with one lag. We include t-statistics in brackets. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Inspired by the discussion above, we hypothesize that our model's prediction is stronger and more prevalent in industries with lower entry costs.[44] To test this conjecture, we perform split sample analyses based on two measures of entry costs. The first measure is the Herfindahl-Hirschman Index (HHI), which reflects the idea that entry costs are intrinsically high in concentrated industries. Because private firms play an important role in industry competition (e.g., Ali et al., 2008), we measure industry concentration using the fitted HHI measure from Hoberg and Phillips (2010b), who consider both public and private firms. The second measure is inspired by the influential work of Bresnahan and Reiss (1991), whose model shows that industries' entry costs can be approximated by fixed costs divided by gross profits (see their Eq. (6) on page 982). We proxy for fixed costs using SG&A expenses (e.g., Gilchrist and Himmelberg, 1998; Gorodnichenko and Weber, 2016; Gilchrist et al., 2017).[45]

We show that the folk-theorem force is prevalent and dominates in the data for most industries. In Table 9, we split all industries into two groups based on their entry cost measures. The first group in columns (1)–(6) consists of industries with low and medium levels of entry costs (bottom 70% of the sample), while the second group in columns (7)–(12) comprises industries with high entry costs (top 30% of the sample). By sorting industries in each group into quintiles based on their gross profitability, we show that the cross-industry GP spread is significantly positive among industries with low and medium levels of entry costs. By contrast, the cross-industry GP spread is insignificant among industries with high entry costs. In Table 10, we further examine the exposure of the GP spread to discount-rate shocks. We find that the cross-industry GP spread loads significantly negatively on discount-rate shocks among industries with low and medium levels of entry costs, while it has an insignificant loading among industries with high entry costs. The above findings suggest that the anti-folk-theorem force can emerge only in a minority of industries characterized by extremely high entry costs, consistent with the results of Wiseman (2017) and Chen et al. (2019).

4.4.3. Discussions on the 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 higher profitability are less exposed to IST shocks, and that their average stock returns are higher because IST shocks carry a negative price of risk.

Following Kogan and Papanikolaou (2013, 2014), we use the difference between the stock returns of investment-good and consumption-good producers, i.e. IMC, as an empirical proxy for IST shocks. We regress the GP spread on IMC, with and without controlling for market excess returns. The results are presented in Table 11. Consistent with Kogan and Papanikolaou (2013), we find that the firm-level GP spread loads negatively on IMC (see panel C), suggesting that the heterogeneous exposure to IST shocks can partially explain the firm-level gross profitability premium. The within-industry GP spread also loads negatively on IMC (see panel B). However, the cross-industry GP spread has an insignificant loading on IMC (see panel A). These results suggest that the exposure to IST shocks is unlikely to explain the cross-industry gross profitability premium. Intuitively, the channel of displacement risk mainly works within industries because it is difficult for one industry to displace another after innovation shocks. Our paper focuses on the cross-industry gross profitability

[44] Nesting the predation channel of Wiseman (2017) inside our model is beyond the scope of this paper. Chen et al. (2019) model the predation channel explicitly and show that when the entry barrier is high, financially strong firms substantially lower their profit margins to drive their financially distressed counterparts out of the market.

[45] Significant SG&A spending signals high fixed costs of operation. Anderson et al. (2003) show that SG&A costs are sticky in the sense that firms cannot easily reduce such expenses when sales decline.

Table 10
Exposure of cross-industry GP spreads to discount rates in industry subsamples with different entry costs.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Panel A: Industry subsamples with different levels of fitted HHI											
	Accumulated portfolio excess returns$_t$											
Industry subsamples	Bottom 70% of the fitted HHI						Top 30% of the fitted HHI					
GP quintiles	Q1	Q2	Q3	Q4	Q5	5 - 1	Q1	Q2	Q3	Q4	Q5	5 - 1
Accumulated	−0.26	−7.97**	−4.51	−8.16**	−8.58***	−8.31**	−5.24***	−5.91***	−2.66	−3.68*	−7.85***	−2.61
smooth_EPshocks$_t$	[−0.06]	[−2.56]	[−1.48]	[−2.31]	[−6.46]	[−1.97]	[−3.82]	[−2.68]	[−1.38]	[−1.89]	[−2.99]	[−1.06]
Observations	337	337	337	337	337	337	337	337	337	337	337	337
R-squared	0.000	0.235	0.088	0.270	0.443	0.148	0.268	0.146	0.038	0.116	0.333	0.032
	Panel B: Industry subsamples with different fixed-costs-to-profits ratios											
	Accumulated portfolio excess returns$_t$											
Industry subsamples	Bottom 70% of the fixed-costs-to-profits ratio						Top 30% of the fixed-costs-to-profits ratio					
GP quintiles	Q1	Q2	Q3	Q4	Q5	5 - 1	Q1	Q2	Q3	Q4	Q5	5 - 1
Accumulated	−7.44***	−6.87***	−7.86***	−9.15***	−13.03***	−5.59***	−11.16***	−10.78**	−11.99***	−8.99***	−10.37***	0.79
smooth_EPshocks$_t$	[−4.65]	[−3.90]	[−3.54]	[−4.24]	[−5.75]	[−2.98]	[−3.46]	[−2.90]	[−4.78]	[−3.54]	[−4.46]	[0.26]
Observations	769	769	769	769	769	769	769	769	769	769	769	769
R-squared	0.297	0.282	0.279	0.420	0.523	0.145	0.198	0.239	0.391	0.339	0.410	0.002

This table shows the heterogeneous exposure to discount rates for industry portfolios sorted on gross profitability in industries with different entry costs. The sample period of panel A is from 1979 to 2007, during which the fitted HHI measure is available. The sample period of panel B is from 1954 to 2018. Newey-West standard errors are estimated with 36 lags. We exclude financial firms and utility firms from the analysis. We omit the coefficients for the constant terms for brevity. We include *t*-statistics in brackets. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 11
Exposure of GP spreads to IST shocks.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Portfolio excess returns$_t$											
GP quintiles	Q1 (low)	Q2	Q3	Q4	Q5 (high)	5 - 1	Q1 (low)	Q2	Q3	Q4	Q5 (high)	5 - 1
	Panel A: Exposure of the cross-industry GP spread											
IMC$_t$	0.52***	0.83***	1.06***	0.78***	0.61***	0.09	−0.01	0.25***	0.44***	0.15***	−0.00	0.00
	[8.68]	[14.36]	[14.32]	[14.51]	[10.52]	[1.51]	[−0.21]	[4.72]	[7.26]	[3.11]	[−0.08]	[0.03]
MktRf$_t$							0.87***	0.95***	1.04***	1.04***	1.01***	0.14***
							[41.37]	[34.86]	[39.40]	[35.53]	[36.77]	[3.65]
Observations	804	804	804	804	804	804	804	804	804	804	804	804
R-squared	0.181	0.316	0.386	0.265	0.178	0.008	0.781	0.806	0.818	0.823	0.762	0.033
	Panel B: Exposure of the within-industry GP spread											
IMC$_t$	0.99***	0.91***	0.88***	0.76***	0.55***	−0.43***	0.36***	0.29***	0.29***	0.17***	−0.04	−0.39***
	[16.96]	[15.36]	[15.50]	[14.83]	[9.99]	[−10.35]	[8.45]	[5.25]	[5.47]	[3.85]	[−1.18]	[−8.66]
MktRf$_t$							1.05***	1.03***	0.99***	0.97***	0.98***	−0.07**
							[43.09]	[37.75]	[38.86]	[40.51]	[52.95]	[−2.52]
Observations	804	804	804	804	804	804	804	804	804	804	804	804
R-squared	0.362	0.331	0.340	0.279	0.179	0.225	0.841	0.833	0.837	0.818	0.833	0.233
	Panel C: Exposure of the firm-level GP spread											
IMC$_t$	0.75***	0.63***	0.75***	0.73***	0.50***	−0.25***	0.11***	0.02	0.15***	0.13***	−0.09***	−0.20***
	[11.10]	[8.36]	[14.79]	[13.77]	[9.20]	[−6.14]	[4.52]	[0.56]	[6.80]	[5.03]	[−3.31]	[−4.73]
MktRf$_t$							1.05***	1.01***	0.99***	1.00***	0.97***	−0.08**
							[50.52]	[47.34]	[58.15]	[54.65]	[47.57]	[−2.29]
Observations	804	804	804	804	804	804	804	804	804	804	804	804
R-squared	0.264	0.216	0.303	0.280	0.152	0.078	0.879	0.870	0.921	0.888	0.829	0.087

This table shows the exposure to IST shocks for portfolios sorted on gross profitability. 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 by Gomes et al. (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. Newey-West standard errors are estimated with one lag. We omit the coefficients for the constant terms for brevity. We include *t*-statistics in brackets. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

premium and proposes a novel mechanism based on endogenous competition to rationalize this premium. Our mechanism complements the displacement-risk mechanism of Kogan and Papanikolaou (2013) in explaining the gross profitability premium.

5. Conclusion

This paper investigates the origin of endogenous fluctuations in industry competition intensity and its asset pricing implications. We propose the first elements of a

tractable dynamic industry-equilibrium model to connect strategic competition and the time-varying discount rate. In our model, industry competition endogenously intensifies as the discount rate rises because firms effectively become more impatient for cash flows and their incentives to undercut profit margins grow stronger. The exposure to discount-rate shocks is determined by the industry's market leadership persistence as a fundamental industry characteristic. Industries with a higher leadership turnover rate are more immune to fluctuations in profit margins driven by the discount-rate shocks. Our theoretical and empirical studies shed new light on the relation between gross profitability and stock returns — the well-known gross profitability premium.

Appendix A. Quantitative analyses

In this section, we quantitatively study the model's ability to explain the asset pricing patterns in the data. In Subsection A.1, we extend the baseline model with nonpecuniary collusion costs to generate endogenous jumps in firms' profit margins. In Subsection A.2, we calibrate the model's parameters and examine whether it can replicate the main findings on stock returns and corporate profitability from the data. Finally, we discuss the quantitative importance of various channels and model ingredients in Subsection A.3.

A1. Endogenous jumps

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

In the baseline model, firms can costlessly cooperate with their competitors by adopting the collusive profit-margin scheme. As a result, the collusive profit-margin scheme is always maintained in equilibrium, and profit margins vary continuously with discount rate γ_t. In this section, we introduce collusion costs to generate endogenous shifts from the collusive regime to the noncollusive regime. One example of collusion costs is monitoring costs (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 nonpecuniary 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 noncollusive 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 noncollusive competition.

As a numerical illustration, panel A of Fig. A.1 shows that when the two firms hold equal shares of the customer base (i.e., $M_{i,t}/M_t = 0.5$), the industry's profit margin jumps downward when the market price of risk γ_t goes above 0.9. Panels B and C show that when shares of the customer base become less evenly distributed, the negative jumps in profit margins occur at a lower market price of risk because of lower collusion benefits.

A2. Calibration and parameter choice

Some of the parameters are determined from external information without simulating the model (see panel A of Table A.1). Others are calibrated internally from moment matching (see panel B of Table A.1).

Externally determined parameters. The risk-free rate is $r_f = 2.5\%$. We set the persistence of the market price of risk $\varphi = 0.13$ as in Campbell and Cochrane (1999) and $\pi = 0.12$ as in Lettau and Wachter (2007). The within-industry elasticity of substitution is set at $\eta = 15$ and the cross-industry elasticity of substitution at $\epsilon = 1.6$, which are broadly consistent with Atkeson and Burstein (2008). We choose a low customer base depreciation rate $\rho = 0.03$, a low accumulation rate $\alpha = 0.01$, and a low volatility $\sigma_M = 0.01$ to capture a sticky customer base (e.g., Gourio and Rudanko, 2014; Gilchrist et al., 2017). We set $h = 0.5$, consistent with the implication of a quadratic adjustment cost function. We assume that the industry-level rate of market leadership turnover λ 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.

Table A.1
Calibration and parameter choice.

Parameter	Symbol	Value	Parameter	Symbol	Value
		Panel A: Externally determined parameters			
Risk-free rate	r_f	2.5%	Persistence of market price of risk	φ	0.13
Volatility of market price of risk	π	0.12	Within-industry elasticity	η	15
Customer base depreciation rate	ρ	0.03	Cross-industry elasticity	ϵ	1.6
Customer base accumulation rate	α	0.01	Customer base volatility	σ_M	0.01
Range of turnover rate	$\underline{\lambda}$, $\overline{\lambda}$	0, 0.18	Weight of contemporaneous demand	h	0.5
		Panel B: Internally calibrated parameters			
Capital depreciation rate	δ	0.1	Punishment rate	ξ	0.09
Volatility of aggregate shocks	ς	0.06	Collusion cost	ν	0.054
Market price of risk for $Z_{\gamma,t}$	ζ	0.5	Market price of risk for Z_t	$\overline{\gamma}$	0.15

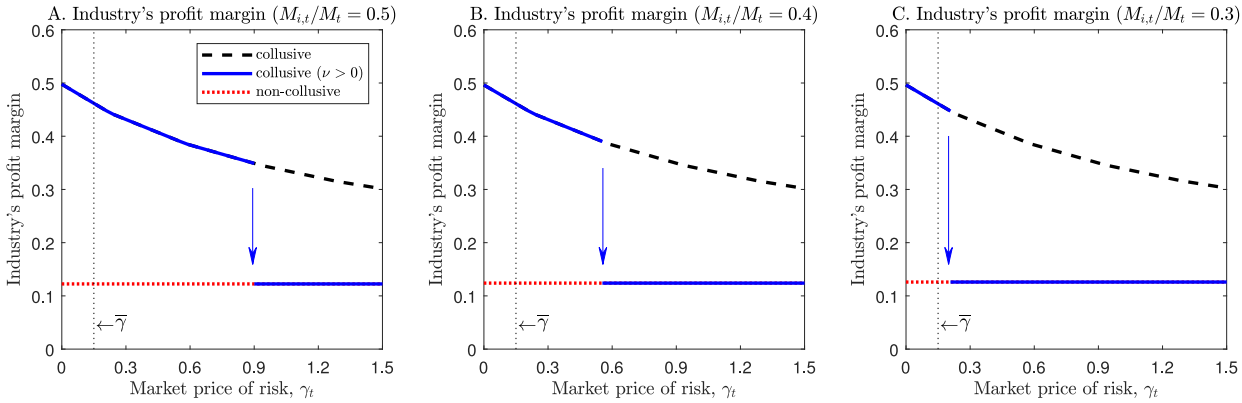

Fig. A.1. Collusion costs and the endogenous jump risk. This figure is plotted using the calibrated parameter values in Table A.1. We consider an industry with $\lambda = 0$. The blue solid line represents the case where $\nu = 0.054$ according to our calibration.

Table A.2
Targeted moments in the data and model.

Moments	Data	Model	Moments	Data	Model
Average gross profit margin (%)	31.39	25.97	Average net profitability (%)	3.92	4.36
	[29.98, 33.00]	[20.27, 32.31]		[2.79, 5.09]	[2.49, 6.51]
Equity premium	6.68	6.38	Volatility of growth rates of	16.22	11.05
($\mathbb{E}(r - r_f)$, %)	[2.34, 10.88]	[3.08, 9.68]	real net profits (%)	[11.11, 19.88]	[9.12, 13.04]
GP premium	5.06	4.81	Volatility of market excess returns	16.89	14.88
(Q5 – Q1, $\mathbb{E}(R_{Q5} - R_{Q1})$, %)	[2.74, 7.05]	[3.52, 5.76]	($\sigma(r - r_f)$, %)	[13.21, 19.39]	[12.56, 17.36]

We construct the above Compustat-based moments using the data from 1950 to 2017. Volatility of the growth rates of real net profits is the volatility of the growth rates of the average industry's real net profits. When constructing the model moments, we simulate a sample of 1,000 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.

Internally calibrated parameters. The remaining parameters are calibrated by matching relevant moments in panel B of Table A.2.

We set the capital depreciation rate $\delta = 0.1$ to match the average net profitability.[46] We set the punishment rate $\xi = 0.09$ to match the average gross profit margin of all industries. We calibrate $\nu = 0.054$ so that the volatility of the growth rates of real net profits of all industries resembles the data. We set $\overline{\gamma} = 0.15$, $\zeta = 0.5$, and $\varsigma = 0.06$ so that the average equity premium ($\mathbb{E}(r - r_f)$) is 6.38%, the GP premium ($\mathbb{E}(R_{Q5} - R_{Q1})$) is 4.81%, and the volatility of market excess returns ($\sigma(r - r_f)$) is 14.88%.

A3. Quantitative results

Columns (1) and (2) of Table A.3 show 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. The model-implied GP premium is about 4.81%, which is also roughly consistent with the 5.06% seen in the data. The model-implied GP spread (Q5 - Q1) is negatively exposed to the earnings-price (EP) ratio (sensitivity $= -2.83$), which is also consistent with the data (sensitivity $= -4.67$). In both the model and data, the GP spread vanishes once we control for the return spread of portfolios sorted on the leadership turnover measure (i.e., λ in the model and $\hat{\lambda}$ in the data).

Next, we evaluate the quantitative implication of jump risks in profit margins caused by nonpecuniary collusion costs. In column (3), we consider an economy without collusion costs (i.e., $\nu \equiv 0$) for all industries. Comparing columns (2) and (3), in the absence of collusion costs, the model implies a higher average net profitability and gross margins because firms can always costlessly collude with each other. Moreover, the volatility of the growth rates of real net profits decreases sharply from 11.05% to 8.50%, resulting in lower equity premium and volatility of market returns. The GP premium decreases from 4.81% to 2.28% once we remove collusion costs.

In column (4), we set $\alpha = 0$ so that firms cannot accumulate customer base from past consumer demand. The average net profitability and gross profit margins decrease because firms have less incentive to collude in setting higher profit margins when the customer base is growing more slowly. Moreover, in the case where $\alpha = 0$, the equity premium, the volatility of market returns, and the GP premium are all higher. Intuitively, a positive α implies that firms grow faster during bad times featuring higher discount rates. This is because when discount rates rise, firms tend to collude on lower profit margins, resulting in higher demand. The higher demand in turn accelerates the growth of the customer base according to Eq. (3.6). Thus, a positive α in our baseline calibration essen-

[46] The net profitability in the model is $NP_{i,t} = GP_{i,t} - \rho$, where $GP_{i,t}$ is defined in Eq. (3.10).

Table A.3
Model mechanisms and asset pricing implications.

	(1) Data	(2) Full model	(3) Model-based counterfactuals	(4)	(5)	(6) Three firms
		collusive	$\nu = 0$	$\alpha = 0$	noncollusive	$n = 3$
Average net profitability (%)	3.92	4.36	6.58	3.34	1.70	3.29
	[2.79, 5.09]	[2.49, 6.51]	[5.14, 8.46]	[1.74, 5.58]	[1.68, 1.71]	[2.52, 4.21]
Average gross profit margin (%)	31.39	25.97	37.15	22.56	11.95	19.22
	[29.98, 33.00]	[20.27, 32.31]	[33.17, 42.01]	[17.56, 29.07]	[11.85, 12.02]	[17.53, 21.50]
Volatility of growth rates of	16.22	11.05	8.50	10.42	6.24	10.24
real net profits (%)	[11.11, 19.88]	[9.12, 13.04]	[7.19, 9.90]	[8.31, 12.54]	[5.00, 7.75]	[7.76, 12.86]
Equity premium	6.68	6.38	5.89	6.91	4.24	6.15
($\mathbb{E}(r - r_f)$, %)	[2.34, 10.88]	[3.08, 9.68]	[4.18, 7.54]	[5.40, 8.42]	[1.84, 6.74]	[4.37, 7.97]
Volatility of market excess returns	16.89	14.88	13.55	16.10	9.74	14.41
($\sigma(r - r_f)$, %)	[13.21, 19.39]	[12.56, 17.36]	[11.01, 16.75]	[12.48, 21.15]	[8.42, 11.11]	[11.64, 17.92]
Sharpe ratio	0.40	0.43	0.43	0.43	0.43	0.43
($\mathbb{E}(r - r_f)/\sigma(r - r_f)$)	[0.13, 0.77]	[0.18, 0.68]	[0.30, 0.57]	[0.25, 0.63]	[0.31, 0.55]	[0.29, 0.57]
Gross profitability Q1	5.20	5.72	6.42	6.46	4.98	5.58
($\mathbb{E}(R_{Q1} - R_f)$, %)	[3.69, 7.05]	[3.24, 8.28]	[4.64, 8.20]	[4.66, 8.34]	[2.50, 7.54]	[4.02, 7.20]
Gross profitability Q5	10.26	10.53	8.70	12.26	4.85	9.90
($\mathbb{E}(R_{Q5} - R_f)$, %)	[8.93, 11.58]	[7.29, 13.28]	[6.88, 10.43]	[10.17, 14.18]	[2.45, 7.31]	[6.57, 12.90]
GP premium	5.06	4.81	2.28	5.80	−0.13	4.32
(Q5 − Q1, $\mathbb{E}(R_{Q5} - R_{Q1})$, %)	[2.74, 7.05]	[3.52, 5.76]	[1.69, 2.78]	[3.82, 7.35]	[−0.26, −0.04]	[2.89, 5.37]
Q5 − Q1 spread after controlling	0.12	0.01	0.01	0.01	0.00	0.01
for the λ spread	[−4.32, 4.37]	[−0.02, 0.03]	[−0.02, 0.03]	[−0.02, 0.03]	[−0.02, 0.02]	[−0.02, 0.02]
Q5 − Q1 spread's exposure to	−4.67	−2.83	−1.22	−3.85	0.12	−2.43
discount rates	[−5.68, −3.36]	[−4.76, −1.42]	[−1.87, −0.55]	[−6.19, −2.22]	[0.05, 0.22]	[−4.38, −1.06]

R represents simple returns and r log returns. When constructing the model moments, we simulate a sample of 1,000 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).

tially provides an insurance effect that dampens the impact of endogenous profit-margin fluctuations on the value of firms.

To evaluate the importance of endogenous competition, we simulate a counterfactual in which firms are forbidden from colluding with each other. That is, the two firms in the same industry adopt the noncollusive scheme, and both set profit margins taking the other's profit margin as given. As shown in column (5), 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 6.24%, merely reflecting shocks to the industry's total customer base (i.e., the term ςdZ_t in Eq. (3.6)). The equity premium drops from 6.38% to 4.24%, indicating that about 34% of the equity premium is attributed to competition risk. The volatility of market excess returns decreases from 14.88% to 9.74%. The model-implied GP premium is largely reduced from 4.81% to −0.13%. Overall, by comparing the implications of our full model with those of the noncollusive model, we show 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 A.3 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 the customer base, and collusion decisions. Thus, solving a generic n−firm model is NP hard.[47] In reality, an industry could 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 (6)). Based on the same parameter values, column (6) reports that the average net profitability and gross profit margins significantly decrease compared with 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 11.05% to 10.24% 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 greatly dampen the model-implied GP 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 GP premium. As a result, increasing the number of firms from two to three only slightly reduces the GP premium from

[47] Our baseline model is solved in C++ with 48 CPU cores running in parallel. Even with parallel computation, however, 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.

4.81% to 4.32%. Of course, further increasing the number of firms will likely further reduce the GP premium implied by the model. However, the marginal impact of doing so is likely diminishing. For tractability reasons, we cannot exhaust all such cases for robustness checks.

Appendix B. Supplementary information for empirical analyses

Profitability, profit margins, and asset turnover. We compute profitability, profit margins, and asset turnover based on Compustat. We construct industry-level gross profitability as gross profits (revenue minus cost of goods sold) scaled by assets, following the definition in Novy-Marx (2013). 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. Following Anderson et al. (2018), we construct the gross profit margin for industry i at year t as $(\text{Sales}_{i,t} - \text{COGS}_{i,t})/\text{Sales}_{i,t}$. We construct the 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. Finally, we construct asset turnover as revenue scaled by asset.

Media and analyst coverage of price wars. We measure the media and analyst coverage of price wars using textual analysis following the recent literature (see, e.g. Loughran and McDonald, 2011; Baker et al., 2016; Manela and Moreira, 2017; Kelly et al., 2019). Specifically, we follow Baker et al. (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, p.1199). 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 et al. (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 do not use historical SIC codes from CRSP because previous studies have concluded that Compustat-based SIC codes are in general more accurate (e.g., Guenther and Rosman, 1994; Kahle and Walkling, 1996; Bhojraj et al., 2003). Earlier studies have also pointed 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 operating more than three segments according to 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 data sets 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 M&A Database 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 is a market leader prior to the M&A 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. We use the logistic regression model (4.1) to estimate the leadership turnover rate. The estimation result, denoted by $\hat{\lambda}_t$, is referred to as *leadership turnover measure*. The estimation procedures for logistic regression models even with high dimensions are discussed in Brown (1986), Brown et al. (2010), and Dou et al. (2012).

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 patents granted from 1976 onward. It covers recent patenting activities more comprehensively than the NBER patent data (see Hall et al., 2001) and the patent data assembled by Kogan et al. (2017) combined.[48] 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 (e.g., Ali et al., 2008). We drop patents granted to individuals and government agencies. We use a fuzzy name-matching algorithm to obtain a pool of potential

[48] 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.

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 U.S. public firms, 132,100 patents to 3,080 U.S. private firms, 241,582 patents to 300 foreign public firms, and 35,597 patents to 285 foreign private firms. The merged sample covers 13,804 firms in 523 four-digit SIC industries from 1976 to 2017.

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

$$\text{similarity}(a, b) = \frac{\mathbf{A} \cdot \mathbf{B}}{\|\mathbf{A}\| \|\mathbf{B}\|}, \tag{28}$$

where $\mathbf{A}$ and $\mathbf{B}$ are the technology vectors of patent a and patent b.[49] 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 classification, 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 three 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 Eq. (28)) 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 produce 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.

[49] 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. (2020), we use CPC for our analyses because USPC is not available after 2015. Our results are robust to the classification based on USPC for data prior to 2015. There are 653 unique CPC classes (four-digit level) in PatentsView. The technology classification vector for a patent consists of 653 indicator variables that represent the patent's CPC classes.

Appendix C. Supplementary empirical results

Alternative industry classifications. We use alternative industry classifications (i.e., SIC3 and FIC) to study the asset pricing implications of gross profitability. Table C.4 examines the sensitivity of profitability to discount rates across industry portfolios sorted on gross profitability. Table C.5 examines the cross-industry GP spreads. Table C.6 examines the sensitivity of the GP spreads to discount-rate shocks. These results with SIC3 and FIC are similar to those with SIC4 (see Tables 1, 2, and 3).

Alternative regression methods. In Table C.7, we use the panel regression approach to replicate the Fama-MacBeth regressions in Table 4. 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.

Asset turnover. We use asset turnover as the sorting variable and study its asset pricing implications. Table C.7 shows that the average profitability comoves more negatively with discount rates in industries with a higher asset turnover. Table C.7 shows that, besides being priced at the firm level, asset turnover is also positively priced both within and across industries. Table C.7 shows that the cross-industry asset turnover spread loads negatively on accumulated discount-rate shocks, while the within-industry asset turnover spread has insignificant loading on accumulated discount-rate shocks. Finally, Table C.7 shows that, unlike the within-industry and firm-level asset turnover spreads, the cross-industry asset turnover spread does not load on IMC, suggesting that the cross-industry asset turnover premium is unlikely explained by industries' heterogeneous exposure to the IST shocks.

Validation of the mimicking portfolio analysis. We conduct two validation tests for the mimicking portfolio analysis. First, we conduct the in-sample validation test. Specifically, we plot the monthly returns of the in-sample LT spread mimicking portfolio estimated by Eq. (4.3) against the monthly LT spread for the sample period from July 1988 to June 2018, during which the leadership turnover measure is available. As shown in panel A of Fig. C.2, the two time series are highly correlated with a monthly correlation of 0.84 and a p-value less than 0.001. Second, we conduct the out-of-sample validation test. We split the sample period from July 1988 to June 2018 into five subsamples, each with six years of data. Next, we leave out the first subsample (i.e., July 1988 to June 1994) and estimate the coefficients in Eq. (4.2) based on the remaining 24 years of data. We then construct the LT spread mim-

Table C.4
Sensitivity of profitability to discount rates with alternative industry classifications.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Panel A: Heterogeneity across SIC3 industries											
	Δ Average net profitability$_t$						Δ Average asset turnover$_t$					
GP quintiles	Q1 (low)	Q2	Q3	Q4	Q5 (high)	5 - 1	Q1 (low)	Q2	Q3	Q4	Q5 (high)	5 - 1
ΔSmooth_EP$_t$	0.34	−0.32*	−0.52*	−0.48***	−0.57**	−0.91***	8.43***	−0.82	−1.24	−6.05*	−4.52	−12.95***
	[1.22]	[−1.69]	[−1.71]	[−3.18]	[−2.34]	[−3.15]	[3.82]	[−0.45]	[−0.69]	[−1.85]	[−1.00]	[−2.81]
Observations	64	64	64	64	64	64	64	64	64	64	64	64
R-squared	0.017	0.043	0.054	0.052	0.060	0.104	0.079	0.010	0.012	0.023	0.015	0.061
	Panel B: Heterogeneity across FIC industries											
	Δ Average net profitability$_t$						Δ Average asset turnover$_t$					
GP quintiles	Q1 (low)	Q2	Q3	Q4	Q5 (high)	5 - 1	Q1 (low)	Q2	Q3	Q4	Q5 (high)	5 - 1
ΔSmooth_EP$_t$	−0.56	−0.94*	−1.68**	−1.25	−3.22**	−2.66	−5.99	2.88	−6.40	−2.44	−22.72	−16.73
	[−0.60]	[−1.92]	[−2.19]	[−0.67]	[−2.21]	[−1.25]	[−0.82]	[0.38]	[−0.65]	[−0.08]	[−0.82]	[−0.59]
Observations	22	22	22	22	22	22	22	22	22	22	22	22
R-squared	0.009	0.038	0.082	0.031	0.066	0.037	0.008	0.005	0.009	0.001	0.014	0.005
	Panel C: Heterogeneity across FIC industries with backfilled FIC codes											
	Δ Average net profitability$_t$						Δ Average asset turnover$_t$					
GP quintiles	Q1 (low)	Q2	Q3	Q4	Q5 (high)	5 - 1	Q1 (low)	Q2	Q3	Q4	Q5 (high)	5 - 1
ΔSmooth_EP$_t$	−0.22*	−0.42***	−0.62***	−1.02***	−0.94***	−0.72**	−2.23	−1.27	−3.71**	−12.35***	−17.24***	−15.01**
	[−1.77]	[−2.98]	[−2.97]	[−3.24]	[−3.49]	[−2.18]	[−1.00]	[−1.10]	[−2.17]	[−2.93]	[−3.11]	[−2.30]
Observations	64	64	64	64	64	64	64	64	64	64	64	64
R-squared	0.004	0.023	0.050	0.063	0.051	0.013	0.004	0.002	0.014	0.048	0.050	0.021

This table examines the sensitivity of profitability to discount rates in industry quintile portfolios sorted on the one-year-lagged gross profitability, with various alternative industry classifications. In panel A, we use the first three digits of SIC codes to define industries. The sample spans the period from 1954 to 2017. In panel B, we use the text-based fixed industry classifications proposed by Hoberg and Phillips (2010a, 2016) to define industries. The sample spans the period from 1996 to 2017 because the FIC industry data are only available after 1996. In panel C, we assume that the FIC codes for all firms before 1996 are the same as those in 1996. The sample of this panel spans the period from 1954 to 2017. We use FIC-500 in panels B and C, and results are similar if we use other FIC definition. We omit the coefficients for the constant terms in all panels for brevity. Standard errors are computed using the Newey-West estimator allowing for serial correlation in the data. We include *t*-statistics in brackets. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table C.5
Cross-industry GP spreads with alternative industry classifications.

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Panel A: Excess returns and CAPM alphas across SIC3 industry portfolios sorted on gross profitability										
	Excess returns (%)					CAPM alphas (%)					
Q1 (low)	Q2	Q3	Q4	Q5 (high)	5 - 1	Q1 (low)	Q2	Q3	Q4	Q5 (high)	5 - 1
5.30***	8.29***	7.70***	9.39***	10.25***	4.95***	−0.81	0.56	−0.60	0.98	2.78**	3.60**
[2.95]	[3.77]	[3.27]	[3.97]	[4.63]	[3.12]	[−0.87]	[0.51]	[−0.53]	[0.94]	[2.50]	[2.29]
Panel B: Excess returns and CAPM alphas across portfolios with backfilled FIC codes and sorted on gross profitability											
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Excess returns (%)					CAPM alphas (%)					
Q1 (low)	Q2	Q3	Q4	Q5 (high)	5 - 1	Q1 (low)	Q2	Q3	Q4	Q5 (high)	5 - 1
5.51	9.63*	10.77**	5.25	11.23***	5.72*	−2.08	1.37	1.94	−1.93	4.69**	6.76**
[1.19]	[1.96]	[2.04]	[1.12]	[2.77]	[1.74]	[−0.95]	[0.59]	[0.60]	[−0.68]	[2.01]	[2.09]

Panel A shows the value-weighted average excess returns and CAPM alphas for SIC3 industry portfolios sorted on gross profitability. Panel B shows the value-weighted average excess returns and CAPM alphas for FIC industry portfolios sorted on gross profitability. We assume that the FIC codes of all firms before 1996 are the same as those in 1996. We annualize average excess returns and alphas by multiplying them by 12. Newey-West standard errors are estimated with one lag. The sample of this table spans the period from 1951 to 2018. We include *t*-statistics in brackets. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

icking portfolio for the six-year out-of-sample period (i.e., July 1988 to June 1994) using Eq. (4.3) based on the estimated coefficients. We repeat the above procedures by leaving out the rest of the six-year subsamples one at a time and obtain the out-of-sample mimicking portfolios for these subsamples. Finally, we piece the returns of all five out-of-sample LT spread mimicking portfolios into a 30-year time series and plot its returns against the LT spreads. As shown in panel B of Fig. C.2, the two time series are highly correlated with a monthly correlation of 0.74 and a *p*-value less than 0.001. The above two validation tests suggest that the mimicking portfolio approach performs well in proxying for LT spreads both in and out of sample.

Table C.6
The exposure of cross-industry GP spreads to discount-rate shocks with alternative industry classifications.

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Heterogeneous exposure to discount rates across SIC3 industry portfolios sorted on gross profitability						
	Accumulated portfolio excess returns$_t$					
GP quintiles	Q1 (low)	Q2	Q3	Q4	Q5 (high)	5 - 1
Accumulated smooth_EPshocks$_t$	−7.06***	−7.23***	−8.98***	−11.75***	−11.66***	−4.61**
	[−4.16]	[−4.08]	[−3.75]	[−4.55]	[−5.82]	[−2.29]
Observations	769	769	769	769	769	769
R-squared	0.279	0.278	0.261	0.460	0.571	0.116
Panel B: Heterogeneous exposure to discount rates across portfolios with backfilled FIC codes and sorted on gross profitability						
	Accumulated portfolio excess returns$_t$					
GP quintiles	Q1 (low)	Q2	Q3	Q4	Q5 (high)	5 - 1
Accumulated smooth_EP shocks$_t$	−7.34***	−9.96***	−11.34***	−10.76***	−12.53***	−5.19***
	[−3.90]	[−5.87]	[−5.89]	[−4.83]	[−7.33]	[−3.45]
Observations	769	769	769	769	769	769
R-squared	0.309	0.516	0.508	0.348	0.621	0.152

Panel A shows the heterogeneous exposure to discount rates for SIC3 industry portfolios sorted on the leadership turnover measure. Panel B shows the heterogeneous exposure to discount rates for industry portfolios with backfilled FIC codes and sorted on the leadership turnover measure. Newey-West standard errors are estimated with 36 lags. We omit the coefficient for the constant term for brevity. The sample of this table spans the period from 1954 to 2018. We include *t*-statistics in brackets. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table C.7
Replicating the Fama-MacBeth regressions using the panel regression approach.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Profitability, market leader turnovers, and the volatility of cash flows								
	$\mathbb{1}_{turnover,i}^{t\to t+\Delta t}$				$\ln(\sigma_{NP,i}^{t\to t+\Delta t})$			
Δt years	3	4	5	10	3	4	5	10
GP$_{i,t}$ (standardized)	−0.02***	−0.02***	−0.02***	−0.02***	0.07***	0.08***	0.08***	0.07***
	[−3.32]	[−2.91]	[−2.72]	[−2.10]	[3.10]	[3.39]	[3.34]	[3.01]
ln(number of firms)$_{i,t}$	0.20***	0.21***	0.21***	0.19***	0.05*	0.04	0.02	−0.02
	[19.86]	[20.04]	[19.90]	[17.95]	[1.73]	[1.23]	[0.77]	[−0.69]
ln(sales)$_{i,t}$	−0.02***	−0.02***	−0.02***	−0.02***	−0.20***	−0.19***	−0.18***	−0.16***
	[−4.62]	[−4.74]	[−4.58]	[−3.44]	[−13.73]	[−13.00]	[−12.13]	[−9.92]
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	24,974	24,208	23,501	20,362	23,400	22,673	21,612	18,415
R-squared	0.211	0.222	0.226	0.209	0.219	0.243	0.261	0.299
Panel B: Leadership turnover measure and profitability								
	Profitability$_{i,t}$ (%)		Profit margin$_{i,t}$ (%)		$\ln(\sigma_{NP,i}^{t\to t+\Delta t})$			
	Gross	Net	Gross	Net	$\Delta t = 3$ y	$\Delta t = 4$ y	$\Delta t = 5$ y	$\Delta t = 10$ y
$\hat{\lambda}_{i,t}$ (standardized)	−1.23***	−0.20*	−2.08**	−0.32*	−0.07***	−0.06***	−0.08***	−0.10***
	[−3.00]	[−1.82]	[−2.43]	[−1.71]	[−3.48]	[−3.65]	[−4.34]	[−4.79]
ln(number of firms)$_{i,t}$	−1.49***	−1.32***	7.29***	−1.57***	0.05**	0.05***	0.04***	0.03**
	[−3.62]	[−7.78]	[8.30]	[−6.87]	[2.57]	[2.83]	[2.74]	[2.10]
ln(sales)$_{i,t}$	−0.22	1.27***	−2.54***	2.41***	−0.20***	−0.19***	−0.19***	−0.16***
	[−1.02]	[15.67]	[−4.93]	[10.97]	[−19.04]	[−20.27]	[−19.88]	[−16.36]
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5,274	5,269	5,274	5,269	4,739	4,540	4,309	3,307
R-squared	0.030	0.133	0.183	0.121	0.154	0.180	0.183	0.148

We replicate the Fama-MacBeth regressions in Table 4 using the panel regression approach. We control for time fixed effects in our analysis. We include *t*-statistics in brackets. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

(Post-formation) discount-rate betas. We estimate the discount-rate beta (β_γ) for each individual stock. Specifically, for each stock, we regress the 36-month accumulated stock excess returns on the 36-month accumulated discount-rate shocks (i.e., AR1 residuals to the smoothed earnings-price ratio) using a five-year rolling window. We then sort stocks into quintiles based on their discount rate betas and compute the value-weighted portfolio returns for each quintile (i.e., $Ret_{\gamma,i,t}$, where $i = 1, 2,..., 5$). Because the estimation of the pre-formation betas can be noisy, we also examine the post-formation betas (e.g., Fama and French, 1992; Pástor and Stambaugh, 2003; Herskovic et al., 2019; Dou et al., 2020b). Specifically, we estimate the post-formation betas from a regression of the 36-month accumulated excess returns of portfolios sorted on the pre-formation betas (i.e., $\sum_{j=0}^{35}(Ret_{\gamma,i,t-j} - r_{f,t-j})$, where $i = 1$,

Table C.8
Sensitivity of profitability to discount rates across industries with different levels of asset turnover.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Δ Average net profitability$_t$						Δ Average asset turnover$_t$					
Asset turnover quintiles	Q1 (low)	Q2	Q3	Q4	Q5 (high)	5 - 1	Q1 (low)	Q2	Q3	Q4	Q5 (high)	5 - 1
ΔSmooth_EP$_t$	0.03	−0.13	−0.48**	−0.50**	−0.52**	−0.55**	0.94	0.32	−2.89	−3.42*	−4.93**	−5.86**
	[0.21]	[−0.47]	[−2.33]	[−3.72]	[−2.46]	[−2.37]	[0.51]	[0.15]	[−1.04]	[−1.77]	[−2.42]	[−2.25]
Observations	64	64	64	64	64	64	64	64	64	64	64	64
R-squared	0.000	0.002	0.031	0.039	0.036	0.036	0.002	0.000	0.008	0.005	0.008	0.011

This table shows the sensitivity of the average asset turnover and profitability to discount rates across industry portfolios sorted on asset turnover. The sample of this table spans the period from 1954 to 2017. Standard errors are computed using the Newey-West estimator allowing for serial correlation in the data. We omit the coefficient for the constant term for brevity. We include *t*-statistics in brackets. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table C.9
Asset turnover premia.

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
		Excess returns (%)						CAPM alphas (%)			
Q1 (low)	Q2	Q3	Q4	Q5 (high)	5 - 1	Q1 (low)	Q2	Q3	Q4	Q5 (high)	5 - 1
				Panel A: Cross-industry asset turnover spread							
6.84***	9.35***	8.21***	8.91***	9.83***	2.99***	−0.30	1.26**	0.02	1.27	2.22***	2.52**
[3.83]	[5.11]	[4.56]	[4.35]	[5.36]	[3.03]	[−0.31]	[2.54]	[0.02]	[1.28]	[3.39]	[2.00]
				Panel B: Within-industry asset turnover spread							
5.51**	7.58***	9.21***	8.73***	9.73***	4.22***	−2.91***	−0.67	1.36	1.34*	2.20***	5.11***
[2.35]	[3.31]	[4.20]	[4.32]	[4.80]	[3.61]	[−2.83]	[−0.63]	[1.37]	[1.65]	[2.81]	[4.13]
				Panel C: Firm-level asset turnover spread							
5.58***	7.79***	7.90***	8.69***	9.54***	3.95***	−2.17***	0.01	0.35	1.22*	2.08**	4.25***
[2.70]	[3.89]	[4.01]	[4.33]	[4.51]	[2.78]	[−2.73]	[0.02]	[0.63]	[1.80]	[2.23]	[2.84]

This table shows the value-weighted average excess returns and CAPM alphas for portfolios sorted on asset turnover. The sample period is from July 1951 to June 2018. Newey-West standard errors are estimated with one lag. We annualize average excess returns and alphas by multiplying them by 12. We include *t*-statistics in brackets. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table C.10
Exposure of asset turnover spreads to discount rates.

	(1)	(2)	(3)	(4)	(5)	(6)
			Accumulated portfolio excess returns$_t$			
Asset turnover quintiles	Q1 (low)	Q2	Q3	Q4	Q5 (high)	5 - 1
			Panel A: Cross-industry asset turnover spread			
Accumulated smooth_EP shocks$_t$	−8.50***	−9.95***	−10.30***	−11.29***	−10.79***	−2.28*
	[−8.07]	[−7.38]	[−10.68]	[−14.55]	[−7.15]	[−1.78]
Observations	769	769	769	769	769	769
R-squared	0.323	0.387	0.492	0.599	0.453	0.039
			Panel B: Within-industry asset turnover spread			
Accumulated smooth_EP shocks$_t$	−9.06***	−9.96***	−10.74***	−8.68***	−9.43***	−0.38
	[−4.14]	[−4.93]	[−5.04]	[−4.49]	[−4.39]	[−0.33]
Observations	769	769	769	769	769	769
R-squared	0.283	0.439	0.443	0.412	0.420	0.001
			Panel C: Firm-level asset turnover spread			
Accumulated smooth_EPshocks$_t$	−8.57***	−9.53***	−9.06***	−10.13***	−10.10***	−1.53*
	[−8.61]	[−12.07]	[−10.63]	[−14.01]	[−14.27]	[−1.80]
Observations	769	769	769	769	769	769
R-squared	0.285	0.454	0.468	0.556	0.552	0.016

This table shows the heterogeneous exposure to discount rates for portfolios sorted on asset turnover. We exclude financial firms and utility firms from the analysis. The sample period is from July 1954 to June 2018. Newey-West standard errors are estimated with 36 lags. We omit the coefficients for the constant terms for brevity. We include *t*-statistics in brackets. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

2,..., 5) on the 36-month accumulated discount-rate shocks (i.e., AR1 residuals to the smoothed earnings-price ratio). Newey-West standard errors are estimated with 36 lags. We find that the post-formation betas across the five quintile portfolios sorted on the pre-formation betas increase monotonically as follows: −11.43, −10.35, −10.02, −9.53, and −8.37, with *t*-statistics equal to −6.43, −6.14, −6.91, −6.28, and −5.06, respectively. The difference in the post-formation betas between the Q5 (high) and Q1 (low) portfolios sorted on the pre-formation betas is statistically significant, with a *t*-statistic of 2.45. These findings suggest that our pre-formation betas are unlikely driven by pure noise.

Table C.11
Exposure of asset turnover spreads to IST shocks.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
						Portfolio excess returns$_t$						
Asset turnover quintiles	Q1	Q2	Q3	Q4	Q5	5 - 1	Q1	Q2	Q3	Q4	Q5	5 - 1
						Panel A: Exposure of the cross-industry asset turnover spread						
IMC$_t$	0.64***	0.83***	0.92***	0.70***	0.59***	−0.05	0.08	0.22***	0.33***	0.10***	−0.04	−0.12
	[9.52]	[14.90]	[17.75]	[12.25]	[8.41]	[−0.68]	[1.48]	[4.94]	[6.69]	[2.99]	[−0.88]	[−1.49]
MktRf$_t$							0.93***	1.00***	0.97***	0.99***	1.04***	0.11**
							[40.77]	[38.54]	[38.55]	[36.13]	[33.39]	[2.50]
Observations	804	804	804	804	804	804	804	804	804	804	804	804
R-squared	0.232	0.315	0.374	0.226	0.165	0.002	0.805	0.857	0.864	0.761	0.766	0.015
						Panel B: Exposure of the within-industry asset turnover spread						
IMC$_t$	0.85***	0.90***	0.83***	0.59***	0.70***	−0.16***	0.22***	0.31***	0.26***	−0.02	0.11***	−0.11***
	[13.45]	[14.05]	[15.87]	[9.77]	[12.55]	[−2.68]	[4.93]	[4.61]	[5.04]	[−0.58]	[3.73]	[−1.82]
MktRf$_t$							1.05***	0.99***	0.96***	1.00***	0.97***	−0.08***
							[46.85]	[37.04]	[38.37]	[51.25]	[42.49]	[−2.63]
Observations	804	804	804	804	804	804	804	804	804	804	804	804
R-squared	0.308	0.339	0.324	0.188	0.258	0.038	0.850	0.817	0.826	0.831	0.842	0.049
						Panel C: Exposure of the firm-level asset turnover spread						
IMC$_t$	0.66***	0.74***	0.66***	0.67***	0.58***	−0.08*	0.04	0.14***	0.05**	0.08**	−0.04	−0.08*
	[11.11]	[13.26]	[11.00]	[13.50]	[9.54]	[−1.93]	[1.55]	[7.28]	[2.32]	[2.11]	[−1.30]	[−1.71]
MktRf$_t$							1.03***	0.99***	1.00***	0.98***	1.02***	−0.01
							[50.71]	[75.62]	[75.27]	[48.42]	[40.86]	[−0.23]
Observations	804	804	804	804	804	804	804	804	804	804	804	804
R-squared	0.229	0.298	0.248	0.247	0.175	0.009	0.877	0.933	0.921	0.871	0.813	0.009

This table shows the exposure to IST shocks for portfolios sorted on asset turnover. We exclude financial firms and utility firms from the analysis. The sample spans the period from July 1951 to June 2018. Newey-West standard errors are estimated with one lag. We omit the coefficients for the constant terms for brevity. We include *t*-statistics in brackets. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

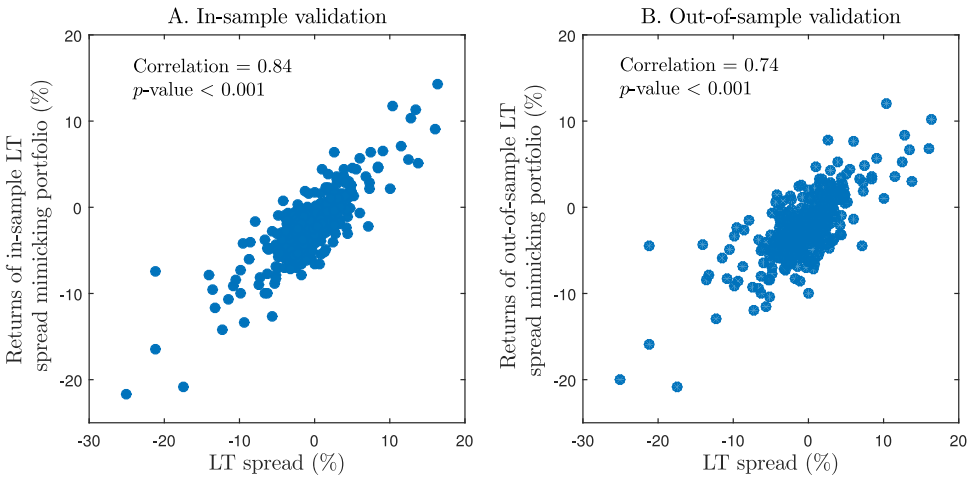

Fig. C.2. Validation of the mimicking portfolio analysis. Panel A illustrates the relation between the LT spread and the returns of the in-sample LT spread mimicking portfolio. Panel B illustrates the relation between the LT spread and the returns of the out-of-sample LT spread mimicking portfolio. The returns plotted in both panels are monthly returns. The sample spans the period from July 1988 to June 2018.

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