Risk Premia along the Technological Race

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Abstract

I study the cross-section of returns from the perspective of firms with differentially advanced technologies. Firms with leading technologies have some market power and enjoy monopolistic rents. Firms with lagging technologies, however, have to sell their products in more competitive markets. Lagging firms innovate to displace leaders in a technological race. I develop a general equilibrium model in which (1) technological leaders have market power and enjoy monopolistic rents, while followers generate no rents, and (2) each period, leaders, followers, and entrants innovate to take or keep the leading positions in the next period. Leading technologies are risky, since market power allows leaders to raise rents in good times and thus their monopoly profits are procyclical. Firms with high exposure to the risk of leading technologies (LTR) have high risk premia. While both current leaders and current followers can be the future leaders, the returns on current followers are more exposed to the future LTR and thus have higher premia, due to the potential large price jump from becoming a new leader. Empirically, I construct the factor that captures LTR. I find that leading technology is risky, and that the LTR price of risk is 7 percent. The followers that actively innovate have high exposure to the future LTR and high risk premia, supporting my model.

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1 Introduction

Firms typically use differentially advanced technologies. The firms with leading technologies naturally have some market power and generate monopolistic rents. Other firms, however, use lagging technologies and have to sell their products in much more competitive environments. By innovating, lagging firms have the chance to displace leaders in a technological race. Because both current leaders and current followers can be future leaders, their returns are all affected by the future values of leading technologies. However, given that firms' current positions in the technological race are different, there is heterogeneity in the sensitivity of returns to the future values of leading technologies, generating heterogeneity in risk premia across these firms.

In this paper, I explain the firm's risk premium through the lens of this technological race. To be specific, in an economy with a single aggregate shock, a firm's conditional risk premium is determined by the conditional exposure of its return to the aggregate risk. From the perspective of the technological race, a firm return's conditional exposure to the aggregate risk can be decomposed into two parts. The first is the exposure of the leading technologies to aggregate shock, which I define as the risk of leading technology (LTR). This part captures the sensitivity of the value of the leading technologies to the aggregate shock. The second part is the firm-specific loading on LTR. This part captures the sensitivity of the firm's return to the change in the value of the leading technologies.[1] That is, a firm's return can be exposed to the aggregate risk through the channel of a technological race.

[1] In a single aggregate shock economy, a firm's conditional risk premium can be written as:

$$E_t\left[R^i_{t,t+1} - R^f_{t,t+1}\right] = \beta^i_{A,t+1}\lambda^A_{t+1},$$

where λ^A_{t+1} is the conditional price of risk of the aggregate shock, and $\beta^i_{A,t+1}$ is the conditional exposure of firm's return $R^i_{t,t+1}$ to aggregate risk. From the perspective of a technological race, $\beta^i_{A,t+1}$ can be decomposed as follows:

$$\beta^i_{A,t+1} = \beta^i_{LT,t+1}\beta^{LT}_{A,t+1} + \text{Other Channels}$$

$\beta^{LT}_{A,t+1}$ is the exposure of the leading technologies to aggregate shock, which I define as the risk of leading technology (LTR). $\beta^i_{LT,t+1}$ is the firm-specific loading on LTR.

To understand the driving forces of LTR and firm-specific loading on LTR, I develop a general equilibrium model with a technological race. The model has two key features. First, the representative household consumes two types of goods: the leading technology goods produced by leaders and the lagging technology goods produced by followers. Leaders have market power and thus enjoy monopolistic rents while the followers, who have no market power, generate no profits. Second, each period, the leaders, followers, and new entrants innovate to take or keep the leading positions in the next period. If the followers and the entrants successfully develop more advanced technologies, the previous leaders of those technologies lose their leading positions and become followers. In the model, the follower-to-leader ratio is time-varying because of the entrants in the technological race.

I demonstrate that, because of the market power, the leading technologies have positive exposure to aggregate risk (that is, the leading technologies are risky). Specifically, the profits of the firms with leading technologies respond positively to aggregate shock. A good aggregate shock increases the aggregate income. The richer representative household then has a high demand for both leading technology goods and lagging technology goods. Leaders who have market power earn high rents. That is, leaders generate procyclical rents because of the procyclical demand for leading technology goods. Therefore, leading technologies are risky, since their cash flows covary with aggregate shocks.

The conditional sensitivity of the value of leading technologies to aggregate shock (or LTR) depends on the follower-to-leader ratio. With more followers contributing to the production of the lagging technology goods, the economy is more productive. When a good aggregate shock takes place, more followers produce more goods, thus increasing aggregate income even further. As a result, the representative household has an even higher demand for the leading technology goods. This leads to an even further increase in the rents earned by the leading firms. That is, the cash flows generated by leading technologies covary more with aggregate shocks and thus are more risky when more followers exist. Therefore, LTR is high when the follower-to-leader ratio is high.

As a result, LTR increases when the economy is booming. When the economy starts booming, entrants and followers innovate more in an effort to take the leading position, because of the stronger incentive to become the more valuable leaders. More entry happens and thus more leaders are displaced and become followers. In a booming economy, while the aggregate technology grows faster, there are more followers, as a result of the intensified technological race. The increase in the follower-to-leader ratio further drives up the LTR. The model implies that the value of new leading technologies can be risky at the end of a booming period (e.g., the information technology firms at the end of the tech boom in the late 1990s).

While leading technology is risky, the model implies that the current followers' returns have higher conditional loadings on LTR (high firm-specific loading on LTR) and thus have higher risk premia than the current leaders. Followers innovate in order to take over leader positions. If they successfully jump to a leader position and claim the risky monopoly profits, the concomitant price jump is large. Thus, the new leader's price has a huge impact on current followers' returns. As a result, current followers' returns have high exposure to future LTR. In contrast, the current leaders have no such dramatic price jumps if they continue being leaders. Moreover, innovation by followers and entrants make leaders less exposed to future LTR by decreasing the probability of their staying in the leading position. Overall, the model implies that the returns on current followers have higher loadings on LTR than the returns on current leaders. In practice, firms often hold a mix of leading and following technologies. The firms that are associated with more following technologies but then radically innovate to take over as leaders expect high risk premia.

Empirically, I investigate the asset pricing implications of the model. I construct the LTR factor that captures the risk of the leading technologies.[2] To construct the factor, I use two approaches to identify firms with leading technologies. In the first approach, the "direct approach", I identify a firm as a technology-leading firm if it provides innovative products to the market. In the second approach, the "indirect approach", I estimate the technology level of the firm using the measure of the value of the patents generated by that firm. For each industry, I sort the firm according to

[2]The model features the endogenous conditional sensitivity of the leading technologies to aggregate shocks, which is driven by the novel state variable follower to leader ratio. However, it is known that it is hard to estimate such conditional single factor model in the data. My approach is in spirit of Jagannathan and Wang (1996), I construct the factor that captures LTR and examine the properties of that factor in a multi-factor framework unconditionally.

its technology level. The top 10 percent of the firms are identified as leading firms and the bottom 10 percent are designated as following. I construct the measure of the excess profit of the leading technology by taking the difference between the average profit of the leading firms and the following firms. As the model implies, the returns that are more sensitive to changes in the excess profit of the leading technologies have high exposure to LTR. Therefore, I construct the tradable LTR factor by longing the returns with high betas on excess profit of the leading technologies and shorting the returns with low betas.

I estimate the price of risk of the LTR factors in multiple formal cross-sectional asset pricing tests and find a significantly positive risk price, supporting the model prediction that leading technology is risky. [3] Specifically, I find that the prices of risk for the LTR factor with the direct and indirect approach are an annual rate of 10 and 7 percent, respectively.[4] Both are statistically significant. This is evidence that investors desire a high premium for their exposure to risky leading technologies.

Further analysis confirms that the LTR factor provides additional pricing information, supporting the model prediction that LTR is endogenous and is driven by the follower-to-leader ratio. I estimate the SDF loading on the LTR factor, while controlling for other factors, in a standard linear specification where SDF prices cross-sectional assets. The significant loading shows that the pricing information of LTR factors cannot be captured by the known factors, e.g., the Fama-French five factors, the momentum factor, and the intermediary risk factor. If the follower-to-leader ratio is constant and thus the conditional sensitivity of the value of leading technologies to the aggregate shock is a constant, the LTR factor should be fully absorbed by the market factor. SDF loading on the LTR factor should be insignificant, which contradicts my empirical findings.

Importantly, I show that, in both approaches, the price-dividend ratio predicts the LTR factor premia positively, which is consistent with the model's prediction that LTR is high in a booming economy. Again, if there is no entry in the technological race, the conditional sensitivity of the

[3] The LTR factor captures $\beta^{LT}_{A,t+1} * \textit{aggregate shock}$. $\beta^{LT}_{A,t+1}$ denotes the sensitivity of the value of the leading technologies to the aggregate shock. If a firm's return has higher exposure to the LTR factor, it has higher exposure to the aggregate risk on net through the technological race channel.

[4] To account for the estimation bias caused by omitting factors, I use the three-stage procedure introduced by Giglio and Xiu (2018).

value of leading technologies to the aggregate shock remains constant. The PD ratio should predict the LTR factor premium negatively similar to the market factor, contradicting my empirical results. Moreover, I demonstrate that, on average, lagging technology firms have higher loadings on the risk of leading technologies and higher expected returns than the leading technology firms, supporting my model.

In summary, my work provides a novel perspective on the cross-section of firm returns by linking firms' risk to their positions in the technological race. I show theoretically and empirically that leading technology is risky and drives the risk premia of the firms in the technological race. Followers that radically innovate have higher premia than leaders because of their greater exposure to future LTR.

Related Literature This work is closely related to the literature studying the implications of innovation in a step-by-step innovation framework (e.g., Aghion and Howitt (1992), Grossman and Helpman (1991), Aghion *et al.* (2001), Aghion *et al.* (1997), Acemoglu and Akcigit (2012), Acemoglu and Cao (2015), and Liu *et al.* (2019)). While only the entrants innovate in the baseline Schumpeterian quality ladder models, several papers study the implication of innovation by incumbents. Aghion *et al.* (2005) study the relationship between product market competition and innovation by technological leaders and followers, with no innovation by entrants. Acemoglu and Cao (2015) explore the implication of innovation by both new firms and existing firms. However, in their model, in which there are no followers, the entrants innovate more radically than the incumbents.

My paper differs from the literature in several dimensions. First, it features the follower-to-leader dynamic by allowing leaders, followers, and entrants to race for the leading positions. Unlike the current literature, in which the aggregate sensitivity of the rents of leaders is constant, the endogenous follower-to-leader ratio in my work drives the risk of leading technologies. Second, my paper focuses on the asset pricing implications of the technological race, while the literature typically studies the economic growth implications of innovation. In particular, in my model, the heterogeneous exposures to the risk of leading technology generate dispersion of risk premia across firms.[5]

This paper is also related to a large body of literature that explores the implications of technology growth for asset prices (e.g., Greenwood and Jovanovic (1999), Laitner and Stolyarov (2003), Pástor and Veronesi (2009), Gârleanu *et al.* (2012), Garleanu *et al.* (2012), Kung and Schmid (2015), Bena *et al.* (2015), Liao and Schmid (2017), Croce *et al.* (2019)). In contrast to the literature, this work focuses on the asset pricing implications of the technological race. In addition, my work is connected to the literature that explores the impact of creative destruction of new technologies on asset prices and firm profits. Kogan *et al.* (2018) studies a general equilibrium model, in which newly developed technologies have asymmetric impacts on the gain captured by innovators and shareholders. Gârleanu *et al.* (2012) shows that innovation can damage an existing firm's profits. While creative destruction can decrease the value of current leading firms, my paper suggests that the creative destruction could also lower the leader firms' risk by making them less exposed to the future risk of leading technology.[6]

My paper also fits into the literature that explores the asset pricing implications of industrial organization (e.g., Loualiche *et al.* (2014), Binsbergen (2016), Bustamante and Donangelo (2017), Corhay *et al.* (2017), Corhay (2017), Garlappi and Song (2017), Dou *et al.* (2019)). Corhay *et al.* (2017) show that more entry leads to lower market power and lower sensitivity to aggregate fluctuations for the incumbent firms. Therefore, the cash flow sensitivity of the incumbent is countercyclical. Loualiche *et al.* (2014) show that the industry that has high exposure to entry risk, which lowers the monopolistic rents of incumbents, has a high risk premium. In those models, the incumbent firms are assumed to be identical. My paper contributes to the literature by showing that, due to their market power, new technological leaders generate more risky rents when there are more followers after an intensified technological race.

[5]My paper is related to the literature that explains the heterogeneity in the cross-section of risk premia by considering the endogenous conditional exposures of the firm returns to the aggregate risk (e.g. Gomes *et al.* (2003), Zhang (2005), Ai *et al.* (2012), Lin (2012), and Belo *et al.* (2014)).

[6]Broadly, my paper is related to the production-based asset pricing literature that explore the implication of technology shocks, as in Papanikolaou (2011), Kogan and Papanikolaou (2013), Kogan and Papanikolaou (2014), and Lin *et al.* (2019).

Methodologically, my model builds on Acemoglu and Cao (2015), Bena *et al.* (2015) and Bansal *et al.* (2019). Specifically, my work considers a two-sector model within the Schumpeterian endogenous growth framework, allowing the existence of the technological race among the leaders, the followers and the entrants.

Structure The paper is organized as follows: Section 2 presents the model. Section 3 discusses the model results and the empirical predictions of the model. Section 4 presents the empirical evidence. Section 5 concludes.

2 Model

2.1 Final Goods Producer

The final goods aggregator converts a continuum of measure one of differentiated industry goods $Y_{j,t}$ into the final consumption goods $\mathcal{Y}_t$ using a constant elasticity of substitution (CES) technology:

$$\mathcal{Y}_t = \left(\int_0^1 Y_{j,t}^{1-\frac{1}{\tau_i}} dj \right)^{\frac{1}{1-1/\tau_i}} \tag{1}$$

where τ_i is the elasticity of substitution among different industry goods. The final goods aggregator buys the industry goods from the industry goods producer at price $P_{j,t}$ and solves:

$$\max_{Y_{j,t}} P_{\mathcal{Y},t}\mathcal{Y}_t - \int_0^1 P_{j,t}Y_{j,t}dj, \tag{2}$$

The optimization of the aggregator yields the demand for industrial good j:

$$Y_{j,t} = \mathcal{Y}_t \left(\frac{P_{j,t}}{P_{\mathcal{Y},t}} \right)^{-\tau_i} \tag{3}$$

Given the final goods markets the aggregator faces is perfectly competitive, the zero profit condition combined with the demand curve Eq.(3) yields the aggregate price index:

$$P_{\mathcal{Y},t} = \left(\int_0^1 P_{j,t}^{1-\tau_i} dj \right)^{\frac{1}{1-\tau_i}} \tag{4}$$

2.2 Industry Goods Producer

The production of industrial goods in industry j requires quality goods $Y_{j,l,t}$ produced with the leading technologies of this industry, and homogenous goods $Y_{j,f,t}$ with lagging technologies as input. The industry goods producer bundles these two types of goods using CES technology:

$$Y_{j,t} = \left[\omega Y_{j,l,t}^{1-\frac{1}{\tau}} + (1-\omega) Y_{j,f,t}^{1-\frac{1}{\tau}} \right]^{\frac{1}{1-1/\tau}}. \tag{5}$$

The elasticity of substitution between these two goods is controlled by τ. The relative production contribution of the leader good with respect to the follower good is governed by ω. I assume that both quality goods and homogeneous goods are equally desirable in the production of industrial goods, i.e., $\omega = 0.5$. The industry goods producer faces perfectly competitive market and solves the profit maximization problem:

$$\max_{Y_{j,l,t}, Y_{j,f,t}} P_{j,t} Y_{j,t} - P_{j,l,t} Y_{j,l,t} - P_{j,f,t} Y_{j,f,t}, \tag{6}$$

With the advanced technologies installed in the product, the quality goods firm has the monopolistic power, while the homogenous goods firm can only take the price as given since the technologies installed in the homogenous goods are common and lagging. Therefore, the homogenous goods are treated as numeraire goods and the price is set to one ($P_{j,f,t} = 1$).[7] Solving the maximization

[7]Because of the existence of symmetric equilibrium discussed in section 2.7.2, the homogenous goods in all industries have identical relative price and thus can serve as numeraire goods.

problem of the industry goods producer implies the demand curve of the quality goods:

$$P_{j,l,t} = \frac{\omega}{1-\omega}\left(\frac{Y_{j,f,t}}{Y_{j,l,t}}\right)^{\frac{1}{\tau}}. \tag{7}$$

As shown above in Eq.(7), the price of the quality goods is increasing with the output ratio $\frac{Y_{j,f,t}}{Y_{j,l,t}}$. Relative to the quality goods, if there are more supply of homogeneous goods in the market, the demand for quality goods equipped with the leading technologies increases since the aggregate income rises. The quality goods producer thus can charge a higher price because of a stronger demand. Optimality also implies the price of the industrial goods:

$$P_{j,t} = \frac{1}{1-\omega}\left(\frac{Y_{j,f,t}}{Y_{j,t}}\right)^{\frac{1}{\tau}}. \tag{8}$$

2.3 Quality Goods Production

The quality goods are produced using capital $K_{j,l,t}$, labor $L_{j,l,t}$ and a continnum of differentiated intermediate goods, produced by a set of leading-technology holders operating in a variety of technological products, as input:

$$Y_{j,l,t} = (K^{\alpha}_{j,l,t}(\Omega_t L_{j,l,t})^{1-\alpha})^{1-\xi} G^{\xi}_{j,l,t}, \tag{9}$$

where α is the physical capital share, and ξ is the share of the bundle of technologies G_t that is defined as

$$G_{j,l,t} \equiv \left[\int_0^1 q_{j,i,t}^{1-\frac{1}{\nu}} x_{j,i,t}^{\frac{1}{\nu}}\, di\right]^{\nu}. \tag{10}$$

Each technology input is indexed by i $\in [0,1]$. The measure of leading technologies is fixed and is normalized to one. $x_{j,i,t}$ denotes the quantity of the input of a specific technology i in industry j. And $q_{j,i,t}$ is the technological level of input i.

The quality goods firm bundles together the technology inputs $x_{j,i,t}$ weighted by its technological level $q_{j,i,t}$. Therefore, only the intermediate goods with the highest technological levels, which are the leading technologies, are used in the production of the quality goods. The measure of the types of leading technologies is fixed and normalized to one. The substituability among the technology inputs is governed by the parameter ν. I assume that there exists the common aggregate shock $\Omega_t = e^{z_t}$ that affects the productivity of all producers in the production sector. And z_t follows an AR(1) process:

$$\begin{aligned} z_t &= (1-\rho_z)\bar{z} + \rho_z z_{t-1} + \sigma_z \epsilon_{z,t} \\ \epsilon_{z,t} &\sim i.i.d.N(0,1). \end{aligned}$$

The firm rents physical capital and labor from the household and buys the intermediate goods from the leading technology holders, taking the capital rental rates r_t^k, the wage rates ω_t and the prices $p_{j,i,t}$ as given. Facing the demand for the quality goods in Eq.(7), the firm optimally chooses the price $P_{j,l,t}$ of its product. The dividends of the quality goods firm are:

$$D_{j,l,t} = P_{j,l,t}Y_{j,l,t} - r_t^k K_{j,l,t} - \omega_t L_{j,l,t} - \left[\int_0^1 p_{j,i,t} x_{j,i,t}\, di \right], \tag{11}$$

r_t^k and ω_t are endogenously determined in the equilibrium. $p_{j,i,t}$ are set by the industry j leading technology producers. With monopolistic power, the quality goods firm can set the price higher than the cost and generate positive profits.

The optimization problem of the firm is:

$$V_{j,l,t} = \max_{Y_{j,l,t},\, K_{j,l,t},\, L_{j,l,t},\, x_{j,i,t},} E_t[\sum_{s=0}^{\infty} M_{t,t+s} D_{j,l,t+s}] \tag{12}$$

where $M_{t,t+s}$ is the stochastic discount factor. $V_{j,l,t}$ denotes the market value of the quality goods firm j at time t.

2.3.1 Leading Technology Holders

Leading technology holders, or the leaders, produce intermediate inputs for the quality goods. For each input i, at any point in time there exists exactly one leader who owns the patent on the leading technology of input i. Therefore, the measure of the leaders is constant and equal to the measure of the types of leading technologies at each time t.

The leading positions grant the patent holders the monopoly power. Given the quality goods producer's demand for intermediate inputs, the leader i converts $x_{j,i,t}$ units of the quality goods into the intermediate goods with the highest technology level $q_{j,i,t}$ with a production cost of μ_l per unit. The leader sets $p_{j,i,t}$ to maximize its profits, $\pi_{j,i,t}$:

$$\pi_{j,i,t} \equiv \max_{p_{j,i,t}} \quad p_{j,i,t} \cdot x_{j,i,t} - \mu P_{j,l,t} x_{j,i,t}. \tag{13}$$

Solving the optimization problem, combined with the optimal conditions from quality goods firm's problem, leads to the equilibrium quantity for input $x_{j,i,t}$:

$$x_{j,i,t} = \left(\frac{\xi}{\nu\mu} \frac{1 - 1/\tau}{1 - \xi/\tau} \right)^{\frac{1}{1-\xi}} K_{j,l,t}^{\alpha} (\Omega_t L_{j,l,t})^{1-\alpha} Q_{j,t}^{\frac{\xi\nu - 1}{1-\xi}} q_{j,i,t} \tag{14}$$

where $Q_{j,t}$ is defined as the aggregate technology level of industry j:

$$Q_{j,t} = \int_0^1 q_{j,i,t} di \tag{15}$$

which is the average of the technology level $q_{j,i,t}$ held by leaders. Optimality implies that the quantity $x_{j,i,t}$ is linear in its technology level $q_{j,i,t}$. Aggregating the output $x_{j,i,t}$ of leaders leads to the equilibrium production of quality goods:

$$Y_{j,l,t} = \left(\frac{\xi}{\nu\mu} \frac{1 - 1/\tau}{1 - \xi/\tau} \right)^{\frac{\xi}{1-\xi}} K_{j,l,t}^{\alpha} (\Omega_t Q_t L_{j,l,t})^{1-\alpha} \tag{16}$$

Combining Eq.(14) with the leader's profit Eq.(13) and Eq.(16) reveals the equilibrium profit of the leader i[8]:

$$\pi_{j,i,t} = (1 - \frac{1}{\nu}) \left(\frac{\xi(1 - 1/\tau)}{1 - \xi/\tau} \right) P_{j,l,t} Y_{j,l,t} \frac{q_{j,i,t}}{Q_{j,t}} \tag{17}$$

The profit of the leader in Eq.(17) is determined by: (1) the sales of the quality goods firm $P_{j,l,t}Y_{j,l,t}$ in the units of the homogeneous goods. Thus, the cash flows of the quality firm drive the leader's profits. (2) the monopolistic power of owning the leading technology that is controlled by ν. With stronger monopolistic power, a leader can claim larger share of the sales of the quality goods. (3) The relative technology level of leader i $\frac{q_{j,i,t}}{Q_{j,t}}$ with respect to the aggregate level. More advanced technology compare to others leads to higher profits of a leader.

2.4 Homogeneous Good Production

The homogeneous goods firm only have access to the patents owned by lagging technology holders, or followers. Without the unique features provided by the leading technology, the firm sells its products competitively with no monopolistic rents. The production of the homogeneous goods requires capital $K_{j,f,t}$, labor $L_{j,f,t}$ and the intermediate goods produced by a continuum of measure $m_{j,t}$ of followers:

$$Y_{j,f,t} = K_{j,f,t}^{\alpha} (\Omega_t G_{j,f,t} L_{j,f,t})^{1-\alpha}$$

where the composite $G_{j,f,t}$ is defined as

$$G_{j,f,t} \equiv \int_0^{m_{j,t}} \bar{g} Q_{j,t} x_{j,i,t}^f di, \tag{18}$$

where the $x_{j,i,t}^f$ is the quantity produced by follower i $\in [0, m_{j,t}]$ and $\bar{g}$ controls the leader-follower technology gap.

[8] Details of the proofs are provided in Appendix Section A.3 and A.4.

2.4.1 Following Technology Holders

I make the following assumption about the technology spillovers: In each industry, there exist knowledge spillovers between leaders and followers such that the followers are able to copy the leading technology imperfectly with gap $\bar{g}$ with no costs.[9] Two implications follow from the assumption. First, this assumption assures that followers can costlessly follow the leading technologies without lagging far behind. Because the leading technology advances also benefit the followers, a balanced growth path exists in the economy.[10] Second, knowledge spillovers allow each follower to copy any type of leading technology within an industry costlessly. The technology held by a follower thus can be fully replicated by the other followers in the same industry. As a result, all the followers have no monopolistic power.

Therefore, the followers sell the intermediate goods to the homogeneous goods firm competitively and make no profits. To stay in business, the followers have to produce at least $\bar{x}^f$ units of intermediate good. The homogeneous goods firm combines the intermediate inputs that have the average technology level $\bar{g}Q_{j,t}$ additively as in Eq.(18). The output of the firm can be rewritten as:

$$Y_{j,f,t} \quad = \quad K^{\alpha}_{j,f,t}(\Omega_t Q_{j,t} m_{j,t} \bar{x}^f L_{j,f,t})^{1-\alpha} \tag{19}$$

Therefore, the productivity of the homogeneous goods firm is also driven by the number of followers who contribute their lagging technologies to the production. Taking the capital rental rates r^k_t, the wage rates ω_t as given, the firm optimally chooses $K_{j,f,t}$ and $L_{j,f,t}$ to maximize its value:

$$V_{j,f,t} \quad = \quad \max_{K_{j,f,t},\, L_{j,f,t},} \quad E_t[\sum_{s=0}^{\infty} M_{t,t+s} D_{j,f,t+s}] \tag{20}$$

[9]Bernstein and Nadiri (1989) studies the effects of intra-industry R&D spillovers.

[10]The technology growths of quality goods firm and homogeneous goods firm are both governed by the aggregate leading technology growth, that is $\frac{Q_{j,t+1}}{Q_{j,t}}$. A large literature studies the relation between technological spillovers and growth (e.g. Griliches (1992) Nadiri (1993), Bloom *et al.* (2013)).

where $D_{j,f,t}$ are the dividends:

$$D_{j,f,t} = Y_{j,f,t} - r_t^k K_{j,f,t} - \omega_t L_{j,f,t} - p_{f,t} m_{j,t} \bar{x}^f, \tag{21}$$

At any point in time, the optimal $D_{j,l,t}$ is zero.[11]

2.5 Technological Race

In each industry, three groups of agents, i.e. the leaders, the followers and the entrants, invest in the quality improving innovation in a quality ladder framework, trying to take leader positions in the future production.[12] The innovation arrives randomly and depends on the innovator's effort. In each period, the leaders, the followers and the entrants choose their innovation effort. The innovation results reveal at the beginning of the next period before all productions take place. The leaders continue enjoying the profits in the next period production if they still hold the patent on the leading technology. The followers and entrants can displace the leaders if their innovation is a success and they hold the newly improved leading technology. The radical innovation of followers and entrants, which jumps from a lagging technology to the leading technology, features the creative destruction.[13]

2.5.1 Radical Innovation

Followers and entrants innovate to take over the leader's positions in order to contribute to the profitable production of the quality goods. If they succeed, the new leading technology level will be raised by a rate of $\kappa > 1$. The innovation of followers and entrants is radical in the sense that it has to improve the current leading technology while starting with less knowledge about it in comparison

[11]Under the assumption that no resource is needed to copy technology. $p_{f,t}$ is equal to zero.

[12]Schumpeterian quality ladder models, e.g. Segerstrom *et al.* (1990), Aghion and Howitt (1992), Grossman and Helpman (1991), Acemoglu and Cao (2015).

[13]The innovation of followers and entrants is disruptive since it hammers the value of the incumbent leaders when succeed.

to the leaders.[14] In order to achieve the radical improvement of technology, followers and entrants develop new ideas. I assume that the direction of new radical ideas cannot be controlled by followers and entrants (Akcigit etc (2016)). This assumption implies that followers and entrants cannot target a specific leading technology during the innovation. The realized improved technology i is uniformly distributed over $[0, 1]$ of the leading technology. As I show in the Appendix A.6, this assumption implies that all leaders choose identical quality adjusted innovation effort.

Entrants Innovation Each period, there is a continuum of entrants normalized to one developing new ideas. They spend resources on R&D in order to achieve leading technology improvements. Given the innovation outcome is stochastic, the probability of an entrant who successfully displaces a leader is $\phi_e(S_{j,e,t})$. $Q_{j,t}S_{j,e,t}$ is the entrant's total innovation expenditure.[15] ϕ_e satisfies $\phi_e'(S_{j,e,t}) > 0$, $\phi_e''(S_{j,e,t}) < 0$, $\phi_e(0) = 0$, and $\phi_e'(0) = +\infty$. This Inada-type assumption assures that $S_{j,e,t} > 0$, that is entrants always put some effort on R&D. A greater effort increases the likelihood of obtaining the patent on upgraded leading technology.

The problem of an entrant in industry j is:

$$\max_{S_{j,e,t}} V_{j,e,t} = -Q_{j,t}S_{j,e,t} + \underbrace{\phi_e(S_{j,e,t})E_t[M_{t+1}\int_0^1 V_{j,i,\kappa q_{j,i,t}}di]}_{\text{become leaders}} \tag{22}$$

where $V_{j,i,\kappa q_{j,i,t}}$ is the value of leader i with improved technology level $\kappa q_{j,i,t}$. $\int_0^1 V_{j,i,\kappa q_{j,i,t}}$ is industry j's average value of leaders at time t+1, which determines the innovation decision made by the entrants.

Follower Innovation A measure of $m_{j,t}$ of followers, which resulted from the technology race in period t-1, enter time t, participating the production of homogeneous goods with no profits. In the

[14] In the model, the followers and entrants can only have access to lagging technology which is a factor of $\bar{g} < 1$ lower than the leading technology level. Successfully innovation can be achieved if they raise their technology level by $\frac{\kappa}{\bar{g}}$.

[15] The expenditure is scaled by the industry technology level $Q_{j,t}$ so that it does not diminish in the growth model. $S_{j,e,t}$ is the effective R&D expenditure.

race at time t, the followers innovate to become leaders. Similar to the entrants, $\phi_f(S_{j,f,t})$ of the followers hold the leading technology patents after spending $Q_{j,t}S_{j,f,t}$ on innovation.[16] The follower solves the optimization problem:

$$\max_{S_{j,f,t}} V_{j,f,t} = \underbrace{\pi_{f_i,t}}_{=0} - Q_{j,t}S_{j,f,t} + \underbrace{\phi_f(S_{j,f,t})E_t[M_{t+1}\int_0^1 V_{j,i,\kappa q_{j,i,t}}di]}_{\text{jump to leaders}} + \underbrace{(1-\phi_f(S_{j,f,t+1}))\phi E_t[M_{t+1}V_{j,f,t}]}_{\text{stay followers}} \tag{23}$$

where $V_{j,f,t}$ is the value of follower at time t. ϕ is the obsolescence rate of the followers who fail in the technology race. The measure of the followers that become leaders is $m_{j,t}\phi_f(S_{j,f,t})$. And the total innovation expenditure of followers is expressed as $m_{j,t}S_{j,f,t}$.[17]

As shown in Eq.(22) and Eq.(23), the future value of leaders is the key determinant of the radical innovation activities of entrants and followers.

2.5.2 Leader Innovation

In each period, leaders innovate to improve their own leading technology.[18] If leader i successfully secures the patent on upgraded technology $\kappa q_{j,i,t}$, she or he maintains the leader position. If fails, the leader can either be displaced and become a follower or stays as a leader with $q_{j,i,t}$ if no followers or entrants improve that technology. The rate for leaders to successfully improve its own technology and stay in leaders is $\phi_l(S_{j,i,t})$. The leader chooses the innovation expenditure $q_{j,i,t}S_{j,i,t}$ to maximize

[16] ϕ_f has the same properties as ϕ_e.

[17] The additive measure of successful follwers $m_{j,t}\phi_f(S_{j,f,t})$ are based on the assumption that the direction of radical ideas cannot be controlled in the innovation and the leading technology space is large in comparison to the successful radical innovations. Two identical radical ideas are highly unlikely to arrive at the same time. That is a follower's innvation result is not affected by other followers' innovation, that is $m_{j,t}$ does not affect $\phi_f(S_{j,f,t})$.

[18] For simplicity, I assume that the cost for leaders to give up their own leading technologies and switch to other technologies is so high that leaders stick to their own technologies.

the value[19]:

$$\max_{S_{j,i,t}} V_{j,i,q_{j,i,t}} = \pi_{j,i,t} - q_{j,i,t}S_{j,i,t} + \underbrace{\phi_l(S_{j,i,t})E_t\left[M_{t+1}V_{j,i,\kappa q_{i,t}}\right]}_{\text{Successfully upgrade}} + \underbrace{(1-\phi_l(S_{j,i,t}) - m_{j,t}\phi_f(S_{j,f,t}) - \phi_e(S_{j,e,t}))E_t\left[M_{t+1}V_{j,i,q_{j,i,t}}\right]}_{\text{Unsuccessful but hold the position}} + \underbrace{(m_{j,t}\phi_f(S_{j,f,t}) + \phi_e(S_{j,e,t}))E_t\left[M_{t+1}V_{j,f,t+1}\right]}_{\text{lose leader's position}}$$

Note that Eq.(24) captures the reative destruction where the rate of success of radical innovation $m_{j,t}\phi_f(S_{j,f,t}) + \phi_e(S_{j,e,t})$ by entrants and followers increases the leaders' probability of losing their position. Greater expenses on radical innovation depress the leader's value. In addition, the stream of profits $\pi_{j,i,t}$ drives the cash flow risks of the leader.

2.5.3 Follower Dynamics

The measure of followers $m_{j,t}$ is time varying, while the measure of leaders is fixed. After each technology race, the entrants with leading technology patents enter into the production as new leaders and a fraction ϕ of failed followers exit the market. The evolution of the measure of followers $m_{j,t}$ is:

$$m_{j,t+1} = \underbrace{(1-\phi_f(S_{j,f,t}))\phi m_{j,t}}_{\text{survived followers}} + \underbrace{[\phi_f(S_{j,f,t})m_{j,t} + \phi_e(S_{e,t})]}_{\text{failed leaders}} + \bar{m}$$

More followers exists and contribute their lagging technologies to the production of the homogeneous goods in the next period when more entrants successfully take leader positions and more leaders fall behind.[20] Therefore, radical innovation affects the future production of homogeneous goods and quality goods by changing the ratio of followers to leaders.

[19] $q_{j,i,t}$ is predetermined. The leader chooses $S_{j,i,t}$ to solve the optimization problem.

[20] $\bar{m}$ is a constant that determines the unconditional mean of m_t, playing no role in the dynamic.

2.6 Household

In the economy, there exists a representative household with the Epstein-Zin preference over a bundle $\mathscr{C}_t$ of consumption C_t and labor L_t:

$$U_t = \left[(1-\beta)\mathscr{C}_t^{1-\frac{1}{\psi}} + \beta\Big(E_t\big[U_{t+1}^{1-\gamma}\big]\Big)^{\frac{1-\frac{1}{\psi}}{1-\gamma}}\right]^{\frac{1}{1-1/\psi}} \tag{24}$$

where ψ denotes intertemporal elasticity of substitution, γ is the relative risk aversion, and β is the subjective discount rate. I assume the household prefers an early resolution of uncertainty, hence $\gamma > \frac{1}{\psi}$. The the utility bundle $\mathscr{C}_t$ is defined as:

$$\mathscr{C}_t = C_t - \bar{\omega}_l \frac{Z_t L_t^{\omega_l}}{\omega_l},$$

where ω_l controls the elasticity of labor. $\bar{\omega}_l$ is a scaling parameter. Z_t is an exogenous process that cointegrates with aggregate technology growth to ensure balanced growth.[21]

The household holds the physical capital K_t. Each period, the household invests to accumulate capital using the following technology:

$$K_{t+1} = (1-\delta_k)K_t + \Phi(\frac{I_t}{K_t})K_t \tag{25}$$

where I_t is the aggregate investment, δ_k is the capital depreciation rate. Φ is the production technology of capital, which features convex adjustment costs (Jermann (1998).).

Each period, the household earns wage $\omega_t L_t$ and receives capital rents $r_t^k K_t$ as income by supplying physical capital K_t and labor L_t to the markets for the use of production. In addition, the household receives dividends from all firms, which are owned by the household. Therefore, the

[21]Specificaly, zq_t, which is the ratio of Z_t over aggregate technology level Q_t, satisfies: $zq_t = (1-\theta_{zq})\bar{\mu} + (1-\theta_{zq})(zq_{t-1} - \Delta q_t)$.. θ_{zq} equals 0 so that Z_t grows at steady state growth rate $\bar{\mu}$.

household's budget constraint is:

$$C_t + I_t = \mathcal{D}_t + r_t^k K_t + \omega_t L_t \tag{26}$$

where $\mathcal{D}_t$ is the aggregate net cash flow from all firms. All terms in Eq.(26) are in the units of homogeneous goods.

The household's optimaziation problem is to maximize the utility in Eq.(24) subject to budget constraint Eq.(26) and Eq.(25). The implied stochastic discount factor is standard:

$$M_{t,t+1} = \delta(\frac{\mathscr{C}_{t+1}}{\mathscr{C}_t})^{-\frac{1}{\psi}}(\frac{U_{t+1}}{E_t^*[U_{t+1}^{1-\gamma}]^{\frac{1}{1-\gamma}}})^{\frac{1}{\psi}-\gamma} \tag{27}$$

2.7 Equilibrium

2.7.1 Market Clearing

In equilibrium, the capital rental rates r_t^k, the wage rates ω_t and the goods prices clear their markets respectively.

The capital market clearing:

$$K_t = \int_j K_{j,l,t} dj + \int_j K_{j,f,t} dj \tag{28}$$

The labor market clearing:

$$L_t = \int_j L_{j,l,t} dj + \int_j L_{j,f,t} dj \tag{29}$$

The goods market clearing:

$$P_{\mathcal{Y},t}\mathcal{Y}_t = C_t + I_t + \int_j \int_i P_{j,l,t} x_{j,i,t} di dj + \int_j \int_i q_{j,i,t} S_{j,i,t} di dj + \int_j Q_{j,t} m_{j,t} S_{j,f,t} dj + \int_j Q_{j,t} S_{j,e,t} dj \tag{30}$$

2.7.2 Symmetric Equilibrium

For the leaders, the profit $\pi_{j,i,t}$ is linear in the leading technology level $q_{j,i,t}$, as shown in Eq.(17). In addition, all leaders are equally likely to be displaced by entrants and followers that resulted from the uncontrollable radical ideas. These two conditions imply that all leaders with heterogeneous technology levels choose the same quality adjusted innovation expenditure $S_{j,i,t}$ in the technology race at time t.[22] Therefore, industry j's innovation activity can be expressed by its average technology level $Q_{j,t}$ and homogeneous $S_{j,i,t} = S_{j,l,t}$ across leading technology i:

$$\int_i q_{j,i,t} S_{j,i,t} di = Q_{j,t} S_{j,l,t} \tag{31}$$

Similarly, Eq.(3) implies that quality adjusted intermediate input $\frac{x_{j,i,t}}{q_{j,i,t}}$ is invariant acroos i. Hence, industry j's aggregate intermediate input can by described by Q_t and the equilibrium $\frac{x_{j,i,t}}{q_{j,i,t}} = \frac{x_{j,l,t}}{q_{j,l,t}}$:

$$\int_i P_{j,l,t} x_{j,i,t} di = Q_{j,t} P_{j,l,t} \frac{x_{j,l,t}}{q_{j,l,t}} \tag{32}$$

In addition, the technology spillover effect ensures that all followers (entrants) are ex-ante identical and make symmetric innovation expenditure decisions in each industry.

A symmetric equilibrium exists in the economy where all industry good firm, quality firms and homogeneous firms make the identical production decisions across industries.[23] The aggregate technology levels and the ratio of followers to leaders are idential, that is $Q_t = Q_{j,t}$ and $m_t = m_{j,t}$ for all j. The aggregate technology growth rate is given by:

$$\begin{aligned} \frac{Q_{t+1}}{Q_t} &= \underbrace{((\phi_l(S_{l,t}) + \phi_f(S_{f,t}) + \phi_f(S_{f,t})m_t)\kappa)}_{\text{Successful Innovation}} \\ &\quad + \underbrace{((1 - \phi_l(S_{l,t}) - \phi_f(S_{f,t}) - \phi_f(S_{f,t})m_t))}_{\text{Stay at the same technology level}} \end{aligned}$$

[22]See the proof for symmetric innovation in Section A.6.

[23]$Y_{j,t} = Y_t = \mathcal{Y}_t$, $Y_{j,l,t} = Y_{l,t}$, $Y_{j,f,t} = Y_{f,t}$ and $P_{j,t} = P_t = P_{\mathcal{Y},t}$, $P_{j,l,t} = P_{l,t}$, $P_{j,f,t} = P_{f,t}$. for all j. The details of the equilibrium conditions and proofs are in Appendix.

The follower-to-leader ratio m_t, the aggregate technology Q_t[24] and the aggregate physical capital K_t are the three endogenous state variables in the economy.

3 Quantitative Analysis

In this section, I present the quantitative analysis of the model. First, I discuss the model calibration and the functional forms for innovation and physical capital production technology. Second, I examine the implications of the technological race for asset prices and technology growth. In particular, the follower-to-leader ratio, as a state variable in the model, drives the cash flow risk of the leading technology, which is a key factor affecting asset prices. In addition, I discuss the empirical predictions of the model.

3.1 Calibration

I report the quarterly benchmark calibration for the model in Table 1. The performance of the model is robust to reasonable variations around the benchmark. I solve the model using third order perturbation methods.

The parameter choices for the preference are standard. In particular, the relative risk aversion γ is set to 10, and the intertemporal elasticity of substitution is set to 2 so that the agent prefers an early resolution an uncertainty, following the production-based asset pricing literature (e.g. Croce (2014), Kung and Schmid (2015), Kung (2015)). This parametrization helps to generate a sizable risk premium as discussed in the long-run risk literature (Bansal and Yaron (2004)). The subjective discount rate is set so that the risk-free rate is within a reasonable range of the empirical estimate. The labor elasticity is set to 1.5 so as to be consistent with the choice in Greenwood *et al.* (1988). And the labor scale parameter $\bar{\omega}_l$ is set so that the steady state labor supply is 1/3.

[24] Q_t can be interpreted as the aggregate technology capital.

In the production of quality goods and homogeneous goods, the capital share α is set to 0.3. And the quarterly physical capital depreciation rate δ_k is set to 1.5%, following the macroeconomic literature. For the physical capital production technology $\Phi(\frac{I_t}{K_t})$, I consider the following standard function form as in Jermann (1998):

$$\Phi(\frac{I_t}{K_t}) = \frac{\alpha_1}{1-\frac{1}{\xi_k}} \left(\frac{I_t}{K_t}\right)^{1-\frac{1}{\xi_k}} + \alpha_0 \tag{33}$$

where the elasticity of capital adjustment costs ξ_k is set to 8 so that the friction on the physical capital accumulation is low, consistent with the choice in Croce (2014). Physical capital adjustment thus is not a major risk in the model.

The leading technology patent share in the production of quality goods ξ is set to 0.49 and the leading technology markup $1/\nu$ is set to satisfy the balance growth restriction $\frac{(\nu-1)\xi}{1-\xi} = 1-\alpha$. The leading technology patent production cost μ_l is set to 1 so that one unit of patented intermediate goods with leading technology needs one unit of quality goods. The three parameters above are set in the spirit of Kung and Schmid (2015).

The follower technology lag parameter $\bar{g}$ is set to be the inverse of the size of technology improvement κ so that the followers are only one step below the leading technology in accordance with Aghion *et al.* (2005). The follower required units of intermediate goods $\bar{x}^f$ is normalized to one. The weight on quality goods is set to 0.5 so that quality goods and homogeneous goods contribute equally to the industry goods. $\bar{m}$ is set so that on average each follower has one corresponding follower who hold the lagging technology.

For the innovation technology, all innovators share the same function from:

$$\phi_i(S) = \chi S^\eta, \quad i = l, f, e \tag{34}$$

The elasticity of innovation rate with respect to R&D η is set to 0.8, which is within the range from 0.6 to 1.0 estimated by Griliches (1998). The size of technology improvement κ is set to 1.2

following the estimates in Bena *et al.* (2015). The innovation scaling parameter χ is set to 0.9 so that the annual average growth rate of aggregate output is 1.9%.

The quality goods elasticity of substitution τ is set to 4.5. This parameter is important in model since it governs the monopoly power of the quality goods. The choice of τ thus affects the value of leading technology, which further affects the innovation activities of all innovator in the economy. The value set in the benchmark calibration implies that the average arrival rate of a radical innovation for a follower or entrant is about 16 years which is consistent with the choice in Acemoglu and Cao (2015).[25]

The implied leader survival cycle, that is the time of staying in leaders, is about 8 years since both followers and entrants conduct radical innovation in each period. In addition, the follower survival rate ϕ is set to 0.8. Therefore, the implied patent survival rate is 0.975 which is consistent with the choice in Comin and Gertler (2006), Comin *et al.* (2009). The implies quality goods markup is 0.28, which is broadly consistent with my empirical evidence given markup is difficult to measure empirically. I conduct comparative static analysis by changing the value of τ and discuss the results in the following section.

The productivity parameters are set to be consistent with macroeconomic moments. The productivity persistence is set to ρ is set to 0.98 and the productivity volatility is set to σ, which are consistent with the estimates in Bansal *et al.* (2019). Table 2 upper panel shows the simulated macro moments from the model. Overall, the calibrated model fits the macroeconomic data reasonably well.

3.2 Results

In this section, I discuss the implications of the model. First, I show the relation between the technological race and the aggregate dynamics. Next, I study how the risk of the leading technology, or LTR, affects asset prices. More importantly, I examine how the novel endogenous state variable follower-to-leader rato m_t drives the LTR.

[25] The choice of τ, χ and $\bar{m}$ jointly determines the annual average growth rate of aggregate output, the radical innovation rate, and the quality goods markup.

3.2.1 Model Dynamics

Figure 1 illustrates the macroeconomic dynamics by demonstrating the impulse responses of macro quantities with respect to a positive productivity neutral shock. Note that good aggregate conditions make the leading technology more valuable by increasing the profits of leaders, as shown in Eq.(17). A positive shock triggers the expanded effort on both the leaders' innovation $S_{l,t}$ and the radical innovation from the entrants $S_{e,t}$ and the followers $S_{f,t}$ since the value of being a leader $V_{l,t}$ increases. The innovation race becomes intense in the sense that more leading technologies are improved by the entrants and followers and more leaders are displaced. The growth of aggregate technology speeds up in response to the increase in innovation effort.

In contrast to the standard quality ladder models in which only the highest technology holders can participate in the production (e.g Acemoglu and Cao (2015), Bena *et al.* (2015)), the leaders who lose their positions do not exit the economy and can still contribute to the production of homogeneous goods as followers in the model. Each period, the number of leaders who are displaced depends on the results of the technological race, which leads to a time-varying measure of the followers m_t. As shown in Figure 2, with respect to a positive neutral productivity shock, m_t rises since more leaders become followers after the race. Without the leading technology for the quality goods production, the followers enjoy no monopolistic rents. However, they can become leaders in the future technology races. The follower's value is determined by the probability of becoming a leader in the future, as Eq.(23) shows. Therefore, the followers have incentives to stay in business even if they generate no profits.

The homogeneous goods producer is more productive in terms of the quantity when the number of lagging technology holders expanded.[26] The larger supply of the homogeneous goods, which increases the aggregate income, drives up the demand for the quality goods. The quality goods firm thus charges a higher price and earns higher profits. As shown in Figure 2, the relative price of the quality goods $P_{l,t}$ surges along with the follower-to-leader ratio m_t. The profit earned by the

[26] One way to interpret the increase in the productivity of homogeneous goods producers as the firms provide more products with similar lagging technologies.

leaders and the profitability measure of the quality goods firm, which is the ratio of the profit to capital, increase since the quality goods are worth more because of a rise in the demand. Given the link between the profit of the quality goods firm and the profit of the leading technology as shown in Eq.(17), each leader who contributes to the production of the quality goods extracts higher rent when quality goods firm becomes more profitable.

The profitability measure of the quality goods firm is important for the following reasons. First, it is informative about the important state variable follower-to-leader ratio m_t introduced by the model. Increased number of technological followers in the market makes the quality goods with cutting-edge technologies more profitable by driving up the demand. Therefore, the profitability of the quality goods firm comoves with the follower-to-leader ratio. Therefore, It gives the empirical guidance to capture this state variable. In addition, empirically, not only the macroeconomic condition but also other shocks can trigger the technological race such as technology booms and the shocks that improve the new idea financing condition. The changes in the profitability of the quality goods firm reflect the resulted follower-to-leader ratio from such shocks. Moreover, the profitability of the quality goods firm is an indirect measure of the average profits of the leading technologies. The average value of leading technologies rises along with the profits of the leading technologies. In the section 4.1, I discuss constructing the empirical counterpart of the measure of the profits of the leading technologies.

3.2.2 Risk of Leading Technology

The value of all firms in the economy are determined by their discounted profits since both the capital and labor are held by the representative household. Furthermore, among the three types of innovators, that are the leaders, the followers and the entrants, only the leaders who own the leading technology can enjoy the profits. In contrast, the values of the followers and entrants who enjoy no monopolistic rents are entirely determined by their small chances to become leaders in the future, as shown in Eq.(23) and Eq.(22). The followers and entrants with low current values have a strong incentive to innovate to displace the leaders and their innovation efforts are driven entirely by the future value of leaders. That is, $S_{f,t}$ and $S_{e,t}$ are both determined by the expected value of future leaders. Their current values are, therefore, fully determined by the future monopolistic rents of leading technology. As a consequence, the risk of follower and entrants is low since their values are not sensitive to the current aggregate productivity shocks.

In comparison to the followers and entrants, the value of leading technology is higher and more risky. Each period, the monopolistic rents gained by leaders are volatile and covary with the aggregate shocks, which make the leaders have greater exposure to the aggregate shocks. I define the risk of leading technology as the sensitivity of $\frac{V_t^l}{V_{t-1}^{l,ex}}$ to the aggregate shock, that is:

$$\beta_{A,t+1}^{LT} = \frac{\partial \frac{V_{t+1}^l}{V_t^{l,ex}}}{\partial z_{t+1}} \tag{35}$$

V_{t+1}^l denotes average value of leaders at time t+1:

$$V_{t+1}^l = \int_0^1 V_{i,q_{j,i,t+1}} di \tag{36}$$

The leader's value is scaled by $V_t^{l,ex}$, which is the average ex-dividend value of leaders at time t. As shown in Figure 2, the value of leading technology response positively to the aggregate shock. Therefore, $\beta_{A,t+1}^{LT}$ is positive and the leading technology is risky. How risky the leading technology is, or $\beta_{A,t+1}^{LT}$, depends on both the monopoly power of the leader firms and the follower-to-leader ratio.

3.2.3 The Demand For Quality Goods

The demand for the quality goods is determined by aggregate household income, which is procyclical. To be specific, when the aggregate productivity increases, the quality goods firm who has monopoly power does not fully expand their production to respond to the good shock so that higher monopolistic rents can be extracted by the firm. On the contrary, the homogeneous goods firm, which sells the goods in a competitive manner, is more responsive to the aggregate shock by fully increasing its production. Overall the rise in the production of all goods increases the aggregate income, driving up the demand for the quality goods, which are produced limitedly. In the goods market, the quality goods, therefore, sell at a higher price. The quality goods firm and the leaders make higher profits, as shown in Figure 2.

The volatile demand affects the cash flow risk of the quality goods firm. How volatile the demand fluctuates further depends on the state variable follower-to-leader ratio. In Figure 3, both the conditional volatility of the quality goods price scaled by its conditional mean $\frac{P_{l,t+1}}{E_t P_{l,t+1}}$, and the profit of leading technology, which is extracted from the quality goods firm's profit, scaled by its conditional mean $\frac{\pi_{l,t+1}}{E_t \pi_{l,t+1}}$ become more volatile along with the increase in the follower-to-leader ratio. That is, the price of the quality goods and the leader's rents are more sensitive to the aggregate shocks when there are more followers in the economy. This is because the homogeneous goods firm is more productive in terms of quantity if more followers exist. When the good aggregate shock happens, compared to the economy with fewer followers, the more productive homogeneous goods firm, who hires more labor and uses more capital, increases their production even further. That further boosts the aggregate income. The richer representative household has an even higher demand for the quality goods. As a result, the leaders earn even higher rents. Tha is, the cash flows generates by the leading technologies covary more with the aggregate shocks and are more risky when the follower-to-leader ratio is high.

As shown in Figure 3, The increased cash flow risk drives up the risk of leading technology as the conditional volatility of $\frac{V_t^l}{V_{t-1}^{l,ex}}$, which is the measure of $\beta_{A,t+1}^{LT}$, increases as well. The results combined with the result in Figure 2 indicate that the value of leading technology is more risky when more followers participate in the production. $\beta_{A,t+1}^{LT}$, therefore, is increasing in the follower-to-leader ratio.

Besides, adjusting by the equilibrium wages and capital rental rate, the resources for production flow more to the homogeneous goods sector because of the high productivity of the homogeneous goods firm and the strong incentive for the quality goods firm to limit its increase in production.[27] The resources are allocated to the more productive sector, which further boosts the aggregate income. As a result, the price of the quality goods and the monopolistic rents boost more when the follower-to-leader ratio is high and vice versa. Figure 4 confirms that the labor and capital reallocations are larger with more followers. The conditional volatilities of the labor share and capital share are increasing in the state variable m_t. Therefore, when more followers exist, a larger share of the resources for production flow towards the homogeneous goods firm in goods time and vice versa.

To better understand the role of monopoly power of the quality goods firm, Figure 3 and 4 also plot the results of the model with a low monopoly power specifications, in which the elasticity of substitution between quality goods and homogeneous goods τ is high. Figure 3 shows that for a given level of the follower-to-leader ratio, the prices of quality goods and the profit of leading technology are less responsive to neutral productivity shocks. And the value of leading technology is less risky. The quality goods firm with low market power cannot earn as high profits as in the case of high market power even if the demand for the quality goods is high. The weaker ability to extract rents makes the cash flows of leading technologies covary less with the aggregate shocks. The cash flow risk for the quality goods firm with low market power is low, which leads to lower risk of leading technology.

Figure 3 also shows that the cash flow sensitivity and the risk of leading technology increase slowly with the follower-to-leader ratio for the low monopoly power case. Due to the lack of ability to extract rents, the leaders cannot raise their profits that much even if the demand is higher. More followers contributing to the production does not make the cash flow much more volatile. Therefore, the cash flow risk and thus the risk of leading technology are less responsive to the changes of the follower-to-leader ratio.

[27] The aggregate supply of labor is higher in good times, while the increased labor is largely hired by the homogeneous goods firms.

3.2.4 Risk Premium

The value of leading technology is risky because the profits of the leaders are more exposed to the aggregate risks. I refer the leading technology risk as LTR. The innovators whose returns have higher loading on the LTR should expect a higher premium. Interestingly, the current followers who actively innovate to become a leader in the future have higher LTR loadings and thus have higher expected returns than the returns on the leaders on average.

I define the quality-weighted average return on the current leaders from time t to t+1 as:

$$\begin{aligned} R^l_{t,t+1} &= \underbrace{[(1-(1-\kappa)\phi_l(S_{l,t}) - m_t\phi_f(S_{f,t}) - \phi_e(S_{e,t}))]}_{\text{Stay as a leader}} \frac{V^l_{t+1}}{V^{l,ex}_t} \\ &+ \underbrace{(m_t\phi_f(S_{f,t}) + \phi_e(S_{e,t}))}_{\text{Become a follower}} \underbrace{\frac{V^{f,ex}_t}{V^{l,ex}_t}}_{\text{Price jump down}} \frac{V^f_{t+1}}{V^{f,ex}_t} \end{aligned} \tag{37}$$

$R^l_{t,t+1}$ can be interpreted as the return of the technology capital of the quality goods firm. The loading of leader's return on the LTR $\beta^i_{LT,t+1}$ mainly depends on both leader's rate of successful technology improvement $\phi_l(S_{l,t})$ and the rate of radical innovation from followers and entrants $m_t\phi_f(S_{f,t}) + \phi_e(S_{e,t})$.[28] Because the technology step size κ is greater than 1, a higher successful rate of leader's innovation makes the leader have greater exposure to the LTR. In contrast, if the rate of successful radical innovation is high, the leader is more likely to be displaced and thus have a lower exposure to the LTR. That is, the distruptive innovation from followers and entrants lower the risk of leader's returns.

The average return from t to t+1 on the current followers is defined as:

$$R^f_{t,t+1} = \underbrace{\phi_f(S_{f,t})}_{\text{Become a leader}} \underbrace{\kappa\frac{V^{l,ex}_t}{V^{f,ex}_t}}_{\text{Price jump up}} \frac{V^l_{t+1}}{V^{l,ex}_t} + \underbrace{(1-\phi_f(S_{j,f,t}))\phi}_{\text{Stay as a follower}} \frac{V^f_{t+1}}{V^{f,ex}_t} \tag{38}$$

[28] Actually, follower's value $\frac{V^f_{t+1}}{V^{f,ex}_t}$ is also positively correlated with leader's value $\frac{V^l_{t+1}}{V^{l,ex}_t}$. However, the correlation is relatively small since the follower has no cash flows.

$R^f_{t,t+1}$ thus can be interpreted as the return of the technology capital of the homogeneous goods firm. The follower's rate of succesfully obtaining the leader's position and the price jump from the follower to the leader are the key elements that affect the follower's loading on the LTR $\beta^i_{LT,t+1}$. The followers' effort on innovation expose them to the LTR. More importantly, once the follower succeed, the price jump from a follower who has no profits to a leader who enjoys monopolistic rents is drastic. This increase in the value makes the return on the follower sensitive to the cash flow shock in the next period.

The future returns on the current followers have greater exposure to the LTR than the returns on leaders because of the price jump, that is $\beta^f_{LTR} > \beta^l_{LTR}$. The conditional exposure of firm's return to aggregate risk, $\beta^i_{A,t+1}$, can be decomposed as follows:

$$\beta^i_{A,t+1} = \beta^i_{LT,t+1}\beta^{LT}_{A,t+1}$$

Because the leading technology is risky ($\beta^{LT}_{A,t+1} > 0$), high loading on the LTR $\beta^i_{LT,t+1}$ makes the return more sensitive to aggregate shocks. The return with high $\beta^i_{LT,t+1}$ has a high risk premium. Therefore, the returns on followers have higher risk premia than the returns on leaders.

The long follower short leader portfolio thus has a positive risk premium. Table 2 lower panel shows that the loading of follower's returns on the LTR β^f_{LTR} is 0.47, while the leader's loading on the LTR β^l_{LTR} is 0.26. The annualized unlevered premium of the long follower short leader portfolio generated by the model is around 0.9%, which is sizable in a production based model with low investment adjustment costs. In addition, the future returns on the current followers are more sensitive to the cash flow risk of the leading technology. The loading of follower's returns on the changes of profitability of leading technology β^f_{LP} thus is also higher than the leader's, as shown in Table 2. That is, β^f_{LP} reflects the return's exposure to LTR. Empirically, I use firms' β^f_{LP} to approximate their exposure to LTR as discussed in section 4.1.1.

Figure 5 shows that the risk premium of return on leaders and the risk premium of return on followers are both increasing in the follower-to-leader ratio since the LTR rises. More importantly, the risk premium of longing followers and shorting leaders rises along with the follower-to-leader ratio. This is due to the rise in LTR. Because the returns on followers have higher exposure to the LTR, the increase in the LTR drives up the premium of the followers more. The second channel is the increase in the aggregate price of risk further drives up the risk premium of return on followers.

Firms often holds a mix of technologies. Therefore, the return of the technology capital of a firm is the value-weighted return of leading technologies and following technologies.

The Aggregate Price of Risk The sensitivity of the aggregate output to the aggregate productivity shocks rises along with the follower-to-leader ratio, as shown in Figure 6. The aggregate output can be expressed as:

$$P_{\mathcal{Y},t}\mathcal{Y}_t = P_{l,t}Y_{l,t} + Y_{f,t} \tag{39}$$

As shown in section 3.2.3, the revenue of the quality goods firm $P_{l,t}Y_{l,t}$ is more volatile with a larger number of followers.[29] The output of the homogeneous goods firm $Y_{f,t}$ is also more volatile because of the larger resources reallocations. The aggregate output thus is more volatile. Therefore, the aggregate price of risk rises along with the increase in volatility of consumption growth. This result implies that the aggregate price of risk could also be high if the follower-to-leader ratio is high.

3.3 Empirical Implications

Recall that $\beta^i_{A,t+1}$, the conditional exposure of firm's return to aggregate risk, can be decomposed as follows:

$$\beta^i_{A,t+1} = \beta^i_{LT,t+1}\beta^{LT}_{A,t+1}$$

$\beta^{LT}_{A,t+1}$ is the exposure of the value of leading technologies to aggregate shock, or the risk of leading technology (LTR). And $\beta^i_{LT,t+1}$ is the firm-specific loading on LTR. Empirically, I construct the LTR factor that captures $\beta^{LT}_{A,t+1} * \textit{aggregate shock}$.[30]

[29] A more sensitive profits implies a more volatile revenue since the quality goods firm has a constant markup.

[30] My model features the endogenous conditional beta on aggregate risk. However, empirically it's difficult to estimate conditional factor models. In the spirit of Jagannathan and Wang (1996), I use an unconditional multifactor

The model implies that LTR factor carries a positive price of risk since $\beta^{LT}_{A,t+1}$ is positive. That is a firm with higher exposure to the LTR should expect a higher premium since its return is more sensitive to aggregate shock (higher $\beta^{i}_{A,t+1}$).

The LTR provides additional pricing information since the LTR is driven by the novel state variable follower-to-leader ratio proposed by the model ($\beta^{LT}_{A,t+1}$ is endogenously driven by the follower-to-leader ratio). As a result, the model predicts that the SDF loading on the LTR factor is significant with the control of other factors. This is because LTR factor is informative about the follower-to-leader ratio that drives the cross-section of risk premia.

Moreover, the LTR price of risk is increasing in the follower-to-leader ratio, which is further positively correlated with the aggregate productivity as shown in section 3.2.1. Therefore, the model predicts that the LTR price of risk, or $\beta^{LT}_{A,t+1}$ is high when the economy is booming.

Empirically, a firm could hold both the leading technologies and the lagging technologies. The model predicts that the firm, who have more lagging technologies and actively innovate, should expect higher returns because of the higher exposure to the LTR (higher $\beta^{i}_{LT,t+1}$). Implied by the model, the follower firm should also spend more resources to innovate than the leader firm since it has a stronger incentive to displace the leaders.

4 Empirical Evidence

In this section, I test the empirical implications of the model. First, I construct the leading technology risk factor in section 4.1. In section 4.2, I perform various formal cross-sectional tests to estimate the price of risk of the leading technology risk factor. In section 4.3, I test if the LTR factor is useful for pricing assets. In section 4.4, I test the LTR procyclicality by showing that price-dividend ratio predicts the LTR factor positively. In section 4.5, I verify the model's implications for returns and innovation activities at the firm level.

approach to capture LTR in my model. I show that the properties of that factor are consistent with my model's prediction.

4.1 Factor Construction

The model implies that the profits of the quality goods firms determines the cash flow risk of the leading technology. According to the definition of the quality goods firm in the model, empirically a firm identified as a technological leader should satisfy two conditions. First, the firm should hold the leading technologies. Note that typically firms hold a bundle of different technologies. Some of the technologies are cutting edge, while the others are common. A firm is more likely to hold the leading technology if the technology level measured by the quality of its patents is higher than other firms in the industry. Second, the firm should already bring innovative products with the leading technology on the market. Importantly, if a firm already obtains the patent on the leading technology but its new product is still in progress, it should not be considered as leaders since the leading technology does not start generating profits yet.

4.1.1 Direct Approach

A natural approach to identify the leader firm is to directly verify whether a firm provides innovative products since they are likely to be equipped with leading technologies. For this reason, I use R&D/Innovation performance indicators from the MSCI ESG KLD STATS dataset, which identify a company as a leader if it brings notably innovative products to market. I match the indicator dataset with CRSP/Compustat to collect the financial data and stock returns for leaders and followers identified by the performance indicator. More importantly, In order to validate the innovation performance indicators, I also use the patent value data from Kogan *et al.* (2017). All details of the data are described in the Appendix.

Table 3 reports the summary statistics of leader firms and follower firms identified by the performance index. Importantly, the citation weighted patents scaled by size of the leader firms is about six times as high as the patents owned by the follower firms. The scaled market value of the patents owned by the leader firms is about five times as high as it is for follower firms.[31] Therefore, the

[31] The citation-weighted measure is based on Hall *et al.* (2005). The market value of the patent is measured based on the firm stock returns. See Kogan *et al.* (2017).

leader firms are more likely to hold the leading technologies.[32] In addition, while it is typically difficult to measure markups, Table 3 suggests that the leader firms have higher markups on average. Moreover, the leader firms have larger size, lower book to market ratio on average.

Following section 3.2.1, I construct the measure of the average profitability of the leading technologies as the average excess profitability of the leader firms:

$$LP_t = \frac{1}{n_{leaders_t}} \sum_{j \in leaders_t} \frac{Profit_{j,t}}{Asset_{j,t}} - \frac{1}{n_{followers_t}} \sum_{j \in followers_t} \frac{Profit_{j,t}}{Asset_{j,t}}$$

LP_t is measured at quarterly frequency and $Profit$ is defined as $Sales - Costs$. I denote the $\Delta LP_t = LP_t - LP_{t-1}$ as the innovation of LP_t.[33] Implied by the model, LP_t is informative about the average follower-to-leader ratio. A rise in LP_t reflects a higher average profitability of the leading technologies. Importantly, the stock returns that are more sensitive to the changes of LP_t have higher exposures to the leading technology risk.

I use the stock returns from the Center for Research in Security Prices with share codes 10, 11 and 12 so that microcap stocks are not considered in the sample. In order to construct the tradable factor of the LTR, for each stock returns in the sample, I estimate its exposure to the ΔLP_t by running the following regression:

$$R^{ex}_{i,t} = \alpha_i + \beta^i_{LP,t} \Delta LP_t + Controls + \varepsilon^i_t$$

$R^{ex}_{i,t}$ is the excess return of stock i at time t. $\beta^i_{LP,t}$ measures its exposure to the LTR. I control the return i's exposures to Fama-French three factors that are the market factor, the size factor and the value factor. For each time t, I sort the stock returns into terciles according to their conditional LTR exposures $\beta^i_{LP,t}$ estimated on a trailing window. I form the value-weighted portfolios for stocks

[32] Note that the leader firm is different from the high R&D firms in the firm innovation literature (e.g. Chan *et al.* (2001),Li (2011), Lin (2012), Croce *et al.* (2019)). High R&D firms are identified based on the R&D expenditure which is an input measure, while the leader index is related to the innovation output, which is innovative products with high valued patents.

[33] The time series of LP_t is in Appendix.

with high LTR exposures and for stocks with low exposures. Then I construct the factor-mimicking portfolio for the LTR by longing the portfolio with high $\beta^i_{LP,t}$ and shorting the portfolio with low $\beta^i_{LP,t}$. The sample period for the tradable LTR factor is from January 1998 to December 2009 at a monthly frequency.[34] Given this LTR factor is constructed directly based on the firms with innovative products which are the closest to the definition of the quality goods firm in the model, I refer it as the LTR factor with the direct approach.

4.1.2 Indirect Approach

In this section, I propose another approach to construct the LTR in order to extend the sample without relying on the performance indicators in section 4.1.1. Ideally, leader firms can be identified if both their products and the embedded technologies can be observed, which is generally difficult to achieve. Instead, I measure the technology level of firms in each industry, assuming that they implement the technologies in their products.

The technology level of a firm includes both the newly developed technologies and the previous technologies. In order to capture the current contribution of the technology developed in the past, I estimate the technology depreciation rates for each industry. The approach I use to approximate the depreciation speed is to measure the average life cycle of the patents in each industry with the assumption that the contribution of a particular technology to the current product is negligible at the end of its lifetime.

The measurement of the average life follows Bilir (2014). First, I match the NBER patent data recorded in the NBER US Patent Citation Data Files to Compustat firms.[35] Second, for industry j, I compute the average life cycle $T^{tech}_{lc,j}$ by averaging the citation lags of the patents owned by the firms in that industry. The citation lag is defined as the time difference between the grant of a patent and the future citations.[36] Table A2 summarizes the estimated life cycle of patents for SIC

[34]The MSCI ESG KLD STATS dataset discontinue the R&D/Innovation performance indicators after 2009. Table A1 in Appendix reports details of the LTR factor.

[35]For patent information, see Bronwyn Hall's data website, https://eml.berkeley.edu// bhhall/patents.html.

[36]For each patent, if the patent is cited more than once, I compute the average citation lag for that patent.

49 industries. Therefore, $T^{tech}_{lc,j}$ indicates the average length of time that the technologies owned by the firms in industry j stay relevant. That is, it is a measure of the average depreciation speed of the technologies of industry j.

I estimate a firm i's technology level in industry j as follows:

$$TechStock_{i,j,t} = (1 - \delta^{tech}_{j})TechStock_{i,j,t-1} + PatentValue_{i,j,t}$$

$TechStock_{i,j,t}$ is the stock of the technologies owned by firm i in industry j at time t. $PatentValue_{i,j,t}$ is the market value of the patents generated by the firm at time t.[37] $PatentValue_{i,j,t}$ thus is the quality-adjusted innovation output of firm i at time t. It is a measure of inflow to the pool of technologies held by the firm and contributes to the firm's products. δ^{tech}_{j} is the average deprecation rate of technologies in industry j based on the measured life cycle $T^{tech}_{lc,j}$.[38] $TechStock_{i,j,t}$ is therefore a measure of the current value of the technologies owned by firm i. $TechStock_{i,j,t-1}$ is zero if firm i starts its business at time t. I define the technology level of firm i $TechLevel_{i,j,t}$ as $TechStock_{i,j,t}$ scaled by its book assets, accounting for the fact that large firms may file more patents.

Note that I use indutry-specific depreciation rate to capture the heterogeneous technology depreciation speeds across industry. More importantly, I use the innovation output, the value of patent, to measure the inflow to the stock of technologies, accounting for the fact that not all R%D expenditures lead to technology improvement.[39]

For each industry, I sort the firms into deciles based on their measured technology level each year. For the next year, I only label the top group as leaders, that is top 10% of the firms within each industry, and the bottom group as followers based on the previous year's groups. Note that this procedure is conservative to assure that the leading technologies are more likely to be held by the labeled leader firms. Moreover, I allow a one-year lag for labeling, assuming the firms implement the

[37] The data for patent values is obtained from Kogan *et al.* (2017).

[38] δ^{tech}_{j} is determined so that after $T^{tech}_{lc,j}$, the depreciated value of the patent is under 5% of the original value.

[39] Eisfeldt and Papanikolaou (2013) and The Bureau of Economic Analysis (Sliker (2007)) use the expenditure measure to construct the stock of organization capital and the stock of R&D respectively, considering a constant depreciation rate.

newly developed technologies in their products fairly quick because of the rent-seeking incentives.[40] After forming the leader group and follower group for each time period, I follow the same procedure in section 4.1.1 to construct the LTR factor-mimicking portfolios, which is referred as the LTR factor with the indirect approach.

In comparison to the factor with the direct approach, the indirect factor is potentially noisier for the following reasons. First, the accuracy of the measurement on the firm's technology level is elusive because of the difficulty of measuring the depreciation rate of each technology. Second, when a firm actually use the newly developed technologies in its product is not observed, which makes the measurement on the average profitability of the leading technologies noisy. However, the factor with the indirect approach has longer test sample period, which is from January 1978 to December 2011. Therefore, more time-series and cross-sectional data are included in the tests. In addition, despite the potential noises, the decomposition of the variances of both direct and indirect factor into the principal components in section 4.3 suggests that they capture similar pricing information.

4.2 Price of Risk

In this section, I estimate the price of risk of the leading technology risk in formal cross-sectional asset pricing tests with a comprehensive set of test assets. In section 4.2.1, I perform the standard two-stage procedure in cross-sectional asset pricing tests with GMM corrected standard errors.[41] In section 4.2.2, for robustness, I perform a three-stage test that allows for omitted priced factors proposed by Giglio and Xiu (2018). I compare the results with the estimates from GMM and the estimates from the Fama-MacBeth procedure. The results support the model prediction that $\beta^{LT}_{A,t+1} > 0$, that is leading technology is risky.

[40] The results are robust to two-year lag and three-year lag.

[41] See Kan and Zhang (1999a), Kan and Zhang (1999b) and Cochrane (2009).

4.2.1 Two-Stage Procedure

I perform the cross-sectional test that include two stages. In the first stage, I estimate the LTR betas for each test asset i from the time-series regressions with the control of other priced factors:

$$R_{i,t}^{ex} = a_i + \beta_{LTR}^i f_{LTR,t} + \sum_{control} \beta_{control}^i f_{control,t} + \varepsilon_t^i$$

$R_{i,t}^{ex}$ is the excess returns on asset i. Then I run a cross-sectional regression where I regress the average excess returns on each test assets on the betas estimated in the first stage:

$$E_T R_i^{ex} = \beta_{LTR}^i \lambda_{LTR} + \sum_{control} \beta_{control}^i \lambda_{control} + \nu_t$$

where λ_{LTR} is the price of risk of the LTR. $\lambda_{control}$ are the risk prices of the control factors. The model implies that the LTR price of risk is time-varying and depends on the state variable follower-to-leader ratio. The esimated λ_{LTR} in the two-stage procedure is the average of the time-varying LTR price of risk.

I use the portfolios obtained from Kenneth French's website as test assets.[42] The set of test assets includes: 25 portfolios sorted by size and book-to-market ratio, which is the 25 Fama and French (1993) Portfolios, 10 portfolios sorted by momentum, 10 portfolios sorted by investment, 10 portfolios sorted by operating profitability, 10 portfolios sorted by market beta, 10 portfolios sorted by net issuance, 10 portfolios sorted by industry. The test assets, therefore, capture various characteristics of the cross-sectional asset returns.

Table 4 reports the estimate of the price of risk for the LTR factor with the direct approach (DA LTR factor). I use GMM, which corrects the cross-sectional correlation among assets and the errors from generated regressor βs in the first stage, to estimate the standard errors. I report the

[42]For all details of the portfolio constructions, see Kenneth French's website: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_librar.html. There are two reasons for using portfolios as test assets. First, the returns on portfolios are less noisy. Second, they suffer less from the issue of missing data.

GMM t-statistics for each risk prices. The test time period for DA LTR factor is from January of 1998 to December of 2009. The LTR risk price is estimated with the presence of different groups of control factors, such as Fama-French three factors, Carhart four factors, Fama-French five factors and Fama-French five factors plus intermediary factor.[43]

The price of risk of the DA LTR factor is positive and significant across different control groups. Moreover, the estimates of the DA LTR risk price 1.7% monthly or 20% annually is one magnitude larger than the estimated market price of risk, which is 0.2% monthly or 2.4% annually. In addition, surprisingly, while the estimates of the DA LTR risk price is consistently significant, the estimated prices of risk of the classic factors are not. The insignificant results are mainly because the classic factor estimation needs more time-series and cross-sectional data to reduce the noise, given the sample size is only from January of 1998 to December of 2009. Table 4 also reports the standard deviation of the betas across assets estimated in the first stage Eq.(40). The dispersion of the loadings on DA LTR factor is one magnitude smaller than the dispersion of the classic factor betas. Overall, the estimation results imply that the risk premium for being exposed to the DA LTR risk is large while the number of the portfolios with relatively high exposures to the DA LTR risks is small.

Table 5 shows the results for the LTR factor with the indirect approach (IA LTR factor) along with other control factors with GMM correction. In this extended sample, from January of 2078 to December of 2011, similar to the results for DA LTR factor, the IA LTR factor risk price is significantly positive and it is also one magnitude larger than the classic factors. However, many of the classic factors become significant in the extended sample. In addition, the standard deviation of betas on IA LTR factor is one magnitude smaller than the classic factors', similar to the results in Table 4.

[43] Fama-French five factors (Fama and French (2015)) are obtained from Kenneth French's website. Intermediary factor is obtained from He *et al.* (2017).

4.2.2 Robustness

The standard two-stage price of risk estimation can be biased for if not all priced factors are controlled. The bias can be potentially large if the factors are highly correlated with omitted priced factors.[44] In order to account for the missing factors, I estimate the price of risk of the LTR using the three-stage methodology proposed by Giglio and Xiu (2018).

The three stages are as follows. In the first stage, I perform the principal component analysis and extract principal components from the set of test assets. The extracted PCs, which span the factor space, capture almost all the pricing information. For each test asset i, I estimate the loadings on the PCs. In the second stage, similar to Eq.(40), I run a cross-sectional regression to estimate the risk prices λ_{PC_j} for each PC using the loadings from the first stage. In the third stage, I regress the observed factors on the PCs and estimate the loadings on each PC β_{f,PC_j}. Therefore, the price of risk of an observed factor, e.g. the LTR, can be expressed as:

$$\lambda_{LTR}^{GX} = \sum_j \beta_{PC_j}^{LTR} \lambda_{PC_j} \tag{40}$$

The estimate λ_{LTR}^{GX} is unbiased as long as the factor space is recovered by the extracted PCs.

Table 6 report the three-stage estimated prices of risk along with results from GMM and Fama-MacBeth procedure (Fama and MacBeth (1973)), which is commonly used in the literature, for both the DA LTR factor and the IA LTR factor. While there is no need to control other factors in the three-stage procedure, for consistency, I also estimate the price of risks of the control factors in the two-stage procedure using the same sample period. The t-statistics for the three-stage estimates are based on the asymptotic theory developed by Giglio and Xiu (2018). The DA LTR price of risk estimated by the three-stage methodology, which is 0.9% monthly, is smaller than the results from two-stage estimation, suggesting that some factors relevant for the LTR risk are omitted in the two-stage procedure even if Fama-French five factors plus intermediary factor are controlled.

[44] If factors in the estimation are correlated with omitted priced factors, the βs estimated in the first stage and the risk prices estimated in the second stage are biased. See Giglio and Xiu (2018).

However, the DA LTR price of risk is consistently positive and significant. Moreover, the estimation results for the classic factors are close to the estimates in the two-stage procedure, which suggests the results in Table 4 may be affected less by the omission of priced factors.

Similar to the DA LTR factor, The three-stage esitmate for the IA LTR price of risk is 0.6% monthly and significant, while smaller than the two-stage estimates. The estimated price of risk for the classic factors are consistent with the results in Giglio and Xiu (2018), while some of the estimates in Giglio and Xiu (2018) are more significant since they use a longer sample, which is from July of 1963 to December of 2015. In addition, for both samples, the results from Fama-MacBeth procedure are consistent with the GMM, while Fama-MacBeth procedure does not account for the estimation errors of βs in Eq.(40).

4.3 Pricing Information

A positive price of risk of the LTR factor answers the question that if the returns with higher exposure to the LTR factor have a high premium. However, the factor with a significant positive price of risk may not be useful for pricing assets since the factor can be a combination of known factors and does not provide additional pricing information.[45] In order to test if the LTR factor explains the cross-sectional returns, I estimate the stochastic discount factor (SDF) loadings on that factor. The results support that $\beta^{LT}_{A,t+1}$ is time-varying and capture additional pricing information so that the LTR factor is not absorbed by the market factor.

I assume that the SDF has the following linear form:

$$m_t = b_0 - \boldsymbol{b}\boldsymbol{f}_t \tag{41}$$

where m_t is the SDF, $\boldsymbol{f}_t$ is a vector of factors and $\boldsymbol{b}$ is a vector of SDF loadings on the factors. A factor is useful for pricing assets if b is significant on that factor controlling other factors. Cochrane

[45]For detailed discussion, see Cochrane (2009), Feng *et al.* (2019).

(2009) shows the relation between price of risk and SDF loadings as follows:

$$\boldsymbol{\lambda} = E(\boldsymbol{f}\boldsymbol{f}')\boldsymbol{b} \tag{42}$$

Inferences for $\boldsymbol{\lambda}$ and $\boldsymbol{b}$ is identical if the factors are uncorrelated with each other, which is often not the case in the data.

Table 7 and Table 8 report the SDF loading estimates for both the DA LTR factor and the IA LTR factor with different controls. The GMM t-statistics are also reported. The LTR factor with both approaches has significant SDF loadings with the presence of classic factors. Importantly, the SDF loading on LTR is significant while controlling the profitability factor RMW. Given the construction of LTR uses the profitability measure, it is important to show that the LTR factor provides pricing information that is different from the information captured by the profitability factor. In addition, for the extended sample, the size factor has significant SDF loading while an insignificant price of risk because of potential noises.[46] The result implies that the size factor is still useful in terms of pricing assets.

PC Decomposition As a supplement to the SDF loading estimates, I perform a variance decomposition by projecting LTR factors along with other test factors onto principal components. Table A3 shows that the percentage of the factor variance is attributed to PCs for each factor.[47] The results suggest that the LTR factors constructed by two different approaches capture similar pricing information. Both DA and IA LTR factors have nontrivial loadings on the first three PCs, which are the strong latent factors that explain most of the cross-sectional asset returns. Specifically, both DA and IA LTR factors load on PC2, where 19% variance of DA LTR and 17% variance of IA LTR are attributed to. Surprisingly, both LTR factors load heavily onto PC13 to PC15 especially PC14, which is responsible for 25% of DA LTR factor variance and 39% of the IA LTR factor variance.

[46] Giglio and Xiu (2018) also find an insignificant price of risk for size factor in the sample from 1970 to 2012.

[47] PCs are ranked from highest to lowest based on their eigenvalues. In addition, by projecting the factor onto PCs, the factor fluctuation unrelated to pricing information is filtered.

In contrast, the loadings of the classic factors on PC13 to PC15 are negligible. Therefore, both LTR factors are distinguishable from classic factors. The SDF loading estimation results combined with the PC decomposition support the prediction that the LTR factor contains additional pricing information.

4.4 Procyclical Premium

The model predicts that the LTR price of risk is procyclical since the leading technology is more risky if more follows exists in the economy, which is more likely to happen in good times ($\beta^{LT}_{A,t+1} > 0$ is high in a booming economy). The empirical implication is that the market PD ratio should predict the LTR factor premium positively. Table 9, where I regress both the DA and IA LTR factors and the market factor on the PD ratio, confirms that prediction.[48] Specifically, I run the following regression:

$$\frac{1}{k} R^e_{f,t\rightarrow t+k} = \alpha + \beta^f_{pd} P_t/D_t + \varepsilon_{t+k} \tag{43}$$

The estimated β^f_{pd} over different horizons and the GMM corrected t-statistics are reported. The β^f_{pd} for both DA and IA LTR factors are significant and positive over the one and two year horizons. And the PD ratio loses its predictability for the LTR factors over longer horizons. The adjusted R^2s also declines along with the horizons after two years. In contrast, the PD ratio predicts the market excess return positively. Moreover, the predictability is stronger for longer horizons because of higher coefficient significance and higher adjusted R^2s, consistent with the finding in the literature (e.g. Cochrane (2011)). The results imply that the LTR factor premium is procyclical, while the market factor price of risk is countercyclical.

4.5 Firm-Level Evidence

I use the panel data of Compustat firms with innovation performance indicator from MSCI ESG KLD STATS dataset to investigate the model's prediction on firms' returns and innovation

[48] Market price and dividend data is from Shiller's website. IA LTR factor is filtered by projecting onto PCs.

activities.

Table 10 shows the relation between future returns and the innovation achievement of the firm. The dependent variable for each column is the average monthly stock returns of the firm from year t to t+2. The result of column (1) shows that the firm expects a lower return if it is identified as a leader controlling the industry and time fixed effects. In column (2), I further control the firm's exposure to market risk, size and book-to-market ratio. In column (3), I add the firm's idiosyncratic risk and profitability as control. The coefficients across these three are similar and significant. More importantly, in column (4), instead of the industry fixed effects, I control and the firm fixed effect. In comparison to the results from other specifications, the leading position has a stronger within-firm effect. That is, if a firm develops the products embedded with leading technologies, it expects a lower return, compared to itself with no innovation output.

In Table 11, the dependent variable is the measure of firm's conditional exposure to changes of leading technology profitability, that is $\beta^i_{LP,t\to t+2}$. With the same controls in Table 10, the results of column (1) to column (3) show that the returns on leader firms on average have lower sensitivity to the changes of leading technology profitability. Column (4) shows that the effect is stronger within firm. Moreover, the results in Table 12, where the average R&D intensity from year t to t+1 is the dependent variable, implies that the leader firms have lower innovation expenditures within industry. In addition, firms tend to lower their innovation efforts if they achieve technology improvement and become leaders. The firm-level evidence supports the model's prediction that the leader firms on average have lower loadings on the cash flow risk of leading technologies and thus have lower expected returns. Moreover, leader firms have less incentive to improve their own technologies.

5 Conclusion

In this paper, I develop a general equilibrium asset pricing model, in which technological leaders, followers and entrants race for the technological leadership to generate high but also risky profits.

The cash flow risk of the leading technology, which further drives the leading technology risk (LTR), depends on the follower-to-leader ratio resulting from the technology race and the market power of the product produced by leading technologies. High follower-to-leader ratio as a result of the intensified technology race leads to a volatile demand for the products with leading technologies and thus sensitive cash flows for leaders. Therefore, the LTR is increasing in the follower-to-leader ratio. The model implies that the LTR carries a positive price of risk. That is the firms with higher exposure to the LTR have high risk premium. And the risk premium is high in a booming economy as follower-to-leader ratio is high in good times. Further, the returns of the technology capital of the firms that have following technologies and actively innovate to seek technology leading positions have high loadings on the LTR and thus have high risk premium.

I find empirical evidence supporting the model predictions. I measure the excess profits of the firms with leading technologies and construct the LTR factor. The estimated LTR risk price is significantly positive. The SDF loading estimation with the control of known factors shows that LTR risk capture unique pricing information. Importantly, the price-dividend ratio predicts LTR factor returns positively. These findings support my model.

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Table 1
Benchmark Calibration

Preferences		
Relative Risk Aversion	(γ)	10
Intertemporal Elasiticity of Substitution	(ψ)	2
Subjective Discount Rate	(β)	$0.988^{\frac{1}{4}}$
Labor Elasticity	(ω_l)	1.5
Labor Scale Parameter	($\bar{\omega}_l$)	0.63
Production		
Capital Share	(α)	0.3
Capital Depreciation Rate	(δ_k)	0.015
Elasticity of Capital Adjustment Costs	(ξ_k)	8
Leading Technology Patent Share	(ξ)	0.49
Leading Technology Markup	(ν)	1.73
Leading Technology Patent Production Cost	(μ_l)	1
Follower Technology Lag	($\bar{g}$)	$1/\kappa$
Follower Required Production	($\bar{x}^f$)	1
Industry Good		
Quality Good Weight	(ω)	0.5
Quality Good Elasticity of Substitution	(τ)	4.5
Industry Good Elasticity of Substitution	(τ_i)	4.5
Innovation		
Innovation Scale Parameter	(χ)	0.9
Innovation Elasticity Parameter	(η)	0.8
Size of Technology Improvement	(κ)	1.2
Follower Survival Rate	(ϕ)	0.8
Follower Number Scale Parameter	($\bar{m}$)	0.2
Productivity		
Productivity Persistence	(ρ)	0.98
Productivity Volatility	(σ)	0.016

This table reports the quarterly benchmark calibration.

Table 2
Macro and Return Moments

Moment	Data		Benchmark	Low MP
	Estimate	Standard Error		($\tau = 9$)
$\sigma(\Delta Y)$ (%)	4.85	(0.90)	3.61	3.60
$\sigma(\Delta C)/\sigma(\Delta Y)$	0.61	(0.11)	0.76	0.76
$\sigma(\Delta I)/\sigma(\Delta Y)$	2.14	(0.11)	1.59	1.60
$\sigma(\Delta S)$ (%)	10.20	(1.88)	11.05	10.88
$\rho(\Delta C, \Delta I)$	0.84	(0.41)	0.97	0.97
$AC1(\Delta C)$	0.42	(0.12)	0.32	0.31
$E\left[r^f\right]$ (%)	0.49	(0.50)	1.93	2.03
$\sigma(r^f)$ (%)	2.75	(0.48)	0.45	0.45
$E\left[R^f - R^l\right]$ (%)			0.88	0.57
β^l_{LP}			0.32	0.29
β^f_{LP}			0.75	0.64
β^l_{LTR}			0.26	0.25
β^f_{LTR}			0.47	0.40

The upper panel of this table reports the model simulated macro moments for the benchmark calibration and the low market power specification, that is Low MP. The macro variables includes the output growth ΔY, the consumption growth ΔC, the investment growth ΔI, the R&D growth ΔS, and the risk-free rate r^f. Sample is from 1929-2014. The empirical moments report both the estimates and the standard errors. Standard errors are computed by statinary bootstrap sampling. Model moments are the average of 100 samples. Each sample has 400 time periods. The lower panel shows the annualized mean of the unlevered returns of longing the return on followers and shorting the return of leaders $E\left[R^f - R^l\right]$. βs are the coefficients of the following regressions:

$$R_{t,t+1} = \alpha + \beta_{LP}\Delta\frac{\pi_{l,t+1}}{K_{l,t+1}} + \epsilon_{t+1}$$

$$R_{t,t+1} = \alpha + \beta_{LTR}\Delta\frac{V^l_{t+1}}{V^{l,ex}_t} + \epsilon_{t+1}$$

for both leader and follower. The variance of independent variables is normalized to 1. The mean of returns and coefficients reported are the average of 100 samples. Each sample has 400 time periods.

Table 3
Summary Statistics

	Follower Firm	Leader Firm	Total
Total Assets	5738.9	13617.7	6042.1
Market Value	7630.1	38870.4	8640.5
EBITDA/Assets	0.142	0.167	0.143
Sale/Assets	1.169	1.073	1.165
CAPX/Assets	0.0580	0.0542	0.0579
Book Leverage	0.304	0.253	0.302
Number of Employee	24.73	39.47	25.29
Citation-Weighted Innovation Output/Assets	114.1	660.2	150.3
Market-Value Innovation Output/Assets	1092.6	5193.7	1364.4
Markup: (Sales-Costs)/Sales	0.393	0.485	0.396
Markup: Operating Income/Sales	0.0974	0.176	0.100
Markup: (Sales-Costs-Others)/Sales	0.0933	0.172	0.0964

This table reports the summary statistics for firms identified by the performance indicator R&D/Innovation (PRO-str-B) from the MSCI ESG KLD STATS performance indicators dataset. The definition of the indicator is: *The company is a leader in its industry for research and development (R&D), particularly by bringing notably innovative products to market.* Citation-weighted innovation output is the value of patents measured based on the citations. Market-value innovation output is the value of patents measured based on the stock market reactions. Both measures are obtained from Kogan *et al.* (2017). All financial data are obtained from Compustat.

Table 4
DA LTR Price of Risk: GMM

Factors	LTR	MKT	SMB	HML			
λ	2.581	0.208	0.284	0.191			
$t-stat_{GMM}$	2.401	0.499	0.893	0.619			
Factors	LTR	MKT	SMB	HML	MOM		
λ	2.183	0.219	0.277	0.221	0.597		
$t-stat_{GMM}$	3.135	0.531	0.860	0.711	1.018		
Factors	LTR	MKT	SMB	HML	RMW	CMA	
λ	1.886	0.211	0.366	0.058	0.139	0.264	
$t-stat_{GMM}$	2.274	0.508	1.197	0.178	0.424	1.074	
Factors	LTR	MKT	SMB	HML	RMW	CMA	IMR
λ	1.696	0.211	0.366	0.098	0.117	0.234	-0.320
$t-stat_{GMM}$	2.304	0.508	1.192	0.308	0.360	1.004	-0.303
Factors	LTR	MKT	SMB	HML	RMW	CMA	IMR
$Std[\beta_f]$	0.057	0.142	0.359	0.282	0.295	0.268	0.076

This table reports the estimated price of risk of the LTR factor based on the direct approach along with various sets of control factors. The control factors include: market factor MKT, size factor SMB, value factor HML, momentum factor MOM, profitability factor RMW, investment factor CMA, intermediary factor IMR. Test assets include 25 portfolios sorted by size and book-to-market ratio, which is the 25 Fama and French (1993) Portfolios, 10 portfolios sorted by momentum, 10 portfolios sorted by investment, 10 portfolios sorted by operating profitability, 10 portfolios sorted by market beta, 10 portfolios sorted by net issuance, 10 portfolios sorted by industry. Sample is 1998M1-2009M12 Monthly. The estimation is the standard two-stage procedure including the first stage time-series regression for each asset and the second stage cross-sectional regression. The t-statistics are GMM corrected, accounting for the cross-sectional correlation and estimation bias for βs in the first stage. The standard deviation of βs estimated in the first stage across assets is reported.

Table 5
IA LTR Price of Risk: GMM

Factors	LTR	MKT	SMB	HML			
λ	9.148	0.572	0.086	0.281			
$t-stat_{GMM}$	5.031	2.489	0.505	1.559			
Factors	LTR	MKT	SMB	HML	MOM		
λ	4.983	0.593	0.097	0.331	0.733		
$t-stat_{GMM}$	3.293	2.580	0.601	2.040	2.922		
Factors	LTR	MKT	SMB	HML	RMW	CMA	
λ	3.341	0.551	0.244	0.070	0.315	0.338	
$t-stat_{GMM}$	2.283	2.412	1.584	0.438	2.292	2.552	
Factors	LTR	MKT	SMB	HML	RMW	CMA	IMR
λ	3.569	0.561	0.250	0.102	0.313	0.262	-0.266
$t-stat_{GMM}$	2.445	2.459	1.613	0.630	2.252	2.125	-0.440
Factors	LTR	MKT	SMB	HML	RMW	CMA	IMR
$Std[\beta_f]$	0.011	0.324	0.342	0.269	0.257	0.257	0.057

This table reports the estimated price of risk of the LTR factor based on the indirect approach along with various sets of control factors. The control factors include: market factor MKT, size factor SMB, value factor HML, momentum factor MOM, profitability factor RMW, investment factor CMA, intermediary factor IMR. Test assets include 25 portfolios sorted by size and book-to-market ratio, which is the 25 Fama and French (1993) Portfolios, 10 portfolios sorted by momentum, 10 portfolios sorted by investment, 10 portfolios sorted by operating profitability, 10 portfolios sorted by market beta, 10 portfolios sorted by net issuance, 10 portfolios sorted by industry. Sample is 1978M1-2011M12 Monthly. The estimation is the standard two-stage procedure including the first stage time-series regression for each asset and the second stage cross-sectional regression. The t-statistics are GMM corrected, accounting for the cross-sectional correlation and estimation bias for βs in the first stage. The standard deviation of βs estimated in the first stage across assets is reported.

Table 6
LTR Price of Risk: Giglio Xiu

			DA LTR				
Factors	LTR	MKT	SMB	HML	RMW	CMA	IMR
λ	1.696	0.211	0.366	0.098	0.117	0.234	-0.320
$t-stat_{GMM}$	2.304	0.508	1.192	0.308	0.360	1.004	-0.303
λ	1.696	0.211	0.366	0.098	0.117	0.234	-0.320
$t-stat_{FM}$	2.453	0.510	1.185	0.298	0.362	0.990	-0.353
λ_{GX}	0.851	0.202	0.326	0.216	0.252	0.186	0.022
$t-stat_{GX}$	1.943	0.379	1.136	0.598	0.728	0.814	0.033

			IA LTR				
Factors	LTR	MKT	SMB	HML	RMW	CMA	IMR
λ	3.569	0.561	0.250	0.102	0.313	0.262	-0.266
$t-stat_{GMM}$	2.445	2.459	1.613	0.630	2.252	2.125	-0.440
λ	3.569	0.561	0.250	0.102	0.313	0.262	-0.266
$t-stat_{FM}$	2.722	2.441	1.653	0.647	2.299	2.253	-0.487
λ_{GX}	0.595	0.584	0.220	0.216	0.300	0.191	0.454
$t-stat_{GX}$	1.830	1.670	1.421	1.230	2.120	1.684	1.082

This table reports the estimated price of risk of the LTR factor for both direct and indirect approach along with various sets of control factors. The control factors include: market factor MKT, size factor SMB, value factor HML, momentum factor MOM, profitability factor RMW, investment factor CMA, intermediary factor IMR. Test assets include 25 portfolios sorted by size and book-to-market ratio, which is the 25 Fama and French (1993) Portfolios, 10 portfolios sorted by momentum, 10 portfolios sorted by investment, 10 portfolios sorted by operating profitability, 10 portfolios sorted by market beta, 10 portfolios sorted by net issuance, 10 portfolios sorted by industry. Sample for direct approach LTR factor is 1998M1-2009M12 Monthly. And sample for indirect approach LTR factor is 1978M1-2011M12 Monthly. The table reports the estimated risk prices based on GMM, Fama MacBeth, and Giglio and Xiu. The Giglio and Xiu estimation is based on the three-stage procedure proposed by Giglio and Xiu (2018), accounting for the omitted factors. t-statitics for Giglio and Xiu are based on the asymptotic theory in Giglio and Xiu (2018), which corrects time-series and cross-sectional heteroscedasticity and correlations and estimation biases.

Table 7
DA LTR SDF Loading

Factors	LTR	MKT	SMB	HML			
b^i	12.531	0.801	0.495	4.978			
$t-stat_{GMM}$	2.407	0.446	0.201	1.903			
Factors	LTR	MKT	SMB	HML	MOM		
b^i	10.450	1.343	0.633	5.144	0.802		
$t-stat_{GMM}$	3.060	0.661	0.268	1.923	0.484		
Factors	LTR	MKT	SMB	HML	RMW	CMA	
b^i	8.518	3.413	3.496	-1.634	6.759	4.680	
$t-stat_{GMM}$	2.163	1.189	1.189	-0.317	1.325	0.688	
Factors	LTR	MKT	SMB	HML	RMW	CMA	IMR
b^i	7.744	5.773	2.872	0.776	5.573	3.719	-2.352
$t-stat_{GMM}$	2.143	1.071	0.912	0.152	1.200	0.608	-0.609

This table reports the SDF loading on the LTR factor based on the direct approach along with various sets of control factors. The control factors include: market factor MKT, size factor SMB, value factor HML, momentum factor MOM, profitability factor RMW, investment factor CMA, intermediary factor IMR. Test assets include 25 portfolios sorted by size and book-to-market ratio, which is the 25 Fama and French (1993) Portfolios, 10 portfolios sorted by momentum, 10 portfolios sorted by investment, 10 portfolios sorted by operating profitability, 10 portfolios sorted by market beta, 10 portfolios sorted by net issuance, 10 portfolios sorted by industry. Sample is 1998M1-2009M12 Monthly. The t-statistics are GMM corrected.

Table 8
IA LTR SDF Loading

Factors	LTR	MKT	SMB	HML			
b^i	10.349	3.688	3.555	3.064			
$t - stat_{GMM}$	5.023	3.058	1.980	1.402			
Factors	LTR	MKT	SMB	HML	MOM		
b^i	5.522	4.533	2.180	6.243	4.165		
$t - stat_{GMM}$	3.207	3.742	1.241	2.980	3.285		
Factors	LTR	MKT	SMB	HML	RMW	CMA	
b^i	3.644	5.739	4.315	-7.980	8.998	19.828	
$t - stat_{GMM}$	2.160	4.115	2.198	-2.125	2.947	3.124	
Factors	LTR	MKT	SMB	HML	RMW	CMA	IMR
b^i	3.928	12.399	3.613	-1.963	8.341	14.414	-5.700
$t - stat_{GMM}$	2.340	2.817	1.782	-0.520	2.782	2.534	-1.762

This table reports the SDF loading on the LTR factor based on the indirect approach along with various sets of control factors. The control factors include: market factor MKT, size factor SMB, value factor HML, momentum factor MOM, profitability factor RMW, investment factor CMA, intermediary factor IMR. Test assets include 25 portfolios sorted by size and book-to-market ratio, which is the 25 Fama and French (1993) Portfolios, 10 portfolios sorted by momentum, 10 portfolios sorted by investment, 10 portfolios sorted by operating profitability, 10 portfolios sorted by market beta, 10 portfolios sorted by net issuance, 10 portfolios sorted by industry. Sample is 1978M1-2011M12 Monthly. The t-statistics are GMM corrected.

Table 9
Return Predictability (Years)

Variables	DA LTR Factor Prediction (Year) 1	2	3	4
P/D	1.115	0.828	0.532	0.377
t-stats	2.756	1.819	1.720	1.613
$AdjR^2$	0.231	0.147	0.128	0.094

Variables	IA LTR Factor Prediction (Year) 1	2	3	4
P/D	0.228	0.172	0.111	0.070
t-stats	1.995	1.795	1.486	1.227
$AdjR^2$	0.147	0.158	0.106	0.055

Variables	Market Factor Prediction (Year) 1	2	3	4
P/D	-0.627	-0.615	-0.521	-0.437
t-stats	-2.327	-2.941	-3.394	-3.506
$AdjR^2$	0.039	0.098	0.129	0.141

This table reports the coefficients of the regression $\frac{1}{k}R^e_{f,t\to t+k} = \alpha + \beta^f_{pd} P_t/D_t + \varepsilon_{t+k}$ for LTR factors with both direct and indirect approach and the market factor. t-stats are GMM corrected. Adjusted R^2s are reported. Sample for direct approach LTR factor is 1998-2009. Sample for indirect approach LTR factor is 1978-2011. Sample for market factor is 1969-2011.Market price and dividend data is from Shiller's website. IA LTR factor is filtered by projecting onto PCs.

Table 10
Firm Returns

	(1) $R_{t,t+2}$	(2) $R_{t,t+2}$	(3) $R_{t,t+2}$	(4) $R_{t,t+2}$
Leader Indicator	-0.35***	-0.36***	-0.34***	-0.40***
	(-5.04)	(-5.23)	(-4.92)	(-5.56)
Market Exposure		Yes	Yes	Yes
Size		Yes	Yes	Yes
Book to Market		Yes	Yes	Yes
Idiosyncratic Risk			Yes	Yes
Profitability			Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	
Firm FE				Yes
Observations	67271	67271	66887	66887

This table reports the coefficients of the regression $R_{t,t+2} = \alpha + \beta_l leader_t + control_t + \varepsilon_t$. The dependent variable for each column is the average monthly stock returns of the firm from year t to t+2. Market exposure is the beta on market factor. Idiosyncratic risk is the volatility of the residuals of regressing returns on four factor linear model. Sample is 1995-2009.

Table 11
Firm Exposures to ΔLP_t

	(1) $\beta^i_{LP,t\to t+2}$	(2) $\beta^i_{LP,t\to t+2}$	(3) $\beta^i_{LP,t\to t+2}$	(4) $\beta^i_{LP,t\to t+2}$
Leader Indicator	-2.684***	-2.574***	-2.748***	-3.172***
	(-3.94)	(-3.77)	(-4.01)	(-4.23)
Market Exposure		Yes	Yes	Yes
Size		Yes	Yes	Yes
Book to Market		Yes	Yes	Yes
Idiosyncratic Risk			Yes	Yes
Profitability			Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	
Firm FE				Yes
Observations	14858	14740	14666	14666

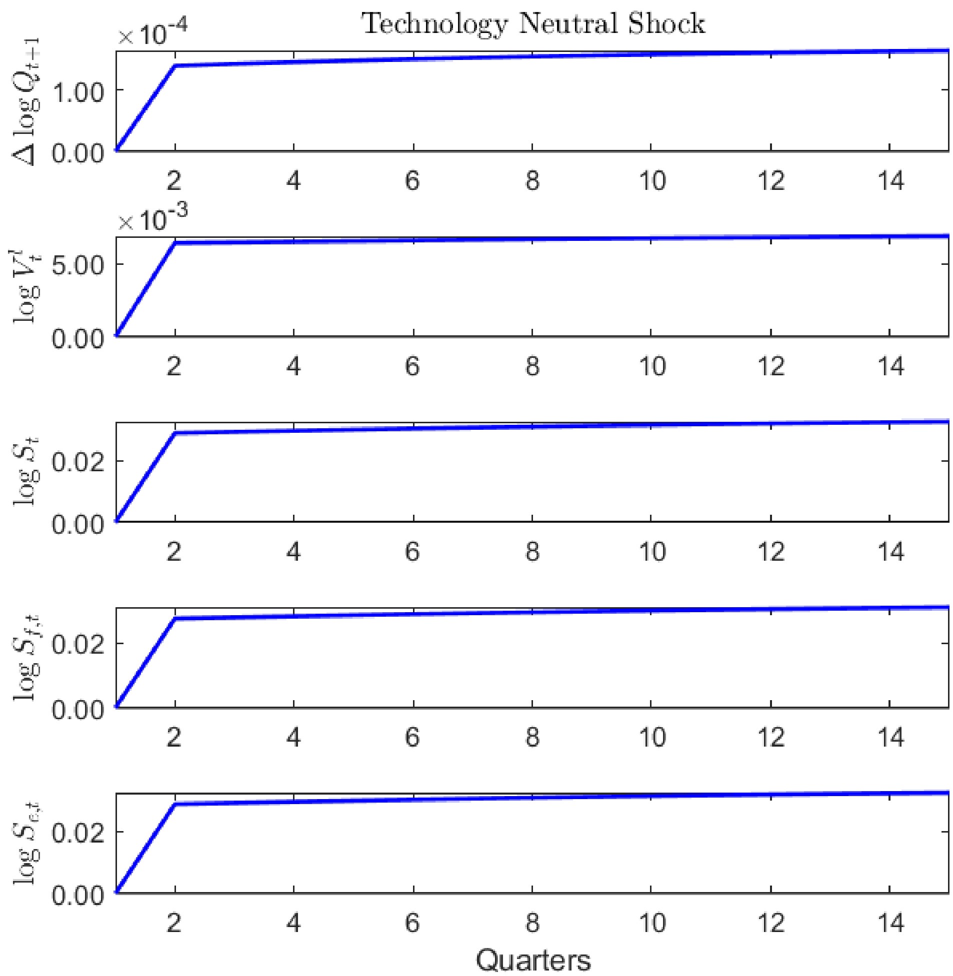
This table reports the coefficients of the regression $\beta^i_{LP,t\to t+2} = \alpha + \beta_l leader_t + control_t + \varepsilon_t$. The dependent variable for each column is the estimated exposure to the innovation of the excess profitability of leading technologies in Eq.(40) from year t to t+2. Market exposure is the beta on market factor. Idiosyncratic risk is the volatility of the residuals of regressing returns on four factor linear model. Sample is 1995-2009.

Table 12
Firm Innovation

	(1) $\frac{R\&D_{t,t+1}}{Assets_{t,t+1}}$	(2) $\frac{R\&D_{t,t+1}}{Assets_{t,t+1}}$	(3) $\frac{R\&D_{t,t+1}}{Assets_{t,t+1}}$	(4) $\frac{R\&D_{t,t+1}}{Assets_{t,t+1}}$
Leader Indicator	-0.00491**	-0.00448*	-0.00426*	-0.00582**
	(-2.09)	(-1.89)	(-1.80)	(-2.42)
Market Exposure		Yes	Yes	Yes
Size		Yes	Yes	Yes
Book to Market		Yes	Yes	Yes
Idiosyncratic Risk			Yes	Yes
Profitability			Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	
Firm FE				Yes
Observations	7106	7106	7038	7038

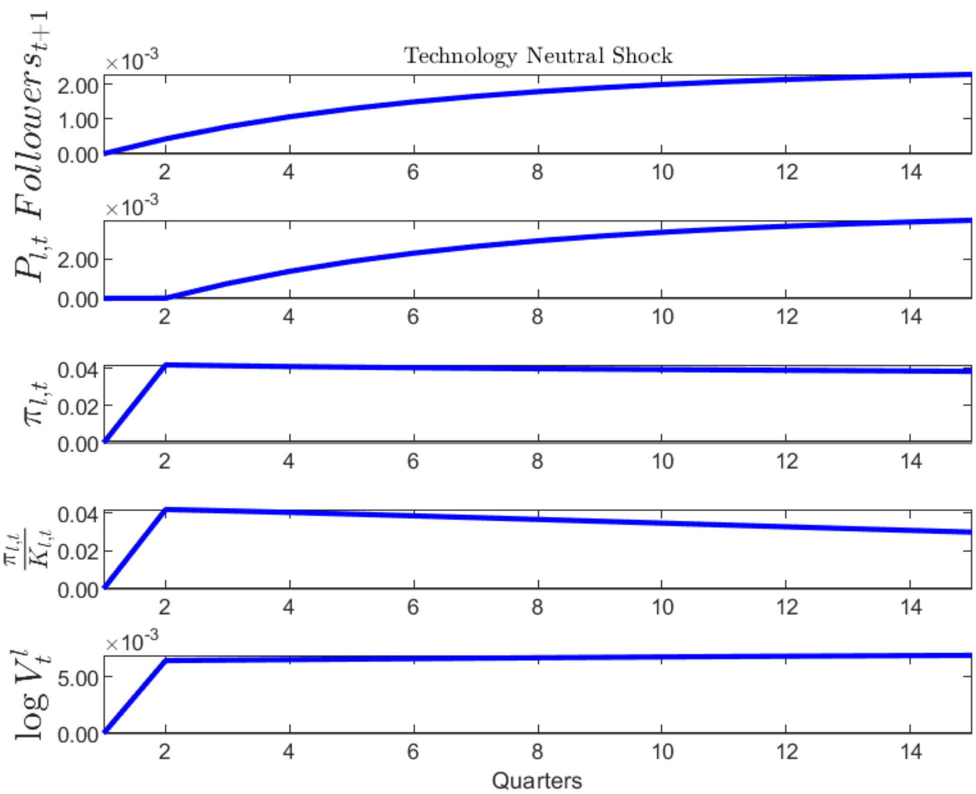
This table reports the coefficients of the regression $\frac{R\&D_{t,t+1}}{Assets_{t,t+1}} = \alpha + \beta_l leader_t + control_t + \varepsilon_t$. The dependent variable for each column is the average R&D intensity from year t to t+1. Market exposure is the beta on market factor. Idiosyncratic risk is the volatility of the residuals of regressing returns on four factor linear model. Sample is 1995-2009.

Figure 1
Technology Growth



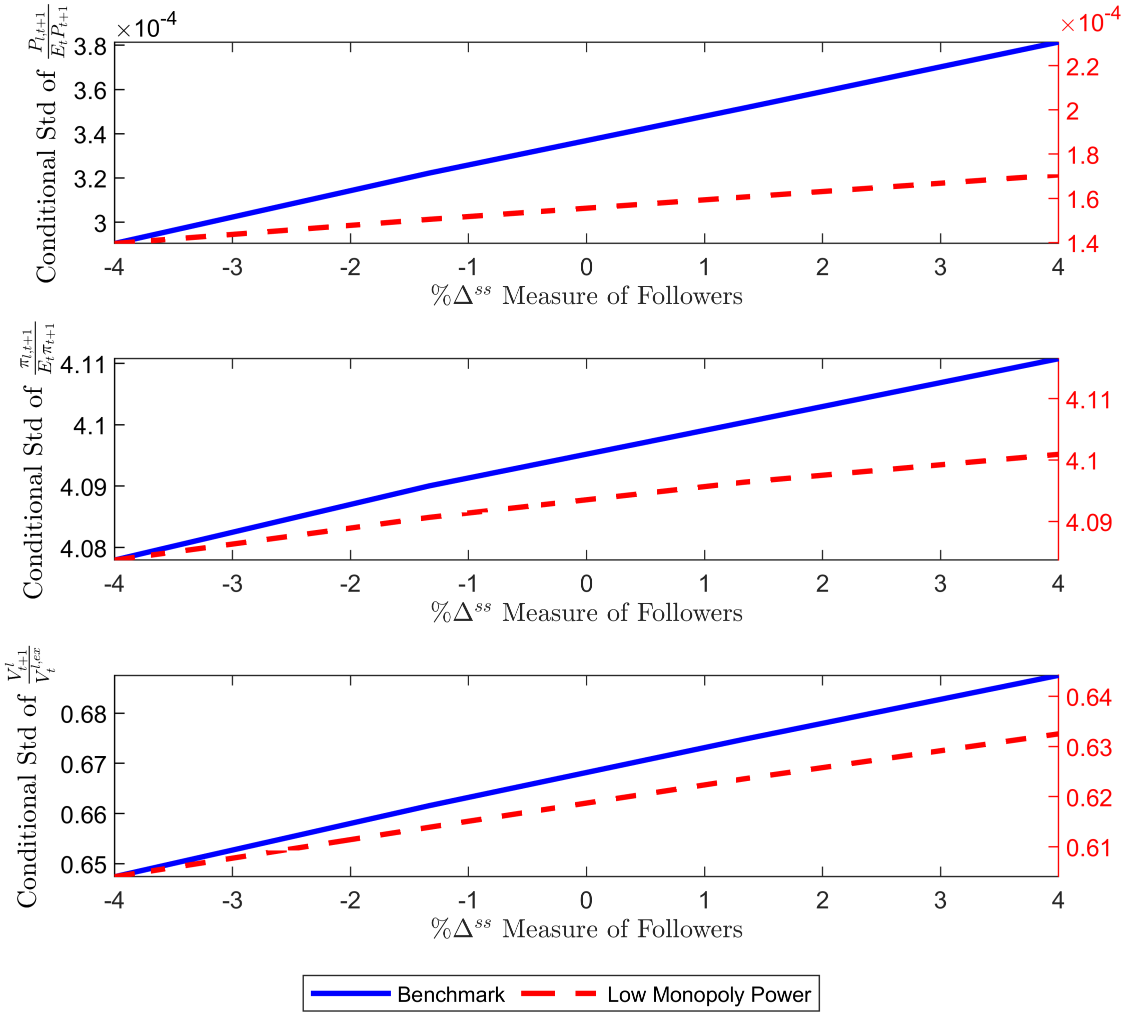
This figure plots the impulse responses of growth and innovation variables with respect to the neutral productivity shock $\epsilon_{z,t}$ in the benchmark model. The variables are the aggregate technology growth rate $\Delta log Q_{t+1}$, the value of the leading technology $log V_t^l$, the quality adjusted average R&D expenditures of leaders S_t, followers $S_{f,t}$ and the entrants $S_{e,t}$.

Figure 2
Prices and Profitability



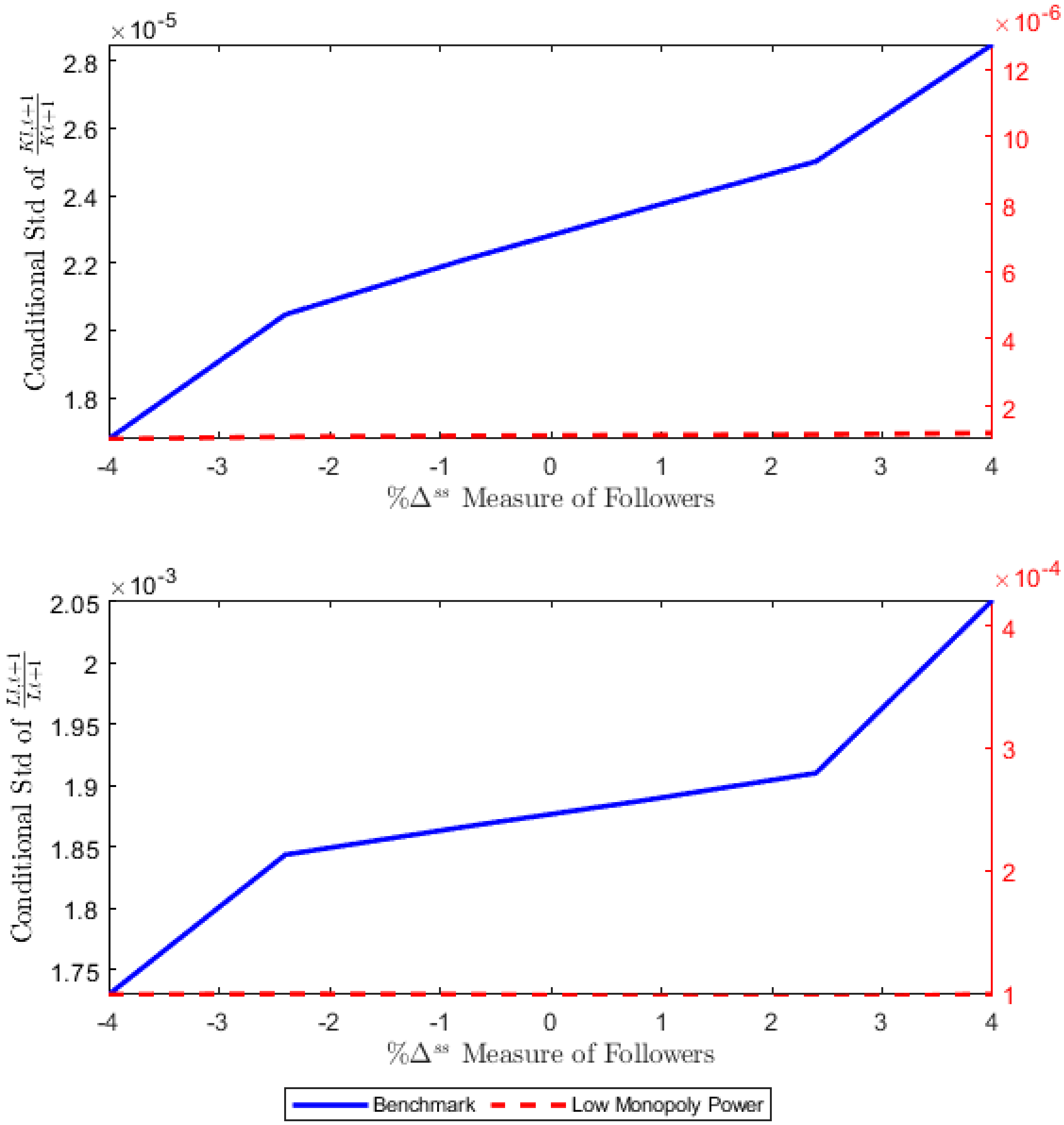
This figure plots the impulse responses of prices and profitability variables with respect to the neutral productivity shock $\epsilon_{z,t}$ and the tech step size shock (i.e. an increase in *kappa*) in the benchmark model. The variables are the follower-to-leader ratio $Followers_{t+1}$ or m_{t+1}, the price of the quality goods $P_{l,t}$, The profitability measure, which is the average profit of leaders scaled by capital used in quality goods production $\frac{\pi_{l,t}}{K_{l,t}}$.

Figure 3
Cash Flow Risk



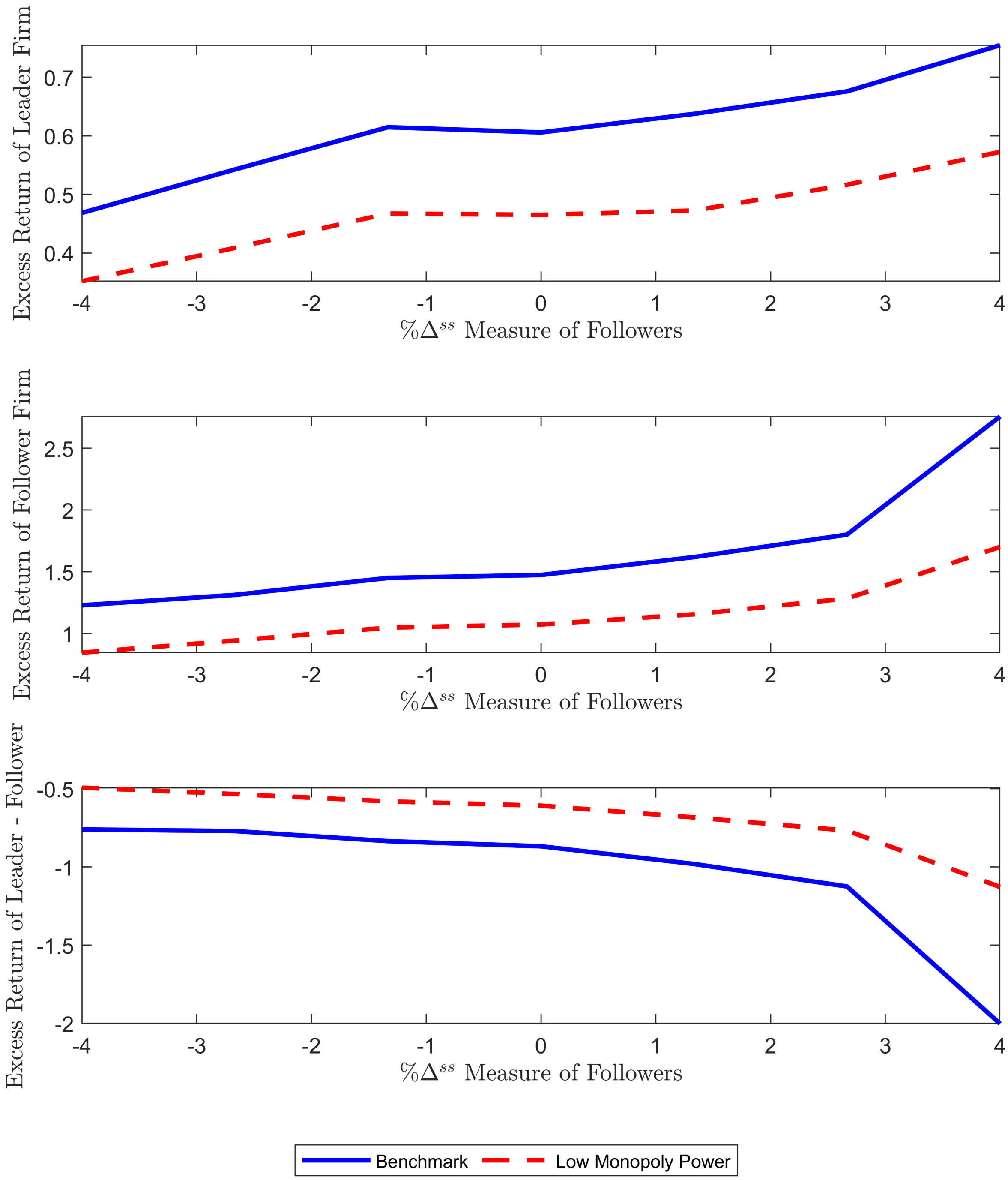
This figure plots the neutral productivity shock conditional sensitivity measure of the price of quality goods, the profit of the leading technology, and the value of the leading technology, that are the conditional standard deviation of $\frac{P_{l,t+1}}{E_t P_{l,t+1}}$, $\frac{\pi_{l,t+1}}{E_t \pi_{l,t+1}}$, and $\frac{V_{l,t+1}}{V^{ex}_{l,t}}$, against the state variable follower-to-leader ratio. The blue lines, which have the y axis on the left, are the benchmark model. The red lines, which have the y axis on the right, are the model with low monopoly power $\tau = 9$

Figure 4
Resource Reallocation



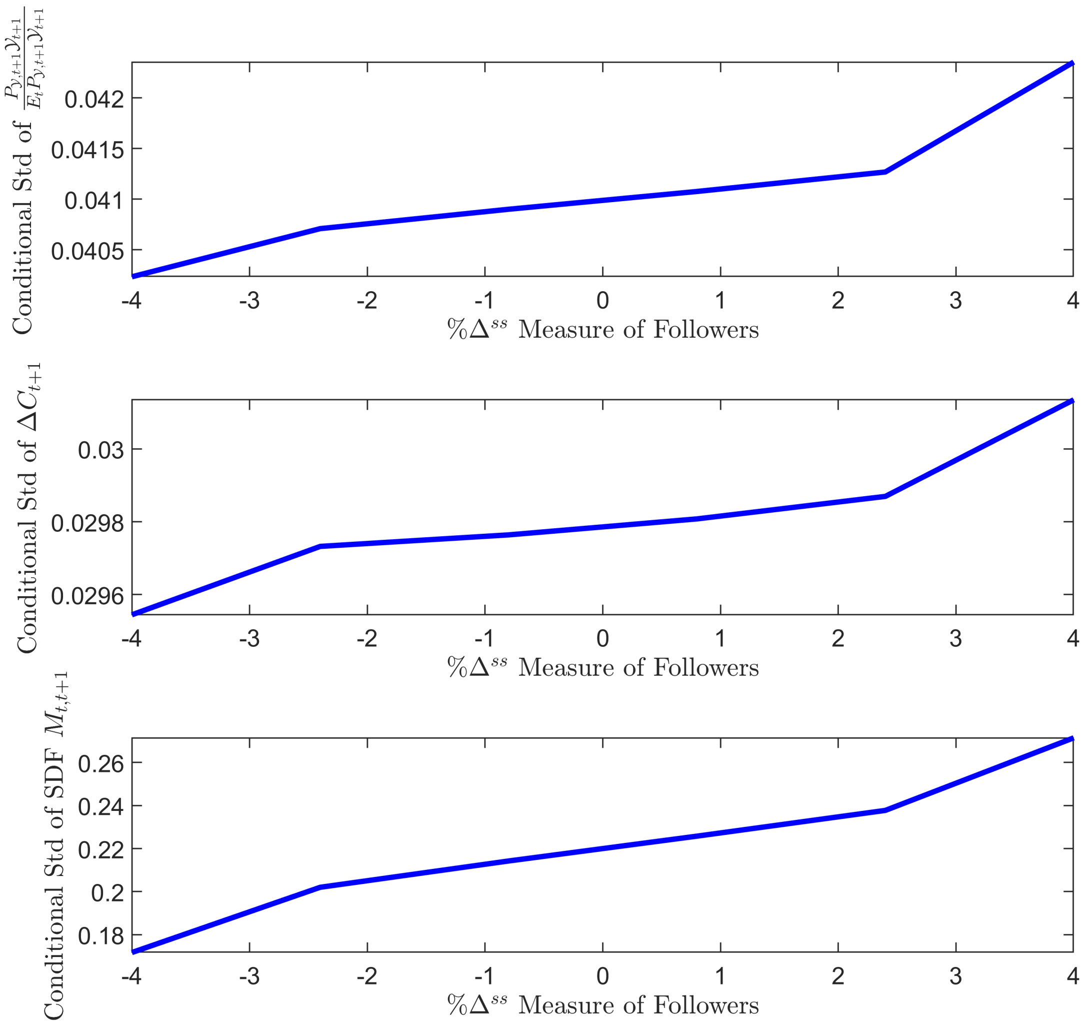
This figure plots the neutral productivity shock conditional sensitivity measure of share of capital and the share of labor used in quality goods production, that are the conditional standard deviation of $\frac{K_{l,t+1}}{K_{t+1}}$, $\frac{L_{l,t+1}}{L_{t+1}}$, against the state variable follower-to-leader ratio. The blue lines, which have the y axis on the left, are the benchmark model. The red lines, which have the y axis on the right, are the model with low monopoly power $\tau = 9$

Figure 5
Leader and Follower Premium



This figure plots the conditional excess returns of leaders, followers and long leader short follower against the state variable follower-to-leader ratio. The blue lines, which have the y axis on the left, are the benchmark model. The red lines, which have the y axis on the right, are the model with low monopoly power $\tau = 9$

Figure 6
Aggregate Risk



This figure plots the neutral productivity shock conditional sensitivity measure of aggregate output, aggregate consumption growth, and stochastic discount factor, that are the conditional standard deviation of $\frac{P_{\mathcal{Y},t+1}\mathcal{Y}_{t+1}}{E_t P_{\mathcal{Y},t+1}\mathcal{Y}_{t+1}}$, ΔC_{t+1}, and $M_{t,t+1}$, against the state variable follower-to-leader ratio. The blue lines, which have the y axis on the left, are the benchmark model. The red lines, which have the y axis on the right, are the model with low monopoly power $\tau = 9$

Appendix

A Equilibrium Conditions

A.1 Final Goods Producer

The final goods aggregator solves:

$$\max_{Y_{j,t}} P_{\mathcal{Y},t} \left(\int_0^1 Y_{j,t}^{1-\frac{1}{\tau_i}} \right)^{\frac{1}{1-1/\tau_i}} - \int_0^1 P_{j,t} Y_{j,t} dj, \tag{44}$$

The optimal condition with respect to $Y_{j,t}$ is:

$$P_{j,t} = P_{\mathcal{Y},t} \left(\int_0^1 Y_{j,t}^{1-\frac{1}{\tau_i}} dj \right)^{\frac{1/\tau_i}{1-1/\tau_i}} Y_{j,t}^{-\frac{1}{\tau_i}} \tag{45}$$

which yields the demand for industrial good j:

$$Y_{j,t} = \mathcal{Y}_t \left(\frac{P_{j,t}}{P_{\mathcal{Y},t}} \right)^{-\tau_i} \tag{46}$$

So for any two industries i and j:

$$\frac{Y_{j,t}}{Y_{i,t}} = \left(\frac{P_{j,t}}{P_{i,t}} \right)^{-\tau_i} \tag{47}$$

Combining Eq.(47) with the zero profit condition:

$$P_{\mathcal{Y},t} \mathcal{Y}_t = \int_0^1 P_{j,t} Y_{j,t} dj \tag{48}$$

yields:

$$P_{\mathcal{Y},t} = \frac{Y_{j,t}}{\mathcal{Y}_t} \frac{\int P_{i,t}^{1-\tau_i} di}{P_{i,t}^{-\tau_i}} \tag{49}$$

Combining Eq.(49) and Eq.(45) gives:

$$P_{\mathcal{Y},t} = \left(\int_0^1 P_{j,t}^{1-\tau_i} \right)^{\frac{1}{1-\tau_i}} \tag{50}$$

A.2 Industry Goods Producer

The industry goods producer solves:

$$\max_{Y_{j,l,t}, Y_{j,f,t}} P_{j,t} \left[\omega Y_{j,l,t}^{1-\frac{1}{\tau}} + (1-\omega) Y_{j,f,t}^{1-\frac{1}{\tau}} \right]^{\frac{1}{1-1/\tau}} - P_{j,l,t} Y_{j,l,t} - P_{j,f,t} Y_{j,f,t}, \tag{51}$$

The optimal condition with respect to $Y_{j,l,t}$ is:

$$\omega P_{j,t} Y_{j,t}^{\frac{1}{\tau}} Y_{j,l,t}^{-\frac{1}{\tau}} = P_{j,l,t} \tag{52}$$

The optimal condition with respect to $Y_{j,f,t}$ is:

$$(1-\omega) P_{j,t} Y_{j,t}^{\frac{1}{\tau}} Y_{j,f,t}^{-\frac{1}{\tau}} = P_{j,f,t} \tag{53}$$

Given the price of homogeneous goods is normalized to 1, that is $P_{j,f,t} = 1$, combining Eq.(52) and Eq.(53) yields the demand curve for the quality goods:

$$P_{j,l,t} = \frac{\omega}{1-\omega} \left(\frac{Y_{j,f,t}}{Y_{j,l,t}} \right)^{\frac{1}{\tau}}. \tag{54}$$

Eq.(53) gives the industrial goods price:

$$P_{j,t} = \frac{1}{1-\omega} \left(\frac{Y_{j,f,t}}{Y_{j,t}} \right)^{\frac{1}{\tau}}. \tag{55}$$

A.3 Quality Goods Firm

The problem of the quality goods prodnuncer is as follows:

$$V_{j,l,t} = \max_{Y_{j,l,t},\,K_{j,l,t},\,L_{j,l,t},\,x_{k,t}} \underbrace{\frac{\omega}{1-\omega}\left(\frac{Y_{j,f,t}}{Y_{j,l,t}}\right)^{\frac{1}{\tau}}}_{P_{j,l,t}} Y_{j,l,t} - r_t^k K_{j,l,t} - \omega_t L_{j,l,t}$$
$$- \int_0^1 p_{j,i,t} x_{j,i,t}\, di + E_t[M_{t+1} V_{l,t+1}]$$

The first order condditions with respect to $L_{j,l,t}$ and $K_{j,l,t}$ give:

$$(1-1/\tau)(1-\alpha)(1-\xi)P_{j,l,t}\frac{Y_{j,l,t}}{L_{j,l,t}} = \omega_t \tag{56}$$

$$(1-1/\tau)\alpha(1-\xi)P_{j,l,t}\frac{Y_{j,l,t}}{K_{j,l,t}} = r_t^k \tag{57}$$

The optimal condition with respect to $x_{j,i,t}$ yields the demand curve for $x_{j,i,t}$:

$$\tilde{p}_{j,i,t} = \frac{p_{j,i,t}}{P_{j,l,t}} = \left(1 - 1/\tau + 1/\tau \frac{\int_0^1 \tilde{p}_{j,i,t} x_{j,i,t}\, di}{Y_{j,l,t}}\right)\frac{\partial Y_{j,l,t}}{\partial x_{j,i,t}} \tag{58}$$

And:

$$\frac{\partial Y_{j,l,t}}{\partial x_{j,i,t}} = \xi (K_{j,l,t}^{\alpha}(\Omega_t L_{j,l,t})^{1-\alpha})^{1-\xi}\left[\int_0^1 q_{j,i,t}^{1-\frac{1}{\nu}} x_{j,i,t}^{\frac{1}{\nu}}\, di\right]^{\nu\xi-1} q_{j,i,t}^{1-\frac{1}{\nu}} x_{j,i,t}^{\frac{1}{\nu}-1}. \tag{59}$$

A.4 Leading Technology Holders

The leader chooses $p_{j,i,t}$ to solve:

$$\pi_{j,i,t} = \max_{p_{j,i,t}} \quad p_{j,i,t}\cdot x_{j,i,t} - \mu P_{j,l,t} x_{j,i,t} = \max_{x_{j,i,t}} P_{j,l,t}\left(\tilde{p}_{j,i,t} x_{j,i,t} - \mu x_{j,i,t}\right). \tag{60}$$

Given the demand curve for $x_{j,i,t}$ in Eq.(58), the optimal condition with respect to $x_{j,i,t}$ yields:

$$\frac{\partial \tilde{p}_{j,i,t}}{\partial x_{j,i,t}} x_{j,i,t} + \tilde{p}_{j,i,t} - \mu = 0 \tag{61}$$

so that:

$$\tilde{p}_{j,i,t} = \nu\mu \tag{62}$$

To reach the equilibrium $x_{j,i,t}$ in Eq.(69), I use the guess and verify method. First I guess the equilibrium $x_{j,i,t}$ is linear in $q_{j,i,t}$:

$$x_{j,i,t} = \Theta_t q_{j,i,t} \tag{63}$$

where Θ_t is a function of aggregate variables. So $\frac{x_{j,i,t}}{q_{j,i,t}}$ is identical across all leading technology i $\in [0,1]$. It yields:

$$\begin{aligned}
\frac{\partial Y_{j,l,t}}{\partial x_{j,i,t}} &= \xi Y_{j,l,t} \left[\int_0^1 q_{j,i,t}^{1-\frac{1}{\nu}} x_{j,i,t}^{\frac{1}{\nu}} di \right]^{-1} q_{j,i,t}^{1-\frac{1}{\nu}} x_{j,i,t}^{\frac{1}{\nu}-1}. \\
&= \xi Y_{j,l,t} \left[\Theta_t^{\frac{1}{\nu}} \int_0^1 q_{j,i,t}, di \right]^{-1} \Theta_t^{\frac{1}{\nu}-1} \\
&= \xi Y_{j,l,t} Q_{j,t}^{-1} \Theta_t^{-1}
\end{aligned} \tag{64}$$

Substituting Eq.(62) and Eq.(64) into Eq.(58) yields:

$$\begin{aligned}
\nu\mu &= (1-1/\tau) \frac{\partial Y_{j,l,t}}{\partial x_{j,i,t}} + \left(\nu\mu/\tau \frac{\int_0^1 q_{j,i,t} \frac{x_{j,i,t}}{q_{j,i,t}} di}{Y_{j,l,t}} \right) \frac{\partial Y_{j,l,t}}{\partial x_{j,i,t}} \\
&= (1-1/\tau) \frac{\partial Y_{j,l,t}}{\partial x_{j,i,t}} + \left(\nu\mu/\tau \frac{\Theta_t Q_{j,t}}{Y_{j,l,t}} \right) \xi Y_{j,l,t} Q_{j,t}^{-1} \Theta_t^{-1} \\
&= (1-1/\tau) \xi Y_{j,l,t} Q_{j,t}^{-1} \Theta_t^{-1} + \xi\nu\mu/\tau
\end{aligned} \tag{65}$$

rearrange Eq.(65) yields:

$$\Theta_t = \frac{\xi}{\nu\mu} \frac{1-1/\tau}{1-\xi/\tau} Y_{j,l,t} Q_{j,t}^{-1} \tag{66}$$

where

$$\begin{aligned} Y_{j,l,t} &= (K_{j,l,t}^{\alpha}(\Omega_t L_{j,l,t})^{1-\alpha})^{1-\xi}\left[\int_0^1 q_{j,i,t}^{1-\frac{1}{\nu}} x_{j,i,t}^{\frac{1}{\nu}}\, di\right]^{\nu\xi} \\ &= (K_{j,l,t}^{\alpha}(\Omega_t L_{j,l,t})^{1-\alpha})^{1-\xi}\Theta_t^{\xi} Q_{j,t}^{\nu\xi} \end{aligned} \tag{67}$$

Combining Eq.(66) and Eq.(67) yields:

$$\Theta_t = \frac{x_{j,i,t}}{q_{j,i,t}} = \left(\frac{\xi}{\nu\mu}\frac{1-1/\tau}{1-\xi/\tau}\right)^{\frac{1}{1-\xi}} K_{j,l,t}^{\alpha}(\Omega_t L_{j,l,t})^{1-\alpha} Q_{j,t}^{\frac{\xi\nu-1}{1-\xi}} \tag{68}$$

Eq.(68) verifies that the equilibrium $x_{j,i,t}$ is linear in $q_{j,i,t}$. It yields the equilibrium quantity for input $x_{j,i,t}$:

$$x_{j,i,t} = \left(\frac{\xi}{\nu\mu}\frac{1-1/\tau}{1-\xi/\tau}\right)^{\frac{1}{1-\xi}} K_{j,l,t}^{\alpha}(\Omega_t L_{j,l,t})^{1-\alpha} Q_{j,t}^{\frac{\xi\nu-1}{1-\xi}} q_{j,i,t} \tag{69}$$

Substituting Eq.(68) into Eq.(67) and assuming the following balanced growth condition is satisfied[49]:

$$\frac{(\nu-1)\xi}{1-\xi} = 1-\alpha \tag{70}$$

yield the production of the quality goods in equilibrium:

$$Y_{j,l,t} = \left(\frac{\xi}{\nu\mu}\frac{1-1/\tau}{1-\xi/\tau}\right)^{\frac{\xi}{1-\xi}} K_{j,l,t}^{\alpha}(\Omega_t Q_t L_{j,l,t})^{1-\alpha} \tag{71}$$

Therefore, the equilibrium profit of leader i is:

$$\begin{aligned} \pi_{j,i,t} &= P_{j,l,t}\,(\nu-1)\,\mu\left(\frac{\xi}{\nu\mu}\frac{1-1/\tau}{1-\xi/\tau}\right)^{\frac{1}{1-\xi}} K_{j,l,t}^{\alpha}(\Omega_t L_{j,l,t})^{1-\alpha} Q_{j,t}^{\frac{\xi\nu-1}{1-\xi}} q_{j,i,t}. \\ &= (1-\frac{1}{\nu})\left(\frac{\xi(1-1/\tau)}{1-\xi/\tau}\right) P_{j,l,t} Y_{j,l,t}\frac{q_{j,i,t}}{Q_{j,t}} \end{aligned} \tag{72}$$

[49]See Kung and Schmid (2015) and Bena *et al.* (2015).

A.5 Homogeneous Goods Firm

The problem of the Homogeneous goods produncer is as follows:

$$V_{j,f,t} = \max_{K_{j,f,t},\,L_{j,f,t}} Y_{j,f,t} - r^k_t K_{j,f,t} - \omega_t L_{j,f,t} + E_t[M_{t+1}V_{j,f,t+1}]$$

The first order condditions with respect to $L_{j,f,t}$ and $K_{j,f,t}$ give:

$$(1-\alpha)\frac{Y_{j,f,t}}{L_{j,f,t}} = \omega_t \tag{73}$$

$$\alpha\frac{Y_{j,f,t}}{K_{j,f,t}} = r^k_t \tag{74}$$

A.6 Symmetric Innovations

The entrant in industry j solves the following problem:

$$\max_{S_{j,e,t}} V_{j,e,t} = -Q_{j,t}S_{j,e,t} + \phi_e(S_{j,e,t})E_t[M_{t+1}\int_0^1 V_{j,i,\kappa q_{j,i,t}}di] \tag{75}$$

The first order condition with respect to $S_{j,e,t}$ is:

$$1 = \phi'_e(S_{j,e,t})E_t[M_{t+1}\frac{\int_0^1 V_{j,i,\kappa q_{j,i,t}}di}{Q_{j,t}}] \tag{76}$$

Therefore, all entrants choose the identical level of innovation effort.

The follower solves:

$$\begin{aligned}\max_{S_{j,f,t}} V_{j,f,t} &= -Q_{j,t}S_{j,f,t} + \phi_f(S_{j,f,t})E_t[M_{t+1}\int_0^1 V_{j,i,\kappa q_{j,i,t}}di] \\ &\quad +(1-\phi_f(S_{j,f,t+1}))\phi E_t[M_{t+1}V_{j,f,t}]\end{aligned} \tag{77}$$

The first order condition with respect to $S_{j,f,t}$ is:

$$1 = \phi'_f(S_{j,f,t})E_t[M_{t+1}\frac{\int_0^1 V_{j,i,\kappa q_{j,i,t}}di - \phi V_{j,f,t}}{Q_{j,t}}] \tag{78}$$

All followers choose the identical level of innovation effort.

The leader chooses the innovation expenditure to solve:

$$\begin{aligned} \max_{S_{j,i,t}} V_{j,i,q_{j,i,t}} &= \pi_{j,i,t} - q_{j,i,t}S_{j,i,t} \\ &+\phi_l(S_{j,i,t})E_t\left[M_{t+1}V_{j,i,\kappa q_{i,t}}\right] \\ &+(1-\phi_l(S_{j,i,t}) - m_{j,t}\phi_f(S_{j,f,t}) - \phi_e(S_{j,e,t}))E_t\left[M_{t+1}V_{j,i,q_{j,i,t}}\right] \\ &+(m_{j,t}\phi_f(S_{j,f,t}) + \phi_e(S_{j,e,t}))E_t\left[M_{t+1}V_{j,f,t+1}\right] \end{aligned} \tag{79}$$

The first order condition with respect to $S_{j,i,t}$ is:

$$1 = \phi'_f(S_{j,f,t})E_t[M_{t+1}\frac{V_{j,i,\kappa q_{i,t}} - V_{j,i,q_{j,i,t}}}{q_{j,i,t}}] \tag{80}$$

then I show that $V_{j,i,\kappa q_{i,t}} - V_{j,i,q_{j,i,t}}$ is linear in $q_{j,i,t}$. To see this, I express $V_{j,i,\kappa q_{i,t}} - V_{j,i,q_{j,i,t}}$ by using Eq.(79):

$$\begin{aligned} V_{j,i,\kappa q_{j,i,t}} - V_{j,i,q_{j,i,t}} &= (\kappa-1)\pi_{j,i,t} - (\kappa S_{j,i,\kappa q_{j,i,t}} - S_{j,i,q_{j,i,t}})q_{j,i,t} \\ &+\phi_l(S_{j,i,\kappa q_{j,i,t}})E_t\left[M_{t+1}\left(V_{j,i,\kappa^2 q_{j,i,t}} - V_{j,i,\kappa q_{j,i,t}}\right)\right] \\ &-\phi_l(S_{j,i,q_{j,i,t}})E_t\left[M_{t+1}\left(V_{j,i,\kappa q_{j,i,t}} - V_{j,i,q_{j,i,t}}\right)\right] \\ &+(1 - m_{j,t}\phi_f(S_{j,f,t}) - \phi_e(S_{j,e,t}))E_t\left[M_{t+1}\left(V_{j,i,\kappa q_{j,i,t}} - V_{j,i,q_{j,i,t}}\right)\right] \end{aligned} \tag{81}$$

As shown in Eq.(72), $\pi_{j,i,t}$ is linear in $q_{j,i,t}$. $(\kappa S_{j,i,\kappa q_{j,i,t}} - S_{j,i,q_{j,i,t}})q_{j,i,t}$ is also linear in $q_{j,i,t}$. Keeping expanding $V_{j,i,\kappa^n q_{j,i,t}} - V_{j,i,\kappa^{n-1} q_{j,i,t}}$ shows that $V_{j,i,\kappa q_{j,i,t}} - V_{j,i,q_{j,i,t}}$ is linear in $q_{j,i,t}$. $\frac{V_{j,i,\kappa q_{i,t}} - V_{j,i,q_{j,i,t}}}{q_{j,i,t}}$ is thus identical across all leading technology i $\in [0,1]$. Therefore, all leading technology holders make identical $S_{j,i,t}$ decisions. Note that this result relies on the implication that all leaders are equally likely to be displaced. In addition, the future profits of all leading technology holders with $\kappa q_{j,i,t}$ are linear in κ. $\int_0^1 V_{j,i,\kappa q_{j,i,t}} di$ can be expressed as $\kappa \int_0^1 V_{j,i,q_{j,i,t}} di$.

A.7 Household

The representative household maximize the utility in Eq.(24) subject to Eq.(25) and Eq.(26). The first order conditions with respect to C_t, I_t and K_{t+1} yields the standard Euler equation:

$$1 = E_t \left[M_{t,t+1} \frac{r^k_{t+1} + \Phi^{-1}_{t+1} \left(1 - \delta_k + \Phi_{t+1} - \Phi'_{t+1} \frac{I_{t+1}}{K_{t+1}}\right)}{\Phi^{-1}_t} \right] \tag{82}$$

where the stochastic discount factor is given in Eq.(27). The first order condition with respect to L_t yields:

$$\omega_t = \bar{\omega} Z_t L_t^{\omega_l - 1} \tag{83}$$

B Data

- The macro data in Table 2 are from the Bureau of Economic Analysis (BEA).
- The market price, dividend data are from shiller's website:
  - http://www.econ.yale.edu/ shiller/data.htm.
- The leader indicator in section 4.1.1 is the R&D/Innovation (PRO-str-B) from the MSCI ESG KLD STATS performance indicators dataset. The definition of the indicator is: *The company is a leader in its industry for research and development (R&D), particularly by bringing notably innovative products to market.*
- The firm accounting data are from Compustat.

- The stock return data in section 4.1.1 and 4.1.2 are from CRSP. Only share codes 10, 11 and 12 are considered. That is microcap stocks are excluded from forming the factors.

- Patent application and citation data and patent/Compustat matching method files are obtained from the NBER US Patent Citation Data Files. Also see Bronwyn Hall's data website: https://eml.berkeley.edu// bhhall/patents.html.

- Patent value measured by market reaction data and patent value measured by citation data are from Kogan *et al.* (2017). Also see https://iu.app.box.com/v/patents

- Portfolios data are from Kenneth French's website:

  - http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_librar.html.

- Fama-French five factors (Fama and French (2015)), momentum factor and risk-free rate are obtained from Kenneth French's website. Intermediary capital risk factor is from He *et al.* (2017). See http://apps.olin.wustl.edu/faculty/manela/data.html

Table A1
LP Beta Sorted Portfolios

Sorted Portfolios: 1998-2009				
Variables	L	H	H-L	t-stat.
Average excess returns (%)	3.17	11.41	8.24	1.77
α_{CAPM}	1.26	9.40	8.14	1.75
α_{FF}	1.11	9.41	8.31	1.83
Sorted Portfolios Pre-Crisis: 1998-2007				
Variables	L	H	H-L	t-stat.
Average excess returns (%)	2.35	17.00	14.65	3.02
α_{CAPM}	-1.63	12.48	14.12	2.95
α_{FF}	-1.35	11.97	13.32	2.83

This table reports average excess returns, alphas of LP sorted portfolios. Columns report portfolios sorted from low (L, Bottom 33%) to high (H, Top 33%) beta. Columns (H-L) and (T-stat) report the portfolio that long high-beta portfolio and short the low-beta portfolio and the t-stat. All returns are annualized. Portfolio return is the value-weighted returns. Stock returns data are obtained from the CRSP with share codes 10, 11 and 12.

Table A2
Patent Life Cycles

Industry	Life Cycle (Years)	Industry	Life Cycle (Years)
Rubbr	10.86	Chems	9.30
Whlsl	8.98	Trans	10.94
Ships	9.73	Txtls	10.44
Steel	10.16	Clths	11.47
Chips	8.87	Other	9.12
Hshld	8.74	Oil	9.37
BldMt	10.73	Food	10.51
Autos	9.42	Beer	10.03
Toys	9.90	Util	9.01
Hardw	8.09	Banks	9.94
LabEq	9.55	FabPr	11.37
BusSv	10.04	PerSv	10.03
Drugs	8.95	Rtail	10.46
Paper	9.92	Guns	10.20
ElcEq	9.11	Gold	8.11
Books	9.79	Smoke	8.68
Insur	10.88	Cnstr	10.06
Mach	10.19	Agric	8.05
Softw	8.66	Hlth	10.59
MedEq	9.90	Meals	7.69
Telcm	9.02	Mines	10.39
Fin	10.16	Soda	9.51
Boxes	11.33	RlEst	9.93
Fun	10.30	Coal	11.77
Aero	9.74		

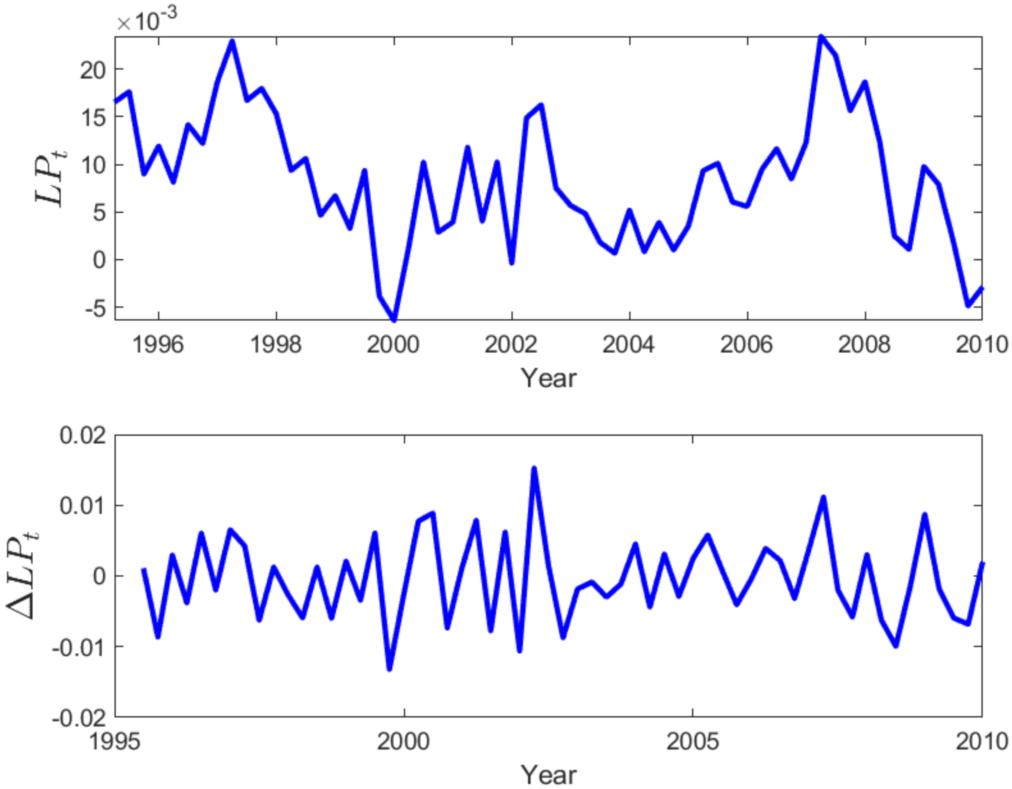
This table reports the measures of patent life cycle for each industry. For each industry, the life cycle is measured by averaging the citation lags of the patents owned by that industry. The definition of the citation lag is the time difference between the grant of a patent and the future citation (See Bilir (2014)). Citation data are obtained from the NBER US Patent Citation Data Files.

Table A3
Variance Decomposition

Factors	PC1-PC3	PC4-PC6	PC7-PC9	PC10-PC12	PC13-PC15
DA LTR	23.5	14.9	15.2	16.5	29.9
IA LTR	21.5	16.5	6.5	11.9	43.6
Market	99.7	0.0	0.1	0.1	0.1
SMB	91.3	6.5	1.8	0.1	0.3
HML	84.0	4.6	9.9	1.0	0.6
MOM	24.4	72.6	2.2	0.6	0.2
RMW	56.0	11.4	25.8	2.9	3.9
CMA	66.6	9.3	7.1	13.9	3.2
IMR	90.4	5.4	2.2	1.4	0.7

This table reports the variance decomposition of the factors onto the principle components extracted from the test assets. Numbers in the table are the percent explained by the PCs. The test assets include 25 portfolios sorted by size and book-to-market ratio, which is the 25 Fama and French (1993) Portfolios, 10 portfolios sorted by momentum, 10 portfolios sorted by investment, 10 portfolios sorted by operating profitability, 10 portfolios sorted by market beta, 10 portfolios sorted by net issuance, 10 portfolios sorted by industry. Sample for DA LTR is 1998M1-2009M12 Monthly. Sample for the other factors is 1978M1-2011M12 Monthly.

Figure A1
LP Time Series



This figure plots the LP_t and ΔLP_t in section 4.1.1