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Dynamics of imitation versus innovation in technological leadership change: Latecomers' catch-up strategies in diverse technological regimes[☆]

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ABSTRACT

We examine how latecomers should allocate resources between innovation and imitation to overtake industry leaders across different technological regimes, characterized by appropriability, cumulativeness, and cycle time of technologies (CTT). Using computational models, we find that a one-sided focus on either innovation or imitation impedes technological leadership changes. Also, findings suggest that at early stages with low-level technologies, latecomers should prioritize imitation by allocating more resources to it. However, as they advance, a greater allocation of R&D resources to innovation becomes crucial. Next, we investigate the role of various technological regime variables in the interplay between this innovation-imitation mix. First, our simulations indicate that under a regime of low appropriability and high cumulativeness, allocating more resources to imitation tends to be more effective than focusing on innovation. Second, our simulations reveal an inverted U-shaped relationship between CTT and the probability of latecomers overtaking industry leaders. There exists a certain level of CTT that maximizes the overtaking possibility because a short CTT offers latecomers opportunities from rapid obsolescence of leaders' technologies but constrains latecomers' learning from existing technologies. With a short CTT, it is advantageous for latecomers, particularly those starting with a low technology level, to allocate more resources to imitation.

1. Introduction

In this study, we examine how and when latecomers overtake industry leaders under Schumpeterian competition. Latecomers often face disadvantages, such as inferior technologies and limited capital (Lieberman and Montgomery, 1988; Wernerfelt, 1984). However, evidence has shown that many overcame such challenges and overtook industry leaders across various industries (e.g., Aghion et al., 2014; Ethiraj and Zhu, 2008; Lee and Malerba, 2017). To successfully overtake leaders, latecomers need to engage in R&D, encompassing both innovative and imitative R&D activities, which demand resources. Although strategy research underscores the significance of resource allocation (e.g., Baldwin and Clark, 1992; Chandler, 1962; Maritan and Lee, 2017; Wibbens, 2019), our understanding of how latecomers navigate resource allocation in the context of Schumpeterian competition is limited. This study sheds light on latecomers' resource allocation strategies to overcome their disadvantages and eventually overtake industry leaders.

Under Schumpeterian competition, latecomers challenge industry leaders using innovation and/or imitation (Audretsch, 1991; Kim, 1997; Mansfield et al., 1981; Nelson and Winter, 1982; Park and Lee, 2006). A gap in the literature is the nuanced role of imitation in resource dynamics. While Nelson and Winter (1978, 1982) include imitation in their computational model on Schumpeterian competition, they largely prioritized innovation over imitation. Many subsequent studies have followed suit, often sidelining imitation as a secondary strategy (e.g., Aghion et al., 2014; Goettler and Gordon, 2011; Grabowski and Vernon, 1987; Lee et al., 2010). Posen et al. (2013, p. 151) articulated imitation in this literature as "a strategy by which a follower can catch up with, but not exceed, the market leader".

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Given this limited perspective on imitation, its potential as a strategy for latecomers to overtake industry leaders remains underexplored in this research stream.

Without resources, firms are unable to engage in either innovation or imitation. Recognizing this, our paper delves deeper: How does allocating resources between innovation and imitation enable latecomers to surpass industry leaders? Central to this inquiry is the role of technological regimes, which significantly influence latecomers' resource allocation decisions. Technological regimes, as defined by Nelson and Winter (1982), comprise the characteristics that dictate the evolution and interaction of technologies in an industry, thereby shaping firms' competitive outcomes. These regimes determine the relative advantages and effectiveness of imitation over innovation, or vice versa (Tushman and Anderson, 1986; Breschi et al., 2000; Park and Lee, 2006). Key elements of these regimes include the rate at which technology evolves (i.e., cycle time), the extent to which firms can secure and benefit from their innovations (i.e., appropriability), and how new technological developments build on earlier ones (i.e., cumulativeness). By delving into the intricacies of these regimes, we examine the most effective resource allocation for latecomers aiming to overtake industry leaders.

As noted by Nelson and Winter (1978, p. 541), "Schumpeterian competition is, like most processes we call competitive, a process that tends to produce winners and losers. Some firms track emerging technological opportunities with greater success than other firms; the former tend to prosper and grow, the latter to suffer losses and decline". Furthermore, Nelson and Winter (1978, p. 524) emphasized that "[c]ompetition, in the everyday sense of the term, is an active process, not a structural state". However, competition in mainstream economics is approximated by several stylized structural states, such as monopoly, duopoly, perfect competition, and so on (Nelson and Winter, 1978). This structural framework often bypass the active processes of firm growth or contraction inherent in competition by assuming equilibrium states.[1] Posen et al. (2013, p. 151) pointed out that the classical framework conveniently wiped out the active process inherent in competition as follows, "[t]he classical view assumes that firms are unboundedly rational actors... It has left research in strategy relatively silent on the details of imitation processes". Given the challenges of analyzing non-equilibrium dynamics like Schumpeterian competition using traditional methods, computational modeling has become as vital in social science as it is in physics for understanding such dynamics (Christensen and Moloney, 2005).[2]

To delve into the role of latecomers' resource allocation between innovation and imitation under Schumpeterian competition, we build a computational model grounded in prior theoretical work (Goettler and Gordon, 2011; Grabowski and Vernon, 1987; Lee et al., 2010; Nelson and Winter, 1978, 1982). Building upon Nelson and Winter's model (1978, 1982), our model is tailored to keep track of the latecomer's resource allocation and technological advancement. In our model, latecomers and an incumbent compete for technological leadership through innovation and imitation. The model captures the dynamics of resources, reflecting the progress or setbacks of latecomers in their innovative and/or imitative R&D efforts. Each firm starts with an initial capital. At each time step, the latecomer allocates a portion of its capital into R&D activities, split between innovative and imitative R&D, aiming to improve its technology. Successes in R&D activities increase the firm's profits, allowing further R&D investments in the following periods. In contrast, a series of failures in R&D activities diminish the firm's capital, potentially leading to its exit from the industry. In our model, the latecomer allocates a fraction p of its R&D budget to innovative R&D and the remainder $1 - p$ to imitative R&D. This model setup allows us to control the latecomer's R&D allocation from a full dedication to imitation ($p = 0$) to a full dedication to innovation ($p = 1$). Also, our model accommodates different technological regimes, examining their impact on the latecomer's resource allocation and overtaking leaders.

Our findings suggest that especially when there is a large gap between the latecomer and the industry leader, overtaking the leaders requires a more balanced approach between imitation and innovation. When this gap narrows, the latecomer must decide when to transition from imitation to innovation to effectively "run faster than their target". In the initial stages of the latecomer's learning, imitation is crucial. It allows them to learn from industry leaders, conserve financial resources, and avoid the inherent risks associated with pioneering technological advancements. Imitation also lays the foundation for the latecomer to develop technological capabilities essential for future innovation. However, just imitating the leader will not enable the latecomer to surpass the leader, who continually innovates and pushes forward technological frontiers. As the latecomer strives to narrow the technological gap by assimilating the leader's technologies, the leader often introduces even more sophisticated technologies, further widening the gap. This dynamic likens the challenge of overtaking to chasing a perpetually moving target. In the semiconductor foundry industry, for instance, the leader, TSMC, consistently advances by introducing more sophisticated, next-generation chip design rules, posing challenges for latecomers aiming to catch up or surpass TSMC. Thus, to truly surpass the leader, the latecomer must strategically determine when to emphasize innovation over imitation.

Also, our findings suggest that there are differences in the balance between innovation and imitation in diverse technological regimes. We particularly focus on the double-edged nature of the short CTT for latecomers, an issue raised in Lee (2013, Ch. 4). On the one hand, a short CTT provides a window of opportunity associated with quick obsolescence of existing technologies and thus low entry barriers (Park and Lee, 2006). On the other hand, a short CTT results in a further source of difficulty, associated with the truncation of learning from existing technologies (Lall, 2000). Our simulations reconcile this theoretical tension, revealing an inverted U-shaped relationship between the CTT and the likelihood of latecomers overtaking industry leaders. Further simulations considering the initial technology level of the latecomer relative to that of the incumbent show that when the CTT is short, and the disruption of technology is frequent, it makes more sense for latecomers to allocate more resources to imitation, especially when their initial technology level is low. By contrast, when the initial technology level of latecomers increases from 20 to 70% of that of incumbents, the risk of innovative R&D is reduced, and thus, latecomers may safely allocate more resources to innovation even under short CTT regimes. A further analysis underscores that these findings remain consistent unless the number of latecomers in the industry is excessively high.

While prior theoretical work, such as studies by Aghion and his colleagues (2006, 2014) and by Nelson and Winter (1978), made significant contributions to the Schumpeterian competition literature, their work centers on macroeconomic factors, exploring country-level and industry-level technological regimes and innovation outcomes. Their insights provide a broader context within which firms operate and innovate.[3] In contrast, our study delves into the micro-level dynamics

[1] For example, under perfect competition, numerous firms copying leaders without restriction are assumed to result in zero profit altogether. However, there is no theoretical step to trace how some firms become winners and others losers. In this structural framework, there is no such thing as the "active process".

[2] Non-equilibrium dynamics have long been studied in other disciplines. In physics, a non-equilibrium state has been understood as a state under which a system is susceptible to external shocks. For example, Christensen and Moloney (2005) articulated that physicists have figured out that the conventional analytical approach is not the best way to understand non-equilibrium systems. Consequently, computational modeling has become popular in physics.

[3] Also, prior theoretical work examined factors influencing innovation and competition dynamics across different factors, including public policies (Dosi

of individual latecomer firms. We examine their strategic decisions on resource allocation between innovation and imitation within various technological regimes. Contrary to prior work, which views technological regimes as determinants of latecomer outcomes, our approach suggests that latecomers can strategically utilize their resources to either exploit or mitigate these regimes, providing a nuanced understanding of how they can potentially surpass established industry leaders.

The remainder of this paper is organized as follows. First, we review the extant literature on the roles of imitation and innovation under Schumpeterian competition and the impact of the technological regime on R&D and leadership change. Second, we describe how we built our model and provide the simulation results. Finally, we discuss the implications of our findings.

2. Literature review

2.1. Schumpeterian competition

At the dawn of the twentieth century, Schumpeter (1911) introduced the concept of "creative destruction". This idea proposed that latecomers could overtake industry leaders by developing new technologies. In the literature, such competitive dynamics are known as Schumpeterian competition. It is a form of rivalry "which commands a decisive cost or quality advantage and which strikes not at the margins of the profits of the existing firms but at their foundations and their very lives" (Schumpeter, 1942, p. 84). Building on Schumpeter's emphasis on the role of innovation for latecomers, subsequent theoretical research has viewed innovation as the primary driver for shifts in leadership (e.g., Grabowski and Vernon, 1987; Lee et al., 2010; Nelson and Winter, 1982). Empirical evidence demonstrates that innovation enables latecomers to leapfrog industry leaders in many industries (e.g., Adner and Zemsky, 2006; Klepper, 1996; Landini et al., 2017; Tripsas, 1997).

Because many studies emphasize innovation as the primary means to overtake leaders, often relegating imitation to a secondary means (e.g., Goettler and Gordon, 2011; Grabowski and Vernon, 1987; Lee et al., 2010), the role of imitation in overtaking leaders has not been fully examined. Recognizing that the execution of either strategy — innovation or imitation — hinges on adequate resources, our study examines how latecomers should allocate their resources between the two to increase their chances of overtaking leaders.

2.2. Imitation, technological catch-up, and technological leadership change

Newly entering latecomers are mostly at a disadvantage because they are not in a position to develop their own technology, or the technology they develop is inferior to that of industry incumbents (Gerschenkron, 1962; Lieberman and Montgomery, 1988; Mathews, 2002). For such firms, imitation can decrease the risk of failure involved with technological innovation because the technological uncertainty inherent in the process is substantially decreased if firms rely on the prior successes of incumbents (Ethiraj and Zhu, 2008; Lake, 1979; Mansfield, 1988). Furthermore, imitation can prevent the squandering of resources for latecomers, saving money and time by allowing them to develop products in-house (Mansfield et al., 1981).

Such imitation is also crucial because it creates a foundation for innovation. According to the argument that innovation comes from borrowing rather than invention, new knowledge is not created on its own, but arises from understanding and learning from existing knowledge (Kim, 1997; March and Simon, 1958). Accordingly, through diverse modes, latecomers use imitative learning to acquire technologies held by incumbents.[4] Over time, as firms improve their technological capabilities, they can use the knowledge gained from imitation to inform their own creative processes and engage in innovation.

Imitation has long been regarded as an easy way of assimilating incumbents' technological capability; therefore, the cost of imitation has been assumed to be little or nothing (Arrow, 1962; Nelson, 1959). In the first-generation evolutionary model of economics, imitation was considered as a costless process, and R&D investment was assumed to be mainly related to innovation (Nelson and Winter, 1978, 1982; Winter, 1984). In reality, imitation of technology, which entails replicating technologies viable in a different firm, is often a difficult, costly, and time-consuming process (Hatch and Mowery, 1998; Kogut and Zander, 1992; Salomon and Martin, 2008). Recent models considered the cost of imitation in various ways depending on industry characteristics (Kim and Lee, 2003; Malerba et al., 1999; Malerba and Orsenigo, 2002).

2.3. Allocating resources between imitation and innovation for technological leadership change

The more fundamental and long-term objective of imitation is to build technological capabilities as an important base for future innovation. Incumbents keep moving by developing more advanced technology, forcing latecomers to aim at "moving targets" (i.e., not static ones) as technological leaders continue to innovate (Acemoglu and Cao, 2015; Freeman, 1988; Malecki, 1997). By the time latecomers assimilate the imported technology, industry leaders may have already proceeded on to a higher level (Aghion et al., 2001); therefore, engaging in imitation without innovation cannot lead to successful technological catch-up and leadership change. As observed in the case of NVIDIA, the leading graphics processing unit (GPU) manufacturer, positive feedback between R&D investment and successful innovation enables the company to continually introduce new technologies (e.g., graphics processors for artificial intelligence) by leveraging their abundant resources.

Since both innovation and imitation are important means of competition (Nelson and Winter, 1982; Schumpeter, 1934), strategic choices may differ regarding the allocation of resources to these two options, and divergent competitive outcomes may result (Benhabib et al., 2014). When latecomers have especially limited resources, allocation decision-making (i.e., to innovation or imitation) may be an important strategic issue. Although imitation in the early stage is crucial for latecomers to catch up with leading companies, as noted above, the strategic decision of when to move away from imitative behavior is very important to latecomers (Alchian, 1950; König et al., 2016; Liao, 2020). In other words, the decision as to when and how resources should be allocated to either imitation or innovation is a dynamic one. Kim (1997) suggested that Korean latecomers shifted their focus from imitation to innovation in the dynamic process of catch-up and technological leadership change. Analyzing the cases of the Korean semiconductor and electronics industries, he found that Korean firms became leaders in many industries as they dynamically changed their R&D investment strategy from imitation to innovation. He argued that this so-called "imitation to innovation" pattern was an effective way to catch up with and overtake industry leaders.

et al., 2021; Landini and Malerba, 2017), country-of-origin bias (Diodato et al., 2018), market segmentation and the roles of foreign MNCs (Li et al., 2019), organizational forms (Kim and Lee, 2003), lock-in behavior by incumbents and radical vs. adaptive innovation (Landini et al., 2017), demand-side shocks and patterns (specifically, demand-led catch-up in green industries; Landini et al., 2020), and the interaction between market regimes and catch-up strategies (Lee et al., 2017).

[4] Many latecomers assimilate technology directly through licensing, reverse engineering, or original equipment manufacturing (OEM). Also, they often acquire new technology through partnerships such as strategic alliances or joint ventures (Almeida, 1996; Mowery et al., 1996; Shan and Song, 1997; Zander and Kogut, 1995). Imitation is also accomplished by employing renowned engineers from leading firms and locating subsidiaries near such firms in order to benefit from any potential knowledge spillover (Chung and Song, 2004; Song et al., 2003; Wang, 2015; Zander and Kogut, 1995).

2.4. Technological regime and leadership change

In a technological regime, economic factors govern the trajectory of technological advancement and innovation. Differences in technological regime explain how patterns of innovation and technological evolution differ by industry (Malerba and Orsenigo, 1997; Tushman and Anderson, 1986). The notion of technological regime was first introduced in Nelson and Winter's (1982) evolutionary theory on technological change. They distinguished two kinds of technological regime: science-based and cumulative. Since then, many researchers from the evolutionary tradition have explored the impact of technological regime on technological change (Dosi, 1982), market structure (Audretsch, 1995; Cohen and Levin, 1989), new-firm survival (Audretsch, 1991), and patterns of innovation (Breschi et al., 2000; Malerba and Orsenigo, 1996). Recent studies further examined the impact of technological regime on latecomers' technological catch-up (Landini and Malerba, 2017; Lee and Lim, 2001; Li et al., 2019; Park and Lee, 2006).

Among the various factors in a technological regime, prior research has highlighted the roles of appropriability (e.g., Breschi et al., 2000; Kogut and Zander, 1992; Nelson and Winter, 1978), cumulativeness (e.g., Nelson and Winter, 1978; Winter, 1984), and the CTT (e.g., Lee, 2013; Park and Lee, 2006; de Rassenfosse and Jaffe, 2018) in competition between incumbents and latecomers. Following this research tradition and using simulation analysis, we explore the effects of appropriability, cumulativeness, and the CTT on technological catch-up and leadership change. These three technological regime variables affect the effectiveness of different R&D strategies (i.e., innovative R&D or imitative R&D) and, by extension, firms' competitive positions.

2.4.1. Appropriability

Appropriability affects imitation and R&D activity. Appropriability has been defined as the capacity of a firm to retain the added value it creates for its own benefit (Kay, 1995). Innovation and profits from innovative activities can be protected from imitation by rival firms (e.g., Breschi et al., 2000). Protection of intellectual property rights (Mansfield et al., 1981), tacitness of knowledge (Kogut and Zander, 1992), strategic complexity (Rivkin, 2000), and interdependency between the technology and the organization (Ethiraj and Levinthal, 2004) increases appropriability. High appropriability may increase the possibility for incumbents to monopolize their outcomes, while lowering the possibility of other firms' benefitting from these outcomes (Levin and Reiss, 1988). Under low appropriability, incumbents' outcomes can enhance utility for other firms, increasing network externality and the possibility of imitation (Levin et al., 1985).

2.4.2. Cumulativeness

Cumulativeness refers to the degree to which today's knowledge and innovative activities form the building blocks of tomorrow's innovation (Breschi et al., 2000). Cumulativeness also affects innovation in R&D activities. Under conditions of high cumulativeness, today's innovators are more likely to innovate in the future by following existing trajectories. When cumulativeness is high, therefore, the economic regime may facilitate increasing returns from technological development. Under such conditions, latecomers with insufficient technological capabilities are less likely to innovate successfully (Park and Lee, 2006). Under low cumulativeness, on the other hand, past technological competency is less likely to affect subsequent innovation because development will not occur along the same or similar technological trajectory (Winter, 1984).

2.4.3. Cycle time of technologies (CTT)

The cycle time of technologies (CTT) refers to how fast the value of commercial and technological knowledge decreases over time (e.g., Park and Lee, 2006; de Rassenfosse and Jaffe, 2018). De Rassenfosse and Jaffe emphasize the importance of the CTT as follows: "The rate of depreciation of technology in different industries and different countries serves also as an indicator of the rate of advance of technology in those different contexts (...) it is also central to the understanding of industry dynamics" (2018, p. 626). Some prior works are related to the role of the CTT in technological leadership change (e.g., Bosworth, 1978; Landini et al., 2017; Pakes and Schankerman, 1984). However, these studies have produced conflicting predictions of the impact of the CTT on technological leadership change because of its dual role in competitive dynamics between incumbents and latecomers. On the one hand, a short CTT (i.e., rapid knowledge obsolescence) tends to be a threat to incumbents and thus an opportunity for latecomers (e.g., Park and Lee, 2006; Suarez and Lanzolla, 2007). Park and Lee argued that "[i]f the life expectancy of knowledge is long, mastering knowledge and technology in that field require more time. (...) However, when knowledge in the field changes quickly, the disadvantages for the latecomer might not be that big" (Park and Lee, 2006, p. 726). Previous empirical studies showed the increased probability of technological leadership change by latecomers under short CTT regimes (e.g., Niosi and Reid, 2007; Petralia et al., 2017).

On the other hand, another body of research has emphasized the possibility that a short CTT could interrupt latecomers' learning and thus be an additional barrier to latecomers (e.g., Lall, 2000; Lee, 2013). Given that building up a technological foundation to a certain level is critical for innovation, rapid obsolescence of knowledge (a short CTT) deters latecomers from building such a foundation because they must switch from learning existing technologies to learning new and different types of technologies, probably within a short time (Lall, 2000).

3. Model

3.1. Investment behavior and technological leadership change

3.1.1. Technology level, allocation of R&D resources, and the CTT

We develop a computational model based on latecomers' imitation and innovation. The first variable in the model is the technological capability of firm i at time t, T_{it}. A latecomer's technological capability at time t is T_{Lt}, and an incumbent's technological capability is T_{Ft}. The size of the physical capital stock of firm i at time t is K_{it}. The latecomer's physical capital stock at time t is K_{Lt}, and the incumbent's physical capital stock is K_{Ft}. In our study, if a latecomer's technological capability exceeds that of the incumbent (i.e., the latecomer becomes an industry leader) during 120 periods, it is considered that technological leadership change has occurred. We assume that one incumbent and one latecomer compete in the market.

Following Nelson and Winter's model (1978, 1982), we assume that the R&D expenditure ($r_i \cdot K_{it}$) of an individual firm is proportional to that individual firm's physical capital stock, and that r_i is identical across firms. Firms invest their R&D resources in two types of R&D activities: (1) R&D for innovation and (2) R&D for imitation. Both the incumbent and the latecomer decide how much of their R&D resources to allocate between innovation and imitation. The proportion of R&D resources allocated to innovation is p_i. Thus, the proportion of R&D resources allocated to imitation is $1 - p_i$. We assume that the incumbent has no target to imitate and allocates all resources to innovation, resulting in $p_F = 1$.

In the baseline model, one incumbent and one latecomer compete. In the extended models, we increase the number of latecomers to accommodate the reality that different latecomers have different resource allocation strategies (i.e., different p_L). Also, we examine two extended models: one with 5 latecomers and another with 21 latecomers. In the 5 latecomer setting, each of the latecomers has a distinct p_L value, with increments of 25% from 0% to 100% (i.e., $p_{L1} = 0$, $p_{L2} = 0.25$, $p_{L3} = 0.5$, $p_{L4} = 0.75$, and $p_{L5} = 1$). In the 21 latecomer setting, each of the latecomers also has a distinct p_L value, with increments of 5%

from 0% to 100% (i.e., $p_{L1} = 0$, $p_{L2} = 0.05$, $p_{L3} = 0.1$, …, $p_{L20} = 0.95$, $p_{L21} = 1$).

The technological capabilities of the latecomer (L) and incumbent (F) are determined as follows.

$$T_{it+1} = \begin{cases} (1-\eta)T_{Lt} + tm_{Lt} + tn_{Lt} & \text{if} \quad i = L \\ (1-\eta)T_{Ft} + tn_{Ft} & \text{if} \quad i = F \end{cases} \tag{1}$$

where T_{it} is the technological capability of firm i of the latecomer in the current period, η is the technological knowledge depreciation rate (i.e., we measure the CTT as $1-\eta$),[5] tm_{it} is the newly gained technological capability from imitation in the prior period, and tn_{it} is the newly gained technological capability from innovation in the prior period. The CTT variable, $1-\eta$, takes a value between 0.97 and 1.0. Under a short CTT, where $1-\eta = 0.97$, each firm's technological capability decreases quickly, while under a long CTT, where $1-\eta = 1$, no firms lose their technological capability through technological knowledge depreciation. For the incumbent, which is committed to innovation with no imitation, technological capability is the sum of its technological capability in the current period (T_{Ft}), which is depreciated by η at each time step, and newly gained technological capability from innovation in the current period (tn_{Ft}).

3.1.2. Imitation and appropriability

Success in imitative R&D follows the Bernoulli distribution with a success probability of κ.[6] The success probability of imitation, $P[\theta^m_{it} = 1]$, is also proportional to the amount of R&D resources allocated to imitation, $1-p_i$, since R&D resources should be allocated to innovation as well. Thus, the average success probability in imitation is $(1-p_i)\cdot\kappa$. For example, the probability of success via imitation equals κ if all resources are allocated to imitation, whereas the probability halves to $(0.5\cdot\kappa)$ if only half of the R&D resources are allocated to imitation.

$$P[\theta^m_{it} = 1] = \begin{cases} (1-p_L)\cdot\kappa & \text{if} \quad i = L \\ 0\cdot\kappa = 0 & \text{if} \quad i = F \end{cases} \tag{2}$$

In addition, technological capability acquired by imitation is proportional to the technological gap between the incumbent and the latecomer, like existing technological capability. In the early stage of catch-up, a wide technological gap suggests an abundance of acquirable technology, which decreases as the technological gap narrows. Then, the technological capability acquired by imitation is proportional to the latecomer's technological capability. If the technological capability of the latecomer is highly inferior to that of the incumbent, it is more difficult to narrow the huge technological gap between the two firms.

Appropriability, α, refers to the degree to which an innovator can protect its innovation outcomes from imitation and secure its economic returns. The range of α is from 0 to 1. The level of technology that the latecomer can accomplish through imitation is $(1-\alpha)\cdot T_{Ft}$. Under no appropriability, where $\alpha = 0$, the latecomer can imitate the incumbent's technology perfectly in the long run, while under $\alpha = 1$, the incumbent's technology cannot be acquired by the latecomer's efforts toward imitation. Finally, if a latecomer's technological capability exceeds $(1-\alpha)\cdot T_{Ft}$, the latecomer cannot increase its technological capability via imitation. Thus, the increase in technological capability via imitation is determined as follows.

$$tm_{Lt} = \begin{cases} 0 & \text{if} \quad \theta^m_{Lt} = 0 \\ max\left[0, T_{Lt}\left(1 - \frac{T_{Lt}}{(1-\alpha)T_{Ft}}\right)\right] & \text{if} \quad \theta^m_{Lt} = 1 \end{cases} \tag{3}$$

3.1.3. Innovation and cumulativeness

The proportion of R&D resources allocated to innovation, p_i, affects the probability of successful innovation, $P[\theta^n_{it} = 1]$, where the parameter θ^n_{it} indicates whether firm i succeeds in innovation R&D at time t; if firm i's innovative R&D is successful at time t, θ^n_{it} is 1, and otherwise θ^n_{it} is 0. The success probability of innovative R&D is also proportional to the amount of R&D investment, RD_{it}. The probability of success in innovation is also proportional to the amount of R&D resources allocated to innovation p_i, since R&D resources should be allocated to imitation as well.

In addition, the probability of success of a firm's innovation is proportional to its technological capability, T_{it}. The probability of successful innovation is also affected by cumulativeness, β, which is included in our model as an exponent of the technological capability variable, T^β_{it} (Knott et al., 2003). Cumulativeness β takes a value between 0 and infinity. Under no cumulativeness, where β is equal to 0, T^β_{it} is equal to 1, and no firms have a technological disadvantage relative to the incumbent. On the other hand, as β increases, the difference between T^β_{Ft} and T^β_{Lt} increases. Thus, as cumulativeness increases, firms with greater technological capabilities are more likely to succeed in innovative R&D than others. The probability of successful innovation $P[\theta^n_{it} = 1]$ of the latecomer and incumbent is determined as follows:

$$Pr[\theta^n_{it} = 1] = \begin{cases} \gamma\cdot p_L\cdot RD_{Lt}\cdot T^\beta_{Lt} & \text{if} \quad i = L \\ \gamma\cdot RD_{Ft}\cdot T^\beta_{Ft} & \text{if} \quad i = F \end{cases} \tag{4}$$

where γ is a positive constant, p_i is the proportion of R&D resources allocated to innovation, $RD_{it}(= r_i\cdot K_{it})$ is the amount of R&D investment, T_{it} is firm i's technological capability, and β is cumulativeness.[7,8]

The increase in technological capability through innovative R&D activity is assumed to follow a log-normal distribution to reflect the reality that impactful innovation rarely takes place. Therefore, the function of increasing technological capability through innovation is as follows.

$$tn_{it} = \begin{cases} 0 & \text{if} \quad \theta^n_{it} = 0 \\ \rho_{it} & \text{if} \quad \theta^n_{it} = 1 \end{cases} \tag{5}$$

where ρ_{it} follows the lognormal distribution with mean μ and variance σ^2.[9]

3.2. Production and investment behavior

3.2.1. Firm state variables in market dynamics

The model for market dynamics used in this study, where firms earn profit and make investment decisions, was borrowed from Nelson and Winter (1978, 1982) and resembles other recent history-friendly models (Kim and Lee, 2003). The basic variables, which define each

[5] An anonymous reviewer raised a concern that the parameter value of η could be too high and may not be in line with empirical work. We reviewed prior empirical work on the CTT (i.e., the depreciation rate of technology) in various contexts (e.g., Ballester et al., 2003; Bessen, 2008; de Rassenfosse and Jaffe, 2018; Huang and Diewert, 2011; Liu et al., 2021). We set the parameter range for η as $0 \le \eta \le 0.03$ (i.e., from 0% knowledge depreciation rate per quarter to 3% knowledge depreciation per quarter) to be in line with this empirical literature (e.g., de Rassenfosse and Jaffe, 2018).

[6] We set the parameter value for κ as 0.3.

[7] Following Nelson and Winter's model (1978, 1982), we assume the same function of increasing technological capability through innovative R&D for the incumbent and the latecomer. Specifically, Nelson and Winter (1978, 1982) set not only (1) the same function for innovative R&D for incumbents and latecomers, but also (2) the same values for the key parameters (i.e., the effectiveness of innovative R&D (γ) and propensity toward capital investment in R&D (r_i)). Firm-level variations in productivity related to innovative R&D arise from the different values for initial capital (K_{i0}) and technological capability (T_{i0}). The summary of differences between our model and prior theoretical work is provided in Appendix A.

[8] Some recent studies (e.g., Aghion and Howitt, 2006; Benhabib et al., 2014; König et al., 2016; Liao, 2020) suggested that (1) incumbents' innovative R&D could be more effective than latecomers' innovative R&D, and (2) incumbents may have a higher propensity toward capital investment in R&D than latecomers. To check whether the key findings of our study are robust, we ran simulations with extended models where these two assumptions are relaxed in the sensitivity test.

[9] As the mean μ or variance σ^2 increases, the average size of outcomes from innovative R&D also increases.

firm's behavior under market competition, are the firm's technological capability, T_{it}, and the size of the firm's physical capital stock, K_{it}. Technological capability determines productivity, while capital stock denotes the size of the firm and its production facilities. When a firm generates positive returns in the market, its physical capital stock will increase in the next period. When it generates no returns or negative returns in the market, its physical capital stock will decrease. A firm is forced to exit the industry when its technology declines below a certain minimum level due to failure in technological catch-up or when its capital stock is completely depreciated, since both conditions result in lack of further production ($Q_{it} = T_{it} \cdot K_{it}$). For simplicity, the model rules out entry over time. This adjustment does not affect the simulation results significantly when entrants are parameterized by the same attributes as the latecomer in the initial state.

3.2.2. Firm output

The output of a firm is proportional to its technological capability and its capital stock. The total output of the industry is defined by the sum of the incumbent's output and the latecomer's output. We assume that demand is given as R. Thus, at time t, firm output, total output of the industry, and market price are determined as follows.

$$Q_t = \Sigma_i Q_{it} = \Sigma_i (T_{it} \cdot K_{it}) \tag{6}$$

$$P_t = \frac{R}{Q_t} \tag{7}$$

There are two categories of costs: variable costs and R&D costs. We assume that these two costs do not change over time and are set as the fixed proportion per unit of capital, as in Nelson and Winter (1982). The firm's profit per unit of capital, (π_{it}), is defined as revenue minus the variable cost per unit of capital (avc_i) minus expenditure on R&D per unit of capital (r_i). The profit of firm i at time t, Π_{it} is therefore determined as follows.

$$\Pi_{it} = \pi_{it} \cdot K_{it} = (P_t \cdot T_{it} - avc_i - r_i) \cdot K_{it} \tag{8}$$

3.2.3. Investment and capital stock

Both incumbents and latecomers adjust their output level by changing capital investment. In this adjustment, the markup ratio is an important determinant in the firm's decisions about capital investment. The current markup ratio (m_{it}) of each firm is determined by the total sales revenue of the product divided by the total cost of production, as in Nelson and Winter (1982).

$$m_{it} = \frac{P_t \cdot T_{it}}{avc_i + r_i} \tag{9}$$

Under market competition, the target markup ratio increases as the market share (s_{it}) increases, resulting in a value of 1 when the market share is 0 and an infinite value when there is a monopoly (Nelson and Winter, 1978). When a firm's perceived demand elasticity is e_{it} and its market share is s_{it}, the target markup ratio (m_{it}^*) is determined as follows (see Nelson and Winter, 1982). We assume that the perceived demand elasticity is set to the true value of the demand elasticity, 1.

$$m_{it}^* = \frac{e_{it}}{e_{it} - s_{it}} \tag{10}$$

If the current markup ratio is higher than the target markup ratio, the firm is inclined to increase output. The investment will increase when the target markup ratio is low, or when the current market ratio is higher than the target markup ratio. Thus, the firm's desired investment is precisely determined by calculating the depreciation ratio per unit of capital (d_i) and the gap between the target and current markup ratio, as follows.

$$I_{it}^* = \left(d_i + \frac{m_{it} - m_{it}^*}{m_{it}} \right) \cdot K_{it} \tag{11}$$

On the other hand, actual investment is related to the total amount of resources available as well as desired investment. The target level of investment can be realized as long as firms can finance it. The firm's actual investment is limited by the amount available and its reserve fund. Therefore, actual investment (I_{it}) and physical capital stock (K_{it+1}) at time $t+1$ are determined as follows.

$$I_{it} = max\left[0, min[I_{it}^*, \pi_{it} \cdot K_{it}]\right] \tag{12}$$

$$K_{it+1} = K_{it} + I_{it} \tag{13}$$

4. Results

The model represents (1) the effect of allocation of R&D resources to innovation and imitation on the probability of technological leadership change and (2) the moderating role of technological regime in the relationship between the two catch-up strategies (imitation vs. innovation) and its effect on the probability of technological leadership change. The incumbent accumulates its technological capabilities by investing resources in innovation only, while the latecomer invests in both imitation and innovation. First, we examine various combinations of innovation and imitation and their effects on technological leadership change as catch-up proceeds. Then, we also examine variations in the probability of technological leadership change with changes in the technological regime.

The results displayed in this paper are averaged over 100,000 iterations of the simulation. Each simulation was run for 120 periods for an equivalent of 30 years in the real world. If the latecomer's technological capability exceeds that of the incumbent during these 120 periods, we regard this simulation run as a case of technological leadership change. To determine the optimal proportion of R&D resources to allocate to innovation, we run 500 simulations of the aforementioned model and calculate the average values for the optimal allocation of R&D resources between imitation and innovation. The parameter values are specified in Appendix B.

First, we examine whether the latecomer striking a balance between innovative R&D and imitative R&D matters in technological leadership change. We vary the proportion p_L of the latecomer's R&D resources allocated to innovative R&D between two extremes, full commitment to imitative R&D ($p_L = 0$) and full commitment to innovative R&D ($p_L = 1$) in the baseline model (i.e., one latecomer) and extended models (i.e., 5 latecomer setting and 21 latecomer setting). Then, we examine boundary conditions by analyzing diverse technological regimes: appropriability, cumulativeness, and the CTT.

4.1. Imitation to innovation

As indicated in the model, the latecomer allocates its R&D resource to both imitation and innovation. In this section, we provide results showing the effects of changes in the ratio of resources allocated to innovation on the probability of technological leadership change.

Fig. 1(A) shows that the probability of leadership change is low when the latecomer allocates too small a portion of its resources to innovation. The probability increases as more resources are allocated to innovation, but after reaching a peak around 0.65, the probability of leadership change decreases, thus indicating an inverted U-shaped relationship. This means that allocating 65% of R&D resources to innovation and 35% to imitation results in the highest probability of leadership change. This result suggests that a balanced allocation between innovation and imitation is better than a lopsided allocation to either innovation or imitation.

A technological leadership change can only occur if a latecomer moves faster than the incumbent. Therefore, we need to understand how the latecomer can move faster than the incumbent. If the latecomer allocates all its R&D resources to innovative R&D, it is likely to run out of capital early on and be unable to invest in R&D (i.e., unable to move faster than the incumbent). In contrast, with a balance between innovative R&D and imitative R&D, enough amount of capital can be maintained, allowing the latecomer to invest in R&D, thereby leaving more room for leapfrogging opportunities (i.e., for moving faster than

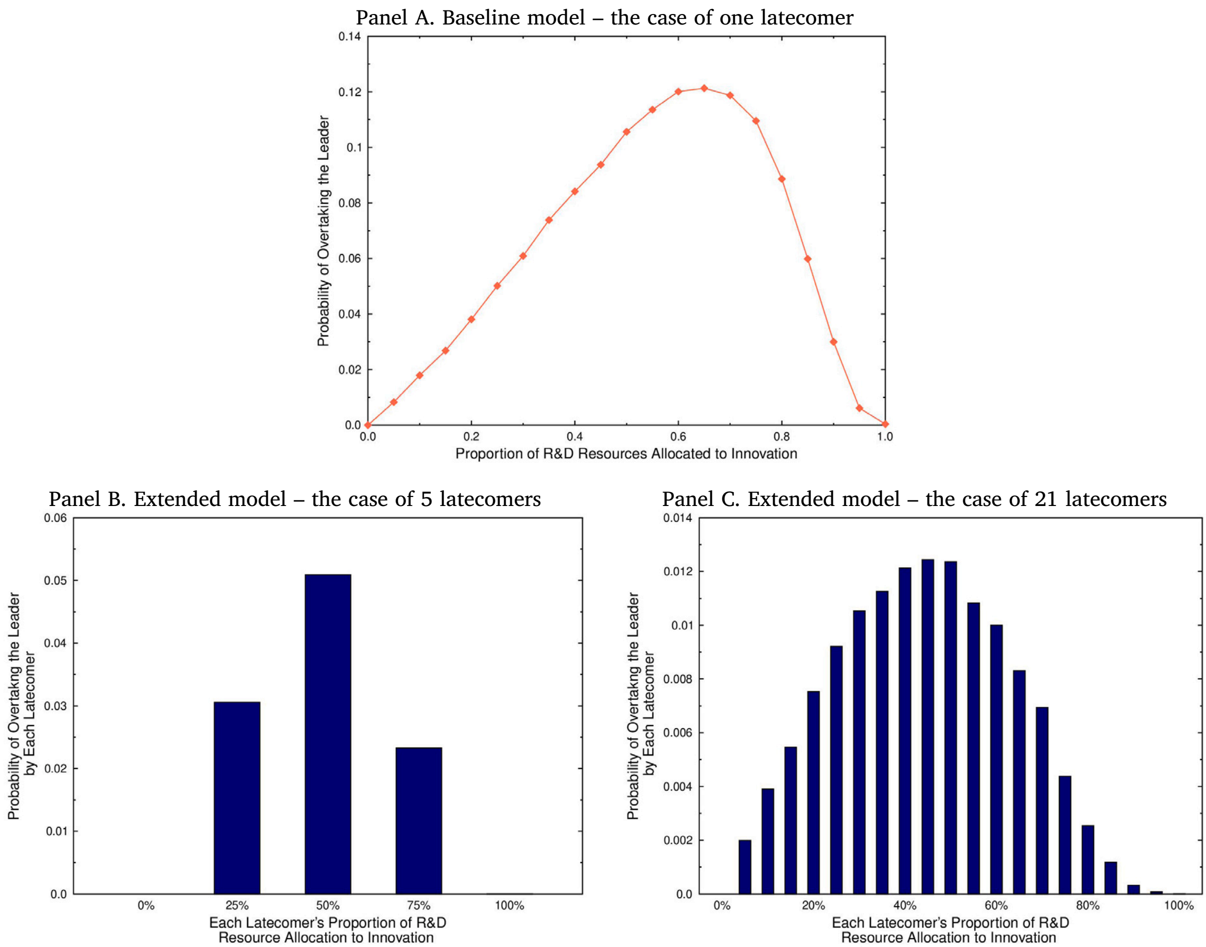


Fig. 1. Allocation of R&D resources and technological leadership change.
Note: The probability of technological leadership change reaches its peak when the latecomer balances the allocation of R&D resources between innovation and imitation. The results from the extended models in Figs. 1(B) and 1(C) yield consistent results. Each data point here is averaged over 100,000 simulations. The parameter values used are specified in Appendix B.

the incumbent). Finally, if the latecomer allocates all its R&D resources to imitative R&D, there is no room for leapfrogging opportunities.

Fig. 1(B) illustrates the pattern in the extended model with five latecomers. Each latecomer possesses a unique p_L value, increasing by increments of 25% from 0% to 100% (specifically, $p_{L1} = 0$, $p_{L2} = 0.25$, $p_{L3} = 0.5$, $p_{L4} = 0.75$, and $p_{L5} = 1$). This figure's horizontal axis represents the varied R&D resource allocations toward innovation for each of the five latecomers, while the vertical axis represents the likelihood of any given latecomer surpassing the leader. A latecomer with a p_L value of 0.25 has a probability of about 0.03 to overtake the leader, whereas one with a p_L value of 1 has a probability of 0. Overall, the findings suggest that even in an extended model featuring multiple latecomers with varied R&D resource allocation strategies, a latecomer with a balanced approach between innovation and imitation holds a greater chance of overtaking the leader. Additionally, Fig. 1(C) reveals that the extended model with 21 latecomers yields consistent results.

As the relative technological capability of the latecomer increases, the optimal amount of resources allocated to innovation also increases, as shown in Fig. 2(A). As the latecomer builds its technological capabilities, the technological gap between the incumbent and the latecomer narrows. Fig. 2(B) shows that a larger technological gap moves the optimal allocation point toward imitation because the relative advantage of investing in imitation increases. A smaller technological gap, by contrast, moves the optimal point toward innovation, increasing the relative advantage of allocating resources toward innovation. For example, when the relative technological capability of the latecomer is close to 0.1 (10% of the incumbent's), the latecomer should allocate about 60% of its R&D resources to innovation in order to maximize the probability of leadership change. When the relative technological capability of the latecomer is larger than 0.8, the latecomer should allocate more than 90% of its R&D resources to innovation in order to maximize the probability of leadership change. Figs. 2(C) and 2(D) demonstrate the impacts of latecomers' relative technological capabilities on the optimal R&D resource allocation to innovation for models with 5 and 21 latecomers, respectively. Both panels align with the patterns observed in Figs. 2(A) and 2(B): as the gap between the latecomers and the leader decreases, a latecomer with greater resource allocation to innovation (indicating a higher p_L value) has an increased likelihood of overtaking the leader.

The results in Figs. 1 and 2 reflect the case where all technological regime variables have moderate values. However, the results are consistent over various technological regime conditions. We check the robustness of the results later on in the sensitivity test section.

4.2. Appropriability

Appropriability, the degree to which incumbents can protect their innovation outcomes from imitation, affects the probability of technological leadership change. Since appropriability hinders imitation, the higher the appropriability of the technology (represented by a higher value of α), the lower the probability of technological leadership change, as shown in Fig. 3(A). The probability of leadership change

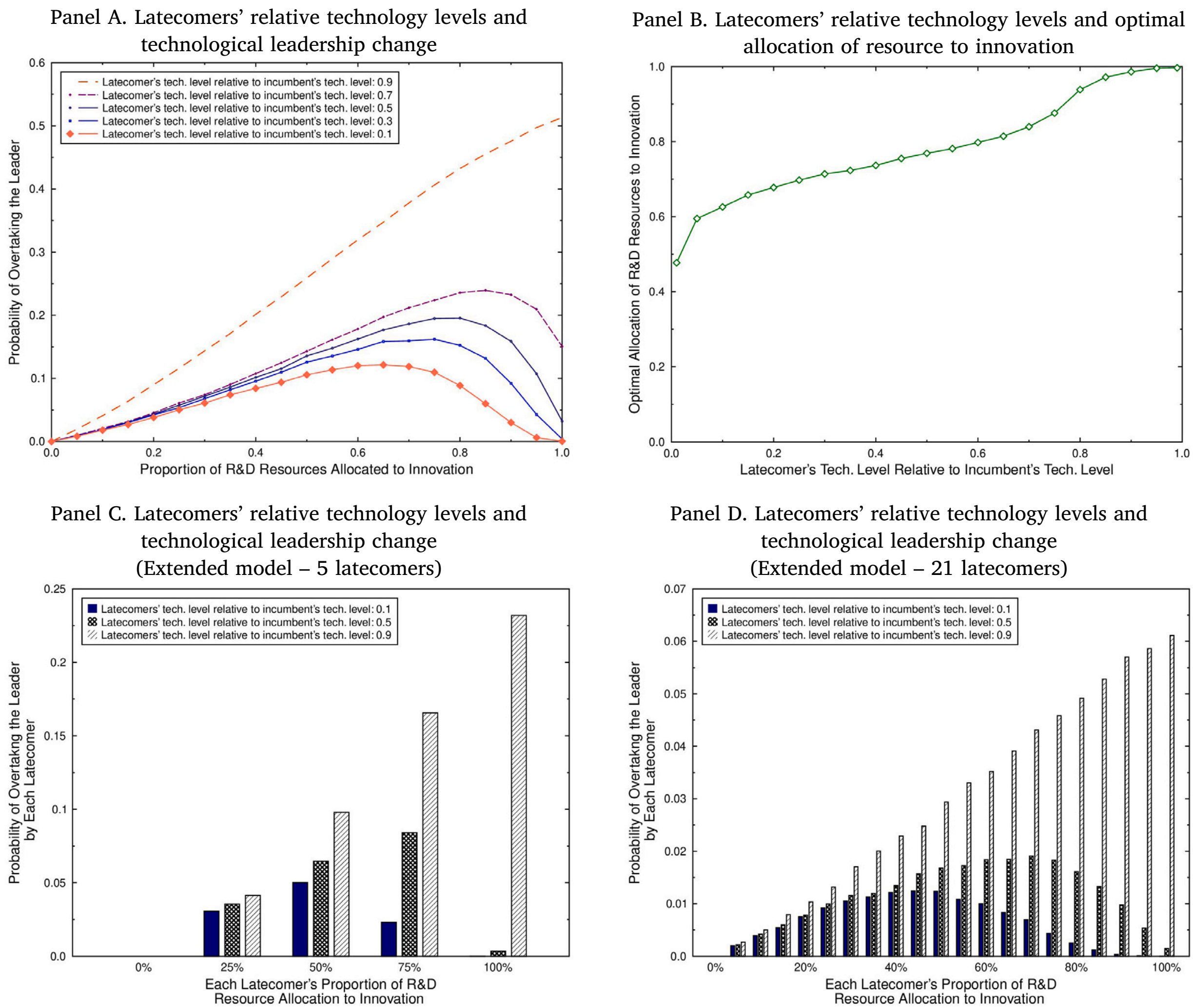


Fig. 2. Latecomers' technology levels, allocation of R&D resources, and technological leadership change.
Note: As the latecomer's technology level relative to the incumbent's increases, the probability of leadership change increases. As the technological gap between the latecomer and the incumbent decreases, the latecomer should allocate more resources to innovation to increase the probability of leadership change. The extended models in Figs. 2(C) and 2(D) yield consistent results. Each data point here is averaged over 100,000 simulations.

is highest when α equals 0, meaning no protection of the incumbent's innovation outcomes. Imitation turns out to be more beneficial for the latecomer since all the incumbent's technologies can be imitated when α equals 0. As appropriability increases, the incumbent's technologies become less imitable, which lowers the probability of technological leadership change. In the extreme case when appropriability exceeds 0.4, the results indicate that technological leadership change rarely occurs.

Latecomers can catch up with incumbents and save resources by engaging in imitative R&D, which is the less risky and less costly option. We identify the optimal proportion of resources allocated to innovation within a range of α from 0 to 0.4 since the probability of leadership change is extremely low when α exceeds 0.4. Fig. 3(B) shows that balancing R&D resources between imitation and innovation is beneficial at different appropriability levels.

As shown in Fig. 3(C), as the level of appropriability increases, the latecomer should allocate more resources to innovation to increase the probability of technological leadership change. In other words, while innovation is relatively more effective under high appropriability, imitation is relatively more effective under low appropriability. For example, when α is larger than 0.06, the latecomer needs to allocate more than 60% of its R&D resources to innovation. However, when α is close to 0, a latecomer should allocate only 40% of its R&D resources to innovation in order to maximize the probability of leadership change.

Finally, Figs. 3(D) and 3(E) illustrate the impacts of appropriability on the probability of leadership change by latecomers for the extended models with 5 and 21 latecomers, respectively. Both panels resonate with the observations in Figs. 3(A) and 3(B): as appropriability rises, the probability of technological leadership change by latecomers diminishes.

4.3. Cumulativeness

Cumulativeness refers to the degree to which past technological capabilities affect the probability of success of the present innovation. When the technological regime is highly cumulative, innovation will be highly dependent on existing technological capabilities and building blocks. This will be beneficial for incumbents in terms of innovative R&D since incumbents have better technological capabilities and more existing building blocks. Fig. 4(A) shows that as the value for the cumulativeness variable, β, changes from 0 (low cumulativeness) to 4 (high cumulativeness), the probability of technological leadership change decreases. When cumulativeness is high, it is difficult for latecomers with lower technological capability to catch up with incumbents since innovative R&D is relatively ineffective. This result confirms that for latecomers, gaining technological leadership is more difficult when innovation is based on past technology.

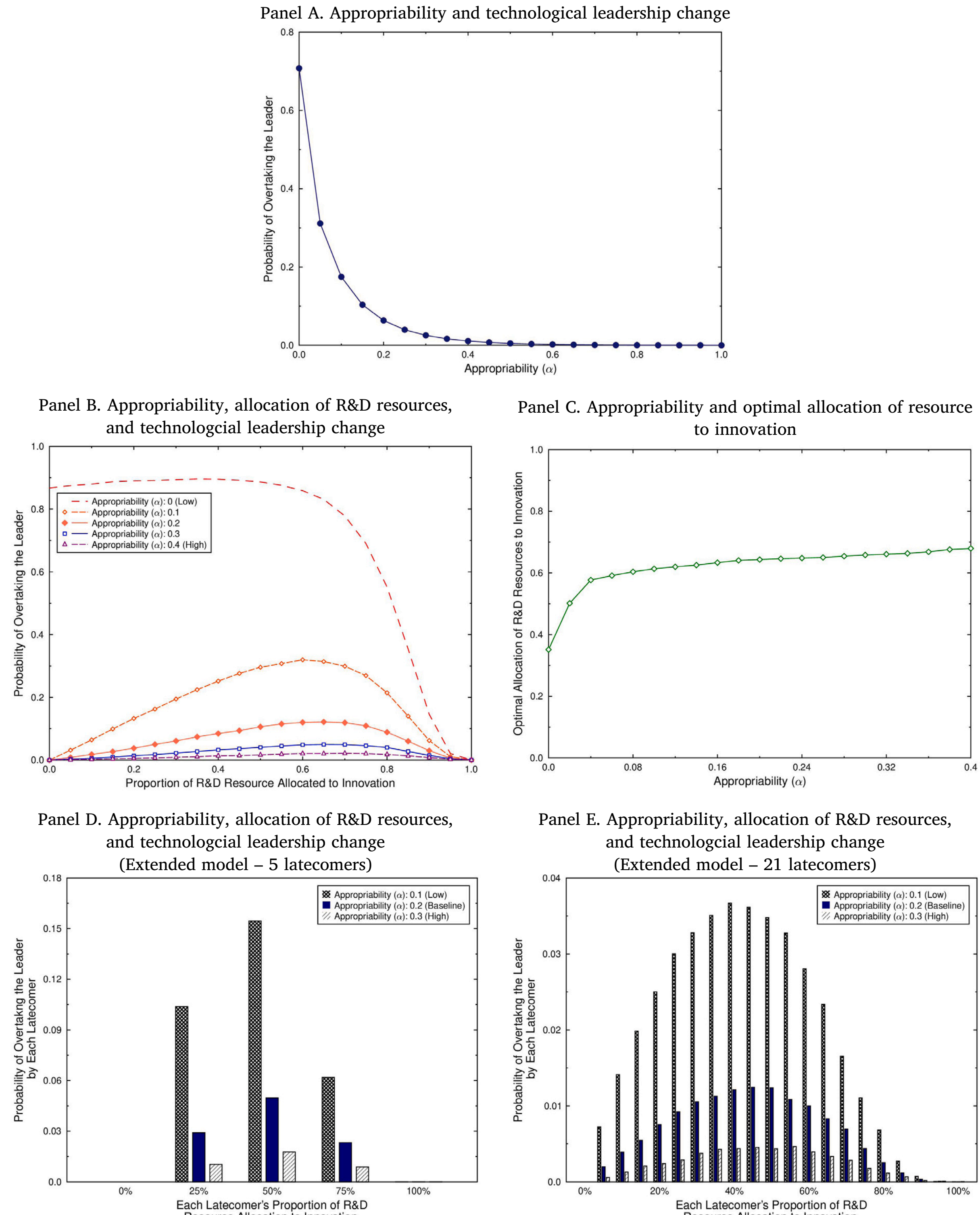


Fig. 3. Appropriability, allocation of R&D resources, and technological leadership change.
Note: Fig. 3(A) shows that as the level of appropriability increases, the probability of technological leadership change increases. The probability of technological leadership change is calculated as the average of the leadership change probabilities for the latecomer's different levels of R&D resource allocation, ranging from 0 to 1. Fig. 3(B) shows that the inverted U-shaped relationship between the proportion of R&D resource allocated to innovation and the probability of technological leadership change is sustained across the entire range of appropriability Fig. 3(C) shows that as the level of appropriability increases, the latecomer should allocate more resources to innovation to increase the probability of technological leadership change. The extended models with multiple latecomers, shown in Figs. 3(D) and 3(E), yield consistent results. Each data point here is averaged over 100,000 simulations.

In addition, Fig. 4(B) shows that in a highly cumulative regime (β = 4), the optimal point moves toward imitation. Since higher cumulativeness implies better technological capabilities for incumbents, technological knowledge gained from imitation becomes more valuable for latecomers. In a low cumulative regime (β = 0), the effectiveness of innovative R&D is higher than in a high cumulative regime; thus, the optimal point moves toward innovation. Looking at the optimal allocation of R&D resources in Fig. 4(C), we see that when β is close to

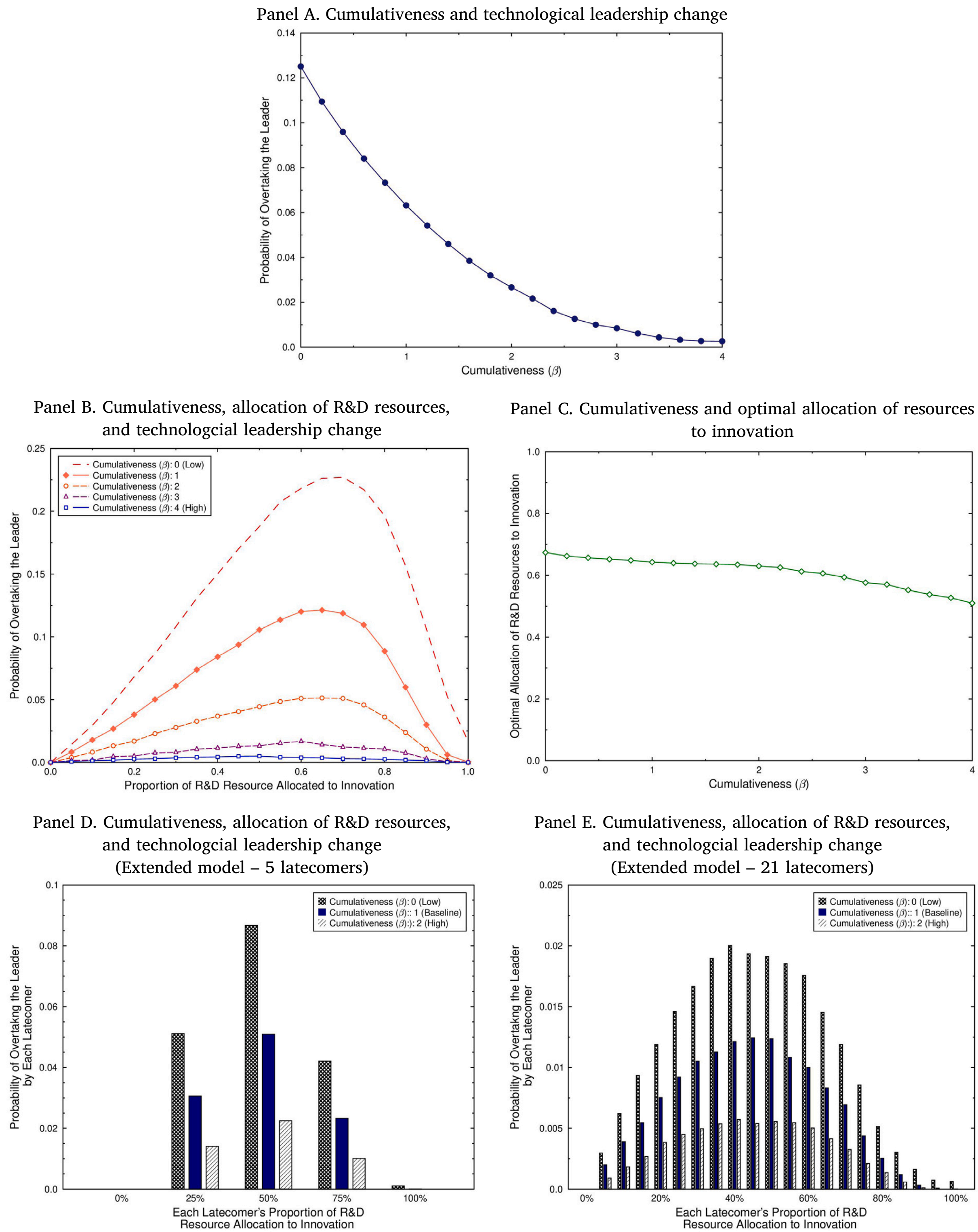


Fig. 4. Cumulativeness, allocation of R&D resources, and technological leadership change.
Note: Fig. 4(A) shows that as the level of cumulativeness increases, the probability of technological leadership change decreases. Fig. 4(B) shows that the inverted U-shaped relationship between the proportion of R&D resource allocated to innovation and the probability of technological leadership change is sustained across all levels of cumulativeness. Fig. 4(C) shows that as the level of cumulativeness increases, the latecomer should allocate more resources to imitation to increase the probability of technological leadership change. The extended models with multiple latecomers, shown in Figs. 4(D) and 4(E), yield consistent results. Each data point here is averaged over 100,000 simulations.

0, the latecomer should allocate more than 70% of its R&D resources to innovation in order to maximize the probability of leadership change. When β is close to 4, the latecomer should allocate about 50% of its R&D resources to innovation.

Figs. 4(D) and 4(E) show the impacts of cumulativeness on the probability of leadership change by latecomers for the extended models with 5 and 21 latecomers, respectively. Both panels align with the patterns observed in Figs. 4(A) and 4(B): as cumulativeness rises, the likelihood of technological leadership change by latecomers diminishes.

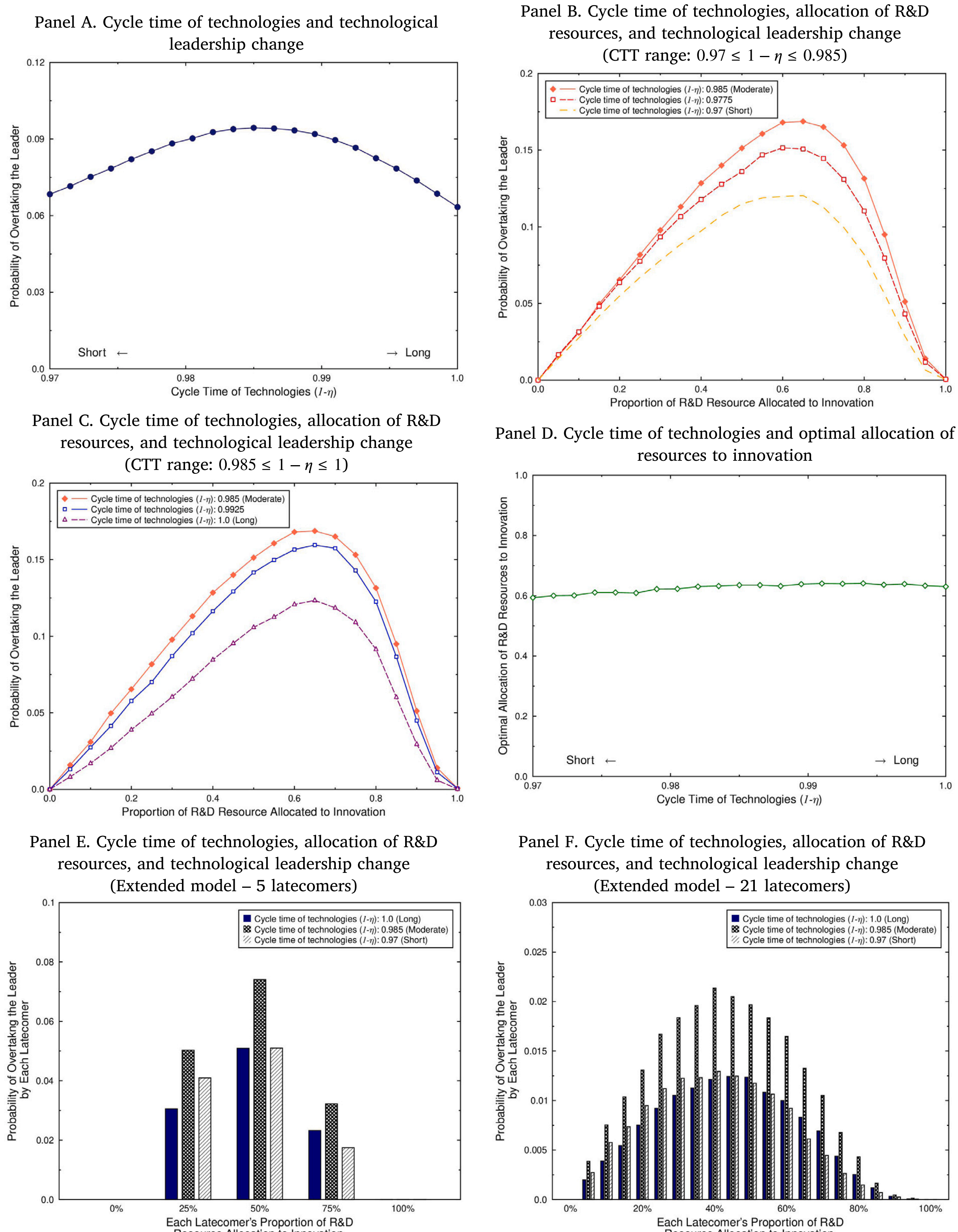


Fig. 5. Cycle time of technologies, allocation of R&D resources, and technological leadership change.

Note: Fig. 5(A) shows an inverted U-shaped relationship between the CTT and the probability of technological leadership change. Figs. 5(B) and 5(C) show that the inverted U-shaped relationship between the proportion of R&D resource allocated to innovation and the probability of technological leadership change is sustained across all values of CTT. Fig. 5(D) shows that the CTT does not significantly change the optimal proportion of R&D resource allocated to innovation. The extended models with multiple latecomers, shown in Figs. 5(E) and 5(F), yield consistent results. Each data point here is averaged over 100,000 simulations.

4.4. Cycle time of technologies (CTT)

We now turn to the question of how the CTT affects technological leadership change and the optimal imitation-innovation balance for latecomers. If the CTT is short, the existing stock of technological capability depreciates quickly for both latecomers and incumbents.

Fig. 5(A) shows an inverted U-shaped relationship between the CTT and the probability of technological leadership change. This pattern is based on the average of the values for leadership change probability in cases where the amount of R&D resources allocated to innovation is between 0 and 1. As the CTT changes from 0.97 (a short CTT or faster depreciation) to 0.985 (a moderate CTT), the probability of technological leadership change increases. The probability of leadership change reaches its peak when the CTT is around 0.985. After this point, as $1 - \eta$ changes from 0.985 (a moderate CTT) to 1.0 (a long CTT), the probability of technological leadership change decreases.

On the one hand, a short CTT in an industry provides a window in which the latecomer may catch up and leadership change may occur (i.e., the positive effect). As the CTT is short, the latecomer encounters many windows because the incumbent's technologies depreciate quickly. However, a short CTT may also hinder catch-up due to truncated learning and rapid obsolescence of knowledge (a short CTT), which deters the latecomer from building a technological foundation, necessitating a switch from learning existing technologies to learning new and different types of technologies, probably within a short time (i.e., the negative effect). Thus, technological leadership change rarely occurs in a short CTT regime.

On the other hand, in an industry with a long CTT, building a technological foundation is easier because there is no need to switch from learning existing technologies to learning new and different technologies. However, under these conditions, the incumbent's technological capability does not depreciate quickly, leaving little room for the latecomer to catch up with the incumbent. Therefore, technological leadership change rarely occurs in a regime with a long CTT.

These results suggest both positive and negative effects of the CTT. Observing the interaction between these effects (i.e., the two functions), we see that an inverted U shape emerges. Thus, technological leadership change is expected to be highest at moderate levels of the CTT.

This inverted U-shaped relationship between the proportion of R&D resources allocated to innovation and the probability of leadership change is sustained across the range of the CTT, as shown in Figs. 5(B) and 5(C). Fig. 5(D) summarizes this relationship between the CTT and the optimal allocation of resources toward innovative R&D. The linear line is somewhat flat, indicating the not-so-dramatic impact of the CTT variable on the relative balance between imitation and innovation. Finally, Figs. 5(E) and 5(F) show the effect of the CTT on the probability of leadership change by latecomers for the extended models with 5 and 21 latecomers, respectively. Both panels align with the patterns observed in Figs. 5(A) and 5(B): the inverted U-shaped relationship between the proportion of R&D resources allocated to innovation and the probability of leadership change is maintained in the extended models.

We further delve into the role of the CTT as it interacts with the latecomer's technological capability relative to the incumbent. Fig. 6(A) shows the impact of the CTT on the probability of technological leadership change at different levels of technological capability of the latecomer. As the technological capability of the latecomer relative to the incumbent increases, the overall probability of technological leadership change increases, and the inverted U-shaped relationship between the CTT and the probability of technological leadership change is sustained. Also, the peak probability of leadership change remains unchanged despite changes in the latecomer's relative technological capability.

Different CTTs impact the optimal mix between imitation and innovation, as Fig. 6(B) shows. Fig. 6(B) focuses on the impact of the CTT on the optimal allocation of R&D resources for the latecomer according to the latecomer's technological capability relative to the incumbent. The important pattern to note here is that when the technological capability of the latecomer relative to the incumbent is low (e.g., 0.2; 20% of that of the incumbent) under a shorter CTT, the latecomer should allocate more R&D resources to imitation to increase the probability of technological leadership change. Then, as its relative capability increases from 0.2 to 0.7, the latecomer should allocate increasingly more resources to innovation even under a short CTT regime. Then, after its capability reaches around 0.7, or 70% of that of the incumbent, we see no significant difference in the optimal allocation of R&D resources across different lengths of the CTT.

These results extend our understanding of the role of the CTT discussed in prior empirical research, emphasizing the disadvantages of a shorter CTT for latecomers whose levels of technology are low (e.g., Lall, 2000; Lee, 2013). Prior work highlighted the initial technological capabilities of latecomers (e.g., Zhang et al., 2021), which play an important role in the early stage of the catch-up process; therefore, latecomers should build their technological capabilities via imitation when the technological gap between them and the leader is wide. Then, after they reach a certain level of capability, they should switch to innovative R&D even under a short CTT regime because of the lower risk involved in innovative R&D. Therefore, the latecomer's need for a dynamic shift from imitation to innovation is valid even when the CTT is short.

We further analyzed the effect of number of latecomers on the relationship between the CTT and the probability of technological leadership change. In this scenario, we expanded to ten latecomers for each p_L value, from 0 to 1, in increments of 5%. This leads to a total of 210 latecomers, from 21 distinct groups (with different p_L values) based on R&D resource allocation, competing against the leader.

Fig. 7(A) illustrates the relationship between the CTT and the likelihood of leadership change when examining the model with 210 latecomers. Notably, the previously observed inverted-U relationship between the CTT and the probability of leadership change is absent when the number of latecomers is excessively high, as in the case of 210. Instead, a negative relationship between the CTT and leadership change is observed, meaning a shorter CTT reduces the chance of technological leadership change. Recall that a short CTT presents a challenge for latecomers: it speeds up the depreciation of the latecomers' own technology, a phenomenon we refer to as the latecomer's truncated learning. The findings suggest that an increasing number of latecomers amplifies the adverse effects of a short CTT, primarily due to this truncated learning. In an industry crowded with numerous latecomers, latecomers often struggle to generate substantial profits or amass enough capital for R&D, hindering their ability to rival the leader. This constraint exacerbates the latecomer's truncated learning, explaining the absence of the inverted U (i.e., the pronounced negative impact of a short CTT). This underscores that the number of latecomers is a boundary condition for the inverted-U relationship between CTT and the likelihood of leadership change. In addition, Fig. 7(B) shows that this inverted-U relationship starts to dissipate as the number of latecomers exceeds 100.

4.5. Additional analysis-adaptive path of latecomer's resource allocation

Extending the baseline model of competition between a latecomer and an incumbent, we relax the assumption that the latecomer's R&D resource allocation remains fixed. Originally set at a fixed split, with p_L for innovation and $1 - p_L$ for imitation, the model now allows for adjustments throughout the simulation. Initially, the latecomer starts with p_L at 0.5, signifying an even split between innovation and imitation. This value is then adjusted in each subsequent period based on the previous period's relative outcome of innovation and imitation. A new parameter, δ, is introduced, determining the degree of change in p_L. If the technological capabilities gained from innovation (i.e., tn_{Lt}) exceed those from imitation (i.e., tm_{Lt}), the latecomer increases its R&D resource allocation to innovation p_L by δ. Conversely, if the capabilities gained from imitation surpass those from innovation, the latecomer decreases its p_L by δ. If the technological capabilities gained from both innovation and imitation are equal, the latecomer retains the existing value of p_L in the next period. In the baseline model, δ is set to 0, indicating that the latecomer keeps p_L constant throughout the simulation. In the extended model, we adjust δ, varying it from 0.05

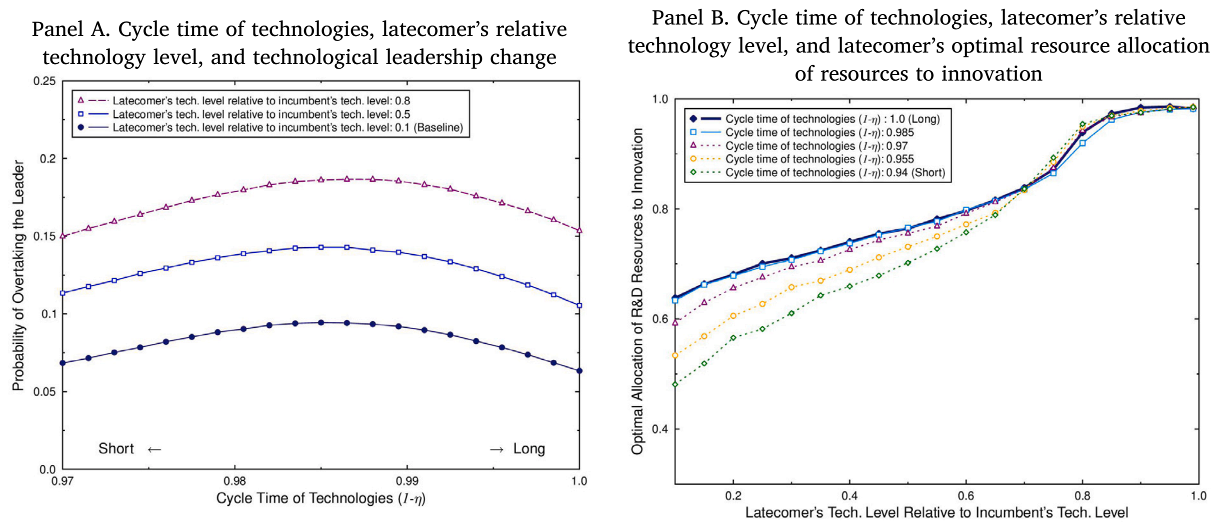


Fig. 6. Cycle time of technologies and latecomer's relative technology level.
Note: Fig. 6(A) shows that the CTT does not change the peak probability of technological leadership change with increasing latecomer's technology level relative to the incumbent's. However, Fig. 6(B) shows that as the technological gap between the latecomer and the incumbent increases, the latecomer should allocate more resources to imitation to increase the probability of leadership change. Each data point here is averaged over 100,000 simulations.

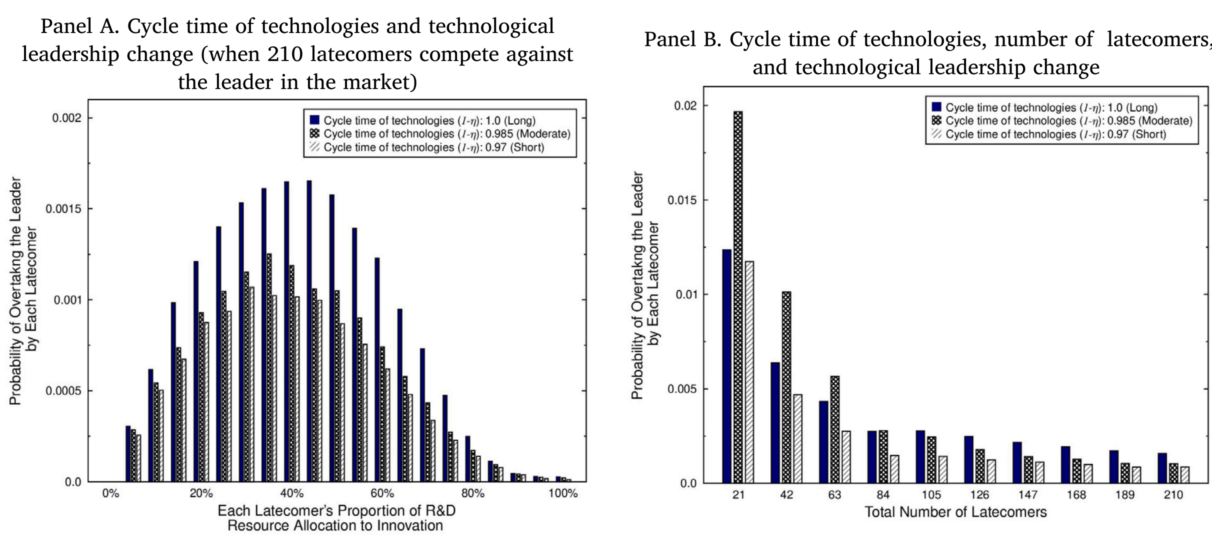


Fig. 7. Cycle time of technologies and number of latecomers.
Note: Fig. 7(A) shows the inverted-U relationship between the CTT and the probability of leadership change is absent when the number of latecomers is excessively high. Fig. 7(B) shows that the inverted-U relationship begins to dissipate when the total number of latecomers exceeds 100. The proportion of R&D resource allocated to innovation (p_L) for all latecomers in Fig. 7(B) is set at 0.5. Each data point here is averaged over 100,000 simulations.

(representing a 5% shift in R&D resource allocation) to 0.2 (indicating a 20% shift).

We conducted 100,000 simulation runs. These simulation runs were categorized into two groups: (1) simulations where the latecomer overtakes the leader during the run, and (2) simulations where the latecomer does not overtake the leader. Subsequently, we calculated the average p_L values across all time periods for the latecomers of each group. Fig. 8(A) illustrates the shift in the average p_L over time for simulation runs where the latecomer successfully overtakes the leader, across different δ values. Initially, there is a minor dip in the latecomers' R&D allocation toward innovation p_L, due to early imitative successes that narrowed the gap with the leader. Yet, this soon reverses, with a noticeable uptick in innovation allocation, indicating that p_L values lean more toward R&D dedicated to innovation. A trajectory from imitation to innovation is distinctly evident for latecomers that manage to overtake industry leaders.

In contrast, Fig. 8(B) portrays the shifts in average p_L over time for simulation runs where the latecomer fails to surpass the leader, across diverse δ values. These outcomes resonate with the recognized 'competency trap' pattern (Levitt and March, 1988; Miner and Haunschild, 1995). After a series of initial imitative successes, there is a consistent decline in R&D emphasis on innovation, solidifying the latecomer's stance predominantly as an imitator. When a latecomer decreases its allocation to innovation too quickly, it typically sees diminished success in innovation endeavors. This cycle of reduced investment and subsequent diminished innovation outcomes can propel many latecomers into a feedback loop, ultimately leading them into the 'imitation trap.'

To sum up, findings from our extended model underscore that a trajectory from imitation to innovation is distinctly evident for latecomers that manage to overtake the leader, but a trajectory entrenched in imitation characterizes latecomers who fail to overtake the leader. A more detailed analysis using this adaptive extended model can be

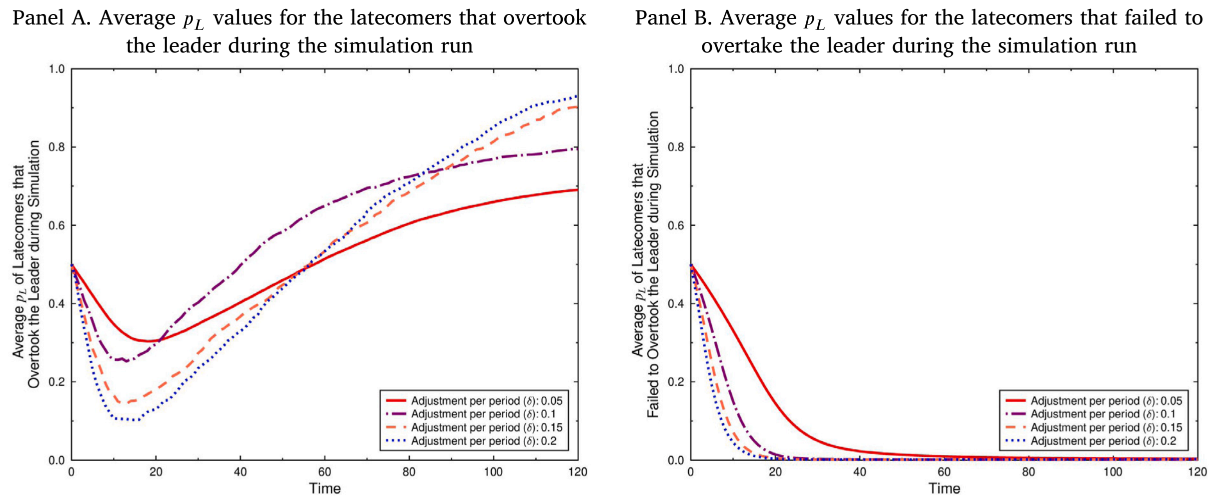


Fig. 8. Adaptive Change in the Latecomer's R&D resource allocation over time.
Note: We conducted 100,000 simulation runs. These were categorized into two groups: (1) simulations where the latecomer overtakes the leader during the run, and (2) simulations where the latecomer does not overtake the leader. Subsequently, we calculated the average p_L values across all time periods for the latecomers of each group. The probability of success of imitative R&D (κ) is set at 0.6, the positive constant gamma (γ) is set at 0.6.

found in Appendix C, and it is worth noting that these results align qualitatively with our findings from the baseline model.

4.6. Sensitivity test

We now examine whether our findings are robust to various combinations of the three technological regime variables. Appendix D shows that in various situations, the relationships between the technological regime variables and the probability of leadership change are sustained. First, as the level of appropriability increases, the probability of leadership change decreases. Second, as the level of cumulativeness increases, the probability of leadership change decreases. Third, there is an inverted U-shaped relationship between the CTT and the probability of leadership change. In addition, Appendix E shows that the "imitation to innovation" strategy is still effective when appropriability, cumulativeness, and the CTT jointly affect the catch-up process. The optimal amount of R&D resources allocated to innovation gradually increases as the latecomer's technology level relative to the incumbent's increases in every case presented.

Further, we allowed the two different parameters (i.e., effectiveness of innovative R&D (γ) and propensity toward capital investment in R&D (r_i)) to vary in our extended models. Appendix F shows the results for these extended models. Appendix F(A) shows that as the incumbent's innovative R&D becomes more effective, the probability of technological leadership change declines and Appendix F(B) shows that as the incumbent's propensity toward investment in innovative R&D increases, the probability of technological leadership change declines. Yet, the main finding of our study (i.e., striking a fine balance between innovative R&D and imitative R&D increases the chance of technological leadership change) is robust to the effectiveness of the incumbent's innovative R&D and the incumbent's propensity toward investment in R&D.

Next, we also we varied the number of periods for each simulation run from 120 periods to 360 periods. The results in Appendix G show that our key findings are qualitatively identical to those of the main analysis.

We also built extended models and ran additional simulations under various demand conditions: (1) increasing demand, (2) decreasing demand, and (3) logistic dynamics (logistic growth of demand). The results from these extended models are presented in Figs. H.1–H.3 in Appendix H. The results from these extended models are qualitatively identical to the results from our baseline model in the paper.

Lastly, we conducted additional sensitivity tests for a wider ranges of the main parameters and various demand conditions. Tables I.1–I.6 in Appendix I show the results of the additional sensitivity analyses. The results of our original analysis are robust to these modification.

5. Discussion and conclusion

We delve into how a latecomer's R&D resource allocation between imitation and innovation affects the likelihood of the latecomer overtaking leaders across various technological regimes. Unlike prior work that focused only on firm strategy or technological regimes, our research investigates their interaction.

5.1. Imitation to innovation

Our research underscores the importance of striking a dynamic balance between imitation and innovation for attaining technological leadership. In the initial catch-up phase, latecomers should emphasize imitation to amass technological capability and resources swiftly. However, as the technological gap narrows, they should pivot more toward innovation, aiming to leapfrog industry leaders. This pivot propelled Korean firms like Samsung Electronics and LG Electronics to the forefront of the consumer electronics industry. In the 1970s, they thrived through duplicative imitation of mature products. The 1980s saw a shift toward creative imitation, where, backed by prior capabilities, they added innovative features. By the 1990s, they expanded their footprint with global R&D centers and strategic alliances with advanced firms in the U.S., Japan, and Germany. Their systematic transition from imitation to innovation heralded their ascent to global consumer electronics leadership in the 21st century.

5.2. Technological regime and technological leadership change

To gain insight into the role of technological regimes on technological leadership change, we examine three major technological regime variables: appropriability, cumulativeness, and the CTT, which are closely related to the effectiveness of imitation and innovation.

5.2.1. Appropriability

Our results indicate that the greater the appropriability of technology, the harder it is for the latecomer to build technological capacity through imitation, resulting in a low probability of technological leadership change. Also, imitation is more effective than innovation under low appropriability, but innovation is more effective than imitation under high appropriability.

Despite the internal combustion engine-based automobile industry being less science-intensive (Pavitt, 1984), it remains highly appropriable due to the significance of tacit knowledge and component complexity (Clark and Fujimoto, 1991; Lee, 2007). Korean automakers, like Hyundai and Kia, evolved from assembly in the 1970s to in-house development by the 1990s but faced challenges with next-generation vehicles. Japanese giants Toyota and Honda, fortified by patents for hybrid vehicles, set higher barriers for technology imitation. In response, Hyundai-Kia pivoted to introduce electric vehicles (EVs) earlier than their Japanese counterparts, showcasing the importance of innovation in high-appropriability settings.

Contrastingly, the PC industry is characterized by low appropriability. IBM's 1981 open standard PC transformed the sector from technology-focused to assembly-focused, reducing appropriability. This shift paved the way for new entrants like Compaq and, later, Korean firms such as Samsung or Sambo Computer in the 1980s (Lee and Lim, 2001). The 1990s and 2000s saw the rise of Chinese and Taiwanese manufacturers like LENOVO and Acer. Their successes demonstrate that in a low appropriability context, imitation can thrive.

5.2.2. Cumulativeness

Next, our results show that the higher the level of cumulativeness, the greater the advantage for incumbents with prior technological capabilities, resulting in a lower probability of leadership change. Also, under higher cumulativeness, imitation is more valuable because incumbents' technological capabilities are more valuable.

A representative case of cumulativeness can be observed in the semiconductor industry. In the system semiconductor industry, technological discontinuities between generations have been few, and small-quantity batch production is the norm, in contrast to the memory semiconductor industry, which relies on mass production (Joo, 2009). Since the design capability for small-quantity batch production is gained mainly from earlier design experiences, the technological advantages of NVIDIA or Qualcomm, the industry's leaders, have been sustained due to high cumulativeness. Conversely, in the memory semiconductor industry, technological discontinuities between generations were more evident in the early stage (until the early 1990s) of the industry's evolution than the later stage (Kim, 1997). These technological discontinuities between generations, resulting from low cumulativeness in the technological regime, facilitated technological catch-up. Leadership positions in the memory semiconductor industry were occupied by US firms such as Intel and Texas Instruments in the 1970s, moved to Japanese firms such as Hitachi and Toshiba in the 1980s, and then to a Korean firm, Samsung Electronics, in the 1990s.

Looking back at the success of Samsung Electronics, we note that technologically new products prepared for the next generation played an important role in this low-cumulativeness industry. Since incumbents such as Texas Instruments, Motorola, NEC, Toshiba, and Hitachi were reluctant to transfer their semiconductor technologies to Samsung Electronics (Kim, 1997), the company initiated in-house development in 1986 and developed 4MB and 16MB chips using its own technologies. After that, Samsung made headway in developing 64MB and 256MB DRAM chips, becoming the leading company in the world (Joo, 2009), as shown in Appendix J. The case of Samsung Electronics supports the result in our study that under low technological cumulativeness, innovation efforts targeting next-generation technology are more effective than the imitation of present-generation technology.

5.2.3. Cycle time of technologies (CTT)

Finally, our findings indicate that there exists an inverted U-shaped relationship between the CTT and the probability of technological leadership change. This suggests that there is an optimal range of CTT where the potential for leadership change is maximized. This non-linear relationship implies that when the CTT is extremely short, the latecomer's overtaking probability is low. Similarly, when the CTT is extremely long, the overtaking probability for latecomers also diminishes. Our findings emphasize the dual nature of a short CTT for latecomers: while it accelerates the depreciation of industry leaders' technology, offering a window of opportunity for overtaking, it also hastens the obsolescence of the latecomers' own technology, a phenomenon termed as the 'latecomer's truncated learning'. The simulation shows that under a short CTT regime, it makes more sense for latecomers to allocate more resources to imitation, especially when the initial technology level of the latecomers is low. By contrast, when the initial technology level of the latecomers is relatively high, the length of the CTT does not significantly affect the optimal balance of resources between imitation and innovation.

One might think that in sectors with a short CTT, latecomers should adopt an innovation-based catch-up strategy. However, our simulation results indicate that it depends upon their initial level of technology. If that level is low, then latecomers should devote more resources to imitation than otherwise. This is consistent with the experience of Korean catch-up in IT industries, which is an example of a short CTT-based sector. While Samsung has achieved remarkable catch-up in this short CTT-based sector, it initially relied on imitation when its technology level was low, as evidenced by its heavy citation of Sony's patents in the early days and in the 1980s (Joo and Lee, 2010). However, over time (toward the end of the 1990s), Samsung reduced its reliance on Sony as a source of knowledge.

5.3. Limitations

Our work also has limitations. Our model does not include the strategic behaviors of the incumbent. In this paper, this simplifying assumption allows us to focus on the main effect of allocation of R&D resources for latecomers on the probability of technological leadership change. In real-world situations, latecomers should try to predict the strategic behaviors of industry incumbents because their strategy may encourage or discourage incumbents' innovative R&D. As has been frequently noted in prior work, incumbents, in reality, strive to prevent technological catch-up by latecomers by registering patents, aggressively investing in R&D and facilities, or implementing strategies to improve the effectiveness of innovative R&D (e.g., Caves and Porter, 1977; Rothaermel and Thursby, 2007). This assumption may be relaxed in future work. It will be interesting to explore competitive interactions between latecomers and industry leaders.

CRediT authorship contribution statement

Sungyong Chang: Conceptualization, Methodology, Formal analysis, Writing – original draft. **Hyunseob Kim:** Conceptualization, Methodology, Formal analysis, Writing – original draft. **Jaeyong Song:** Conceptualization, Writing – review & editing. **Keun Lee:** Conceptualization, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

No data was used for the research described in the article.

Appendix A. Theoretical studies of schumpeterian competition

	Number of firms	Symmetry of firms at the initial period	Assumption of technological progress: Step-by-step innovation	Existence of leapfrogging	Focus of the model
Aghion, Harris, Howitt, and Vickers (2001)	2	Symmetric (all parameters for each firm have the same values)	Yes	No	Effect of competition on industry-level technological progress (i.e., productivity growth)
Nelson and Winter (1978, 1982)	4, 16	Symmetric (all parameters for each firm have the same values)	No	Yes	Effect of technological attributes on competition
Our model	2, 6, 22, 43, 64, 85, 106, 127, 148, 169, 190, 211 (One incumbent and 1 to 210 latecomers)	Asymmetric (technology and capital levels of the latecomer are lower than those of the incumbent)	No	Yes	Effect of technological attributes and latecomer's resource allocation strategy on technological leadership change

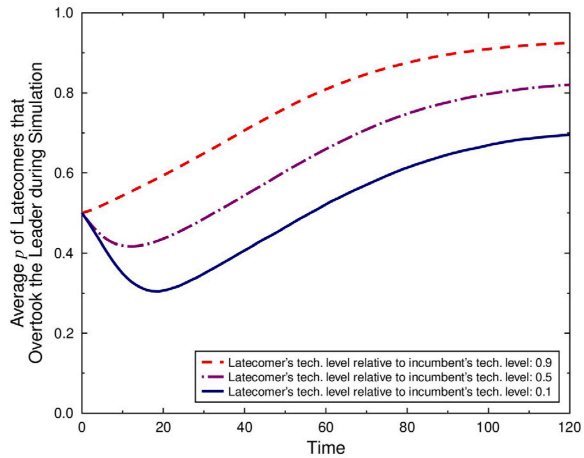
Appendix B. List of model parameters

Parameters	Remarks	Parameter values							
		Fig. 1	Fig. 2	Fig. 3	Fig. 4	Fig. 5	Fig. 6	Fig. 7	Fig. 8
T_{L0}	Latecomer's initial technology level	0.05	From 0.01 to 0.499	0.05	0.05	0.05	From 0.01 to 0.499	0.05	0.05
T_{F0}	Incumbent's initial technology level	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5
K_{L0}	Latecomer's initial capital stock	50	50	50	50	50	50	50	50
K_{F0}	Incumbent's initial capital stock	100	100	100	100	100	100	100	100
R	Total consumer demand	64	64	64	64	64	64	64	64
avc_i	Average variable cost per unit of capital	0.146	0.146	0.146	0.146	0.146	0.146	0.146	0.146
r_i	R&D expenditure per unit of capital	0.004	0.004	0.004	0.004	0.004	0.004	0.004	0.004
μ	Average of log-normal distribution[a]	−3	−3	−3	−3	−3	−3	−3	−3
σ	Standard deviation of log-normal distribution	1	1	1	1	1	1	1	1
κ	Success probability of imitative R&D	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.6
γ	Gamma	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.6
α	Appropriability	0.2	0.2	From 0 to 1	0.2	0.2	0.2	0.2	0.2
β	Cumulativeness	1.0	1.0	1.0	From 0 to 4	1.0	1.0	1.0	1.0
η	Technological knowledge depreciation (Cycle time of technologies $=1-\eta$)	0	0	0	0	From 0 to 0.03	From 0 to 0.06	From 0 to 0.03	0
δ	Adjustment per period	0	0	0	0	0	0	0	From 0.05 to 0.2

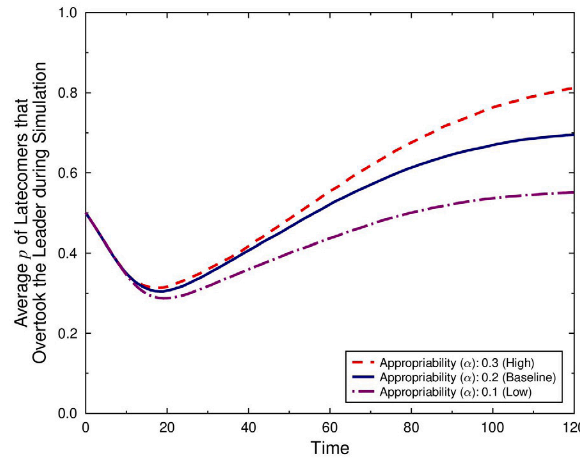
[a] *Note:* Values drawn from a log-normal distribution are always positive.

Appendix C. Change in average p_L values for latecomers that overtook the leader during the simulation: across different technology levels and technological regimes (adjustment on latecomer's r&d resource allocation per period, δ: 0.05)

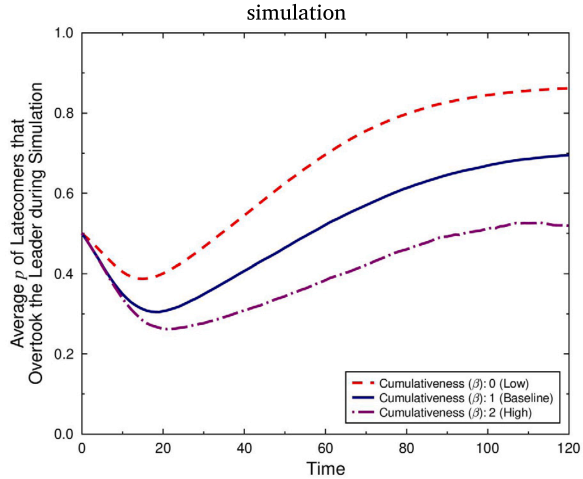
(A) Impact of the latecomers' technology level on the change in average p_L values for latecomers that overtook the leader during the simulation



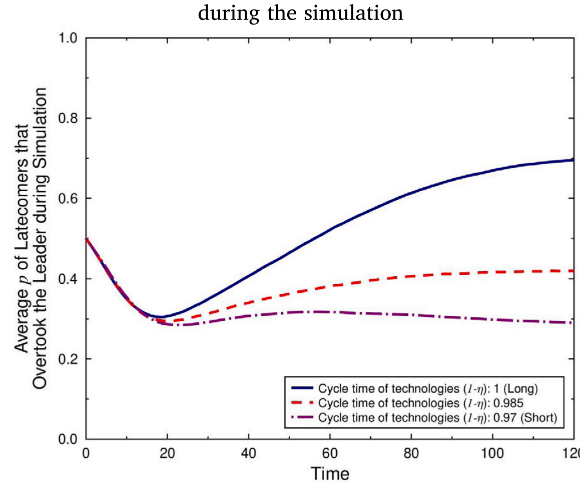
(B) Impact of appropriability on the change in average p_L values for latecomers that overtook the leader during the simulation



(C) Impact of cumulativeness on the change in average p_L values for latecomers that overtook the leader during the simulation



(D) Impact of the cycle time of technologies on the change in average p_L values for latecomers that overtook the leader during the simulation



Note: The probability of success of imitative R&D (κ) is set at 0.6, the positive constant gamma (γ) is set at 0.6, and the adjustment per period (δ) is set at 0.05. Each data point here is averaged over 100,000 simulations.

Appendix D. Probability of technological leadership change in various technological regimes

Technological regime			Probability of leadership change for latecomer (latecomer's initial technology level is 10% of incumbent's)
Appropriability	Cumulativeness	Cycle time of technologies	
High (0.3)	High (1.5)	Long (1.0)	1.48%
High (0.3)	High (1.5)	Moderate (0.985)	1.82%
High (0.3)	High (1.5)	Short (0.97)	1.03%
High (0.3)	Low (0.5)	Long (1.0)	4.09%
High (0.3)	Low (0.5)	Moderate (0.985)	19.41%
High (0.3)	Low (0.5)	Low (0.2)	18.12%
Low (0.1)	High (1.5)	Long (1.0)	12.38%
Low (0.1)	High (1.5)	Moderate (0.985)	13.21%
Low (0.1)	High (1.5)	Low (0.2)	5.71%
Low (0.1)	Low (0.5)	Long (1.0)	21.90%
Low (0.1)	Low (0.5)	Moderate (0.985)	33.24%
Low (0.1)	Low (0.5)	Low (0.2)	31.46%

Note: The relationships between the technological regime variables and the probability of leadership change are sustained *over all possible cases in the technological regime.*

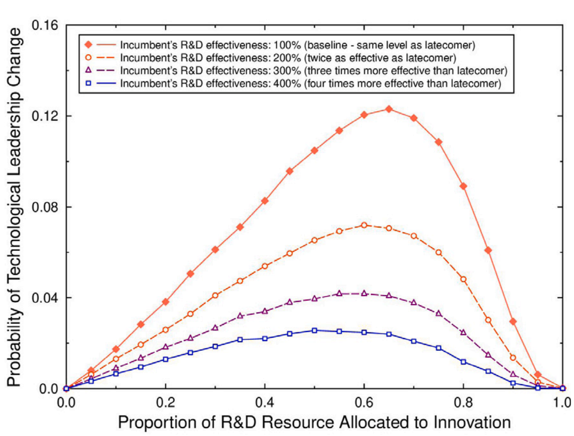
Appendix E. Optimal allocation of resources to innovation under various technological regimes

Technological regime			Optimal allocation of resources to innovation (p^*)		
Appropriability	Cumulativeness	Cycle time of technologies	Low technology level for latecomer relative to incumbent (0.1 level)	Moderate technology level for latecomer relative to incumbent (0.5 level)	High technology level for latecomer relative to incumbent (0.9 level)
High (0.3)	High (1.5)	Long (1.0)	0.67	0.83	0.99
High (0.3)	High (1.5)	Moderate (0.985)	0.68	0.83	0.98
High (0.3)	High (1.5)	Short (0.97)	0.63	0.82	0.97
High (0.3)	Low (0.5)	Long (1.0)	0.63	0.78	0.98
High (0.3)	Low (0.5)	Moderate (0.985)	0.63	0.78	0.98
High (0.3)	Low (0.5)	Short (0.97)	0.58	0.75	0.97
Low (0.1)	High (1.5)	Long (1.0)	0.61	0.72	0.86
Low (0.1)	High (1.5)	Moderate (0.985)	0.61	0.72	0.86
Low (0.1)	High (1.5)	Short (0.97)	0.58	0.72	0.86
Low (0.1)	Low (0.5)	Long (1.0)	0.60	0.72	0.88
Low (0.1)	Low (0.5)	Moderate (0.985)	0.57	0.71	0.92
Low (0.1)	Low (0.5)	Short (0.97)	0.51	0.67	0.95

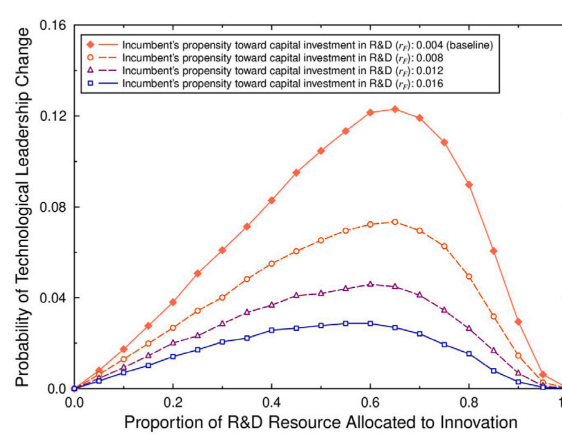
Note: Appendix E shows that the "imitation to innovation" strategy is useful for technological leadership change in all possible cases.
In each case, as the latecomer's technology level increases, the optimal amount of resources allocated to innovation gradually increases.

Appendix F. Behavior of the incumbent and technological leadership change

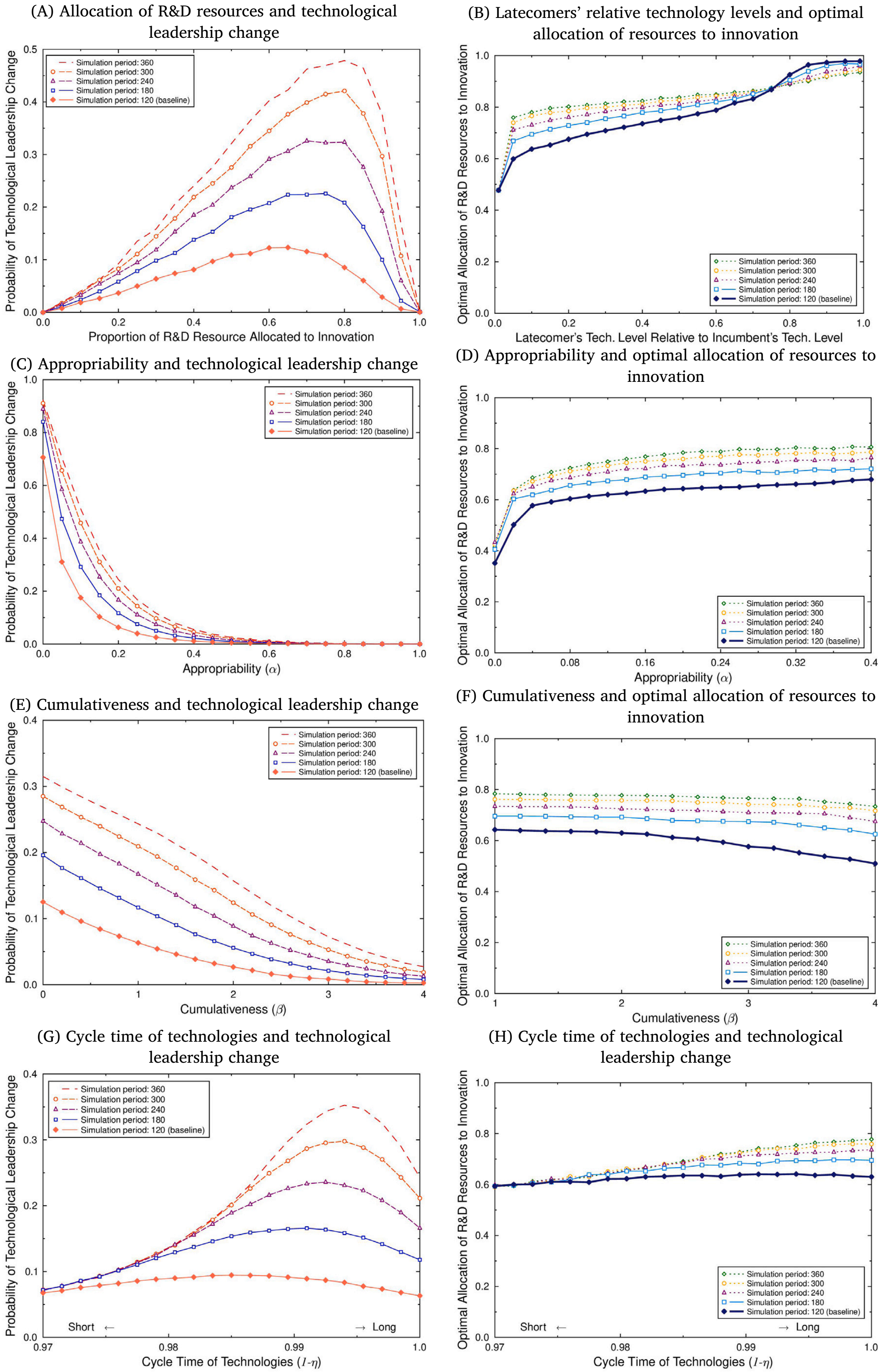
(A) Incumbent's R&D effectiveness and technological leadership change



(B) Incumbent's R&D investment and technological leadership change



Appendix G. Robustness check - length of simulation run



Appendix H. Robustness check - demand condition

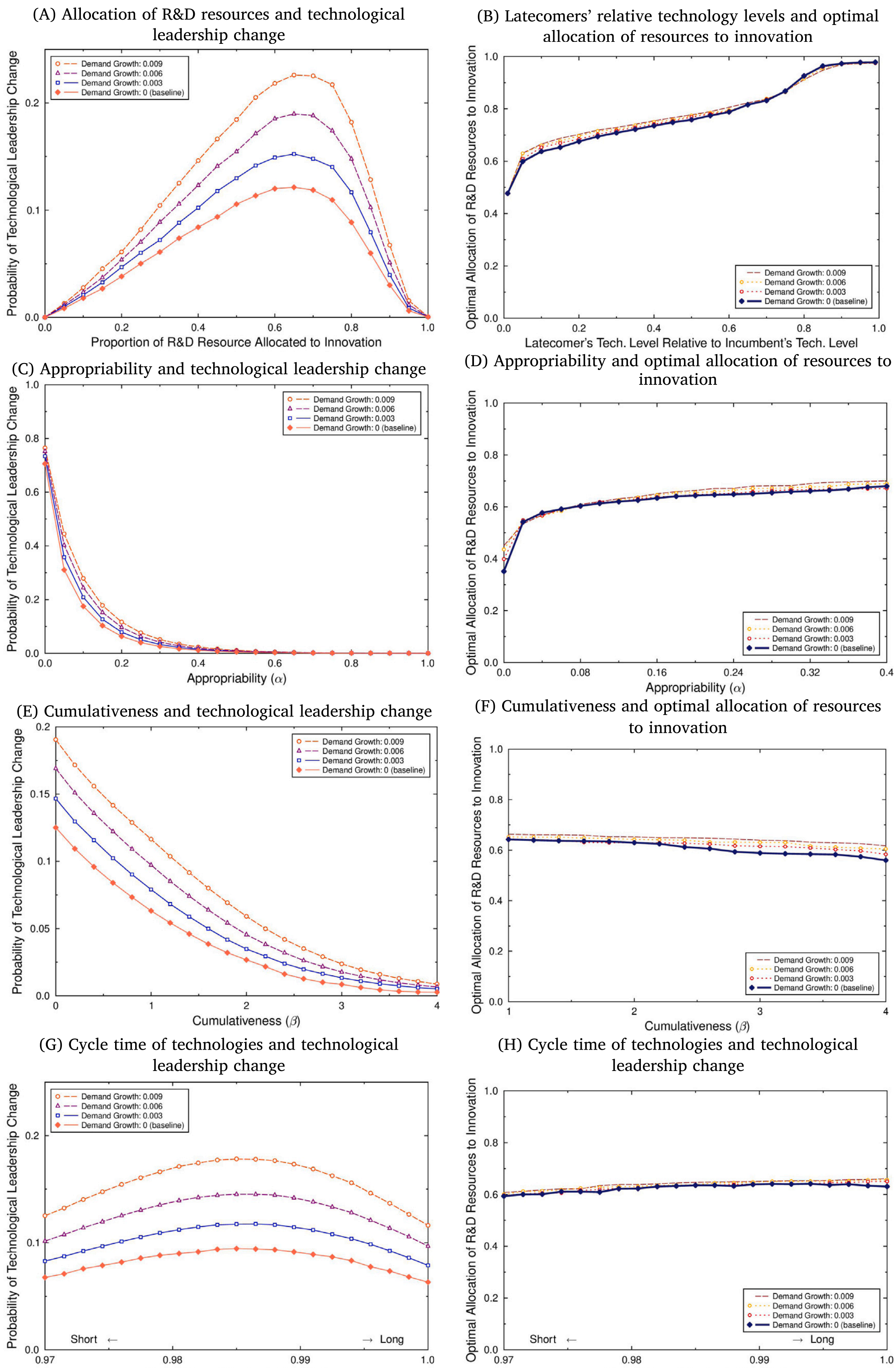


Fig. H.1. Increasing Demand

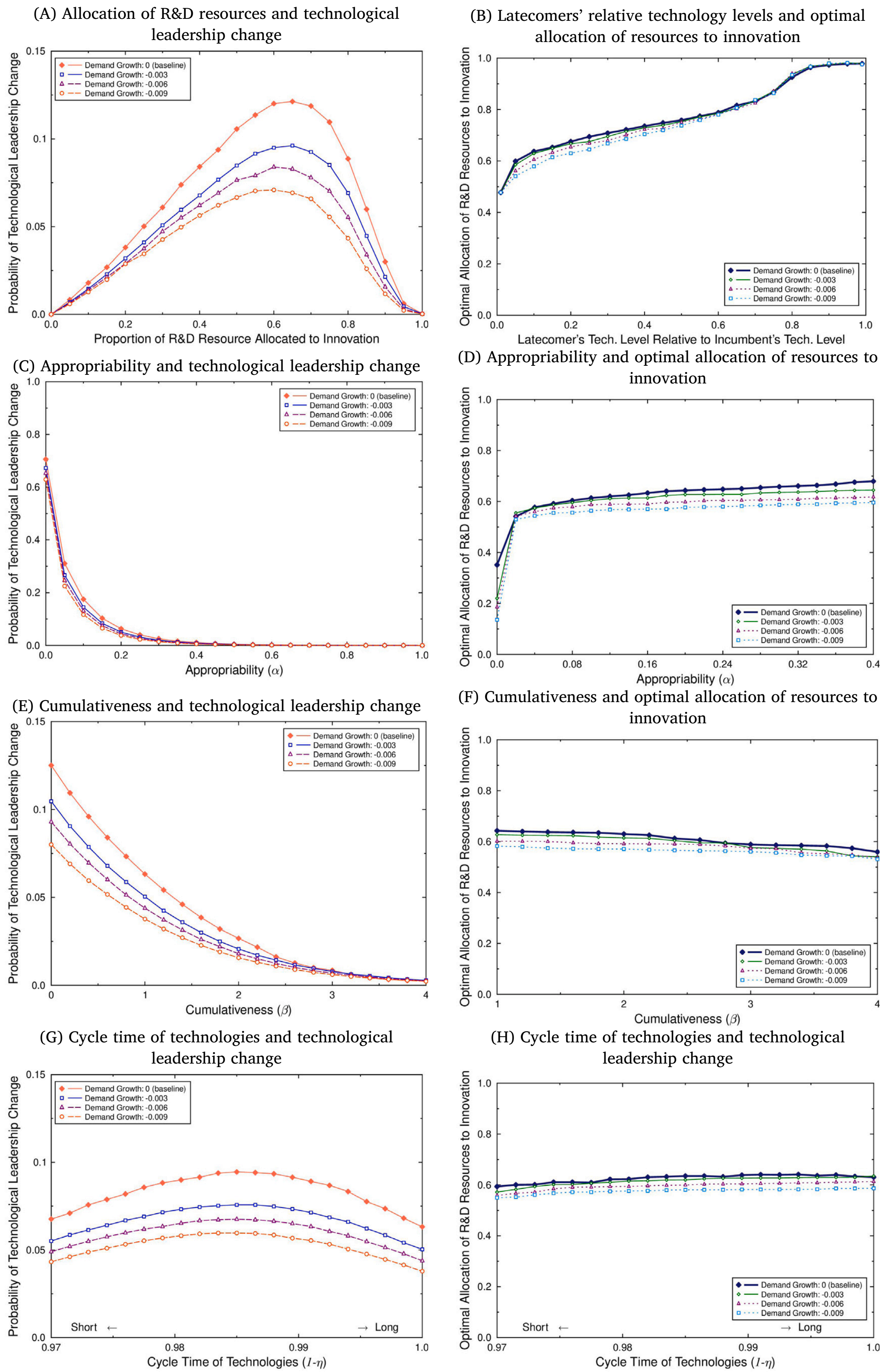


Fig. H.2. Decreasing Demand

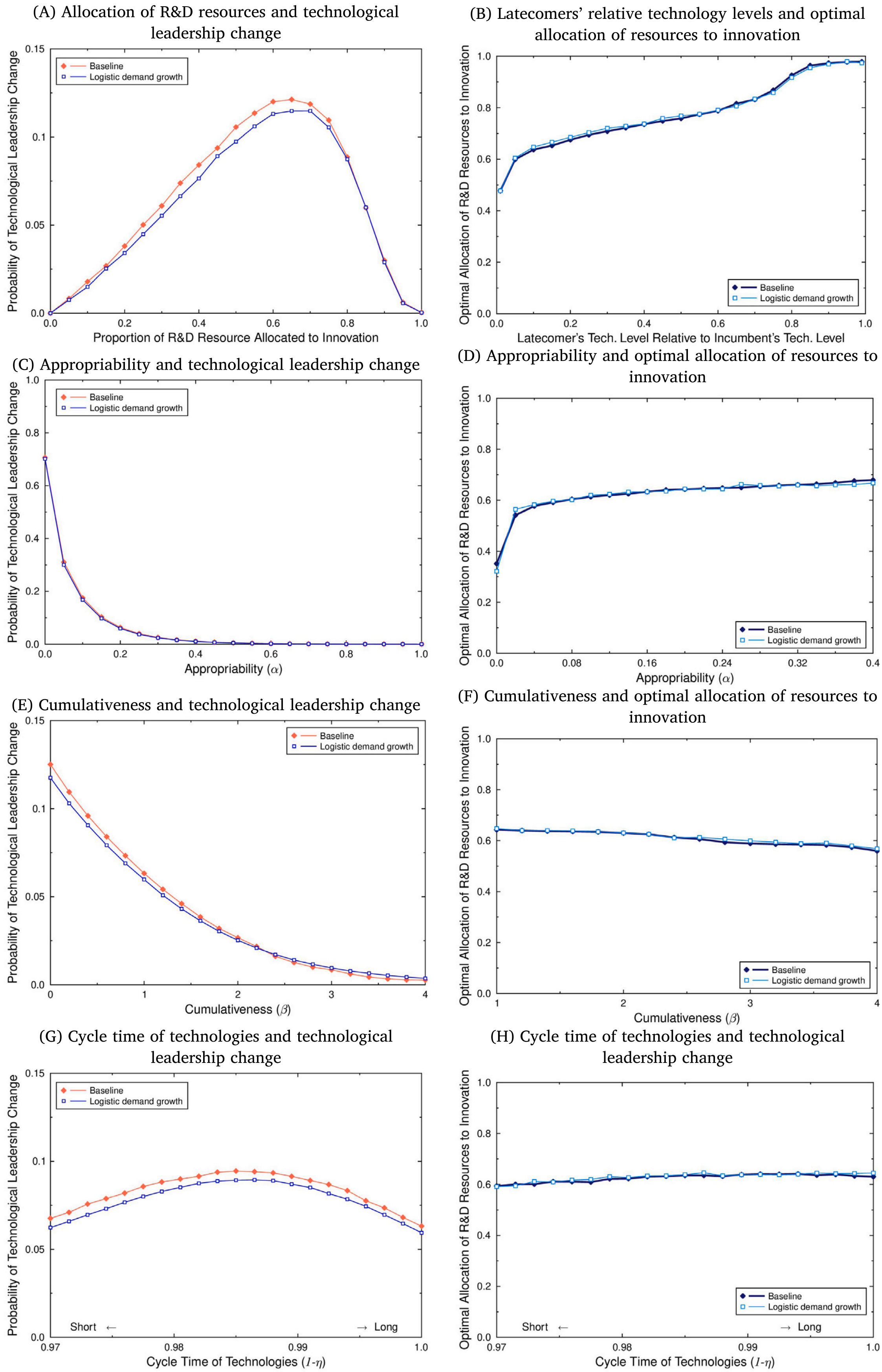


Fig. H.3. Logistic Growth of Demand

Appendix I. Sensitivity tests

Table I.1
Probability of technological leadership change with increasing demand.

(A) Demand growth: 0.3% per period

Technological regime			Probability of leadership change for latecomer
Appropriability	Cumulativeness	Cycle time of technologies	(latecomer's initial technology level is 10% of incumbent's)
High (0.3)	High (1.5)	Long (1.0)	1.97%
High (0.3)	High (1.5)	Moderate (0.985)	2.32%
High (0.3)	High (1.5)	Short (0.97)	1.25%
High (0.3)	Low (0.5)	Long (1.0)	5.15%
High (0.3)	Low (0.5)	Moderate (0.985)	23.23%
High (0.3)	Low (0.5)	Low (0.2)	21.30%
Low (0.1)	High (1.5)	Long (1.0)	15.31%
Low (0.1)	High (1.5)	Moderate (0.985)	16.26%
Low (0.1)	High (1.5)	Low (0.2)	3.51%
Low (0.1)	Low (0.5)	Long (1.0)	25.38%
Low (0.1)	Low (0.5)	Moderate (0.985)	38.15%
Low (0.1)	Low (0.5)	Low (0.2)	36.40%

(B) Demand growth: 0.6% per period

Technological regime			Probability of leadership change for latecomer
Appropriability	Cumulativeness	Cycle time of technologies	(latecomer's initial technology level is 10% of incumbent's)
High (0.3)	High (1.5)	Long (1.0)	2.56%
High (0.3)	High (1.5)	Moderate (0.985)	2.96%
High (0.3)	High (1.5)	Short (0.97)	1.52%
High (0.3)	Low (0.5)	Long (1.0)	6.32%
High (0.3)	Low (0.5)	Moderate (0.985)	27.39%
High (0.3)	Low (0.5)	Low (0.2)	25.51%
Low (0.1)	High (1.5)	Long (1.0)	18.29%
Low (0.1)	High (1.5)	Moderate (0.985)	19.67%
Low (0.1)	High (1.5)	Low (0.2)	4.20%
Low (0.1)	Low (0.5)	Long (1.0)	28.79%
Low (0.1)	Low (0.5)	Moderate (0.985)	43.00%
Low (0.1)	Low (0.5)	Low (0.2)	41.59%

(C) Demand growth: 0.9% per period

Technological regime			Probability of leadership change for latecomer
Appropriability	Cumulativeness	Cycle time of technologies	(latecomer's initial technology level is 10% of incumbent's)
High (0.3)	High (1.5)	Long (1.0)	3.33%
High (0.3)	High (1.5)	Moderate (0.985)	3.82%
High (0.3)	High (1.5)	Short (0.97)	1.87%
High (0.3)	Low (0.5)	Long (1.0)	7.54%
High (0.3)	Low (0.5)	Moderate (0.985)	32.00%
High (0.3)	Low (0.5)	Low (0.2)	29.71%
Low (0.1)	High (1.5)	Long (1.0)	22.90%
Low (0.1)	High (1.5)	Moderate (0.985)	23.38%
Low (0.1)	High (1.5)	Low (0.2)	4.99%
Low (0.1)	Low (0.5)	Long (1.0)	31.91%
Low (0.1)	Low (0.5)	Moderate (0.985)	47.47%
Low (0.1)	Low (0.5)	Low (0.2)	46.09%

Note: The relationships between the technological regime variables and the probability of leadership change are sustained *over all possible cases in the technological regime.*

Table I.2
Allocation of resources to innovation with increasing demand.

(A) Demand growth: 0.3% per period

Technological regime			Optimal allocation of resources to innovation (p^*)		
Appropriability	Cumulativeness	Cycle time of technologies	Low technology level for latecomer relative to incumbent (0.1 level)	Moderate technology level for latecomer relative to incumbent (0.5 level)	High technology level for latecomer relative to incumbent (0.9 level)
High (0.3)	High (1.5)	Long (1.0)	0.65	0.79	0.98
High (0.3)	High (1.5)	Moderate (0.985)	0.63	0.78	0.97
High (0.3)	High (1.5)	Short (0.97)	0.57	0.75	0.97
High (0.3)	Low (0.5)	Long (1.0)	0.69	0.82	0.99
High (0.3)	Low (0.5)	Moderate (0.985)	0.68	0.82	0.98
High (0.3)	Low (0.5)	Short (0.97)	0.64	0.82	0.96
Low (0.1)	High (1.5)	Long (1.0)	0.61	0.72	0.87
Low (0.1)	High (1.5)	Moderate (0.985)	0.59	0.70	0.91
Low (0.1)	High (1.5)	Short (0.97)	0.52	0.66	0.94
Low (0.1)	Low (0.5)	Long (1.0)	0.61	0.72	0.84
Low (0.1)	Low (0.5)	Moderate (0.985)	0.61	0.71	0.82
Low (0.1)	Low (0.5)	Short (0.97)	0.58	0.72	0.84

(B) Demand growth: 0.6% per period

Technological regime			Optimal allocation of resources to innovation (p^*)		
Appropriability	Cumulativeness	Cycle time of technologies	Low technology level for latecomer relative to incumbent (0.1 level)	Moderate technology level for latecomer relative to incumbent (0.5 level)	High technology level for latecomer relative to incumbent (0.9 level)
High (0.3)	High (1.5)	Long (1.0)	0.66	0.80	0.99
High (0.3)	High (1.5)	Moderate (0.985)	0.64	0.77	0.98
High (0.3)	High (1.5)	Short (0.97)	0.58	0.76	0.96
High (0.3)	Low (0.5)	Long (1.0)	0.69	0.84	0.99
High (0.3)	Low (0.5)	Moderate (0.985)	0.69	0.82	0.97
High (0.3)	Low (0.5)	Short (0.97)	0.63	0.81	0.96
Low (0.1)	High (1.5)	Long (1.0)	0.62	0.73	0.85
Low (0.1)	High (1.5)	Moderate (0.985)	0.59	0.71	0.89
Low (0.1)	High (1.5)	Short (0.97)	0.53	0.67	0.93
Low (0.1)	Low (0.5)	Long (1.0)	0.63	0.72	0.84
Low (0.1)	Low (0.5)	Moderate (0.985)	0.60	0.70	0.80
Low (0.1)	Low (0.5)	Short (0.97)	0.57	0.71	0.82

(C) Demand growth: 0.9% per period

Technological regime			Optimal allocation of resources to innovation (p^*)		
Appropriability	Cumulativeness	Cycle time of technologies	Low technology level for latecomer relative to incumbent (0.1 level)	Moderate technology level for latecomer relative to incumbent (0.5 level)	High technology level for latecomer relative to incumbent (0.9 level)
High (0.3)	High (1.5)	Long (1.0)	0.67	0.81	0.99
High (0.3)	High (1.5)	Moderate (0.985)	0.64	0.79	0.98
High (0.3)	High (1.5)	Short (0.97)	0.60	0.77	0.97
High (0.3)	Low (0.5)	Long (1.0)	0.71	0.85	0.99
High (0.3)	Low (0.5)	Moderate (0.985)	0.69	0.82	0.97
High (0.3)	Low (0.5)	Short (0.97)	0.63	0.80	0.95
Low (0.1)	High (1.5)	Long (1.0)	0.62	0.72	0.84
Low (0.1)	High (1.5)	Moderate (0.985)	0.60	0.71	0.88
Low (0.1)	High (1.5)	Short (0.97)	0.54	0.68	0.93
Low (0.1)	Low (0.5)	Long (1.0)	0.62	0.72	0.83
Low (0.1)	Low (0.5)	Moderate (0.985)	0.60	0.70	0.79
Low (0.1)	Low (0.5)	Short (0.97)	0.57	0.70	0.80

Note: The ‘‘imitation to innovation’’ strategy is useful for technological leadership change in all possible cases.
In each case, as the latecomer’s technology level increases, the optimal amount of resources allocated to innovation gradually increases.

Table I.3
Probability of technological leadership change with decreasing demand.

(A) Demand growth: −0.3% per period

Technological regime			Probability of leadership change for latecomer
Appropriability	Cumulativeness	Cycle time of technologies	(latecomer's initial technology level is 10% of incumbent's)
High (0.3)	High (1.5)	Long (1.0)	1.17%
High (0.3)	High (1.5)	Moderate (0.985)	1.44%
High (0.3)	High (1.5)	Short (0.97)	0.84%
High (0.3)	Low (0.5)	Long (1.0)	3.27%
High (0.3)	Low (0.5)	Moderate (0.985)	15.64%
High (0.3)	Low (0.5)	Low (0.2)	14.59%
Low (0.1)	High (1.5)	Long (1.0)	9.18%
Low (0.1)	High (1.5)	Moderate (0.985)	10.67%
Low (0.1)	High (1.5)	Low (0.2)	2.56%
Low (0.1)	Low (0.5)	Long (1.0)	18.71%
Low (0.1)	Low (0.5)	Moderate (0.985)	28.64%
Low (0.1)	Low (0.5)	Low (0.2)	26.87%

(B) Demand growth: −0.6% per period

Technological regime			Probability of leadership change for latecomer
Appropriability	Cumulativeness	Cycle time of technologies	(latecomer's initial technology level is 10% of incumbent's)
High (0.3)	High (1.5)	Long (1.0)	0.99%
High (0.3)	High (1.5)	Moderate (0.985)	1.26%
High (0.3)	High (1.5)	Short (0.97)	0.75%
High (0.3)	Low (0.5)	Long (1.0)	2.77%
High (0.3)	Low (0.5)	Moderate (0.985)	13.58%
High (0.3)	Low (0.5)	Low (0.2)	12.13%
Low (0.1)	High (1.5)	Long (1.0)	8.57%
Low (0.1)	High (1.5)	Moderate (0.985)	9.57%
Low (0.1)	High (1.5)	Low (0.2)	2.36%
Low (0.1)	Low (0.5)	Long (1.0)	17.06%
Low (0.1)	Low (0.5)	Moderate (0.985)	26.30%
Low (0.1)	Low (0.5)	Low (0.2)	24.67%

(C) Demand growth: −0.9% per period

Technological regime			Probability of leadership change for latecomer
Appropriability	Cumulativeness	Cycle time of technologies	(latecomer's initial technology level is 10% of incumbent's)
High (0.3)	High (1.5)	Long (1.0)	0.84%
High (0.3)	High (1.5)	Moderate (0.985)	1.09%
High (0.3)	High (1.5)	Short (0.97)	0.63%
High (0.3)	Low (0.5)	Long (1.0)	2.32%
High (0.3)	Low (0.5)	Moderate (0.985)	11.63%
High (0.3)	Low (0.5)	Low (0.2)	10.70%
Low (0.1)	High (1.5)	Long (1.0)	7.45%
Low (0.1)	High (1.5)	Moderate (0.985)	8.53%
Low (0.1)	High (1.5)	Low (0.2)	2.15%
Low (0.1)	Low (0.5)	Long (1.0)	15.23%
Low (0.1)	Low (0.5)	Moderate (0.985)	23.99%
Low (0.1)	Low (0.5)	Low (0.2)	22.31%

Note: The relationships between the technological regime variables and the probability of leadership change are sustained *are over all possible cases in the technological regime.*

Table I.4
Allocation of resources to innovation with decreasing demand.

(A) Demand growth: −0.3% per period

Technological regime			Optimal allocation of resources to innovation (p^*)		
Appropriability	Cumulativeness	Cycle time of technologies	Low technology level for latecomer relative to incumbent (0.1 level)	Moderate technology level for latecomer relative to incumbent (0.5 level)	High technology level for latecomer relative to incumbent (0.9 level)
High (0.3)	High (1.5)	Long (1.0)	0.62	0.77	0.98
High (0.3)	High (1.5)	Moderate (0.985)	0.61	0.77	0.97
High (0.3)	High (1.5)	Short (0.97)	0.56	0.74	0.96
High (0.3)	Low (0.5)	Long (1.0)	0.65	0.81	0.99
High (0.3)	Low (0.5)	Moderate (0.985)	0.67	0.81	0.98
High (0.3)	Low (0.5)	Short (0.97)	0.62	0.82	0.97
Low (0.1)	High (1.5)	Long (1.0)	0.61	0.71	0.89
Low (0.1)	High (1.5)	Moderate (0.985)	0.58	0.69	0.92
Low (0.1)	High (1.5)	Short (0.97)	0.53	0.65	0.94
Low (0.1)	Low (0.5)	Long (1.0)	0.61	0.71	0.87
Low (0.1)	Low (0.5)	Moderate (0.985)	0.61	0.72	0.85
Low (0.1)	Low (0.5)	Short (0.97)	0.58	0.73	0.88

(B) Demand growth: −0.6% per period

Technological regime			Optimal allocation of resources to innovation (p^*)		
Appropriability	Cumulativeness	Cycle time of technologies	Low technology level for latecomer relative to incumbent (0.1 level)	Moderate technology level for latecomer relative to incumbent (0.5 level)	High technology level for latecomer relative to incumbent (0.9 level)
High (0.3)	High (1.5)	Long (1.0)	0.60	0.76	0.98
High (0.3)	High (1.5)	Moderate (0.985)	0.59	0.75	0.97
High (0.3)	High (1.5)	Short (0.97)	0.54	0.72	0.96
High (0.3)	Low (0.5)	Long (1.0)	0.63	0.81	0.99
High (0.3)	Low (0.5)	Moderate (0.985)	0.65	0.81	0.98
High (0.3)	Low (0.5)	Short (0.97)	0.60	0.81	0.98
Low (0.1)	High (1.5)	Long (1.0)	0.58	0.70	0.89
Low (0.1)	High (1.5)	Moderate (0.985)	0.56	0.68	0.92
Low (0.1)	High (1.5)	Short (0.97)	0.49	0.65	0.94
Low (0.1)	Low (0.5)	Long (1.0)	0.59	0.70	0.87
Low (0.1)	Low (0.5)	Moderate (0.985)	0.58	0.71	0.86
Low (0.1)	Low (0.5)	Short (0.97)	0.56	0.72	0.88

(C) Demand growth: −0.9% per period

Technological regime			Optimal allocation of resources to innovation (p^*)		
Appropriability	Cumulativeness	Cycle time of technologies	Low technology level for latecomer relative to incumbent (0.1 level)	Moderate technology level for latecomer relative to incumbent (0.5 level)	High technology level for latecomer relative to incumbent (0.9 level)
High (0.3)	High (1.5)	Long (1.0)	0.57	0.76	0.98
High (0.3)	High (1.5)	Moderate (0.985)	0.57	0.76	0.97
High (0.3)	High (1.5)	Short (0.97)	0.52	0.72	0.96
High (0.3)	Low (0.5)	Long (1.0)	0.60	0.80	0.99
High (0.3)	Low (0.5)	Moderate (0.985)	0.62	0.80	0.98
High (0.3)	Low (0.5)	Short (0.97)	0.57	0.80	0.97
Low (0.1)	High (1.5)	Long (1.0)	0.57	0.70	0.90
Low (0.1)	High (1.5)	Moderate (0.985)	0.53	0.69	0.93
Low (0.1)	High (1.5)	Short (0.97)	0.49	0.65	0.94
Low (0.1)	Low (0.5)	Long (1.0)	0.57	0.70	0.87
Low (0.1)	Low (0.5)	Moderate (0.985)	0.57	0.71	0.86
Low (0.1)	Low (0.5)	Short (0.97)	0.55	0.71	0.88

Note: The "imitation to innovation" strategy is useful for technological leadership change in all possible cases.
In each case, as the latecomer's technology level increases, the optimal amount of resources allocated to innovation gradually increases.

Table I.5
Probability of technological leadership change with logistic growth of demand.

Technological regime			Probability of leadership change for latecomer
Appropriability	Cumulativeness	Cycle time of technologies	(latecomer's initial technology level is 10% of incumbent's)
High (0.3)	High (1.5)	Long (1.0)	1.41%
High (0.3)	High (1.5)	Moderate (0.985)	1.70%
High (0.3)	High (1.5)	Short (0.97)	0.93%
High (0.3)	Low (0.5)	Long (1.0)	3.82%
High (0.3)	Low (0.5)	Moderate (0.985)	18.51%
High (0.3)	Low (0.5)	Low (0.2)	16.70%
Low (0.1)	High (1.5)	Long (1.0)	10.95%
Low (0.1)	High (1.5)	Moderate (0.985)	12.59%
Low (0.1)	High (1.5)	Low (0.2)	2.60%
Low (0.1)	Low (0.5)	Long (1.0)	21.06%
Low (0.1)	Low (0.5)	Moderate (0.985)	32.15%
Low (0.1)	Low (0.5)	Low (0.2)	29.94%

Note: The relationships between the technological regime variables and the probability of leadership change are sustained *are over all possible cases in the technological regime.*

Table I.6
Allocation of resources to innovation with logistic growth of demand.

Technological regime			Optimal allocation of resources to innovation (p^*)		
Appropriability	Cumulativeness	Cycle time of technologies	Low technology level for latecomer relative to incumbent (0.1 level)	Moderate technology level for latecomer relative to incumbent (0.5 level)	High technology level for latecomer relative to incumbent (0.9 level)
High (0.3)	High (1.5)	Long (1.0)	0.64	0.78	0.98
High (0.3)	High (1.5)	Moderate (0.985)	0.64	0.77	0.97
High (0.3)	High (1.5)	Short (0.97)	0.58	0.75	0.95
High (0.3)	Low (0.5)	Long (1.0)	0.67	0.81	0.99
High (0.3)	Low (0.5)	Moderate (0.985)	0.68	0.82	0.97
High (0.3)	Low (0.5)	Short (0.97)	0.63	0.81	0.96
Low (0.1)	High (1.5)	Long (1.0)	0.61	0.72	0.87
Low (0.1)	High (1.5)	Moderate (0.985)	0.60	0.71	0.91
Low (0.1)	High (1.5)	Short (0.97)	0.53	0.68	0.93
Low (0.1)	Low (0.5)	Long (1.0)	0.62	0.73	0.84
Low (0.1)	Low (0.5)	Moderate (0.985)	0.62	0.73	0.84
Low (0.1)	Low (0.5)	Short (0.97)	0.58	0.72	0.86

Note: The "imitation to innovation" strategy is useful for technological leadership change in all possible cases.
In each case, as the latecomer's technology level increases, the optimal amount of resources allocated to innovation gradually increases.

Appendix J. History of Samsung's DRAM development

Products	Samsung's introduction	Incumbents' introduction	Gap	Line width
64K	Nov. 1983	May. 1978	5.5 years behind	2.4 μm
256K	Oct. 1984	April. 1979	4.5 years behind	1.1 μm
1M	Jul. 1986	Jul. 1984	2 years behind	0.7 μm
4M	Feb. 1988	Aug. 1987	6 months behind	0.5 μm
16M	Aug. 1990	July. 1990	1 month behind	0.4 μm
64M	Sep. 1992	–	Ahead	0.35 μm
256M	Aug. 1994	–	Ahead	0.25 μm
1G	Oct. 1996	–	Ahead	0.18 μm
4G	Feb. 2001	–	Ahead	0.13 μm

Note: Data in the table are from Samsung Homepage and Song (2008).

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