경제학박사학위논문

An Evolutionary Model of Changes in Industrial Leadership and Catch-up by Latecomers

-Collective Learning-by-doing, Endogenous Innovation, and the “Incumbent Trap”-

산업주도권 이동과 후발자의 추격에 관한 진화경제학적 모델

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기 지 훈

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이 논문을 경제학박사학위논문으로 제출함

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Abstract

When a radical technological innovation arrives in an industry, incumbents tend to fall behind because they are locked-in to the established technology that they have mastered. Meanwhile, latecomers adopt the new technology. As a result, industrial leadership tends to shift from incumbents to latecomers as new technology dethrones the established one. This tendency is termed as the "incumbent trap" or "incumbent's curse" in the literature. The incumbent trap phenomenon has been observed repeatedly in the history of leadership changes in various industries.

However, this phenomenon is not universal. There are many counterexamples in which leadership doesn't shift from incumbent leaders to latecomers or followers after a radical technological change. The literature has insufficiently identified the boundary conditions for the incumbent trap phenomenon, which has resulted in controversy and confusion in the literature. Especially, the incumbent trap research has largely unaddressed "collective learning-by-doing" effects on the incumbent trap dynamics. In many industries, firms within the same technology camp benefit from externalities of other firm's learning-by-doing, which I term collective learning-by-doing. The present study identifies boundary conditions for the incumbent trap dynamics in which collective learning-by-doing plays a role.

For this purpose, the present study focuses on two factors: 1) the basic productivity of new technology and 2) the expected proportion of firms adopting the new technology. I argue that industrial leadership is more likely to shift from incumbent leaders to followers or latecomers if the basic productivity of new technology is neither too high nor too low (Hypothesis 1). In addition, I argue that

leadership change is more likely to occur if the two factors have opposite values: the basic productivity of new technology is high (low) and the expected proportion of firms adopting the new technology is low (high) (Hypothesis 2).

To support my theoretical arguments, I build an agent-based simulation model in an evolutionary economics perspective. Two situations are modeled. In the basic model, a radical innovation is exogenously given to firms at a certain period of time, and afterwards in each period, each firm decides whether to adopt this innovation or not in its search for more profit. Their adoption decisions are based on the comparison of the expected productivity of their currently employing technology and that of the new technology. Adding to this setting, an extended model allows for firms to do R&D so that the firms can improve the productivity of the technology they are employing, which I term as “endogenous innovation”.

Hypotheses 1 and 2 are supported both in the basic and the extend models. In the extended model, the probability of leadership change decreases overall, compared with those of the basic model, in which innovation are only exogenous to firms. This is because incumbent leaders have superior R&D capabilities to followers, which helps incumbents defend their leadership.

The present study makes three contributions. First, it links the incumbent trap phenomenon to externalities caused by firm's learning-by-doing, or collective learning-by-doing. Second, I demonstrate numerically that the initial gap in productivity between old and new technologies affects the probability of changes in industrial leadership from incumbents to latecomers. Third, the present study demonstrates in a formal model R&D effects in the incumbent trap phenomenon.

Keywords: catch-up; radical innovation; technology adoption; agent-based model; productivity; R&D

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1. Introduction

When a radical technological innovation arrives in an industry, incumbents tend to stay with the old technology while latecomers or followers adopt the new technology. As a result, industrial leadership tends to shift from incumbent firms to the latecomers or followers (Christensen 1997, Lee and Malerba 2016a, Perez and Soete 1988). This tendency is termed as "incumbent trap" (Lee and Malerba 2016a) or “incumbent’s curse” (Chandy and Tellis 2000). The notion of incumbent trap is an interpretation of the notion of “incumbent’s curse” (Chandy and Tellis 2000) from a perspective of latecomer’s catch-up. When a radical innovation arrives in an industry, the innovation tends to be adopted first by latecomers.

According to Lee and Malerba, incumbents have rational reasons to stay with the old technology. Incumbents have invested to the old technology so that have mastered the old technology. New technology is normally inferior to the old technology incumbents have mastered and, moreover, it is uncertain for the new technology to surpass the old technology in the future. Thus, it can be a rational decision for incumbents not to adopt the initially inferior new technology but to stay with the old technology. On the other hand, latecomers are relatively free from their investment to the old technology because they entered the industry later than the incumbents so that normally they have made smaller investment to the old technology and thereby have achieved lower productivity with the old technology. Thus, for the latecomers, if even initially inferior new technology can give them a

higher productivity than the old technology, the latecomers switch to the new technology. And if the new technology takes off for some reasons, the latecomers which has adopted the new technology before incumbents take industrial leadership (in terms of market shares) as the new technology dethrones the old technology. There are many industrial cases of leadership change that can be explained by the incumbent trap thesis (e.g., Giachetti and Marchi 2016, Kang and Song 2016, Lee and Ki 2016, Shin 2016). Incumbent trap was referred to as “conventional wisdom” (Chandy and Tellis 2000) or a “truism” (Taylor and Helfat 2009).

However, the incumbent trap phenomenon is not universal (Chandy and Tellis 2000, Hill and Rothaermel 2003). In many examples, even after a radical technological change, incumbents maintain their leadership or survive. Against this backdrop, there have been attempts to identify the boundary conditions under which incumbent's late adoption leads to leadership change (Landini et al 2016, Malerba et al. 2007, Hill and Rothaermel 2003, Roy and Sarkar 2016, Obal 2013, Ansari and Krop 2012).

My work aims to identify such boundary conditions by focusing on collective learning, which has been largely unexplored in the literature on the incumbent trap. Collective learning is defined here as learning made by the group of the firms adopting the same technology. The effects of collective learning such as increases in productivity are shared by all the firms adopting the same technology. Moreover, new joiners can also enjoy the technology improvement which is achieved before they join to the camp of the technology.

For example, as one firm uses production equipment, the firm reports bugs or suggestions to the equipment makers. Then the makers fix the bugs and upgrade the equipment by reviewing the suggestions. Then the upgraded version of the equipment can be sold to other firms who want to use the same technology which is embodied in the equipment. This is one possible form of collective learning. Normally, the more firms adopt a technology, the more quickly and the higher the technology improves. The improved technology will attract more firms; due to the new joiner, the improvement of the new technology accelerates. Over time, this self-reinforcing process will eventually make the new technology good enough to attract existing leaders, who have the highest tendency to stay with the old technology among all the firms in the industry.

Collective learning effects on the leadership change dynamics are found in many industries. For example, in the steel industry, when an earth-breaking process technology, Basic Oxygen Furnace (BOF), appeared in the industry in the 1950s, with? By the coordination of the Japanese government, latecomer Japanese steelmakers collectively adopted the BOF, while then-incumbent leader American steelmakers stayed with the old technology Open-hearth Furnace (OHF) they have mastered. The BOF, which was initially inferior to the OHF, quickly improved. This is because one firm's follow-on innovations are intentionally and unintentionally shared by other Japanese steelmakers. Then another firm improves the technology based on the last improvement by another firm. This process has repeated so that the initially inferior BOF has improved with increasing speed. As a result, the BOF has replaced the existing old technology OHF. In recent years, OLED technology has arrived to the TV industry. However, OLED technology has attracted only one major firm, LG Display. The rest of the major firms including Samsung Display have not

joined to the camp of the OLED technology. Thus the speed of the improvement of the new technology is to slow to replace the existing LCD technology. If I assume that there exists collective learning among firms adopting the same technology, the camp of the OLED technology needs more firms to achieve a higher size of collective learning effects. The above-mentioned two examples suggest that the importance of collective learning on leadership change dynamics following radical technological changes. However, the literature on the incumbent trap has largely unaddressed the boundary conditions of leadership change when collective learning effects exist.

My theoretical work in this study focuses on two factors: (1) basic productivity of new technology and (2) the expected proportion of firms adopting the new technology. The former captures the initial degree of inferiority (or superiority) of the new technology compared with the established one, which, in turn, indicates the initial gap in productivity between the two technologies. The latter captures the expected size of collective learning-by-doing effects on increases in productivity of new technology. I demonstrate numerically that these two factors determine the boundary conditions for changes in industrial leadership from incumbents to latecomers if there exist collective learning-by-doing effects.

I conduct three simulation experiments. In the first simulation experiment, I investigate only the effects of the first factor, or the relative level of the basic productivity of new technology. When the basic productivity of new technology is neither too high nor too low, the new technology is initially adopted by neither too high nor low proportion of firms, or followers, while incumbent leaders decide to remain with the existing technology. Then the latecomers which have adopted the new technology begin to improve their productivity while the leaders keep using the

old technology. Due to the collective learning for the new technology, the expected productivity of the new technology improves enough to attract the incumbent leaders, and thus the leaders eventually switch to the new technology. But it's too late. As the old leaders did in the old technological paradigm so that they benefitted from the first mover advantages with the old technology, early adopting latecomers have already achieved higher productivity of the new technology when the leaders have just switched to the new technology. In these cases, leadership change tends to occur.

On the other hand, when the basic productivity of a new technology is too high, incumbent leaders also recognize that the new technology has a potential to be the next dominant technology so that adopt the new technology not long after followers have adopted the new technology. As a result, the leaders also adopt the new technology soon after the followers did, and thus overcome their short late adoption and defend their leadership due to their superior capabilities such as capital, human resources to followers.

In the second simulation experiment, I investigate the combined effects of the two factors. When the basic productivity of a new technology is high (low) and the expected adoption proportion of the new technology is low (high), their effects are balanced by each other in firm′s calculation of the expected productivity of a new technology. As a result, the new technology is initially adopted by neither too high nor low proportion of followers while incumbent leaders decide to remain with the existing technology, which in turn, leads to the new technology and its adopters rising to technological and market dominance, respectively. In this situation, leadership change tends to occur.

On the other hand, when both factors are high or low, the probability of leadership change is relatively low. When both factors are high, incumbent leaders adopt the new technology as quickly as followers do and thus maintain their leadership even in the era of the new technology. When both factors are low, the new technology fails to survive, and incumbent leaders maintain their leadership in the continuing era of the existing technology.

So far, in the model, a radical innovation is *exogenously* given to firms at a certain period of time ("exogenous innovation model"). In the third simulation experiment, I extend the model to allow for a firm to conduct in-house innovation activities ("endogenous innovations") so that the firms can improve the productivity of the technology they are employing. I find the probability of leadership change decreases in overall compared with the probability of the exogenous innovation model.

My model is an evolutionary model, following a tradition of Nelson and Winter (1982). However, in my model, firms make intentionally the adoption decision of new technology. In other evolutionary models, firms *search* new technology with a random probability (Nelson and Winter 1982, Landini et al. 2016).

The present study makes three contributions. First, it links the incumbent trap phenomenon to externalities caused by firm's learning-by-doing, or collective learning-by-doing. Collective learning-by-doing plays an important role in the incumbent trap dynamics. However, often observed in the reality, collective learning-by-doing has been largely missed in the literature on the incumbent trap phenomenon. By employing computational analysis, I am able to investigate

collective learning-by-doing (effects) in the incumbent trap phenomenon, which is often observed in the reality but largely missed in the literature.

Second, I demonstrate numerically that the initial gap in productivity between old and new technologies affects the probability of changes in industrial leadership from incumbents to latecomers. The literature pays little attention to the relationship between the initial productivity gap between the old and new technologies and the resultant probability of leadership change from incumbents to latecomers. This is a surprise given that the concept of productivity is important in economics. Taking advantage of computer simulation, I find the degree of initial inferiority of new technology matters in a way different from my naïve intuition, which is formed without investigation on the underlying mechanism. simulation model enabled us to investigate the underlying mechanism.

Third, the present study demonstrates in a formal model the effects of R&D, one of the most effective responses of incumbents to radical technological changes. Despite of the importance of the role of the R&D in the incumbent trap phenomenon, there has been no attempt to demonstrate the role of the R&D in the incumbent trap phenomenon in a formal model. The present study demonstrates in a formal model that incumbents are able to defend leadership by taking advantage of their superior R&D capabilities to latecomers after radical technological change.

The Organization in brief

In Chapter 2, I survey the literature in order to know the state-of-the-art research on my question and to find a research gap that I attempt to fill. In Chapter 3, I propose

three hypotheses for the boundary conditions of the incumbent trap. In Chapter 4, I introduce a methodology and a perspective that I use to support my claims. In Chapter 5, I develop a model to test the hypotheses. In Chapter 6 and 7, I provide simulation results that support the hypotheses. In Chapter 8, I conclude the study.

2. Literature Review and Theory

The gap the present study attempts to fill can be better understood if I know the development of the literature on the incumbent trap. I survey the literature in two fields. The first field is innovation studies in economics and management. It is this field in which the incumbent trap has been mainly explored. Examples of seminal works include (Christensen 1997; Foster 1986; Perez and Soete 1988; Tushman and Anderson 1986; Utterback 1994).

The second field I survey is "economics of catch-up." Economics of catch-up is an associated field of economics of innovation and focuses on latecomer's catch-up with an incumbent at various levels (e.g. firm- and country-levels). The field regards knowledge as a driving force for economic catch-up. See (Lee 2013) to understand the field in general. Economics of catch-up has been increasingly using the concept of incumbent trap to explain its main theme, or economic catch-up by latecomer firms or countries (for example, Lee et al. 2005, Lee and Malerba 2016a), and Lee et al. 2014)

My literature review first goes into the field of innovation studies in economics and management in order to understand in general how the topic of the incumbent trap has been explored. Then my review goes into the field of economics of catch-up in order to pinpoint the research gap the present study attempts to fill.

2.1. Incumbent Trap in Economics of Catch-up

So far I have reviewed the topic of incumbent trap in the literature of innovation. Now I survey the literature of economics of catch-up, an associated of economics of

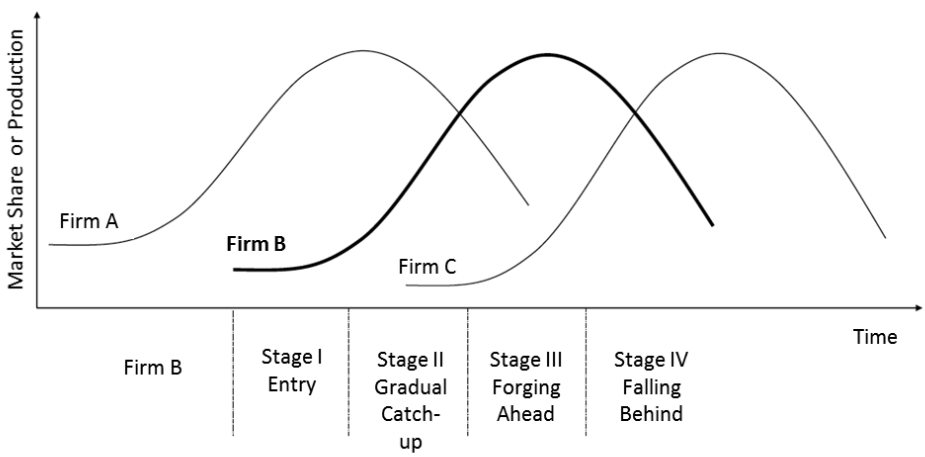
innovation because incumbent trap is one of critical factors in latecomer's catch-up and economics of catch-up is the field the present study primarily contributes to.

Incumbent trap has long been an important topic in economics of catch-up because the arrival of new technology serves as a "window of opportunity" for a latecomer to catch up with an incumbent (Perez and Soete 1988). The notion of windows of opportunity refers "to the role of the rise of new techno-economic paradigms to generate the leapfrogging of latecomers who then take advantage of a new paradigm and surpass the incumbents" (Lee and Malerba 2016a). "For example, the shift from analogue to the digital era serve as the critical momentum through which Korean electronics firms wrested control of the market from Japanese firms (see the cases of display industry analysed in Lee et al. 2005)" (Lee and Malerba 2016a). The concepts of incumbent trap and window of opportunity are roughly synonymous because incumbent trap is initiated by the arrival of new technology. In the field of economics of catch-up, the concept of incumbent trap has been increasingly used to explain the industrial cases of latecomer firms or countries' catch up with incumbents (Giachetti and Marchi 2016; Kang and Song 2016; Lee and Ki 2016; Lee et al. 2005; Lee and Malerba 2016a; Lee et al. 2014; Shin 2016).

Recently in this field, a theory that synthesizes existing knowledge on the principles of latecomer's catch-up has proposed by Lee and Malerba (2016a). The theory's name is catch-up cycle theory. In the theory, incumbent trap plays a key role. The catch-up cycle theory explains the whole process of latecomer's catch-up and industrial leadership change from incumbents to latecomers. A catch-up cycle consists of four stages: Stage 1: Entry, Stage 2: gradual catch-up, Stage 3: forging ahead, and Stage 4: falling behind. See Figure 1. It is Stage 3: forging ahead where

the destiny of the catch-up cycle is determined. If the latecomer succeeds in forging ahead, the latecomer achieves industrial leadership. The catch-up cycle names this pattern a normal catch-up. If fails in forging ahead, the latecomer fails to reach the leadership position. The catch-up cycle theory names this pattern an aborted catch-up. The catch-up cycle theory argues that the arrival of new technology and thereby incumbent trap is a key ingredient of latecomer's successful forging ahead.

Figure 1. Stages in a Catch-up Cycle



Source: Adapted from Lee and Malerba (2016a).

Catch-up cycle theory provides an explanation on why an incumbent trap occurs. Its explanation is a holistic view combining economic, organizational, and strategic reasons of an incumbent and the attacker's advantage of a latecomer. According to Lee and Malerba (2016a),

> The incumbent remains with the existing technology because its capabilities and investments are related to such technology. Moreover, in their early days, new technologies are often inferior or subject to a greater degree of uncertainty (as exemplified by the S-Curve path of technologies, see Chandy and Tellis, 1998; Foster 1986). Thus, the leader continues to use the current technology and tends to ignore the possible devastating potential of new technologies or products, as in the case of disruptive innovations (Christensen, 1997). Finally, the new competences required for the new technology may differ drastically from the ones utilised by the established leader; hence, the incumbent is unable to change them promptly and effectively, as in the case of a competence-destroying technology (Tushman and Anderson, 1986; Henderson and Clark, 1990).

Lee and Malerba continue:

> By contrast, latecomers in terms of firms and systems may enjoy the advantage of being free to choose the most up-to-year or emerging technologies available.

According to them,

> Leadership changes occur even without any apparent 'mistake' from the incumbents. The system in which the current leaders are embedded may not be able to change or adapt to the new window, thus impeding or affecting the incumbents in a negative way.

Catch-up cycle theory is applied to explain successive changes in industrial leadership in six industries ("cell phones (Giachetti and Marchi, 2016), memory chip segment of semi-conductor (Shin, 2016), camera (Kang and Song, 2016), steel (Lee and Ki, 2016), mid-sized jets (Vertesy, 2016) and wine (Morrison and Rabellotti, 2016)" (Lee and Malerba 2016b)) Among the six case studies, incumbent traps have been observed in four (Mobile phone: Giachetti and Marchi, 2016, memory semiconductor: Shin, 2016, camera: Kang and Song, 2016, steel: Lee and Ki, 2016).

Landini et al. (2016) is a formal model of the "appreciative theory" (Nelson and Winter 1982: 46) of catch-up cycle. An appreciative theory "aims to provide a

‘causal explanation of observed patterns’” (Lee and Malerba 2016a) in an industrial dynamics of interest. By building a history-friendly model, Landini et al. (2016) find incumbent trap conditions regarding the characteristics of technology and incumbent's attribute and response to the arrival of a new technology. In specific, their simulation analysis reveals that:

> a) the more disruptive the new technology and the lower the incumbents’ capabilities, the greater the shake-up of market shares between the incumbents and the latecomers; b) a leadership change is more likely to occur when it coincides with certain responses to the window by the actors, such as a high lock-in behaviour on the side of incumbents; and c) a technology driven change of industrial leadership is more likely to occur in presence of increasing returns to technological investments.

Now, I can understand state-of-the-art research on the topic of incumbent trap in economics of catch-up. First, incumbent trap has been identified as a key ingredient in the theory of a change in industrial leadership and catch-up by latecomer firms and countries (Lee and Malerba 2016a). Second, industrial cases of industrial leadership change and catch-up have been increasingly explored by the catch-up cycle theory, in which incumbent trap plays a critical role (Giachetti and Marchi, 2016, Shin, 2016, Kang and Song, 2016, Lee and Ki, 2016). Lastly, the field of economics of catch-up attempts to identify supplementary conditions of incumbent trap (Landini et al. 2016). The last point is the same as in innovation studies (Adner and Snow 2010; Ansari and Krop 2012; Malerba et al. 2007; Obal 2013; Roy and Sarkar 2016). The present study finds a research gap regarding the third point.

2.2. Incumbent Trap in Innovation Studies

Incumbent trap is "a persistent theme in the literature on innovation." (Hill and Rothaermel 2003)

"A considerable body of research and writing has developed and supported" (Malerba et al. 2007) the phenomenon of incumbent trap "(e.g., Christensen 1997; Ghemawat 1991; Henderson 1993; Utterback 1994)" (Chandy and Tellis 2000).

Cases of incumbent trap "have been observed repeatedly over the years, in numerous studies (e.g., Abernathy & Utterback, 1978; Christensen, 1997; Cooper & Schendel, 1976; Foster, 1986; Henderson & Clark, 1990; Rosenbloom & Christensen, 1998; Sull, Tedlow, & Rosenbloom, 1997; Tripsas & Gavetti, 2000; Tushman & Anderson, 1986; Utterback, 1994)" (Hill and Rothaermel 2003).

"Scholars often attribute this decline to incumbents' failure to embrace the new technology. The reasons given to explain such failure include the differential economic incentives new entrants and incumbents confront, forces of inertia within incumbent firms, and the embeddedness of incumbents within an established industry network that does not initially value the new technology." (Hill and Rothaermel 2003) "These explanations complement each other and help to illuminate the phenomenon of incumbent inflexibility" (Hill and Rothaermel 2003). In addition, "the attacker's advantage" (Foster, 1986) also plays a role (Hill and Rothaermel 2003). For a detailed explanation on each reason, see Chandy and Tellis (2000) and Hill and Rothaermel (2003). Recently, behavioral economics also attempts to explain incumbent trap.

By the 1990s, with the evidence based on case studies, incumbent trap increasingly became a prominent stylized fact in the literature on innovation (Rosenbloom and Christensen 1994: 655, requoted from Chandy and Tellis 2000). This academic tendency reached its pick with Christensen's famous book Innovator's dilemma, published in 1997.

However, the literature had a turning point in the early 2000. Chandy and Tellis (2000) "reexamine the incumbent's curse using a historical analysis of a relatively large number of radical innovations in the consumer durables and office products categories" (Chandy and Tellis 2000). Their empirical results "suggest that incumbents or large firms are not necessarily doomed to obsolescence by nimble outsiders" (Chandy and Tellis 2000). In other words, "Results from the study suggest that conventional wisdom about the incumbent's curse may not always be valid" (Chandy and Tellis 2000).

Hill and Rothaermel (2003) argue incumbent trap "is not universal." (Hill and Rothaermel 2003). Incumbent firms "can and do adopt" (Hill and Rothaermel 2003) and maintain their leadership. "Rosenbloom (2000), for example, outlines in great detail how NCR, a dominant enterprise in the era of mechanical cash registers, was able to adapt and ultimately prosper after the arrival of electronics and then digital computing." (Hill and Rothaermel 2003) "Pointing to such cases, several authors have argued that the counterexamples to the standard model are too numerous to be ignored (Ahuja & Lampert, 2001; Leifer et al., 2000; Methe, Swaminathan, Mitchell, & Toyama, 1997; Rosenbloom & Christensen, 1998; Rothaermel, 2001)" (Hill and Rothaermel 2003).

Hill and Rothaermel (2003) "develop a set of falsifiable propositions" on "the characteristics of an incumbent enterprise that enable it to successfully embrace and use a radical technological innovation … for future empirical" test (Hill and Rothaermel 2003). Their propositions are drawn “from the literature on economics, organization theory, and strategic management” (Hill and Rothaermel 2003). Each category of Hill and Rothaermel (2003)'s propositions corresponds to economic, organizational, strategic reasons of incumbent trap, respectively. Their propositions "complement each other to provide a more holistic perspective on the phenomenon" of incumbent trap (Hill and Rothaermel 2003). The specific propositions are found in Appendix A.

Following Hill and Rothaermel (2003), there have been further attempts to identify supplementary conditions in which an incumbent trap occurs (Ansari and Krop 2012, Hill and Rothaermel 2003, Malerba et al. 2007, Obal 2013, Roy and Sarkar 2016). These attempts can be classified by the aspects on which a study finds supplementary conditions. Below is the brief description of such studies. Specific supplementary conditions of the respective studies are found in Appendix A.

The literature focusing on demand-side includes Malerba et al. (2007). Malerba et al. (2007) find those conditions on the characteristics of the demand. Malerba et al. (2007) argue that "[t]he successful introduction of radically new technology in an industry, where a dominant design and a small collection of dominant firms had emerged using the older technology, may be dependent upon the presence of a group of experimental customers, or diverse preferences and needs among potential users, or both" (Malerba et al. 2007). They use a history-friendly model to support their argument. A history-friendly model is an agent-based model to explore industrial

dynamics from a perspective of evolutionary economics. For details, see Malerba et al. 1999; Malerba and Orsenigo 2002.

The literature focusing on the interactions among the agents in the industry includes Obal (2013). As a possible explanation for incumbent's success "with the diffusion of disruptive technologies," Obal (2013) proposes "the influence of pre-existing levels of trust already developed between incumbents and potential buyers of disruptive technologies" (Obal 2013). "Due to pre-existing relationships, incumbents are generally more trusted by potential buyers than new entrant suppliers."[1] "By surveying 134 current and potential Software-as-a-Service (SaaS) users" (Obal 2013), [Obal] empirically shows "pre-existing levels of interorganizational trust influence the decision to adopt a disruptive technology."[2]

The literature focusing on the characteristics of an incumbent includes Roy and Sarkar (2016). Roy and Sarkar (2016) explore a factor that mitigates "the incumbent's curse during radical technological change" (Roy and Sarkar 2016). They "suggest that, during such a change, the presence of both in-house upstream knowledge and downstream market linkages, within a firm's boundary, has its advantages" (Roy and Sarkar 2016). By empirically testing their predictions in robotic industry, they "find that "preadapted" firms—the ones with prior relevant technological knowledge and with access to internal users of [the new technology]—

[1] Quoted from Highlights of the study at http://www.sciencedirect.com/science/article/pii/S0019850113001132, accessed July 18, 2016.

[2] Quoted from Highlights of the study at http://www.sciencedirect.com/science/article/pii/S0019850113001132, accessed July 18, 2016.

were the innovation leaders in the emerging new technology but were laggards in the old technology" (Roy and Sarkar 2016).

The literature that attempts to form a holistic view on the dynamics of incumbent trap. Ansari and Krop (2012) derive several propositions on in which conditions the probability of incumbent survival is higher "in the face of radical innovation" (Ansari and Krop 2012). Their propositions are under three categories: the "industry setting," the "incumbent firm" and the "challenge" from new entrants (Ansari and Krop 2012).

The above-mentioned literature review helps us to understand the recent situation of innovation study on incumbent trap. A research steam to find supplement conditions of incumbent trap continues even now from various aspects (e.g. demand, firm's characteristics) using various methodologies: simulation modeling (Malerba et al. 2007); empirical test (Obal 2013; Roy and Sarkar 2016); theorizing based on case studies (Adner and Snow 2010) and on the literature (Ansari and Krop 2012).

2.3. Collective Learning-by-doing

The literature reviews so far paved the way for identifying research gaps in the literature on the incumbent trap. Before elaborating the gaps, I first explain a relevant theoretical concept: "collective learning-by-doing."

The objective of my work is to identify such boundary conditions by focusing on "collective learning-by-doing," which has been largely unaddressed in the discussion of the incumbent trap. Collective learning-by-doing is defined here as an externality caused by individual firm's learning-by-doing. Collective learning-by-

doing I focus here is one that occurs among the firms using the *same* technology. A firm's learning-by-doing increases the firm's productivity of the technology it is employing but also has the added benefit of increasing the general level of knowledge on the technology within the industry. Thus, while a firm benefits from its own learning-by-doing, all the firms using the same technology benefit in the form of a commonly shared increase in their respective productivities.

After a new technology arrives in an industry, leadership change between incumbents and latecomers largely depends on the presence of the self-reinforcing process of collective learning-by-doing. When more firms adopt a new technology, collective learning-by-doing effects of the camp of the new technology get larger, and thus productivity benefits when a firm adopts the new technology increases more quickly, which in turn attract more new firms to the new technology from the camp of the old technology. This self-reinforcing process, or positive feedback process, will eventually attract incumbent leaders, who initially had the least incentive to adopt the new technology. Note that the self-reinforcing process of collective learning-by-doing lead the leaders to adopting the new technology which was initially unattractive to them. However, their adoption is too late. Latecomers have adopted the new technology much earlier so that have achieved higher productivities than the leaders who joined the new technology camp late. As a result, industrial leadership shifts from incumbent leaders to latecomers in the paradigm of the new technology.

Possible forms of collective learning-by-doing within a technology camp include equipment improvement by user firm's feedback. Suppose a firm use production equipment in which a certain production technology is embodied. As the

firm uses the equipment in its production, the firm obtains knowledge on how to improve its productivity of the equipment. The firm may need to report their ideas to the equipment supplier. Then the supplier upgrades the software or hardware of the equipment accordingly. Equipment improvements are now available to other firms which are employing or which are considering to adopt the technology. Costs (e.g. royalty) may be incurred for other firms to use the improvements, but the point here is that firms benefit from other firms' learning.

It is often observed for the self-reinforcing process of collective learning-by-doing to play an important role in leadership change from incumbents to latecomers. For examples, in the steel industry of the 1950s and 1960s, a radical steel making innovation, basic oxygen furnace (BOF), served as a window of opportunity for leadership shift from incumbent American steel firms to latecomer Japanese ones (Lee and Ki, 2016). The BOF was more quickly adopted by latecomer Japanese steel firms than by incumbent American ones, which stayed with the established technology they have mastered, open-hearth furnace (OHF). Two Japanese steel firms, Yawata and NKK, were the earliest adopters of initial versions of the BOF. NKK's confidence in the BOF was helped by Yawata's evaluation of the adoption of the BOF (Lynn 1982: 80-81). Yawata benefited from NKK's BOF license agreement, which was better than Yawata's (Lynn 1982: 83). Later Japanese adopters were able to have their employees trained by the two early adopters (Lynn 1982: 111). Moreover, Yawata's equipment parts suppliers also supply their parts to other steel firms, which solved technical problems for late adopters (Lynn 1982: 112 and 118). Technical journal articles and meetings also promoted the sharing of the BOF technology (Lynn 1982: 111). As a result of these collective learning-by-doing, the BOF further improved so that attracted new firms from the camp of the old

technology. This self-reinforcing process eventually results in the BOF adoption of American incumbent leaders such as the US Steel. Meanwhile, new technology BOF dethroned the old technology OHF. However, the American leaders' adoption was late. It were the latecomer Japanese steel firms that became new leaders in the era of the BOF. Their early adoption enabled them to accumulate much more knowledge on the BOF than the incumbent American ones which longer stayed with the OHF.

Another example implies that a small camp of a new technology has small effects of collective learning-by-doing so that the new technology slowly develops. That is the TV industry of the mid-2010s. While the established display technology was LED-backlit LCD ("LCD"), a new display technology OLED was commercialized in 2013. As of July 2016, three years later, OLED TVs still have lower price competitiveness than LCD TVs employing color enhancement technologies, including Quantum Dots. This situation is the reason why the sole mass-producer of OLED TV panels, LG Display, hopes the world's largest display maker, Samsung Display, to decide to mass-produce OLED TV panels. If that happens, much bigger collective learning-by-doing effects are expected within the OLED camp, especially through the improvement of OLED production equipment in various dimensions such as performance and price.

The above-mentioned two examples suggest that the importance of collective learning on leadership change dynamics following radical technological changes. However, the literature on the incumbent trap has largely unaddressed the boundary conditions of leadership change when collective learning-by-doing effects exist. This research gap is elaborated in the following section.

2.4. Research Gaps

The present study identifies three research gaps.

Collective Learning-by-doing

First, the literature largely unaddressed collective learning-by-doing in the incumbent trap dynamics. As described in Subsection 2.3, collective learning-by-doing plays an important role in the incumbent trap dynamics. However, collective learning-by-doing has been largely missed in the literature even though it is often observed in the reality. The reason may be that collective learning-by-doing is a kind of interaction among actors creating (nonlinear) collective dynamics, which is not easy to understand intuitively and not easy to expect its outcomes. Another reason may be due to the fact that collective learning-by-doing is a dynamic externality. The size of externalities increases as more firms join the camp of a technology, which makes it harder for us to understand the dynamics and outcomes of the incumbent trap phenomenon including collective learning-by-doing. Computational analysis can help us at this point because computer simulation enables us to observe the underlying mechanism of a dynamic issue of internet such as an incumbent trap phenomenon. Indeed, computational analyses on the incumbent trap phenomenon are found in the literature (Landini et al. 2016, Malerba et al. 2007) but their computational analysis didn't pay attention the col le effects on the incumbent trap phenomenon. By employing computational analysis, I am able to investigate collective learning-by-doing effects in the incumbent trap phenomenon, which is often observed in the reality but largely missed in the literature.

Initial Productivity Gap Between Old and New Technologies

Second, the literature on the incumbent trap phenomenon largely assumes that new technology is initially inferior to the old one but has a potential to become superior (Christensen 1997, Lee and Malerba 2016a, Malerba et al. 2007). But they stop there. The literature pays little attention to the relationship between the initial productivity gap between the old and new technologies and the resultant probability of leadership change from incumbents to latecomers. This is a surprise given that the concept of productivity is important in economics. Indeed, Landini et al. (2016) took a similar but different step in this direction. By developing a computational model of the incumbent trap phenomenon, Landini et al. (2016) demonstrate that the more "disruptive" the new technology is, the more likely industrial leadership shifts from incumbents to latecomers. By their definition, a technology is more disruptive if the technology has a higher technological frontier (e.g. a higher maximum productivity level a firm can achieve after adopting the technology). Although the degree of disruptiveness in their model also affects firm's adoption decision of the new technology like the degree of initial productivity gap between the old and new technologies in my model, their degree of disruptiveness cannot capture how much the new technology initially is inferior to the old technology unlike my degree of initial productivity gap. Taking advantage of computer simulation, I will show the degree of initial inferiority of new technology matters.

Incumbent's Response: Endogenous Innovation

Third, incumbent's response to a radical technological change is largely unexplored *by formal modeling*. Incumbents are not fools: they don't ignore radical changes and lose leadership. There are many examples of incumbent survival and empirical studies on it. For incumbents, one of the most effective, powerful ways to respond radical technological changes is R&D because they have taking advantage of superior R&D capabilities to latecomers. In other words, in exploring the incumbent trap phenomenon, the reason why R&D is important is R&D is a major and common option to defend their leadership in the face of radical changes. Despite of the importance of the role of the R&D in the incumbent trap phenomenon, there has been no attempt to demonstrate the role of the R&D in the incumbent trap phenomenon *in a formal model*. Only case studies and appreciative theorizing are found in the literature. Formal models using computer simulation can address this issue. However previous simulation studies on the incumbent trap phenomenon don't focus on this factor. For example, in the formal computational model of Landini et al. (2007), innovation is given to firms only exogenously. In the model of Malerba et al. (2007), firms do R&D but they don't investigate how the R&D changes the probability of leadership change. Therefore, Malerba et al. (2007) say nothing about firm's R&D is an important option to respond the change.

2.5. Definitional Issues

The present study has several key terms, including incumbent and latecomer firms, radical innovation, and industrial leadership. Different readers may have different definitions of these terms. My operational definition of some key terms is provided in this subsection in order to help readers to clear understand my argument.

Incumbent and Latecomer Firms

Terms incumbent and latecomer can be understood from a perspective of economics of catch-up. Incumbent firms refer to leader firms in terms of market share; latecomer firms refer to follower firms in terms of market share. Thus, incumbent and leader firms are used interchangeably in the present study; so are latecomer and follower firms. These definitions reflect that the present study explores a situation in which incumbent firms have higher market shares than latecomers. This situation is a typical situation to which the field of economics of catch-up pays attention. For brevity, incumbent and latecomer firms are sometimes referred to as just incumbents and latecomers in the present paper.

Industrial leadership

My definition of industrial leadership is leadership in terms of market share. Thus, a firm with the highest market share has industrial leadership. I focus on changes in industrial leadership from incumbent firms to latecomers. Hereinafter this long term is sometimes referred to as “leadership change” for brevity.

Radical technological innovation

Hill and Rothaermel (2003) provide a definition of radical innovation:

> An *incremental* technological innovation builds squarely upon the *established* knowledge base used by incumbent firms, and it steadily improves the methods or materials used to achieve the firms' objective of profitably satisfying customer needs. In contrast, a *radical* technological innovation involves methods and materials that are novel to incumbents. These novel methods and materials are derived from either an entirely different knowledge base or from the recombination of parts of the incumbents' established knowledge base with a new stream of knowledge (Freeman & Soete, 1997). To incorporate novel knowledge into their activities, incumbent firms must have absorptive capacity and must be able to develop new capabilities (Cohen & Levinthal, 1990).

A radical technological innovation requires "a quantifiably different knowledge base, from which methods and materials were developed to satisfy the needs of consumers served by incumbents" (Hill and Rothaermel 2003).

3. Hypothesis Development

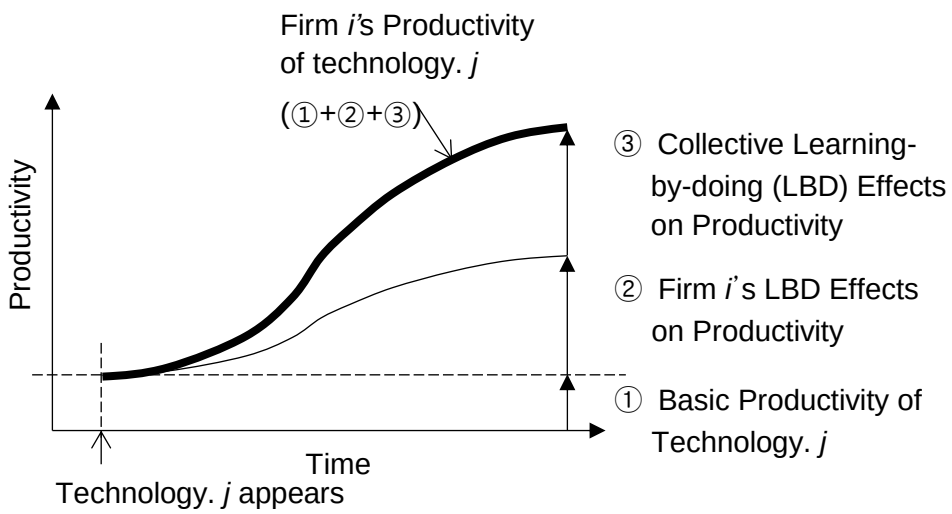
In the previous chapter, I found research gaps by focusing on three key notions: collective learning-by-doing, initial productivity gap between old and new technologies, and endogenous innovation. My work aims at to identify boundary conditions for the incumbent trap in terms of these notions. For this purpose, my theoretical work in this study focuses on two factors: (1) basic productivity of new technology and (2) the expected proportion of firms adopting the new technology. The former captures the initial degree of inferiority (or superiority) of the new technology compared with the established one, which, in turn, indicates the initial gap in productivity between the two technologies. The latter captures the expected size of collective learning-by-doing effects on increases in productivity of new technology. Boundary conditions in terms of these factors are proposed in this chapter.

Assumptions

Before introducing my hypotheses, I should make explicit the major assumptions underlying my incumbent trap dynamics. First, I assume that new technology is exogenous to firms. Second, when a new technology arrives, a firm should decide to adopt it or not. In this decision making, a firm compares the expected productivity between the established and the new technology. If that of the new one is higher than that of the established one, the firm adopts the new one. Third, I assume that a firm's productivity of the technology the firm is employing is the sum of three factors, in addition to a stochastic term: (1) basic productivity of the technology, which is

exogenously given at the time of the arrival of the technology, (2) productivity increasing with the firm's learning-by-doing, and (3) productivity increasing with collective learning-by-doing of all firms adopting the technology. Naturally, the second and third components are a function of the amount of industry's and individual firm's output, respectively. Figure 2 shows a firm's productivity is determined by adding up these three components.

Figure 2. How a firm's productivity of a technology is determined: 3 components



Given these assumptions, I propose that the basic productivity of new technology determines the boundary conditions for the probability of changes in industrial leadership from incumbents to latecomers.

3.1. Basic Productivity of New Technology: Hypothesis 1

Naïve Intuition

According to the incumbent trap thesis (Lee and Malerba 2016a), latecomers tend to adopt new technology before incumbents. Then, naïve intuition may suggest that the higher the basic productivity of a new technology is, the more advantage early adopters, or latecomers, have, and thus the more likely industrial leadership is to shift to the latecomers.

My Claim

I suspect this intuition is not the case. If the basic productivity of new technology is too high (but still lower than leaders' productivities of the established technology), most of latecomers will adopt the new technology as soon as the new technology appears. In such circumstances, collective learning-by-doing effects are too large from the beginning within the new technology's camp. Thus, the new technology become attractive to leaders soon after followers adopted it. The incumbents overcome their little late adoption by exploiting their superior capabilities in terms of, for example, R&D, capital, and consumer base. As a result, industrial leadership is less likely to shift to latecomers.

Meanwhile, if the basic productivity of new technology is too low, few latecomers will adopt the new technology. In addition, the adopters' productivities are much lower than those of firms staying with the old technology. Then, their collective learning-by-doing effects are too small to keep attracting other firms from the old technology's camp. In the absence of a self-reinforcing process, latecomer

firms which have adopted the new technology cannot achieve higher productivities than the leaders which stay in the old technology's camp. The new technology and its adopting latecomers fail to coevolve to domination. As a result, leadership is less likely to shift to latecomers in the new technology's camp.

On the other hand, if the basic productivity of new technology is neither too high nor too low, the new technology is initially adopted by neither too high nor low proportion of firms, or followers, while incumbent leaders remain with the old technology. In such circumstances, collective learning-by-doing effects of the new technology are large enough to keep attracting other firms from the old technology's camp. A self-reinforcing process will eventually attract the incumbent leaders. But they are too late. There are latecomers that have adopted the new technology much earlier than the incumbents so that the latecomers have already achieved high productivity of the new technology when the leaders have just switched to the new technology. In this situation, leadership tends to shift to latecomers in the new technology's camp.

In summary, if the basic productivity of new technology is neither too high nor too low, there are two advantages for leadership change. First, not too low basic productivity ensures that the initial number of new technology adopters is large enough for the new technology and the adopters coevolve to the dominance (via a self-reinforcing process of collective learning-by-doing). Second, not too high basic productivity ensures that the initial number of new technology adopters is small enough to moderate the speed of the self-reinforcing process. As a result, the leaders are trapped in the old technology while latecomers sufficiently enjoy first-mover advantages. This is an incumbent trap. Therefore, I propose:

Hypothesis 1. Following a radical innovation in technology, industrial leadership is more likely to shift from incumbent firms to latecomers if the basic productivity of new technology is neither too high nor too low.

3.2. Expected Proportion of Firms Adopting the New Technology: Hypothesis 2

Naïve Intuition

I explore the combined effects of the basic productivity and the expected adoption proportion of new technology on the probability of leadership change from incumbents to latecomers. When both factors are high, a firm perceives the expected productivity of the new technology as high. Then large proportion of firms join the camp of the new technology, and thus the new technology is more likely to dethrone the existing technology. Thus, naïve intuition might suggest that in this situation latecomers are more likely to achieve industrial leadership from incumbents given that latecomers tend to adopt new technology before incumbents.

My Claim

I suspect this intuition is not the case. If both factors are high, incumbent leaders adopt the new technology as quickly as followers do and thus maintain their leadership even in the era of the new technology by exploiting their superior capabilities. If both factors are low, the new technology fails to survive and incumbent leaders maintain their leadership in the continuing era of the existing

technology. Thus, when both factors are high or low, the probability of leadership change will be low following a radical innovation. On the other hand, if one factor is high while the other one is low, the effects of the two factors are balanced by each other when a firm calculates its expected productivity of new technology. Then, the new technology will be initially adopted by neither too high nor low proportion of latecomers while incumbent leaders remain with the existing technology. Such a proportion leads to leadership change via a self-reinforcing process of collective learning-by-doing as explained when I developed Hypothesis 1. Therefore, I propose:

> *Hypothesis 2. Following a radical innovation in technology, industrial leadership is more likely to shift from incumbent firms to latecomers if the basic productivity of a new technology is high (low) and the expected adoption proportion of the new technology is low (high).*

Hypothesis 2 is tabulated in Table 1.

Table 1. A table presentation of Hypothesis 2

		Basic Productivity of New Technology	
		Low	High
Expected Proportion of Firms Adopting the New Technology	Low	Low	High
	High	High	Low

Two factors are independent

Naïve intuition may hold that these two parameters are positively correlated with each other so that it is unrealistic that they have opposite values, in which leadership change is more likely to occur. However, this is not necessarily the case: they are fundamentally independent. For example, consider the following cases. If a new technology is fully developed outside of an industry of interest before it is introduced to the industry, its basic productivity is high but its potential to further improve within the industry can be considered to be low so that firms in the industry expect not many firms will join the camp of the new technology. The opposite case is also possible: the basic productivity of a new technology is low and the expected adoption proportion of the new technology is high. If the current basic productivity of a new technology is the outcome of very small amount of R&D investment outside of an industry of interest, the technology's potential to further improve within the industry can be considered to be high, which in turn lead to many firms expected to join the camp of the new technology.

3.3. Endogenous Innovation: Hypothesis 3

I attempt to answer to this question: How does the probability of changes in industrial leadership alter when firms do "endogenous innovation" activities as a response to the arrival of a radical innovation in technology? Endogenous innovation is defined here as increases in the productivity of the technology a firm is employing. In other words, endogenous innovation doesn't create new technology, which makes a firm's productivity of the established technology obsolete. my definition of an endogenous technological innovation is confined to refer to firm's in-house incremental

technological innovation. An incremental innovation is an improvement that builds on "established knowledge base" (Hill and Rothaermel 2003), which plays a role like a competence-enhancing technological advance (Tushman and Anderson 1986).

Incumbents normally have more capabilities in R&D than latecomers. Those capabilities include financial resources, know-how on how to conduct R&D, and organizational supports for R&D. If both incumbents and latecomers do endogenous innovation activities, incumbents tend to achieve more improvement in the productivity of the technology they are employing than latecomers, other things being equal. Therefore, I propose:

> *Hypothesis 3: Industrial leadership is less likely to shift from incumbents to latecomers when firms are allowed to do endogenous innovation activities, or R&D to increase productivity of the technology they are employing, than when innovation is only exogenously given to firms.*

4. Methodology: Evolutionary Modeling

I follow an evolutionary approach to test my hypotheses on the dynamics of an incumbent trap. An evolutionary model has the following characteristics: “firms are boundedly rational agents; their behavior is guided by routines; learning is driving change; agents and capabilities are heterogeneous” (Landini et al. 2016).

The present study explores incumbent trap dynamics. The dynamics of a phenomenon can be well analyzed by agent-based computational modeling (ABM). This is because the ABM enables researchers to observe how such dynamics evolves, or the underlying mechanism of a dynamics. This observation is not easy with analytic models. The underlying mechanism is also hardly observed in an empirical study using regression analysis by nature. This is because regression can say something only about the correlation between the variables of interest, not about the underlying mechanism between the variables. Thus, in economics, the dynamics of a phenomenon has been studied largely by case studies. This tendency has been the same in research on the incumbent trap dynamics. However, case studies cannot draw a general theory because there are always counter examples. In addition, hand-picked cases in case studies tend to be biased toward supporting researcher’s claims.

In addition, simulation experiments can be repeated without any impact to the reality. Such an iteration allows researchers to know an average tendency of a variable of interest. This point complements case studies. Thus, computation analysis often goes with case studies. First, researchers find common tendency from the small number of cases; and then build a computational model to test the generality of their findings from the case studies. The present simulation study also accompanies with industrial case studies of the incumbent trap such as Giachetti and

Marchi 2016 (cell phone), Shin 2016 (DRAM), Kang and Song 2016 (camera), Lee and Ki 2016 (steel).

Meanwhile, my incumbent trap dynamics plays out with collective learning-by-doing, which is a nonlinear interaction among firms. Such a nonlinear behavior makes it difficult for a researcher to anticipate what the dynamics results in. Computational analysis can show numerically the outcome of such a nonlinear behavior.

Ones may criticize that simulation models can create any results that researchers want by making a biased model and adjusting its parameter values. This criticism is attempted to not necessarily true. Simulation modelers build a model bases on relevant theory so that readers can verify that the model is theoretically acceptable. In addition, sensitivity tests on parameter values provide the validity of the results.

In summary, the ABM and its computational simulation is a suitable methodology to investigate incumbent trap dynamics including nonlinear interactions of collective learning-by-doing. Meanwhile, for a further discussion on the ABM, "see Garavaglia (2010) and Yoon and Lee (2009)" (Landini et al. 2016).

5. Basic Model

To support my theoretical arguments, I build a simulation model in an evolutionary economics perspective. In the basic model, a radical innovation is exogenously given to firms at a certain period of time, and afterwards in each period, the firms decide whether to adopt these innovations or not in their search for more profit. Their adoption decision is based on comparison of the expected productivity of their currently employing technology and that of the new technology.

My model is a simplified and modified version of the evolutionary model of Nelson and Winter (1982). R&D activities (innovation and imitation) is removed. Instead, learning-by-doing is added. The model starts with one production technology, and a new technology is introduced in a certain period of the simulation run when the gaps in market share among the firms are sufficiently widened.

The model is of an industry in which several firms employ a production technology to produce a single homogeneous product. Market shares of the firms are determined by productivity competition. Firm productivity of a specific technology is the sum of basic productivity (BP) that is exogenously given at the time of the arrival of the technology and additional productivity through learning-by-doing of the firm and the industry (individual and collective learning-by-doing, respectively). After a new technology appears, firms choose old or new technology in their search for more profit.

For simplicity, there are some assumptions:

- All the firms have the perfect information on the basic productivity and productivity increment by collective learning-by-doing of a technology

- No cost occurs when a firm adopts a new technology.
- Firms takes ""Cournot" strategy: a firm picks a target capital stock on the basis of a correct appraisal of the industry demand elasticity and a belief that the other firms will hold output constant" (Nelson and Winter 1982, hereinafter NW82,: 284).
- New technology is given to firms exogenously. No R&D is conducted by firms themselves.
- No new entry and exit

"[F]ormally, the model has the following structure" (NW82: 284).

$$Q_{it} = A_{ijt}K_{it} \quad (1) \text{ (NW82: 284)}$$

"The output of firm *i* at time *t* equals its capital stock times the productivity of [technology *j*,] it is employing" (NW82: 284).

K_{it} represents firm *i*'s general capabilities which is still available after changing technologies. Such capabilities include consumer base, brand, service network, organizational power, etc. These elements are normally still available after changing technologies.

The productivity of technology *j* of firm *i* at time *t* (A_{ijt}) is the sum of three factors: (1) the BP that is exogenously given at the time of the arrival of technology *j*, which the firm is employing, (BP_j), (2) productivity increases obtained through the collective learning-by-doing of all the firms adopting technology *j* ($CoLbd_{jt}$),

and (3) increases in the productivity of firm *i* through its learning-by-doing (Lbd_{ijt}). The second and third components are stochastic functions of the cumulative amount of collective and individual output, respectively.

$$A_{ijt} = (BP_j + CoLbd_{jt}) + Lbd_{ijt} \quad (2)$$

$BP_j + CoLbd_{jt}$ is common to all the firms employing the same technology, and each firm has its own value of IP_{ijt}.

$$BP_{j=New\ \ tech.} = \alpha \ \times \max_i(A_{i(j=Old\ \ tech.)t=t^*}) \quad (3)$$

I define the *BP parameter*, alpha(α), as the ratio of the BP of the NT to the highest productivity of the old technology (OT) achieved by a firm in the industry, which is normally achieved by the firm with the largest market share. When an NT appears in the industry in period t^*, the NT's BP is exogenously given and is equal to α times the highest (best practice) productivity level of the OT in the industry in period *t*.

For instance, 'α = 80%' means the merit of the NT is 80% of the highest productivity level of the old technology in the period when the NT appears. To test the H1, I will change the value of this parameter (α), from 0% to 150%.

The collective learning-by-doing effects on firm *i*'s productivity at *t*, $CoLbd_{ijt}$, is:

$$CoLbd_{ijt} = CoLbd_{ijt-1} + \Delta CoLbd_{jt}. \ (5)$$

Increases in collective learning-by-doing effects at *t*, $\Delta CoLbd_{jt}$, is:

$$\Delta CoLbd_{jt} = \left(1 + a_1 \times n_{jt}^{f}\right) \times \left\{\max\left(CoLbd_{jt-1},\ \widetilde{CoLbd}_{jt-1}\right) - CoLbd_{jt-1} + a_2\right\}$$

where $\widetilde{CoLbd}_{jt} \sim N\left(\lambda_C\left(\sum_t \sum_i Q_{ijt}\right), \sigma_C^2\right)$

with $\lambda_C\left(\sum_t \sum_i Q_{ijt}\right) = a_3 \times \left(\sum_t \sum_i Q_{ijt}\right)^{a_4}$

in which a_4 < 1 to ensure diminishing returns. (6) (NW82: 302)

Note that $\Delta CoLbd_{jt}$ is affected by the number (or proportion) of firms employing technology *j* at *t*, n_{jt}^{f}. The more firms use a technology, the larger increases in collective learning-by-doing effects at *t*, $\Delta CoLbd_{jt}$, are within the technology's camp. σ_C has a form that ensures that the standard deviation of $\widetilde{CoLbd}_{jt}$ has a certain percentage of $\lambda_C\left(\sum_t \sum_i Q_{ijt}\right)$. Here, $\widetilde{CoLbd}_{jt}$ is a random variable that is the result of the collective learning by-doing of all the firms adopting the same technology.

Firm *i*'s learning-by-doing effects at *t*, Lbd_{ijt}, is a stochastic function of the firm's cumulative outputs that has produced by this technology ($\sum_t Q_{ijt}$).

$$Lbd_{ijt} = \max\left(Lbd_{ijt-1},\ \widetilde{Lbd_{ijt-1}}\right)$$

where $\widetilde{Lbd_{ijt}} \sim N\left(\lambda_{Lbd}\left(\sum_t Q_{ijt}\right), \sigma_{Lbd}^2\right)$

with $\lambda_{Lbd}\left(\sum_t Q_{ijt}\right) = a_5\left(\sum_t Q_{jt}\right)^{a_6}$ (7) (NW82: 302)

σ_{Lbd} has a form that ensures that the standard deviation of $\widetilde{Lbd_{ijt}}$ has a certain percentage of $\lambda_{Lbd}\left(\sum_t Q_{ijt}\right)$. Here, $\widetilde{Lbd_{ijt}}$ is a random variable that is the result of the individual firm's learning by-doing.

$$Q_t = \sum_i Q_{it} \qquad (8) \text{ (NW82: 302)}$$

$$P_t = R/Q_t \qquad (9) \text{ (NW82: 302)}$$

"Industry output, Q_t, is the sum of individual firm outputs. Price, P_t, is determined by industry output" (NW82: 284), given the fixed size of the market demand, *R*.

$$\pi_{it} = P_t A_{ijt} - c \qquad (10) \text{ (NW82: 285)}$$

"The profit on capital of that firm equals product price times output per unit of capital, minus production costs (including capital rental) per unit of capital" (NW82: 285).

"A firm's desired expansion or contraction is determined by the ratio of price to production cost, $P/(c/A)$ – or equivalently, the percentage margin over cost – and its market share. But a firm's ability to finance its investment is constrained by its profitability, which is affected … by revenues and production costs" (NW82: 285).

$$K_{i(t+1)} = I\left(\frac{P_t A_{ij(t+1)}}{c}, \frac{Q_{it}}{Q_t}, \pi_{it}, \delta\right) \times K_{it} + (1-\delta)K_{it} \qquad (11) \text{ (NW82: 285)}$$

"Here, δ is the physical depreciation rate, and the gross investment function $I(\cdot)$ is" (NW82: 286) given by:

$$I(\rho, s, \pi, \delta) = \max\left[0, \min\left\{\left(1 + \delta - \frac{(2-s)}{\rho(2-2s)}\right), f(\pi)\right\}\right],$$

where $f(\pi) = \delta + \pi$ for $\pi \leq 0$ or $\delta + 2\pi$ for $\pi > 0$ (12) (NW82: 303)

An NT is exogenously introduced in an industry at period t^*. In that period and afterward, a firm evaluates the NT to determine whether to adopt it or not. If the expected productivity of the NT is higher than that of the OT, then that firm adopts the NT (Landini et al. 2016). Formally:

If $E\left(A_{i(j=NT.)t^*+1}\right) \geq E(A_{i(j=OT.)t^*+1})$,

firm *i* adopts the NT. Otherwise, firm *i* maintains using the OT.

Note that $E\left(A_{i(j=NT)t^*+1}\right) = E(BP_{j=NT} + CoLbd_{(j=NT)t^*+1})$ and

$$E\left(A_{i(j=OT)t^*+1}\right) = E(BP_{j=OT} + CoLbd_{(j=NT)t^*+1} + \ Lbd_{i(j=OT)t^*+1}). \quad (13)$$

A firm's expected productivity of the NT does not include increases in productivity through the firm's learning-by-doing in the following period ($Lbd_{i(j=NT)t^*+1}$). The reason is that the firm has no output using the NT before adopting the NT. For a similar reason, $CoLbd_{(j=NT)t^*+1} = 0$.

Once a firm adopts the NT, its capital stock (K_{it}) is used with the NT to produce the same homogeneous product. I assume that the adoption of the NT is not reversible.

When a firm calculate the expected productivity of the new technology at t^*+1, $E\left(A_{i(j=NT)t^*+1}\right)$, the firm uses the expected proportion of firms adopting the new technology, $E(n_j^f)$. This is a model parameter, and I change the parameter from 0% to 100% to test the H1.

$$E\left(A_{i(j=NT)t^*+1}\right) = E(BP_j + CoLbd_{j,t^*+1} + Lbd_{ij,t^*+1})$$

where $E\left(CoLbd_{jt}\right) = CoLbd_{j,t-1} + \left(1 + a_1 \times \boldsymbol{E}(\boldsymbol{n_{jt}^f})\right) \times$

$$\left\{\max\left(CoLbd_{jt-1},\ \widetilde{CoLbd}_{jt-1}\right) - CoLbd_{jt-1} + a_2\right\}$$

with $E(n_{jt}^f) = max(E(n_j^f), n_{jt}^f)$. (14)

$E(n_{jt}^f) = max(E(n_j^f), n_{jt}^f)$ indicates that if the actual adoption rate of the NT in the industry, n_{jt}^f, has go beyond the value of the parameter $E(n_j^f)$ as time goes by, a firm uses the actual adoption rate as the expected adoption rate of the next period.

6. Simulation Results for Hypotheses 1 and 2

6.1. The Settings

The simulation starts with eight firms and one technology. The BP of the OT ($BP_{j=OT}$) is set to a positive real number. The eight firms' initial values of cumulative outputs are equally set to 0, and the initial values of their individual learning-by-doing of the OT are also equally 0. As a result, all the firms have the same initial value of productivity (A_i). All the firms have the same initial value of capital stocks (K_i). Thus, with the same productivity (A_i) and capital stocks (K_i), all the firms' outputs ($Q_{i(t=1)}$) and market shares in period 1 are also the same each other. There are no new entry and exit of a firm.

An NT appears in period 150. A simulation run ends after period 300. I declare "leadership change occurs" if the firm with the largest market share is different between at the emergence of new technology (t=150) and at the end of the simulation (t=300). 100 runs for each combination of parameters, parameter of merit of the new technology., from 0% to 150%, and the expected proportion of firms that adopt the NT, $E(n^f_{j=NT})$, from 0% to 100%.

All the parameter settings can be provided upon by request. My simulation experiments are conducted by using a simulation modeling software named Laboratory for Simulation Development (LSD).[3]

[3] This software, LSD, is developed by Dr. Marco Valente, who is now an associate professor of Economics at University of L'Aquila, Italy. The tool was really convenient for evolutionary modeling

In the model, I focus on the firm with the highest market share and name it the leader. The other firms in the model are followers. So my model is about the leadership shift from the leader to one of the followers.

6.2. Results

How do the incumbent trap and therefore leadership changes occur? How do the effects of the incumbent trap on leadership changes vary according to the values of α? When they occur, which firm assumes the leadership?

To answer such questions, I begin with single runs of the model over time by the value of the parameter.

6.2.1. Single Run Cases That Replicate an Incumbent Trap

If no new technology appears at t = 150, incumbent leader (light blue line) typically maintain its leadership (in terms of market share). This case is presented in Figure 3-(a). The other figure in Figure 3, or Figure 3-(b), presents a single run case of incumbent trap. When an NT whose merit is 65% of the highest productivity level of the established technology (α = 65%) in the period when the NT appears at t = 150, leadership has shifted (from light blue to green).

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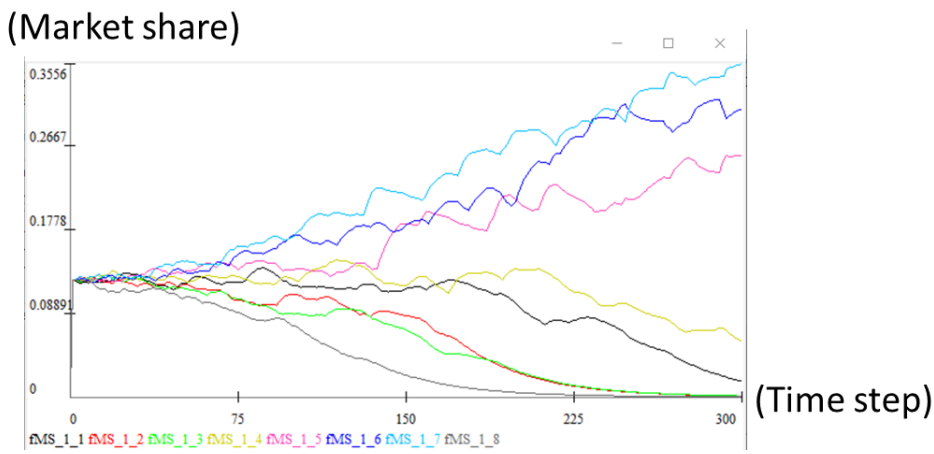
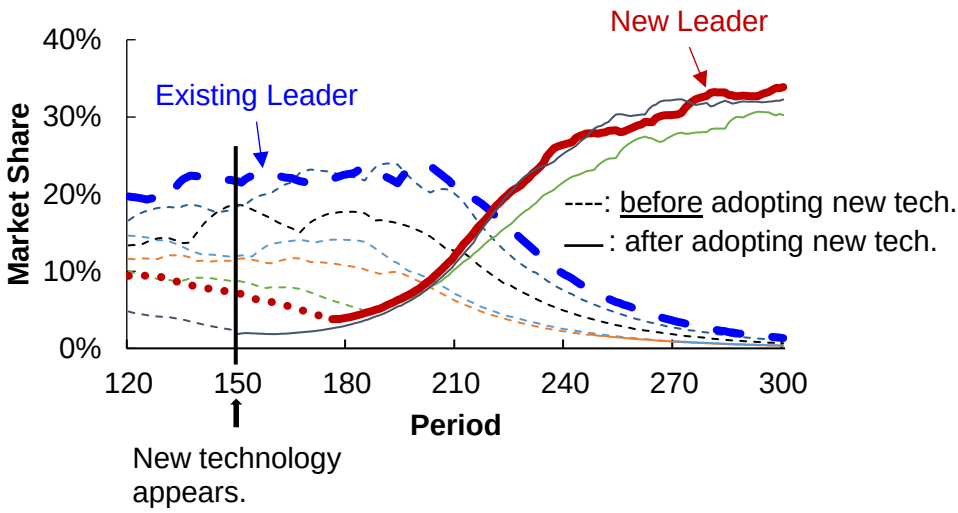
and computational experiments. I really appreciate it. For details of the LSD, see its website at http://www.labsimdev.org.

Figure 3. Typical incumbent trap dynamics.

(a) Typical simulation run with no new technology at t = 150.



(b) Typical simulation run of leadership change following a radical innovation



6.2.2. Hypothesis analysis

Now, I present the probability of a change in leadership by the value of BP parameter. I change the basic productivity parameter (α), from 0 to 1.5 by an interval of 0.1. This interval is reduced to 0.01 in some ranges for detailed analysis on interesting results. For each basic productivity parameter (α), simulations are iterated 1,00 times. The values of the other parameters can be provided upon request.

The occurrence of a change in leadership is decided by whether the firm with the largest market share at the end of the simulation (*t*=300) is different from the firm with the largest market share at the emergence of new technology. (*t*=150). If different, I can say a change in industrial leadership from the incumbent leader to a latecomer after the new technology is introduced in the industry. You can notice I assume that the reverse order of the market shares in the period when the NT appears is the order of the lateness of the entering the industry. This assumption can be justified given that, in the reality, the order of market share roughly reflects the order of industry entry.

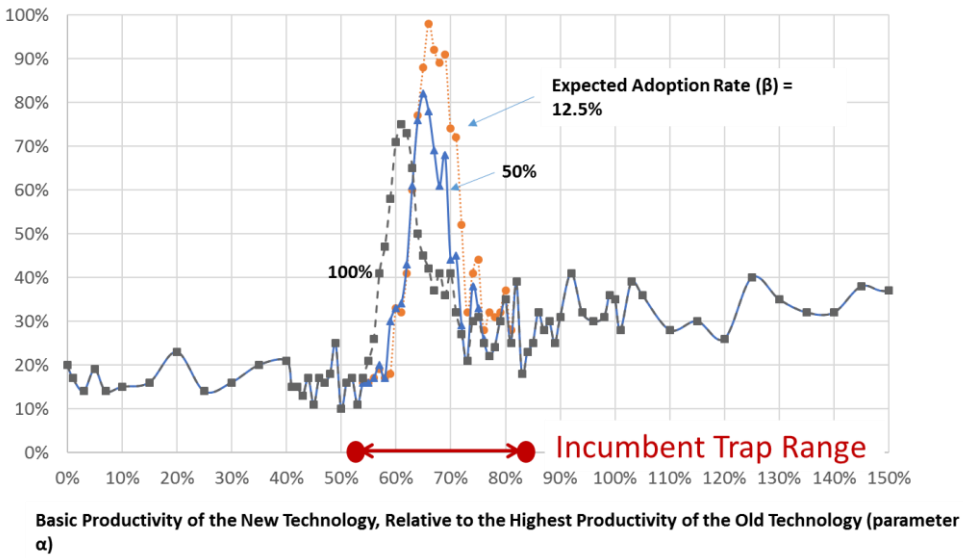
The probability of leadership change is defined as:

$$\textit{Probability of Leadership Change} = \frac{\#\ Leadership\ Changes}{\#\ Simulation\ Runs}$$

I declare "leadership change occurs" if the firm with the largest market share at the emergence of new technology (*t*=150) is replaced with another one at the end of the simulation (*t*=300).

Figure 4 presents the probability of a change in leadership from a leader to a latecomer after the NT is introduced in period 150. Averaged from 100 simulation runs for each value of the expected NT adoption proportion (β).

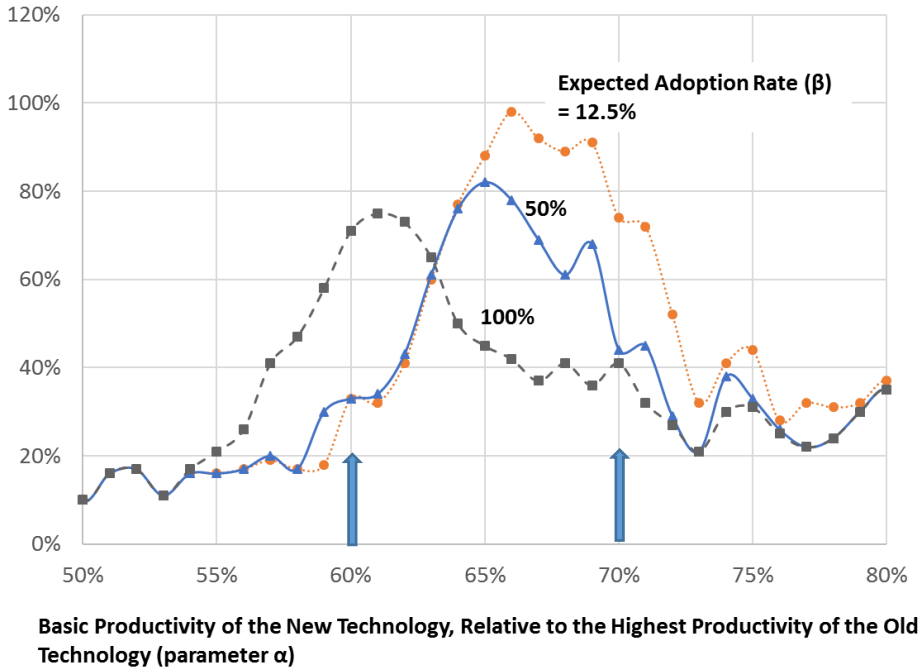
Figure 4. The Probability of Leadership Change by the Expected Proportion of Adoption (β)



I found an incumbent trap range: when the NT appears with technological merit of between around 50% and 80% of the maximum productivity of the established technology, the incumbent leader and latecomers choose different technologies, and the leader loses its leadership. I also found the leadership change is more likely to occur in this range than outside the range.

The results of Hypothesis 2 are presented in Figure 5 and Table 2.

Figure 5. The Probability of Leadership Change within the Incumbent Trap Range



Results support Hypothesis 2: Conditions in which incumbent trap is more likely to occur. In the table 2, the indications High/Medium/Low in the parentheses represent Hypothesis 1.

Table 2. Test Results of Hypothesis 2

		The BP of NT	
		Low (α = 60%)	High (α = 70%)
Expected NT Adoption Rate	Low (β=12.5%)	**33% (Low)**	**74% (High)**
	High (β=100%)	**71% (High)**	**41% (Low)**

One minor interesting point is that leadership change probability is higher *right* outside the incumbent trap range than *left* outside of the range. In the right outside of the incumbent trap range, all the firms adopt the new technology at the same time when the new technology arrives. In the left outside of the range, none of the firms adopt the new technology. In both cases, incumbents and latecomers use the same technology; however, when all the firms adopt the new technology, the productivities of the all the firms reset to the same level. Due to this reset, latecomers have even slightly higher chance to surpass the incumbents than when all the firms stay with the old technology. In contrast, when both of incumbents and latecomers don't adopt the new technology, which is the case left outside of the incumbent trap range, incumbent's superiority in productivity of the old technology continues.

7. Simulation Results for Hypothesis 3

7.1. Introduction

In the basic model, innovations are given only exogenously to firms. This setting may seem to make incumbent leaders look like fool because leaders do nothing except passive learning-by-doing while they lose their leadership. Then, ones may ask 'In your model, why don't incumbent leaders do R&D to improve their productivity in order to defend their leadership in the face of a radical innovation?'

Now I extend the basic model to allow for a firm to conduct R&D to improve the productivity of the technology they are employing. I call this extended model "endogenous innovation model" while I call the basic model "exogenous innovation model." Endogenous innovation is defined here as increases in the productivity of the technology a firm is employing. In other words, endogenous innovation doesn't create new technology, which makes a firm's productivity of the established technology obsolete. Note that new technology is still exogenously given to firms in the endogenous innovation model.

Firm's endogenous innovation is important in incumbent trap research. In reality, incumbent leaders can do R&D to respond to followers' early adoption of the new technology. Incumbent leaders normally have more R&D capabilities than latecomers. Thus, adding firm's R&D behavior to the model means allowing incumbent leaders more response options to a radical technological change. This is a more realistic setting, compared to the basic model, in which incumbents do nothing except passive learning-by-doing while they lose their leadership.

The endogenous innovation model will be used to test Hypothesis 3.

7.2. Model Extension

In Essay 1, the productivity of technology *j* of firm *i* at time *t* (A_{ijt}) is the sum of three factors: (1) the BP that is exogenously given at the time of the arrival of technology *j*, which the firm is employing, (BP_j), (2) the productivity increment obtained through the collective learning-by-doing of all the firms adopting technology *j* ($CoLbd_{jt}$), and (3) the increase in the productivity of firm *i* through its learning-by-doing (Lbd_{ijt}).

$$A_{ijt} = (BP_j + CoLbd_{jt}) + Lbd_{ijt} \quad (7\text{-}1)$$

In the extended model, I *add* R&D to the basic model, in which new technology exogenously given to firms. The productivity of technology *j* of firm *i* at time *t* (A_{ijt}) additionally has the productivity increment obtained through firm' R&D, $R\&D_{ijt}$.

$$A_{ijt} = \left(BP_j + ColLbd_{jt}\right) + Lbd_{ijt} + \boldsymbol{R\&D_{ijt}} \quad (7\text{-}2)$$

Firm's endogenous innovation is enabled AFTER at least one firm adopts the NT. A firm conducts R&D only when its market share has decreased for n consecutive periods. By this, firms in the "endogenous innovation" model has exactly the same state as those in the "exogenous innovation" model (the basic model) when at least one firm adopts the NT in terms of productivity (A), capabilities (K), and corresponding market share. This setting ensures that the comparison of the probability of leadership change becomes correct.

$\boldsymbol{R\&D_{ijt}}$ is determined as follows. A firm conducts R&D only when its market share has decreased for *n* consecutive periods. Successful R&D increases

productivity of the technology the firm is employing. The random process of R&D is a simplified version of Nelson and Winter (1982: 285)'s two-stage random process. A firm succeeds in R&D with the following probability:

$$Pr(d_{R\&D} = 1) = a_{R\&D} r_{R\&D} K_{it} \quad \text{(7-3) (NW82: 285)}$$

"Parameters are chosen so that the upper-bound probability of one is not encountered" (NW82: 285). If a firm succeeds in R&D, its R&D gain is *r*% of the current level of productivity.

R&D costs per unit of capital, $\boldsymbol{c_{R\&D}}$, is added in the profit equation.

$$\pi_{it} = P_t A_{ijt} - c - \boldsymbol{c_{R\&D}} \quad \text{(7-5) (NW82: 285)}$$

7.3. Results

7.3.1. Initial Settings

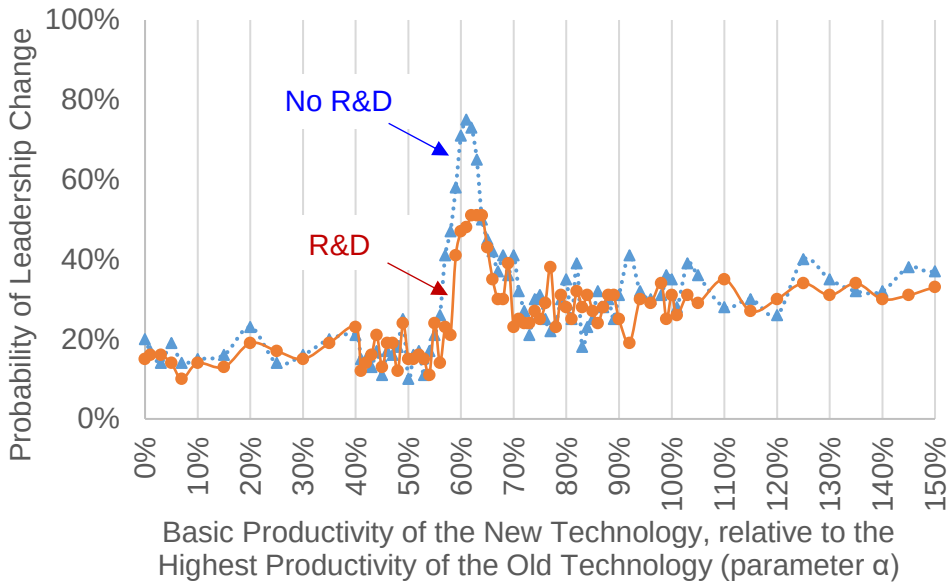
Once the new technology is adopted by at least one firm, firms conduct R&D only when their market shares decrease for 1 period. When a firm succeeds in R&D, its R&D gain is 2% of the current level of productivity.

7.3.2. Results

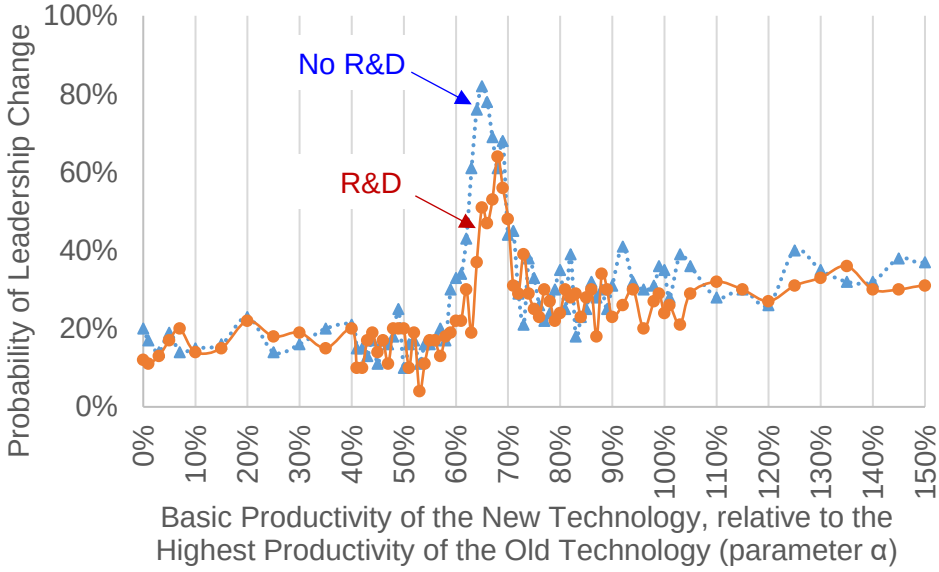
Simulation results for Hypothesis 3 test are shown in Figure 6. The figure presents the average value of 100 simulation runs for each parameter value set.

Figure 6. The Probability of Leadership Change with Firm's R&D Behavior

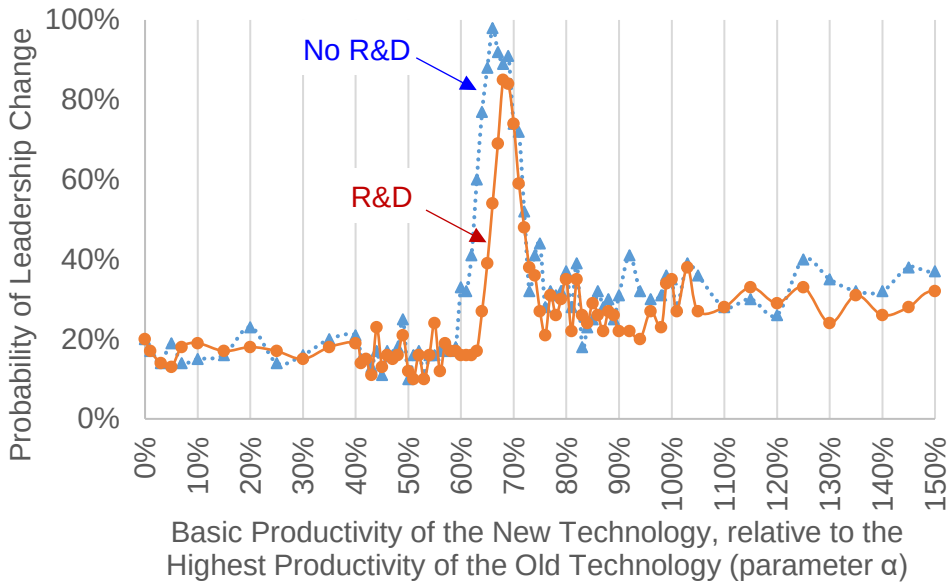
(a) When the expected adoption rate of the NT (β) is 100%



(b) When the expected adoption rate of the NT (β) is 50%



(c) when the expected adoption rate of the NT (β) is 12.5%



There is a common pattern regardless of the value of the expected adoption rate of the NT (parameter β). When firms do endogenous innovation activities, a change in industrial leadership is, in overall, less likely to occur than when innovation is only exogenously given to the firms. This result supports my claim that incumbent's superior endogenous innovation capabilities help the incumbents to maintain their leadership in the face of a radical technological change. See Figure 7.

Figure 7. R&D reduces the leadership change probability in two ways

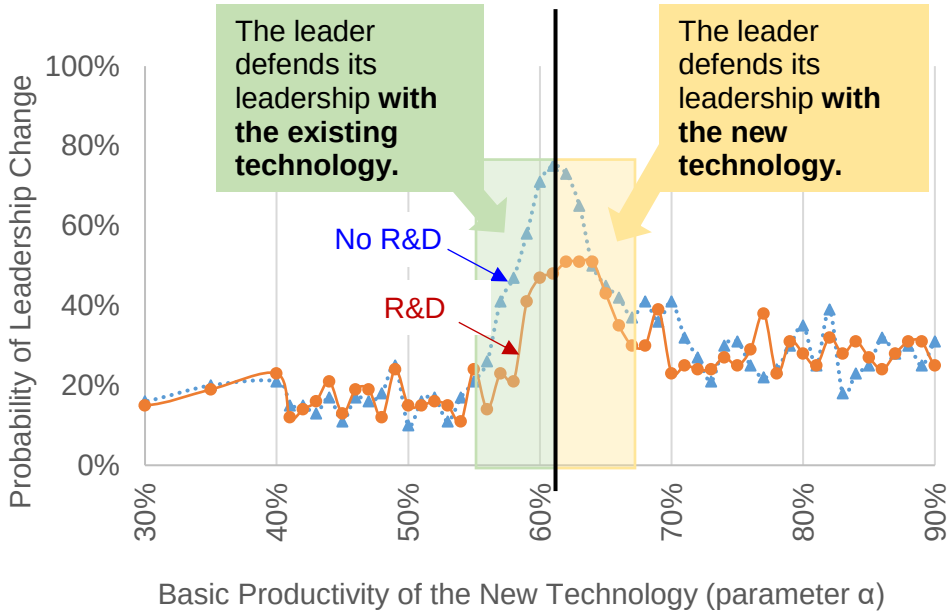
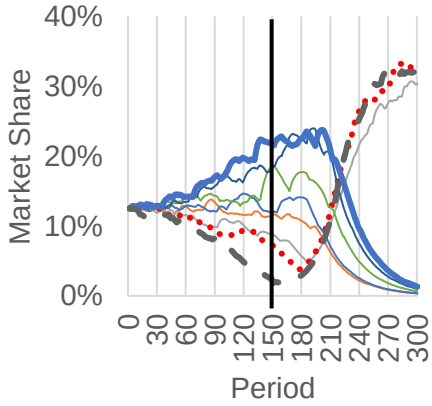
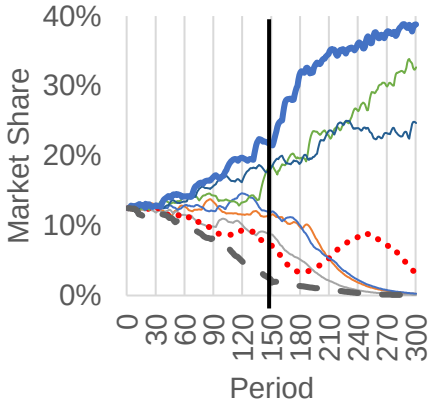


Figure 8. Typical leadership defense for low alpha (0.6) (β = 100%)

a. Exogenous Innovation Model



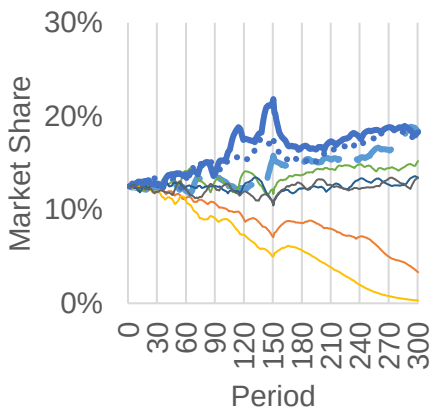
b. Endogenous Innovation Model



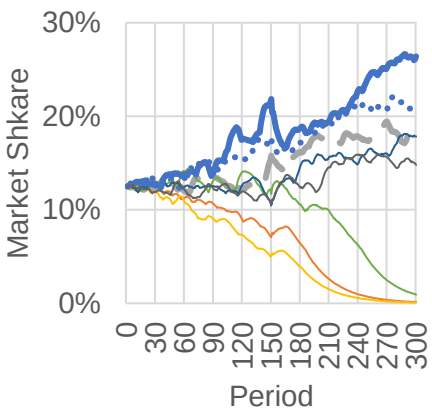
In Figure 8-(a), leadership change occurs: Early NT adopting followers (red, grey lines) takes leadership from the leader. On the other hand, in Figure 8-(b), Leadership change doesn't occur: the leader (blue line) defends its leadership with the existing technology by taking advantage of its superior endogenous innovation capabilities.

Figure 9. Typical leadership defense for high alpha (0.8) (β = 100%)

a. Exogenous Innovation Model



b. Endogenous Innovation Model



In Figure 9-(a), Leadership change occurs: All the firms adopt the NT almost simultaneously. On the other hand, in Figure 9-(b), Leadership change doesn't occur: The leader (blue line) defends its leadership with the existing technology by taking advantage of its superior endogenous innovation capabilities.

In summary, I added endogenous innovation activities, or R&D, to the basic model. This setting gives a more response options to incumbent leaders in the face of radical innovation. R&D reduces the probability of leadership change. But, the

underlying mechanism of R&D effects are different according to the level of the basic productivity of the NT (alpha). When alpha is low, R&D enables the leader to defend its leadership with the existing technology. When alpha is high, R&D enables the leader to defend its leadership with the new technology.

8. Conclusion

Summary of My Claims

By employing an evolutionary model, my theoretical work in this study tested boundary conditions for the incumbent trap phenomenon by focusing on basic productivity by focusing on three key notions: (1) collective learning-by-doing, (2) initial productivity gap between old and new technologies, and (3) endogenous innovation. In specific, my theoretical work explored two factors in two situations. The two factors are basic productivity of new technology and the expected proportion of firms adopting the new technology; the two situations are of exogenous and endogenous innovations. My findings are as follows.

First, in an industry in which collective learning-by-doing effects exist, following a radical technological innovation, industrial leadership is more likely to shift from incumbent firms to latecomer firms if the basic productivity of new technology is neither too high nor too low. Second, within this range, the probability of changes in industrial leadership from incumbents to latecomers affected by the expected adoption proportion of the new technology: leadership change is more likely to occur if the basic productivity of a new technology is high (low) and the expected adoption proportion of the new technology is low (high). Third, an additional experiment revealed that industrial leadership is less likely to shift from incumbents to latecomers when firms are allowed to increase productivity of the technology they are employing than when innovation is only exogenously given to firms. This result supports that incumbents take advantage of their superior R&D capabilities to defend their leadership in the face of radical technological change.

Contributions

The present study makes three contributions. First, it links the incumbent trap phenomenon to externalities caused by firm's learning-by-doing, or collective learning-by-doing. Collective learning-by-doing plays an important role in the incumbent trap dynamics (as discussed in the Introduction of the present study). However, often observed in the reality, collective learning-by-doing has been largely missed in the literature on the incumbent trap phenomenon. The reason may be that collective learning-by-doing is a kind of interaction among actors creating (nonlinear) collective dynamics, which is not easy to understand intuitively and not easy to expect its outcomes. Moreover, collective learning-by-doing is a dynamic externality. The size of externalities increases as more firms join the camp of a technology, which makes it harder for us to understand the dynamics and outcomes of the incumbent trap phenomenon including collective learning-by-doing. Computational analysis can help us at this point because computer simulation reveals the underlying mechanism of a dynamic issue of internet such as an incumbent trap phenomenon. Indeed, computational analyses on the incumbent trap phenomenon are found in the literature (Landini et al. 2016, Malerba et al. 2007) but their computational analysis didn’t pay attention the col le effects on the incumbent trap phenomenon. By employing computational analysis, I am able to investigate collective learning-by-doing (effects) in the incumbent trap phenomenon, which is often observed in the reality but largely missed in the literature.

Second, I demonstrate numerically that the initial gap in productivity between old and new technologies affects the probability of changes in industrial leadership from incumbents to latecomers. In specific, the results of my simulation show that

only when the initial productivity gap is neither too large nor too small, leadership change tends to occur. The literature on the incumbent trap phenomenon largely assumes that new technology is initially inferior to the old one but has a potential to become superior (Christensen 1997, Lee and Malerba 2016a, Malerba et al. 2007). But they stop there. The literature pays little attention to the relationship between the initial productivity gap between the old and new technologies and the resultant probability of leadership change from incumbents to latecomers. This is a surprise given that the concept of productivity is important in economics. Indeed, Landini et al. (2016) took a similar but different step in this direction. By developing a computational model of the incumbent trap phenomenon, Landini et al. (2016) demonstrate that the more "disruptive" the new technology is, the more likely industrial leadership shifts from incumbents to latecomers. By their definition, a technology is more disruptive if the technology has a higher technological frontier (e.g. a higher maximum productivity level a firm can achieve after adopting the technology). Although the degree of disruptiveness in their model also affects firm's adoption decision of the new technology like the degree of initial productivity gap between the old and new technologies in my model, their degree of disruptiveness cannot capture how much the new technology initially is inferior to the old technology unlike my degree of initial productivity gap. Taking advantage of computer simulation, I find the degree of initial inferiority of new technology matters in a way different from my naïve intuition, which is formed without investigation on the underlying mechanism. simulation model enabled us to investigate the underlying mechanism.

Third, the present study demonstrates in a formal model the effects of R&D, one of the most effective responses of incumbents to radical technological changes.

Incumbents are not fools: they don't ignore radical changes and lose leadership. There are any examples of incumbent survival and empirical study on it. For incumbents, one of the most effect, powerful ways to respond radical technological changes is R&D because they have taking advantage of superior R&D capabilities to latecomers. In other words, in exploring the incumbent trap phenomenon, the reason why R&D is important is R&D is a major and common option to defend their leadership in the face of radical changes. Despite of the importance of the role of the R&D in the incumbent trap phenomenon, there has been no attempt to demonstrate the role of the R&D in the incumbent trap phenomenon in a formal model. Only case studies and appreciative theorizing are found in the lit. formal models using computer simulation can address this issue. However previous simulation studies on the incumbent trap phenomenon don't focus on this factor. For example, in the formal computational model of Landini et al. (2007), innovation is given to firms only exogenously. In the model of Malerba et al. (2007), firms do R&D but they don't investigate how the R&D changes the probability of leadership change. Therefore, Malerba et al. (2007) say nothing about firm's R&D is an important option to respond the change. On contrast, my extended model becomes relatively more realistic by including firm s R&D and enable us to investigate R&D effects on the probability of changes in industrial leadership. The results show that by taking advantage of superior R&D capabilities, incumbents can reduce the probability of leadership change compared with when innovation is only exogenous to firms. Meanwhile, the findings of the basic model hold in the extended model, which implies that those findings are from more fundamental factors: alpha and beta. In summary, the present study demonstrates in a formal model that incumbents are able to defend leadership by taking advantage of their superior R&D capabilities to

latecomers after radical technological change, which tendency was explored only in case studies.

Appendix

A. Incumbent Trap Conditions Identified in the Literature

In the literature, after CT2000, there have been attempts to identify conditions in which industrial leadership shifts from incumbent firms to latecomers (or to followers or to new entrants) (Hill and Rothaermel 2003, Malerba et al. 2007, Ansari and Krop 2012, Obal 2013, Roy and Sarkar 2016, Landini et al. 2016).

Hill and Rothaermel 2003

By identifying and collating the key findings of the existing literature, Hill and Rothaermel (2003) derive propositions on when incumbent firms survive and prosper following radical technological changes. Their propositions are about three factors: economic, organizational, and strategic factors. Details are as follows.

a) Propositions in terms of economic factors

Following a radical innovation, incumbent performance will be higher

1. "if the firm's basic research function is loosely, [but not too loosely,] coupled with applied research functions" (Hill and Rothaermel 2003);
2. "if the decision-making paradigm that managers use when evaluating investments in technology is consistent with a real options perspective" (Hill and Rothaermel 2003).

b) Propositions in terms of organizational factors

Following a radical innovation, incumbent performance will be higher

3. "if the values and norms of the firm legitimize autonomous action" (Hill and Rothaermel 2003);

4. "if autonomous action is institutionalized through internal systems and procedures specifically designed to encourage and fund the initiation as well as provide regular evaluation of new products and services" (Hill and Rothaermel 2003);

5. "if the markets the firm serves have a history of turbulence that the firm has navigated in the past" (Hill and Rothaermel 2003);

6. "if the firm establishes a loosely coupled, stand-alone division to commercialize the new technology" (Hill and Rothaermel 2003).

c) Propositions in terms of strategic factors

Following a radical innovation, incumbent performance will be higher

7. (Breadth of Impact) "if the firm possesses downstream complementary assets that are critical to the commercialization of the new technology" (Hill and Rothaermel 2003) such as marketing channels, sales networks, and after-sales service (Abernathy and Clark 1985, re-quoted from Hill and Rothaermel 2003; Rothaermel, 2001).

8. (Gestation period) if the gestation period[4] of that technological innovation is longer (Hill and Rothaermel 2003).

9. If, "[w]hen Propositions 7 and 8 hold, an incumbent can use strategic alliances to gain access to radical technological innovations pioneered by new entrants" (Hill and Rothaermel 2003).

Hill and Rothaermel 2003 derive an addition proposition, which is not classified into any category.

10. “Following a market discontinuity triggered by a radical technological innovation, the performance of an incumbent firm will be higher if the firm has accumulated significant organizational slack from its established operations" (Hill and Rothaermel 2003).

Malerba et al. (2007)

Malerba et al. (2007) focus “on the characteristics of the demand” (Malerba et al. 2007). By developing a simulation model, Malerba et al. (2007) reveal that leadership change from incumbent firms to new firms is more likely to occur when

4 "The gestation period for a radical technological innovation can be defined as that period between invention and successful commercialization." (Hill and Rothaermel 2003)

fringe (or niche or separate) markets "which the old technology does not serve well, or experimental users, or both" (Malerba et al. 2007) exist.

Ansari and Krop 2012

By reviewing the existing literature of more than 100 studies[5], Ansari and Krop 2012 identify and collate 11 factors that influence incumbent survival in the face of radical innovation. The factors are divided into three categories: the industry setting, the incumbent firm properties, and the challenge. Specific factors under each category are as follows:

- 5 factors in the industry setting category: “complementary markets,” “institutional environment,” “customers,” “suppliers,” and “level of rivalry” (Ansari and Krop 2012).
- 3 factors in the incumbent firm properties category, “boundary management,” “incumbent configuration for change,” and “complementary capabilities” (Ansari and Krop 2012).
- 3 factors in the challenge category, “innovation type,” “commercialization requirements,” and “incubation time horizon” (Ansari and Krop 2012).

5 Ansari and Krop 2012 tabulate these studies and their key findings as Table 1 in their paper.

For each factor, Ansari and Krop (2012) derive one proposition on the conditions of incumbent survival in the face of radical innovation so that 11 propositions in total. Then they "develop a holistic multi-level framework for understanding incumbent-challenger dynamics" (Ansari and Krop 2012) following radical innovations. Ansari and Krop (2012) argue incumbent-challenger dynamics "can only be understood when several multi-level factors are *concurrently* considered" (Ansari and Krop 2012). Specific propositions under each category are as follows.

- In the industry setting category,

Proposition 1a. (complementary markets) "The less evolved is the complementary market for an innovation dependent on that market and the less control challengers have over its evolution, the higher is the probability of incumbent survival" (Ansari and Krop 2012).

Proposition 1b. (institutional environment) "For an innovation likely to feature regulatory interventions, the more protective the intervention is at the national or industry levels, the more favourable it is for incumbents in the short term, but the more it may constrain their overall ability to respond to the challenge" (Ansari and Krop 2012).

Proposition 1c. (demand) "Following an innovation with a substitutive effect, the more 'inert' are the existing consumers – making frequent low-cost decisions – the more likely it is for incumbents to survive" (Ansari and Krop 2012).

Proposition 1d. (supplier) **"**Following an innovation, the more nonstandardized and diversified are the suppliers and the more entrenched are the incumbent-supplier relationships, the higher is the probability of incumbent survival" (Ansari and Krop 2012).

Proposition 1d is similar to Obal (2013)'s finding that incumbent's success with the diffusion of disruptive technologies can be explained by "the influence of pre-existing levels of trust already developed between incumbents and potential buyers of disruptive technologies" (Obal 2013).

Proposition 1e. (the level of rivalry) "The stronger (weaker) the rivalry is in an industry and in different strategic groups within an industry, the higher (lower) are the chances for incumbent survival" (Ansari and Krop 2012).

- In the incumbent firm properties category,

Proposition 2a. (boundary management) "The more incumbents engage in symbiotic cross-boundary management (i.e. effective partnerships with challenger firms), the higher the chances of incumbent survival when faced with radical innovations" (Ansari and Krop 2012).

Proposition 2b. (incumbent configuration for change) "The more appropriately an incumbent organization is configured in terms of organizational form, structure and preparedness for disruptive change and the formalization of ambidextrous

processes to seek and exploit business opportunities, the higher the probability of its survival in the face of radical innovations" (Ansari and Krop 2012).

Proposition 2c. (complementary capabilities) "The more effectively an incumbent is able to build and leverage linkages between the innovation and the complementary capabilities needed to commercialize the innovation, the more difficult it is for new entrants to acquire and access such complementary capabilities, and the higher is the probability of incumbent survival" (Ansari and Krop 2012).

- In the challenge category,

Proposition 3a. (innovation type) "The more (less) extensively an innovation devalues the incumbent value network, the less (more) likely it is for an incumbent firm to survive" (Ansari and Krop 2012).

Proposition 3b. (commercialization requirements) "The more specific (generic) or proprietary (open) are the assets required for the profitable commercialization of an innovation, the higher (lower) is the probability of incumbent survival" (Ansari and Krop 2012).

Proposition 3c. (incubation time horizon) "The longer (shorter) is the incubation time horizon - the period between incumbents' awareness of the innovation and its profitable commercialization - relative to the industry average, the higher (lower) is the probability of incumbent survival" (Ansari and Krop 2012).

Propositions 3c is almost identical to Hill and Rothaermel 2003's Proposition 8, which states that "Following a market discontinuity triggered by a radical technological innovation, the longer the gestation period of that technological innovation, the higher the performance of an incumbent firm" (Hill and Rothaermel 2003).

Obal (2013)

Obal (2013) finds that incumbent's success with the diffusion of disruptive technologies can be explained by "the influence of pre-existing levels of trust already developed between incumbents and potential buyers of disruptive technologies" (Obal 2013). Obal (2013)'s findings suggest leadership change is more likely to occur when an incumbent has lower levels of "trust with potential buyers" (Obal 2013) of disruptive technologies.

Roy and Sarkar (2016)

By the empirical analysis on the industrial robotics industry, Roy and Sarkar (2016) argue that incumbent firms will be leaders in the new technological paradigm if they have in-house prior knowledge on the new technology and "in-house users of the products designed with the radical new technology" (Roy and Sarkar 2016).

In-house users of the new technology can be regarded as a kind of "downstream complementary assets that are critical to the commercialization of the new technology" (Hill and Rothaermel 2003), which is mentioned in Hill and Rothaermel

(2003)'s proposition 7. Thus, Roy and Sarkar (2016)'s argument can be considered to be similar to Hill and Rothaermel (2003)'s proposition 7, which states that following a radical innovation, incumbent performance will be higher "if the firm possesses downstream complementary assets that are critical to the commercialization of the new technology" (Hill and Rothaermel 2003).

Landini et al. (2016)

By simulation experiments, Landini et al. (2016) find that a change in industrial leadership from incumbents to latecomers is more likely to occur 1) when the new technology is more disruptive, 2) when incumbents' initial capabilities is lower; 3) when the degree of technological lock-in is sufficiently high; and 4) when technological investments have increasing returns like in high-technology sectors (Landini et al. 2016).

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국문초록

산업주도권 이동과 후발자의 추격에 관한 진화경제학적 모델

-집단 학습과 내생적 혁신이 "선발자 함정" 현상에 미치는 영향에 대한 연구-

서울대학교 대학원
경제학부 경제학전공
기지훈

이 연구는 같은 기술을 사용하는 기업 간에 집단 학습(collective learning-by-doing)이 이루어지는 산업에서 근본적 기술혁신이 등장했을 때 선발자 기업에서 후발자 기업으로 산업주도권이 이동("선발자 함정" 현상)이 발생할 가능성이 높아지는 조건을 규명한다. 선발자 함정은 혁신 및 경제 추격 연구에서 중요한 주제이고, 집단 학습은 많은 산업에서 관찰되는 현상이다. 그러나 선발자 함정 현상에서 집단 학습을 고려한 선행연구는 부족한 상황이다.

선발자 함정 이론에 따르면, 리더 기업보다 후발 기업이 새 기술을 먼저 채택하는 경향이 있고, 이 점이 후발자가 리더를 추격하는 원동력이 된다. 따라서 새 기술의 등장 시점의 생산성("기초 생산성")이

클수록 산업 주도권이 선발자에서 후발자로의 이동할 가능성이 높을 것이라고 추측할 수 있고, 이 추측은 일견(一見) 타당해 보인다. 그러나 흥미롭게도 진화경제학적 행위자 기반 모델을 이용한 시뮬레이션 실험 결과는 그렇지 않다. 산업주도권 이동 가능성이 가장 높아지는 조건은 새 기술의 기초생산성이 너무 높지도, 낮지도 않을 때이다. 오히려 새 기술의 기초생산성이 너무 높으면 리더 기업도 새 기술의 가치를 빠르게 인식하고, 후발자 못지않게 빠른 속도로 새 기술을 채택한다. 그리고 리더 기업은 자신이 가진 다른 역량 우위 (예: 브랜드, 조직 역량 등)을 활용하여 새 기술 채택이 후발자보다 약간 늦었던 것을 극복, 그 결과, 산업주도권(시장점유율)을 방어한다.

두번째 발견도 직관과 다른 흥미로운 발견이다. 새 기술의 등장은 기존 기술과 새 기술 진영간의 경쟁을 뜻한다. 따라서 새 기술 진영에 많은 기업이 가담할 것으로 예상될수록 새 기술이 기존 기술을 대체하는 지배 기술로 등극하고, 이와 더불어 새 기술 진영의 후발자가 주도권을 장악할 가능성이 높을 것이 직관적으로 타당해 보인다. 그러나 시뮬레이션 실험의 결과는 직관과 달랐다. 새로운 기술의 기초 생산성이 높고 (낮고), 새 기술 진영에 적은 (많은) 기업이 가담할 것으로 예상될수록 주도권 이동 가능성이 높아진다.

한편, 시뮬레이션 실험에서 추가적으로 확인한 점은, 기업이 R&D 를 통해서 사용중인 기술의 생산성을 높일 수 있게 해주었을 때("내생적 혁신"을 할 수 있을 때)는 그렇지 않을 때보다 선발자가 주도권을 방어할 가능성이 높아진다 점이다.

이 연구의 공헌은 다음과 같다. 첫째, 집단 학습 효과가 존재하는 상황에서 선발자 함정 발생 조건을 규명하였다. 집단 학습은 현실의 많은 산업에서 존재하는데 그동안 선발자 함정에 관한 연구에서 고려되지 못했다. 둘째, 신/구 기술 간 생산성의 초기 격차에 따라 산업 주도권 이동 가능성이 달라짐을 밝혔다. 기존의 문헌에서는 '새 기술의 초기 생산성은 기존 기술의 생산성보다 낮다'고 가정할 뿐 낮은 정도에 따라 주도권 이동 가능성이 달라짐을 간과하였다. 셋째, 선발자가 R&D 를 통해 주도권을 방어할 수 있음을 엄밀한 모델(formal model)을 통해 입증하였다.

주요어: 후발자의 추격, 근본적 혁신, 기술 채택, 행위자 기반 모델, 생산성, R&D

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