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A study of Japan and the United States with multiagent simulation

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How Institutional Arrangements in the National Innovation System Affect Industrial Competitiveness: A study of Japan and the United States with multiagent simulation

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Abstract

The Japanese national innovation system (JP NIS) and that of the United States (U.S. NIS) differ. One of the differences is that firms in the JP NIS are likely to collaborate with historical partners for the purpose of innovation or rely on in-house research and development (R&D), approaches that form a "relationship-driven innovation system." In the U.S. NIS, however, firms have a relatively weak reliance on prior partnerships or internal R&D and are likely to seek entities that know about the necessary technology. Thus, U.S. players acquire technologies through market transactions such as mergers and acquisitions (M&A). This paper primarily discusses how this institutional difference affects country-specific industrial sector specialization. Then, by using a multiagent model of the NIS and conducting simulation, we examine what strategy would help Japanese firms in industries dominated by radical innovation. The results show that the JP NIS provides an institutional advantage in industries with fast-changing consumer demand that require incremental innovation. However, the U.S. NIS benefits industries that require frequent radical innovation. Our analysis reveals that extending the partnership network while keeping internal R&D capability would be a beneficial strategy for Japanese firms in industries driven by radical innovation. Therefore, the present research suggests that policymakers need to differentiate policy that emphasizes business relationship and market mechanism importance according to industrial characteristics in order to improve overall national industrial competitiveness. At the same time, Japanese firms need to strengthen their R&D capability while trying to extend their pool of technology partners in order to improve the flexibility of their responses to radical changes in an industry.

Keywords: National innovation system, Innovation policy, Multiagent model, Simulation, Innovation strategy

JEL Classification: O31, O33

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1 Introduction

The innovative division of labor does not occur independently from the business relationship (Arora, Fosfuri, & Gambardel, 2001; Kani & Motohashi, 2013). Therefore, the institutional structure of the business relationship should be understood according to micro- and macro-level innovation dynamics.

The Japanese (JP) national innovation system (NIS) has been characterized as a long-term business relationship-driven innovation system. Individuals collaborate with prior business partners in an environment of mutual trust that is driven by an institutionally sanctioned system (Hagen & Choe, 1998). A long historical partnership between *Toyota Motors* as a primary auto-parts consumer and *Denso* as a major auto-parts supplier is an example (Kani & Motohashi, 2013). Repeated collaboration creates patient capital and trust, which leads to further collaboration. From this perspective, a long-term relationship provides competitive advantage in innovation for which a high degree of productivity and manufacturing flexibility is required in areas such as automobiles and electronics. The significant likelihood of internal R&D among Japanese firms can also be understood as another example of the "relationship-driven innovation system" in the sense that it essentially requires strong internal communication and collaboration. Further, studies have highlighted that trust-based long-term business relationships are the reason why JP firms have so far been market leaders in certain industries (Abegglen, 1986; Clark, 1989; Fruin, 2006; Hagen & Choe, 1998; Odagiri, 1994). A long-term trust-based business relationship, which might be vulnerable to the hold-up problem because of the opportunistic behavior of partners, can be maintained because the long-term relationship between JP players drives the repeated game. The repetitive game enables the imposition of harsh punishment for opportunistic behavior (Baker, Gibbons, & Murphy, 2002; Holmström & Roberts, 1998; Holmström & Roberts, 1998). Thus, opportunistic behavior can be effectively self-regulated in the JP system.

Hall and Soskice (2001) argue that maintaining a long-term relationship is beneficial in an industry that requires incremental innovation. Incremental innovation is likely to be created by using accumulated knowledge about a particular technology. A long-term relationship with a particular partner secures the technology sourcing and stimulates knowledge accumulation. An historical relationship also lubricates the collaboration efficiency between two entities. Further, repetitive collaboration encourages a partner to develop the next new technology by giving a sense of what technology would be necessary for the technology buyer in the future. Therefore, maintaining a long-term partnership is advantageous for sourcing incrementally innovative technology. However, radical innovation is achieved by introducing brand new ideas that may not be familiar to the partners nor the technology buyer. Thus, heavily relying on historical partners or internal R&D personnel who are unlikely to know about radically innovative technology may be disadvantageous for efficient technology sourcing. This type of economic system is called the coordinated market economy (CME). Hall and Soskice (2001) categorize Japan and Germany as CMEs.

However, the U.S. NIS is known as the liberal market mechanism-based innovation system. Firms try to identify the necessary technology for new product or service implementation. Then, they attempt to acquire the technology through market transactions such as licensing and mergers and acquisitions (M&A). They actively seek other entities that know about the necessary technology and rely less on prior partners or internal R&D compared to Japanese firms. This system emphasizes competition rather than trust-based long-term collaboration. Further, entities with a one-time contract are more likely to be exposed to the hold-up problem because the provisional nature of the relationship lets the entities believe that engaging in opportunistic behavior would be more profitable (Holmström & Roberts, 1998).

This market-based innovation system can have an institutional advantage in an industry that requires radical innovation, such as information technology (IT) or biotechnology (BT), and in which Japanese firms are less competitive (Motohashi, 2005). The technological performance improvement of a product or service is not radical innovation. Radical innovation requires the introduction of new technology or a new concept of technology's use in a new product or service (Tidd, Bessant, & Pavitt, 2005). Therefore, the market mechanism-based system provides significant flexibility for the creation and sourcing of radical innovation. Hall and Soskice (2001) describe this system as the "liberal market economy (LME)."

Japanese policymakers have been discussing whether Japan's recent weakened industrial competitiveness in high-tech industries stems from the institutional configuration that emphasizes a long-term business relationship between innovative economic players. In particular, it has been debated whether the Japanese government needs to encourage a policy whereby Japanese firms adopt the liberal market-driven technology sourcing strategy used by U.S. firms.

Using an agent-based model (ABM), the present study sheds light on how the institutional difference in relationship-dependency affects national-level industrial sector specialization. An ABM provides a suitable way to virtualize a complex social system (Macal & North, 2011). Key players and their actions in the real world system are modeled as the software agents, and a set of the interaction rules drives the overall dynamics. The aggregated result of their interaction generates system-level dynamics that are virtualized society-level outcomes. Thus, the ABM enables the navigation of the probable dynamics that emerge though the interaction of individual factors in a complex social system. In this sense, it is a more suitable research methodology than the conventional methodology used in complex social dynamics studies. In the present research, we examine how the relationship dependency between economic players in the innovation process generates the different innovation patterns and to what extent. Following the simulation result, we suggest that policymakers design a policy to enhance national industrial competitiveness and to establish a better corporate technology sourcing strategy for Japanese firms in industries driven by radical innovation.

The present paper is structured as follows. Section 2 reviews prior studies on the institutional differences between the JP NIS and the U.S. NIS. We also review prior studies that employ ABM to examine innovation dynamics. In Section 3, we describe the ABM according to “overview, design concepts, and details,” an approach that is the standard ABM documentation protocol suggested by Grimm et al. (2006). We explain the simulation plan and results in Section 4. Section 5 provides an analysis of the results. We then discuss the results in Section 6 and draw conclusions in Section 7. The details of the model and the implemented algorithm are illustrated in the appendix.

2 Literature Review

2.1 Varieties of Capitalism and Country-Specific Industrial Sector Specialization

Hall and Soskice (2001) introduce the varieties of capitalism (VoC) theory to formalize how institutional configuration of a national economic system drives country-specific industrial sector specialization. The VoC theory divides the world’s affluent economies into two types: liberal market economies (LMEs) and coordinated market economies (CMEs). The U.S. and the U.K. are categorized as LMEs. Germany and Japan are grouped into CMEs. The theory converts the characteristics of each economic system into the primary innovation pattern in which each system is strong. LMEs are strong in industries that require radical innovation such as biotechnology or microprocessor technology. In addition, LMEs are advantageous in large complex systems where the technology changes rapidly. However, CMEs are an advantageous institutional arrangement of the national economic system for low-medium tech industries. Based on this proposition, Hall and Soskice (2001) argue that LMEs primarily export high-tech products and services, while CMEs export low-medium tech products. The VoC theory’s core proposition is aligned with a basic idea of Porter (1990) who claims that country-specific institutional conditions affect the sector-specific innovation competitiveness of companies and countries.

Akkermans, Castaldi, and Los (2009) test the VoC proposition. They consider whether LMEs specialize in radical innovation that drives industry while CMEs use a more traditional system of incremental innovation through patent analysis. The authors calculate and compare national-level generality and the originality of patents in LMEs and CMEs. The originality indicator estimates how patented technology is created based on the original idea. This indicator has been employed before to estimate patent quality (e.g., Organization for Economic Cooperation and Development (OECD) patent statistics). The generality indicator quantifies how patent technology broadly covers various technological fields (or can be employed to create a further invention). Thus, these indices are employed as the proxies of patented technology's radicality. The results show more complex dynamics than indicated by Hall and Soskice's (2001) proposition. According to the generality analysis, LMEs specialize in radical innovation in chemicals and electronics while CMEs are strong in radical innovation in machinery and transport equipment industries. The originality analysis supports the VoC proposition but in conclusion, the study argues that the proposition oversimplifies the entangled national-level innovation dynamics.

Schneider and Paunescu (2012) argue that affluent countries' economic systems cannot be simply divided into LMEs and CMEs. Through clustering analysis of the OECD's national-level macro-economy data for 26 countries, they find that the institutional configuration of national economic systems is dynamically transformed and that other clusters exist that do not fit into either the CMEs or the LMEs. For example, in their analysis, Japan, which has usually been considered a CME, is re-categorized as a "hybrid economy" that has features of both an LME and a CME. Schneider and Paunescu (2012) argue that this discrepancy with Hall and Soskice's (2001) proposition shows that the national economic systems of some countries are in a process of transformation. They also criticize Hall and Soskice's (2001) theory by claiming that it does not consider the effect of "knowledge learning" in a national economic system. However, they also reconfirm Hall and Soskice's (2001) main argument that an LME has strong high-tech industries while a CME has advantageous low to mid-tech industries.

Apart from the VoC theory, a number of scholars have attempted to understand why there is country-specific industrial sector specialization. Kitschelt (1991) argues that Japanese players are willing to maintain a cooperative relationship with other players across business and government frontiers. This Japanese system is an especially efficient means of governance in an industry that requires intermediate coupling but has moderate complexity among technological components. The intermediate coupling of such different technological components promotes cooperative business relations. The cooperative business network gives the production system flexibility, which allows continual improvement of the technological components. Thus, Japanese national governance provides institutional benefits to Japanese firms in an industry that requires medium- or long-term production runs. This approach is also institutionally advantageous in an industry that requires technology that can be sustainably improved through the incremental innovation of processes and products. However, the structure places too little importance on the high-risk technology that may bring radical innovation. Overall, the Japanese governance structure drives Japanese firms to have strength in industries where "incremental innovation" and "cooperative operations" are necessary.

Lehrer, Tylecote, and Conesa (1999) argue that country-specific industrial sector specialization originated from variations in the national structure of corporate governance. The national-level financial system can be divided into the "insider-dominated system (I-system)" and the "outsider-dominated system (O-system)." The U.S. and the U.K. fall into the "O-system," but most East Asian countries and continental European countries have the "I-System." The authors point out that the I-system is a conventional system whereby technological progress involves a great deal of cumulative learning and cooperation among employees as part of the innovation process. The O-system is advantageous in an industry that requires rapidly changing and high-novelty technology because the investor in the O-system invests in the whole industrial system rather than focusing on a particular industry.

Haake (2002) suggests a similar idea that explains how the institutional configuration of a national innovation system relates to industry-specific competitiveness. He uses the term national business system instead of NIS and suggests that this national business system can be categorized as two types: an individualistic system with loose interfaces between actors and a communitarian system with tighter interfaces. Communitarian business systems may be advantageous in industries where players are likely to rely on an accumulated knowledge pool of organization-specific knowledge. Such systems require a closer and long-term relationship among actors, an approach that enables companies to retain and accumulate specific knowledge. However, individualistic business systems are advantageous in industries where diffusion or reallocation of organization-unspecific knowledge occurs. In this regard, knowledge is not retained within a specific company because more fluid and short-term relations dominate the system. The type of knowledge that matches each configuration is explained with the concept of organization-specificity of knowledge, which is defined as the degree to which the knowledge that individual members of the organization use in their work is specific to the company for which they work. Haake (2002) claims that the individualistic business system is advantageous in an industrial environment where organization-specificity of knowledge is low, and that the communitarian system enjoys institutional benefits in an industry that requires a high degree of organization-specificity of knowledge.

2.2 Studies of Dynamics in Innovation Systems Using the ABM and Simulation

The ABM is increasingly being used in the social science field (Wooldridge & Jennings, 1995) and for theory development that is focused on organizational strategy (Davis & Bingham, 2007). The ABM is one of the established approaches for examining complex dynamics that emerge through social system and human interaction (Gilbert & Troitzsch, 2005; Gilbert, 2007; Wooldridge, 2009). In this sense, the ABM approach has been employed to study innovation dynamics. Here, we review ABM studies on innovation systems and dynamics.

A milestone of ABM studies on innovation dynamics is the Simulating Knowledge Dynamics in Innovation Networks project (the SKIN project). In this regard, Gilbert, Pyka, and Ahrweiler (2001) introduce an ABM to describe knowledge sharing and the innovation diffusion process whereby R&D intensive firms, venture capitalists, and university/research institutes are modeled into software agents. A new firm is then created by an agent that successfully develops new knowledge that fits a given innovation hypothesis. Existing agents can establish or disband partnerships with other agents over the network. In this way, the entire network structure is dynamically organized. The employment of ABM for innovation studies has been extended across various topics such as national innovation system dynamics (Ahrweiler, Pyka, & Gilbert, 2011; Jianhua, Wenrong, & Xiaolong, 2008), the innovation diffusion and adoption process (Cantono & Silverberg, 2009; Faber, Valente, & Janssena, 2010; Schwarz & Ernst , 2009), innovation policy evaluation (Lopoliro, Morone, & Taylor, 2013), the process of new technological knowledge generation and dynamics imposed by the intellectual property regime (Antonelli & Ferraris, 2011), and the patent system and policy evaluation (Kwon & Motohashi, 2014). Table 1 summarizes the ABM studies regarding the innovation process and innovation system dynamics.

Table 1. Innovation Studies that Use ABM

Authors	**Research Topic**	**Type of Agents**	**Key Findings (Contributions)**
Gilbert, Pyka, & Ahrweiler, 2001	Innovation diffusion process over innovation network	Firm, Policymaker Venture capitalist University Innovation oracle	Introduction of Simulating Knowledge Dynamics in Innovation Networks and model description with two case studies for model validation.
Jianhua, Wenrong, & Xiaolong, 2008	Studying innovation generation process	Enterprise Government	Product market competition is a major driver of innovation generation. The ABM is applicable to the study of innovation systems.
Schwarz & Ernst, 2009	Innovation diffusion and policy implications	Household	Geographic innovation diffusion of water-saving innovation in Germany. Water-saving diffusion would be continued without specific promotion.
Cantono & Silverberg, 2009	New energy innovation diffusion process, and role of learning economies with policy evaluation	Consumers who have different levels of reservation prices for new energy technology	Subsidy policy would be effective if the initial new energy technology price is fairly high when learning economies exist. The effect of the policy depends significantly on the desired level of diffusion.
Faber, Valente, & Janssen, 2010	New technology diffusion process and policy evaluation for promoting the technology’s adoption	Consumer of energy technology	Diffusion of micro-CHP technology can be inhibited by the decreased demand for natural gas. Various subsidy schemes for promoting the adoption of new energy technology should be considered based upon assumed policy criteria.
Ahrweiler, Pyka, & Gilbert, 2011	Effect of industry–university links on innovation performance	Firm Venture capitalist University Innovation oracle	Industry–university links promote innovation performance.
Antonelli & Ferraris, 2011	Generation of new technological knowledge	Worker Shareholder Researcher Consumer Enterprise	Innovation is likely to emerge faster with better quality in organized complex systems that are characterized by high levels of dissemination and accessibility to knowledge externalities.

Lopoliro, Morone, & Taylor, 2013	Which policy would be appropriate to stimulate the emergence of an innovation niche?	Producing firm	Policy intervention is important in innovation niche creation. The study shows the dominance of information-spreading activities over subsidies. Such a policy is fundamentally helpful in order to promote efficient knowledge diffusion and the effective use of individual and network resources.
Kwon & Motohashi, 2014	What would be net effect of NPE on innovation society and how can we reduce the negative effect of it?	Firm University NPE Bank Court	NPEs' business model will have a negative impact rather than a positive effect. P olicymakers need to primarily consider reducing the injunction rate in NPE lawsuits and placing some regulation on the amount of damages that can be awarded to NPEs.

We construct an ABM of a generalized NIS. We differentiate the present model from prior studies (Gilbert, Pyka, & Ahrweiler, 2001; Jianhua, Wenrong, & Xiaolong, 2008) in the following two ways. First, the present model virtualizes product market competition as well as technology competition. By combining these mechanisms, we aggregate industrial competitiveness dynamics with competitive innovation dynamics, thereby making the model reflect the real-world dynamics in a more realistic manner. Second, we introduce more dynamic mechanisms such as the knowledge-learning process, information sharing/learning, and the R&D process with the network model. Since network structure plays an important role in generating innovation dynamics (Oerlemans, Meeus, & Boekema, 1998), these network dynamics make the present model capture a greater variety of innovation network patterns. Although the implemented dynamics in the model might be too complex, they are all essential compartments for the generation of the major system dynamics for the present research. The model is described according to "overview, design concepts, and details (ODD)," an approach that is a general documentation protocol for ABM suggested by Grimm et al. (2006). Details about the implemented algorithms are provided in Appendix 3 with the PSEUDO code.

3 The ABM of Virtualized NIS

3.1 Objective

We virtualize NIS with an ABM in order to study how institutionally arranged "relationship dependency" and the degree of "reliance on internal R&D" in technology sourcing affect NIS dynamics with respect to the industrial sector specializations process. Agents build a social network through interaction with other agents. As the relationship-dependency grows, the agents are more likely to interact with those agents with whom they have interacted before rather than new agents, or to rely on internal R&D for technology sourcing. We consider the system with low relationship dependency as the U.S. NIS and the system with high relationship dependency as the JP NIS. We also consider that the agents with significant reliance on internal R&D rather than outsourcing represent JP players and that the agents with significant reliance on outsourcing rather than internal R&D represent U.S. players.

3.2 State Variables and Core Components

The present model has two types of agent: firm-type (*FIRM*) and university-type (*UNIV*). Such agents have capital assets (*Ca*) and technology assets (*Ta*). An agent spends a certain amount of *Ca* whenever it engages in the R&D process. Further, a technology owner can license out the owning technologies. In this context, the model virtualizes a product market. Consumer demand in this product market regularly changes. Agents make guesses about changing consumer demand through the information-learning process. Because consumer demand is not specified to agents, the virtualized product market is close to a B2C type.

Only a *FIRM* can enter the product market (as a manufacturer) and earn sales revenue by selling a product to consumers. The product is created by combining technological components that are essential for product implementation (Utterback & Abernathy, 1975). "Technological component" is not the same as "technology" in the present model because multiple "technologies" might correspond to a particular technological component. For example, a cell phone has a telecommunication function, which is a technological component; however, the technology behind the telecommunication is not necessarily fixed to one technology (e.g., 2G, 3G, and 4G LTE). In this sense, the technological component captures the conceptual essential functions that should be implemented in the product, and "technology" refers to the technological option that realizes the function of the technological component.

[Insert Figure 1. Product Concept in the Present Model]

This concept makes it possible to capture technological innovation at the product level. In this regard, technological performance improvement in a technological component corresponds to incremental innovation (Tidd, Bessant, & Pavitt, 2005). Such improvement is represented in the model by "technology generation increase." For example, technology "A2" has a higher performance than "A1." However, technological performance improvement occurs only one generation at a time, which means that the agent cannot develop "A3" technology directly from "A1." In addition, a product concept is radically changed by the introduction of a new technological feature. For example, a smartphone can be understood as an entirely new mobile device concept that includes many features similar to a personal computer that were not in a conventional cell phone. Based on this conceptualization, the present model defines "radical innovation" as the introduction of a new technological component that was unnecessary for the prior product. For instance, at t = t0, a product is implemented through a combination of the technological components {A1, B1, C1}. At t = t0+1, the consumer demands a new product that comprises {A2, B1, C1, and D1}. The new product design requires radical innovation because it should have a new technological feature provided by a new technological component "D1." At the same time, the new product comprises an incrementally improved technological component in the form of component "A" (the index denotes the technological performance level). Figure 2 illustrates the product level innovation pattern and technological components.

[Insert Figure 2. Product Level Innovation Pattern and Technological Component Change]

A *FIRM* must satisfy the following two conditions in order to enter the product market. First, it must have technologies that correspond to all the essential technological components required for product implementation. Second, it must have a production facility (factory). In this regard, a *FIRM* spends a certain amount of *Ca* in order to have the factory. Following this, two technology acquisition strategies (modes) are available to the *FIRM*: "developer mode" and "aggregator mode." A *FIRM* in "developer mode" develops its own technology without outsourcing. A *FIRM* in "aggregator mode" can obtain the necessary technology from either an external source or internal R&D. With regard to external technology sourcing, agents can obtain licenses for target technologies from other agents or engage in R&D collaboration with them. The licensee pays contracted royalties to the licensor as long as the former uses the licensed technology. Once an agent establishes R&D collaboration or a license contract with another agent, the licensor and licensee build a "business relationship." The business relationship generates the network linkage between them. *UNIVs* only engage in internal R&D and licensing activity. A *UNIV* receives a regular R&D budget from the system as a "public fund for research." Both a *UNIV* and *FIRM* can form a new spin-off *FIRM*.

The present model virtualizes the product market with the concept of "consumer group." The consumer group is the imaginary group of consumers who buy products from manufacturing *FIRMs*. In this regard, we assume that such consumers have an homogeneous preference system. The consumer group periodically defines the technological specification of the product that they demand most. This specification includes the technological components that should be improved or introduced. Such information is transmitted to the agents with stochastic noise and individually perceived information is shared with other agents over the established partnership network. Once the agents fully recognize the technological specification that the consumer group demands, they start to acquire the necessary technologies to produce the newly demanded product. If a manufacturing *FIRM* fully obtains the necessary technologies, it earns the largest share of the market and sales revenue. After a given delay that reflects the consumer demand cycle (CDC), the technological specification of the product is redefined by the consumer group. The amount of time that it takes to produce the new product that meets the consumer group's new demands depends on how quickly the agents correctly guess the technological specification of the new product and how efficiently *FIRMs* acquire the corresponding technologies. The delay in releasing a new product from the time when the consumer group's new demand has been generated (referred to here as first catch-up delay or *FCUD*) represents the extent to which manufacturers efficiently satisfy the new market demand.

An agent invests in R&D and has operating costs. This expenditure of an individual agent flows back into the entire agent society through a component called "capital reservoir." Thus, the total amount of the capital asset circulating through the whole system is sustained at the same level as the initial total amount of the capital asset. The capital reservoir is primarily redistributed to *UNIVs* as a public R&D fund and the leftover capital defines the market size. Figure 3 illustrates the entire model.

[Insert Figure 3. Overview of the NIS Model]

The mechanism for economic growth by innovation is not captured in the present model. Because the purpose of the present study is to examine system-level efficiency in terms of technology (or innovation) sourcing imposed by a particular institutional configuration, economic expansion by innovation is not necessarily implemented. Also, modeling the mechanism of economic growth that is driven by innovation outcomes increases the overall model's complexity with an arbitrarily designed computational mechanism.

3.3 Process Overview and Scheduling

During simulation, the consumer group changes the technological specification of the market-demanded product 10 times (*prod_wave* is equivalent to 10 new products). Whenever the consumer group creates a new demand for the product, the information about the technological specification of the newly demanded product is delivered to the agents' society with stochastic noise. Once the new information is released, the agents start to guess what technological components are required and which of these should be technologically improved while retaining the previously perceived information. This process works through the internal information-learning and mutual information-sharing process with other networked agents. The information-learning process is repeated 12 times for every simulation turn. One simulation turn is set to one year; thus, a cycle of 12 iterations assumes that an individual agent updates its information monthly. To conduct statistical analysis, we repeat the simulation 10 times in every set of conditions (parameters). The following provides more detail of the timing of events and the scheduling of the process during simulation.

At t = 0, agents start to learn about the technological specification of the consumer-demanded product and decide on the technology sourcing strategy in the context of the perceived information. This iteration occurs 12 times for a unit simulation turn. After 12 iterations, the next simulation turn (t = 1) starts. The process from t = 0 to t = 1 becomes the unit process of simulation. The unit process is repeated 10 times during a simulation, which means that the consumer group demands changes 10 times during the simulation. Every simulation condition experiences 10 changes of consumer demand, which gives 10 *FCUDs*. When the final, tenth, “consumer demand” is satisfied by some of the agents, the simulation has finished. The whole simulation process is repeated 10 times. In this sense, simulation with each simulation parameter set gives 100 *FCUDs* (10 *FCUDs* in a simulation and 10 repetitions). All agents retain their previously updated information about consumer demand. If consumer demand changes, the new information gradually replaces the agents’ prior information. Readers need to be aware that the present simulation model does not have a definitive time horizon until the simulation’s end. Instead, the simulation model fixes the times of consumer demand change, and the simulation is finished when the last consumer's demand is satisfied by some of the agents.

[Insert Figure 4. Simulation Timing and Outcomes]

The following sub-processes are operated in each simulation turn: (a) a capital reallocation process through the capital reservoir, (b) cost and revenue calculations for agents, (c) information sharing alongside learning and technology sourcing, (d) a spin-off process, and (e) the elimination of bankrupted agents. The agent-partnership network is updated during the technology transaction process.

3.4 Design Concept

Emergence. System-level dynamics emerge as a result of the interaction between the agents. This interaction generates a partnership network during the information-sharing/technology-sourcing process. We observe that the partnership network structure and system-level knowledge sourcing efficiency are the primary simulation outcomes.

Adaptation. Manufacturing *FIRMs* make decisions about whether they will stay with or exit from the product market by calculating expected profits (expected sales revenue – expected costs). In the technology sourcing process, the technology owner considers the following two factors: (1) the economic benefits and (2) the non-economic benefits of a long-term partnership.

In economic benefits estimation, the technology owner considers the following trade-off: the royalty revenue that the technology owner can obtain from a licensee if the owner licenses the technology compared to the expected loss of market share due to competition with the licensee in the product market.

In non-economic benefits estimation, the technology seller considers the intangible benefit from a long-term partnership. The seller can consider licensing the technology to a potential licensee even though the expected economic benefit is negative if two parties are in a historical partnership. This mechanism considers the potential benefit from a "mutual trust-based long-term business relationship." Thus, the likelihood of considering the non-economic benefit in license negotiation is proportional to relationship dependency (*rel_dep*) and the agent's internal stochastic decision process.

Fitness. An agent tries to maximize the expected benefits and survive. A *FIRM* tries to obtain the latest technology in order to gain a competitive edge when it becomes a manufacturer. A *UNIV* tries to produce new technology as much as possible. In the negotiation for a license contract or R&D collaboration, an agent can accept or reject the negotiation according to the expected benefit. If an agent's retained capital asset falls below a given threshold, the agent stops the R&D process and reclaims the invested R&D asset in order to survive.

Prediction. In the negotiation for a license contract, a potential licensor predicts the amount of royalty revenue that it can earn from the potential licensee. The royalty rate is fixed for every license contract, but the sales revenue that the licensee will obtain depends on various conditions. When an agent predicts expected sales revenue, it first estimates expected market power, which is an index that aggregates technological fitness with market demand and marketing capability. Then, the expected market share is calculated by using the ratio of the agent's market power to the total sum of the manufacturer's market power.

Sensing. Agents sense the following information. First, they know manufacturers' current market power and market share. Second, When an agent interacts with another agent, it knows which technologies will be used if the other agent is (or becomes) a manufacturer. Third, an agent can identify which agents are its historical partners. Fourth, an agent perceives noisy information and aggregates the partner's information about consumer demand. However, it cannot know non-partners' information.

Learning. The present model comprises two learning processes as follows.

(1) Information learning. Agents share information about the consumer group's demand with the networked agents. The agents guess the technological specification of the consumer group's demanded product through self-information collection and learning about other agents' information.

(2) Technology learning. Agents learn other agents' technology through license contracts. The licensee learns about the licensed technology even after the license contract has expired. Thus, the speed of the overall learning process (the degree of a target technology's diffusion across the agent community) depends on how quickly the agent finds other agents that may license the target technology and how easy

it is to obtain a license. If many agents have the target technology, the agent will obtain the technology relatively quickly because it is easier to identify the technology-owning agents. However, if few agents have the target technology, the agent may spend more time identifying the agents that have the target technology and obtaining a license. In this sense, the smaller the number of agents that have the target technology, the more the delays in target technology sourcing and the slower the learning speed.

Interaction. Agents engage in the following three types of interaction. First, an agent communicates with other networked agents to guess the consumer group's new demand correctly. Second, agents interact in order to obtain license contracts. An agent that needs a particular technology can seek other agents that have the technology already and can ask for the technology owner to license the technology. Third, an agent collaborates with other agents in order to acquire technology. An agent that requests R&D collaboration pays half of the expected R&D expenses to the partner agent. The partner calculates the expected benefit from the R&D investment. If it is positive, the partner agent pays the remaining half of the expected R&D expenses and starts the R&D process to develop the target technology. Alternatively, in a stochastic process, the other agent decides whether to engage in the collaborative R&D process by considering a historical partnership with the agent that requested the R&D collaboration. Once two parties agree on the R&D collaboration and the target technology is developed successfully, the technology is shared between the two parties.

Stochasticity. The present model includes a number of stochastic processes. First, the initialization process randomly assigns the initial technology asset to each agent. Second, the information-sharing and learning process is stochastic. The system stochastically generates noisy information about the consumer-demanded product's technological specification. Agents try to guess the correct technological specification of the consumer-demanded product through network-based learning. To implement this process, we employ the non-Bayesian network learning model (Epstein, Noor, & Sandroni, 2008; Epstein, Noor, & Sandroni, 2010; Jadbabaie, Molavi, Sandroni, & Tahbaz-Salehi, 2012). This model has a Bayesian learning model as a key mechanism and additionally includes the mutual learning process of agents over the given agent network (see AP 7). Third, the internal R&D process has stochastic processes. The R&D process follows a "linear model" that comprises three ordered R&D stages: basic research, applied research, and development (Godin, 2006; Greenhalgh & Rogers, 2010). For every R&D stage transition, an agent must make unit R&D investment. Once an agent has invested in R&D, the internal stochastic process determines the R&D stage transition. If the R&D investment is successful, the R&D stage moves from basic research to applied research and applied research to the commercial research stage and so on. Fourth, the spin-off process includes a stochastic process. The system assigns an "entrepreneur" to *FIRM* or *UNIV* randomly. An agent that has an entrepreneur randomly creates a new *FIRM*. The newly created *FIRM* copies the technologies of a particular technological component from the parent agent. The commerciality of the technology that is currently required by the consumer group randomly becomes either the “applied stage” or the “commercialization stage.” Fifth, the consumer group defines the technological specification of the new product that it demands most through a stochastic process. This requires innovation of two technological components in order to define the technological specification. The innovation can be either a “technological performance improvement of the selected technological components” (incremental innovation) or the “introduction of a new technological component that is not required in the prior product” (radical innovation). As the simulation factor *p_dis* (the likelihood of requiring radical innovation) becomes higher, the new product that the consumer group will demand in the future is more likely to comprise “new technological components.”

Observation. First, we analyze the generated partnership network structure with regard to the distribution of network degree and the distribution of the age of bankrupted agents in order to check the present model’s validity. We check whether the distribution of the degree of the generated network follows the power law, which is the general pattern in the real-world R&D collaboration network. The distribution of the age of bankrupted agents is observed in order to find consistency with the theoretical studies on firm exit and entry dynamics. Second, we analyze the average of the *FCUD* and the standard deviation of the *FCUD (std_FCUD)* as system-level outcomes. *FCUD* estimates the delay in releasing new products after the consumer group changes its demand. *std_FCUD* measures how much the *FCUD* fluctuates during the simulation. It estimates the stability of releasing a new product that satisfies consumer demand in terms of *FCUD*.

3.5 Initialization

Initially, five manufacturers, 25 non-manufacturing *FIRMs*, and 10 *UNIVs* are used. The initial number of essential technological components for product implementation is set at 10. Each of the manufacturers begins with five internally developed items of commercialized technology, and the remaining five are licensed from five randomly selected non-manufacturing *FIRMs*. Therefore, the initial network starts with five one-to-five links between a manufacturer and five *FIRMs*.

The licenses are given on an exclusive contract basis. The technology is no longer available for another license contract until the prior license has expired. *UNIVs* initially have five technological components including an eleventh component that is not yet essential technology for a given product implementation. Allowing *UNIVs* to have a non-essential technological component reflects the point that universities are used to engaging in the development of radically innovative technology that is based on scientific knowledge and that is new to the world. All the technology initially given to *UNIVs* is “basic-idea level” to reflect that universities mainly engage in R&D for technology that is relatively less commercial than technology created by corporate R&D.

When the spin-off process is initiated, the process checks whether the focal agent has an entrepreneur. This entrepreneur decides whether to create a new firm or stay with the parent agent. The probability (or rate) at which entrepreneurs decide to create spin-offs is fixed. Therefore, the spin-off rate is the same across the simulation for the U.S. NIS and the JP NIS. If the entrepreneur decides to form a new firm, the entrepreneur is removed from the parent agent. The newly created *FIRM* is set to non-manufacturing *FIRM*. One technological component is selected, and all the technologies associated with the technological component are copied from the parent agent to the new *FIRM* within a stochastic process. The implemented spin-off mechanism is the same regardless of the simulation factor, such as the relationship dependency between agents. However, the variation in the simulation parameters might produce a different systemic environment that affects the spin-off agent's survival. For example, in a low relationship-dependency system, more agents have the opportunity to sell their technology and generate revenue by doing so. In this system, the spin-off agents have a better chance of survival than in a system that has high relationship-dependency. The agents that survive again form new spin-offs through the same process, which eventually expands the number of agents in the system. If we consider that the high relationship-dependency system is the JP NIS and that low relationship-dependency corresponds to the U.S. NIS, the U.S. system may have a greater number of spin-off *FIRMs* that survive, and the JP system has fewer.

3.6 Input

Table 2 summarizes the necessary parameters for the simulation. Whenever the consumer group requires radical innovation, one additional technological component that was unnecessary in the prior product becomes a new required technological component in the new product.

Category	Variable	Value	Description
Property of agent	Agent's index	Random integer number	Identity of agent (a unique value)
	Agent type	A value among [1,2,3]	1: big firm (initial manufacturer); 2: small firm; 3: university
	Asset(*Ca*)	Integer number	Initial capital asset of Big firms: 100 Small firms: 10 University: 10
	State	A value of [1,2]	1: non-manufacturing state; 2: manufacturing state
	Factory	0 or 1	0: does not have a factory; 1: has a factory
	mkt	Incremental integer number	Agent has marketing experience Firm-agent: period that the agent has been a manufacturer University-agent: fixed to 0
	tech	2-D matrix	Technologies that the agent owns (refer to tech-portfolio matrix in appendix)
	birth	Integer number	The time at which the agent was created
	entre	Value of [0,1]	0: agent does not have entrepreneur; 1: agent has entrepreneur
	belief	Continuous value of [0,1]	0: customers do not need an improved technological performance or new introduction of tech in the new product 1: Customer needs an improved technological performance or introduction of new tech in the product
	budget	Nx3 matrix	Retaining budget plan for R&D project (refer to protocol in the appendix)
Simulation factors	CDC	1, 3, 5, 7, 9	Consumer demand cycle (CDC). 1: very short; 9: very long
	rel_dep	0.1, 0.3, 0.5, 0.7, 0.9	Likelihood of relying on internal R&D or historical partners for technology acquisition
	p_dis	0, 0.1, 0.3, 0.5, 0.7, 0.9	Probability that a new technological component is required for new product (probability of requiring radical innovation)
	Inhouse (inh)	0.1,0.2,0.3,0.4,0.5,0.6,0.7,0.8,0.9	Likelihood of relying on internal R&D for technology acquisition (in-house R&D likelihood)
Non-simulation parameters	prod_wave	10	Total number of new product designs during simulation
	rnd_th	0.8	Threshold of R&D investment decision about particular technological component based on consumer demand information
	wt (wm)	0.25 (0.75)	Contribution of technological fitness of product for market demand (market experience) to market power
	fac_invst	20	Required investment for factory building
	fac_mc	10	Factory maintenance cost
	fac_sv	10	Factory salvage value
	op_cost	1	Fundamental operating cost
	rnd_cost	1	Required minimum R&D expenditure for every R&D process engagement
	sim_trial	50	Repetition of simulation in same condition
	init_mkt	10000	Initial product market size
	entre_spirit	0.1	Probability of spin-off from the agent that has an entrepreneur

Table 2. Parameters and Variables

The new product should also have the previously required technological components. Thus, the number of the product's technological components and the product's technological complexity increase (accumulation). If the consumer group requires incremental innovation at the product level, the selected technological component of the prior product must provide "technological performance improvement."

Whenever the consumer group requires a new product, the new demand is transformed into innovation in terms of two technological components for the new product's technological specification. The probability of requiring radical innovation (*p_dis*) stochastically determines whether a new product should include "new technological components" that were not essential technological components in the prior product. The probability of requiring incremental innovation is 1-*p_dis*. Therefore, the higher *p_dis* becomes, the greater the differentiation of the new product from the prior product.

3.7 Sub-Model

When an agent decides on the technology sourcing strategy, it selects one of the following options: sourcing by an internal R&D process, sourcing from historical partners, or sourcing from non-historical partners. The decision-making follows a probabilistic process, illustrated in Figure 5.

[Insert Figure 5. Strategy Selection for Technology Sourcing]

At a given probability (1-*rel_dep*), the agent seeks non-historical partners that have the target technology and tries to obtain a license. Alternatively, the agent decides whether it should source the technology from internal R&D or an historical partner. At a given probability (*INH*), the agent decides to source the technology from the internal R&D process, or the agent tries to source the target technology from historical partners.

4 Validity Test and Simulation Plan

4.1 Internal Validation

We check whether the model produces reliable outcomes in relation to the internal stochastic noise (internal validation). We observe the following outcomes: (1) the number of agents, and (2) the survival rate of *FIRMs*. These outcomes represent the system-level outcomes because the system-level dynamics emerge from the interaction among individual agents; in addition, only *FIRM* has exit-entry dynamics. Figure 6 demonstrates that the system responds to the given stochastic noise in a reliable way.

[Insert Figure 6. Internal Validation]

4.2 External Validation

External validation checks whether the model reflects real-world dynamics. In most cases, however, suitably comparable real-world data are not available, nor does the obtained real-world data have the same scale as simulated data. In the present study, we adopt two validation points. First, we compare the distribution of the degree of the R&D partnership network. The second point is the distribution of firm exit rate by firm age.

(1) Distribution of the Degree of the R&D Partnership Network

According to a study by Powell, Koput, and Smith-Doerr (1996), the degree of the R&D collaboration network follows power law in the life-science industry. In addition, Okamura and Vonortas (2006) find that alliance and knowledge network degree distributions adopt power law across the industry that they investigate. If the present model is consistent with the real-world dynamics of collaboration, collaboration network degree distribution must follow the power law.

Figure 7 shows a left to right declining straight line that matches the power law. The vertical axis is the log value of the population of agents that have the corresponding degree, and the horizontal axis is the log value of a degree in the network. We observe the power law in the distribution of network degree across every simulation condition. Therefore, we argue that the distribution pattern comes from the implemented dynamics in the present model and not from a particular set of simulation parameters.

[Insert Figure 7. Distribution of Partnership Network Degree (Empirical vs. Simulation)]

(2) Distribution of Agents' Exit Rate by Age

Because the agent community drives the major dynamics in the simulation, it is important to look into the pattern or characteristics of agent exit/entry. According to an empirical study by Dunne, Roberts, and Samuelson. (1989), the distribution of firm exit rate by firm age follows the exponential distribution in the semiconductor industry. A theoretical study of Clementi and Palazzo (2014) confirms that the distribution of firm exit rate by age follows the exponential distribution across industries.

Figure 8 shows a left to right declining straight line that largely matches an exponential distribution. The vertical axis is the log value of the population of exit *FIRMs* that have the corresponding age, and the horizontal axis is the age of exit firm agents. We observe the exponential distribution of *FIRM* exit rate by age in every simulation condition. Therefore, we consider that the distribution pattern comes from the implemented dynamics and not from a particular set of simulation parameters.

[Insert Figure 8. Distribution of Agents' Exit Rate by Age (Theory vs. Simulation)]

4.3 Experimental Setup For Simulation

The stylized simulation factors are: (1) the degree of relationship dependency in technology sourcing (*rel_dep*), (2) the reliance on in-house R&D for technology sourcing (*INH*), (3) the consumer demand cycle (*CDC*), and (4) the likelihood of requiring a radically innovative feature (*p_dis*) in the new product. The other parameters are fixed. The following two outcomes are analyzed. Figure 9 summarizes the overall simulation plan and Table 3 describes the experimental setup.

- First catch-up delay (*FCUD*)
  - *Accumulated FCUD*. In the simulation, the consumer group generates new demand for the product 10 times. Once the 10 new products are completely implemented, the simulation has ended. We estimate the length of time to complete the simulation. Overall, when it is shorter, the agent implements the newly demanded product more efficiently.
  - *Average of FCUD.* During the simulation, we have 10 time delays with regard to the release of the newly demanded product. We estimate the average of 10 generated *FCUD*s.
- Standard deviation of the *FCUD* (*std_FCUD*)
  - The standard deviation of the 10 individual *FCUDs* measured during the simulation estimates the stability of implementing a new product that meets the consumer group's new demand.

[Insert Figure 9. Simulation Plan and Experimental Setup]

Table 3. Experimental Setup

Simulation factors	CDC	1,3,5,7,9	Consumer demand cycle. 1: very short; 9: long
	rel_dep	0.1, 0.3, 0.5, 0.7, 0.9	Likelihood of relying on internal R&D or historical partners for technology sourcing
	p_dis	0,0.1, 0.3, 0.5, 0.7, 0.9	Probability of requiring a new technological component in new product (probability of radical innovation)
	Inhouse(INH)	0.1,0.2,0.3,0.4,0.5,0.6,0.7,0.8,0.9	Likelihood of relying on internal R&D for technology acquisition (in-house R&D likelihood)
Initial parameters	prod_wave	10	Total number of new product designs during simulation
	rnd_th	0.8	Threshold of R&D investment decision as to whether certain technological components should be improved (or introduced) to meet specification of new product

wt (wm)	0.25 (0.75)	Weight on the value of technology (market experience) when calculating the market power of a manufacturer
fac_invst	20	Required investment for building a factory
fac_mc	10	Factory maintenance cost
fac_sv	10	Factory salvage value
op_cost	1	Operating cost
rnd_cost	1	Required minimum R&D expenditure in order to engage in R&D process
sim_trial	10	Repetition of simulation in same condition
init_mkt	10000	Initially given product market size
entre_spirit	0.1	Probability of creating new firms by the agent that has an entrepreneur
n_big	5	Initially introduced number of manufacturers
n_sme	25	Initially introduced non-manufacturing firm agents
n_univ	10	Initially introduced number of UNIVs

5 Simulation Results

We employ graphical presentation in order to analyze the system-level outcomes of the stylized simulation factors and use statistical analysis for more detailed interpretation. We analyze 13,500 records (*CDC* variation × *rel_dep* variation × *p_dis* variation × *INH* variation × *simulation repetition time* = 5 x 5 x 6 x 9 x 10=13,500).

5.1 Effect of Relationship Dependency on the *FCUD*

(1) Graphical Representation

Figures 10 and 11 illustrate the change among *FCUDs* according to the simulation condition. At *CDC* = 1, a low *rel_dep* forms the minimum *FCUD* when radical innovation probability is high (*p_dis* = 0.7, 0.9). However, high relationship dependency (*rel_dep* = 0.9) gives a minimum *FCUD* when radical innovation probability is low (*p_dis* = 0, 0.1). This pattern implies that relying more on historical partners or internal R&D capability for technology sourcing is beneficial when consumer demand is fast-changing and a greater need exists for incrementally innovative technological features in a new product. However, searching for a new partner that knows about the required technology and then sourcing the technology is advantageous when consumer demand is fast-changing and a greater need exists for radically innovative technology in a new product.

[Insert Figure 10. Accumulated FCUD]

The simulation result for a long *CDC* (*CDC* = 9) and a low likelihood of requiring radical innovation in a new product (*p_dis* = 0, 0.1) shows that the *FCUD* is indifferent across the *rel_dep*, the reason for which could be the corner solution. High radical innovation probability (*p_dis* = 0.7, 0.9) still gives a minimum *FCUD* at a low level of *rel_dep*. This pattern implies that a long *CDC* dilutes the effect of *rel_dep* on *FCUD*.

[Insert Figure 11. FCUD Minimum and its Trajectory according to p_dis and rel_dep]

(2) Statistical Analysis and Dynamics

We employ regression analysis in order to examine the dynamics that drive the overall pattern according to the simulation factors. We apply the Tobit model with a lower bound 0 because the dependent variables (*FCUD and std_FCUD*) have continuous positive values.

The regression coefficient of *CDC* on *FCUD* is negatively significant (Model 1-1). This result indicates that the longer the *CDC*, the shorter the *FCUD*. The coefficient also demonstrates the "learning effect" imposed by a long *CDC*. Agents learn about other agents' technology through license contracts. If most agents have enough time to interact with other agents with regard to licensing before consumer demand changes, most agents are likely to know about the required technology for product implementation. In other words, a longer *CDC* would drive most agents to share the necessary technology for currently demanded product implementation, a situation that reduces the delay to acquire the focal technology.

The regression coefficient of *p_dis* on *FCUD* (Model 1-1) is positively significant. This coefficient implies that when a consumer group requires a radically innovative technological feature more than incremental innovation for a new product, manufacturing *FIRMs* experience greater delay before providing the newly demanded product. Very few agents in the agent society have radically innovative technology; therefore, searching for agents that have the technology and acquiring it takes more time, which causes longer delays for the implementation of new products. As a result, the higher the likelihood of requiring radically innovative technological features in new products, the higher the *FCUD*.

The regression coefficient of *rel_dep* on *FCUD* is positively significant (Model 1-1). The coefficient shows that relying more on historical partners or internal R&D for technology sourcing causes greater delay for new product implementation. A high degree of relationship dependency limits the pool of agents with whom the technology-seeking agent can negotiate to obtain a license. As a result, the technology-seeker loses opportunities to source technology more quickly. Therefore, on average, the agents that are more likely to rely on historical partners or internal R&D rather than new partners experience greater delay in technology sourcing.

The regression coefficient of *INH* on *FCUD* is positively significant (Model 1-1). As in-house R&D dependency increases, so *FCUD* rises overall. The interpretation of this situation is that more reliance on internal R&D might further limit the pool of agents that have the necessary technology and the consequent licensing of it to the technology seeker. An agent that does not have enough internal R&D capability to develop the target technology, and does not yet have the corresponding technology, should find other agents that own the technology in order to source it. Therefore, relying more on internal R&D removes opportunities to source the necessary technology from other agents, a situation that increases *FCUD*.

The regression coefficient of the interaction term of *CDC* and *rel_dep* ($CDC \times REL$) is positively significant on *FCUD* (Model 1-2). The marginal effect of *CDC* decreases as *rel_dep* increases. This effect indicates that relying more on an historical partner or internal R&D capability for technology sourcing drives down the learning effect. Interaction with more diverse agents that have different technologies that are not owned by historical partners or the agents themselves allows the agent to learn about a greater variety of technology. Another dynamic is the information-learning process. If an agent has a broad partnership network because of a low *rel_dep*, the agent can guess the newly demanded product's technological specification more quickly because the broader partnership network provides more information regarding consumer demand at a given time. Indeed, such an agent is more likely to guess the consumers' new demand both correctly and quickly.

The coefficient of $PDIS \times REL$ is positive. The coefficient tells us that it is beneficial to rely less on historical partners or internal R&D for technology sourcing when the consumer group frequently demands radically innovative technological features for a new product. Very few agents own radical innovation. Further, relying on historical partners or internal R&D may extend any delay in sourcing technology because the historical partners or agent mostly know about the technologies that were necessary for the prior product. In this regard, the agent and the historical partners are likely to know about incrementally innovative technology based on the prior technology stock that they possess. Such pre-owned technology stock does not help to develop radical innovation because radically innovative features are new to the entire agent society. Therefore, the "limited technology sourcing pool effect" associated with high relationship dependency is aggravated when the consumer group is likely to require radical innovation in a new product.

The negative coefficient of the $PDIS \times INH$ shows that it is beneficial to have greater internal R&D dependency in technology sourcing in order to reduce the delay generated by the requirement for radically innovative technological features in new products. Thus, the analysis of the marginal effect of *p_dis* suggests that a partnership with various players, while retaining internal R&D capability, is an effective strategy to cope with the increased delay in meeting consumer demand imposed by the radically innovative technology requirement.

The negative coefficient of $REL \times INH$ implies that if an agent decided not to source technology from new partners, relying more on internal R&D capability rather than historical partners for technology sourcing helps to reduce any delay in product implementation. This approach benefits the agent because it can reduce the time to obtain a license contract with historical partners. The agent is likely to know about the technology fields in which the historical partners are also knowledgeable because the agent has learned about the historical partners' technologies through repetitive partnership. Therefore, it is plausible that the agent and the historical partners would have comparable technology and development capability. In this case, relying on internal R&D rather than historical partners for technology sourcing helps to reduce any delay in technology sourcing.

5.2 The Effect of Relationship Dependency on the Stability of Technology Sourcing

We estimate the standard deviation of *FCUD* (*std_FCUD*) in order to check system-level technology-sourcing stability. The simulation generates *FCUD* whenever consumer demand is first satisfied. We gather the *FCUDs* and calculate standard deviation. A low standard deviation indicates that the system provides a stable environment for technology sourcing and product implementation.

(1) Graphical Representation

Figure 12 shows the pattern of *std_FCUD* according to the *CDC* and *p_dis*. At the lowest *CDC* (*CDC* = 1), a low *rel_dep* forms the minimum *std_FCUD* as *p_dis* increases. This pattern implies that having a strong relationship with prior partners would help stable technology sourcing when a consumer group requires incrementally innovative technological features in a new product and *CDC* is very short. On the other hand, relying more on historical partners or internal R&D capability for technology sourcing may cause greater time delay fluctuations when sourcing suitable technology (increased *std_FCUD*).

[Insert Figure 12. std_FCUD according to Simulation Parameters]

std_FCUD is indifferent across all *rel_dep* when the likelihood of radical innovation is small and the *CDC* is long. As Figure 11 shows, almost all *rel_dep* with a radical innovation ratio that is less than 0.3 gives zero *std_FCUD*. This pattern again confirms that through the learning process, a long *CDC* and low radical innovation likelihood make most agents knowledgeable about the technology that may be necessary for the next new generation product. Zero *std_FCUD* means that manufacturers are ready to implement the newly required technology into the product before the consumer group demands it. We acknowledge that the indifference of the *std_FCUD* regardless of the level of *rel_dep* may come from the corner solution in the simulation. We detail the findings through statistical analysis.

(2) Statistical Analysis and Dynamics

The statistical analysis of *std_FCUD* largely aligns with the *FCUD* analysis. In particular, the coefficient signs and significances in the basic model without the interaction terms of *CDC×REL* and *PDIS×REL* are the same as in the *FCUD* analysis. When the interaction terms are introduced, the coefficient of *CDC×INH* becomes negatively weakly significant. This coefficient indicates that when the *CDC* is long enough, relying more on internal R&D rather than other agents for technology sourcing helps stable technology sourcing. When the *CDC* is long, most agents have enough chances to learn about other agents' technologies through mutual transactions. Therefore, the technologies that agents know about are largely similar to each other. In this case, seeking technology from other agents essentially takes more time, and such time spent sourcing fluctuates to a greater extent because of the delay caused by technology transaction negotiation for technology acquisition. However, if the agent has the technology, relying on internal R&D for technology sourcing does not cause a delay. Therefore, a high reliance on internal R&D in a long *CDC* may provide an environment that stabilizes the technology sourcing delay. Table 4 illustrates the relevant regression analysis.

Table 4. Regression Analysis

	FCUD		std_FCUD	
VARIABLES	Model 1-1	Model 1-2	Model 2-1	Model 2-2
Consumer Demand Cycle (CDC)	**-0.074*** **	**-0.139*** **	**-0.547*** **	**-1.164*** **
	(0.020)	(0.023)	(0.042)	(0.054)
Radical Innovation Likelihood (p_dis)	**5.237*** **	**-2.543*** **	**13.868*** **	**4.237*** **
	(0.177)	(0.202)	(0.393)	(0.488)
Relationship Dependency (rel_dep)	**6.594*** **	**-0.549** **	**15.047*** **	0.643
	(0.200)	(0.251)	(0.427)	(0.553)
Likelihood of In-house R&D (INH)	**1.689*** **	**1.689*** **	**2.984*** **	**2.974*** **
	(0.300)	(0.266)	(0.641)	(0.587)
Interaction of CDC and rel_dep (CDC×REL)		**0.132*** **		**1.263*** **
		(0.029)		(0.067)
Interaction of p_dis and rel_dep (PDIS×REL)		**15.561*** **		**17.578*** **
		(0.254)		(0.596)
Interaction of CDC and Inh (CDC×INH)	**-0.039**	**-0.039**	**-0.109**	**-0.121* **
	(0.035)	(0.031)	(0.075)	(0.071)
Interaction of p_dis and Inh (PDIS×INH)	**-1.498*** **	**-1.498*** **	**-2.184*** **	**-2.120*** **
	(0.315)	(0.279)	(0.696)	(0.647)

Interaction of rel_dep and inh (REL×INH)	**-3.063*** **	**-3.063*** **	**-5.592*** **	**-5.578*** **
	(0.355)	(0.314)	(0.760)	(0.709)
Sigma	3.011***	2.662***	5.640***	5.265***
	(0.018)	(0.016)	(0.042)	(0.040)
Constant	-2.265***	1.306***	-10.028***	-2.346***
	(0.169)	(0.174)	(0.361)	(0.386)
Observations	13,500	13,500	13,500	13,500

*** p<0.01, ** p<0.05, * p<0.1, Standard errors in parentheses

5.3 Sensitivity Test

We use a sensitivity test to assess how the simulation outcomes respond to the variation in the non-simulation parameters. Including the simulation parameters, we use a 10% variation for each parameter and obtain 2,500 records. We measure how much of the total variation in the simulation outcomes is explained by the variation in non-simulation parameters and simulation factors. Also, we estimate to what extent each of the factors uniquely explains the total variation in the outcomes. First, we run an ordinary least squares (OLS) regression on *FCUD* and *std_FCUD* on the simulation parameters only. Then, we calculate the ratio of the total sum of the squares of the outcomes and the parameters. The analysis shows the extent to which the simulation factors explain the total variation in the simulation outcomes. Second, we regress the *FCUD* and *std_FCUD* on the non-simulation parameters only. Then, we estimate the ratio of the total variation in the dependent variables and the explained variation according to the non-simulation parameters. The result shows the extent to which the non-simulation parameters explain the variation in the dependent variables. Table 5 reports the sensitivity analysis. The “Explained Variation” in “Simulation Parameter Only” shows that 62.31% of the total variation in *FCUD* and 41.54% of the variation in *std_FCUD* is explained by the variation in the simulation parameters. The “Explained Variation” in “Non-Simulation Parameter Only” shows that only 3.13% and 4.23% of the variations in *FCUD* and *std_FCUD* respectively are explained by the variation in the non-simulation parameters. Thus, the sensitivity analysis implies that most of the variation in *FCUD* and *std_FCUD* is explained by the variation in simulation factors and not by the variation in non-simulation factors. We conclude that the simulation result is marginally affected by the non-simulation parameter.

Table 5. Sensitivity Test

Simulation Outputs	FCUD		std_FCUD	
Category	Parameter	% Variance	Parameter	% Variance
Simulation Parameter Only	CDC	56.10%	CDC	37.80%
	p_dis	43.80%	p_dis	39.90%
	rel_dep	31.60%	rel_dep	34.50%
	INH	3.38%	INH	3.20%
	Explained Variation	62.31%	Explained Variation	41.54%
Non-Simulation Parameter Only	mkt_size	1.61%	mkt_size	0.59%

ent_spirit	16.20%	ent_spirit	19.30%
ent_th	0.47%	ent_th	0.57%
rnd_th	0.81%	rnd_th	1.88%
fac_invst	1.73%	fac_invst	3.38%
fac_mc	0.91%	fac_mc	1.94%
fac_sv	0.75%	fac_sv	1.93%
op_cost	0.71%	op_cost	0.50%
rnd_expense	2.26%	rnd_expense	3.30%
Explained Variation	3.13%	Explained Variation	4.23%

6 Discussion

6.1 Findings from the Simulation

First, the optimal institutional relationship-dependency in technology sourcing varies according to condition. When the consumer primarily requires incremental innovation in a new product and consumer demand frequently changes, relying more on internal R&D capability or historical partners (high *rel_dep*) helps to shorten the delay in creating the consumer-demanded product. When consumer demand changes slowly (a long *CDC*), and product innovation is mainly incremental innovation (a low *p_dis*), the effect of relationship dependency on tech-sourcing efficiency is marginalized by the increased learning and technology diffusion effect. When product innovation is mainly radical innovation, less reliance on internal R&D or historical partners in technology sourcing helps to reduce the delay in new product implementation. As in-house R&D dependency increases, the overall delay in acquiring the necessary technologies for new product implementation increases.

Second, the degree of the impact of each simulation factor differs by the degree of other simulation factors. Because the primary simulation factor comprises the institutional variables of "relationship-dependency" and "in-house R&D dependency," we interpret the marginal effect of *rel_dep* and *INH* on *FCUD*.

(1) Marginal Effect of *rel_dep* on *FCUD*

When *p_dis* is large, the marginal effect of *rel_dep* becomes positive regardless of other simulation parameters. This pattern shows that it helps to have low relationship-dependency in order to achieve a shorter delay in technology sourcing if product innovation mainly requires radically innovative technology.

(2) Marginal Effect of *INH* on *FCUD*

The marginal effect of *INH* on *FCUD* turns negative when *p_dis* and *rel_dep* are large enough. Thus, if economic agents are in an institutional environment that obliges them to rely heavily on historical partnerships or internal R&D for technology sourcing, it is better to rely more on internal R&D capability if radical innovation mainly drives product innovation. However, when *rel_dep* is small enough, the marginal effect of *INH* turns positive. Thus, when economic agents are in an institutional environment that encourages liberal technology transactions (e.g., the U.S.), less reliance on internal R&D capability for technology sourcing and acquiring technology from other agents comprise an approach that is more efficient.

6.2 Juxtaposing with the Real World

First, the marginal effect of *rel_dep* on *FCUD* analysis predicts that the U.S. system would outperform the JP system in an industry where radical innovation is the primary innovation pattern. In an industry that requires incremental innovation and where consumer demand changes quickly, the JP system is likely to outperform that of the U.S. in terms of technology sourcing efficiency. We consider that information technology (IT) and biotechnology (BT) are examples of industries that require radical innovation in new products and services. In these industries, innovation is usually realized by implementing radically innovative features in a product or service. For example, 10 years ago, a conventional cell phone was nothing but a device for calling and messaging. Today, its replacement, the smartphone, is a radical innovation because it comprises new features such as Internet access, mailing, and social networking that were not available with the conventional cell phone. The simulation results show that an institutional arrangement that highlights liberal market transactions for technology, rather than maintaining strong relationships with historical partners or using internal R&D, helps industrial competitiveness. In the real world, we observe that world-leading companies in the IT industry have originated in the U.S., which has a liberal market economy. However, Japanese and German firms are not in the top tier of this industry. Thus, in the context of real-world juxtaposition with the simulation results, the JP NIS may institutionally impose unnecessary delays for firms that source radically innovative technology by stressing the historical relationships with prior partners.

Further, we can regard consumer electronics as an example of an industry that mainly requires incremental innovation and has fast-changing consumer demand. Consumer electronics such as home appliances and audio-video systems mainly need functional improvements in the technological components of the products. In addition, the market demand cycle is extremely short. For example, the functional performance of the display aspect of televisions has improved with developments such as enhanced resolution and graphics processing speeds that have very short product life cycles. Japanese firms such as Panasonic, SONY, and Hitachi have traditionally led this industry, and recently Korean firms such as Samsung and LG that also consider historical relationships as significant business assets are competing with the Japanese players. Another example is the automobile industry. Here, most new models of car include incrementally innovative technology such as more reliable and powerful engines and noise reduction systems. We observe that Japanese (e.g., Toyota, Honda, and Mazda) and German (e.g., BMW, AUDI, and Volkswagen) automakers have led the global automobile industry. The simulation results show that the Japanese and German systems, which institutionally encourage firms to have a strong business relationship with historical partners, have provided an institutional advantage for the firms that lead the industry.

Second, the marginal effect of *INH* and *rel_dep* on *FCUD* provides an interesting strategic implication for Japanese firms to enable them to survive in an industry that is heavily dependent on radical innovation. When we consider that the JP system is a system driven by historical relationships, the way for Japanese players to cope with the shock of radical innovation is to engage in more dynamic partnerships with a greater variety of players rather than remain with historical partnerships, while at the same time strengthening internal R&D capability (see AP 13). In an industry driven by incremental innovation, relying on internal R&D still benefits technology sourcing efficiency when the institutional environment is based on "long-term historical relationships." This explains why JP players have a strong tendency to rely on internal R&D, as a survey on Japanese firms' technology acquisition strategy shows (Kani & Motohashi, 2013). Therefore, we suggest that it is necessary for Japanese firms to have a more dynamic relationship with a variety of economic agents while keeping and strengthening internal R&D capability and for the Japanese NIS to promote this approach.

7 Conclusion

We propose the following implications for policymakers and Japanese business strategists. First, policymakers need to implement industry-specific policy. They should not necessarily adhere to a particular policy that either solely supports long-term historical relationships among economic players or promotes a liberal market mechanism across industries. As the simulation results and the real-world industrial landscape show, the optimal level of relationship dependency among players depends on industrial conditions. For example, Japanese firms and the government need to be careful about intentionally loosening the historical partnership network in the automobile industry. However, in an industry that requires radical innovation such as the IT industry, policymakers need to consider above all how to encourage the players to employ a liberal market mechanism in technology sourcing rather than relying on historical relationships. Second, Japanese firms need to retain and strengthen their internal R&D capabilities while having a more dynamic partnership network with a variety of players. This strategy is particularly effective for an industry that requires a greater amount of radical innovation. By building more dynamic business relationships and technology transactions with a variety of partners, JP firms can gain a better perspective of industrial change and a wider pool of partners that may have suitable technology that corresponds to radical innovation.

Some large firms have multiple business divisions for different industries. For example, Sony and Hitachi make home appliances and are also involved with the IT industry. Such companies need to adopt a different strategy for technology sourcing. The business divisions that deal with the IT industry need to strengthen their approach to purchasing radically innovative technologies from firms or universities that have the ideas they need, while at the same time strengthening their internal R&D capabilities by investing more in R&D and obtaining further well-qualified talent (e.g., through aggressive M&A). However, business divisions that target the home appliance market should maintain their strong business relationships with historical partners. Further, such divisions should maintain repetitive R&D collaboration, long-term contracts for technology sharing, and so on with prior business partners while keeping a strong internal R&D capability.

Our study makes two distinct contributions. First, we suggest the implications for Japanese policymakers and strategists who are struggling with the issue of how to rehabilitate Japanese national-level and individual firm-level industrial competitiveness. We show that the JP NIS does not need to change its institutional configuration radically so as to mimic the U.S. NIS; instead, it needs to stress the "importance of dynamic partnerships" for technology sourcing and support firms' efforts to strengthen "internal R&D capability." Also, JP firms need to manage their partner pools so as to have broader partnership relationships with a greater variety of players; however, they need to put greater effort into improving their internal R&D capabilities at the same time. Second, we extend the traditional framework that describes national-level industrial sector specialization. VoC theory explains how relationship dependency is related to industrial competitiveness with regard to the major innovation pattern of each industry. However, we reveal that the industry-level learning process and industry-specific characteristics in terms of consumer demand are also important factors in driving the national-level industrial sector specialization process.

Acknowledgements

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Tokyo. Any opinions, findings, conclusions, and recommendations expressed in this material are those of the authors and do not necessarily reflect the views of the RIETI.

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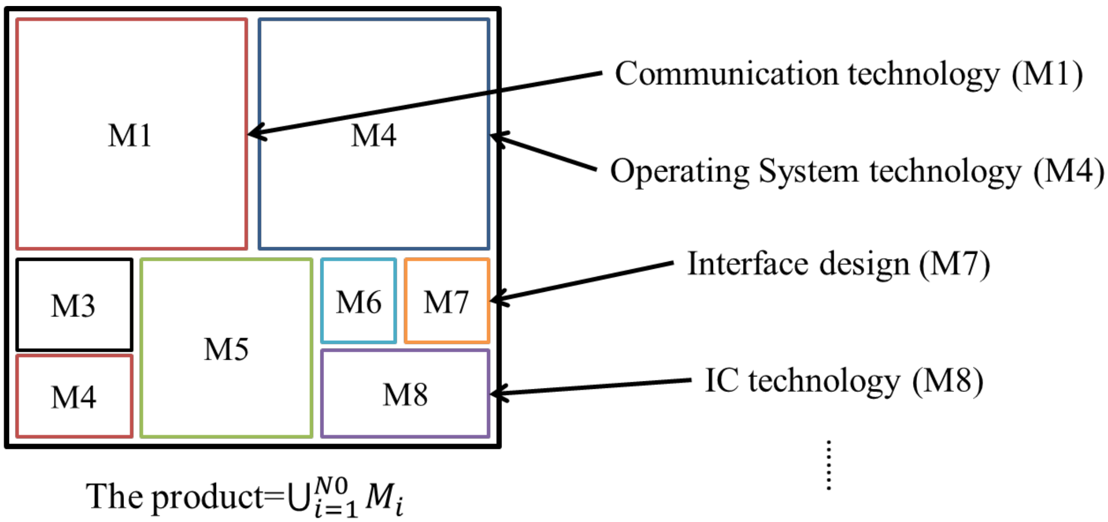
List of Figures



M_i: technological component "i""

Figure 1. Product Concept in the Present Model

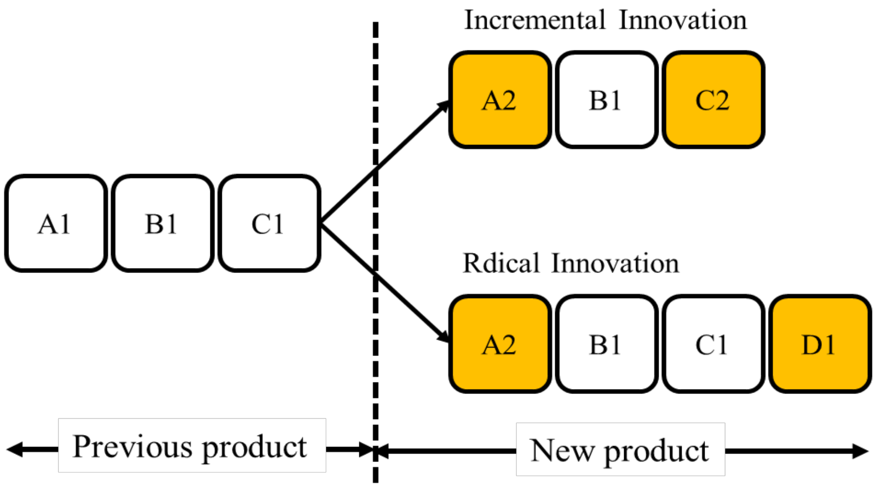


Figure 2. Product Level Innovation Pattern and Technological Component Change

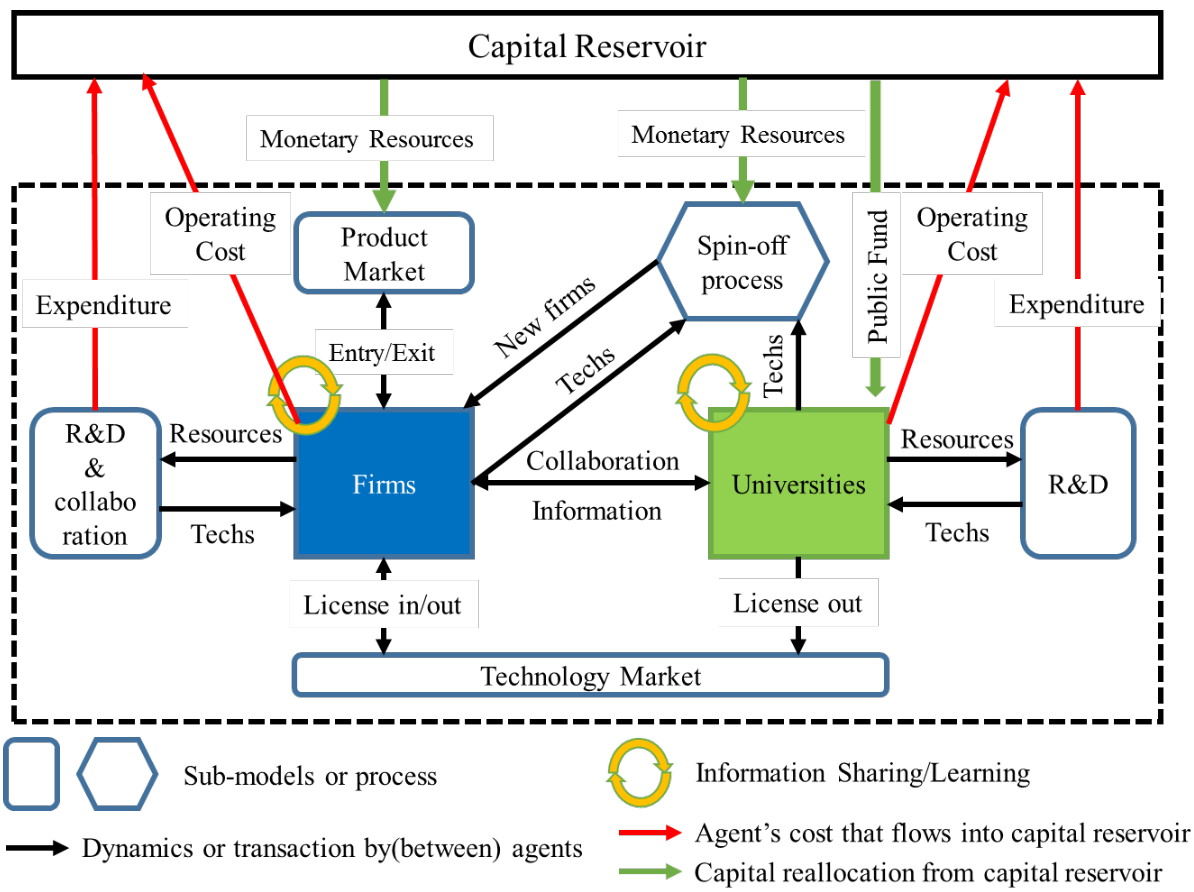


Figure 3. Overview of the NIS Model

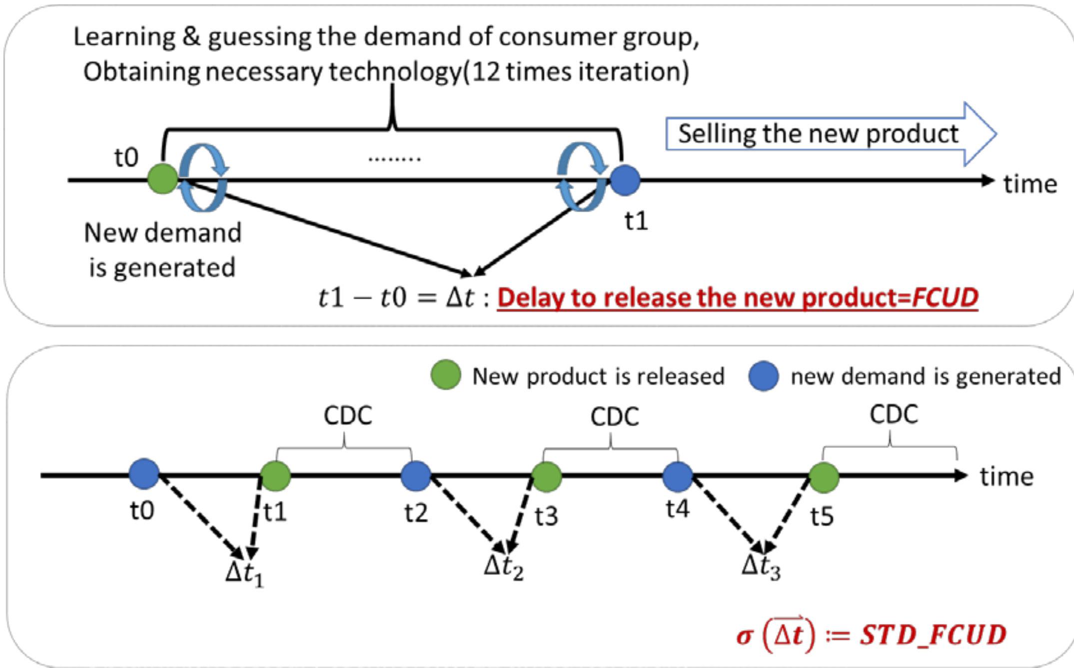
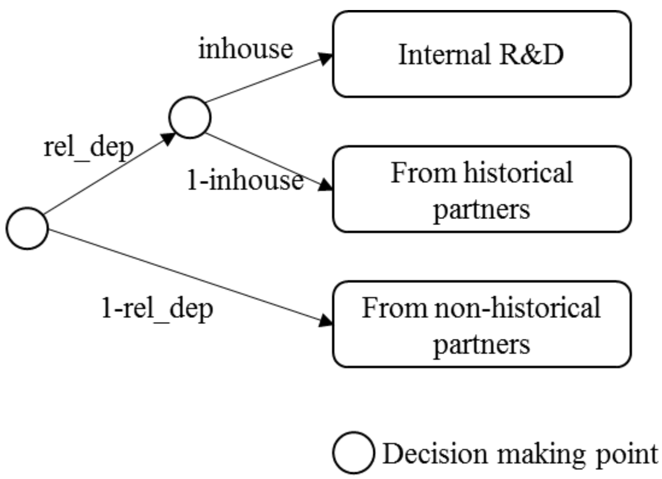


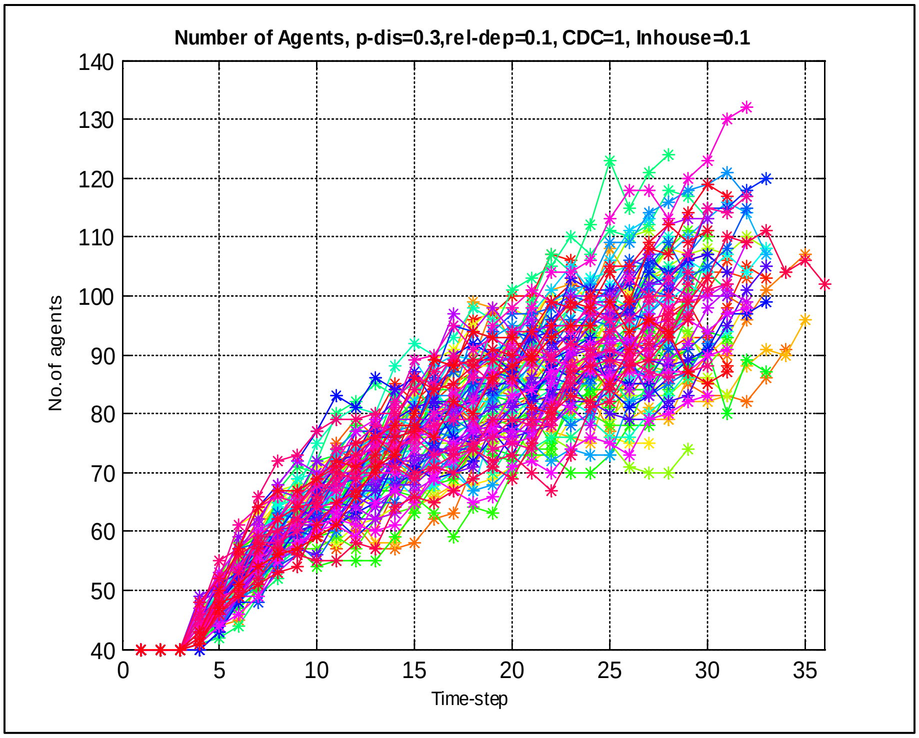
Figure 4. Simulation Timing and Outcomes



inhouse: probability of selecting in-house R&D if agent decided to source from historical partner or internal R&D,

rel_dep: relationship dependency (0 to 1)

Figure 5. Strategy Selection for Technology Sourcing



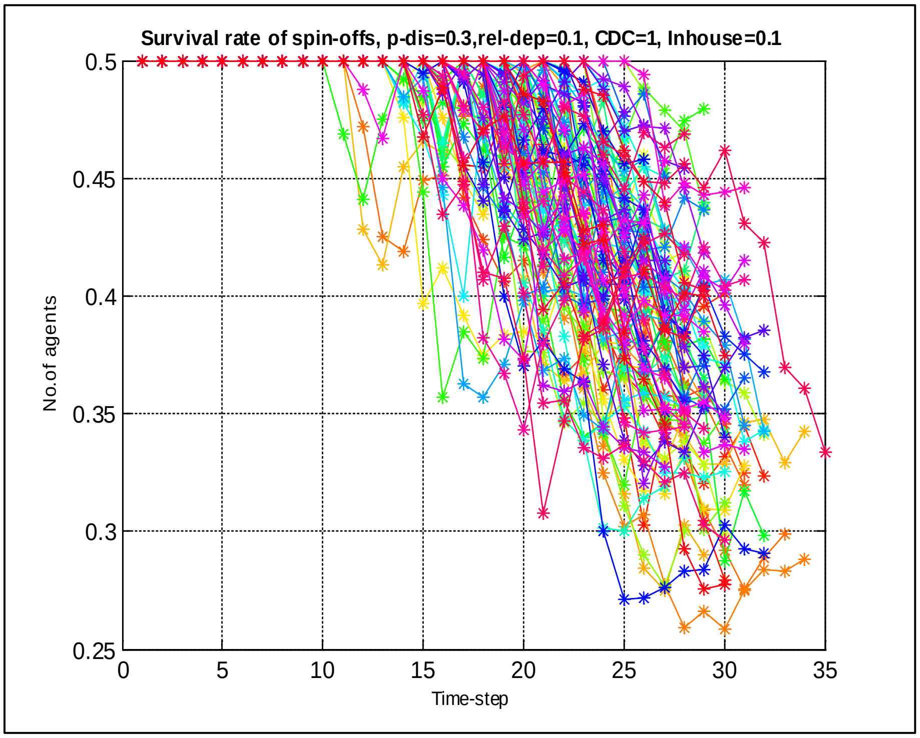


Figure 6. Internal Validation

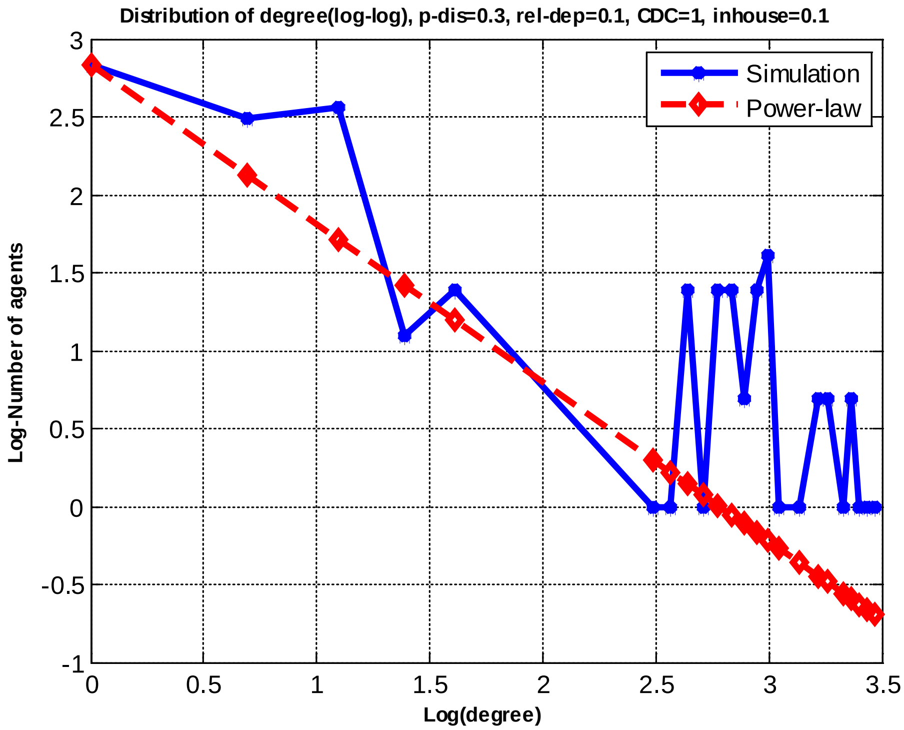


Figure 7. Distribution of Partnership Network Degree (Empirical vs. Simulation)

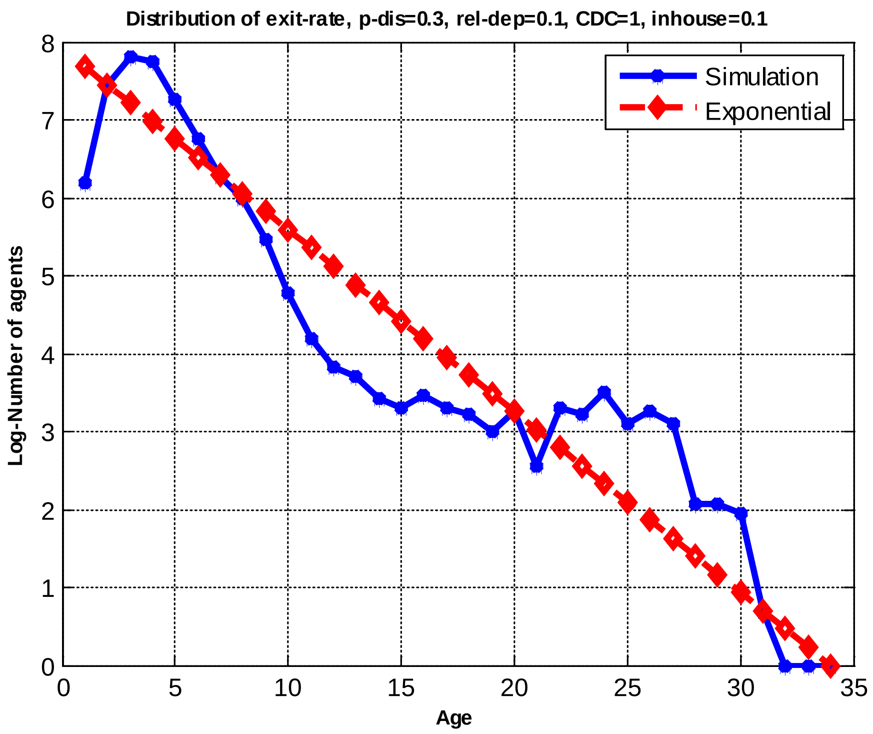


Figure 8. Distribution of Agents' Exit Rate by Age (Theory vs. Simulation)

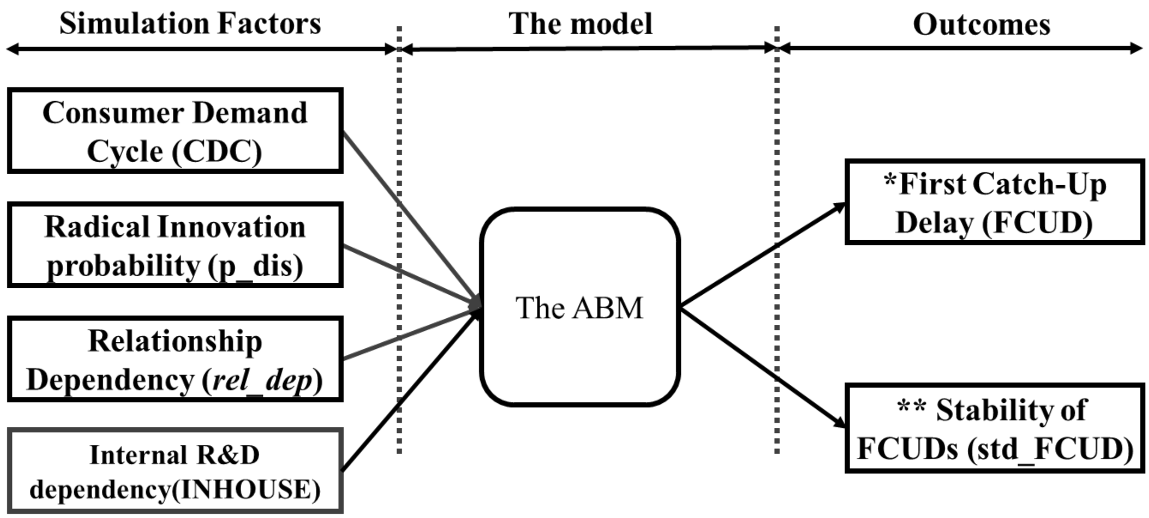


Figure 9. Simulation Plan and Experimental Setup

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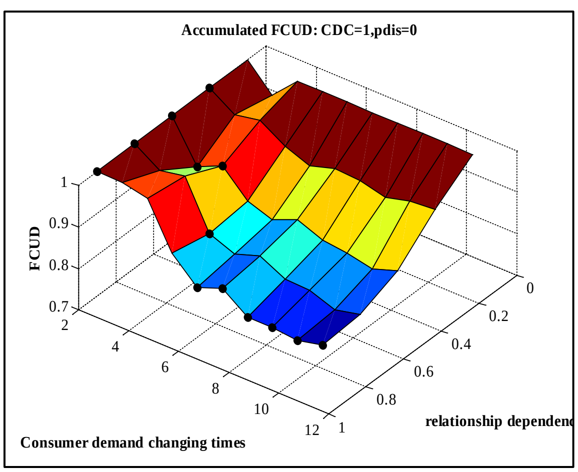

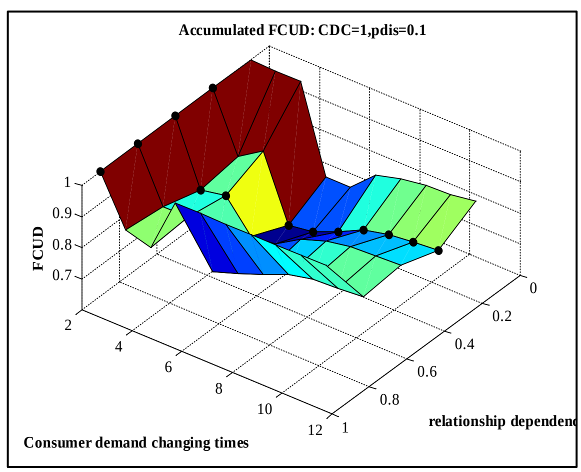

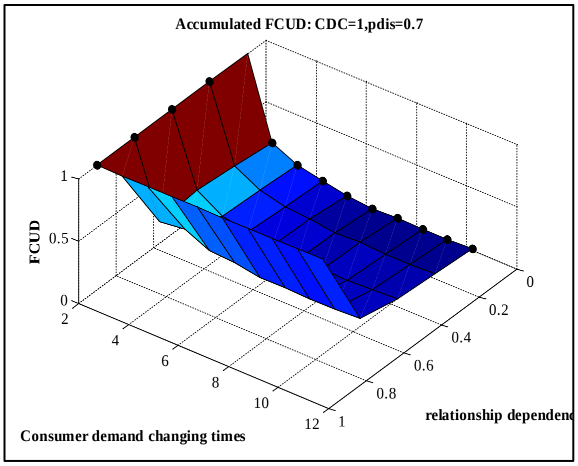
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FCUD
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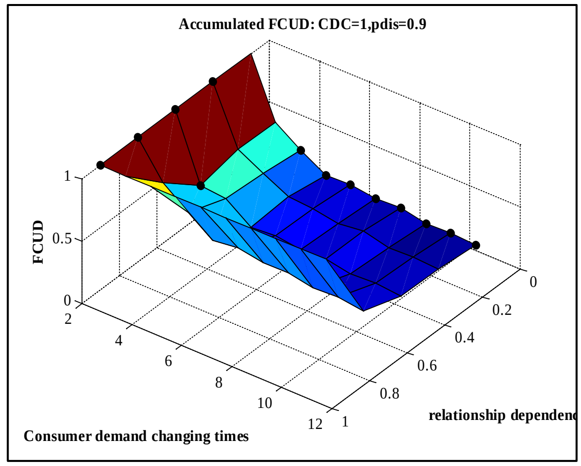
relationship dependen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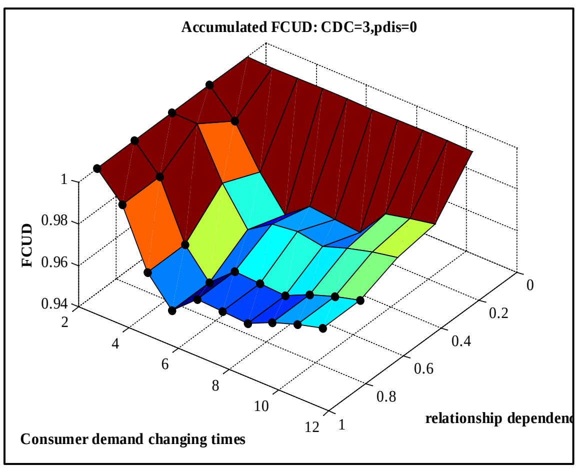
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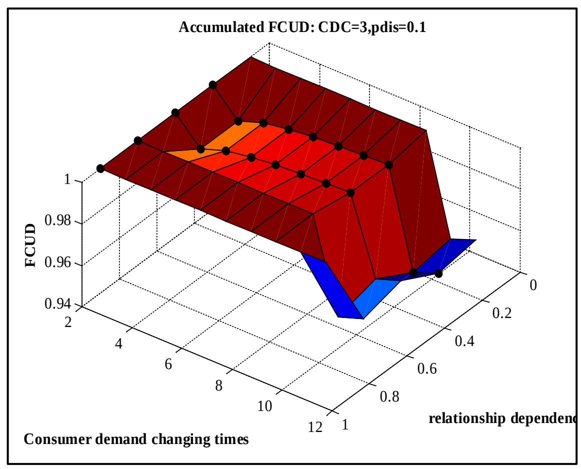
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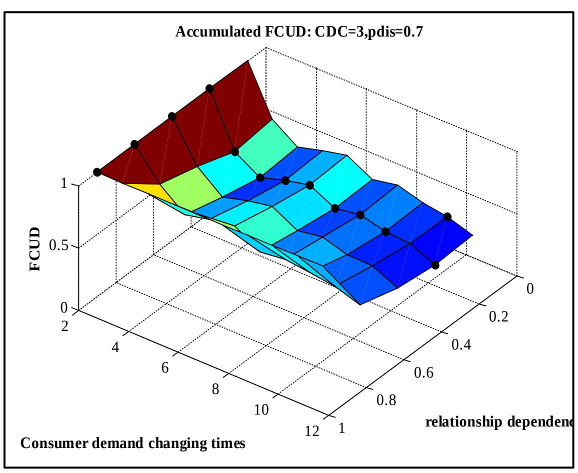
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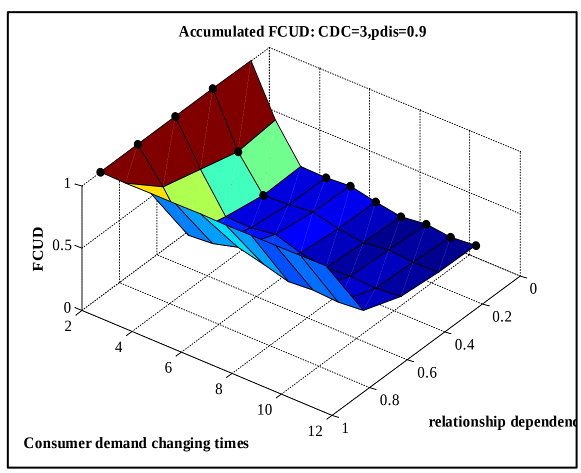
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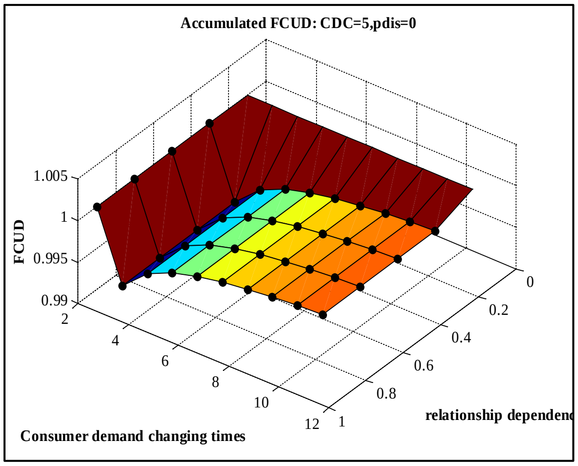
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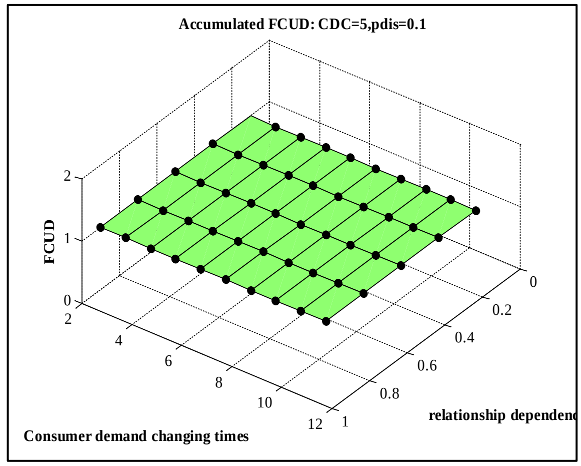
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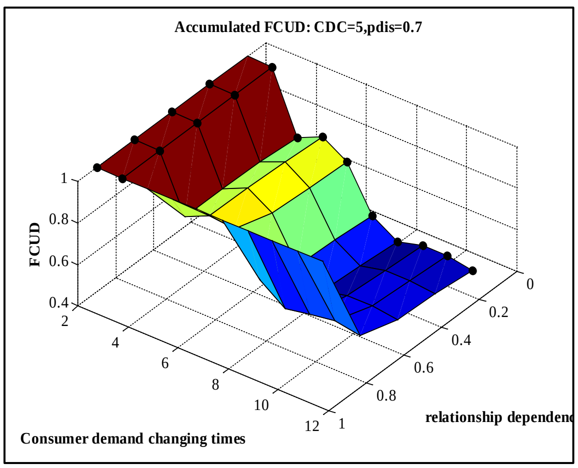
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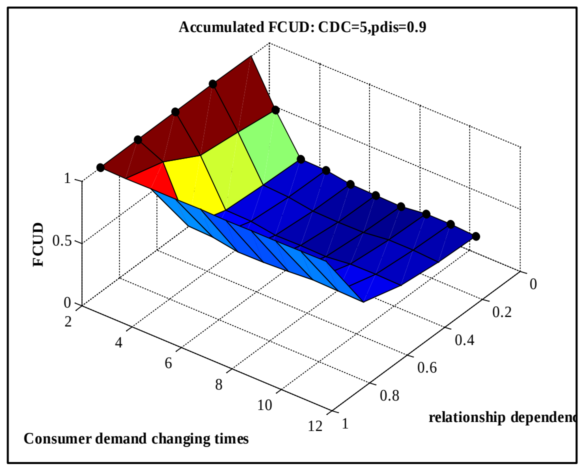
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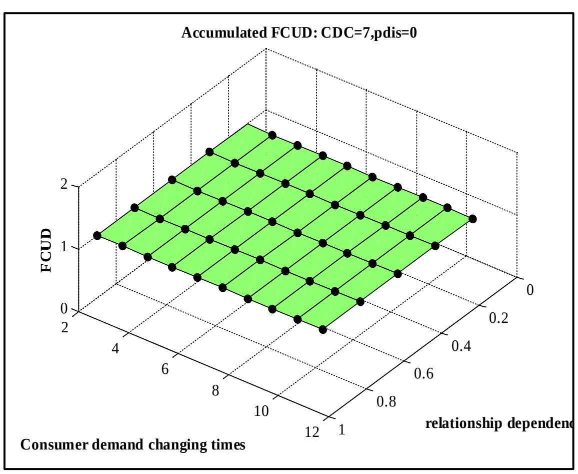
[4] CDC = 7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Consumer demand changing times
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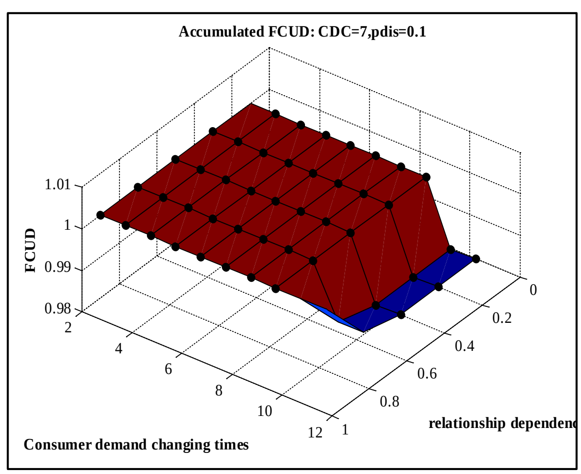
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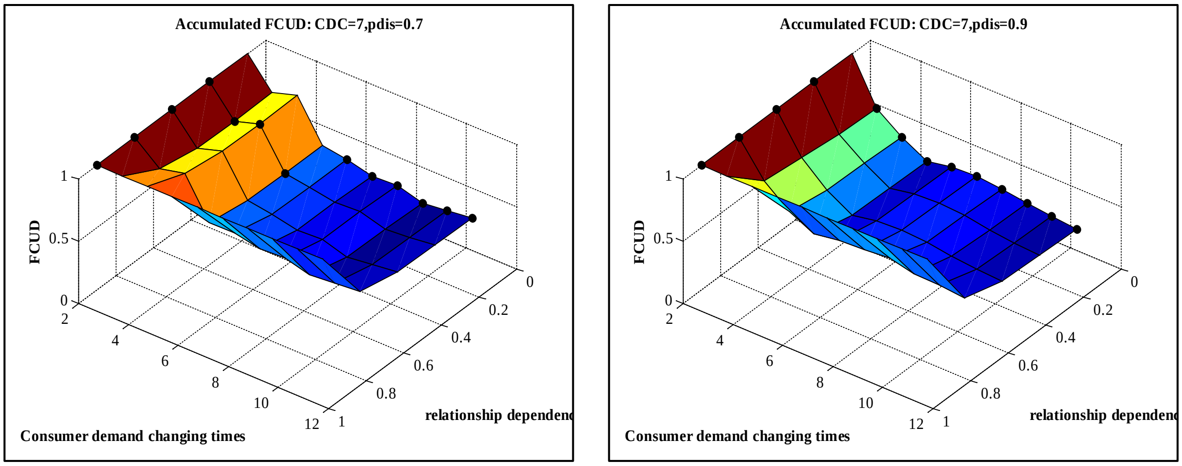

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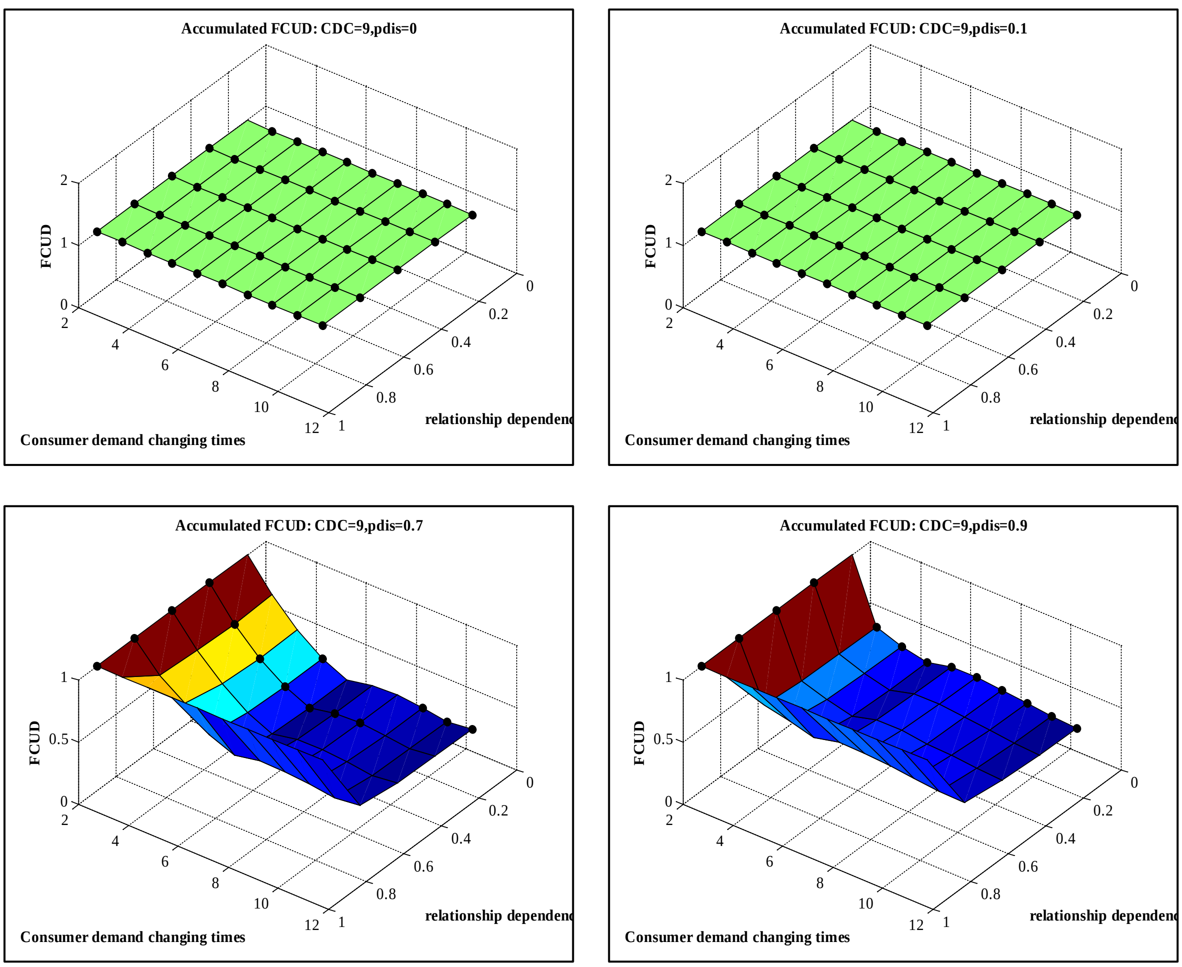
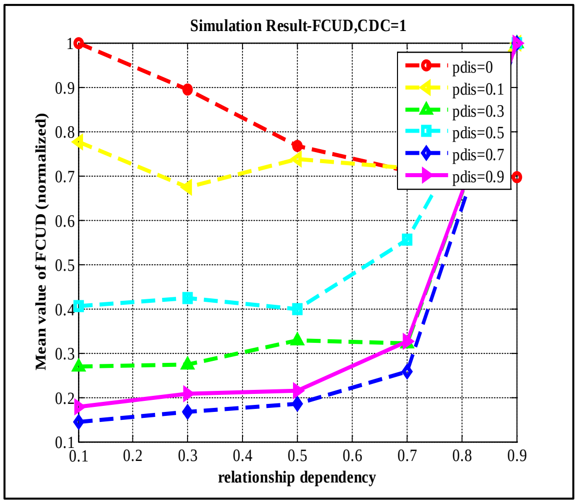
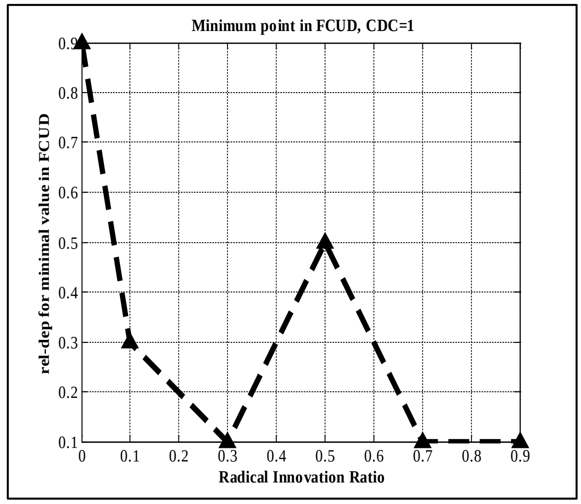
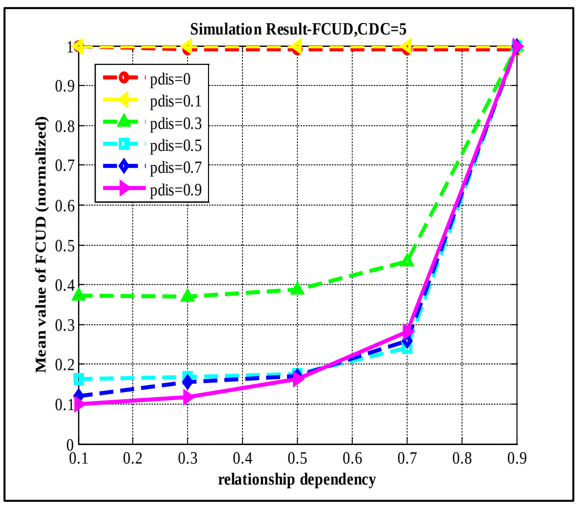


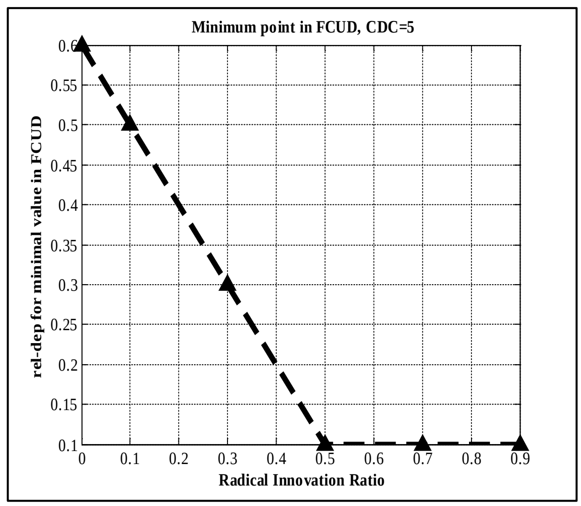
Figure 10. Accumulated FCUD

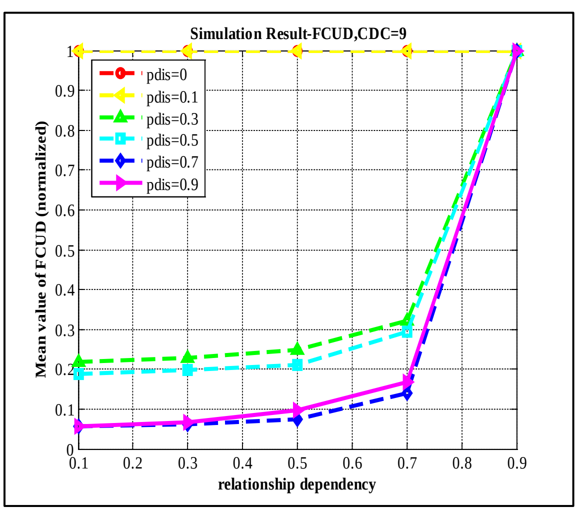
Note: The black dots represent the minimum points











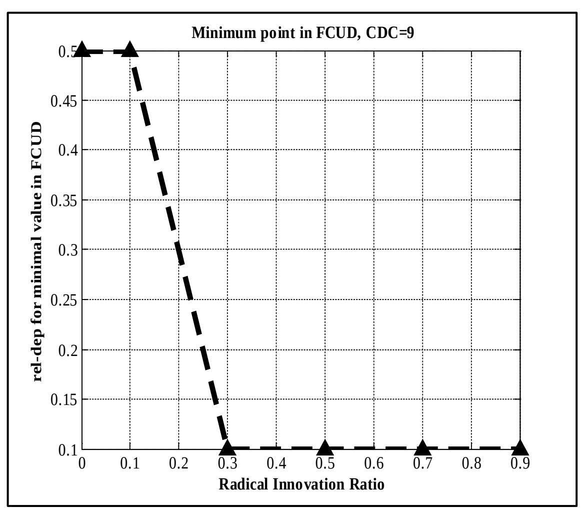
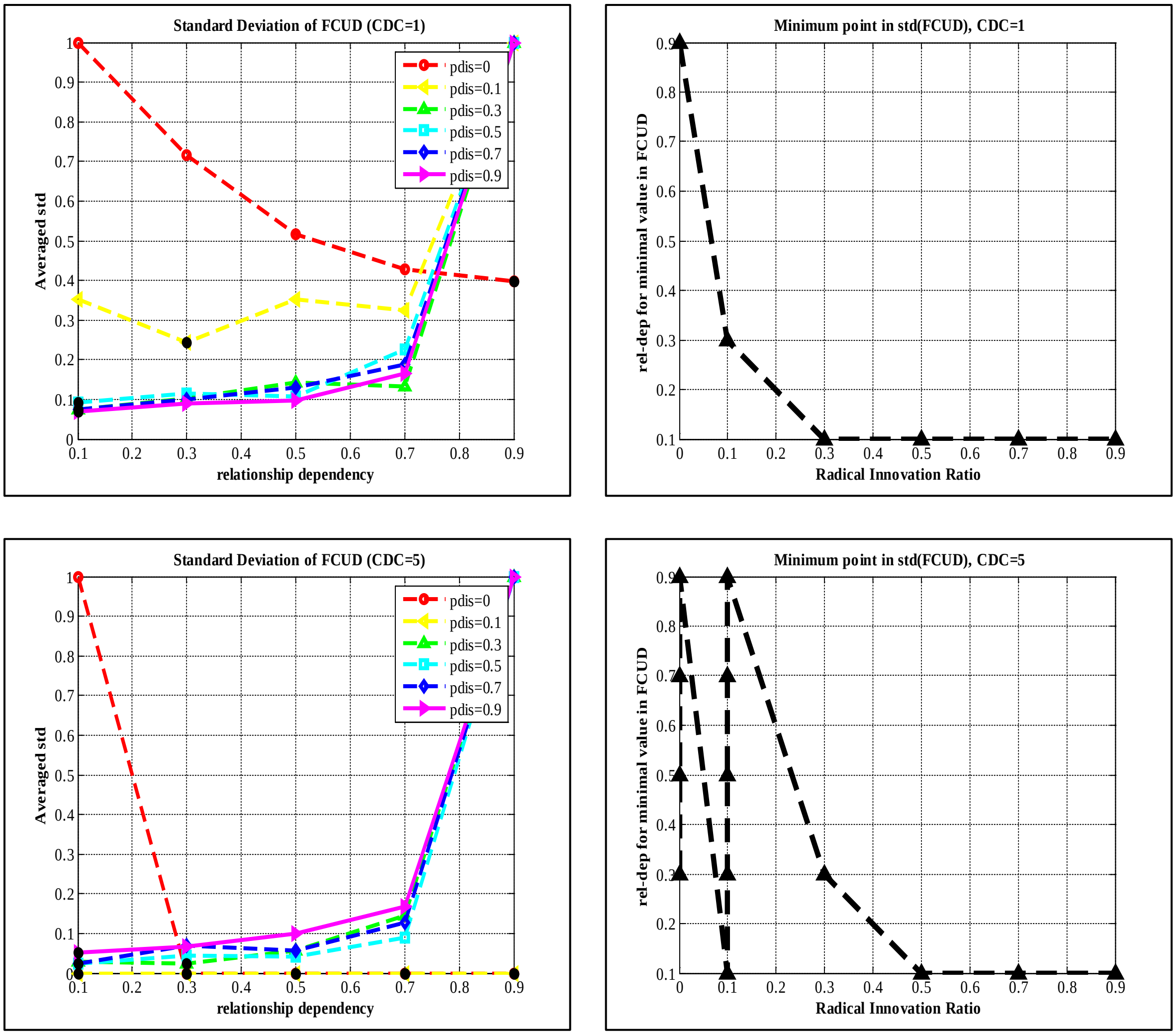


Figure 11. FCUD Minimum and its Trajectory according to p_dis and rel_dep

Note: The maximum FCUD is set to 1 at every simulation condition



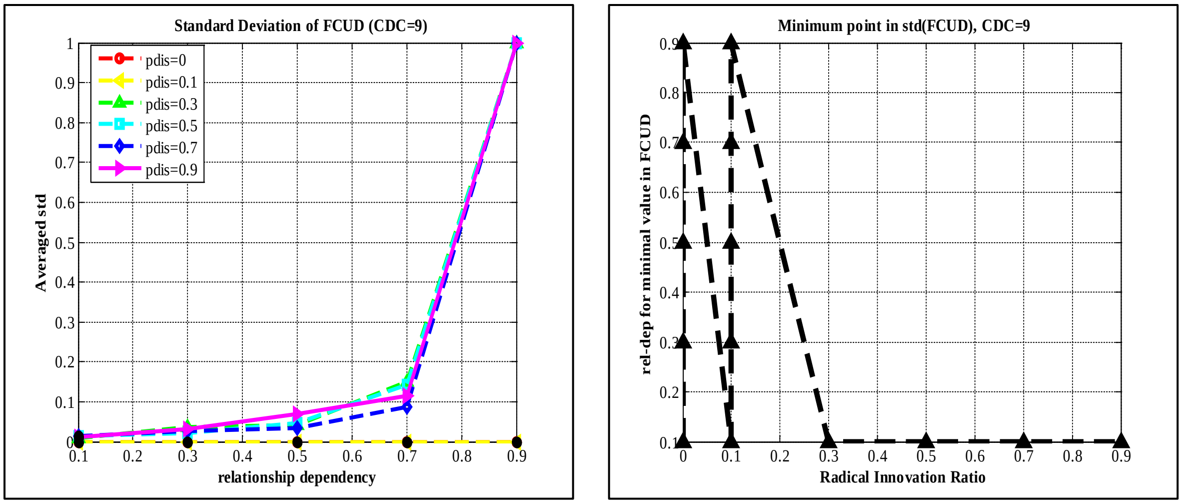


Figure 12. std_FCUD according to Simulation Parameters

Appendix. Sub-Models

AP 1. Technology portfolio matrix

TC	TL	Com	Owner	Licensee	Royalty	Source
A	1	1	Firm 1	Firm 1	0	ID
B	1	1	Firm 3	Firm 1	8%	LICENSE
D	1	0.5	Firm 1	Firm 1	0	ID
A	2	1	Firm 1	Firm 1	0	ID
A	3	0.1	Univ 5	Firm 1	5%	LICENSE
B	2	0.5	Firm 3	Firm 1	5%	COLLA
C	1	0.1	Univ 3	Firm 1	1%	COLLA
…	…	…	…	…	…	…

TC: technological component; TL: technological performance level; Com: commerciality (0.1: basic idea; 0.5: applied research; 1: fully commercialized); ID: internal development; LICENSE: sourced by license contract; COLLA: sourced by R&D collaboration.

Figure AP1. Technology portfolio

A technology portfolio is assigned to every agent. The portfolio is a two-dimensional matrix that includes the following information: 1) an index of the technological component of the technology (TC) and its technological performance level (TL); 2) the commerciality of the technology (com: basic idea, applied research, fully commercialized); 3) the technology owner’s name (OWNER); 4) the royalty rate according to the license contract; and 5) the source type of the technology (ID: internal development; LICENSE: licensed; COLLA: technology obtained by collaboration). An agent cannot have more than one technology that has the same identity (the same TC and TL). Also, an agent can only have technology that is newer than the technology that is currently fully commercialized (if the agent is a UNIV, the prior technology should at least be at the applied research stage). For example, if an agent has a technology (B, 1) that is not fully commercialized yet, it cannot develop (B, 2) technology unless (B, 1) is fully commercialized.

A manufacturing agent implements its own technologies that are closest to the required technology for a new product. The following describes how the manufacturing (potential) agent selects the technologies that are to be implemented in the product from its technology portfolio.

Technology selection for product implementation
Technological components for product implementation: {A, B, C} Technological performance level that is mainly demanded for the product: {3, 5, 1}

Component A	Component B	Component C
3	5	2

Technological specification of the product that is most in demand

Technology portfolio of Agent "i"

TC	TL	Com	Owner	Licensee	Royalty	Source
A	1	1	I	I	0	ID
A	2	1	Firm Q	Firm I	5%	LICENSE
C	1	1	K	I	1%	LICENSE
B	1	1	I	I	0	ID
B	5	1	Firm I	Firm I	0	ID
B	6	0.1	P	I	1%	COLLAB
C	2	1	UNIV K	Firm I	1%	COLLAB
A	3	0.1	I	I	0	ID

Agent "" selects (A, 2), (B, 5), and (C, 2) for product implementation. (A, 2) is the closest technology to (A, 3) among the fully commercialized technology. The agent can use (B, 5) technolo gy that meets market demand. It is also able to use (C, 2), which is sourced from R&D collaboratio n with university *K*. The reason "i" does not select (A, 3) for component "A" is that (A, 3) is not ful ly commercialized yet.

AP 2. Internal R&D process

The present model comprises an internal R&D process so that each R&D capable agent engages in new technology development. The R&D process model follows a "linear model" that roughly comprises three ordered R&D stages: basic research, applied Research, and development (Godin, 2006). In this model, only technology that has been through all these three stages successfully can be used for product implementation as a fully commercialized technology. The agents engaging in R&D should make R&D investments in order to reach the next stage in the R&D process. Success probability corresponds to the move to each new stage. Figure AP2 shows the conceptual model of the R&D process.

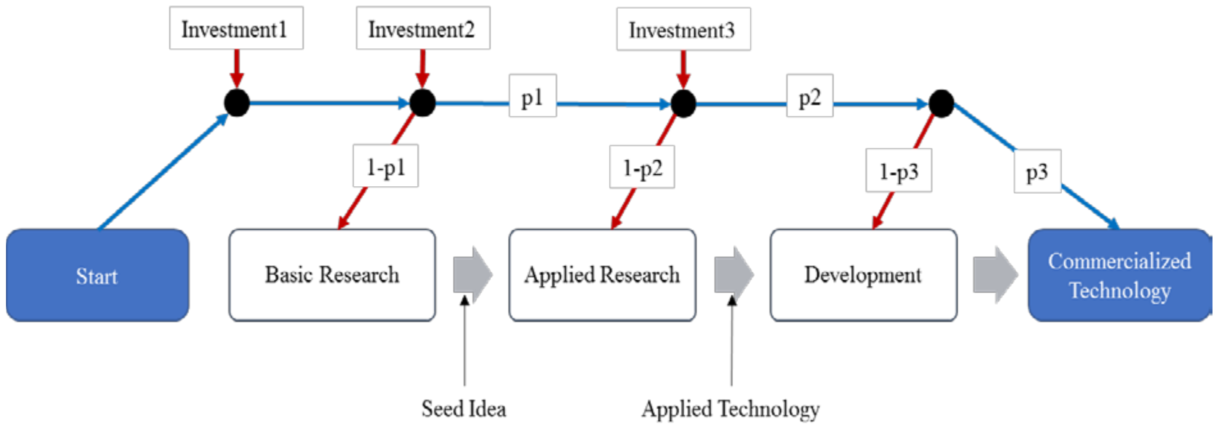


Figure AP2. Internal R&D process and model

p1 is the probability of moving from the basic research stage to the applied research stage. If the process moves to the applied research stage, the agent becomes the owner of the basic idea of the target technology. Likewise, p2 corresponds to the probability of moving from the applied research stage to the development stage, which allows the agent to have applied technology. Finally, the agent owns fully commercialized technology with probability p3.

The probability of transition to the next R&D stage consists of the following three factors: type of agent, the agent's relevant knowledge about the target technology, and the technological performance level of the target technology. Thus:

$$\boldsymbol{\pi} = \mathbf{f}(\mathbf{E}, \mathbf{K}, \mathbf{N})$$

K: prior knowledge of target technology; N: technological performance level of the target technology

Each factor is assumed to be mutually independent. The following is the analytical model for the probability function. *UNIV* is designed to have a higher success rate in *p1* but a lower rate in *p2* with no engagement in the development stage for technology commercialization. *Firm* agent, however, has lower *p1* but a higher *p2* than *UNIV* with involvement in transition to the development stage. The following illustrates the probability function.

$$\mathbf{f}(\mathbf{E}) = \frac{\sum_i \boldsymbol{C_i}}{\boldsymbol{TL_j}}$$

i: technology of technological component (j); C_i: degree of commerciality of the technology "i" $(C_i \leq 1)$

f(E) estimates an agent's experience in the commercialization of prior technologies that are in the same technological component as the target technology. It calculates the relative value of the total commerciality of owning technology that is related to the target technology. Therefore, it takes a value within 0 and 1.

$$\boldsymbol{f(K) = 2 - \frac{2}{1 + e^{-1.1*|N - TL_{max,agent}|}}}$$

f(K) measures the proximity between the agent's ownership of technology to the target technology. If the agent has technology that is close to the target technology (e.g., (B, 3) technology is closer to (B, 4) than (B, 1) or (C, 4)), it is relatively easy to develop a new idea for the target technology.

$$\boldsymbol{f(N) = \begin{cases} 1, \textit{if the } N \leq TL_{max,i} \\ (2 - \frac{2}{1 + e^{-1.1*|N - TL_{max,i}|}})^2, \textit{elsewhere} \end{cases}}$$

f(N) measures the technological difficulty in developing the target technology that has technological performance "N." If N is less than or equal to the performance of technology ($TL_{max,i}$) that is necessary to make the product that is most in demand, it produces "1," which means that there are no particular difficulties in developing the technology through technological performance advancement. However, if N is higher than $TL_{max,i}$, technological difficulty exponentially increases. Therefore, the probability that the agent can develop N-technological performance technology declines. The individual probability function jointly calculates p1, p2, and p3.

Case 1) UNIV agent

$$\mathbf{p1 = f(K),\ p2 = f(E) * f(N)^2,\ p3 = 0}$$

Case 2) Firm agent

$$\mathbf{p1 = f(K)*f(N),\ p2 = f(E),\ p3 = f(E)*f(N)}$$

With this partial probability function, each agent predicts the total necessary investment for completing the R&D before they engage in the R&D process. The following formula describes the calculation of expected R&D expenditure.

$$\mathbf{E(R\&D)} = \boldsymbol{\frac{tri(1) * rnd}{p1 * p2 * p3}}$$

rnd: expense of unit trial in R&D

tri(1) is a random variable selected in triangular distribution with 0 as lower bound, 2 as upper bound, and 1 as medium. This factor considers the difference in individual entity's expectations about expenditure. The following diagram illustrates how an agent engages in the R&D process with the flow of R&D spending.

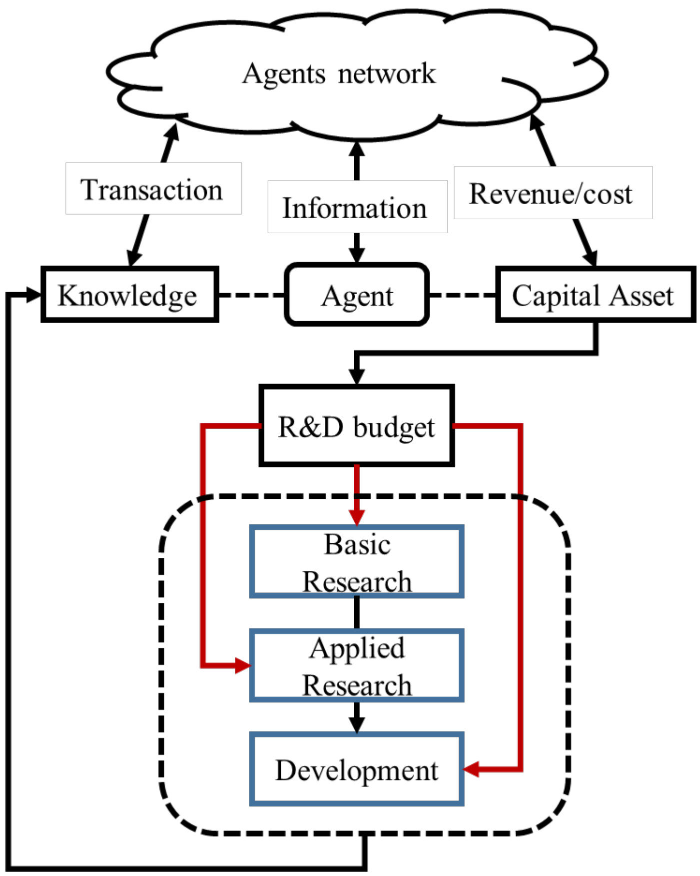


Figure AP3. Internal R&D process

AP 3. Technology source selection algorithm

Firm agent has the following three technology sourcing strategies: 1) in-house R&D, 2) acquisition from other agents (licenses), and 3) R&D collaboration (Kang & Kang, 2009). The strategy selection process is controlled by given stylized simulation factors, and technology outsourcing is completed by negotiation with others. The following is a PSEUDO code of the technology source selection algorithm.

Technology sourcing strategy selection algorithm

If agent knows about target technology (TC',TL')
  If agent = technology aggregator
    Generate random number R1 in [0,1];
    If R1 <= rel_dep
      Generate random number R2 in [0,1];
      If R2 <= in-house

```
            Do internal R&D (TC',TL');
          Else
           Seek the technology in group of historical partners;
        End-If
      Else
           Seek the technology in group of non-historical partners;
      End-If
    Else
     Do internal R&D (TC',TL');
   End-If
Else
 If agent = technology aggregator
    Generate random number R1 in [0,1];
    If R1 <= rel_dep)
      Seek the technology in group of historical partners;
    Else
       Seek the technology in group of non-historical partners;
    End-If
 Else
   Pass the R&D;
 End-If
End-IF
```

Dependency on an inner circle (composed of the agent itself and historical partners) for technology sourcing (coded as *rel_dep*), and a tendency to rely on in-house R&D (coded as *inhouse*) controls the overall technology source selection mechanism.

AP 4. Technology sourcing from partners

An agent that selects an historical partner for technology sourcing communicates with the partner by asking whether the partner has the target technology at the applied research or fully commercialized stage. If so, the two parties start negotiations for a license contract. The technology owner considers the trade-off effect and estimates the expected net revenue if the license contract is agreed: royalty revenue (+) and expected market share loss according to the licensee's market penetration (-) (Motohashi, 2008; Arora & Fosfuri, 2003; Arora, Fosfuri, & Gambardella, 2001). If the technology owner is not a manufacturer or unlikely to be a manufacturer, the expected market share loss is marginal compared to the royalty revenue that the owner can earn. However, if the technology owner is a manufacturer or likely to be a manufacturer in the immediate future, the expected market share loss is relatively large, which prompts the technology holder to reject the license contract. The royalty rate is set to 1/(number of essential technological components + 1). For example, if a product is implemented by combining ten essential technological components, a licensor that licensed the technology that corresponds to one of the technological components earns 1/11 of the sales revenue of its licensee.

If any of the historical partners does not have the target technology, the agent checks each partner's R&D experience with the technological component. The agent selects the most experienced partners and starts negotiations for R&D collaboration. In this collaboration, the agent pays half of the expected total R&D expenditure to the partner. In the negotiation process, the partner first calculates the expected market share it can additionally obtain if it develops the technology exclusively. Then, it estimates the expected market share if it shares the technology with its collaborator. If the aggregated value is positive, the partner engages in the R&D collaboration. However, anticipated negative net revenue does not always prompt the partner to reject the proposal. To introduce the concept of patient capital through a strong business relationship between the parties, the partner agrees to R&D collaboration within a stochastic decision-making process even though the expected payoff is not profitable. The following describes the algorithm.

Technology sourcing from prior partner

```
Check all the partners' technology portfolios to seek (TC',TL') with commerciality over 0.5
If there are such partners
 Select a partner with the least impact on its market share;
 Calculate payoff (POFF) of the partner from license contract;
 If POFF >0
   Make license contract;
 Else
   Generate random number R in [0,1];
   If R <= rel_dep
     Make license contract;
   Else
     Reject the contract;
   End-If
 End-If
Else
 Check R&D experience of each partner on (TC');
 Select most experienced partner;
 Calculate payoff (POFF) of the partner from the R&D collaboration;
 If POFF >0
     Start R&D collaboration;
 Else
   Generates random number in [0,1], R2;
   If R2 <= rel_dep
     Start R&D collaboration;
   Else
     Reject;
   End-If
 End-If
End-If
```

AP 5. Technology sourcing from non-historical partners

An agent can source the necessary technology from non-historical partners. The tendency to acquire the technology from them is set to 1-rel_dep. An agent that is willing to source technology from new partners follows the same algorithm as the algorithm of technology sourcing from partners. In the algorithm, an agent selects the entire number of agents with whom it will interact except historical partners. The number of agents for whom the agent will search is set to the same number as the agent's historical partners. Then, the agent randomly selects one of the agents in the group of non-historical partners. Following this, the agent scans the selected agent's technology portfolio. The agent does not interact with those agents that only have the technology at the basic research stage.

AP 6. Update rule of the partnership network

The present model includes a simple partnership network update rule. An agent that establishes a relationship with another agent for the first time sets the linkage value to 1. Agents who have historical partners increase the linkage value (intensity) by 1 whenever they engage in interaction for technology sourcing (license or R&D collaboration) with the prior partners. Since this rule makes the linkage value increase as the two agents interact, the value represents the intensity or frequency of interaction of the two agents.

AP 7. Information learning over the partnership network

Agents share and learn each other's information about the consumer group's technological specification of the demanded product over the partnership network. To implement the process, the present model implants a non-Bayesian network learning model (Epstein, Noor, & Sandroni, 2008; Epstein, Noor, & Sandroni, 2010). The model aggregates the Bayesian learning model and the learning obtained over the network. According to the model, individual agents obtain noisy signals about consumer demand. Then, each agent updates its own information and shares it with the networked agents. The agents acquire their own views about consumer demand according to the following mathematical model (Epstein, Noor, & Sandroni, 2010).

$$\mu_{i,t+1}(\theta) = a_{ii}\mu_{i,t}(\theta)\frac{l_i\left(\omega_{i,t+1}\middle|\theta\right)}{m_{i,t}\left(\omega_{i,t+1}\right)} + \sum_{j\in N_i} a_{ij}\mu_{j,t}(\theta)$$

where $\mu_{i,t}(\theta)$ is the opinion about the state of θ agent "i" at time t; a_{ij} is the weight of the opinion of agent j; $\omega_{i,t}$ is the noisy signal that the agent "i" captures at t; $l_i(\omega_{i,t}|\theta)$ is the likelihood function at state θ; and $m_{i,t}(\omega_{i,t+1})$ is the probability that the signal $\omega_{i,t+1}$ will be realized at time t.

AP 8. Market power and market share

A manufacturer earns sales revenue from the product market according to its market share. In order to calculate market share, it is necessary to consider market power, which aggregates the degree of technological fitness to the consumer-demanded product's technological specification, and marketing experience, which is the time that an agent has spent as a manufacturer. Market power is calculated by using the average technological distance (DIS) of an agent's technology with regard to the market-demanded technology (TECH) for all the technological components, and the relative value of the agent's marketing experience with regard to the maximum marketing experience among the exiting manufacturers (MKT). The formula is as follows.

$$\mathrm{DIS} = \frac{1}{N0}\sum_{i=1}^{N0} |TL_i - \overline{TL_\iota}|$$

$$\mathrm{TECHV}_i = e^{-4.6*DIS_i}$$

$$\mathrm{TECH} = \frac{1}{N0'}\sum_{i=1}^{N0} \delta_i * TECHV_i$$

$$\mathrm{MKT} = \frac{agent_i.mkt}{Max(agent.mkt)}$$

The calculated *TECH* and *MKT* are combined with the probability function that the agent becomes a manufacturer. The probability is determined by how much the agent is likely to use the technology for all the necessary technological components (*Ft*) and whether the agent can invest money in building a factory (*Ff*). In the model, the two factors are mutually independent. The (expected) market power is calculated by the following formula.

$$\mathrm{MP}_a = \{\omega \times TECH + (1-\omega) \times MKT\} \times F_f \times F_t$$

ω: weight of technological fitness with regard to the new consumer demand on market power; a: index of the agent

The market share (MS) becomes the ratio of the agent's MP to the sum of the MP of other manufacturers. The formula is as follows.

$$\mathrm{MS}_i = \frac{MP_i}{\sum_{j\in\forall\{k\cup i\}} MP_j}$$

The (expected) sales revenue is calculated by multiplying MS and the market size at the turn.

$$\mathrm{SV}_i = \mathrm{MS}_i \times M_0(t0)$$

AP 9. Model of license contract and royalty payment

The license contract in the present model is based on an exclusive license contract. Once a technology is licensed to another agent, it cannot be licensed to other agents until the prior license contract is invalidated (expires). The license contract is invalidated or expires if the licensed technology is no longer used by the licensee (in manufacturing). As long as the licensee uses the technology, it must pay a royalty to the licensor. The royalty rate is established by the system and is set according to the number of essential technological components for product implementation. In order to avoid the problematic royalty stacking problem (Lemley & Shapiro, 2007), the royalty rate is set to 1/(*Ne*+1), where *Ne* is the number of essential technological components for product implementation. The present model assumes that the licensee learns the licensed technology during the license contract period. Therefore, the licensed technology remains in the licensee's technology portfolio even though the license contract is invalidated.

AP 10. R&D collaboration model

The present model includes the R&D collaboration process. R&D collaboration is based on "demander request." That is, an agent that needs a certain technology selects a suitable partner for R&D collaboration and requests the collaboration of the selected agent. Once the latter is asked to collaborate on R&D, it considers the expected R&D cost it must spend and the benefits from royalties, or the possibility that the newly developed technology can be used to enhance its own market power. For R&D collaboration, an agent adopts the following process: 1) calculate expected R&D expenditure, *E(rnd)*; 2) assign half of *E(rnd)* to the R&D budget; 3) suggest the R&D collaboration project to the potential partner; 4) provide half of *E(rnd)* to the partner if it agrees with the R&D collaboration; 5) the partner then creates the R&D budget by investing the remaining half of *E(rnd)* into the R&D project. In the present model, the agent that requests collaboration sees a new market opportunity and tries to obtain it through R&D collaboration with another agent that may know about the target technology. Therefore, this process can be viewed as one that splits R&D expenditure and shares knowledge. The process is based on the resource-based view of a strategic alliance, which states that firms essentially use alliances to gain access to other firms' valuable resources (Das & Teng, 2000). Figure AP4 illustrates the R&D

collaboration process and its negotiation mechanism.

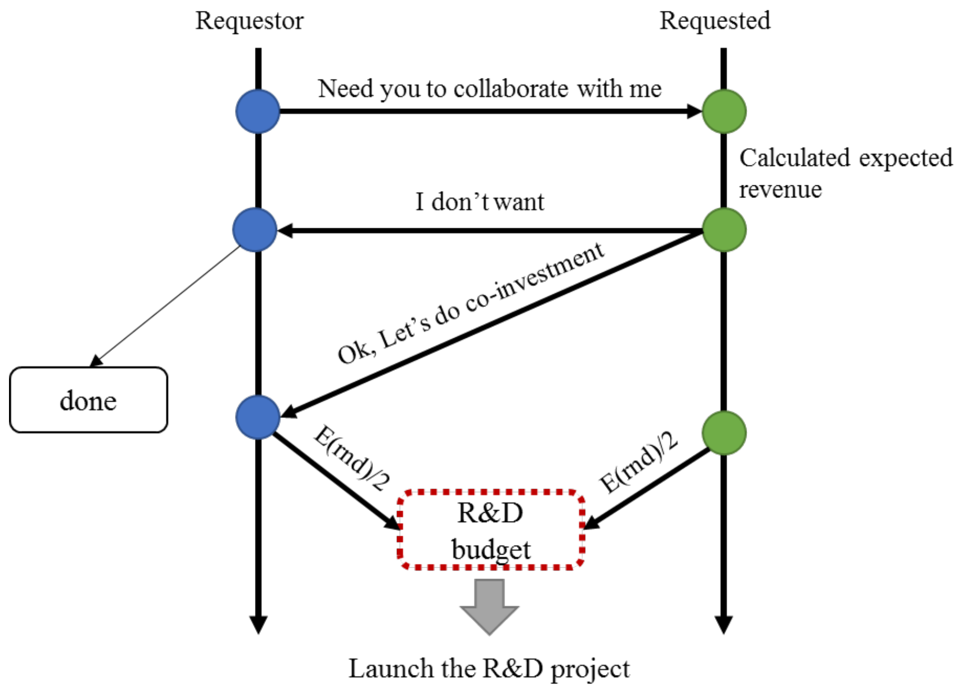


Figure AP 4. Model of R&D collaboration

AP 11. Spin-off process

In the present model, an agent can form a new firm agent through the spin-off process. The design of the process is based on a theoretical framework that explains how entrepreneurship emerges and how it links to new firm formation (Ardichvilia, Cardozo, & Ray, 2003). The spin-off process comprises the following two sub-processes: 1) making a decision about the spin-off, and 2) selecting the technological component that the new firm copies from the parent agent's technology portfolio.

1) Making a decision about the spin-off

Only the agent that is eligible to form a new firm can start the decision-making process for a spin-off. In order to be the eligible agent, an agent must satisfy the following two conditions: It should have 1) technologies related to at least one technological component and 2) entrepreneurs. The agent then uses a stochastic process to decide whether or not to form a new firm. The existence of an entrepreneur is represented by "spirit of entrepreneurship (SOE)," which is an internal variable of an agent. The SOE is periodically charged and dissipated when a new firm is formed. This mechanism models the situation whereby a parent organization trains human resources to know about the business/technology field in which the parent company operates and also helps the employees consider the startup. Thus, this process can be represented as a “periodical entrepreneurship charging and dissipation mechanism.” Since the present model is based on the closed economy structure, the total amount of the capital asset should be maintained at the same level. If the spin-off process works without system-level control, it can make the total amount of the capital asset continue to increase because the new firm is created with its capital asset. In order not to violate the capital source preservation rule, the spin-off process is controlled by a “capital reservoir.” This is a component that controls the total amount of the capital asset in the system.

2) Selecting the technological component that the new firm will use

First, the technology portfolio of the parent agent is scanned. Then, the technological components that the agent knows about are identified. Second, the total number of technologies for each of the technological components in the system is counted. Third, the technological component that has the minimum number of technologies in the system and that the parent agent is knowledgeable about is selected. Fourth, the parent’s entire technologies about the selected technological component are copied to the new firm. The following algorithm summarizes the overall spin-off process.

Algorithm for spin-off process

Making profile of technology in simulation, PRO_T
Identifying the technology field that the parent agent (A) is knowledgeable about, TF_A
Selected technological group TC = TF_A, where TF_A = Min(PRO_T)
If size (CR) >0
 Generate random number, Rn in [0,1]
 If Rn <= ENT & agent (A).entrepreneurship >=1
   Create SME-type new firm, B
      Copy all the technology of A in TG to B
      B.capitalasset = default SME asset, (SME_asset)
      CR = CR-SME_asset
    End If
End-if

AP 12. Codifying the product innovation pattern

The present model comprises two different patterns of product-level innovation: incremental and radical. Incremental innovation means that a new product has enhanced technological performance but does not have new technological features. Introducing a new central processing unit (CPU) that has greater processing power into a new model of a personal computer is an example of an incremental innovation at product level. In the present model, incremental innovation becomes a technological performance improvement in a particular technological component of the product. Radical innovation at product level is the “introduction of a new technological component that was not required in the prior product.” For example, a conventional cell phone’s function only concerns telecommunication (e.g., texting and calling). However, a smartphone includes new functions such as accessing the Internet, sending and receiving e-mails, and even watching a movie or gaming. Therefore, a smartphone is a new product that comprises radical innovation according to the concept of the present model.

To implement these product-level innovation patterns, the present model employs a binary string. 0 means that the corresponding technological component does not need to be improved or introduced for new product implementation. 1 means that the corresponding technological component should be improved or newly introduced for new product implementation.

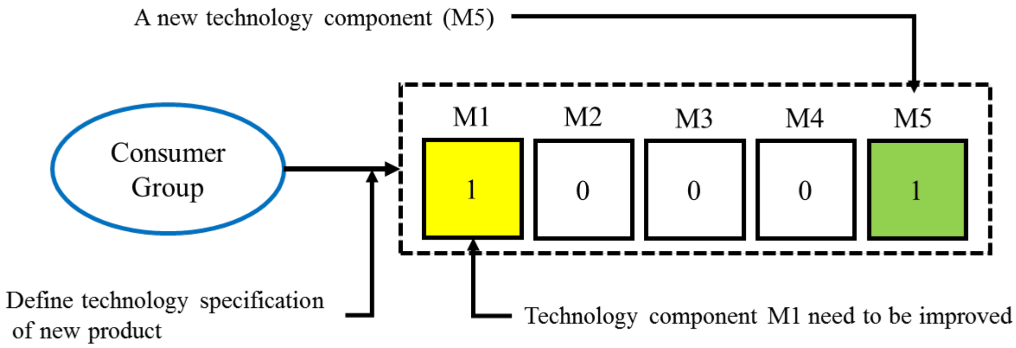


Figure AP 5. Product level innovation pattern and coding scheme

AP 13. Marginal effect of p_dis

		rel_dep									
INH		0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
	0	-2.54	-0.99	0.57	2.13	3.68	5.24	6.79	8.35	9.91	11.46
	0.1	-2.85	-1.29	0.26	1.82	3.38	4.93	6.49	8.04	9.60	11.16
	0.2	-3.16	-1.60	-0.04	1.51	3.07	4.62	6.18	7.74	9.29	10.85
	0.3	-3.46	-1.91	-0.35	1.21	2.76	4.32	5.87	7.43	8.99	10.54
	0.4	-3.77	-2.21	-0.66	0.90	2.46	4.01	5.57	7.12	8.68	10.24
	0.5	-4.07	-2.52	-0.96	0.59	2.15	3.71	5.26	6.82	8.37	9.93
	0.6	-4.38	-2.82	-1.27	0.29	1.84	3.40	4.96	6.51	8.07	9.62
	0.7	-4.69	-3.13	-1.57	-0.02	1.54	3.09	4.65	6.21	7.76	9.32
	0.8	-4.99	-3.44	-1.88	-0.33	1.23	2.79	4.34	5.90	7.46	9.01
	0.9	-5.30	-3.74	-2.19	-0.63	0.92	2.48	4.04	5.59	7.15	8.71

The U.S. system: higher rel_dep -> same as JP
Smaller rel_dep -> better for radical innovation
In-between: depends on INH

JP system: always better for incremental innovation