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Essays on the value of learning in strategic investment decision

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Abstract

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Through three essays, this dissertation examines the implications of learning in strategic investment decision making under uncertainty by introducing the Bayesian real option model, which extends the existing real option theory. The existing real option theory mainly assumes exogenous uncertainty that is resolved through waiting and passive learning. However, in the real business environment, information about given investment opportunities is difficult to acquire through waiting. Therefore, this dissertation emphasizes active learning by assuming endogenous uncertainty that is resolved only through active information acquisition by the corporation as a major uncertainty source. This approach calls for a shift from the “wait and see” principle to the “learning and see” doctrine to explain the value of decision-making flexibility in the existing real option theory.

The first essay compares two approaches for new market entry under uncertainty: “experience-driven planning,” which blindly assumes existing knowledge and experience of a firm, and “discovery-driven planning,” which continuously updates the initial assumptions through information obtained by early entry into the market, without accepting existing knowledge and experience. The former is associated with the wait and see approach of the existing real option theory, and the latter is linked to the learning and see principle. Experience-driven planning is modeled as determining the optimal time of entry based on prior knowledge and experience. The discovery-driven planning invests a portion of the total opportunity at the present time, then modifies the initial assumption based on the information gained in the market, and finds the optimal time to acquire the remaining portion of the opportunity based on the modified assumption. However, in order to carry out discovery-driven planning, additional learning costs arise because the market is not yet sufficiently developed but the information is acquired from the market through early entry. The effects of maturity and relevance, which are the characteristics of the market in which the firm is seeking to enter, and the level of the core competence, which is a characteristic of the firm, on the relative value of these two defined approaches are analyzed. The value of discovery-driven planning is maximized when the market a firm aims to enter is highly irrelevant, but mature, and the core competency of the firm is low. On the contrary, experience-driven planning is advantageous when the firm targets an emerging, highly relevant market and the firm has a high level of core competence.

The second essay expands the discussion of the first essay and developed a model with

sequential learning and flexibility in decision making about the innovation opportunities that the company has. As companies pay for learning and acquire information about a given opportunity, they can update the expectations of the opportunity from the learning outcome. Thus, the company has three options at each point in time: to stop learning activities and acquire opportunities, to continue learning activities, and to stop meaningless learning activities and give up opportunities. Under these assumptions, I assume that the value of a given opportunity is the Bellman equation with the expected value of the opportunity, which is continuously updated by learning activities and time. Then, using dynamic programming, I analyzed how the firm's optimal behavior and the value of the opportunity change accordingly. From the analysis, higher prior uncertainty about the firm's opportunity increases the value of the opportunity, while the uncertainty of the opportunity itself reduces the value of the opportunity. This result occurs because the coefficient that determines the variation of the posterior expectation over time is not an increasing function of the uncertainty about the opportunity, but an increasing function of prior uncertainty about the value of the opportunity. Moreover, it has been confirmed that even when the present value of a given opportunity is considerably negative, there is room to increase the value of an opportunity through an optimal learning strategy. In addition, a decrease in the value of opportunities relative to the increase in unit learning costs was relatively small. Further, higher prior uncertainty about the value of an opportunity has been shown to further increase the downward (posterior expectation) areas where continuous learning is the optimal behavior.

The third essay attempts to analyze the implications of learning effects on strategic investment decisions under uncertainty of the firm. Under uncertainty, companies fall into a dilemma of a trade-off between commitment and flexibility in strategic investment decisions. The reason is that the increase in uncertainty positively affects both commitment and flexibility. However, as can be seen in the first and second essays, the learning effect is created only through commitment, which represents the immediate action of a company. Therefore, increase in learning has a positive effect on commitment and a negative effect on flexibility. Thus, the effect of uncertainty on commitment and flexibility will vary with the magnitude of the learning effect. Through the theoretical model, I found the following results. If there is a learning effect over a certain scale, the increase in uncertainty is favorable for commitment. However, if the learning effect drops below a certain level, the increase in uncertainty favors flexibility. In addition, it was noted that the magnitude of the learning effect varies according to the type of investment and the environment in which the investment takes place, which empirically confirms the argument of the theoretical model. The type of investment is considered as R&D versus capital investment, while R&D investment environment signifies a comparison between high- and low-tech industries. In each case, the analysis of existing literature shows that the former investment is associated with more learning effects. From the analysis, it was found that uncertainty about R&D investment had the same threshold effect (negative impact below threshold and positive impact above threshold) as R&D investment only in high-tech industry.

Overall, the implication of this dissertation is that, under extreme and complex

uncertainty, the company should not adopt a wait and see attitude but follow an active learning approach. To this end, companies can consider adopting active post-audit systems throughout the investment decision-making process. The main contribution of this dissertation is that it reflects on endogenous uncertainty, which receives little attention in the existing real option theory, by integrating Bayesian learning into real options theory. Future research should reflect on more advanced Bayesian learning techniques and develop a model to help companies make more informed decisions.

Keywords: Real options, Bayesian learning, Endogenous uncertainty, New market entry, Optimal learning, Trade-off between commitment and flexibility

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Chapter 1. Overall introduction

1.1 Research background

Through many previous studies, uncertainty has become a major factor impeding efficient decision making (Jauch & Kraft, 1986; Koh & Saad, 2002; McCaskey, 1982; Tong & Reuer, 2007). It is not a recently recognized phenomenon, given that uncertainty and its associated concepts, such as risk and ambiguity, have long been found in the literature on decision making (Lipshitz & Strauss, 1997). However, uncertainty has become increasingly important and influential in decision making with the increasing speed of progress and the intensity of competition due to globalization, especially in the aftermath of the recent economic downturn caused by global financial crisis. According to an online survey (in-depth interviews with 40 senior executives based on a 50-item questionnaire) conducted by Ashridge Consulting Group in 2010, corporate leaders believe that the great environmental change caused by the global financial crisis in 2008 will last for quite a long time. (Syrett & Devine, 2012). Heifetz, Grashow, and Linsky (2009) also predict that even after the current economic crisis, high levels of uncertainty will become the norm of the new economy. The current high levels of uncertainty, difficult to witness in the past, have had a strong impact on corporate decision makers. In particular, it has made a big difference in strategic planning. Traditionally, corporate decision makers have been convinced of their ability to predict business outcomes to make clear strategic choices, by applying powerful

analytical tools. However, this strategic plan is no longer valid because none can fully predict the future through any tools. Therefore, decision-makers' strategic approach is also changing to concentrate on risk management in order to preemptively respond to uncertainties. According to HBRAS (2011), more than two-thirds of the world's leading companies surveyed are tightening their focus on enterprise risk management since the global financial crisis. In addition, many companies are already using various strategic tools such as scenario planning, decision trees, and simulation techniques to cope with future uncertainties (Peter, Andy, & Terry, 2007).

Real option theory is in the spotlight as one of the various means by which decision makers respond to uncertainty (Miller & Waller, 2003). The term option is a natural notion derived from a reasonable human way of thinking. The way options have been opened for a long time to cope with the uncertain future has led to the use and development of various option contracts so that individuals can maintain their right to make certain decisions in the future without obligations (Cox & Rubinstein, 1985). The most basic (European) call options that are widely used in the financial market can explain the value of an option. The buyer of the call option believes that the value of the underlying stock is going to rise in the future. However, since the future is uncertain, there is also a possibility that the value of the stock will fall. Therefore, the investor will want to minimize the loss if the stock falls, while retaining the benefit from an increase in the value of the underlying stock. At this time, the investor can buy a call option at a fixed price, which is the right to purchase the stock at a predetermined price (exercise price) at a predetermined point in the future. If the

value of the stock is greater than the exercise price at the time of maturity, the option can be exercised to gain the benefit. Conversely, if the exercise price is greater than the value of the stock, the loss can be avoided by abandoning the option exercise. These options allow the option buyer to respond to uncertainty by providing the right to choose to make a decision at the expense of the option.

Initially, the option theory was actively studied in financial economics literature. Financial economics literature has focused on the valuation of options, and much progress has been made, especially since the birth of the Nobel Prize-winning "Black-Scholes equation" (Black & Scholes, 1973). Since then, it has become clear that investment decision making for real assets of the enterprise was similar to the option structure (Myers, 1977), and real option theory was born and actively applied as a strategic approach (Trigeorgis & Reuer, 2016). The greatest difference between real options and financial options is that decision-making flexibility (making decision only when it is advantageous to the decision maker and not making decision when it is disadvantageous), the mechanism that creates the economic value of an option, does not exist by explicit contracts. Instead, in the real option literature, decision-making flexibility can be guaranteed by the unique knowledge possessed by the firm. Because of the unique nature of knowledge possessed by each firm, the right to preferential access to arbitrary investment opportunities is possible. It is also not an explicit contract, but tools such as patents or joint ventures may provide exclusive rights for the given firm to preferentially use a given opportunity. However, in most companies, flexibility of decision making is generally achieved through an initial small

investment to secure options for future strategic investments (Bowman & Hurry, 1993). Here, the cost of the initial small investment is equal to the value of the option's price or premium in the financial option. This initial small investment allows the firm flexibility to make decisions that delay the full commitment before the uncertainties are resolved. These include, for example, joint ventures (Kogut, 1991), multinational manufacturing network management (Kogut & Kulatilaka, 1994), venture capital investment (Li, 2008), and management of R&D programs (McGrath & Nerkar, 2004). According to Bowman and Moskowitz (2001), these real options are subject to the following two-step process. In the first phase, companies gain flexibility of decision making through small investments. Based on the acquired flexibility, it will delay the irreversible decision making and acquire necessary information for future decision making. In the second phase, as the uncertainty becomes increasingly certain due to the information obtained, the firm makes decisions about whether or not to make the final investment. Thus, a real option can be defined as an opportunity to purchase real assets under favorable conditions (Myers, 1977).

Since real options theory explicitly reflects the flexibility of decision making, it has a greater advantage over traditional static evaluation techniques in assessing a given opportunity under uncertainty (Amram & Kulatilaka, 1999). However, it has been quite a while since real option theory was introduced, but many companies still make investment decisions using the NPV (Net Present Value) method based on DCF (Discounted Cash Flow). As pointed out by many real options studies (Dixit & Pindyck, 1994), NPV is highly unsuitable under uncertainty because it is based on the "now or never" proposition. Based

on the proposition, the NPV method compares the expected current value of the estimated cash flow with the expected current value of the cost under the most probable scenario and justifies the investment if it is greater than zero. Therefore, there is no room for considering managerial flexibility in the NPV method. If the uncertainty associated with the project is insignificant, the value of the project derived through the NPV method may not differ significantly from the actual value. However, under high uncertainty, the value assessed by the NPV method is highly different from the reality as initial scenarios or strategies established are likely to be modified by the arrival of new information. Therefore, by using real option theory, the flexibility of decision making in response to uncertainty must be taken into account to properly evaluate the value of the project. The advantage of real options that can explicitly account for uncertainty is that it gives academics and practitioners a big insight by making a 180-degree turn compared to existing thinking on the attitude to uncertainty. Under the NPV-based valuation or thinking, high uncertainty lowers the attractiveness of a given opportunity by increasing the discount rate needed to obtain the present value of the opportunity. On the other hand, real option theory provides a different interpretation of uncertainty. High uncertainty implies that the future value is likely to rise and is likely to decline at the same time. If the downside loss is constrained to a certain level, high uncertainty becomes more attractive to decision makers if they have means to maintain access to the upside potential. These means here are options or flexibility of decision making.

Real options theory is based on the tenet that, under uncertainty, securing flexibility of

decision making will help decision makers to make better decisions by waiting for the uncertainty to be resolved (Trigeorgis, 1993). Resolving uncertainty is equivalent to learning about the nature of uncertainty. Until now, the real option literature has largely addressed two uncertainties: exogenous uncertainty and endogenous uncertainty. The former refers to a type of uncertainty that cannot be reduced through organizational efforts, and the latter refers to a type in which uncertainty can be reduced only through certain activities of the organization (Folta, 1998; McGrath, Ferrier, & Mendelow, 2004; Roberts & Weitzman, 1981). Thus, the former is primarily concerned with uncertainties in the market, such as the demand and price of products that a single firm cannot control, and the latter is related to technical aspects such as the physical difficulties of the project. From a learning perspective, the former uncertainty is associated with passive learning, and the latter with active learning. If exogenous uncertainty prevails, firms can simply confirm that uncertainty is resolved through waiting. However, if endogenous uncertainty prevails, firms simply cannot expect uncertainty to be resolved through waiting, and some action must be taken to resolve uncertainty. For example, companies that are considering bringing new products to the market encounter uncertainty about the performance criteria of the products customers require. A too low level of product performance is a problem, but a too high level of performance can increase the price of the product and make it unfit for consumers (Ottum & Moore, 1997). Therefore, information on appropriate product performance levels is a very important decision criteria for new product launches. In most cases, the company can resolve this uncertainty, unlike the exogenous uncertainty, by

directly releasing the product and analyzing the response of the consumer, because the market is not yet formed, and not by simply waiting (Artmann, 2009). Therefore, many companies are responding to endogenous uncertainty by carrying out small-scale projects, called pilot projects, ahead of the actual project (Errais & Sadowsky, 2008). In other cases, there are a variety of alternatives for developing specific technologies for use in products (Guo, 2012). However, whether a technical alternative will actually be the best alternative is difficult to predict in advance, and can only be inferred through scientific knowledge or results obtained through direct R&D activities. Therefore, considering endogenous uncertainty in R&D, the main application of real option theory, is not an option but a necessity (Pindyck, 1993).

Until now, most real option studies have mainly modeled uncertainty focusing on exogenous uncertainty. This is because exogenous uncertainty, which is the subject of financial option theory and the origin of real options, is more dominant in the financial market. Since the price of a financial asset can be updated by simply observing the market, the uncertainty of the financial asset can be modeled using exogenous uncertainty. However, real assets that are subject to real option theory differ compared to the previous situation. Except for certain areas such as natural resources and real estate, there is no market where real assets are traded, so it is difficult to expect uncertainty to be resolved simply by waiting. Therefore, many criticisms of real option theory focus on the futility of the wait and see strategy, where decision makers simply wait for uncertainty to be resolved by delaying decision making under uncertainty (Wadeson, 2010).

This dissertation attempts to explicitly incorporate endogenous uncertainty into real option theory as a means to overcome such criticism. In order to incorporate endogenous uncertainty into real option theory, we first need to see how existing real option theory modeled exogenous uncertainty. In general, uncertainty in real option theory is modeled through the stochastic process for the value of a given opportunity. In the literature, the geometric Brownian motion, which is a continuous version of the discrete time random walk process, is mainly used as follows.

$$S_t = S_0 exp\left[\left(\mu - \frac{1}{2}\sigma^2\right)t + \sigma B_t\right]. \quad (1.1)$$

From equation (1.1), the geometric Brownian motion has two parameters: drift parameter (μ) and volatility parameter (σ). Under the concept of exogenous uncertainty, these two parameters are known values. Under this assumption, the stochastic process is a process adapted to filtration, which indicates the size of the information set of the decision maker. This indicates that, at each time point, the decision maker knows the value of the stochastic process accurately. However, endogenous uncertainty assumes that the parameter value that characterizes the stochastic process is not a constant but an arbitrary random variable (Armstrong, Galli, Bailey, & Couët, 2004). Under this assumption, the stochastic process can no longer be adapted to the filtration process. Moreover, endogenous uncertainty may be different from exogenous uncertainty in the construction of the filtration process. Under exogenous uncertainty, the magnitude of the information set of the decision

maker can be expressed as the value of the probabilistic process observed up to the present time. Under endogenous uncertainty, however, the filtration process is more appropriately regarded as an indexed set of decision-makers' behaviors, rather than a condition changing over time.

We need to introduce endogenous uncertainty into real option theory to change the wait and see strategy, which is the rationale for decision making flexibility in the existing real option theory. It should now be recognized that the flexibility of decision making is generated not by simply waiting, but by active learning through direct execution or investment. Therefore, the keyword of the real option needs to change from the existing "wait and see" to "learning and see." According to economic search theory (Lippman & McCall, 1976), learning is not free but an action that costs money. Thus, if you pay too much before making a full-scale investment, it can be a problem because the cost of learning can be higher than the benefit of learning. Therefore, companies need to acquire information that can contribute to the resolution of endogenous uncertainty for the opportunity through a sequential learning process. In addition, sequential investments or learning provide opportunities for companies to rethink opportunities based on information they have learned (Herath & Herath, 2008). In other words, acquiring new information through learning can provide a fundamental momentum for change in the value of opportunity. The importance of this approach has been proven by many business cases. "Little bet" (Sims, 2011) reveals the importance of sequential investment or learning through a small start, as the title of the book says. The real business environment is so

highly uncertain that it is difficult to know where the company is heading. Under these circumstances, firms cannot simply wait for the resolution of uncertainty and expect uncertainty to be solved only through the results obtained through direct actions. Many companies (e.g., Amazon, Pixa, P & G, Google, and GM) that have grown into global giants today have achieved great success by discovering opportunities in new markets through small experiments (Sims, 2011).

Therefore, in order to emphasize the criticism of the existing real option theory and the importance of learning, which is gradually recognized in the current business environment, this thesis will show that flexibility of decision making is not caused by the wait and see attitude but by the learning and see approach. In order to introduce endogenous uncertainty into the existing real option framework, we need to model the active learning process. This study attempts to apply active learning through Bayesian learning for the following reasons. The core principle of Bayesian learning is that decision makers have prior beliefs about the parameters in which uncertainty exists and that this prior belief can be continuously updated through the collection of data related to the parameters. Here, the collection of data is the result of efforts by decision makers to obtain information, which can be considered as an active learning process (Miller & Park, 2005). As data are continuously collected, the posterior distribution of the parameters of the decision maker asymptotically converges to the actual parameter values. Thus, a decision maker with an updated posterior distribution can expect to make a more optimal decision than a decision maker with an un-updated prior distribution.

In addition to the learning effects highlighted in this dissertation, other types of learning effects are considered in the literature. In particular, “learning-by-doing,” which is based on the seminal paper of Arrow (1962), is a commonly used learning concept. According to Arrow (1962), learning-by-doing represents an improvement in productivity that is achieved by continuously performing certain behaviors. Extant research applies learning effects based on the concept of learning-by-doing in the real option literature (Childs & Triantis, 1999; Della Seta, Gryglewicz, & Kort, 2012; Koussis, Martzoukos, & Trigeorgis, 2007; Xiaotong, 2009). Most existing studies assume that learning activities conducted prior to acquiring opportunities will deterministically lower investment costs or unit production costs. Exceptionally, however, Errais and Sadowsky (2008) found that prior learning activities have the effect of lowering the volatility of stochastic learning costs. However, these learning effects are an analysis of contexts different from Knightian uncertainty (Knight, 1921), which this dissertation ultimately deals with. The learning concept that this dissertation focuses on is not a repetition of a certain behavior like learning-by-doing, but an approach to the unknown value of opportunity that does not even have a specific probability distribution. Therefore, this dissertation excludes learning effects based on the concept of learning-by-doing.

This dissertation contributes to the related literature as follows. First, it is meaningful to explicitly incorporate endogenous uncertainty, which was insufficiently considered in the existing real option literature, into the model. Existing real option studies also consider endogenous uncertainty, but most of them are empirical studies based on qualitative

methods (Folta, 1998; Li, 2008; McGrath et al., 2004; Oriani & Sobrero, 2008). However, this dissertation explicitly incorporates endogenous uncertainty into the existing real options model. As pointed out in the above-mentioned studies, the effects of endogenous uncertainty on investment value and optimal investment strategy are very different from those of exogenous uncertainty. In particular, endogenous uncertainty, unlike exogenous uncertainty, is an element that facilitates, rather than delays, corporate behavior (Pindyck, 1993). Therefore, this study considers both exogenous and endogenous uncertainty to shed light on not only the effect of each uncertainty but also the interaction effects of both uncertainty types. It will help to re-establish the role of uncertainty in the real options literature. Second, this dissertation update the studies applying Bayesian learning theory in modeling real options. Although Bayesian learning theory has already been applied to the modeling of real options in some studies (Herath & Herath, 2008; Miller, 2010; Miller & Park, 2005), no study has applied endogenous learning processes through investment, as Chapter 2 does. Chapter 3 shows that the optimal stopping problem of real option theory can be applied to study the optimal experiment level, which is mainly utilized the Bayesian learning process. In addition, the assumption in Chapter that unknown parameters have a continuous distribution is significant for the research model in the existing study, which expands the two-point distribution assumption (Ryan & Lippman, 2003). Finally, this dissertation contributes to changing corporate decision makers' thinking processes when they are faced with uncertainty (especially endogenous uncertainty). I would like to emphasize that active learning through commitment (e.g., preemptive behavior), rather

than simply waiting to avoid risk, is a correct countermeasure to uncertainty.

1.2 Structure of the study

This dissertation consists of five chapters, including Chapter 1, which presents an overview of the entire study.

Chapter 2, the first essay of this dissertation, discusses experience-driven and discovery-driven planning, available to companies considering entry into new markets. The fact that the existing experience and knowledge of the company is crucial to new market penetration is well recognized through previous studies (Klepper & Simons, 2000; Thompson, 2007). Recent studies, however, show that the existing experience of a company does not always positively affect the performance of the company. This is because the core competencies of incumbent companies do not always extend to new markets (Hoskisson & Busenitz, 2002). Therefore, if the core competency of the company differs from that of the market it aims to enter, the company should follow the learning approach rather than rely on blind faith in its existing experience and knowledge. The use of the learning approach to enter new markets is visible in the “small acquisitions” literature that has recently drawn attention. According to Cai (2016), about 70% of acquisitions for diversification in recent decades have been found to be small acquisitions. It was also revealed through an additional analysis that this small acquisition was actually a preemptive investment for learning. Netter, Stegemoller, and Wintoki (2011) confirmed

that the periodic up-and-down movements in M&A were not observed when small acquisitions, which account for a large share of total acquisition activities, were not included. Under these circumstances, experience-driven planning implies the establishment of an optimal strategic plan under assumptions based on the existing knowledge and experience of the company. However, discovery-driven planning refers to strategic planning to revise the existing assumptions through acquisition of information through preemptive entry without relying on existing knowledge and experience (McGrath & Macmillan, 1995).

Chapter 3, the second essay of this dissertation, analyzes the effect of learning activities through small-scale experiments on the value of unknown innovative opportunities. The technical uncertainty inherent in innovation opportunities makes the value of opportunities difficult to accurately estimate at the beginning of the decision-making process. A company cannot expect technological uncertainty, as opposed to the market uncertainty mentioned in the standard real option literature, to be resolved without any effort. For example, assuming that an innovation opportunity has a variety of technological alternatives, one can hardly know which alternative would be the best unless each of the alternatives is applied. Thus, companies can approach the true value of opportunity by learning the technical uncertainty inherent in the innovation opportunity before actually acquiring the opportunity. Thus, undertaking a learning investment such as a pilot project or a demonstration plant before acquiring the given innovation opportunity is a common practice (Frishammar, Söderholm, Bäckström, Hellsmark, & Ylinenpää, 2015). Moreover, according to Xu, Zhou,

and Phan (2010), adopting a sequential acquisition strategy in M&A shows better performance than a single transaction. These results imply that the presence of proactive learning activities can make a big difference in the performance of the company on any opportunity. In Chapter 3, therefore, I try to analyze the optimal learning strategy that can be used when a company encounters unknown innovation opportunities within the framework of the optimal stopping problem.

Chapter 4, the third essay in this dissertation, demonstrates how the effects of learning under uncertainty can resolve the dilemma between commitment and flexibility through both theoretical and empirical models. Many empirical studies and real business cases establish that, in contrast to the prediction in the canonical real option theory, companies do not always choose a strategy that considers flexibility under uncertainty. According to Carruth, Dickerson, and Henley (2000), empirical studies on the relationship between uncertainty and investment show mixed results, unlike the prediction in real option theory. In addition, despite the initial high uncertainty, many companies are making commitments, such as in the Airbus's A380 development case (Pacheco-De-Almeida, Henderson, & Cool, 2008). Therefore, this study attempts to resolve the dilemma by introducing a new viewpoint of the learning effect in order to help companies make investment decisions under uncertainty.

Finally, Chapter 5 draws the main implications of this dissertation, suggests investment strategies for firms under uncertainty, and concludes the dissertation.

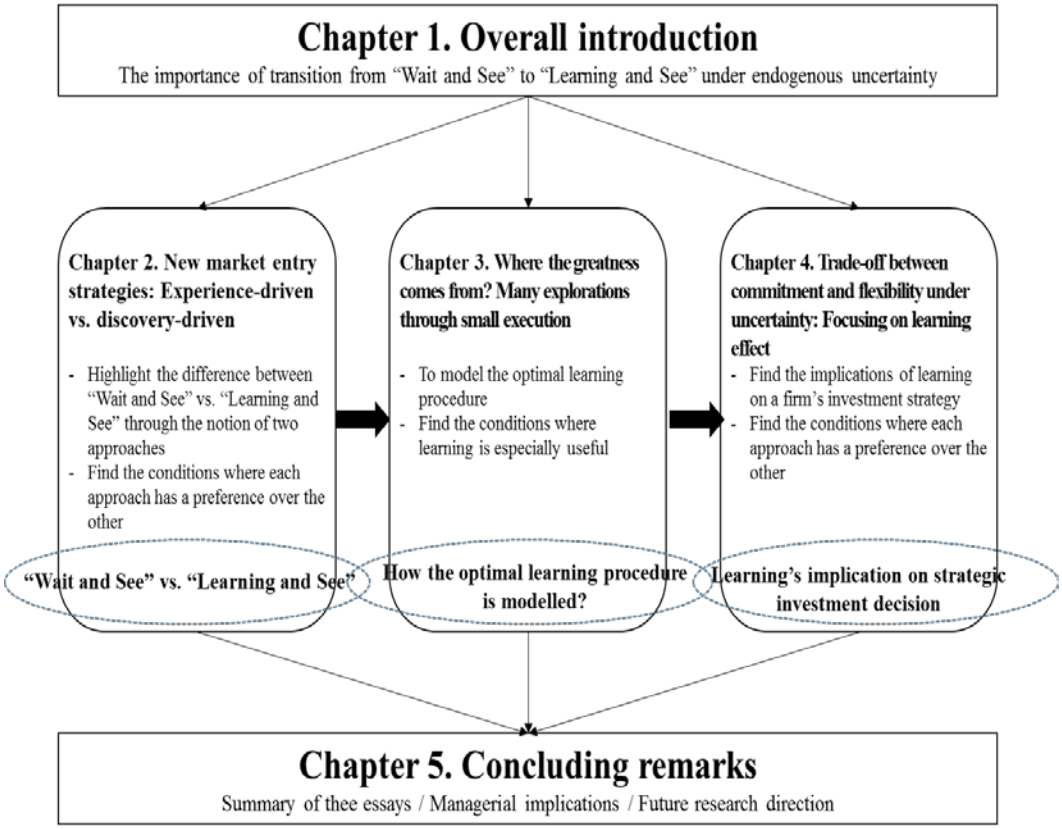

Figure 1. Research outline

Chapter 2. New market entry strategies: Experience-driven versus discovery –driven

2.1 Introduction

Incumbent firms consider entering into new markets to find opportunities to pursue another profit streams as their market matures (Geroski, 1995; Gort & Klepper, 1982). As existing markets mature, new innovation opportunities decrease and competition intensifies, making it difficult for existing firms to achieve abnormal returns (Dixit, 1980). Generally, a new market refers to a market that has not been experienced by incumbent firms in various aspects, such as technological, geographical, institutional, and consumer types. Therefore, entry into new markets is essentially an adventurous move made under very high uncertainty. Thus, previous empirical findings that corporate diversification performance, on average, undermines shareholder value are not surprising (Lang & Stulz, 1994).

According to previous studies, one of the important factors that influence the decision to enter new markets is the existing experience and knowledge of the firm. According to Klepper and Simons (2000), previous experience in radio technology was found to be a major determinant of success in the rapidly growing TV market from 1950 to 1970. In addition, Thompson (2007) also shows a similar phenomenon in the digital camera market. Accumulated experience and knowledge help a firm to enter a new market fundamentally

because the uncertainty involved in developing new business opportunities is reduced by their utilization (Liu & Hsu, 2011). In addition, cumulative knowledge and experience can facilitate “learning by doing” to improve productivity (Nelson & Winter, 1982). However, studies analyzing the acquisition performance of firms that have diversified through acquisition activities show that accumulation of knowledge and experience can have a negative influence. According to Fuller, Netter, and Stegemoller (2002), the average CAR (Cumulative Average Return) of at least five acquisitions in the last three years of research periods was about 1.7%, while the CAR after five acquisitions was about 0.52%. Billett and Qian (2008) pointed out that this decline in average CAR was due to overconfidence or behavior bias caused by experience accumulation. In addition, the use of existing knowledge and experience of incumbent firms does not always have a positive effect on performance because their core competencies are not always extendable to new markets (Hoskisson & Busenitz, 2002).

The new market entry strategy based on existing knowledge and experience of the firm is not successful because the actual business environment is different from the initial assumptions based on the knowledge and experience of the firm (McGrath & Macmillan, 1995). The usefulness of existing knowledge and experience of a firm will decrease as the gap between the target markets that incumbent firms want to enter and the existing market in which the current firms operates. This is complemented by the knowledge and experience associated with the markets in which the firm is seeking to enter, which plays a role in complementing the performance of unrelated diversifications, which is less

successful than related diversifications on average (Ramaswamy, Li, & Petitt, 2004). However, many firms are building new market entry strategies based on their existing experience and knowledge without considering these contexts, and this tendency is greater for larger firms that already have accumulated success experiences (Miller, 1992). McGrath and Macmillan (1995) refer to “experience-driven planning” as entry into new markets based on existing experience and knowledge. In addition, the authors point out that firms adopting experience-driven planning commonly make the following four mistakes. First, firms tend to accept their assumptions as facts if some key decisions are made, despite the lack of clear data. Second, firms do not find any implications even though they have the necessary data to reevaluate their assumptions. Third, firms use inappropriate assumptions in their implementation of the plan, even though they have all the data needed to find true opportunities. Fourth, firms start business with accurate data, but assume that the surrounding environment is static.

Therefore, an alternative to complement the experience-driven planning starts with discarding certainty about assumptions based on existing experience and knowledge of the firm. To this end, businesses must always leave room for early-stage assumptions to be modified at any time by new discoveries. This approach is called “discovery-driven planning” (McGrath & Macmillan, 1995). Discovery-driven planning is based on the belief that firms can resolve uncertainties by performing real investments and observing the results as the literature of learning from investment theory suggests (Aghion, Bolton, Harris, & Jullien, 1991). For example, firms can confirm their competitiveness (Jovanovic, 1982),

demand function (Grossman, Kihlstrom, & Mirman, 1977), and R&D project uncertainty (Berk, Green, & Naik, 2004) by committing their resources in related activities. Since the resolution of uncertainty by investment increases the value of decision-making flexibility, this study attempts to analyze discovery-driven planning through the lens of real options (Dixit & Pindyck, 1994). As mentioned above, the core of the discovery-driven plan is the learning process for assessing the validity of existing assumptions. Traditional real options theories adopt a passive attitude in which uncertainty is naturally resolved over time in the learning process, which is an inadequate assumption in modeling discovery-driven planning. It is difficult to obtain evidence to overturn an existing assumption unless you jump into the market and experience it yourself. Therefore, there is a need to model the active learning process in order to apply discovery-driven planning to real option theory. Active learning incurs a kind of learning cost compared to passive learning. For example, firms must preemptively enter a market where there is not enough demand in order to learn new markets that are not yet clear. At this time, it is difficult to expect that the profit from initial entry will be enough to offset entry costs. Therefore, firms need to build a kind of foothold through small investments to minimize learning costs (Cyert, Degroot, & Holt, 1978; Lin & Lee, 2011; Upson, 2008). Too much investment in learning leads to unacceptable losses if the investment goes wrong (Moeller, Schlingemann, & Stulz, 2005). Firms that enter new markets within the limits of loss that they can afford can reassess and revise the assumptions made at the early stages of the decision-making process as they discover new evidence and benefit from making more informed decisions based on more

accurate assumptions.

Therefore, this study intends to derive a comparative analysis of experience- and discovery-driven planning, which can be considered by firms seeking to enter into uncertain new markets, by applying real option theory. In particular, we attempt to integrate the Bayesian learning process into existing real option theory to model active learning processes that are central to discovery-driven planning. The Bayesian learning process intuitively depicts the process of discovery-driven planning accurately. First, the inaccurate assumptions that firms have in the discovery center plan represent prior beliefs in the Bayesian learning process, the results obtained through investment represent the acquisition of data in the Bayesian learning process, and the process of reassessing and revising existing assumptions indicates the updating of existing prior beliefs to posterior beliefs in the Bayesian learning process (Herath & Herath, 2008).

This study is composed as follows. In Section 2.2, we discuss the implications of experience-driven planning and discovery-driven planning, which are the background of this study, in the context of new market entry. In Section 2.3, we build a model to evaluate the value of new market entry through experience-driven planning and discovery-driven planning based on the discussion in Section 2.2. In Section 2.4, we try to evaluate experience- and the discovery-driven planning by analyzing the model constructed in Section 2.3. Finally, Section 2.5 concludes the paper with implications and suggestions for corporate strategy based on the results.

2.2 Research background

The cumulative information that a firm currently has is key to discovering and exploiting new opportunities (Shepherd & Levesque, 2002). The cumulative information of the firm ultimately determines the evaluation and execution of the given opportunity. Therefore, opportunity evaluation and the optimal behavior differ depending on how accurate the initial assumption based on the cumulative information of a firm is.

The biggest strategic decision the firm has to make in entering new markets is the timing of entry (Tan, Hung, & Liu, 2007). With regard to the timing of entry, experience-driven planning and discovery-driven planning approaches have different attitudes. Firms that have adopted experience-driven planning believe that their existing knowledge and experience is accurate. Therefore, when there is uncertainty about the new market, they will maintain flexibility through delaying the decision making and determine the optimal time of entry through assumptions derived from their existing knowledge and experience (Kim, Ashuri, & Han, 2013). For example, firms will decide to enter the market based on their initial assumptions when market demand reaches the optimal level. Therefore, it should be seen that experience-driven planning does not ignore uncertainty but instead believes that the nature of uncertainty is perceived through existing knowledge and experience.

However, if the existing knowledge and experience of a firm is significantly different from the reality, the optimal plan installed under the initial assumption is not likely to be

optimal in practice. The usefulness of existing experience and knowledge of the firm will greatly reduce particularly when the new market has an environment much different from that in which the firm operates (Dahl & Reichstein, 2007). Unlike the market uncertainty that is mainly considered in real options literature, uncertainty about the initial assumption is not a type that can be solved by simply waiting. In order to determine whether the initial assumptions are right or wrong, one has no choice but to embark on the road to direct action to resolve the uncertainty (Aghion et al., 1991). Therefore, the right and wrong of the initial assumptions need to be judged based on information obtained from the results of preemptive entry into a market not yet known and matured. If the initial assumptions are incorrect, firms must update the assumptions about the market based on newly obtained information. As this process repeats, the existing uncertain assumptions can be transformed into more reliable assumptions closer to the true value of the market (McGrath & Macmillan, 1995).

2.3 Model descriptions

First, we try to define the investment strategies through experience- and discovery-driven planning. Experience-driven planning means building a strategy based on the knowledge and experience a firm has already had. The existing knowledge and experience of a firm can be used to create prior beliefs about the value of opportunities in new markets (Miller & Park, 2005). Based on the given prior belief, the decision-maker decides to enter

new markets that bring the best benefit to the firm, at the optimal time. On the other hand, firms adopting discovery-oriented planning enter a new market through small investments at present. By actually entering the market, firms can observe how the market is evolving, and based on the observation results, the existing prior beliefs can be updated with more accurate posterior belief through Bayesian learning techniques. More precise posterior belief becomes more efficient decision making in the rest of investment decisions than prior belief does. For analytical simplicity, in this study, discovery-driven planning will invest some part of the project initially with prior belief about the project, and the remaining project will be acquired later based on the updated posterior belief. In other words, in the case of discovery-driven planning, the order of investment is composed of two stages. In addition, the initial small investment generates negative NPV and sees it as a learning expense. Figure 2 shows how investment strategies for experience-driven planning and discovery-driven planning are structured under the above-mentioned assumptions.

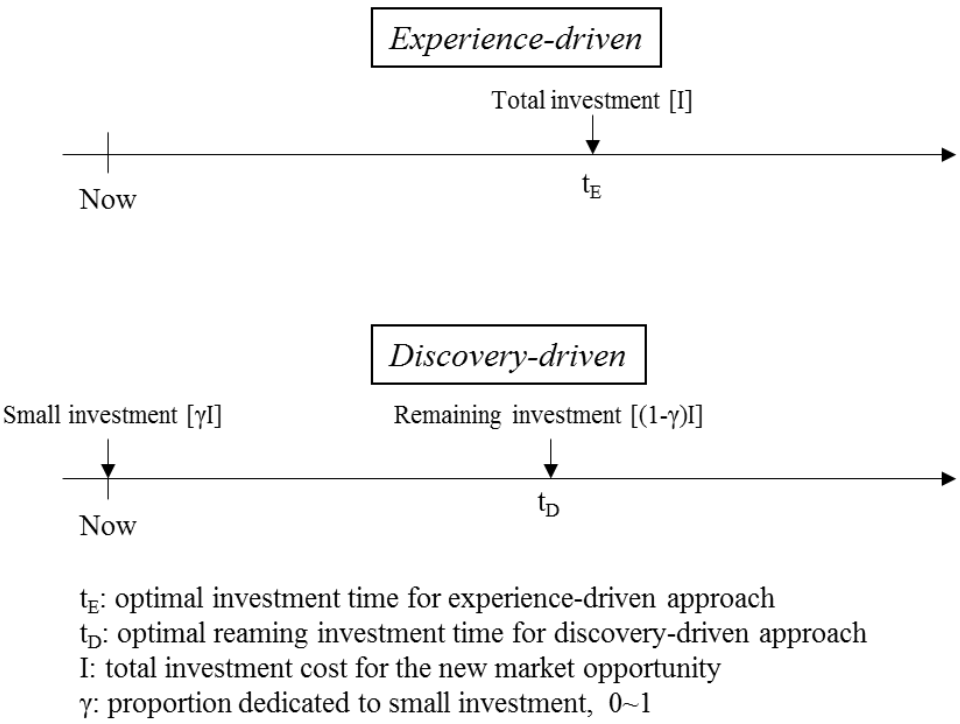

Figure 2. Investment strategy for experience-driven and discovery-driven planning.

Next, we show how the value of the investment opportunity identified in the new market evolves. To reflect uncertainty about the value of the investment opportunity, we assume that the value of the opportunity follows the geometric Brownian motion as follows:

$$dV_t = \mu V_t dt + \sigma V_t dZ_t, \text{ (2.1)}$$

where μ is the parameter representing the expected growth rate of value, σ is the volatility of growth rate of the value, and dZ is the increment of the Wiener process. Equation (2.1) has the following implications. At each moment, the opportunity value

grows by μ percent on average, but the growth rate has a volatility of σ due to exogenous factors (mainly market demand uncertainty) that firms cannot control. The size of σ indicates the magnitude of market uncertainty associated with the opportunity. The implication of market uncertainty implies that once a new opportunity occurs, unforeseen events (such as the emergence of competitors, changes in consumer preferences, and changes in institutions) happen constantly. In general, uncertainties due to these unpredictable events are outside the control of a single firm, so the impact of this uncertainty on the value of an opportunity assumes zero on average. (Dixit & Pindyck, 1994). In general real option studies, the parameters μ and σ are considered to be known values. The assumption that the parameters governing the movement of opportunity values for the firm are known and constant is valid only as long as the existing knowledge and experience of the firm is perfectly matched to the market it seeks to enter.

However, in reality, world-class global companies that have accumulated a lot of success stories and experiences encounter many failures in expanding into new businesses (McGrath & Macmillan, 2013). This is caused by the difference between the core competencies derived from the knowledge and experience of incumbent firms and those needed in the identified markets (Hoskisson & Busenitz, 2002). Therefore, this study assumes that firms' prior beliefs about opportunity value movements may differ from the actual situation in the new market. Accordingly, the parameter μ, which represents the expected growth rate of the value of a given opportunity, is assumed to be an unknown constant (instead, σ is a known value) with a probability distribution of $\mu \sim \mathrm{N}(\mu_0, \sigma_\mu^2)$.

Therefore, firms adopting experience-driven planning do not have an opportunity to resolve the uncertainty of μ, so they derive optimal decision rules based on μ_0, the best estimate of μ. However, firms adopting discovery-driven planning have the opportunity to update their beliefs on μ based on the values of V observed in the market.

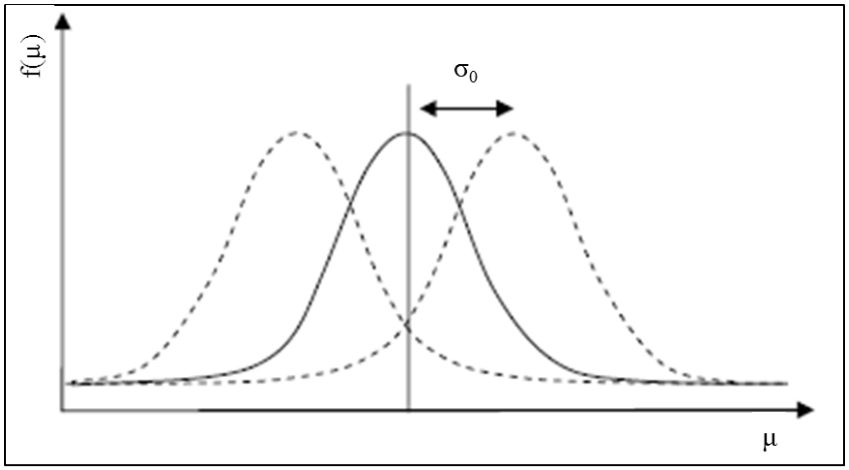

Figure 3. Prior distribution on μ

Since the value of the opportunity evolves stochastically, I try to derive it through both approaches by using a real option technique that can incorporate uncertainty into optimal decision making. First, the value function of the given opportunity to a firm adopting experience-driven planning is called $F_E(V_0)$. The Bellman equation for the value function of experience-driven planning is derived as follows.

$$F_E(V_0) = max\big[V_0 - I, (1+\rho dt)^{-1} E[F_E(V_0 + dV)]\big]. \quad (2.2)$$

The first term in the max operator on the right-hand side of Eq. (2.2) represents the value obtained with investment made immediately, at the current point in time, and the second term the expected value obtained when the investment decision is postponed. This problem is a typical example of an optimal stopping problem and can be solved as follows. Under dynamic programming terms, the first term in Eq. (2.2) is expressed as a termination payoff and the second term as a continuation value. Depending on the range of the state variable V, the right-hand side of equation (2.2) may be the first term or the second term. Under general conditions, optimal decisions can be made based on the unique reference value V_E. In this case, it is optimal to postpone investment if V is less than V_E and to invest immediately if V is greater than V_E (Dixit & Pindyck, 1994). First, I try to calculate the opportunity value when the current V is less than V_E so that it is optimal to postpone the investment. In this case, Eq. (2.2) is the second term in the max operator, and the value function satisfies the following differential equation.

$$\frac{1}{2}\sigma^2 V^2 F_E''(V) + \mu_0 V F_E'(V) - \rho F_E(V) = 0. \quad (2.3)$$

Eq. (2.3) is an ordinary differential equation and has the following general solution: $F_E(V) = A_0 V^{\beta_0}$, where $\beta_0 = \frac{1}{2} - \frac{\mu_0}{\sigma^2} + \sqrt{\left(\frac{\mu_0}{\sigma^2} - 0.5\right)^2 + \frac{2\rho}{\sigma^2}} > 1$ and A_0 is an unsettled constant as of now. Now, I am going to use the value-matching and smooth-pasting

conditions to obtain V_E, which is still an unknown value and determines the optimal investment decision rule. The former means that the two value functions have continuity when $V = V_E$, and the latter refers to the technical optimality condition to prevent arbitrage opportunities (Dixit & Pindyck, 1994). The value function and the corresponding two conditions can be represented as follows by Eq. (2.4):

$$F_E(V_0) = \begin{cases} V_0 - I, V_0 \geq V_E \\ A_0 V^{\beta_0}, V_0 \leq V_E \end{cases} \textit{: Value function,}$$
$$F_E(V_E) = F_E(V_E) = AV_E^{\beta_0} = V_E - I \textit{: Value-matching condition}$$
$$\frac{\partial}{\partial V} F_E(V_E) = \frac{\partial}{\partial V}(V_E - I) \textit{: Smooth-pasting condition. (2.4)}$$

From equation (2.4), the value of the given investment opportunity and the value of V_E, the point at which the investment is carried out, can be expressed as follows for a firm adopting experience-driven planning:

$$V_E = \frac{\beta_0}{\beta_0 - 1} I,\ \beta_0 = \frac{1}{2} - \frac{\mu_0}{\sigma^2} + \sqrt{\left(\frac{\mu_0}{\sigma^2} - 0.5\right)^2 + \frac{2\rho}{\sigma^2}} > 1,$$
$$F_E(V_0) = A_0 V_0^{\beta_0}, A_0 = \beta_0^{-\beta_0}(\beta_0 - 1)^{\beta_0 - 1}(I)^{1-\beta_0}. \textit{(2.5)}$$

In other words, when V hits V_E for the first time, the firm can obtain the value $F_E(V_0)$ by paying investment cost I. Of course, this value would be optimal if the value of the given opportunity perfectly follows the firm's prior belief on the unknown value of μ. However, if σ_μ^2>0, there is a possibility that the true value of μ is different from μ0, which is the

firm's best estimate of μ. In this case, the firm adopting experience-driven planning faces a sub-optimality problem that makes it hard to acquire the full-blown value of the opportunity.

Next, the value function of the given opportunity for a firm adopting discovery-driven planning is called $F_D(V_0)$. It is also assumed that firms adopting discovery-driven planning have the same prior belief on the unknown parameter μ, as do firms that have adopted experience-driven planning. However, firms adopting discovery-driven planning can update their prior belief by directly participating in the market through a small investment at the present time. First, the firm invests a proportion of γ ($0 < \gamma < 1$) against the total investment opportunity and obtains the following NPV: $NPV_0 = \gamma(V_0 - I)$. If the NPV_0 is negative, it can be considered as a learning cost to assess a market that has not yet been fully developed. The firm paying learning costs and entering the market can update its prior beliefs about the unknown parameter μ by observing the actual value of V at each point of time through the Bayesian learning technique. This is possible because the value of V at each point of time follows a lognormal distribution conditioned on μ as follows: $\log\frac{V_t}{V_0} = \left[\left(\mu - \frac{1}{2}\sigma^2\right)t + \sigma Z_t\right] \sim N\left(\left(\mu - \frac{1}{2}\sigma^2\right)t, \sigma^2 t\right)$, where $Z_t \sim N(0, t)$ (Oksendal, 2003). Therefore, the firm at a position where the value of V is continuously observed can approach the true value of the unknown parameter μ as shown in Figure 4.

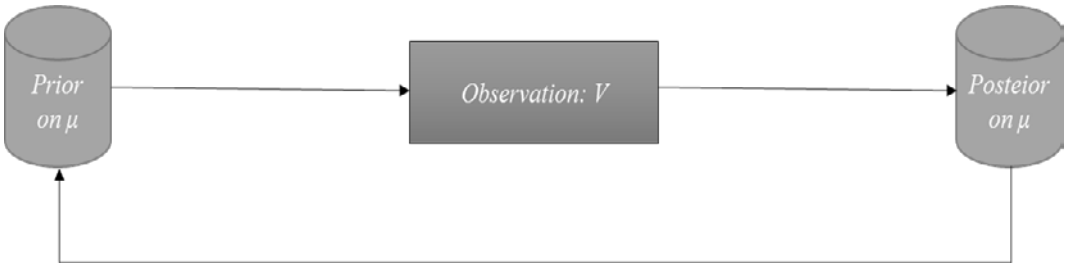

Figure 4. Bayesian learning process for μ

The Bayesian learning process in Figure 4 can be described as follows. Initially, the firm has μ_0 as the prior expected value of μ. At the next point, the firm observes the value of V and obtains a new expected value of μ_1 for μ according to the posterior belief formula. Now, μ_1 becomes a prior belief on μ in the process of observing the next value of V and deriving a new posterior expected value of μ_2 (Xie, Park, & Zheng, 2013). Thus, Bayesian learning is a kind of recursive process. In this study, I use the conjugate prior method to derive the process of updating the expected value of μ as shown in Eq. (2.6) below (DeGroot, 1970):

$$\mu_{t_{j+1}} = \frac{\sigma^2}{\sigma^2+\sigma_\mu^2 dt}\mu_{t_j} + \frac{1}{\sigma^2+\sigma_\mu^2 dt}\left(log\left(\frac{V_{t_{j+1}}}{V_{t_j}}\right) + 0.5\sigma^2 dt\right),$$
$$dt = t_{j+1} - t_j, \forall j, \mu_{t_0} = \mu_0 \;\&\; V_{t_0} = V_0. \quad (2.6)$$

A firm adopting discovery-driven planning to continuously update the expected value of μ should solve the problem of when to invest the rest of the investment. The basic problem structure is similar to the case of experience-driven planning, but with a crucial

difference that the value of μ perceived by the firm changes over time. If the value of μ recognized by the firm changes over time, β, which determines the optimal stopping point in Eq. (2.4), also changes. Thus, the optimal stopping point, V_D, also changes. If the expected value of μ derived from the Bayesian learning process at time t_j is μ_{t_j}, the β value at that point is given by $\beta_j = \frac{1}{2} - \frac{\mu_{t_j}}{\sigma^2} + \sqrt{\left(\frac{\mu_{t_j}}{\sigma^2} - 0.5\right)^2 + \frac{2\rho}{\sigma^2}}$. Thus, for a firm adopting discovery-driven planning at time t_j, the criterion for determining investment in the remaining opportunity is as follows: $V_{D_j} = \frac{\beta_j - 1}{\beta_j} \frac{(1-\gamma)I}{1-\gamma}$. Therefore, if the value of V at time t_j is equal to or greater than the value of V_{D_j}, then the firm pays the remaining investment cost of $(1-\gamma)I$ and acquire the remaining opportunity. Under this approach, the opportunity value for a firm adopting discovery-driven planning can be express by Eq. (2.7). Finally, I assume that full-information acquisition is possible only if the whole opportunity is acquired. Accordingly, if only a fraction of the investment is made, it is assumed that the point at which information can be acquired is determined in proportion to the initial investment scale (learning cost). Figure 5 shows how the timing of Bayesian learning is determined in proportion to the initial investment.

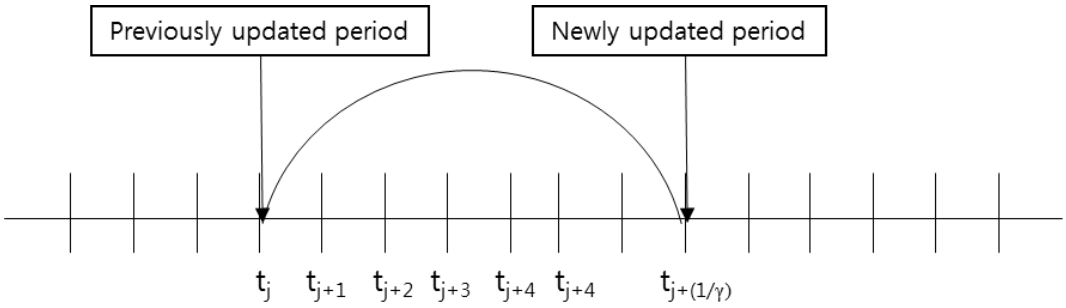

Figure 5.The relationship between gamma (proportion of small investment) and the amount of learning

$$F_D(V_0) = \frac{(1-\gamma)(V_{t_j}-I)}{1+(\rho\times t_j)} + NPV_0, if\ and\ only\ if\ V_{t_j} \geq\ V_{D_j} = \frac{\beta_j - 1}{\beta_j}\frac{(1-\gamma)I}{1-\gamma}. \ (2.7)$$

In fact, the firm needs information on the observed value of V to calculate the value of adopting discovery-driven planning. Therefore, the following simulations were performed based on the assumptions of the given parameters and the stochastic process. First, the μ value is stochastically generated 1000 times through the distribution of $\mu \sim N(\mu_0, \sigma_0^2)$. Next, for each μ value generated, a sample path representing the evolution of the opportunity value is derived as follows:

$$\log V_{t_{j+1}} - \log V_{t_j} = (\mu - 0.5\sigma^2)(dt) + \sqrt{dt} \times Z_t, Z_t \sim N(0,1),\ j = 0,1,\dots,N, \ (2.8)$$

where $dt = \frac{T}{N}$ (T: the length of planning horizon, N: the number of intervals) and $\mathrm{t_j} = 0 + \mathrm{j} \times \mathrm{dt}, \mathrm{j} = 0, \dots, \mathrm{N}$.

Averaging the discovery-driven planning values for different sample paths gives the value of the given opportunity for a firm adopting discovery-driven planning. The value of the given opportunity can be derived similarly for experience-driven planning as well. Averaging the experience-driven planning values for different sample paths gives the value of the given opportunity for a firm adopting experience-driven planning.

2.4 Model implications

To calculate the opportunity value under both approaches based on the model presented in Section 2.3, the initial parameter values should be set first. The parameters used in this study are shown in Table 1.

Table 1. List of the parameters in the model

Parameter	Description
V_0	Initial value of the opportunity
I	Total investment cost of the opportunity
γ	Proportion dedicated to small investment for the discovery-driven approach
μ_0	Initial guess for expected growth rate of opportunity value
σ_μ	Prior uncertainty on initial guess of μ
σ	Market uncertainty
ρ	Discount rate

From the given parameters, the state of the market that the firm is going to enter and the

characteristics of the firm can be described in detail. First, depending on the magnitude of σ, which indicates market uncertainty, the firm can distinguish whether it is looking at a relatively emerging or mature market. According to the literature on industry life cycle, emerging markets are generally characterized by more market uncertainty than mature markets (Tushman & Anderson, 1986; Utterback & Abernathy, 1975). Emerging markets have high market uncertainty compared to mature markets, as the market has not yet established standards, resulting in disequilibrium, represent by a number of firm entries and exits (Jovanovic & MacDonald, 1994; Klepper & Simons, 1996). Thus, given the same conditions, opportunity values would be subject to greater variability in emerging markets than mature markets. Next, the two parameters (μ_0, σ_μ) of the probability distribution for expected growth rate of the given opportunity have the following implications. As mentioned above, a firm's existing knowledge and experience is used to identify and evaluate opportunities (Shepherd & Levesque, 2002). The reason for heterogeneity in investment behavior among firms for the same opportunity is that the given opportunity is perceived differently by the firm's unique knowledge base (McGrath et al., 2004). Therefore, the greater the value of a firm's current knowledge and experience, other conditions being the same, the higher is the expected growth rate of the identified opportunities. Considering that knowledge and experience are core competencies of a firm (Grant, 1996), the level of core competency is a criterion for better identifying and assessing the same opportunities. Therefore, in this study, we assume that μ_0, which indicates the magnitude of the prior expectation value of the firm about μ, represents the

core competence of the current firm. However, firms with high core competencies are not always successful in entering new markets. The main reason for this phenomenon is the lack of relevance between the markets in which the firm is currently operating and those in which the firm is planning to enter. The higher the degree of non-relevance, the greater the uncertainty about whether existing competencies can be used in new markets (Markides & Williamson, 1994). Therefore, this study assumes that the greater the non-relevance of the market the firm aims to enter, the larger the value of σ_μ, which represents the difference between the actual and the prospective μ_0 values of the firm.

We now propose to derive the implication of the model through numerical analysis by arbitrarily assigning parameter values, as shown in Table 2. The assumed parameter values have the following implications. If an investment opportunity has a negative NPV (V_0-I=-4), it is considered that the market has not yet grown sufficiently. Therefore, a firm adopting discovery-driven planning needs to pay NPV ($0.2\times -4 = -0.8$) as initial learning costs. It is assumed that μ for the expected growth rate of the opportunity has a normal distribution with an expected value of 0.05 and a standard deviation of 0.05. Therefore, the expected growth rate of the actual opportunity has a value of $0{,}05 \pm 2 \times 0.05(= \sigma_\mu) = [-0.05{,}0.15]$ at a confidence level of 95%. In addition, the volatility of the growth rate of the opportunity is 10% per unit time.

Table 2. Comparison of the experience- and discovery-driven planning under the benchmark case

Parameter	Values
V_0	1
I	5
γ	0.2
μ_0	0.05
σ_μ	0.05
σ	0.3
ρ	0.07
Experience-driven	1.3092
Discovery-driven	0.9546

The results of the benchmark case suggest that the discovery-driven planning is not always superior to experience-driven planning. Firms that adopt discovery-driven planning must pay learning costs. Therefore, if the efficiency of Bayesian learning is low, firms do not need to adopt discovery-driven planning. From a resource-based view, the existing experience and knowledge that a firm has is a strategic resource that other companies cannot easily duplicate. These strategic resources have asset-specificity, so their value is determined based on context (Williamson, 1985). Therefore, experience-driven planning would be emphasized when the new market is not much different from the existing market because the value of strategic resources of the company is maximized. However, if this implication is reversed, firms will benefit from adopting discovery-driven planning in situations where Bayesian learning efficiency is high. Higher Bayesian learning efficiency means that the accuracy of the prior estimates of μ, expressed as un-relatedness of the new

market, is low in this study model. In other words, the value of existing knowledge and experience is reduced by asset-specificity in different new market contexts.

We now want to conduct a comparative analysis that changes the parameter values used in the benchmark case one by one. It can be used to identify which strategy is superior under certain conditions. First, we change the value of σ_μ, which indicates the magnitude of non-relevance for the market that the firm intends to enter, leaving the remaining variables used in the benchmark case intact. The results of the analysis are shown in Figure 6.

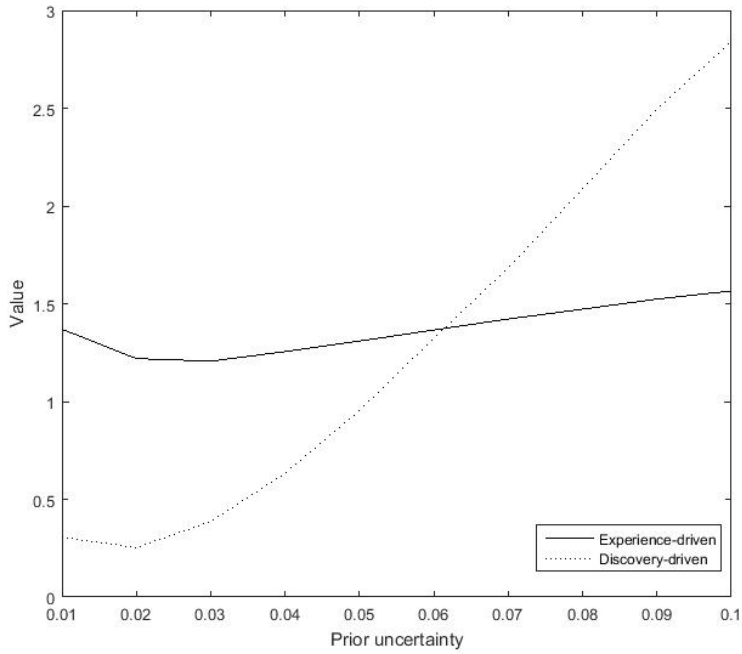

Figure 6. The effect of target market relatedness (prior uncertainty) on the value functions

As the degree of non-relevance of the target market increases, the value of discovery-driven planning increases significantly, but the value of experience-driven planning does not change much. The relationship between the increase in non-relevance and the value of discovery-driven planning can be explained as follows. As mentioned above, the uncertainty about the effectiveness of the core competencies of the firm may increase as the non-relevance of the target market increases. In other words, because of its core competency level, the firm expects an average growth of about 5% if it jumps into the new market, but this forecast could be less accurate with the market becoming increasingly non-relevant. In fact, it could be 3% lower or 7% higher than expected. The larger the difference between the actual and initial predicted values of μ, the higher the value of understanding the correct μ through learning activities. Discovery-driven planning has the advantage that it can identify new market niches that experience-driven planning cannot confirm through learning activities, even if the firm has paid learning costs. This can be a great advantage when the firm enters an unrelated market. On the other hand, as non-relevance increases, experience-driven planning relies only on the existing core competence, so the firm has no room to create new opportunities and the true opportunity value cannot be confirmed.

Next, we consider the maturity level of the market to be entered. Under the same conditions, the more emergent markets we enter, the greater is the market uncertainty that we face. According to the analysis results shown in Figure 7, the value of experience-driven planning increases monotonically with the newness of the market the firm intends to enter. This is due to the fact that the experience-driven planning considered in this study has an

option-like feature. Firms with experience-driven planning have the flexibility to make decisions only when market conditions are favorable, so it is advantageous to enter emerging markets that are likely to grow later in the same circumstances. However, in the case of discovery-driven planning, it has been found that the change in value has a non-linear relationship as the degree of market newness increases. In particular, below a certain level, the value of discovery-driven planning decreased as the degree of market newness increased. This is related to the learning effect of the unknown parameter μ, which is the greatest advantage of discovery-driven planning. The more emergent the market is, the less likely the actual market data contain information on factors that determine the fundamental opportunity value. Therefore, the higher the degree of market newness, the lower is the possibility of confirming the true opportunity value through learning under the same conditions. Therefore, the value of discovery-driven planning could be lower as the degree of market newness increases. The results of previous studies suggest that many pioneering firms that have entered the market early in the hope of achieving the learning effect experience high failure rates (Olleros, 1986). If the market is too new to the firm, and accordingly the market uncertainty is extremely high, discovery-driven planning becomes a much inferior strategy because it makes learning activities meaningless with the same investment decisions made as in experience-driven planning, but at greater cost due to learning activities.

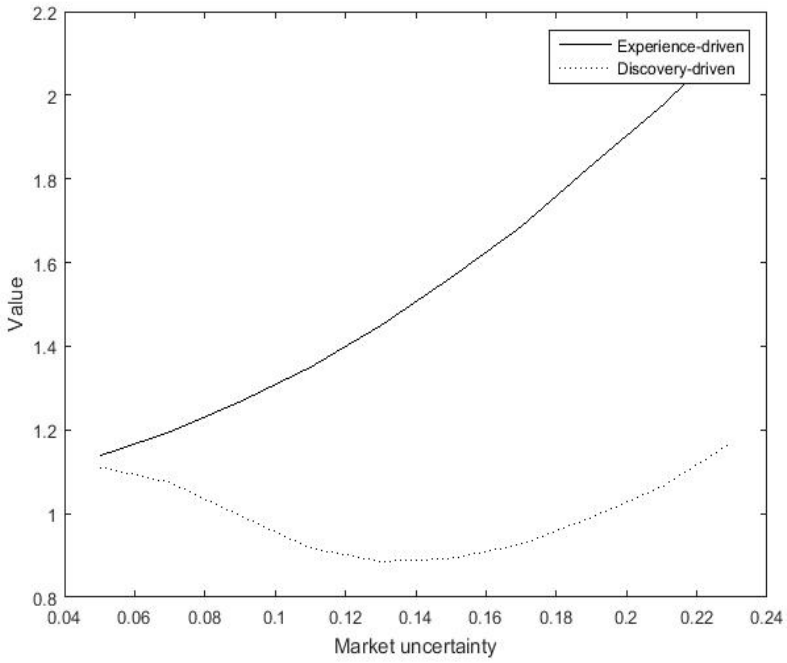

Figure 7. The effect of newness of the target market (market uncertainty) on the value functions

Rather than considering the effects of the characteristics of the markets the firm is seeking to enter, we will now focus on the effects of the firm's core competencies on experience-driven planning and discovery-driven planning. In this study the magnitude of the firm's absolute core competence determines the prior predicted value of the expected growth rate of the opportunity (μ_0). Figure 8 shows that as the size of the firm's core competency increases, both approaches gain value, but the value of experience-driven planning increases more. This has the following implications. If the market is non-relevant, the suitability of the firm's core competency is uncertain. However, a high degree of absolute core competency can offset the uncertainty about its suitability. In other words, if

the absolute core competence of a firm is large, the possibility of newly discovered opportunities through learning activities is not significant to the firm. Therefore, as the efficiency of learning decreases, the core competence of the firm increases, and more experience-driven planning will be preferred.

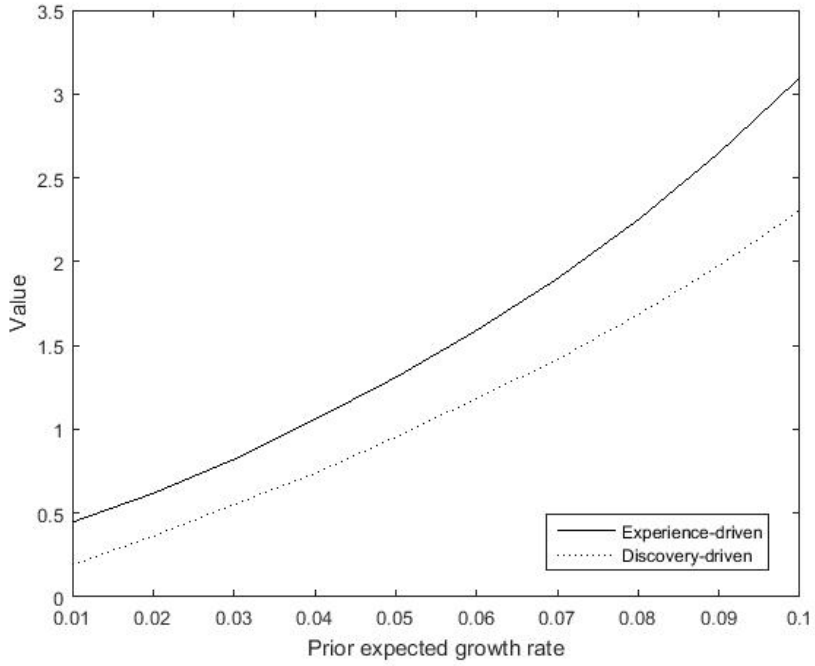

Figure 8. The effect of absolute core competence of the firm (prior expected growth rate) on the value functions

In the preceding comparative analysis, we saw the market only in one dimension. However, the market that the firm seeks to enter is not only an emerging market but also an unrelated or related market. In other words, the market that the firm intends to enter

under the framework of this study can be analyzed from the two-dimensional view of market maturity and relevance. The maturity and relevance of the market are expressed in the form of a 2 × 2 matrix, and then the comparative analysis of the relative value of the discovery-driven and experience-driven planning is conducted. If the uncertainty of a mature market is 0.1 in benchmark case, uncertainty of the expected growth rate of an opportunity in a related market is assumed to be 0.05 in the benchmark case. In the case of emerging markets and non-related markets, we have defined 0.2 and 0.1, respectively, twice the previous values. The analysis results are shown in Figure 9.

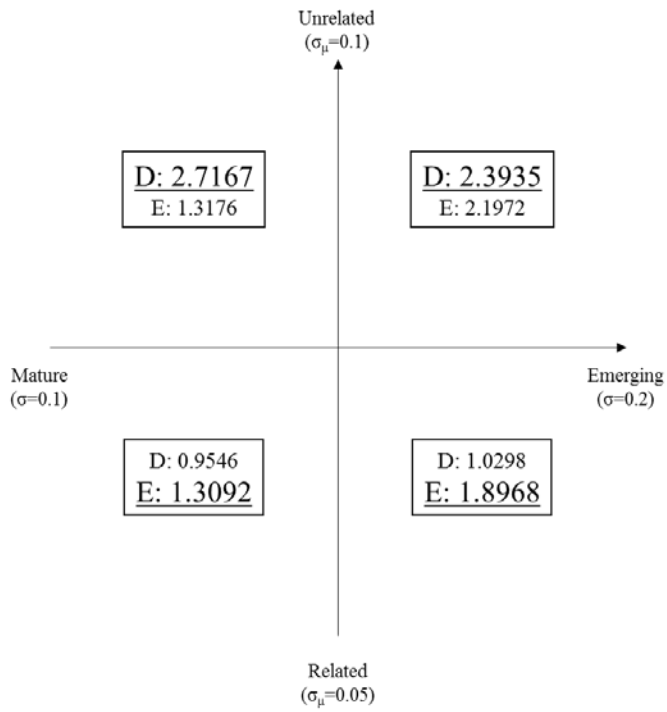

Figure 9. Optimal entry strategies in terms of market maturity and relatedness (under low core competencies, $\mu_0 = 0.05$)

Under the same conditions, greater non-relevance was more favorable for discovery-driven planning, and a higher degree of market newness was more favorable for experience-driven planning. In the recent low-growth era, markets that firms have been considering to enter as engines of new growth are largely unrelated and emerging markets. The results of this study show that although the emerging markets have lowered the efficiency of learning, which is an advantage for discovery-driven planning, new opportunities arising from the unrelatedness of the new market, not previously seen, may need to be identified by discovery-driven planning.

However, as the above-mentioned results show, the absolute core competence of the firm may influence the comparative analysis of experience-driven and discovery-driven planning. Therefore, we considered a firm with high core competencies under the same conditions as in Figure 9 but with double the value of μ_0, which represents the firm's core competencies. The analysis results are shown in Figure 10.

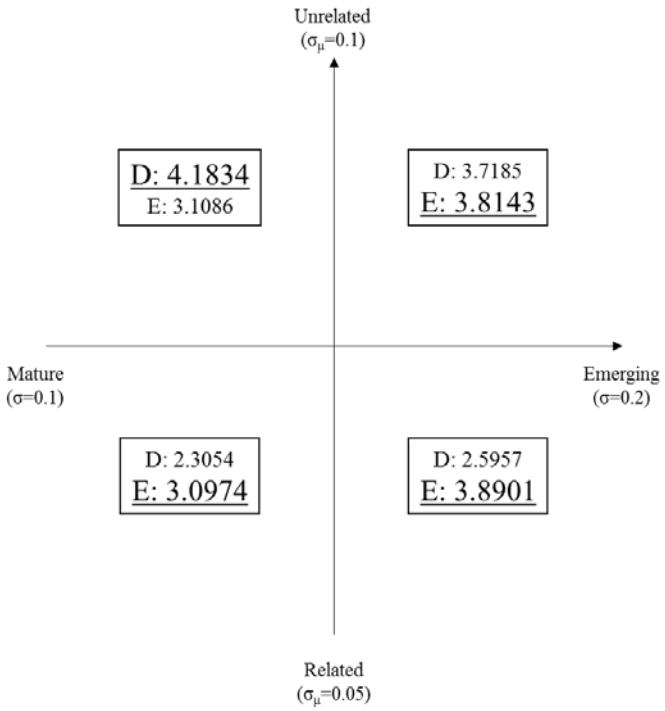

Figure 10. Optimal entry strategies in terms of market maturity and relatedness (under high core competencies, μ_0=0.1)

As a result of the analysis, the increase of the absolute core competency of the firm basically makes experience-driven planning more favorable than discovery-driven planning. Unlike in the previous case, experience-driven planning is preferred to discovery-driven planning, especially in unrelated and emerging markets. This implies that firms with lower core competencies need to be more explicit about the importance of learning.

The results of Figures 9 and 10 suggest that it is important to consider the interaction between the firm's absolute core competencies and the characteristics of the markets that the firm is seeking to enter. Therefore, the optimal entry strategy according to the

characteristics of the market the company aims to enter, as well as the characteristic of the firm, can be derived as shown in Table 3.

Table 3. Optimal entry strategies in terms of both market and firm characteristics

	Mature	Emerging
Related	**Experience driven**	**Experience driven**
Unrelated	**Discovery driven**	**Depending on core competencies**

The essence of discovery-driven planning is to carry out learning activities through an initial small start. One of the most important decisions here is to decide how much of the initial entry to take. This is because of a correlation between the initial entry scale and the learning speed, as assumed in this study. In particular, if market growth is not sufficient and the firm enters the market on a large scale, increasing the learning speed, the burden of learning costs increases and may ultimately lead to a large loss. The optimal initial entry size can vary depending on the relative size of the two types of uncertainty affecting Bayesian learning. First, we analyze how the opportunity value changes as the initial entry size increases at different levels of prior uncertainty. Figure 11, which shows the results of the analysis, reveals that if prior uncertainty is not above a certain level, increasing the initial entry size has the effect of lowering the value of discovery-driven planning. This is

because as the learning activity declines when prior uncertainty is low, entering the market on a large scale in the early stage only increases learning costs. Even if prior uncertainty is above a certain level, increasing the pace of learning does not always increase the value of discovery-driven planning. Instead, the relationship between the learning rate and the value of discovery-driven planning is inverse U-shaped, indicating that there is an optimal small initial entry size. The increase in prior uncertainty has a role in increasing the optimal size of initial entry. One notable point is that, once the learning effect occurs, entry into the market, even on a small initial scale, creates a large change in value. Therefore, if prior uncertainty is above a certain level, it is very important for firms to learn about the true potential of the opportunity through discovery-driven planning.

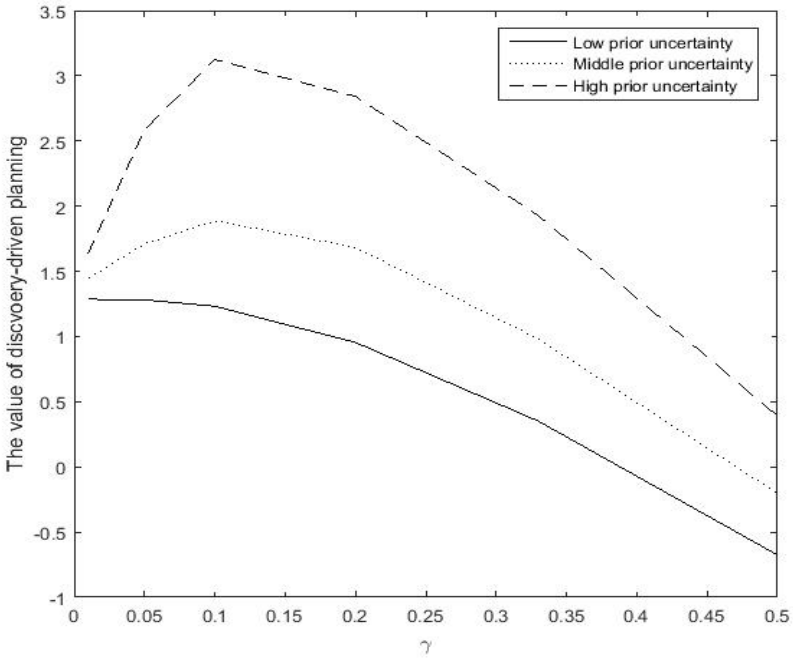

Figure 11. The effect of initial entry scale on the value of discovery-driven planning (low prior uncertainty=0.05, middle prior uncertainty = 0.075, high prior uncertainty = 0.1)

As mentioned above, the increase in market uncertainty lowers the efficiency of Bayesian learning. The level of prior uncertainty required for learning activities to be meaningful increases as market uncertainty increases. According to the analysis of Figure 12, the threshold effect of initial entry size, which existed at a low level of market uncertainty, disappears with increasing market uncertainty.

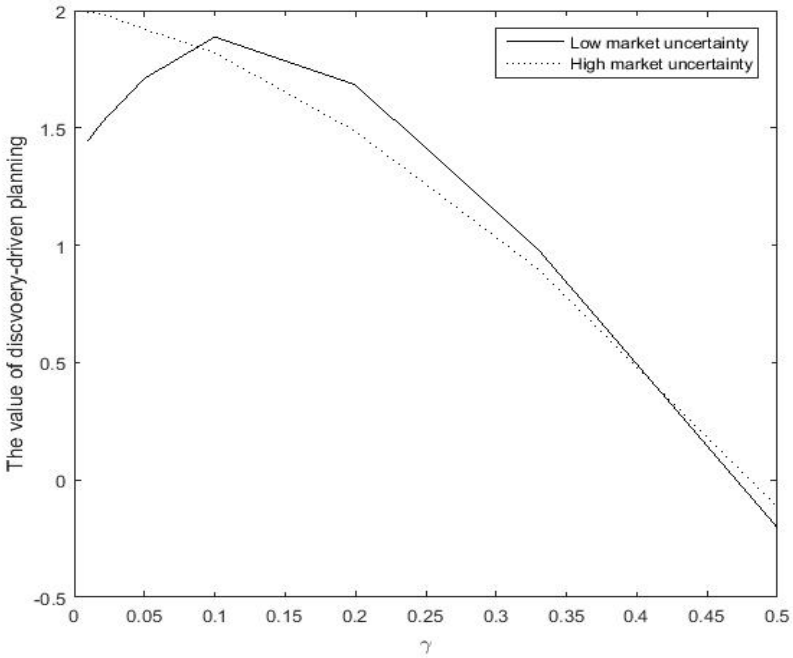

Figure 12. The effect of initial entry scale on the value of discovery-driven planning (low market uncertainty = 0.1, high market uncertainty = 0.2)

2.5 Conclusion and implications

This study is based on a study by McGrath and Macmillan (1995), which try to find out why even the best companies in the world have a difficulty in entering a new market. In contrast to the previous research focusing on cases, I tried to verify the validity of discovery-driven planning by integrating the Bayesian learning into the real option model. In particular, this chapter focuses on analyzing under what conditions discovery-driven planning is superior to experience-driven planning, unlike the previous research, which

concentrates on the advantage of discovery-driven planning. To do this, I considered the characteristics of the market that firms enter and the nature of the company itself. The characteristics of the market refer to the maturity and relevance of the market that firms are seeking to enter. The former is associated with the market uncertainty that firms contemplating new market entry face. The latter is associated with the prior expectation uncertainty about the growth rate of the opportunity. Regarding the firm's characteristics, the absolute core competencies of the firm are considered in the research model. Based on these factors, I derive the optimal entry strategies. Moreover, a trade-off appears between the initial entry size and the learning rate in applying discovery-driven planning. The degree of conflicting relationships varies depending on the level of the firm's prior expectation uncertainty and market uncertainty. The results of the analysis are summarized as follows. The value of discovery-driven planning is maximized when the market to be entered is highly irrelevant and mature, and the core competency of the firm is low. On the contrary, experience-driven planning is advantageous when the market to be entered is an emerging, highly relevant market, and the firm has a high level of core competence.

Discovery-driven planning provides the following advice on the diversification strategies of companies. Companies seeking unrelated diversification cannot but have high prior expectation uncertainty about the market growth rate. Therefore, a learning process is necessary to continually revise prior expectations. However, as the learning process is costly, the cost effectiveness of learning will increase in markets with high accuracy of acquired information, that is, markets with low market uncertainty, which will increase the

value of discovery-driven planning. Therefore, companies considering unrelated diversification are encouraged to adopt discovery-driven planning as the market matures. Here, if the firm's absolute core competency is low, the value of discovery-driven planning in unrelated diversification increases. Experience-driven planning also suggests the following advice on corporate diversification strategy. Companies that want to pursue related diversification have some certainty about the accuracy of their existing experience and knowledge. Therefore, it is highly likely that the optimal strategy based on existing experience and knowledge is actually an optimal strategy. The more uncertain the market, the less efficient is the learning through information acquisition. Therefore, it is better to act under the existing plan without risking the learning cost. Moreover, if the firm has a high level of absolute core competence, the value of experience-driven planning in related diversification will become even greater.

Next, the linear relationship between learning costs and learning rates suggests that there is an optimal initial entry scale for discovery-driven planning. This suggests that comparing the expected cost of learning with the expected benefit from learning, as suggested by economic search theory (Lippman & McCall, 1976), can lead to the right decision. In particular, the result shows that the optimal entry size depends on the decision-makers' prior expectation uncertainty and the level of market uncertainty and that a minimum level of prior uncertainty is required for the learning to be effective. Contrary to popular belief, it implies that learning activities are not always beneficial to companies.

Chapter 3. Where does greatness come from? Multiple explorations through small executions

3.1 Introduction

To achieve excellence, a company must continuously develop innovative products compared with competitors and successfully launch them in the market to secure competitive advantage (Eisenhardt & Brown, 1998; Lewis, 2000). For this, a company must continually invest a lot of resources in exploration-oriented activities (March, 1991). It can be said that innovations resulted from search activities, which in turn led to the emergence of new products, services, and processes that did not exist before. However, even though many companies have made great efforts to achieve innovation, few companies have successfully achieved innovation. According to Berner, Brady, and Nussbaum (2005), the probability of innovation failure ranges from 40 to 90 percent by industry, and is stationary – with no change over time. In addition, only about 5% of the countless new product development plans are finally commercialized (Artmann, 2009). Therefore, the question of why it is difficult to achieve successful innovation and how to achieve innovation with a higher probability is an important topic for both academics and practitioners.

There are many reasons, but fundamentally, innovation is difficult to achieve because of uncertainties inherent in innovation activities (Brown & Eisenhardt, 1997). Generally innovation activities are investments for the future, so it is natural that results are uncertain. Innovation activities face various sources of uncertainty, such as market returns, project budgets, product performance, project schedules, market requirements, and competitor movements (Huchzermeier & Loch, 2001). Companies facing uncertainty can choose strategies that set the future direction through large investments, hedges risks through small, diversified investments, or delays investment (Courtney, Kirkland, & Viguerie, 1997). The first option is the strategy that large companies such as Eastman Kodak and Xerox used. In the so-called industrial formation strategy, the key is to form the market itself rather than to respond to the market reaction. If there is a reasonable level of uncertainty, a firm that implements this strategy can gain large profits by securing a monopoly position in that market. However, the current level of uncertainty has become extremely high compared to the uncertainties of the past. In particular, since the global financial crisis in 2008, terms such as new-normal have become widespread, and high uncertainties are predicted to be the natural routine we will experience (Syrett & Devine, 2012). Therefore, the usefulness of the industrial formation strategy, which is accompanied by a high failure cost, is expected to decrease in the future. In addition, there are only a few companies in the world that are capable of forming the future themselves, so this strategy cannot be universally applied to all companies. The second and third strategies are all based on real options theory, which helps firms to utilize uncertainty to their advantage. A strategy of hedging risk through

small-scale, diversified investment is an example of utilizing step-by-step investment options, and a strategy of delaying investment and observing how things work utilizes deferral options (Amram & Kulatilaka, 1999). Both strategies are based on the principle that uncertainty induces firms obtain more information and make better decisions. However, the two strategies show significant differences in the stance on uncertainty.

In the real option literature, uncertainty is largely categorized as either exogenous uncertainty or endogenous uncertainty (Folta, 1998; Oriani & Sobrero, 2008). The most distinct difference between the two uncertainties lies in the mechanism by which uncertainty is resolved. In the former case, the uncertainty gradually dissolves over time regardless of the decision maker's behavior. In the latter case, the uncertainty is resolved only by the actions of the decision maker. Which type of uncertainty prevails depends on the various situations the firm faces, but recent examples of companies that have grown into global best practices show that endogenous uncertainties dominate the current market scenario. The experiences of companies such as Amazon, Pixar, Apple, Toyota, 3M, P&G, and Google demonstrate that they achieved success by learning the uncertainties they faced through numerous experiments with small runs (Sims, 2013). They have achieved competitive advantage, which has eluded other companies, by reducing the uncertainty of their goals through small experiments that they could afford. Existing empirical studies also show that a variety of experiments through small runs bring competitive advantage. According to Xu et al. (2010), companies can achieve successful M&As by adopting a sequential acquisition strategy, rather than a single transaction, for successful outcomes, if

the industry or market they intend to enter is characterized by high uncertainty. Moreover, a sequential approach to innovation can help companies acquire learning and leader's advantage in a wide range of fields by enabling experiments on a variety of projects (Kogut & Kulatilaka, 1994).

With this prevailing endogenous uncertainty, we should acknowledge that waiting and delaying cannot be a valid learning tool to reduce uncertainty, and identification of results through action is the only means to reduce uncertainty (Harford, 2011). Companies, in particular, have the opportunity to learn a number of alternatives sequentially before making choices in various situations. Therefore, this study attempts to analyze the value of many searches through small execution under the real options framework. The advantage of this approach is the accumulation of learning effects through sequential decision making. In order to reflect this appropriately in the model, we intend to integrate the Bayesian learning method into the real option theory. As the company gradually progresses through a number of explorations, it is possible to obtain information that can be used to learn the value of the entire project, which was not known at the initial stage. In terms of Bayesian theory, companies have a preliminary belief (distribution) about the value of the overall project initially, and the likelihood function of the distribution associated with the value of the whole project can be obtained from the search results. This combination of prior belief and likelihood function allows decision makers to update existing inaccurate prior beliefs with more accurate posterior beliefs. In fact, firms can always set a prior expectation, and if it does not match with the reality, they go through a flexible trial-and-error approach to

update their expectations (Chesbrough & Rosenbloom, 2002), so the model of this study is consistent with the real world.

This study is composed as follows. In Section 3.2, we try to examine previous studies related to this study. Section 3.3 builds a research model to derive the value of a number of explorations through small runs developed in this study. Section 3.4 attempts to interpret the results obtained by analyzing the derived models. Finally, Section 3.5 concludes by suggesting strategic and policy implications for innovation opportunities in high uncertainty.

3.2 Research background

The concept discussed in this study – multiple explorations through small implementations – is similar to the success pattern of high-growth firms described in the book “Great by choice” (Collins & Hansen, 2011). The authors identify the following fundamental success factors for highly successful firms under extreme uncertainty: fanatic discipline, empirical creativity, and productive paranoia. In particular, the concept of empirical creativity enables us to identify the optimal strategies that companies should take under uncertainty. Successful companies do not follow intuition, but rather seek effective empirical evidence and take action based on it. The authors describe the empirical creativity of successful companies as follows: “bullets, then cannonballs.” Successful companies first shoot bullets that are less expensive than cannonballs, and then focus on finding decisive

empirical evidence that will be helpful for future results. Once empirical evidence is collected, it is typical for the so-called successful companies to concentrate resources on successfully shooting cannonballs.

This study is also related to the literature on the optimal level of experimentation using Bayesian learning. The study by Moscarini and Smith (2001) is one of the leading studies in this area, and constructed a continuous-time model of sequential experiments that clearly considers information purchasing in the R&D environment. Under the assumption that experiments have a cost, the authors analytically proved that increasing the intensity of the experiment can increase the expected profit of the unknown project. Zhao and Chen (2009) modeled the optimal stopping point problem under the Bayesian learning framework, a dilemma often encountered by researchers in real laboratories – whether to continue research in order to make a perfect product or stop research and development at some point to make profits under a given deadline. Bergemann and Hege (2005) modeled the optimal level of experimentation also considering the agency conflict between financier and recipient that can occur during financing innovation. Finally, while existing studies have modeled the learning process of a single alternative, Ke and Villas-Boas (2016) simultaneously considered optimal resource allocation and optimal stopping time issues that determine each point-in-time learning decision and choice decision for multiple alternatives.

What should be considered through existing research models is that learning is not free. Shooting a bullet before shooting a cannonball is costly. Therefore, decision makers should

design an optimal stopping model that maximizes learning efficiency under the constraints of learning costs. Additionally, it should be noted that sequential learning can increase the value of a given opportunity, but it should also be recognized that the given opportunity does not solely belong to the decision maker (Smit & Trigeorgis, 2006). The presence of competitors can actually reduce the window of opportunity to utilize those opportunities (Shepherd & Levesque, 2002). Therefore, this study attempts to develop a model that simultaneously considers the advantages and disadvantages of learning, by considering the learning cost and possibility of entry of competitors into modeling the optimal level experiment under Bayesian learning.

3.3 Model descriptions

Generally, economic agents have the opportunity to learn through sequential learning before making any decision. Consumers may use sample products or participate in beta testing opportunities to obtain information about an item before purchasing it. This learning process is utilized not only by a consumer during decision making but also by various economic entities. The model of this study focuses on how this sequential learning process can improve the value of innovation opportunities given to companies and find out the nature of optimal learning in the learning process.

First, assume that a company has a distribution opportunity equal to Eq. (3.1).

V - the value of the opportunity: $V \sim N(\mu, \sigma^2)$ *and* $\mu \sim N(m_0, s_0^2)$
I - the investment cost. (3.1)

Studies using option theory generally assume a lognormal distribution, and not a normal distribution, for the value of an opportunity so that values do not become negative. For real options, however, assuming a normal distribution may be better for the following reasons (Alexander, Mo, & Stent, 2012). Real option theory is mainly used to analyze multiple projects that a company conducts simultaneously. In this case, a misplaced project can affect a company's ongoing projects badly and reduce its market value. From Eq. (3.1), the expected opportunity value is not a known constant but an unknown value with a probability distribution. It is assumed, however, that the firm has a prior belief on the expected value of the opportunity. If a company is currently making investments without any learning activities, the NPV arising from the investment is as follows: $\text{NPV} = m_0 - I$. Unlike previous real option models, firms cannot expect uncertainty about the value of opportunities to be resolved through simple waiting. The resolution of uncertainty is only possible by observing information about the realization value for V directly, through an experiment related to the opportunity. In other words, the uncertainty considered in this study is an endogenous type of uncertainty.

It is now assumed that there is a learning opportunity to acquire the information associated with the true value of opportunity through exploration activities, before a firm starts actual investment. Using the analogy in Section 3.2, the actual investment is like

shooting a cannonball, and the exploration activity is like shooting a bullet. Exploration refers to the process of accumulating information about a given opportunity. The amount of relevant information accumulated by the decision maker is important because it is an important determinant of the opportunity assessment and the following success. If there is no learning cost, it will be best for the company to maximize the amount of information accumulated through as much learning as possible. However, as bullets require some costs, it is natural for exploration to incur costs. Therefore, we assume a constant C as unit exploration cost. Some research considers “experience effects” in which unit exploration costs are reduced as time goes by, but this study follows the assumption in previous research that information on the value of unknown opportunities is considered to be independent of each other (Shepherd & Levesque, 2002). Since exploration costs exist, companies fall into the following dilemma: whether to acquire a project based on the information that they already have and stop further exploration or add another costly search, acquire new information, and then get back on the project. Of course, companies have an option to give up the opportunity itself if the prospects for the opportunity are found to be very bad through cumulative learning processes. Thus, the decision-making choices of companies at each time point are composed of three parts: Commit, Continue, and Abandon.

Next, we try to model the learning process of the unknown parameters as follows. A firm’s learning activity can be described as random sampling on any population associated with the value of the opportunity. On the assumption of one random sampling per unit time, the firm can be considered to have a total of t samples up to time t. Therefore, the

information obtained up to time t can be defined as the sample sum, which can be regarded as a sufficient statistic in this case.

$$X(t) = \sum_{i=0}^{t} V_i$$

$$dX(t) = \mu dt + \sigma dz(t), \textit{(3.2)}$$

where $dz(t)$ is the increment of the Wiener process and σ is the uncertainty of the opportunity itself and, at the same time, indicates the degree of noise in the observation process. Uncertainty of opportunity itself represents the level of various technological alternatives to realize the opportunity. If the technological alternatives are clearly defined, the learning process can exactly identify the expected value of the actual opportunity, but unless the technical alternative is clear, the true value of μ cannot be known clearly through the learning process (Kwon & Lippman, 2011). The best that companies can do through uncertain observations is to update their prior beliefs (Ryan & Lippman, 2003). Under a given circumstance, the posterior belief about μ that a firm has at time t can be expressed as follows (Chernoff, 1968):

$$m(t) = s(t)\left[m_0 s_0^{-1} + \sigma^{-2}\int_0^t dX(u)\right]. \textit{(3.3)}$$

$$s(t) = (s_0^{-1} + \sigma^{-2}t)^{-1}. \textit{(3.4)}$$

Eq. (3.3) shows that the mean value of posterior beliefs for μ is a random variable, and follows the martingale process based on the information the company has. Moreover, m(t) has a normal distribution as in the case of the prior distribution, and has a distribution that converges toward μ, the true parameter value, as learning progresses:

$$m(t) = s(t)\left[m_0 s_0^{-1} + \sigma^{-2}\int_0^t dX(u)\right]$$
$$= s(t)[m_0 s_0^{-1} + \sigma^{-2}\mu t + \sigma^{-1}z(t)]$$

, then,

$$m(t) \sim N\left(\frac{m_0 s_0^{-1} + \mu\sigma^{-2}t}{s_0^{-1} + \sigma^{-2}t}, \frac{\sigma^{-2}t}{\left(s_0^{-1} + \sigma^{-2}t\right)^2}\right) \to N(\mu, 0) \; as \; t \to \infty.$$

Equation (3.4) represents the variance of the posterior beliefs for μ, which is deterministic unlike the mean value, and decreases with time as a function of time (necessary and sufficient condition of m(t) to converge to μ).

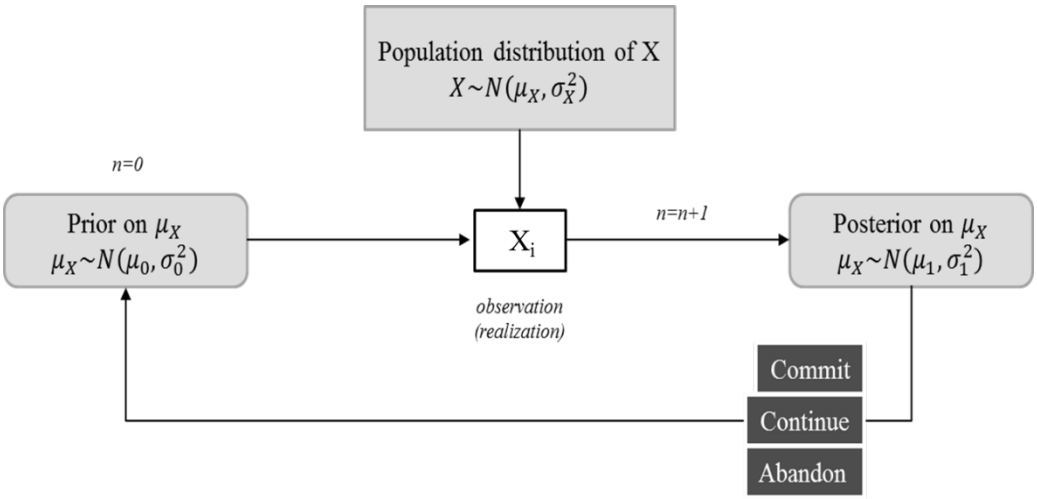

Figure 13. Bayesian learning process

Figure 13 shows the Bayesian learning process according to the exploration activity and following decision-making process of the company. Based on the belief on μ derived from the information obtained so far at each moment, the firm should choose the best behavior that gives the highest value among the three choices (Commit, Continue, and Abandon). This type of problem can be defined as an optimal stopping point question, and it can be solved by using dynamic programming after defining the value function, which is the Bellman equation. Under given circumstances, the value of a given opportunity is based on the posterior belief of the decision maker's expectation of μ, and the posterior belief of this study is a function of time, so the value function is determined by two state variables as follows:

$$F(m(t),t)$$
$$= max\{m(t) - I, -Cdt + (1 + rdt)^{-1}E[F(m(t) + dm(t), t + dt)], 0\}, \textit{(3.5)}$$

where the term r represents the discount rate of the firm. The first term in the max operator in Eq. (3.5) represents the value of Commit, where the firm stops exploration and immediately acquires the opportunity. The second term represents the value of Continue, where the firm pays the unit discovery cost C, performs additional search, and then makes the decision again with the posterior belief updated by the newly obtained information. Finally, the third term represents the value of the abandon strategy, where the firm gives up the opportunity entirely.

One of the issues considered as a step toward exploration activities is that the opportunity can be preempted given the presence of competitors (Huisman & Kort, 2004). The probability that an arbitrary competitor enters at any point is represented in the model by a Poisson process with intensity λ: $\Pr[t < \textit{Preemption} < t + dt] = \lambda dt$, where λ is a parameter indicating the intensity of competition. To reflect this expression (3.6) can be revised as follows:

$$F(m(t),t) =$$
$$max\{m(t) - I, -Cdt + (1 + (r + \lambda)dt)^{-1}E[F(m(t) + dm(t), t + dt)], 0\}, \textit{(3.6)}$$

where λ represents competition intensity. To determine the value of Continue in Eq. (3.6), we need to know how m(t), the expected value of the posterior belief on μ, evolves. From

Eqs. (3.3) and (3.4), dm(t) from m(t) can be expressed as

$$dm(t) = -m(t)s(t)\sigma^{-2}dt + s(t)\sigma^{-2}dX(t) = s(t)\sigma^{-2}(dX(t) - m(t)dt), \quad (3.7)$$

where $dm(t) = m(t)s(t)^{-1}ds(t) + s(t)\sigma^{-2}dX(t)$ and $ds(t) = -s(t)^2\sigma^{-2}dt$. Eq. (3.7) can also be defined as follows when observations are assigned as follows:

$$dm(t) = s(t)\sigma^{-2}\big([\mu - m(t)]dt + \sigma dz(t)\big). \quad (3.8)$$

Eq. (3.8) implies that if there remains something to learn (s(t)>0), the posterior expectation m(t) converges toward the actual value μ.

Again combining the given equations (3.7) and (3.8), we can see that the evolution of posterior expectation represents the Wiener process as follows:

$$dm(t) = s(t)\sigma^{-1}d\tilde{z}(t), \quad (3.9)$$

where $d\tilde{z}(t) = \sigma^{-1}(dX(t) - m(t)dt) = \big([\mu - m(t)]dt + \sigma dz(t)\big)$ represents the increment of the Wiener process.

To solve Eq. (3.6) for the value function, we first divide the value function into a region where stopping is optimal (Commit or Abandon) and a region where continuation is optimal. First, in a region where continuation is optimal, the value function follows the partial differential equation:

$$
\begin{aligned}
F(m,t) &= -Cdt + (1+\rho dt)^{-1} E_t[F(m+dm, t+dt)], \\
(1+\rho dt)F(m,t) &= -Cdt(1+\rho dt) + E_t[F(m+dm, t+dt)], \\
\rho F(m,t)dt &= -Cdt(1+\rho dt)E_t[dF(m,t)], \\
\rho F(m,t) &= -C + \frac{1}{dt} E_t\left[F_m dm + F_t dt + \frac{1}{2} F_{mm} dm^2\right], \qquad , (3.10) \\
0 &= -C - \rho F(m,t) + F_t + \frac{1}{2} F_{mm}\left(\frac{s(t)^2}{\sigma^2}\right), \\
0 &= -C - \rho F(m,t) + F_t + \frac{1}{2} F_{mm} \frac{\sigma^2 s_0^2}{(\sigma^2 + s_0 t)^2}
\end{aligned}
$$

where ρ=r+λ. Eq. (3.10) does not have an analytic solution, so we can use numerical techniques to calculate the value.

Next, in the region where stopping is optimal, the value function takes the following form:

$$F(m(t), t) = max\{0, m(t) - I\}. \ (3.11)$$

Eq. (3.11) is used to determine the "free-boundary" in computing Eq. (3.10). By "free-boundary," the decision maker has two critical posterior expectations at each point of time: $m^*(t)$ and $m_*(t)$. If the posterior expected value m(t) is larger than $m^*(t)$, the company ceases the exploration activity and takes the opportunity. On the other hand, if the posterior expected value m(t) is smaller than $m_*(t)$, the firm abandons the opportunity itself. Lastly, if the posterior expected value m(t) is between the two threshold values, the company continues its exploration.

$$\begin{cases} Commit,\ m(t) \geq m^*(t) \\ Continue,\ m_*(t) < m(t) < m^*(t) \\ Abandon,\ m(t) \leq m_*(t) \end{cases}$$

Figure 14. Optimal strategies for the decision-maker

In this study, we use the finite difference method to calculate the value function of (3.6) using the conditions of (3.10) and (3.11).

3.4 Model implications

In order to determine the value function using the finite difference method, an arbitrary value should be assigned to the parameters in the model as follows. Therefore, this study sets the parameter value corresponding to the benchmark case as follows.

Table 4. List of parameters in the model (benchmark case)

Name	Descriptions	Value
m_0	Initial belief about the opportunity value	10
s_0	Prior uncertainty on initial belief	5
σ^2	Uncertainty about the opportunity value	3
I	Investment cost for the opportunity	10
C	Unit learning (exploration) cost	1
λ	Degree of competition	0.05
r	Discount rate	0.05
T	Maximum time for exploration	5

Under the benchmark case, a company that does not consider exploration through small execution can obtain the following values: $NPV_0 = m_0 - I = 10 - 10 = 0$. However, companies actively involved in learning could increase the value of opportunity in the same situation as $F(m_0, 0) = 1.1670$. Now, let us look at how the value of exploration through small execution changes as the parameters in the model change. First, we attempted to increase the uncertainty about the firm's prior beliefs, compared to the benchmark cases. It is highly possible that the difference between the real μ value and initial estimate m_0 is high. Thus, the value of explorations through small executions is expected to increase. Next, uncertainty on the opportunity (uncertainty on the observation process) increased compared to benchmark case. In contrast to prior belief uncertainty, an increase in uncertainty on opportunity is expected to reduce the accuracy of the learning process, thus reducing the value of exploration through small execution. Figures 15 and 16 illustrate these results. This result can also be proved mathematically. According to Eq. (3.9), a change in posterior

expected value according to learning activity depends on $s(t)\sigma^{-1}$. Whereas $\frac{d}{ds_0}\left(\frac{S(t)}{\sigma}\right) > 0$, $\frac{d}{d\sigma}\left(\frac{s(t)}{\sigma}\right) >, < 0$ (depending on parameters). Therefore, while an increase in prior uncertainty increases the variability of posterior expectations, uncertainty on opportunity may not. As the volatility of posterior expectations grows, firms with more flexible decision-making opportunities can expect greater value, proving that increase in prior uncertainty increases the value of opportunity.

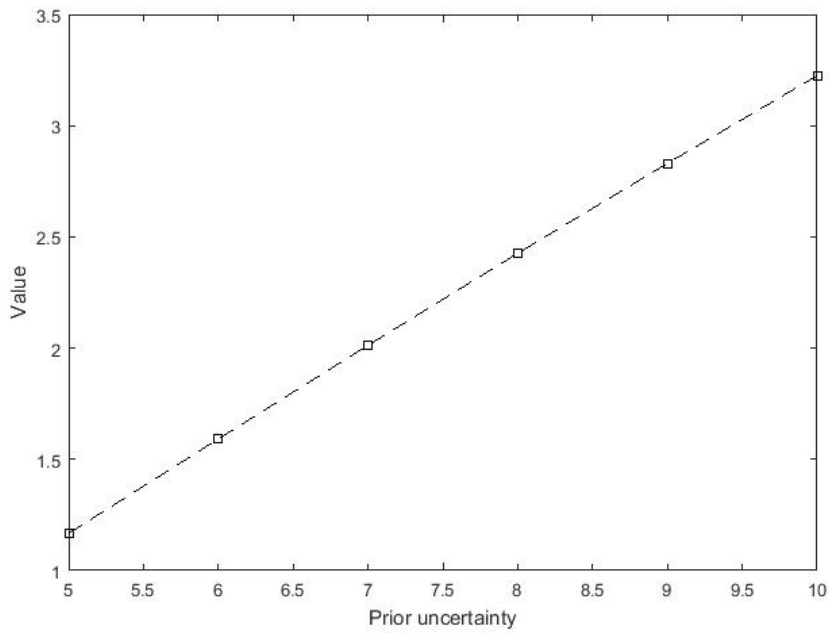

Figure 15. The effect of prior uncertainty on the value

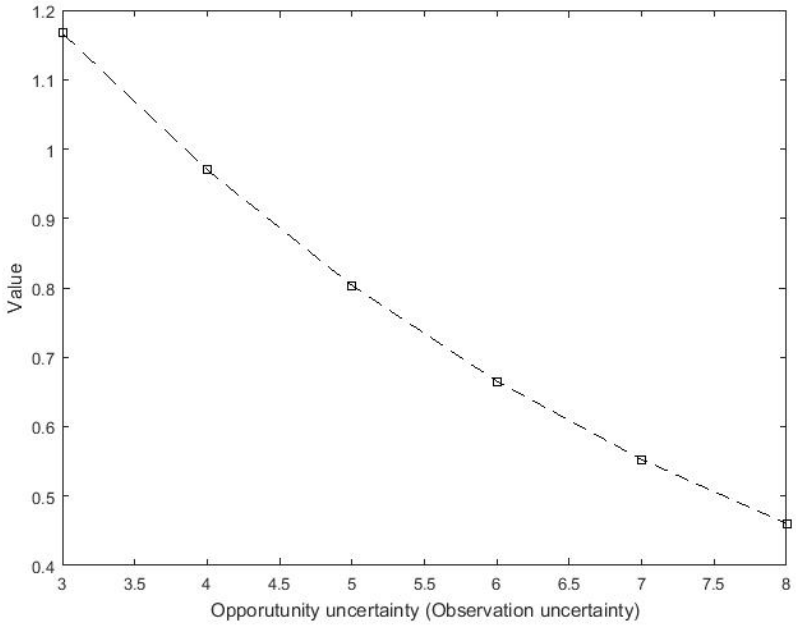

Figure 16. The effect of opportunity uncertainty (observation uncertainty) on the value

The next step is to increase the investment cost to acquire opportunities. Intuitively, an increase in the investment cost of an opportunity will lower the value of the opportunity. However, the search through small execution shows that there is room for investment even if the project is expected to have a negative value when the learning effect is reflected. From Figure 17, while the NPV decreased by -5, the value of the opportunity, reflecting the search through small runs, reduced by only -1. Therefore, it is important to recognize that, even when the present value of opportunities is negative, active learning efforts can greatly change the outcome. An increasing number of companies do not consider NPV when deciding to enter a new market because under opportunity and forecasting uncertainties,

projects that can ultimately make profits cannot be justified through initial NPVs (Sims, 2011).

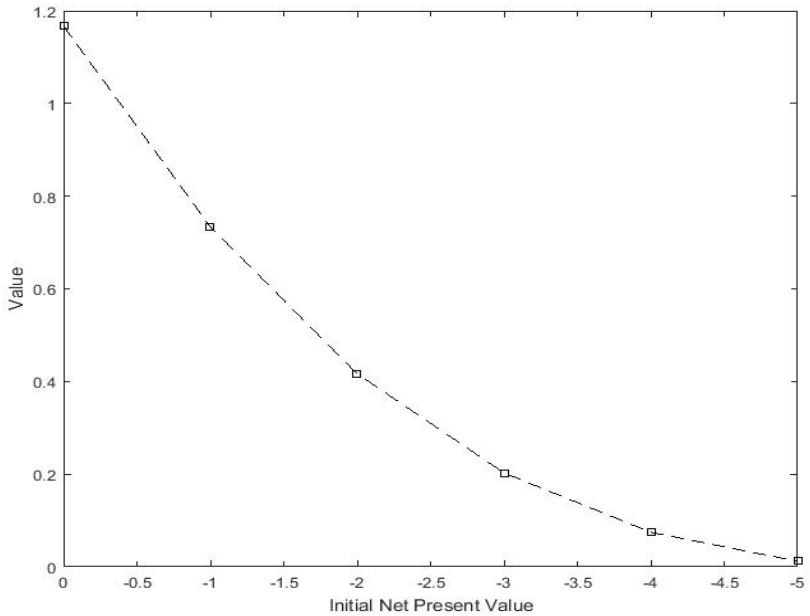

Figure 17. Initial NPV and the value of the opportunity

Next, we examine the effect of increasing learning costs on the value of exploration through small executions. Intuitively, an increase in learning costs seems to lower the value of opportunities. However, the decrease in the value of the actual opportunity is very small compared to the increase in unit learning costs. However, from the analysis of Figure 18, while the unit learning cost increased from 1 to 5, the value of opportunity decreased by only about half. This is because the variance of posterior expectation decreases with time.

Following Eq. (3.8), the larger the variance of posterior expectations, the more the company learns, and the greater the marginal utility of learning. Thus, the learning process for μ is more cost-effective in the early days when the variance of post-expectation is still large. Therefore, even if the learning cost is large, since the learning has already been completed in the early part of the learning process, there is no significant difference in the value of the actual opportunity even if the learning is stopped sooner than where the learning cost is small. This result suggests that a large learning effect can be achieved through a small amount of learning, despite a certain amount of learning cost for the company.

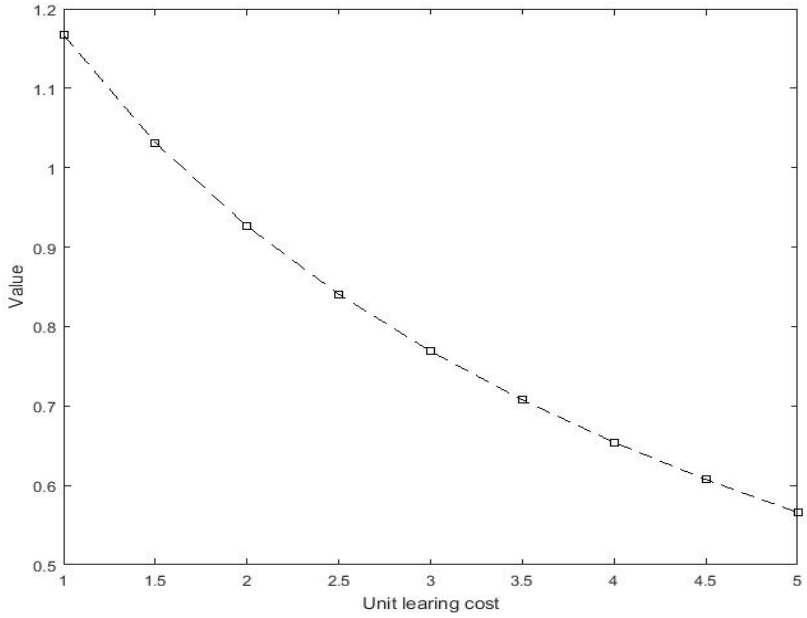

Figure 18. The effect of unit learning cost on the value

This research model is based on the posterior expected value at each point in time,

depending on whether to continue the search, discontinue the search and take the opportunity, or give up the opportunity altogether. In other words, the optimal strategy of the firm can be expressed as the expected value at each point in time. First, under the benchmark case, the “free boundary” that measures the optimal strategy at that time and the prior expectation plane can be expressed as shown in Figure 19.

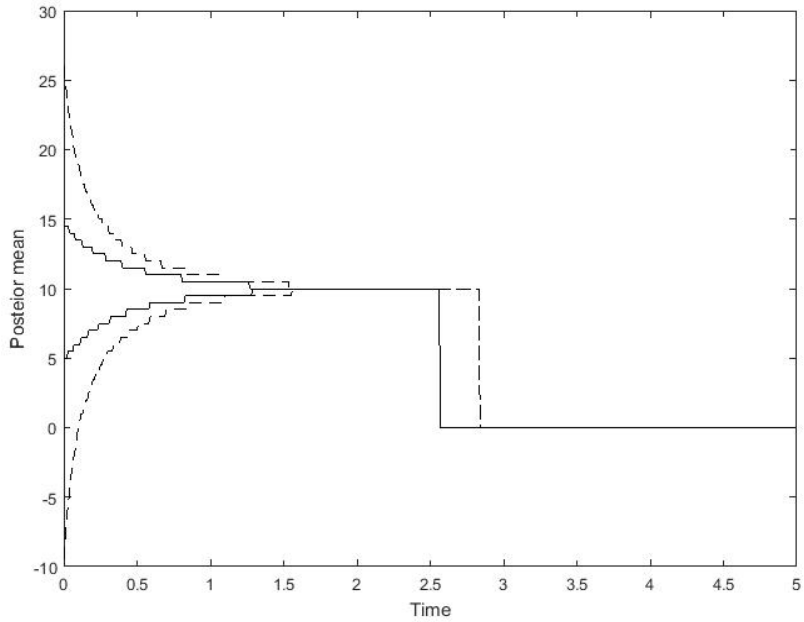

Figure 19. Optimal decision rule for low prior uncertainty and high prior uncertainty (solid line = 5, dashed line = 10)

As described above, the optimal behavior at each time point can be represented by two threshold values: $m^*(t)$ and $m_*(t)$. If at the present time, the posterior expected value

m(t) is larger than $m^*(t)$, the company stops exploration and takes the opportunity. On the contrary, if the posterior expected value m(t) is smaller than $m_*(t)$, the company abandons the exploration activity. Lastly, if the posterior expected value m(t) occurs between the two threshold values, the company continues exploration. The solid line hyperbolically depicts $m^*(t)$, and the dotted line $m_*(t)$, the former under comparatively low and the latter under comparatively high prior uncertainty. At each point of time, the upper part of the hyperbola has Commit, the lower part Abandon, and the middle part Continue as the best action. Increase in prior uncertainty widens the area of Continue that first continues to learn. In both cases, learning is not optimal until the point learning can be maximized, but the validity of learning disappears beforehand. Maximum learning time increases with prior uncertainty. Moreover, the optimal learning area decreases rapidly over time. This indicates that many uncertainties are resolved at the beginning of the learning process. It is also noteworthy that the increase in prior uncertainty increases the area where learning is best in the downward direction of posterior expectation. This indicates that it is important to learn as the value of the present opportunity is more unpromising.

Next, Figure 20 analyzes the impact of uncertainty of opportunity (uncertainty in the observation process) on the optimal behavior of the firm by dividing it into relatively low and high levels. Increased uncertainty of opportunity reduces the efficiency of learning itself. Thus, as the uncertainty of opportunity increases, the optimal learning area decreases naturally. However, it is interesting to note that as the uncertainty of opportunity increases, the time to maximize learning increases significantly. This is also due to the low efficiency

of learning because of the uncertainty of the opportunity itself. This is because more learning time is needed when the uncertainty of opportunity itself is low.

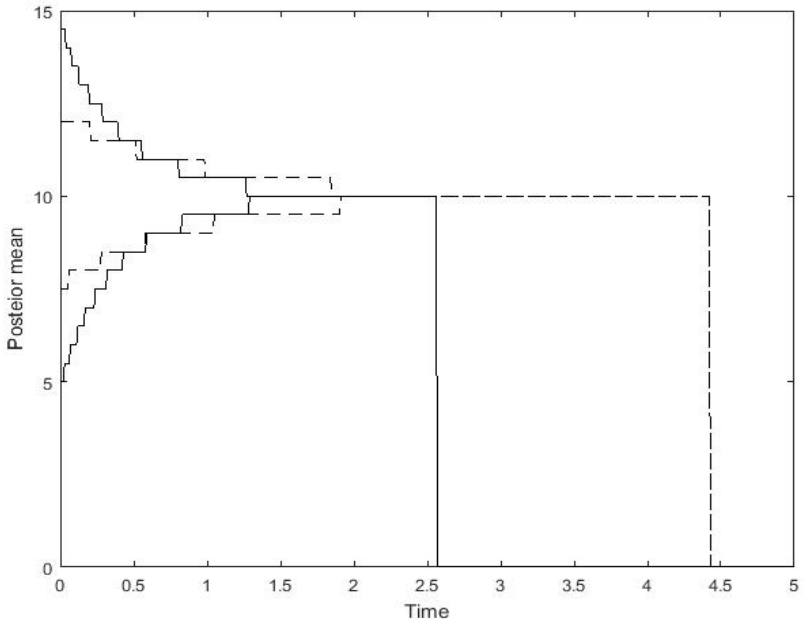

Figure 20. Optimal decision rule for low as well as high opportunity uncertainty (solid line = 3, dashed line = 6)

Next, we try to analyze the effect of increasing learning costs on optimal behavior. The analysis results in Figure 21 are consistent with the intuitive prediction of optimal behavior. The increase in the learning cost decreases the area where continuing to learn is optimal and hastens the point where learning is no longer valid.

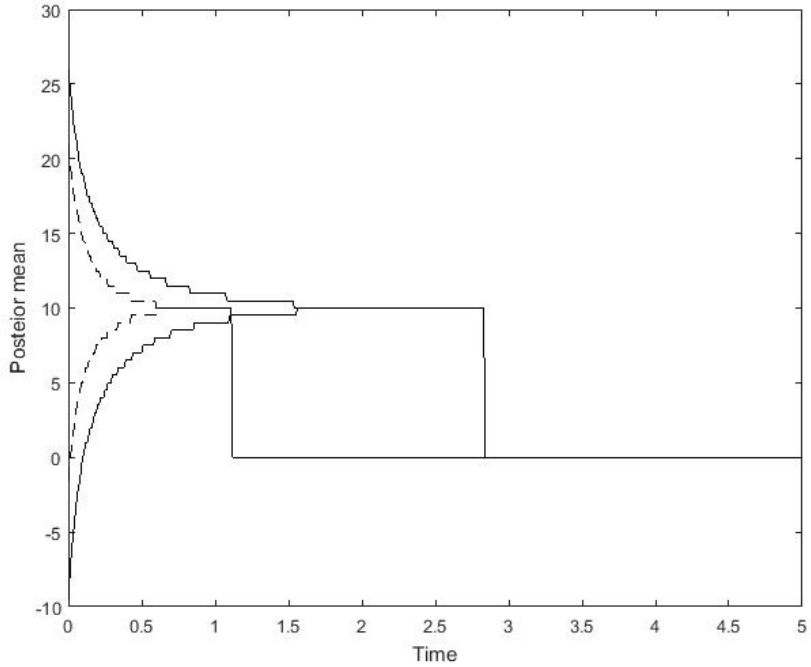

Figure 21. Optimal decision rule for low as well as high learning cost uncertainty (solid line = 1, dashed line = 5)

The rest of the factors (investment cost, intensity of competition) were found to have no effect on the optimal behavior reflecting the learning process, since these factors affect the value of opportunity itself in the assumption of the research model (only shifting the area up and down as much as the impact on value).

3.5 Conclusions and implications

This study analyzed the value of exploration through small execution to the innovation

opportunity of the firm under the framework of the optimal learning model. Learning is necessary because uncertainty of innovation opportunities is endogenous and can be expected to be solved only if the company acts directly (Folta, 1998; Oriani & Sobrero, 2008). The wait and see strategy previously emphasized by real option theory is based on the assumption that uncertainty can be resolved through waiting. However, the uncertainty of an actual innovation opportunity cannot be expected to be resolved without direct action related to the opportunity (Solak, Clarke, Johnson, & Barnes, 2010). Therefore, the wait and see strategy requires conversion to the learning and see strategy.

As economic exploration theory claims, learning is clearly effective but costly (McCall, 1970). Therefore, we should consider optimal learning or optimal stopping, taking into account the benefits and costs of learning. The benefit of learning is basically getting to know the uncertain parameters of the unknown. Costs are determined by the learning cost and the side effects (for example, entry of competitors) associated with the time required for learning. The results of this study suggest some points to be considered in determining optimal learning. First, we must take the uncertainties of the company into account. The higher the prior uncertainty, the more value it gains from learning. This is because learning occurs from the difference between one's belief and the actual value, and the greater the prior uncertainty, the greater the difference between these values. The process of acquiring the information necessary for learning is described as the process of acquiring data on the parameters that determine the value of the opportunity from the action taken in relation to the opportunity. However, the higher the uncertainty of opportunity, the more difficult it is

to extract true values from the data. For example, when innovation opportunities are achieved through a variety of alternatives, it is difficult to predict the true value of innovation opportunities through a single search. Therefore, increasing the uncertainty of opportunity lowers the efficiency, and therefore the benefits, of learning. It also requires more learning time. The greatest implication of this study is that it is foolish to abandon opportunities even if the opportunities do not currently seem promising. Through small executions, the company can learn about the nature of the opportunity as it goes through the exploration process. It is not important that the currently evaluated NPV is negative. This is because the evaluation is done under insufficient evidence. Therefore, learning is more likely to be more optimal if the current opportunity is not promising. Successful innovation is not born with a large vision from the beginning, but is usually born during the development process (Sims, 2011). We should not forget that Google started as a small project for the Stanford Digital Library Project giving priorities to online library search results. A common feature of companies with competitive advantage for a long time is their ability to adapt to the environment (De Geus, 1988). In other words, companies that have the ability to recognize and respond to environmental changes will continue to enjoy a competitive edge. Considering that uncertainty is unavoidable in the business environment, it is essential for the company to have a learning strategy that helps it adapt appropriately by resolving uncertainty to survive and secure competitive advantage.

The limitation of this research model is that it does not consider explicit external costs that may occur in learning. Innovation opportunities are not exclusive to one company, but

can be shared with other companies. Therefore, there is a possibility that other companies preempt the opportunity during learning. In this study, although the possibility of preemption of competitors was reflected exogenously, it is necessary to consider strategic effects by including a large number of contestants for clearer analysis. Future research should consider the possibility of endogenous competition, as previous studies (Keller & Rady, 2010) that considered competition in optimal learning did.

Chapter 4. Trade-off between commitment and flexibility under uncertainty: Focusing on the learning effect

4.1 Introduction

Under imperfect competition and uncertainty, the firm follows an investment strategy of deciding between commitment through an early investment and flexibility through postponement of investment (Krychowski & Quélin, 2010). Many previous studies have defined this as a dilemma of conflict between commitment and flexibility (Ghemawat, 1991). Real option theory (Dixit & Pindyck, 1994), which studies investment under uncertainty, explains that selecting flexibility under high uncertainty is a more optimal strategy for an investor. As the uncertainty of the future return on investment increases, the incentive to postpone investment also increases. This is because a flexible strategy is based on the following asymmetric payoff structure. Even if the value of the current investment is negative, the future value of the investment can be positive due to uncertainty. If the future value of the investment is positive, the company can undertake the investment and make a profit. Conversely, if the future value of the investment is negative, the investor can escape the risk of loss by simply giving up the investment. Thus, the asymmetric value of

a flexible strategy, which can deliver the positive realized value as its own revenue, while at the same time negating the realized negative value, increases with the variability of the future value of the investment opportunity. This is the rationale of real options theory, which suggests that firms select flexibility (over commitment) under uncertainty; therefore, uncertainty decreases investment activities under real options theory.

However, empirical analysis of real option theory shows that uncertainty does not always deter investment. These mixed empirical results are due to the dilemma between the commitment and flexibility mentioned above (Smit & Trigeorgis, 2004). The value of deferring investment while maintaining flexibility under high uncertainty can be offset by the value of commitment that can arise through early entry. The following business example demonstrates that firms may pursue commitment through early investment, despite high uncertainty (Pacheco-De-Almeida et al., 2008). In December 2000, Airbus announced an $11.9B A380 development plan, despite large demand uncertainty in the super jumbo jet market. Boeing, Airbus's competitor, also had plans to develop a new type of jumbo jet by expanding the existing B747 plane, but Boeing's plan was in its earliest stage. Airbus's strategic decision to choose commitment despite high uncertainty, was largely due to the assumption that since the market for the super jumbo jet does not have enough demand to include both firms, Boeing will choose not to compete with Airbus by entering. Therefore, through early investment commitment, Airbus

managed to acquire monopolistic position in the super jumbo jet market, despite abundant uncertainty when the investment decision was made.

As can be seen, commitment can also be a factor that determines the value of investment opportunities. Previous research explains the mechanisms of creating value through early investment as follows. First, commitment through early investment can provide the first-mover (leader) advantage to the firm. The leader (first-mover) advantage enables early-entry firms to exploit the endogenous opportunities in the market ahead of competitors (Lieberman & Montgomery, 1988). Lieberman and Montgomery (1988) argue that the learning effect is the primary mechanism that creates the leader advantage. In their research, learning effect refers to the relative cost advantage acquired through the accumulation of experience in production or management. Moreover, the learning effect also enables firms to acquire the leader advantage through information acquisition. On early entry, the target market is likely to be immature so that the leader firm may acquire strategic information, such as technological and customer characteristics, prior to its competitors (Kerin, Varadarajan, & Peterson, 1992). In terms of organizational learning, too, firms that invest in promising technology early can develop their absorptive capacity, which enables more efficient exploitation of new technology compared to their competitors (Krychowski & Quélin, 2010). In summary, the value of commitment through early investment provides strategic advantage to the leader firm relative to its competitors. The explanation for this phenomenon in real options

theory is that the leading firm possesses the growth option (Folta & O' Brien, 2004). In case the market experiences explosive growth upon the leading firm's early investment, the accumulated learning effect will greatly increase the value of the growth option. This is the stage in which the dilemma arises. This is due to the fact that the possibility of explosive growth in the future market increases according to the level of uncertainty. Hence, the tendency of pursuing flexibility, based on the conventional real option theory, might not always be the case when the market faces high uncertainty. At the same time, this does not imply that firms should always pursue commitment in a highly uncertain market environment. In case early investment has failed to achieve expected growth, the firm must take responsibility over the irreversible investment cost. On the other hand, flexibility could help alleviate risk on the irreversible investment cost for firms.

Such a trade-off between flexibility and commitment in firms' investment under market uncertainty results in dilemmas for decision makers. This study presents theoretical models of the dilemmas that firms' decision makers face and empirically describe how firms tackle such problems. Key findings suggested by the theoretical model in this study are generally the factors that impede investment under uncertainty, but a significant level of the learning effect could rather evolve to turn early investment into optimal conditions, which would expedite investment. The key findings of the empirical study demonstrate that the learning effect in R&D investment, which is expected to be more significant factor than in facility

investment, demonstrate a different response to uncertainty and firms, when classified into high-tech and low-tech industry according to the industry's technological characteristics, demonstrate opposite R&D investment responses under uncertainty.

Next, the study is organized in the following format. Section 4.2 models the decision-making process, based on the theoretical models, for firms to adopt commitment and flexibility when the learning effect is intact under uncertainty. Section 4.3 introduces the data used for the analysis and the analysis model for the empirical study. Section 4.4 derives and interprets the results of empirical studies. Lastly, Section 4.5 sums up the study and presents the implications of the research results for firms' investment strategy.

4.2 Theoretical model

Modeling the decision-making procedure for firms to adopt commitment and flexibility when the learning effect is intact under uncertainty requires consideration of the multi-agent environment, rather than the single-agent environment that is currently considered the mainstream of real option theory. This is the prerequisite for firms to embrace the learning effect accumulated through early investment to serve as the competitive capacity against rival firms. The research model is built upon the model introduced by Kulatilaka and Perotti (1998).

For simplification of analysis, the model is considered as a two-stage duopoly model. The focal firm that is central to the decision-making process is referred to as firm A, and the rival firm as firm B. In stage 1, firm A takes the investment opportunity where the cost is I. Here, I can be interpreted as the entrance cost. In stage 1, the market is not mature enough, so uncertainty on demand is assumed to exist. Thus, if in stage 2, where the market is mature enough, uncertainty on demand disappears, and the realized demand fails to meet the expectation, firm A's early investment in stage 1 becomes the irreversible sunk cost. The learning effect is demonstrated in various measures, but this study plans to derive the learning effect, in line with previous studies, as the reduction in production cost (Dixit, 1980). Thus, firm A, which has made early investment has a cost advantage over firm B in stage 2 under competition. Firm A also has an option to compete against the competitor firm B under the same cost conditions, by avoiding early investment to wait for the uncertainty to be resolved in stage 2.

When reaching stage 2, the market opens up, and the competition between firms A and B becomes severe. This study aims to model the firms' competition using the Cournot competition model, in which companies compete on the amount of output they produce. First, we define the reverse demand function of the market as follows: $P(Q, \theta)= \theta-Q$, where the value of θ is unknown to both firms in stage 1. The production cost of firm A in stage 1 is k or K (>k), depending on the early investment decision, while firm B's production cost is assumed to be K at all times.

We will now consider firm A's early investment decision-making process. Firm A decides whether to invest early by comparing the expected values with and without early investment. First, the expected value of early investment is set as V^{Invest}. The Cournot competition between the two companies in stage 2 is then expressed as follows with backward induction, which is regularly used to solve multi-stage games. Since firm A is assumed to have early investment, the competition between the two firms leads to an asymmetrical Cournot equilibrium:

$$q_A^{Invest} = \frac{\theta - 2k + K}{3},\ q_B^{Invest} = \frac{\theta - 2K + k}{3}. \ (4.1)$$

$$\pi_A^{Invest} = \frac{1}{9}(\theta + K - 2k)^2,\ \pi_B^{Invest} = \frac{1}{9}(\theta - 2K + k)^2 - I. \ (4.2)$$

Eq. (4.1) shows both firms' optimal production level, and Eq. (4.2) represents both firms optimal profit when they choose the optimal level of production. Due to the assumption that k < K, firm A achieves a higher optimal production level than firm B, since firm A has a lower marginal production cost. In Eq. (4.2), 'I' represent firm B's entry cost at the optimal profit level. Due to the existence of entry costs, firm B does not always engage in the market. Unless the actual demand θ is higher than a certain level, i.e., $\theta \geq \theta_B^* = \sqrt{9I} + 2K - k$, firm B has no incentive to enter the market. If the actual demand is $\theta \leq \theta_B^*$, firm A will enjoy a monopoly position in the market. Firm A's optimal production level and optimal profit in this case is as follows:

$$q_M^{Invest} = \frac{1}{2}(\theta - k),$$

$$\pi_M^{Invest} = \frac{1}{4}(\theta - k)^2. \textit{ (4.3)}$$

As can be seen from Eq. (4.3), firm A does not always engage in production activity. Firm A only produces when the actual demand is $\theta \geq \theta_M^* = k$. Therefore, depending on the actual demand in the market, firm A has following profit function.

$$\pi_A^{Invest} = \begin{cases} 0, \theta < \theta_M^* = k \\ \frac{1}{4}(\theta - k)^2, \theta_M^* < \theta < \theta_B^* = \sqrt{9I} + 2K - k \\ \frac{1}{9}(\theta + K - 2k)^2, \theta \geq \theta_B^* \end{cases}. \textit{ (4.4)}$$

Based on Eq. (4.4), firm A's expected value in case it commits to early investment in stage 1 can be derived as follows:

$$V^{Invest} = E_1[\pi_A^I] - I$$
$$= E_1\left[\frac{1}{9}(\theta + K - 2k)^2 | \theta \geq \theta_B^*\right] Pr[\theta \geq \theta_B^*] + E_1\left[\frac{1}{4}(\theta - k)^2 | \theta_M^* < \theta < \theta_B^*\right] Pr[\theta_M^* < \theta < \theta_B^*] - I$$
$$. \textit{ (4.5)}$$

Next, firm A's expected value in case it has not committed to early investment is represented by $V^{NoInvest}$, which can also be derived through backward induction. If firm A did not commit to early investment in stage 1, the marginal cost of production in stage 2 is

equal for both firms A and B. Thus, following symmetric Cournot equilibrium is achieved:

$$q_A^{Noinvest} = q_B^{Noinvest} = \frac{1}{3}(\theta - K). \ (4.6)$$

$$\pi_A^{Noinvest} = \pi_B^{Noinvest} = \frac{1}{9}(\theta - K)^2 - I. \ (4.7)$$

Due to the entry cost I, both firms only decide to produce when the actual demand is large enough to accommodate both of them. Considering this factor, firm A's optimal profit can be represented as follows:

$$\pi_A^{Noinvest} = \begin{cases} 0, \theta < \theta_A^{**} = \sqrt{9I} + K \\ \frac{1}{9}(\theta - K)^2 - I, \theta \geq \theta_A^{**} \end{cases}. \ (4.8)$$

From Eq. (4.8), the value of $V^{NoInvest}$, the expected value to firm A when it has not committed to early investment can be derived as follows:

$$V^{Noinvest} = E_1\left[\pi_A^{Noinvest}\right]$$
$$= E_1\left[\frac{1}{9}(\theta - K)^2 - I | \theta \geq \theta_A^{**} = \sqrt{9I} + K\right] Pr\left[\theta \geq \theta_A^{**} = \sqrt{9I} + K\right]. \ (4.9)$$

Now, by comparing the values derived from equation (4.5) and (4.9), the firm can decide whether to commit to early investment or to choose flexibility through delaying investment. This decision-making process, under real options theory, can be interpreted as

follows. The trade-off relationship between commitment and flexibility leads to the decision between the growth option and the delay option. The value of the growth option is based on the learning effect acquired through early entry, which allows the early entry competitive advantage over its rivals when uncertainty is unveiled. The value of the delay option occurs when the firm maintains flexibility in its decision making under uncertainty. The growth option yields value only if investment is made, while the delay option does so only if investment is postponed. Therefore, these two options have a trade-off relationship (Folta & O' Brien, 2004). In other words, it is difficult to have both options at the same time. In order to calculate the value of the growth and delay options, we define the following value function. $V^{Invest(No\ learning)}$ is defined as the expected value to firm A, in case the learning effect has not occurred despite early investment. Subtracting the value of early investment with no learning effect from the value of early investment with a learning effect gives the value of the growth option: $\left(V^{Invest} - V^{Invest(No\ learning)}\right)$. Furthermore, subtracting the value of investment with no learning effect from the value of non-early investment gives the value of the delay option: $\left(V^{Noinvest} - V^{Invest(No\ learning)}\right)$. The trade-off relationship between the growth and delay options represent following strategic decision between commitment and flexibility:

$$V^{Invest} - V^{Noinvest} = \left(V^{Invest} - V^{Invest(No\ learning)}\right) - \left(V^{Noinvest} - V^{Invest(No\ learning)}\right) = V_{S.G.} - V_{D}. \quad (4.10)$$

Therefore, the firm will choose commitment if the value from equation (4.10) is larger than 0 and flexibility if the value is less than 0. All of the derived value functions are expected value functions from the probability demand θ. Therefore, the threshold level, which induces early investment, can be represented as the expected value from the probability demand. First, we make the following algebraic normal distribution assumption about the probability demand as follows:

$$ln\left(\frac{\theta}{\theta_1}\right) \sim N\left(-\frac{1}{2}\sigma^2, \sigma^2\right) \; s.t. \; E_1(\theta) = \theta_1. \; (4.11)$$

Lastly, the value of k is set as 0 in this study. Thus, K can be regarded as a parameter that represents the magnitude of the learning effect.

Now, we try to derive the implications of the theoretical model through numerical analysis. Figure 22 depicts the value of commitment and flexibility depending on the changes in the expected values of the stochastic demand. Our numerical analysis shows that the value of flexibility is larger than that of commitment when the expected value of the probability demand is low. Conversely, the value of the commitment is larger than that of flexibility when the value of expected value of probability is high. Since the low expected value of the probability demand implies a large risk of loss for early entry, it is better to remain flexible. On the contrary, if the expected value of the probability demand is large, which implies large market growth potential, the firm should acquire the

advantages of the learning effect through commitment. The threshold level of the expected value of the probability demand, which induces early investment, is the intersection between the values of commitment and flexibility.

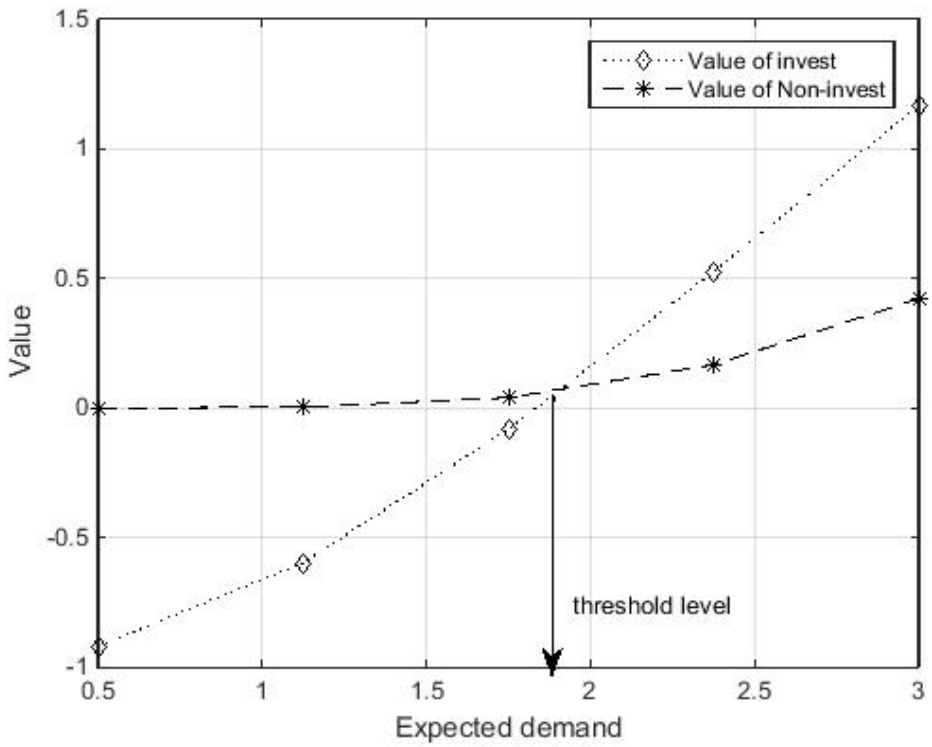

Figure 22. Value of commitment and flexiblity in terms of E[θ]

Figure 23 shows the influence of the size of learning effect on the threshold level of the expected value of probability demand that induces early investment. Based on our assumptions, the magnitude of learning effect is determined by the value of K, which is the difference between marginal cost under early investment and marginal cost under non-

investment. Our analysis shows that the threshold point of the expected value of probability demand decreases as the size of learning effect increases. Future competitive advantage increases as the magnitude of learning effect increases, allowing investors to take the risk of failure for early entry, although the expected value of probability demand is low. Furthermore, we confirmed that the commitment value increases, but the flexibility value decreases, with a large learning effect. This result is in accordance with the research finding that preemptive strategies, such as commitment, are preferred in the presence of the learning effect (Kauffman & Kumar, 2008; Xiaotong, 2009).

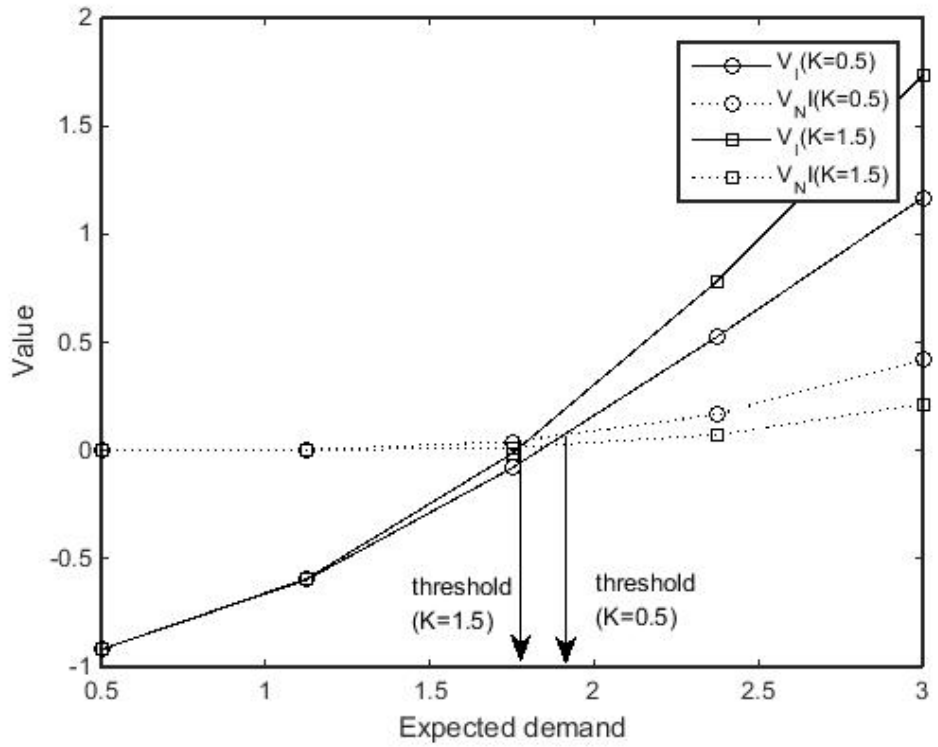

Figure 23. The effect of learning effect on the threshold level of E[θ]

Now, the influence of learning effect on the trade-off relationship between commitment and flexibility will be discussed. Figures 24 and 25 show the impact of uncertainty on the threshold level of the expected value of probability demand. A low learning effect is assumed in Figure 20, where with the threshold level of the expected value of probability demand increases with uncertainty. Therefore, if the learning effect is not large enough, uncertainty has a favorable impact on flexibility. Figure 21 shows a setting in which the learning effect is high where, in contrast to the previous case, the threshold level of the expected value of probability demand decreases as uncertainty increases. Thus, with a large learning effect, uncertainty has a favorable impact on the firm's commitment.

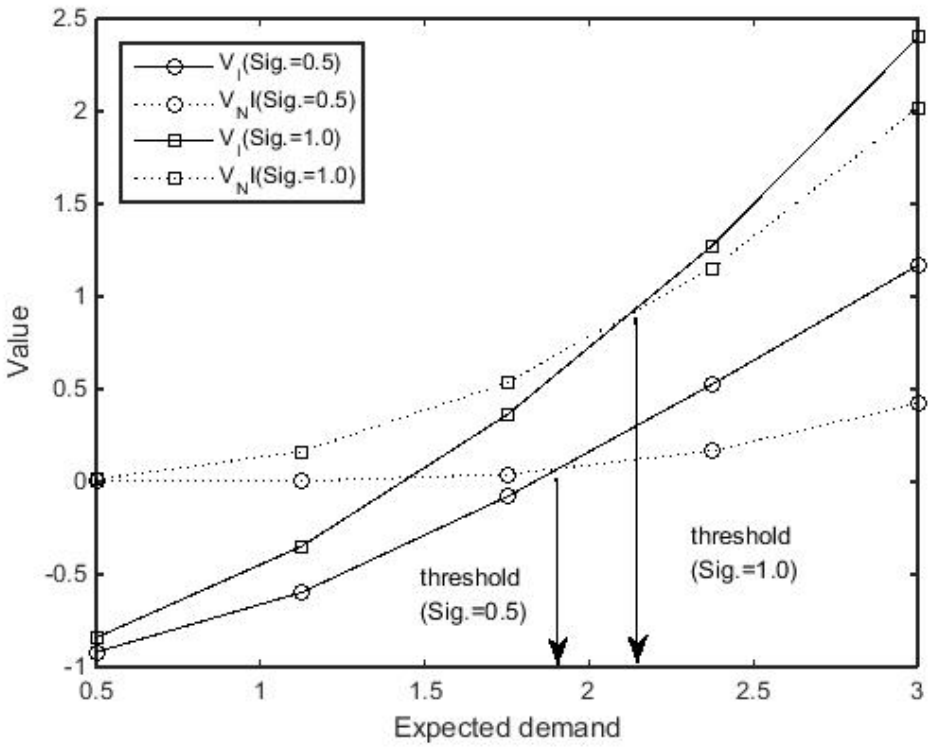

Figure 24. The effect of uncertainty on the threshold level for inducing early investment under a low learning effect (K = 0.5)

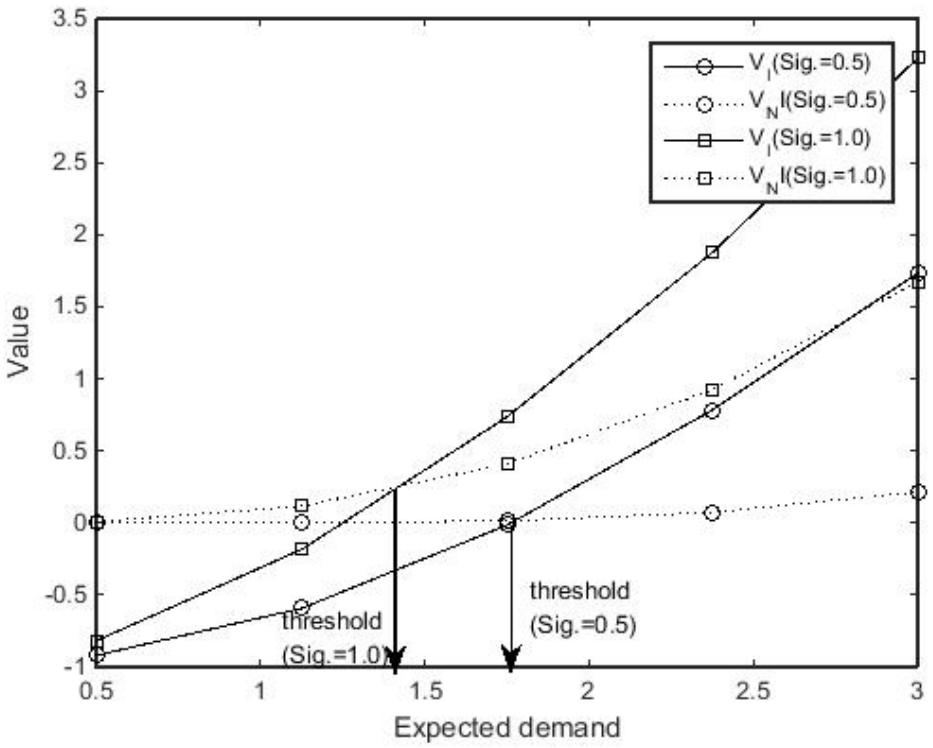

Figure 25. The effect of uncertainty on the threshold level for inducing early investment under a high learning effect (K = 1.5)

To sum up the results of the theoretical model, the primary factor that determines the relative values of commitment and flexibility is the size of the learning effect. If the learning effect is large enough, uncertainty no longer deters investment but, rather, acts as a catalyst for investment. The above results will be verified through empirical analysis in Section 4.3. An overview of the empirical analysis is as follows. First, assuming that the learning effect from early investment differs for every investment opportunity, we will consider two different investment environments: R&D investment and capacity investment.

In R&D investment, the learning effect of early investment is important because the purpose of R&D investment is to develop products and services that do not exist in the market (Cooper, Edgett, & Kleinschmidt, 1997). In particular, uncertainty in R&D investment can usually be revealed only through direct investment or initiation of an R&D project (Pindyck, 1993), which provides an incentive for firms to act preemptively. Conversely, capacity investment, which is related to existing products and services, is less influenced by the learning effect. Furthermore, the industrial technological system is also related to the importance of the learning effect. In high-tech industry, the speed of innovation is fast, and discontinuous innovation occurs regularly, in comparison to low-tech industry. Therefore, the importance of learning effect is magnified and many trial-n-errors are generated (Chiesa & Frattini, 2011). Thus, the size of the learning effect would differ between R&D investment and capacity investment as well as between high-tech and low-tech industry. This implies that, depending on the investment type and the size of uncertainty, uncertainty may either deter or act as a catalyst for investment. Moreover, since the threshold point (which is subject to an opposite effect from investment uncertainty) is also influenced by the size of the learning effect, the influence of uncertainty on the threshold point will also vary depending on the investment type. Therefore, this study sets two hypotheses.

Hypothesis 1. The influence of uncertainty on R&D investment has a threshold effect (negative impact below threshold and positive impact above threshold), while the influence of uncertainty on capacity investment has no threshold effect but only a negative impact.

Hypothesis 2. R&D investment in high-tech industry, compared with R&D investment in low-tech industry, has a threshold effect at a lower uncertainty level.

4.3 Empirical analysis

4.3.1 Data

This study uses the "KIS Value" database of NICE Investors Service for empirical analysis. KIS Value provides information on the financial statements of Korean companies. To acquire reliable data on firms' financial statements, I limit the level of analysis to firms in the manufacturing sector, which are subject to external audit. The analysis period is from 2002 to 2014, and data were extracted from 1997 to generate several variables, which will be explained later. The estimation method used in this study, "fixed-effect threshold regression (Hansen, 1999)," requires balanced panel data. To this end, only firms that were continuously subject to external audit during the sample period were included in the sample. Accordingly, we obtained 36,790 observations for a total of 2,830 companies over 13 years. The 2,830 companies comprised 1,563 companies in high-tech industries and 1,267 companies in low-tech industries. About 55.2% of companies belong to high-tech

industries and 44.8% to low-tech industries. This study uses two dependent variables: intensity of R&D investment and intensity of capital investment. First, data on R&D investment are needed to calculate the R&D investment intensity of each company. Among the various methods of measuring a company's R&D investment in a year, based on financial data, the method adopted by OECD was used in this study. This approach includes both expenditure directly related to the creation, production, and use of the asset, and indirect expenditure that is reasonably and consistently allocated, on the basis of accrual, to the acquisition cost of development costs, which are intangible assets for R&D activities. Specifically, the total R&D expenditure of a company is calculated as the total sum of ending development cost minus the beginning development cost in the balance sheet, the depreciation on the development cost for the period reported in the income sheet, and the current development cost reported in manufacturing cost sheet (Park & Jo, 2007). For normalization of the R&D investment intensity variable to the firm size, the total R&D expenditure is divided by the value of the tangible assets of the year as follows:

$$R\&D\ Intesnity_{it} = \frac{R\&D_{it}}{Tangible\ asset_{it}},\ \textit{where i represents a firm and t does time.}$$

The second dependent variable, capital investment intensity, is based on the company's capital investment, calculated from the financial statements. This study define the value which deducts the cash inflow from the disposal of facility-related assets from the cash outflow from the purchase of facility-related assets based on the cash flow financial

statement as capital investment of a firm (Lim, 2008). Likewise, the capital investment of a company is divided by the value of a firm's tangible assets of the year to normalize it to firm size.

$CAPEX\ Intensity_{it} = \frac{CAPEX_{it}}{Tangible\ asset_{it}}$, *where i represents the firm and t stands for time.*

Next, I explain how uncertainty, which is a key explanatory variable, is defined in this study. This study attempted to derive uncertainty at the firm level by using financial statements of each company. This study assumes that the standard deviation of the total return on assets over the past five years is the uncertainty of the investment opportunity faced by each firm.

$$Vol_{it} = SD(g\_\mathrm{ROA}_{it}.\, g\_\mathrm{ROA}_{it-1}, g\_\mathrm{ROA}_{it-2}, g\_\mathrm{ROA}_{it-3}, g\_\mathrm{ROA}_{it-4}),$$

$$where\ g\_ROA_{it} = \frac{\mathrm{ROA}_{it} - \mathrm{ROA}_{it-1}}{\mathrm{ROA}_{it-1}} \times 100.$$

In order to clearly observe the effects of uncertainty on investment, this study attempted to control other factors that affect the investment decisions of a company as follows. First, we considered the change in sales, which is a key explanatory variable of the acceleration model widely used in explaining corporate investment. According to Abel and Blanchard (1986), I considered the change in sales, including the lagged variable of sales to tangible

assets. Next, the size of the company was considered. The larger the company, the more likely it is to be motivated by risky investments and to withstand long-term investment returns (Audretsch & Elston, 2002). Therefore, the size of the firm needs to be controlled for as it can affect the relationship between uncertainty and investment. In this study, firm size is defined as the logarithm of the value of total assets. The debt ratio is also a variable to be considered in making investment decisions. This is because efforts to improve a company's financial structure affect investment (Cleary, 1999). In this study, the debt ratio is defined as the ratio of total assets to total liabilities. Next, the liquidity ratio was considered. The higher the liquidity ratio, the more would be the company's ability to withstand long-term investment returns (Cleary, 1999). The liquidity ratio is defined as the ratio of liquid assets to liquid liabilities. I also consider financial constraints because the use of external financing, which is more expensive than internal financing, can have an impact on investment (Bond & Meghir, 1994). In this study, we define financial constraints as the ratio of operating cash flow to the value of total assets. Finally, by controlling the time lag dummy variable, we control for the impact that may occur in a certain period. Table 5 shows all the variables and definitions used in the study.

Table 5. The descriptions of variables in the econometric model

Dependent Variables	Name	Descriptions
	R&D Intensity	$R\&D_{intensity} = \frac{R\&D_{it}}{Sales_{it}}$
	Capex Intensity	$CAPEX_{\text{intensity}} = \frac{INV_{it}}{Sales_{it}}$
Independent Variables	**Name**	**Descriptions**
	Uncertainty	$SD(g\_\text{ROA}_{it}.\, g\_\text{ROA}_{it-1}, g\_\text{ROA}_{it-2}, g\_\text{ROA}_{it-3}, g\_\text{ROA}_{it-4})$, $where\ g\_ROA_{it} = \frac{\text{ROA}_{it}-\text{ROA}_{it-1}}{\text{ROA}_{it-1}} \times 100$ and SD stands for standard deviation.
	Change of Sales	$\left(\frac{\text{Sales}}{\text{Tangible asset}}\right)_{\text{i,t~t-3}}$
	Firm size	$Size_{it} = \log(Asset\_Total_{it})$
	Debt ratio	$Debt\_ratio_{it} = \frac{Debt\_Total_{it}}{Net\_Asset_{it}} \times 100$
	Currency ratio	$\frac{Asset\_current_{it}}{Debt\_current_{it}} \times 100$
	Financial constraint	$\frac{O.P.\_CF_{it}}{Asset\_Total_{it}}$

The descriptive statistics of the variables defined in Table 5 are shown in Table 6 (all industries), Table 7 (high-tech industries), and Table 8 (low-tech industries). The average

value of R&D investment intensity of the entire industry sample is higher than that of capital investment, which is caused by the extremely high intensity of R&D investment in high-tech industries. In low-tech industries, however, capital investment intensity is higher than R&D investment intensity. In addition, the average uncertainty level in high-tech industries was found to be higher than the uncertainty level in low-tech industries.

Table 6. Descriptive statistics for the entire sample

Variable	Unit of measurement	Number of observations	Mean	Std. Dev.	Min	Max
R&D_Intensity$_{it}$	Ratio	36,790	0.0923	0.6281	-0.0122	62.7087
CAPEX_Intensity$_{it}$	Ratio	36,790	0.0872	0.4993	-5.3055	72.0000
(Sales/ Tangible asset)$_{t}$	Ratio	36,790	66605.2300	4089162.0000	0.0311	324000000.0000
(Sales/ Tangible asset)$_{t-1}$	Ratio	36,790	61846.4100	3992232.0000	0.2343	324000000.0000
(Sales/ Tangible asset)$_{t-2}$	Ratio	36,790	52940.5500	3618050.0000	0.2343	316000000.0000
(Sales/ Tangible asset)$_{t-3}$	Ratio	36,790	45057.9000	3287024.0000	0.1443	316000000.0000
Debt_Equity_ratio$_{t-1}$	Ratio	36,790	267.9401	11169.6700	-79086.7500	2033208.0000
Curreny_ratio$_{t-1}$	Ratio	36,790	199.2168	529.8125	-173.7959	33558.6000
Size$_{t-1}$	Numeric value	36,790	24.4868	1.2591	17.6071	32.6733
Financial_constrain$_{t-1}$	Ratio	36,790	0.0735	0.3306	-42.6661	10.1347
Uncertainty$_{t-1}$	%/100	36,790	0.5082	8.5152	0.0062	756.6854

Table 7. Descriptive statistics for the high-tech sample

Variable	Unit of measurement	Number of observations	Mean	Std. Dev.	Min	Max
R&D_Intensity$_{it}$	Ratio	20,319	0.1378	0.7498	-0.0122	62.7087
CAPEX_Intensity$_{it}$	Ratio	20,319	0.0951	0.3998	-5.3055	34.3514
(Sales/Tangible asset)$_{t}$	Ratio	20,319	980.3866	31296.5900	0.6814	3523080.0000
(Sales/ Tangible asset)$_{t-1}$	Ratio	20,319	799.0920	19191.0100	0.4792	2703312.0000
(Sales/ Tangible asset)$_{t-2}$	Ratio	20,319	661.5974	2820.5040	0.4792	140310.9000
(Sales/ Tangible asset)$_{t-3}$	Ratio	20,319	659.5767	2503.0440	0.1443	134077.1000
Debt_Equity_ratio$_{t-1}$	Ratio	20,319	307.8593	14851.2000	-65141.0700	2033208.0000
Curreny_ratio$_{t-1}$	Ratio	20,319	209.9066	494.3316	-173.7959	33173.4600
Size$_{t-1}$	Numeric value	20,319	24.5125	1.2739	17.8210	32.6733
Financial_constrain$_{t-1}$	Ratio	20,319	0.0840	0.2130	-7.0063	10.1347
Uncertainty$_{t-1}$	%/100	20,319	0.5896	9.1192	0.0108	756.6854

Table 8. Descriptive statistics for the low-tech sample

Variable	Unit of measurement	Number of observations	Mean	Std. Dev.	Min	Max
$R\&D\_Intensity_{it}$	Ratio	16,471	0.0362	0.4263	0.0000	27.6584
$CAPEX\_Intensity_{it}$	Ratio	16,471	0.0775	0.5996	-3.2396	72.0000
$(Sales/\ Tangible\ asset)_{t}$	Ratio	16,471	147561.5000	6110412.0000	0.0311	324000000.0000
$(Sales/\ Tangible\ asset)_{t-1}$	Ratio	16,471	137155.8000	5965716.0000	0.2343	324000000.0000
$(Sales/\ Tangible\ asset)_{t-2}$	Ratio	16,471	117433.0000	5406681.0000	0.2343	316000000.0000
$(Sales/\ Tangible\ asset)_{t-3}$	Ratio	16,471	99828.6900	4912087.0000	0.1840	316000000.0000
$Debt\_Equity\_ratio_{t-1}$	Ratio	16,471	218.6947	2566.3740	-79086.7500	158483.1000
$Curreny\_ratio_{t-1}$	Ratio	16,471	186.0295	570.2900	-2.1379	33558.6000
$Size_{t-1}$	Numeric value	16,471	24.4550	1.2400	17.6071	31.6245
$Financial\_constrain_{t-1}$	Ratio	16,471	0.0606	0.4335	-42.6661	4.6778
$Uncertainty_{t-1}$	%/100	16,471	0.4077	7.7043	0.0062	558.8311

4.3.2 Empirical model

This study aims to examine whether the independent variable of uncertainty ultimately has a threshold effect on the dependent variable of investment and, if it does, how the effect changes with the threshold value. Therefore, the threshold effect regression model of Hansen (1999), an analytical model that can confirm the critical effect, is used to analyze the existence of the threshold effect. First, the following model is established for regression analysis:

$$y_{it} = \alpha_i + \boldsymbol{x}_{it}'\boldsymbol{\beta} + q_1\sigma_{it}I(\sigma_{it} \leq \gamma) + q_2\sigma_{it}I(\sigma_{it} > \gamma) + \varepsilon_{it}, \text{ (4.12)}$$

where y_{it} is the dependent variable, α_i is the individual effect, x_{it} is the control variable, σ_{it} is the uncertainty, γ is the threshold level at which the effect of uncertainty on investment changes, and ε_{it} is an independent and identically distributed random variable.

Hansen (1999) derives the threshold level of uncertainty as follows. First, the entire observations are sorted according to the value of uncertainty, which is the variable to find the threshold value. Next, we estimate Eq. (4.12) setting γ in turn to each of the uncertainty values in the data, using the ordinary least squares (OLS) technique. Thus, depending on the level of uncertainty, we can derive a sum of squared residuals. The uncertainty level with the smallest value based on the sum of squared residuals is the estimate of γ we want to estimate.

From the estimation results of Eq. (4.12), the following results are identified. First, we can confirm whether the uncertainty, which is an explanatory variable, really has a threshold effect on the dependent variable (investment intensity). If it does, the threshold value of the variable is derived. We can also confirm the difference in the effect of uncertainty on investment based on the threshold value by comparing the estimated coefficient values q_1 and q_2.

4.4 Results

As can be seen in Table 9, the empirical analysis in this study consists of four different models. Results from models (1) and (2) were estimated using equation (4.12) with two different explanatory variables, R&D investment intensity and infrastructure investment intensity, respectively. Results from models (3) and (4) were estimated using equation (4.12), and the sample was divided into high-tech and low-tech industry groups. Results from models (1) and (2) provide answers to hypothesis 1. Estimation results from model (1) confirm the existence of an uncertainty threshold for R&D investment. The threshold occurs at the uncertainty level of approximately 32%. Further, if uncertainty is below the threshold, it hinders investment. On the other hand, if uncertainty is above the threshold, it promotes investment. Estimation results from model (2) also confirm the existence of an uncertainty threshold for infrastructure investment. However, the uncertainty threshold level is 49% for infrastructure investment, which is relatively higher than that of R&D

investment. The uncertainty threshold had a statistically insignificant impact on infrastructure investment when the level of uncertainty was higher than 49%. Estimation results from models (1) and (2) partially confirm hypothesis 1, introduced in chapter 2. The existence of an uncertainty threshold was confirmed for both R&D and infrastructure investments. The different uncertainty thresholds for the two types of investment imply that the importance and magnitude of the learning effect are larger for R&D investment. Thus, it can be inferred that uncertainty, at a relatively low level, may act as a catalyst for investment. In other words, uncertainty favors commitment over flexibility in this case. As discussed in chapter 2, uncertainty has a more favorable impact on commitment than flexibility if the learning effect is high. Thus, it can be inferred that when there exists a threshold point for both kinds of investment, the learning effect is larger for R&D investment than for capacity investment since the threshold point for R&D investment is lower. Moreover, in order for uncertainty to have a favorable impact on commitment, a certain level of uncertainty is required, despite the existence of the learning effect. In other words, a large learning effect does not have a positive influence on commitment if the market potential (or uncertainty) is limited.

Estimation results from models (3) and (4) can be used to verify hypothesis 2. The importance of the learning effect for R&D investment may differ, depending on the industrial and technological characteristics. Our estimation results show that the investment threshold for high-tech industries occurs at an uncertainty level of approximately 48%. Uncertainty deters investment if it is below the threshold point within an industry, but

promotes investment if it is above the threshold point. Thus, the level of uncertainty determines whether it is favorable for commitment or flexibility in high-tech industries. For low-tech industries, however, the investment threshold point was not observed, and it is confirmed that uncertainty always deters investment. Therefore, hypothesis 2 is confirmed; that is, the importance and magnitude of the learning effect on R&D investment is much larger for high-tech industry than for low-tech industry, since the rate of technological change is much faster and innovation often occurs incrementally in high-tech industries.

Table 9. Estimation results

	(1)		(2)		(3)		(4)	
	Coefficients	**T-value**	**Coefficients**	**T-value**	**Coefficients**	**T-value**	**Coefficients**	**T-value**
$Uncertainty_{t-1}(\sigma<\gamma)$	**-1.44E-01*****	-4.06	**-0.1053*****	-3.79	**-0.1510*****	-4.72	**-0.0874****	-2.85
$Uncertainty_{t-1}(\sigma>\gamma)$	**1.20E-03*****	3.30	0.0004	1.30	**0.0018*****	4.7	-0.0002	-0.5
p-value	**0.0750***		**0.0650***		**0.0050****		0.6850	
γ(95% interval)	0.3249(0.3145 ~ 0.3894)		0.4881(0.4470 ~ 0.4946)		0.4786(0.4624 ~ 0.4829)		0.5016(0.4015 ~ 0.5099)	
$(Sales/Asset\_fixed)_t$	6.21E-10	0.26	-1.04E-09	-0.46	**-2.68E-07***	-1.66	-2.62E-10	-0.17
$(Sales/Asset\_fixed)_{t-1}$	5.11E-09	1.34	1.46E-09	0.40	**2.37E-05*****	87.16	2.07E-10	0.09
$(Sales/Asset\_fixed)_{t-2}$	-5.70E-09	-1.25	-5.06E-10	-0.12	**2.17E-05*****	10.13	6.09E-11	0.02
$(Sales/Asset\_fixed)_{t-3}$	4.59E-10	0.15	-2.07E-10	-0.07	**-1.94E-05*****	-8.34	-1.06E-10	-0.05
$Debt\_Equity\_ratio_{t-1}$	-4.95E-09	-0.02	3.70E-09	0.02	5.56E-09	0.03	-5.89E-07	-0.57
$Curreny\_ratio_{t-1}$	**4.15E-06*****	-12.46	9.74E-06	1.62	1.66E-06	0.2	5.96E-06	1.12
$Size_{t-1}$	**-9.17E-02*****	-12.46	**-0.0922*****	-13.25	**-0.1215*****	-14.45	**-0.0244*****	-3.33
$Financial\_constrain_{t-1}$	-1.02E-02	-1.16	**-0.0177****	-2.13	**-0.0798*****	-4.63	0.0029	0.47
Constant	**2.32E+00*****	13.08	**2.3751*****	14.19	**3.0805*****	15.22***	**0.6368*****	3.61
Time dummies	Omitted		Omitted		Omitted		Omitted	
Number of observations	36,790		36,790		20,319		16,741	

Significance level: *p = 0.1, **p = 0.05, ***p = 0.01

The estimation results and theories introduced in this study can help solve the dilemma between commitment and flexibility. In case the investment opportunity has high uncertainty and a high learning effect, the decision maker should not wait but commit immediately to make an early entry. Otherwise, the decision maker should choose flexibility over commitment.

Table 10. Optimal strategy matrix for commitment and flexibility

	Low learning effect	High learning effect
Low uncertainty	Flexibility	Flexibility
High uncertainty	Flexibility	**Commitment**

4.5 Conclusion and implications

This study attempted to solve the dilemma between commitment and flexibility in the context of investment decision making. Consider the learning effect is crucial to an examination of this matter because the learning effect has different influences on commitment and flexibility. Uncertainty has a positive influence on both commitment and flexibility, whereas the learning effect has a positive impact on commitment but a negative

impact on flexibility. Therefore, an investigation of the learning effect would lead to an in-depth analysis of the two contrasting strategies. Uncertainty affects commitment through a mechanism by which the value of the strategic effect of learning increases with a significant increase in the demand within the market. Therefore, when the learning effect is small, the value of the strategic advantage from a significant market growth will be smaller than the risk of high sunk cost when the market fails. However, when the learning effect is large, the risk of high sunk cost can be offset by the possibility of exponential future market growth, in which the possibility is measured by the level of uncertainty. Thus, in order for decision makers to choose commitment over flexibility, high uncertainty must co-exist with a high learning effect within the investment opportunity. If this condition is not satisfied, the ideal investment strategy will be flexibility, as suggested in many previous real option studies.

A few important implications can be drawn from our analysis, especially for firms' decision makers, who face high economic uncertainties in an era of rapid technological changes. Managers generally are risk aversive and, thus, try to avoid the risk of failures. In other words, they tend to choose flexibility when making investment decisions. However, the importance and magnitude of the learning effect increases with a high rate of technological development (Archibugi, Howells, & Michie, 1999). According to our estimation and analysis, managers in high-tech firms need to initiate a plan or invest immediately through commitment when windows of opportunities emerge in an era of high economic uncertainty and rapid technological development. This implication is applicable

not only at the firm level but also at the national level. Nations seeking new growth engines should aid firms' commitment activities to exploit the advantages of uncertainty.

Chapter 5. Concluding remarks

5.1 Summary

This study consists of three essays for exploring the value of learning in strategic investment decision making. The first essay analyzes the discovery-driven planning that continuously revises the initial assumptions generated from existing knowledge and experience through learning and experience-driven planning based on solely existing knowledge and experience that firms can consider to enter into new markets. The second essay builds a model of optimal learning strategies through exploration to help companies make decisions with uncertain innovation opportunities. Finally, the third essay analyzed the trade-off between commitment and flexibility, a dilemma for executives in investing under uncertainty, through the lens of learning effect. The results of each essay can be summarized as follows.

The first essay compares two approaches for new market entry under uncertainty: experience-driven planning which blindly assume the existing knowledge and experience of a firm and discovery-driven planning which continuously updates the initial assumptions through information obtained by early entry into the market, without accepting existing knowledge and experience. The former is associated with the "wait and see" of the existing real option theory, and the latter is linked with "learning and see". Experience-driven

planning is modeled as determining the optimal time of entry based on prior knowledge and experience. The discovery-driven planning invests a portion of the total opportunity at the present time, then modifies the initial assumption based on the information gained in the market, and finds the optimal time to acquire the remaining portion of the opportunity based on the modified assumption. However, in order to carry out the discovery-driven planning, additional learning costs arise because the market is not yet sufficiently developed but the information is acquired from the market through early entry. The effects of maturity and relevance, which are the characteristics of the market in which the firm is seeking to enter, and the level of the core competence, which is a characteristic of the firm, on the relative value of these two defined approaches are analyzed. The value of discovery-driven planning is maximized when the market to enter is highly irrelevant, mature market, and the core competency of a firm is low. On the contrary, experience-driven planning is advantageous when the market to be entered is an emerging market, highly relevant, and a firm has a high level of core competence.

The second essay expanded the discussion of the first essay and developed a model with sequential learning and flexibility in decision making about the innovation opportunities that the company has. As companies pay for learning and acquire information about a given opportunity, they can update the expectations of the opportunity from the outcome of the learning. Thus, the company has three options at each point in time: to stop learning activities and acquire opportunities, to continue learning activities, and to stop meaningless learning activities and give up opportunities. Under these assumptions, I assume that the

value of a given opportunity is the Bellman equation with the expected value of the opportunity which is continuously updated by learning activities and time. Then, using dynamic programming, I analyzed how the firm's optimal behavior and the value of the opportunity accordingly change. As a result of the analysis, the increase of the prior uncertainty about the opportunity the firm has increases the value of the opportunity, while the uncertainty of the opportunity itself reduces the value of the opportunity. This result occurs because the coefficient that determines the variation of the posterior expectation over time is not an increasing function with respect to the uncertainty of the opportunity, but an increasing function with respect to the prior uncertainty of the value of the opportunity. Also, even when the present value of a given opportunity is considerably negative, it has been confirmed that there is room to increase the value of an opportunity through the optimal learning strategy. In addition, the decrease in the value of opportunities relative to the increase in unit learning costs was relatively small. In addition, the increase in the prior uncertainty of the value of an opportunity has been shown to further increase the downward (posterior expectation) areas where continuing learning is the optimal behavior.

The third essay attempted to analyze the implications of learning effects on strategic investment decisions under uncertainty of the firm. Under uncertainty, companies fall into a dilemma of a trade-off between commitment and flexibility in strategic investment decisions. The reason is that the increase in uncertainty positively affects both commitment and flexibility. However, as can be seen in the first and second essays, the learning effect

is created only through commitment that represents the immediate action of a company. Therefore, the increase in learning effect affects positively for commitment and negatively for flexibility. Thus, the effect of uncertainty on commitment and flexibility will vary with the magnitude of the learning effect. Through theoretical model, I found following results. If there is a learning effect over a certain scale, the increase of uncertainty is more favorable to commitment. However, if there is a learning effect below a certain level, the increase in uncertainty is more favorable to flexibility. In addition, in order to confirm the argument of the theoretical model empirically, it was noted that the magnitude of the learning effect varies according to the type of investment and the environment in which the investment takes place. The type of investment is considered in the comparison between R&D investment and capital investment, and the investment environment considers the comparison between high-tech and low-tech industries in R & D investment. In each case, the analysis of existing literature shows that the former investment is associated with more learning effects. As a result of the analysis, it was found that a threshold effect of uncertainty in R&D investment (negative impact below threshold and positive impact above threshold), and only R&D investment in high-tech industry had a same threshold effect of uncertainty.

5.2 Managerial implications

Uncertainty has been the main reason for the plagued decision-makers in strategic

decision making that has long been an ongoing competitive advantage for the firm (Vecchiato, 2012). Technological and market uncertainties and intensified competition from globalization are making matters worse. Many companies take a compliant attitude under the guise of instinctively making decision - making flexibility under fluoridation. Thus, major decisions in the enterprise tend to be deferred often. This attitude has a vague expectation that uncertainty will be solved simply by waiting. However, in fact, strategic decisions are influenced by a variety of uncertainty sources (Vassolo, Anand, & Folta, 2004). The flexibility of decision making through simple waiting is meaningless in situations where endogenous uncertainty prevails. There is no change in the information about the opportunity given to the corporation. If you are in a position that is not yet in a leading position and imitates other companies, then there is room for acquiring information from simply waiting. This is because there is a possibility to observe and learn the trial and error of leading companies.

However, companies that want to move to the position of leading companies or leading companies are in a position where they cannot be imitated at the forefront of the innovation environment. These companies need to be actively engaged in direct action rather than maintaining flexibility under uncertainty. Through step-by-step decision-making in order to incorporate sequential learning and the resulting endogenous uncertainty into the decision-making process in the future, companies will have the opportunity to create innovative results. From this point of view, it is important to recognize that the flexibility of decision-making occurs through learning rather than through existing simple waiting. In

other words, it is now necessary to switch to "Learning and See" rather than to "Wait and See".

Indeed, a helpful introduction to the "learning and see" attitude within companies is the active introduction of post-audit systems. In the general capital budgeting process, follow-up audits are a process used to identify, develop and evaluate opportunities, select and approve, and assess projects after the end of implementation (Giovanni & Paolo, 2001). The introduction of aggressive post-audit refers to the introduction of post-audit throughout the life cycle of the investment process. By establishing a Bayesian learning system that can reevaluate the entire decision-making process to be taken at a later stage, leaving the passive level of simply entering the next step after monitoring the project at each stage, Is expected to be able to take advantage of the "Learning and See" approach.

5.3 Limitations and future research directions

This dissertation analyzes how the learning-effect impacts the value and optimal investment rule of an opportunity associated endogenous uncertainty in real options framework. Another literature which studies the similar issue is industrial organization theory. Especially, the theory of industrial organization considers the investment problem considering strategic interactions of the multi-agents by using a tool called game theory. Although Chapter 4 of this dissertation considers multiparty competition, these considerations are underestimated in Chapter 2 and Chapter 3. Particularly in considering

the relationship between learning activities and investment, multilateral strategic interactions should be considered as in industrial organizational theory because knowledge that is a by-product of learning activities is non-rivalry (Nelson, 1959). If a firm cannot internalize the knowledge gained from learning activities, it cannot appropriate the benefits of learning activities. Therefore, the externality created by learning activities are likely to sub-optimize the efforts of the company's learning activities to the optimal level of society. (Mowery, Nelson, & Martin, 2010). In future research, it will be necessary to try to consider externalities of learning activities by using the methodology of industrial organization theory.

One of the most important tasks in modeling beige learning is the modeling of a firm’s prior beliefs. This is because the Bayesian learning process cannot be applied without assuming a prior belief. If the object of uncertainty has a continuous value, the conjugate prior distribution is modeled because of the mathematical tractability problem as traditionally. If a data generating process is assumed, it is possible to know the likelihood function naturally and assume a conjugate prior distribution proportional to the likelihood function, so that the posterior distribution follows the same distribution group as the conjugate prior distribution the decision-maker assume. However, if the data generation process has a special case that does not have a conjugate prior distribution, there is a tail behavior in the generation process, or a combination distribution for a large number of random variables (Herath & Kumar, 2015), we have to find another alternative. Therefore, it will be necessary to model the firm's prior beliefs using statistical techniques such as

"Copula methods" (Herath & Kumar, 2007) that are easy to model non-linear relationships in the future.

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Abstract (Korean)

본 학위논문은 베이지인 학습 기법을 통합한 실물옵션 모형이 적용된 세 개의 에세이를 통해서, 불확실성 하의 전략적 투자 의사결정에 있어 학습이 가지는 함의를 연구하고 있다. 기존의 실물옵션 이론은 주로 기다림을 통해서 불확실성이 해소되는 수동적인 학습을 가정하고 있다. 그러나, 실제 비즈니스 환경에서는 기다림을 통해서 주어진 투자 기회와 연관된 정보를 획득하는 것이 어렵다. 그러므로, 본 학위논문은 직접적인 정보 획득 활동을 통해서만 그 불확실성이 해소되는 내생적 불확실성을 주요 불확실성으로 간주하는 능동적인 학습을 강조하고 있다. 이런 접근은 기존의 실물옵션 이론에서 의사결정의 유연성을 설명하는 메커니즘을 '기다리며 지켜보기(wait and see)' 에서 '학습하며 지켜보기(learning and see)' 으로 전환을 유도한다.

첫 번째 에세이는 불확실성 하에서 신시장에 진입하는 두 가지 접근법인 '경험에 의한 계획(experience-driven planning)' 과 '발견에 의한 계획(discovery-driven planning' 을 비교하고 있다. 전자는 기존 실물옵션 이론의 기다리며 지켜보기와 연관되어 있고, 후자는 학습하며 지켜보기와 연관되어 있다. 경험에 의한 계획은 사전에 가진 지식과 경험에 기반한 가정으로 최적의 진입시점을 결정하는 것으로 모형화 하였다. 발견에 의한 계획의 가치는 현재 시점에서 전체 기회의 일정 부분을 투자한 후, 시장에서 획득한 정보를 기반으로 초기 가정을 수정해 나가면서, 수정된 가정에 기반하여 기회의 남은 부분을 획득하

는 최적의 시점을 결정하는 것으로써 모형화 하였다. 다만, 발견에 의한 계획을 수행 하기 위해서는 아직 시장이 충분히 성장하지 않았음에도 불구하고 조기 진입을 통해 시장에서 정보를 획득하여만 하므로, 추가적인 학습비용이 발생한다. 기업이 진입하고자 하는 시장의 특성인 시장의 성숙도와 관련성, 그리고 진입 기업의 특성인 기업이 가진 핵심 역량의 수준은 두 접근법의 상대적인 가치에 영향을 미친다. 발견에 의한 계획은 진입하고자 하는 시장이 매우 비관련성이 높으나 성숙되어 있고, 그리고 기업의 보유한 핵심 역량이 낮을 때 그 가치가 극대화 된다. 반대로, 경험에 의한 계획은 진입 시장이 매우 관련성이 높고 새로운 시장이며, 그리고 기업이 가진 핵심 역량의 수준이 높을 때 그 가치가 극대화 됨을 확인하였다.

두 번째 에세이는, 첫 번째 에세이의 논의를 확장하여 기업이 가진 혁신기회에 대하여 순차적인 학습과 그에 따른 의사결정의 유연성을 가진 모형을 개발하였다. 학습비용을 지불하고 주어진 기회의 대한 정보를 획득해 나가면서, 기업은 학습의 결과로부터 기회가 가진 사후 기대치를 업데이트해 나갈 수 있다. 이에 따라 기업은 매 시점과 다음과 같이 세 가지 선택지를 가진다: 학습활동을 중단하고 기회를 획득, 학습활동을 지속, 무의미한 학습활동을 중단하고 기회 자체를 포기. 이런 기업의 의사결정을 업데이트 되는 사후 기대치와 시간을 상태변수로 하는 벨만 방정식 (Bellman equation)을 가정한 후, 동적 계획법을 통해 기업의 최적행동전략과 그로 인한 기회의 가치가 어떻게 변화하는지를 도출하였다. 분석 결과, 기업이 기회에 대하여 가진 사전적 불확실성의 증가는 기회의 가치를 증가시키고, 반대로 기회 자체의 불확실성은 기회의 가

치를 감소시켰다. 이런 결과는, 사후 기대치의 시간에 따른 변동을 결정하는 계수가, 사전적 불확실성에 대해서는 증가함수이나, 기회의 불확실성에 대해서는 증가함수가 아니기 때문에 발생한다. 또한 주어진 기회의 현재 가치가 상당히 음일 때에도, 최적학습전략을 통해서 그 가치를 양으로 전화할 여지가 큼이 확인되었다. 그리고, 상대적으로 단위학습비용 증가 대비 기회의 가치가 감소하는 폭이 상대적으로 작은 것으로 드러났다. 추가적으로, 사전적 불확실성의 증가는 학습을 지속하는 것이 최적의 행동이 되는 영역을 하방 (사후 기대치의)으로 더 많이 증가시키는 것으로 드러났다.

세 번째 에세이는, 학습효과가 기업의 불확실성 하의 전략적 투자 의사결정에 주는 함의를 분석하고자 하였다. 불확실성 하에서 기업은 전략적 투자 의사결정에 있어 헌신 (Commitment) 과 유연성 (Flexibility) 간의 상충관계의 딜레마에 빠진다. 그 이유는, 불확실성의 증가는 헌신과 유연성 양쪽에 모두 긍정적으로 작용하기 때문이다. 그러나, 첫 번째 에세이와 두 번째 에세이에서 알 수 있듯이, 학습효과는 기업의 즉각적인 행동을 나타내는 헌신을 통해서만 창출된다. 그러므로, 학습효과의 증가는 헌신에는 긍정적, 유연성에는 부정적으로 영향을 미친다. 따라서, 학습효과의 크기에 조건부로 불확실성이 헌신 과 유연성에 미치는 효과가 달라질 것이다. 이를 이론 모형을 통해서, 일정 규모 이상의 학습효과가 발현이 되면 불확실성의 증가는 오히려 헌신에 더 호의적이며, 발현된 학습효과의 크기가 작을 경우 불확실성의 증가는 유연성에 더 호의적임을 도출하였다. 추가적으로, 이론 모형의 논의를 실증적으로 확인하기 위해 투자의 유형별, 투자가 이뤄지는 환경 별로 학습효과의 크기가 달라짐에

주목하였다. 투자의 유형은 R&D 투자와 설비 투자의 비교를 고려하였고, 투자의 환경은 R&D 투자에 있어 하이테크 (High-tech) 산업과 로우테크 (Low-tech) 산업의 비교를 고려하였다. 각각의 경우 모두 전자의 투자가 더 많은 학습효과와 연관된 것임을 기존 문헌의 분석을 통해 알 수 있다. 분석결과, R&D 투자에 있어서 불확실성의 임계 효과 (임계 수준 이하의 불확실성에서는 불확실성이 투자를 저해, 임계 수준 이상에서는 불확실성이 불확실성이 투자를 촉진)가 발견되었으며, 하이테크 산업에서의 R&D 투자만 역시 동일한 임계 효과가 관측되었다.

전반적으로, 본 연구가 주고자 하는 함의는 불확실성 하에서 앞으로 기업이 취해야 할 전략적 투자 자세는, 기존의 기다림을 통해서 확보되는 의사결정의 유연성의 자세에서 끊임없는 학습을 통해서 창출되는 의사결정의 유연성의 확보로의 전환이 필요하다는 사실이다. 이를 위해 기업은 투자 의사결정의 전 단계에 걸쳐 있어 적극적인 사후감사 (post-audit) 시스템의 도입의 중요성을 강조한다. 또한 본 연구는 학술적으로 기존의 실물옵션이론들이 고려가 부족했던 내생적 불확실성을, 베이지안 학습을 통합함으로써 반영했다는 의의가 있다. 추후 연구에서는 좀 더 발전된 베이지안 학습 기법을 반영함으로써 좀 더 실질적으로 기업의 의사결정을 돕는 모형의 개발이 필요할 것이다.

주요어: 실물옵션, 베이지안 학습, 내생적 불확실성, 신시장 진입, 최적 학습, 헌신과 유연성의 상충관계

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