Determinants of Technological Breadth in the U.S. Semiconductor Industry: Performance Feedback, Recency of Technological Inputs, and Technology Maturity*

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Technology not only has been acknowledged as an important factor in driving economic growth but also for individual organizations, technology serves as a powerful tool for attaining competitive advantage. This study investigates the influence of performance feedback as motivation on an organization's technological breadth, and also examines the moderating effects of recency of technological inputs and technology maturity on the relationship between performance feedback and technological breadth. These moderators are tested because they are expected to have close association with new learning opportunity and risk propensity of organizations. The key findings show that poor performance motivates organizations to pursue increase in technological breadth when performance is under the aspiration level. Increase in technological breadth usually accompanies higher risk because R&D is likely to produce superior result when it is concentrated and this is in agreement with the risk-seeking tendency of poor performers. For moderating effects, the findings are rather mixed for recency of technological inputs depending on relative position compared to aspirations. The results show that the negative relationship between technological breadth and past performance becomes stronger for firms with more recent technological inputs from others only when the performance is above the aspiration. This is because such organizations will likely perceive that not much new learning opportunity is remaining since they have up-to-dated technology assets and their motivation for technological change is negatively affected by the recency of technological inputs. The opposite effect is found when the performance is below the aspiration, probably because some firms are desperate to implement greater technological changes for survival. Nonetheless, the results are consistent for moderating effects of technology maturity in which success-strategic persistence tendency is stronger for firms with immature technology. It implies that the key interest of participants with immature technology will be to achieve certain level of technology improvement and to increase adoptions rather than meeting the short-term financial performance, unless the performance is so bad that they consider their attempts as failures. This study contributes to previous work by applying the effect of performance feedback on changes in technological breadth and also integrating the learning tendency and risk propensity of organizations with performance feedback theory.

Key words: technological breadth, performance feedback, recency of technological inputs, technology maturity, semiconductor industry

최초투고일: 2013. 6. 17　수정일: (1차: 2013. 10. 9)　게재확정일: 2013. 12. 20
* 이 논문은 2011년도 정부재원(교육과학기술부 사회과학연구지원사업비)으로 한국연구재단의 지원을 받아 연구되었습니다 (KRF- 2011-330-B00076).

Ⅰ. Introduction

Technological change has gathered interests among scholars and managers in disciplines such as strategic management, organization theory, and marketing. The main research topic involves insights about how technology affects the competitive dynamics of markets or how successful implementation of technology strategy may be attained. However, drivers or antecedents of technological change at an individual organization level have been addressed limitedly. Related studies confirm that firms increase R&D search intensity when performance relative to aspiration level decreases (Chen & Miller, 2007; Greve, 2003).

For each organization, technological change may be considered as a specific type of strategic change. In evolutionary perspectives, high tendency of local search is a central assumption (March & Simon, 1958; Nelson & Winter, 1982) and organizations are constrained in their ability to adapt to frequent strategic changes, which together provide justifications on the general tendency for strategy to be preserved rather than radically changed (Hannan & Freeman, 1989). Such strategic persistence is reinforced by past success because the resultant success makes firms to believe that their current strategies are proven to be appropriate (Boeker, 1997; Lant, Milliken, & Batra, 1992; Miller & Chen, 1994). On the contrary, poor performance is one of the clearest indicators of inappropriate operation and signals that strategic changes may be necessary (Boeker & Goodstein, 1991). The association between failure and strategic change may be comparable to the risk seeking behavior of under-performing organizations. According to the behavioral theory of the firm, decision makers assess organizational performance by comparing it with an aspiration and decide whether to make changes or not (Cyert & March, 1963). Organizations are not motivated to change when their performance meets or exceeds their aspiration levels (Cyert & March, 1963; Greve, 1998). Thus, failure or poor performance provides strong incentive for strategic changes, and it is also easier to overcome the pressure for stability coming from internal and external shareholders when performance is poor (Hannan & Freeman, 1984).

With theoretical notions of motivation, this study investigates causes of technological change, and newly integrates firms' knowledge inputs and technology maturity to examine how they influence the motivation factor in technological change. That is, this study approaches technological management as a strategic process and attempts to provide a framework which integrates drivers of technological change with crucial moderators such as recency of technological inputs and technology maturity of an organization. While technological change may involve multifaceted actions, this study addresses how the organization makes a decision on technological breadth. We expect lower prior performance to drive organizations to increase technological breadth. With respect to recency of technology inputs and technology maturity, this study expects them to have significant moderating effects because these tendencies are closely linked with new learning opportunities and risk preferences of focal firms.

This study investigates empirically the technological change of the U.S. semiconductor firms during 1987-2000. Sample firms are selected from Standard and Poor's Compustat North America database having 4-digit SIC code 3674. A total of 288 firms are found but only 217 of those firms participate in patenting activity which enables analyses of firms' technological changes. The semiconductor industry is known for its high propensity of patenting inventions so that limitations or bias in using patent data are minimized (Podolny, Stuart, & Hannan, 1996; Wilson, Ashton, & Egan, 1980) in this research setting.

This study attempts to advance prior studies by deepening the understanding of increase in technological breadth, motivated by poor performance. Furthermore, the study is aimed at providing theoretical contributions to the organizational change by applying the technology diffusion theory which contends that differences in learning tendency and technology maturity are closely related with risk propensity and technology opportunity (Karshenas & Stoneman, 1995; Lissoni & Metcalfe, 1994; Rogers, 1983).

Ⅱ. Theory and Hypotheses

2.1 Performance feedback on technological breadth

Although the effects of technological change on industries and economics have been studied with great interests, less considered and less understood are the influence of performance feedback on an organization's technological change. The research model of this study builds upon the previous research that motivation affects organizational changes (Chen & Miller, 1994; Hannan & Freeman, 1984; Miller & Chen, 1994; Milliken & Lant, 1991; Schelling, 1971; Tushman & Romanelli, 1985). Organizations will pursue changes when there are incentives or motivations to change. Prior studies suggest poor performance as the major source of motivations arising inside the organization because that makes decision makers to question the adequacy of their current methods and motivates them to search for improvements (Milliken & Lant, 1991; Starbuck & Milliken, 1988). Prior researches on performance feedback as a motivator for technological change have covered R&D intensity (Greve, 2003) and adoption of technological routines (Massini, Lewin, & Greve, 2005). That is, prior studies have found that organizations tend to increase R&D search or the rate of adopting R&D-related routines when they are further behind an aspiration level.

The notion of threshold or reference point is fundamentally same as what the behavioral theory of the firm refers to goals and aspirations of organizations. An aspiration level is used by "boundedly rational" decision makers to determine the boundary between success and failure in continuous measures of performance (March & Simon, 1958). The behavioral theory of the firm expects similar association such that organizations are not motivated to change when their performance meets or exceeds their aspiration levels (Greve, 1998; Lant & Montgomery, 1987). Decision makers assess organizational performance by comparing it with social and historical aspirations, and the gap between their own performance and the aspiration level influences their behavior toward risk taking (Cyert & March, 1963). When performance is below the aspiration level, organizations tend to take more risks and become risk averse when performance is above the aspiration level (Baum *et al.*, 2005; Cyert & March, 1963; Greve, 2003; Greve, 1998; Kahneman & Tversky, 1979).

This study focuses on technological change among various kinds of strategic changes. Classical studies of technology emphasize demand conditions for driving technological change (Scherer, 1982; Schmookler, 1966) but the problem is, it is very hard or sometimes impossible to accurately assess demands ex-ante and be motivated by them. Since demand is closely followed by economic factors, it would be legitimate to claim that organizations respond to ex-post performance of current technological strategy and make change decisions accordingly. This performance feedback mechanism will stimulate decision makers to be motivated by low performance, seeking changes and risks. Furthermore, the resultant technological change may take many different forms because strategy involving technology has multiple dimensions. In this study, we will examine how widely a firm is technologically diversified. Technological diversity, i.e., the breadth of technology portfolio produced by the firm's R&D activities reflects a firm's strategy regarding technological concentration during a given period of time. When a firm concentrates on narrow scope of technologies or pursues R&D in small number of technological categories, its technological breadth must be limited and product strategy will likely be simple.

Although technological diversification may be valuable to all firms (Miller, 2006; Teece, 1980), it is also arguable that pursuing multiple technological categories induces additional burdens and risks in terms of information process requirement and project budget constraints. Similar concept of "diversification discount" has been found in several financial economic studies (Berger & Ofek, 1995; Lins & Servaes, 1999; Rajan, Servaes, & Zingales, 2000) and the firm's decision on technological breadth in behavioral approach with regard to risk takings, should not be overlooked. Regarding the direction of diversification motivated by poor performance, it will be hypothesized that breadth will increase rather than decrease because organizations will want to search more alternatives if their previous technological direction has turned out to be ineffective. That is, as performance worsens, search activity intensifies and covers more broad range. In a similar vein, prior study posits that inventors with past success are less likely to enter new technological categories (Audia & Goncalo, 2007). Success-induced search is inclined to fall into a competency trap so that firms are eager to follow past routines and pursue areas where they are more familiar with. Increase in technological breadth will accompany higher risk because R&D will produce superior result when it is concentrated, which is in agreement with the risk-seeking tendency of poor performers.

Hypothesis 1: Technological breadth increases as firms' past performance decreases below aspirations.

When an organization is motivated for changes, it will assess the current knowledge base and technological environment to find out the likelihood of potential opportunities and successful transformation. Organizational tendencies in learning from others and technology adoption reflect responsiveness and risk propensity of an organization and may significantly moderate the rate of change by interacting with motivation.

2.2 Recency of technological inputs

Firms tend to learn from others and imitate them in the pursuit of legitimacy and this tendency will be salient when environmental uncertainty is high (DiMaggio & Powell, 1983; Haunschild & Miner, 1997). It can be claimed that such environmental condition may be the consequences of highly uncertain technology development activities in the industry. As a result, learning processes must be present at the population and community levels most prominently in the form of vicarious learning (Levitt & March, 1988; Miner & Haunschild, 1995). Among various attributes of learning from others, responsive learning or up-to-dated learning means that an organization learns promptly from others by referencing their most recent technological ideas or inventions in producing its own inventions. Since inventions differ in terms of the age of knowledge base they build upon, it is possible to assess the difference in technological inputs for organizations from their patenting activities. Interests surrounding the recency of technological inputs have been investigated in prior research, mainly to find out its impact on financial performance or new product development (Heeley & Jacobson, 2008; Katila, 2002). For instance, Heeley and Jacobson (2008) find that firms whose new patents utilize median-aged technological inputs tend to experience the highest returns and Katila (2002) argues that old intraindustry knowledge input hurts new product development while the opposite is true for old extraindustry knowledge inputs. However, the impact of the age of knowledge base or technological inputs on the rate of technological change or risk taking has not been considered before. When the age of knowledge base is young because an organization has been prompt in learning from others' new inventions, it also indicates that the organization has been up-to-date with the technological trend and has attempted to seize very recent technological opportunities in the industry. Then how will this recency of technological inputs affect the organization's perception on additional technological opportunity and behavior toward risk taking?

Technological opportunity has been the core research interest in the field of technology studies. Technological opportunity reflects the likelihood of innovation for any given amount of money invested in technological search and high opportunities provide powerful incentives to the undertaking of innovative activities (Breschi, Malerba, & Orsenigo, 2000). It should be pointed out that technological opportunity may be determined by the intrinsic nature of technology and also may greatly change in the course of the evolution of industries (Klepper, 1996). On the other hand, organizations may face different opportunities at the individual organization level with respect to their societal positions in the technological environment. During the process of learning from others, organizations are likely to perceive potential amount of new opportunities relative to the newness of their prior learning experience. That is, if the organization had been monitoring and taking advantage of others' technology with agility, it would recognize a fewer potential opportunity left in learning from others, even when the moment requires urgent supply of new knowledge. Thus, even when the motivation for technological change is substantially high, it will be negatively affected by the recency of technological inputs from others because organizations will likely perceive that not much new learning opportunity is remaining. In this case, inertial forces prevail and organizations become less willing to change their current technological development, especially when their performance is moderate. On the other hand, if the organization had been responding slowly to the technology development of competitors, it will become eager to absorb up-to-dated knowledge of others and to attempt something new when the needs for change rises.

Hypothesis 2: The relationship in Hypothesis 1 becomes stronger for firms with recency of technological inputs.

2.3 Technology maturity

Technology maturity is related with uncertainty (Karshenas & Stoneman, 1995; Lissoni & Metcalfe, 1994; Rogers, 1983). Thus organization's technology maturity may influence the motivation in the pursuit of technological changes. As technologies evolve, both continuous and discontinuous changes occur along 'technological paradigms and trajectories' (Dosi, 1982; Nelson & Winter, 1982). While some paradigms and trajectories last longer, other paradigms and trajectories are short lived. Such life cycle of technology has been shown to conform to an S-shape curve represented by the rate at which the technology is adopted in the marketplace. At the initial stage of slow improvement, the amount of effort and money invested in the technology is small because only few participants are involved, and adoption starts to accelerate as the technology becomes better understood and more participants enter the race.

During initial stage of technology development, participants experiment with different form factors or product features to assess how the market responds. As a result, various form factors compete for dominance and until a dominant design emerges, organizations keep introducing new ideas and different forms of the technology. Anderson and Tushman (1990) term this period as 'the era of ferment' and since there is little agreement about what the major subset of the technology should be or how they should be configured, participants are more likely to pursue various experimentations for technological change. The occurrence of technological change will slow down when producers and customers begin to arrive at some consensus about the desired product attributes, i.e., a dominant design, and only incremental changes are made during this era (Anderson & Tushman, 1990). Once a proven trajectory or a dominant design has been formed, firms focus on achieving greater market share by offering different models and price cuts through efficiency improvement instead of seeking further technological diversity.

Due to intrinsic characteristics of technological environment being turbulent and uncertain, the key interest of participants with immature technology will likely be to achieve certain level of technology improvement and to increase adoptions rather than meeting the short-term financial performance, unless the performance is so bad that they consider their attempts as failures. Thus, these firms will be less sensitive or vulnerable to short-term performances, making them less likely to be swayed or motivated by such short-term past performance in changing strategies toward subsequent R&D activities. Moreover, when an organization consists of relatively immature technology, it is reasonable to assume that it has already been taking highly risky R&D projects so that success-strategic persistence has stronger impact on its behavior toward further change or risk taking.

Hypothesis 3: The relationship in Hypothesis 1 becomes stronger for firms with more immature technology.

Ⅲ. Method

3.1 Sample and Data

The setting for empirical analyses of this study is the U.S. semiconductor industry during 1987-2006: main analyses cover period of 1987-2000 but additional years were chosen to allow for the observation of subsequent citations to those patents filed before. The semiconductor industry is defined by rapid technological advancement, short product life cycle, and steep price decline. Although the industry is growing continuously, it has characteristics of a cyclical pattern with high volatility. Sometimes the industry experiences dramatic cyclical swings so that firms are required to possess high degree of flexibility and innovative capability in order to constantly adjust to the rapid pace of change in the market. Moreover, many products embedding semiconductor devices often have a very short life cycle so that semiconductor firms must keep developing new devices and be ready with the next generation product technology. On the other hand, many categories of semiconductor devices are standardized due to the digital nature of products and the price-performance is systematically determined by the market. As a result, semiconductor firms are exposed to international competition and under the pressure of price erosion and race to introduce new products first to market.

While semiconductor companies engage in the design and fabrication of semiconductor devices, there has been a trend toward industry disintegration, resulting in the organizational separation of value chain activities. Traditional firms are classified as IDMs (integrated device manufactures) which design, manufacture, and sell integrated circuit (IC) products. In addition to IDMs which handle manufacturing in-house, fabless semiconductor firms design and market new semiconductor products, but rely on third parties for manufacturing. The specialized manufactures are called foundries. Besides the three types of business operations, many other forms of business players are distributed in the industry ranging from semiconductor equipment makers, back-end assemblers, components manufactures, and software/IP (intellectual property) specialists.

The main data for this study were obtained from Standard and Poor's Compustat North America and the National Bureau of Economic Research (NBER) Patent Citations Data File. The sample was selected by 4-digit semiconductor SIC code 3674 from Compustat database to obtain the financial panel data and the patents information on corresponding sample was gathered from the NBER Data File. A total of 217 patenting firms were found during the study period. In addition, various sources including company websites, Hoover's database, Yahoo Finance, Wikipedia, and Google were used for information on founding years and type of business operations they pursue.

The NBER Patent Citations Data File contains information concerning every patent granted in the period 1969-2006 (Hall, Jaffe, & Trajtenberg, 2001; https://sites.google.com/site/patentdataproject). The data file lists application and grant year of each patents, assignee match to Compustat that applied for each patents, the technological class to which each patent belongs (1-digit, 2-digit, and 3-digit classifications), and the cited patents associated with each patents. A number of previous scholars have used patents as a proxy for innovation, search, and technological position (Argyres & Silverman, 2004; Fleming & Sorenson, 2004; Podolny *et al.*, 1996; Rosenkopf & Nerkar, 2001; Stuart & Podolny, 1996) because patents have been recognized as a rich source of data concerning organizational innovation and technological change.

The U.S. Patent and Trademark Office is in charge of granting property rights to inventors or assignees (organizations that own the patent). By law, patent applications must include in applications all "prior art", which refers to previous patents relating to the invention they are seeking to patent. A citation of antecedent patents by current invention indicates that the current invention builds upon previously existing knowledge embodied in such prior patents (Song, Almeida, & Wu, 2003). Including all the relevant prior arts is important to avoid potential legal disputes surrounding the claims of the patent.

Although patents information is useful in assessing the overall R&D activity of organizations, some caution is needed in analyzing patents and patent citations. On the one hand, inventors might not patent certain inventions in the fear of damaging their competitive position through public exposure of the invention, and rather decide to take the risk of being unprotected. To keep the invention as a secret is a matter of a strategic issue. On the other hand, industries may vary considerably in the extent to which inventions are patented even if they are made public (Scherer, 1984). In this case, the validity of patent analysis in reflecting R&D activities of organizations would be severally eroded.

Despite these limitations of patent data, the semiconductor industry has been known to substantially avoid such concerns (Podolny *et al.*, 1996). The semiconductor industry is characterized with high propensity to patent inventions and all of the landmark inventions have associated patents (Wilson *et al.*, 1980). One of the reasons is because semiconductor firms have strong economic incentives to patent their technology for royalty income from licensing their patented technology. Moreover, semiconductor firms tend to actively engage in patent infringement lawsuits to protect the revenue generated by their products.

3.2 Variables

Technological breadth is computed based on the information on 3-digit technological category of patent applications filed in year t for each firm. To test the causal relationship, dependent variable was lagged by two years by considering the fact that the usual R&D projects take six to eighteen months in the semiconductor industry. During the observation years, 330 different 3-digit technological categories were entered by sample firms when filing patent applications and the value of 1-HHI (Herfindahl-Hirschman Index) of technological categories of patents filed is used.

The measure is bounded by zero and one: zero means that a focal firm has filed patents in a single category while the value approaches one when patent applications are evenly distributed along many technological categories in year t. Prior studies also measure technological breadth or diversity based on patent activities and the Herfindahl Index is becoming popular to measure technological breadth (Garcia-Vega, 2006; Quintana-Garcia & Benavides-Velasco, 2008).

Motivation is assessed by the performance aspiration gap based on historical aspirations and is specified as a spline function since the motivation effects may vary for firms below and above an aspiration level. That is, the difference between return on assets (ROA) from year t-1 to t was incorporated and separate variables were entered for performance below and above aspiration level (Greve, 2003). In fact, both social and historical aspirations

$$\text{Tech. breadth} = 1 - \sum \left(\frac{\text{\# of patents applied in 3\_digit tech. category i}}{\text{Total \# of patents applied}}\right)^2$$

were tested in this study with two separate models: social aspirations refer to the experience of other reference firms as in prior research (Bromiley, 1991; Greve, 2003). For more relevant measure of social aspirations, reference groups were delineated according to eleven types of business operations among the sample firms and mean ROA was computed for each group's social aspirations. However, the results were stronger with historical aspirations, probably because changes in technological position or strategy are more of a firm's own experience-and-history dependent matter. During the computation, ROAs that were less than three standard deviations were treated as missing values in order to adjust extreme outliers.

Recency of technological inputs from others was operationalized by the average time lag between filing dates of a focal firm's patents and cited patents at t (i.e. average age of cited patents), excluding self-citations.

Difference in filing dates of citing and cited patents has been used in prior research with different perspectives. On the one hand, Jaffe, Trajtenberg, and Romer (2005) argue that knowledge becomes obsolete as time passes and the speed of obsolescence differs significantly by technology regimes. They contend that such aspect can be expressed as technology cycle of patents, measured by the average age of prior arts cited by patents filed in the current year. When one technology regime cites older prior arts compared to other technology regime, then it can be said to have a longer technology life cycle where the unit of analysis is a technology regime or an industry. On the other hand, difference in filing dates has also been studied in the organizational level by the construct of 'recency of technological inputs' (Deng, Lev, & Narin, 1999; Golder & Tellis, 1993; Heeley & Jacobson, 2008; Katila, 2002). These studies focus on how using mature verses nascent technological inputs affect inventive or financial value of firms. In this study, the same measurement is used as a proxy for knowledge base of firms in learning from others. Thus, when the average time lag is small, it means that a focal firm has absorbed up-to-dated knowledge of others when filing patents at t.

Technology maturity was constructed by measuring the average age of 3-digit technology categories in which a focal firm's patents were filed for at t. 330 different 3-digit categories were entered by sample firms during the observation period and the year in which

$$\text{Recency of technological inputs} = \frac{\sum(\text{Application year of focal patent} - \text{Application year of cited patent})}{\text{Total \# of cited patents}}$$

each category first appeared in the U.S. Patent Office were traced back. The NEBR Data File covers patents applied back in 1967 and new technological categories were continuously introduced. This is in alignment with the notion of technological trajectories in which as technologies evolve, many derived technologies may be introduced as new trajectories while some trajectories become 'dead ends' (Kim & Kogut, 1996).

When a focal firm's filed patents at t belong to relatively young technology categories, it may be interpreted that the firm has entered that specific area of technology at the immature stage of technology development. As a technology category matures, more knowledge builds up in the corresponding category, resulting in the abundance of knowledge base available to participating firms.

3.3 Control variables

Numerous factors beyond motivation may influence the technological change. Thus control variables were included in the panel data related to within-firm changes over time.

First of all, industry-level and reference group-level variables were considered. Total industry size was controlled because it will likely influence a firm's technological strategy. When the industry experiences high growth in size, the industry sentiment will likely turn optimistic, motivating firms to actively seek more opportunity and get prepared for the future. Since one of the representative characteristics of semiconductor industry is strong cyclicality, it is necessary to control for the industry effects that could influence firm's decision on technological strategy. Annual semiconductor chip market size measured in U.S. dollars was used to control such effects. Since chip market is positioned at the final downstream of semiconductor industry, it is reasonable to assume that the chip market size reflects the macro industry sentiments for sample firms. The data came from SIA (Semiconductor Industry Association). Also, average R&D intensity of industry participants was included to control for institutionalized R&D activity of firms (Chen & Miller, 2007). The firm's R&D investment is highly conformable to industry trends of R&D resource allocation and this may have significant impact on individual firm's technological strategy. Since sample firms pursue different types of business operations, the average R&D intensity

$$\text{Tech maturity} = \frac{\sum(\text{Application year of focal patent} - \text{First historical application year of corresponding 3\_digit tech. category})}{\text{Total \# of patents applied}}$$

was computed for each reference group operating with same forms of business.

Firm specific control variables were also included. Organizational change process is under the influence of inertial forces and inertia usually increases with organizational size and age (Amburgey, Kelly, & Barnett, 1993; Hannan & Freeman, 1984; Peli *et al.*, 1994). The natural logarithm of sales was entered as a measure of firm size and firm age was measured as the number of years since firm founding. Firm's R&D intensity (R&D expenditure divided by sales) was used as a proxy for its total R&D inputs to the technological development process. These data also control for the total amount of a firm's innovation search activities (Cohen, 1995). In addition, since the degree of rivalry that a focal firm was facing could also influence its technological strategy, actual rivalry was included, measured by reference group HHI (Herfindahl-Hirschman Index) less the contribution by own-firm market share. Another important control variable involves patent resources of a focal firm. Because dependent variables were computed based on patenting activities, a focal firm's current patent resources may have significant impact on further patenting activity. Firm patent stock was measured as the stock of granted patents during the past five years. Gaps in growth aspiration (based on historical aspiration) were included to control for a focal firm's position relative to growth aspirations. Growth aspect was considered significant especially in the field of technology studies in which growth opportunity was assumed to be a critical factor in selecting a certain technological trajectory (Dosi, 1982; Nelson & Winter, 1982). Thus, a firm's growth experience relative to growth aspirations may also influence future direction of technological change. In addition, two kinds of slacks were included to control for 'slack search' of a firm (Cyert & March, 1963; Greve, 2003): absorbed and unabsorbed slacks. As in prior research, absorbed slack was computed as the ratio of SGAE (selling, general, and administrative expenses) to sales and unabsorbed slack as the ratio of quick assets (current assets - inventories) to liabilities (Bourgeois & Singh, 1983; Bromiley, 1991; Greve, 2003). Because absorbed and unabsorbed slacks have been found to differ in their influence on search intensity (Greve, 2003), separate measures were entered. Finally, innovative capability was employed because a firm's capability also affects how far it extends in the knowledge network. Innovative capability was measured by counting the number of citations received by patents of a focal firm filed at t during the five years after the patents have been issued. Five-year time window was used because the life cycle of semiconductor technology is usually known to range between three to five years.

The research model uses fixed effects panel regression models with first-order autoregression (AR1) to test hypotheses in this study, controlling for significant firm differences in technological changes.

Ⅳ. Results

Descriptive statistics for variables are reported in 〈Table 1〉, showing means, standard deviations, and correlations. Although most correlation coefficients are small, there are a few exceptions. Most of all, firm RDI and absorbed slack are highly correlated (0.837), meaning that the higher the amount of absorbed slack, the larger the R&D investment a firm makes. It is also noticeable that technology maturity is highly correlated with industry size (0.80) which suggests that when the industry sentiment is good, a firm is likely to seek new inventions in the mature technological category. Although these correlation coefficients were rather high, all variables were included in our analyses because the constructs were clearly distinct and multicollinearity did not seem to be a serious concern.

〈Table 2〉 shows the fixed effect panel regression results for Models 1 to 5 of the research model. Model 1 on the first column is the baseline model consisting only control variables. Independent variables are added to the baseline model to test our hypotheses in Models 2 to 5, with Model 5 showing the coefficients for the full model. Among control variables, firm size and absorbed slack are found to be statistically significant in a number of models: the larger the firm size and the absorbed slack, the greater the technological breadth of the firm. The number of observations used in each model is included at the bottom of the table along with autocorrelation coefficient, R^2, and F-statistics.

As can be seen, Models 2 tests the main effects of performance feedback as motivation on technological breadth (Hypothesis 1). The negative coefficient of performance-aspiration gap in Model 2 supports Hypothesis 1 that low performance feedback motivates increase in technological breadth. However, such finding is statistically significant with anticipated coefficient only when performance is below the aspiration level. In fact, the motivation by past performance below the aspiration level is statistically significant with anticipated negative coefficients throughout the models except in Model 3. When performance is above the aspiration level, the motivation effect is rather inconsistent through Models 2 to 5.

Models 3 and 4 test moderating effects of recency of technological inputs and technology maturity. Due to the ways that these variables have been measured, the coefficients of interaction variables should be positive to

〈Table 1〉 Descriptive statistics

	Mean	Std. Dev.	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
1.Tech Breadth (t+2)	0.715	0.259	1															
2.Industry size	104812.4	35545.6	-0.0781	1														
3.Average RDI	0.248	0.185	-0.0758	0.2358	1													
4.Firm size	5.766	1.587	0.5693	-0.0037	-0.1959	1												
5.Firm age	20.447	14.345	0.181	-0.0192	-0.1791	0.5771	1											
6.Firm RDI	0.140	0.076	-0.1323	0.1388	0.2838	-0.3743	-0.3898	1										
7.Actual rivalry	0.166	0.070	0.0256	-0.093	-0.4462	-0.0075	0.0498	-0.1906	1									
8.Patent stock	194.3	610.8	0.247	0.1044	-0.0836	0.5918	0.6572	-0.1632	-0.1096	1								
9.Growth-Aspiration < 0	-0.170	0.309	0.1436	-0.1068	-0.114	0.1838	0.1779	-0.1492	0.1608	0.0775	1							
10.Growth-Aspiration > 0	0.093	0.248	-0.01	0.1105	0.1929	-0.0631	-0.1051	0.083	0.0106	-0.0477	0.2074	1						
11.Absorbed slack	0.315	0.113	-0.2064	-0.0331	0.2624	-0.49	-0.2802	0.8371	-0.1692	-0.1823	-0.1325	-0.0046	1					
12.Unabsorbed slack	1.972	1.742	-0.1274	0.1822	0.2095	-0.3681	-0.2967	0.1507	-0.0988	-0.1856	0.0093	0.1489	0.1263	1				
15.Innovative capability	580.3	1254.0	0.3219	0.1641	-0.1202	0.7079	0.4602	-0.1522	-0.0387	0.698	0.0753	-0.0444	-0.2502	-0.2317	1			
13.ROA-Aspiration < 0	-0.037	0.071	0.1007	-0.1078	-0.0571	0.0812	0.0904	-0.2015	0.0886	0.0268	0.4712	0.1566	-0.2148	0.0862	-0.0154	1		
14.ROA-Aspiration > 0	0.041	0.146	-0.1209	0.0791	0.1316	-0.231	-0.1052	0.1024	-0.0725	-0.0446	-0.0091	0.1145	0.1192	0.0518	0.1487	-0.0606	1	
16.Recency of tech inputs	6.278	1.567	-0.0242	0.1207	-0.0967	-0.0957	0.1668	-0.2248	0.1374	-0.0554	0.1576	0.002	-0.1567	0.0643	0.1198	-0.0477	-0.1632	1
17.Tech maturity	21.558	3.094	-0.1511	0.8031	0.1318	-0.0569	0.0382	0.1682	-0.0125	0.0805	-0.0543	0.1123	0.0205	0.1174	-0.1573	0.0832	0.13	0.0634

Correlations with absolute values greater than 0.107 are significant at $p < 0.05$ level

〈Table 2〉 Fixed-effect panel regression with AR(1)

	Model 1	Model 2	Model 3	Model 4	Model 5
Industry size	-0.000	-0.000	0.000	-0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Average RDI	-0.021	-0.042	-0.050	-0.038	-0.045
	(0.056)	(0.056)	(0.055)	(0.054)	(0.053)
Firm size	0.089*	0.072	0.114**	0.045	0.083*
	(0.049)	(0.048)	(0.049)	(0.049)	(0.049)
Firm age	0.002	0.001	-0.010	0.027*	0.017
	(0.011)	(0.011)	(0.011)	(0.016)	(0.015)
Firm RDI	-0.570	-0.533	-0.444	-0.609*	-0.524
	(0.347)	(0.340)	(0.334)	(0.339)	(0.327)
Actual Rivalry	0.168	0.152	0.227	0.135	0.223
	(0.280)	(0.274)	(0.267)	(0.273)	(0.262)
Patent stock	-0.000	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Growth-Aspiration < 0	0.044	0.101*	0.089	0.073	0.059
	(0.055)	(0.058)	(0.057)	(0.057)	(0.056)
Growth-Aspiration > 0	-0.035	-0.025	-0.007	-0.026	-0.007
	(0.078)	(0.078)	(0.077)	(0.076)	(0.074)
Absorbed slack	0.840***	0.732**	0.734**	0.712**	0.675**
	(0.298)	(0.294)	(0.294)	(0.296)	(0.291)
Unabsorbed slack	0.003	0.009	0.016	0.005	0.011
	(0.016)	(0.016)	(0.015)	(0.016)	(0.015)
Innovative capability	-0.000	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ROA-Aspiration < 0		-0.589***	1.261**	-4.121***	-2.612*
		(0.191)	(0.597)	(1.340)	(1.349)
ROA-Aspiration > 0		0.419**	-2.136*	-0.495	-3.067
		(0.212)	(1.169)	(2.400)	(2.635)
Recency of tech inputs			-0.018*		-0.017*
			(0.010)		(0.010)
Recency of tech inputs x ROA-Aspiration < 0			-0.315***		-0.374***
			(0.098)		(0.097)
Recency of tech inputs x ROA-Aspiration > 0			0.389**		0.404**
			(0.176)		(0.170)
Tech maturity				-0.017	-0.017
				(0.012)	(0.012)
Tech maturity x ROA-Aspiration < 0				0.162***	0.192***
				(0.061)	(0.059)
Tech maturity x ROA-Aspiration > 0				0.045	0.041
				(0.112)	(0.110)
Constant	0.001	0.094	0.145	0.078	0.161
	(0.180)	(0.185)	(0.191)	(0.171)	(0.178)
Autocorrelation coefficient	0.362	0.344	0.328	0.398	0.362
Model F	1.00	1.68	2.18	2.07	2.76
R^2 (Within)	0.057	0.107	0.161	0.154	0.225
Number of observations	264	264	263	264	263

Note: *** p<0.01, ** p<0.05, * p<0.1; Standard errors are in the parentheses.

support Hypotheses 2 and 3: the value of technological inputs is lower for organizations with recency of technological inputs and also the value of technology maturity is lower for organizations with immature technology. The finding in Model 3 indicates the anticipated moderating effect of recency of technological inputs is partially supported: Hypothesis 2 is supported with statistical significance at $p < 0.05$ level only when performance is above the aspiration level in which the negative relationship between technological breadth and past performance becomes stronger for firms with more recent technological inputs from others. But the coefficients of main and interaction variables have the opposite signs from the anticipated result when performance is below the aspiration level in Model 3. Regarding the moderating effect of technology maturity on motivation and technological breadth, Model 4 strongly supports Hypothesis 3 when performance is below the aspiration. Although the moderating effect of technological maturity is statistically significant and stable in the full model as well, the technological maturity itself is not found to be statistically significant. However, the value of standard error for the technology maturity in Models 4 and 5 ($p = 0.012$) may be considered as statistically significant based on its interaction effect. On the other hand, the moderating effect of recency of technological inputs when performance is below the aspiration level is not consistent with anticipated result in the full model (Model 5).

4.1 Robustness check

Thus far, the analyses have provided partial evidence that the prior performance motivates organizations to pursue technological changes and during the process, their recency of technological inputs and technology maturity moderate the main relationship. However, it is possible that some of organizations may strategically decide not to execute any patenting activities after they have assessed their odds of success in the change process due to firm-specific characteristics (such as managerial ability, R&D capacity, attitudes toward competition). If so, the result will be that only organizations that consider themselves to be competent enough in innovativeness or seizing technological opportunity respond to prior performance and attempt changes in their inventing activities. In this case, the technological change decision must be treated as endogenous because it has to be taken into account that different technological changes are not being randomly selected by firms, but are chosen by firms in response to other organizational characteristics. Consequently, it is important to address this possible selection bias in the patenting activity and investigate whether the earlier analyses results were an artifact of treating technological changes based

〈Table 3〉 Descriptive statistics – Selection model

Selection Model	Mean	Std. Dev.	1	2	3	4	5	6	7	8	9	10
1.Patenting(t+1)	0.715	0.452	1									
2.ROA	0.042	0.268	0.1069	1								
3.Firm RDI	0.188	0.979	0.0328	-0.2878	1							
4.Sales growth	0.351	0.902	0.0524	-0.068	0.1587	1						
5.Market share	0.058	0.138	-0.0513	0.0082	-0.0327	-0.0416	1					
6.Firm age	18.450	13.790	0.0335	0.1382	-0.0964	-0.2102	0.0673	1				
7.Firm size	4.687	1.878	0.4589	0.3791	-0.1512	-0.1341	0.1986	0.3863	1			
8.Absorbed slack	0.424	1.693	0.0096	-0.3348	0.993	0.1565	-0.0323	-0.0918	-0.1843	1		
9.Unabsorbed slack	2.143	2.451	0.1196	0.0815	0.0891	0.1276	-0.1018	-0.1751	-0.142	0.0783	1	
10.Industry average patents filed	48.433	14.863	0.0699	-0.0051	0.0882	0.1247	-0.0365	-0.0235	0.0294	0.069	0.2505	1
11.Year dummies			*	*	*	*	*	*	*	*	*	*
12.Operation type dummies			*	*	*	*	*	*	*	*	*	*

Correlations with absolute values greater than 0.067 are significant at $p < 0.05$ level

Technological change	Mean	Std. Dev.	1	2	3	4	5	6	7	8
1.Tech breadth (t+1)	0.655	0.284	1							
2.Industry size	107707.2	39496.5	-0.0603	1						
3.Average RDI	0.296	0.580	-0.0672	0.1698	1					
4.Firm size	5.344	1.783	0.5326	-0.0403	-0.2249	1				
5.Firm age	18.8	14.7	0.1786	-0.0197	-0.1025	0.5802	1			
6.Firm RDI	0.223	1.200	-0.0226	0.0655	0.4879	-0.212	-0.0964	1		
7.Absorbed slack	0.460	2.051	-0.0268	0.0534	0.4768	-0.2199	-0.0906	0.9955	1	
8.Unaborbed slack	2.224	2.956	-0.0713	0.1764	0.1378	-0.2933	-0.1736	0.0837	0.0756	1
9.Patent stock	169.9	600.2	0.2522	0.0711	-0.05	0.549	0.6167	-0.029	-0.0284	-0.1199

Correlations with absolute values greater than 0.083 are significant at $p < 0.05$ level

〈Table 4〉 Fixed-effect panel regression with AR(1)

	Model 1	Model 2	Model 3	Model 4	Model 5
Industry size	-0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Average RDI	-0.021	-0.059	-0.061	-0.056	-0.057
	(0.056)	(0.056)	(0.055)	(0.054)	(0.053)
Firm size	0.089*	0.112**	0.139***	0.085*	0.109**
	(0.049)	(0.051)	(0.052)	(0.051)	(0.051)
Firm age	0.002	-0.002	-0.011	0.026*	0.017
	(0.011)	(0.011)	(0.011)	(0.015)	(0.015)
Firm RDI	-0.570	-0.258	-0.256	-0.282	-0.307
	(0.347)	(0.363)	(0.357)	(0.362)	(0.350)
Actual Rivalry	0.168	0.207	0.260	0.207	0.263
	(0.280)	(0.272)	(0.267)	(0.271)	(0.261)
Patent stock	-0.000	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Growth-Aspiration < 0	0.044	0.109*	0.095*	0.081	0.066
	(0.055)	(0.058)	(0.057)	(0.056)	(0.056)
Growth-Aspiration > 0	-0.035	-0.004	0.006	-0.001	0.008
	(0.078)	(0.078)	(0.077)	(0.076)	(0.075)
Absorbed slack	0.840***	0.550*	0.608**	0.478	0.522*
	(0.298)	(0.303)	(0.304)	(0.307)	(0.302)
Unabsorbed slack	0.003	0.025	0.027	0.023	0.023
	(0.016)	(0.017)	(0.017)	(0.017)	(0.017)
Innovative capability	-0.000	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
nonselection hazard		0.408**	0.290	0.476**	0.326*
		(0.200)	(0.199)	(0.201)	(0.195)
ROA-Aspiration < 0		-0.665***	1.059*	-4.137***	-2.738**
		(0.192)	(0.610)	(1.322)	(1.343)
ROA-Aspiration > 0		0.352*	-1.995*	-1.060	-3.248
		(0.213)	(1.169)	(2.387)	(2.628)
Recency of tech inputs			-0.016		-0.015
			(0.010)		(0.010)
Recency of tech inputs x ROA-Aspiration < 0			-0.289***		-0.347***
			(0.100)		(0.098)
Recency of tech inputs x ROA-Aspiration > 0			0.360**		0.371**
			(0.176)		(0.170)
Tech maturity				-0.019	-0.019*
				(0.012)	(0.011)
Tech maturity x ROA-Aspiration < 0				0.159***	0.187***
				(0.060)	(0.059)
Tech maturity x ROA-Aspiration > 0				0.067	0.057
				(0.111)	(0.110)
Constant	0.001	-0.194	-0.071	-0.213	-0.057
	(0.180)	(0.209)	(0.217)	(0.187)	(0.198)
Autocorrelation coefficient	0.362	0.335	0.321	0.388	0.354
Model F	1.00	1.88	2.19	2.32	2.79
R^2 (Within)	0.057	0.127	0.176	0.179	0.237
Number of observations	264	264	263	264	263

Note: *** p<0.01, ** p<0.05, * p<0.1; Standard errors are in the parentheses.

on patenting activity as exogenous. The robustness of earlier analyses may be secured by utilizing a two-step Heckman selection modeling (Heckman, 1979).

About one fourth of the Compustat sample firms were not involved in patenting activities and thus excluded in the earlier analyses. In the first step of Heckman's self-selection model, the dependent variable takes the value of 1 if the firm is patenting its inventions and a value of 0 otherwise. The inverse Mill's ratio calculated from this first-stage model is introduced as a predetermined variable in the model accounting technological change to control for selectivity effect in the second model. The descriptive statistics for the selection model is shown in 〈Table 3〉 and the fixed effect panel regression results after controlling the selectivity bias (inverse Mill's ratio) are presented in 〈Table 4〉. Although the estimated coefficient for the selectivity bias is statistically significant in a few models, the earlier results hold consistently.

Ⅴ. Conclusion

Technology is an important factor in driving economic growth, and individual organizations in high-tech industry struggle to make excess returns by employing effective strategies involving technological development. The fields of technology studies and evolutionary economics have employed the concept of technological paradigms and trajectories to provide explanations on continuous and discontinuous changes in technology. However, knowledge about how individual organizations make decisions on technological changes has been developed limitedly.

Prior studies have found high tendency of local search in which organizations search for solutions in the neighborhood of its current expertise (March & Simon, 1958; Nelson & Winter, 1982; Stuart & Podolny, 1996). Local search implies that organizations prefer to maintain the status quo unless they are strongly motivated. For instance, organizations are likely to increase search intensity and adopt new routines when their performance is low (Cyert & March, 1963; Greve, 2003; Massini *et al.*, 2005). Nevertheless, organization's capability and risk preference also affect decision maker's choice among technology alternatives (Miller & Chen, 1994; Rogers, 1983; Stinchcombe, 1965). Moreover, technology life cycle inherently affects the industry's technology development trends and has strong influence on its participants toward risk assessment (Anderson & Tushman, 1990). To provide a more systematic research frame in predicting the direction of technological change, this study attempts to integrate the motivation factor with organizations' learning and technology adoption tendencies in making technological changes. The study focuses on the behavioral perspectives of technological change and has investigated what drives organization to widen its technological breadth. How the tendencies in learning from others and technology adoption affect the degree of change has also been examined.

Key findings of this study include the following. First, organizations become motivated by low prior performance to change technological strategy and such effects differ depending on their position relative to the aspiration level. Second, the moderating effects of recency of technological inputs present rather mixed and unstable findings: the hypothesis is supported only when performance is above the aspiration level. It may be so because when performance is below the aspiration, some firms are desperate to implement greater technological changes for survival even though their current technology asset is based on up-to-dated technological inputs. But the moderating effects of technology maturity are more consistently supported, showing that the negative main relationship becomes stronger for firms with immature technology as predicted when positioned below the aspiration level. Overall, the moderating effects may be summarized as follows: organizational learning and technology adoption tendencies have significant effects during the process of technological change when firms are motivated to pursue changes by poor performance. However, the effects differ by the relative position of firms whether they are above or below the aspiration levels.

Before discussing the theoretical contributions of this study, it may be worthwhile to point out a few limitations. Since the empirical setting is based on a single industry, the generalization of results should be made with caution. The strong tendency of high R&D investment and emphasis on patenting own inventions in the semiconductor industry make the patents data a rich source of technological strategy. However, some industries may value other forms of technological changes such as technology alliance, licensing, or acquisition, especially where the technology's network externality effect is high. In such industries, organizations would be less willing to take a new road and instead, they will attempt to collaborate with other participants. Thus, the conclusion of this study will fit better for industries where competition is much more emphasized than cooperation. In addition, this study treats increase in technological breadth with the same weight whether it involves related or unrelated technological diversification. To be more strict and relevant on the amount of risks or changes pursued by organizations, it is desirable to make distinctions between the two since widening the breadth toward unrelated technological domains should provide higher hurdle and organizations must bear more risk.

Despite these caveats, this study contributes to previous work in several ways. First of all, it applies effects of performance feedback on changes in technological breadth. Also, the moderating effects of recency of knowledge inputs and technology adoption tendencies are examined. According to a diffusion theory, differences in learning tendency and technology maturity are closely related with risk propensity, technology opportunity, and capability (Karshenas & Stoneman, 1995; Lissoni & Metcalfe, 1994; Rogers, 1983), suggesting that these may be important moderating factors in pursuit of technological changes. Such moderating effects on technological change have not been addressed before. For further studies, it would be interesting to extend the current study by including how organizations choose between cooperative and competitive means in technological contexts, with the moderating effects of learning and technology adoption tendencies as well.

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미국 반도체 산업의 기술 범위 결정 요인에 관한 연구:
성과 피드백, 참조 기술의 최신성, 기술 성숙도

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요 약

기술은 경제 성장을 촉진시키는 중요한 요소일 뿐 아니라 개별 기업의 경쟁 우위를 가능하게 하는 유용한 도구이다. 본 연구는 성과 피드백이 기업의 기술 범위 결정에 어떠한 영향을 미치는지 살펴보고, 참조 기술의 최신성과 기술 성숙도 등의 조절 효과를 연구한다. 이러한 조절 변수는 새로운 학습 기회 및 조직의 위험에 대한 성향과 밀접한 관계가 있을 것으로 예상됨에 따라서 선정되었다. 실증 연구 결과, 성과가 기대에 미치지 못하는 경우 성과가 나쁠수록 기업은 기술 범위를 확장시키는 경향을 보인다. 기술 범위의 확장은 특정 영역에 R&D를 집중하는데 비해 주로 높은 위험을 수반하며, 이는 성과가 좋지 않을수록 위험한 도전을 시도하는 경향이 강하다는 기존 연구와 맥을 같이 한다. 조절 효과의 경우, 참조 기술의 최신성은 기대 수준 대비 성과의 상대적 위치에 따라서 다소 혼재된 결과를 보인다. 성과가 기대에 비해 높을 경우, 참조 기술이 최신 기술일수록 기술 범위와 지난 성과간의 음의 관계는 강해진다. 이는 기업이 외부의 최신 기술을 지속적으로 자사의 기술 자산에 반영해 왔다면 새로운 학습 기회가 많이 남아있지 않다고 인지하고 있을 가능성이 높기 때문이다. 즉, 참조 기술의 최신성은 기술 변화의 동력을 약화시키는 효과가 있는 것이다. 성과가 기대에 비해 낮을 경우에는 반대의 효과가 나타났는데, 이는 일부 기업의 경우 생존 자체에 위협을 느껴 절실하게 큰 폭의 기술 변화를 시도하는 사례가 존재하기 때문일 것으로 판단된다. 반면 기술 성숙도의 조절 효과는 미성숙 기술을 보유한 기업일수록 성공-전략의 연속성 경향이 강하다는 일관성 있는 결과를 보여준다. 이는 미성숙 기술을 가지 기업은 단기적인 재무 성과를 달성하는 것보다 해당 기술의 성능을 향상시켜 시장의 선택을 받는 것이 핵심 관심 사항임을 반영한다.

본 연구는 기존의 성과 피드백 이론을 기술 범위의 결정 요인에 적용하고, 추가적으로 기업의 학습 및 위험 성향을 통합함으로써 기술 전략의 실증 연구에 기여하고 있다.

주제어: 기술 범위, 성과 피드백, 참조 기술의 최신성, 기술 성숙도, 반도체 산업

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