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Technological regime and firm innovative entries: A knowledge structure perspective

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Abstract

This study investigates the effects of technological regime on firm innovation behavior in knowledge intensive industries. Researchers of learning and knowledge theories regard technological regime as the knowledge environment in which firms learn and create new knowledge and propose four dimensions to depict technological regime: opportunity, appropriability, cumulativeness, and knowledge complexity. Instead of relying on survey data, this study explicitly models the knowledge environment in knowledge intensive industries by patent citation and patent class co-assignment information. The empirical results indicate that higher level of opportunity and knowledge complexity significantly increases the propensity of firm innovative entries. In contrast, higher level of appropriability and cumulativeness decrease the propensity of firm innovative entries.

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1. INTRODUCTION

The effects of environmental factors on firm's behavior have long been a critical inquiry for scholars in strategy management domain. Assuming that firms operating under the same environment tend to show similar patterns of behavior, technological strategy researchers (e.g., Nelson & Winter, 1982; Malerba & Oesenigo, 1993) advocate that firm's patterns of innovation behavior is closely linked to technological environment. In the maturity stage of technological environment (e.g., dominant design), innovations mainly come from few existing companies. On the other hand, in the emerging stage, new entrants continuously contribute to innovations. This suggests that the patterns of innovation activities are technology-specific (Malerba & Oesenigo, 1996; Schumpeter, 1983).

Studies of technological regime offers a description of technological environment in which firms operate and a regularity generated by technological incentive to decide a firm's patterns of behavior (Dosi, 1982). Technological regime shapes the propensity and direction of innovation within a technological domain by differing technological opportunities, appropriability conditions, and cumulativeness conditions. Firms choose their innovation behaviors according to the combination of these three conditions. This denotes that the technological regime sets a specific boundary for firm innovation behavior.

From the learning perspective, Winter and Nelson (1982) suggested that technological regime can be defined as the knowledge environment in which firms learn and create new knowledge based on the knowledge conditions. Winter (1984) explained the technological regime as follows:

"There are differences in a variety of related aspects, including such matters as the intrinsic ease or difficulty of imitation, the number of distinguishable knowledge-bases relevant to a productive routine, the degree to which successes in basic research translate easily into successes in applied research (and vice versa), the size of the resource commitment typical of a project and so forth. To characterize the key features of a particular knowledge environment in these various respects is to define a technological regime".

Malerba and Orsenigo (1993,1996, 1997) further elaborated the concept of knowledge environment. By classifying 49 technological classes into widening and depending patterns of innovation (i.e. Schumpeterian Mark I & II), their studies empirically show that the patterns of innovation are highly related to the nature of technology. These technology-specific patterns are invariant across countries (Malerba & Orsenigo,1996). They suggested that the technological regime exist in the technological domain and claimed that technological regime determines the specific way of accumulating knowledge in a technological class across countries. Specifically, the four dimensions were proposed to depict technological regime: opportunity conditions, appropriability conditions, degree of cumulativeness of knowledge, and knowledge properties (Malerba & Orsenigo,1997). The combinations of four dimensions fundamentally affect the innovation strategies and activities of firms operating within a technological domain.

This study aims to contribute to this on-going research by explicitly model the knowledge environment in a technological domain. In particularly, this study proposes that knowledge structure, which is modeled by knowledge elements and interdependence among knowledge elements, can reveal the underlying directions and opportunities for knowledge creation and accumulation in a certain technological domain. Empirically, this study extracts patent information from USPTO database to model knowledge structure. Each patent class is regarded as an element of knowledge structure and patent class co-assignment, classes assigned together to a single patent, therefore implies the combination, coordination, or interdependence among knowledge elements. Utilizing co-assignment information to model knowledge structure of a firm or an industry has become new research trend recently (Baldwin, MacCormack, & Rusnak, 2014; Dibiaggio, Nasiriyar, & Nesta, 2014). Regarding technological regime as the knowledge structure of a technological domain, this study attempts to answer the research question: How technological regime affects the propensity of firm entering new technological domain in knowledge-intensive industries.

The technological regime of knowledge intensive industries requires a more precise description of knowledge environment that firms carry innovation activities. The perspective of knowledge structure provides a particular approach to subjectively evaluate the technological conditions. While previous empirical studies did show technological regime is industry- or sector-specific, most studies relies on large scale survey across industries and countries (Castellacci & Zheng, 2010; Peneder, 2010). The scope of industry ranges from manufacturing to service industries or from low technology to high technology industries. In such setting, the use of patent or the frequency of patenting activity is a useful indicator to differentiate the technological regime across industries. However, in knowledge-intensive industries, such as semiconductor industry and biotechnology industry, patenting activities are very common and necessary means to protect innovation. Frequency of patent activities cannot distinguish the fundamental knowledge environment of knowledge-intensive industries. Instead, the knowledge environment can be differentiated by the knowledge structure that governs the directions and opportunities for knowledge creation and accumulation. Two main drawbacks based on survey-based studies of the technological regime are identified.

For example, survey-based studies usually evaluate the appropriability condition by whether firms use patent or trademark to protect the rent from innovation (e.g., Castellacci & Zheng, 2010). In other words, means of appropriability (appropriability breadth) is under investigation but the level of appropriability (appropriaiblity depth) (Malerba & Orsenigo,1997) is not. In industries that every firm participates in patenting activities, level of appropriability, measured by the ease of imitation, is more crucial to identify technological regime.

Cumulativeness condition is another example for the disadvantage of survey-based studies. Survey-based studies usually evaluate the cumulativeness condition by whether a firm continuously engaged in patenting activities year after year (Breschi, Malerba & Orsenigo, 2000). While such question item captures the persistence of innovation, it fails to capture the extent of innovation build upon previous knowledge. In knowledge-intensive industries, the reliance of existing knowledge and the path of knowledge accumulation are more critical to firms' search of new ideas.

In the following of this study, we start to review literature on technological regime from the perspective of learning and knowledge in the Section 2. The method of data collection and variable construction are presented in the Section 3. The empirical results are shown in the Section 4. Section 5 offers remarkable conclusions and discusses the implications for policy implications.

2. LITERATURE REVIEW

2.1 Overview of the Technological Regime

Firms conduct in variation environments and change rapidly in complex situations where no best prior way can be determined. This results the taxonomy of diversity firm patterns to describe similar behaviors and strategies that are in groups to understand their movement (Archibugi, 2001). The taxonomy offers a comprehensive way to organize the diversity of patterns of innovation for firms and sectors (Pavitt, 1984). As the theoretical precedent of the taxonomy, it was developed from a concept of a technological regime (Dosi, 1982; Nelson, 1982). The technological regime offers a description of knowledge environment in which firms operate (Nelson, 1982) and a regularity generated by technological incentive to decide a firm's behavior (Dosi, 1982). This denotes that the technological regime sets a specific boundary where firms operate within the reign. (Winter, 1984) explained the technological regime as follows:

> *"There are differences in a variety of related aspects, including such matters as the intrinsic ease or difficulty of imitation, the number of distinguishable knowledge-bases relevant to a productive routine, the degree to which*

successes in basic research translate easily into successes in applied research (and vice versa), the size of the resource commitment typical of a project and so forth. To characterize the key features of a particular knowledge environment in these various respects is to define a technological regime".

As a basis of the assertion of Winter (1984), Malerba(1996;2000) proposed specific definition of the technological regime combining some fundamental properties: opportunity conditions, appropriability conditions, and the degree of cumulativeness of knowledge. Specifically, the technological regime offers the notion of knowledge environment described in terms of opportunities, appropriability conditions, and degree of cumulativeness has major effects on the intensity of innovation and the rate of entry in an industry. Having reviewed the origin of the technological regime, each development of the technological regime is now pursed.

2.2 Opportunity Conditions

Opportunity conditions refer to the abundance of knowledge external to an industry (Malerba, 2000). Its condition reflects the ease of innovating for given amount of knowledge invested in search and offers innovation incentive for firms' undertaking (Malerba, 1990; 1993). These opportunity conditions decide possibilities of knowledge accessibility and affect knowledge concentration of an industry. Given superior opportunities, greater accessibility of knowledge arises but reduces the knowledge concentration in the industry. Otherwise, when a condition of a technological paradigm or a dominant design emerges (Dosi, 1982; Utterback, 1975), the knowledge external to the industry has lower accessibility chance but it offers a uniform distribution of knowledge environment.

The opportunity conditions in this paper are understood as a combination of knowledge components which occur from institutions external to the industry to firms, or between firms and within firms of an industry (Fleming, 2001). From the perspective of (Fleming, 2001), they addressed that innovation was a process of recombinant search over technological landscapes. Specifically, innovations take place while a series of knowledge components combined deliberate either a new synthesis of existing and/or a new component of prior combination of technologies (Fleming, 2001). Knowledge combination creates possibilities of interdependence and complementarity that increase the success by bringing opportunities creation (Almeida, 1996; Dibiaggio, 2014; Foss, 2013). A series of studies have examined the relations between knowledge components combination and opportunities creation. For instance, the emergence of mechatronics and optoelectronics that combine machinery, electronic, and optics can be traced back to the convergence of physics and engineering that were increasingly integrated into the knowledge component combination (Kodama, 1986; Kodama, 1991; Fujimoto, 2000). Likewise, other studies also find similar results in the combination of knowledge components of biotech as well as pharmaceutical industries (Nesta, 2003). Therefore, following these ideas above, we conceptualize the technological opportunities as a serious combination of knowledge components over fitness the technological landscape.

2.3 Cumulativeness conditions

Cumulativeness represents properties of the fact that today's knowledge and innovative activities form the based and offer the building blocks of tomorrow's knowledge advancements (Breschi, 2000;Malerba, 2000). This implies that the cumulativeness captures the features that current innovations as starting point formulate tomorrow's innovations and today's innovative activities are likely to be the bases to innovate in the future based on specific trajectories (Malerba, 1997). High level of cumulativeness shows an economic environment characterized by continuities in innovative activities and increasing returns.

A best known innovative cumulativeness is the distinction of product and process innovations proposed by (Abernathy, 1978; Utterback, 1975). This distinction is frequently to use in the technological-level cumulativeness investigation to understand specific features of technologies (Malerba, 1990). However, these measures of cumulativeness applied in innovative activities are mainly restricted because they reflect some relevant of innovative forms showing features of technologies usage rather than cognitive nature of learning process and knowledge advancement (Malerba, 2000).

2.4 Appropriability Conditions

Appropriability conditions refer to possibilities of protection innovations from imitation and extract monopolistic profits from innovative activities (Malerba, 2000). The appropriability can separate into two basic conditions: high and low. High appropriability condition denotes that ways exist successfully to protect knowledge from imitation. Low appropriability implies that an economic environment characterizes widespread existence of knowledge externalities and knowledge spillovers (Levin, 1987). These particular two situations have two different effects on innovation output: incentive effect and efficiency effect (Breschi, 2000). High appropriability offers a greater incentive effect to push firms to increase R&D investment or enhance external knowledge combination. On the country, low appropriability condition has a premium efficiency effect to benefit other firms from such technical advances. This implies that low condition of appropriability regime provides a positive efficiency effect on technical advances at the industry level because of spillovers (Levin, 1988).

The appropriability in this study is mainly considered as a formal method of patents. While there are a variety of appropriability methods ranging from the formal, informal and complementary asset controls (Harabi, 1995 #347;Levin, 1987 #288;Teece, 1986 #43), the patent offers the strongest form of appropriable protection and provides the owners monopolistic right to exclude others from economically exploiting, using and selling the certain innovations. In knowledge intensive industries such as semiconductor manufacturing and pharmaceutical industries, the formal method of patents is widely adopted by firms. Therefore, this study investigates the difficulty of imitation from another perspective: knowledge similarity. It is suggested that, comparing to firms with different knowledge structures, firms sharing similar knowledge structures will imitate each other's new innovation more easily (Yayavaram & Ahuja, 2008). In knowledge environment that most firms share similar knowledge structure, the level of appropriately is relatively low.

2.5 Complexity of knowledge base

In addition to previous three conditions of technological regime, Malerba and Orsenigo (1990, 1993) also proposed that the characteristics of knowledge base are also a fundamental property of technologies upon which firms' innovative activities are based. This study focuses on knowledge complexity, i.e. the integration of knowledge from different scientific and technological disciplines for innovations. Knowledge complexity varies in different industries.

In some industries, knowledge required for innovation comes from few and limited disciplines. The functions of an innovation are also limited to certain areas. In some other industries, such as industries with high level convergence or blurred boundaries, knowledge required from innovation comes from diverse disciplines. The functions of an innovation can be widely applied to other relevant areas.

2.6 Patterns of Innovation: Schumpeter Mark Ⅰ and Schumpeter Mark Ⅱ

A typical taxonomy is inspired to describe patterns of innovative activities in a manufacturing sector: Schumpeter Mark Ⅰ & Ⅱ (Schumpeter, 1983). These two patterns concern the environmental conditions and firms' roles played in the innovative activities. Specifically, Schumpeter Mark Ⅰ characterizes the creative destruction as a widening pattern that relates to technological ease of entry in an industry and main roles played by new firms in the innovative activities. Schumpeter Mark Ⅱ denotes the creative accumulation as a deepening pattern that has presence of technological entry barriers to new entrants in an industry and prevalence dominant roles of established and larger-size firms. According to this theory, the first pattern of "widening" form implies innovative activities that enlarge the entry of new entrants but erode the technological advantage of the established firms. A deepening pattern of innovation, however, considers the dominance of large firms which continuously invests learning process through the accumulation over time of the technological or knowledge advancement. Hence, following Schumpeter's idea, we believe that deliberating different patterns of innovative activities has to consider different conditions of environment control because these given conditions may distinguish constrains to guide firms how to operate. This suggests that different patterns of innovative activities require different technological regimes thinking (Breschi, 2000). Having reviewed the basis of Schumpeter's patterns, the relations discussed between environmental conditions of the technological regimes and firms' operations are now offered.

2.7 Technological Regime and Innovative Entry

Scholars who advocate an industry life cycle tradition argue that evolution of industries changed follows specific dynamic of Schumpeterian patterns (Klepper, 1997). Such a statement explains that industry evolution starts from Schumpeter Mark Ⅰ and it eventually turns into a Schumpeter Mark Ⅱ. This shift suggests industries knowledge and technological progress may change because of a new regime emerged. Specifically, in the early stage of the industry life cycle, while the environment is uncertainly, the knowledge accessibility opportunity is high, the appropriability protection is weak, the cumulativeness condition is low, and then high degree of innovative entry may take place. This implies that new entrants play major elements in industrial dynamics. Oppositely, when the industry develops matures, environmental situations follow well-defined trajectories as well as learning curves, established firms and presence of high barriers to entry for new firms occur in this stage. This regime is obviously characterized by the dominance of stability, suggesting that the knowledge accessibility grows into weak opportunity, the appropriability condition becomes strong protection, the cumulativeness condition associate with high stable, and these conditions have limit the degree of innovative entry for new entrants. As prior theoretical models show (Jovanovic, 1982; Winter, 1984), the higher opportunity condition provides potential new entrants with available knowledge accessible possibilities that affect their innovative entry in a positive way. Hence, based on the argument, we postulate higher opportunity condition is positively associated with degree of innovative entry.

H1: The higher opportunity condition is positively associated with the degree of innovative entry

Ceteris paribus, the high degree of cumulativeness allows for lower degree entry of new entrants. Specifically, higher cumulativeness suggests high degree of stability and it considers continuities in developing innovative activities (Dosi, 1995). In such a situation, the selection process favors the established firms having accumulated technological knowledge and capabilities that build up innovative advantages to act powerful barriers to new entrants and maintain their top industrial positions (Breschi, 1997). (Winter, 1984) argued that higher cumulativeness of technical advances implies that established firms increasingly build on their existing innovations that affect the rate of innovative entry. Therefore, we postulate higher cumulativeness condition is negatively associated with the degree of innovative entry.

H2: The higher cumulativeness condition is negatively associated with the degree of innovative entry

Ceteris paribus, the higher appropriability condition decreases the degree of entry of new entrants. The high degree of appropriability constrains the extent of knowledge spillover and allows successful firms to maintain their innovative advantages. This is expected to result in higher level of industrial concentration and a lower number of innovators. Conversely, low appropriability condition may lead to the presence of a large population of entrants. As previous theoretical models have shown (Jovanovic, 1988; Nelson, 1982), the higher appropriability of condition allows greater advantages to established firms and leads to a greater concentration of innovative activities. This high degree decides the low rate of innovative entry for new entrants. Therefore, we postulate that higher appropriability condition is negatively associated with the degree of innovative entry.

H3: The higher appropriability condition is negatively associated with the degree of innovative entry

Knowledge complexity plays a major role in integration and specialization of innovative activities. It is expected that the more complex the knowledge base is, the stronger need of integration mechanisms for firms to access and connect diverse knowledge elements. In the case that knowledge base is too complex to develop by a single firm, firms have to identify the scope of knowledge specialization and also choose collaboration partners to process knowledge out of the scope. While established firms have advantages on existing field of knowledge, new entrants tend to be more specialized in emerging fields of knowledge. The R&D collaboration among biotech firms and pharmaceuticals is a typical example that how established firm rely on new entrants to deal with complex knowledge (Orsenigo et al. 2001). We predict that the high degree of knowledge complexity increase the needs of collaboration between established firms and new entrants and therefore encourage new entries.

H4: The higher knowledge complexity is positively associated with the degree of innovative entry.

3. METHOD

3.1 Data and sample

The empirical setting for this study includes pharmaceutical industry (SIC is 2834) and semiconductor manufacturing industry (SIC is 3674) in the period 1976 to 2008. A number of reasons motivated the choice of these two industries. First, both pharmaceutical industry and semiconductor manufacturing industry are knowledge intensive. Second, frequent patenting activities and patent litigation indicate that most firms in these two industries prefer formal appropriability method. Patents are not only a method to protect technological advantages but also a tool to codify and distribute knowledge Therefore, we believe that the knowledge structure, modeled by patent data, preserve the underlying technological regime conditions. The key dependent variable and independent variables are based on patents granted by U.S Patent Office (USPTO). USPTO provides a terrific patent database with substantial technical information across industries over a long time period. Patent data represent a very homogeneous measure of innovation across industries and are available for long time series. We take advantage of detail information of patent provided by USPTO database such as application date, grant date, inventors and owners (assignees) of patent, and technical information including patent class and reference prior art.

A patent classification is a code which provides a method for categorizing the invention. Each patent must receive one primary classification and one or many secondary classifications based on a patent's claims disclosed in patent application. Classifying examiner appraises the main inventive concept of the claims and then assigns the primary classification. Secondary classifications are then assigned to all additional invention information disclosure.

3.2 Model knowledge structure of focal industry

Prior studies have viewed technology classes assigned to patents as the knowledge elements of industry's knowledge base (Fleming and Sorenson, 2001; Yayavaram & Ahuja, 2008). While two classes are assigned together to a patent, it implies that two knowledge elements jointly contribute to a new invention. These two elements are interrelated because they have to coordinate or complement to each other in order to fulfill desired functions. In this study, we consider the patent class co-assignment between primary and secondary patent class as the coupling of knowledge elements.

The knowledge structure of an industry is therefore modeled by the aggregation of all class co-assignment found in industry knowledge base. An industry's knowledge base at t is assumed to consist of all the patents that the industry has accumulated during $t - 3$ to $t - 1$ years. To ease the computation of knowledge base, we choose only fifty patent classes of each industry as the most important knowledge elements. Only patents assigned to top-50 patent classes are considered to constitute the knowledge base of a focal industry. Since, in general, patents assigned to top-50 patent classes cover more than 80% patents of a focal industry, the main structure and key characteristics of an industry's knowledge base are well extracted.

Figure 1 illustrates class co-assignment relationship viewed as a network. Assuming the knowledge base of a certain industry in a specific time period consists of four knowledge elements, we use four nodes to represent four knowledge elements and ties between nodes to represent class co-assignment relationship. Theoretically, there are six possible pairs for class co-assignment. However, not every pair can be observed in the knowledge base if a pair of two classes has not yet been co-assigned to any granted patent. The unconnected pairs therefore indicate opportunities for future inventions that combine existing knowledge elements by novel ways.

Figure 1 also shows that two firms sharing the same set of knowledge elements have different pairs of knowledge combination. Both firm A and firm B recognize the interrelationship between class 714 and 713 as well as the interrelationship between class 714 and 257. In other words, firm A overlaps firm B' knowledge structure on these two class-pairs and vice versa. However, there are some other mismatch class-pairs. For example, the co-assignment between class 257 and 370 is not found in firm A's knowledge base but found in firm B's knowledge base. In contrast, the co-assignment between class 713 and 370 was found in firm A's knowledge base but was not found in firm B's knowledge base.

<<INSERT Figure 1>>

3.3 Measures

Annual innovative entry of a focal firm in year t is measured by the total number of firm innovative entries in industry-related classes in year t. For each firm, we identify its innovative entry into a technology class by its first patent of which primary class is assigned to the class. In other words, before the innovative entry, a firm has no patent activity in the target class no matter how long has the firm been established. Among 174 sample firms, 15 firms apply patents in only one class. Remaining 158 firms have 2,322 diversified innovative entries.

Opportunity condition is defined as ease of exploration. Viewing class co-assignment pairs as knowledge combinations, it is assumed that previously unconnected class-pairs indicate new opportunities for knowledge combinations (Fleming et. al,, 2007). The level of opportunity in a focal industry in year t is therefore measured as the number of unconnected class-pairs that remains in focal industry's knowledge base. To calculate the measure, we stepped through the class co-assignments and identified the first appearance of a previously unconnected class-pairs.

Cumulativeness condition is defined as favor of exploitation of existing technologies along a certain path. While cumulativeness condition is relatively high in an industry, it is expected that the concepts of new patent mainly rely on prior patents that perform similar functions. The value of new patent falls in incremental improvement of existing processes or products. Since the primary class of a patent indicates the main function a patent designed for, a new patent exploiting more existing knowledge in the same technological field should cite more prior patents that were assigned to the same class as the new patent's primary class. Therefore, we assume that higher portion of same-class backward citation implies higher level of cumulativeness. Patent-level same-class citation ratio is the ratio of the number of same-class backward citations to the total number of backward citations made by a patent. To calculate industry level same-class citation ratio in year t, we average patent-level same-class citation ratio by total number of industry-related patents which were applied in year t-3, t-2, and t-1.

Appropriability condition is defined as difficulty of imitation. From the perspective of knowledge structure, firms differ in what knowledge elements constitute a firm's knowledge base and in how knowledge elements are connected to each other. In industries that new inventions cannot not be easily imitated by competitors, we expect that each firm possesses distinctive knowledge structure to its competitors. In contrast, if the knowledge of new inventions easily spill over an industry, firms in the focal industry share similar knowledge structures. A firm's knowledge structure is highly overlapped by other firms.

We proxy the difficulty of imitation in a focal industry in year t by the inverse of overall similarity of knowledge structure among top five firms in the focal industry. Overall similarity is the summation of S_{ij}, which denotes the degree that firm i's knowledge structure is overlapped by firm j's knowledge structure. To calculate knowledge similarity S_{ij}, we first identify the total number of class-pairs found in firm i's knowledge structure (CP_i) and then identify the number of overlapped class-pairs, i.e. class-pairs found in both firm i and firm j's knowledge structure (CP_{ij}). The knowledge similarity Sij is the ratio of CP_{ij} to CP_i. One remark here is that S_{ij} differs to S_{ji} because CP_i and CP_j are different. The overall similarity among top 5 firms can be formulated as follow.

$$Overall\ Similarity = \sum_{j=1}^{5}\sum_{i=1}^{5} S_{ij} = \sum_{j=1}^{5}\sum_{i=1}^{5} \frac{CP_{ij}}{CP_i}$$

Knowledge complexity is defined as the degree of integration among different scientific disciplines and technologies. At patent level, knowledge complexity is measured by the average number of assigned classed per patent. To calculate industry level knowledge complexity in year t, we average patent-level knowledge complexity by total number of industry-related patents which were applied in year t-3, t-2, and t-1.

4. RESULT

Table 1 shows the descriptive statistics and correlations for all variables. The correlation coefficients in Table 1 revealed that there is slight multicollinearity among cumulativeness and appropriability (correlation coefficient exceed 0.60). In order to assess the extent of multicollinearity, the variance inflation factor (VIF) was computed. The VIFs ranged from 1.128 to 1.754, which are significantly below the cut-off value of 10, and therefore suggested that the multicollinearity is not problematic in our models.

<<INSERT Table 1>>

Results of the negative binomial regression model was presented in Table 2. As the control variable, number of granted patent has positive effect on innovation entry. Opportunity condition (H1) have a significant positive effect on the degree of innovative entry, providing support that higher level of technological opportunities encourage more innovative entries. Cumulativeness condition (H2) has a significant negative effect on the number of innovative enter in year t, providing support that the higher level of cumulativeness decrease the number of innovative entry. The prediction of negative effect of appropriability condition (H3) is also supported. Knowledge complexity (H4) has a significant positive effect on the degree of innovative entry, providing support that higher level of knowledge complexity increase the propensity of innovative entries.

<<INSERT Table 2 >>

5. DISCUSSION and CONCLUSION

This study examines the effects of four technological regime conditions on the propensity of innovative entries in knowledge-intensive industries. From the perspective of knowledge structure, we view technological regime as the underlying knowledge environment of an industry that governs the technological opportunities and incentives for firms to innovate in new-to-firm technological domains. The empirical results confirm the theory of Schumpeter Mark Ⅰ & II patterns. Higher level of opportunity condition and lower lever of cumulativeness condition encourage new firm entries in new technological domains.

While the formal method of appropriability (i.e. patent application and litigation) is highly valued in knowledge intensive industries, the empirical results confirm that higher level of appropriability deters firms entering into new technological domains. If new knowledge is strictly protected and only very few firms enjoy the benefit of technological advance, entering into new areas are risky. In other words, the efficiency effect still has its role in knowledge intensive industries.

The role of knowledge complexity in knowledge intensity industries is also confirmed by the empirical results. More characteristics of knowledge base can be investigated in future studies since patent class co-assignment provide a new approach to model knowledge structure of knowledge base.

Our results also show that the innovation patterns in semiconductor and pharmaceutical industries are different. Following previous findings from (Malerba & Orsenigo, 1993), these both two industries of pharmaceutical and semiconductor are characterized by similar technological regime. This suggests that they have homogeneous patterns of innovation behavior in responding to their idiosyncratic situations. However, many literature have demonstrated that these two pursue different innovative patterns to face their technological change (Achilladelis & Antonakis, 2001; Orsenigo, Pammolli, & Riccaboni, 2001; Wang & Chiu, 2014). Examine technological regime from knowledge structure does provide finer measures of technological regime that differentiate industries in knowledge intensive sectors.

This study contributes to technological regime research by introducing knowledge structure as a new approach to subjectively model the knowledge environment proposed by Winter & Nelson (1984). This approach enable researchers better explain the technological regime in knowledge-intensive industries, such as pharmaceutical industry and semiconductor manufacturing. Analyzing technological regime on the basis of patent class allow us to distinguish the knowledge environment from industry environment and therefore clarify the pure effect of technological regime.

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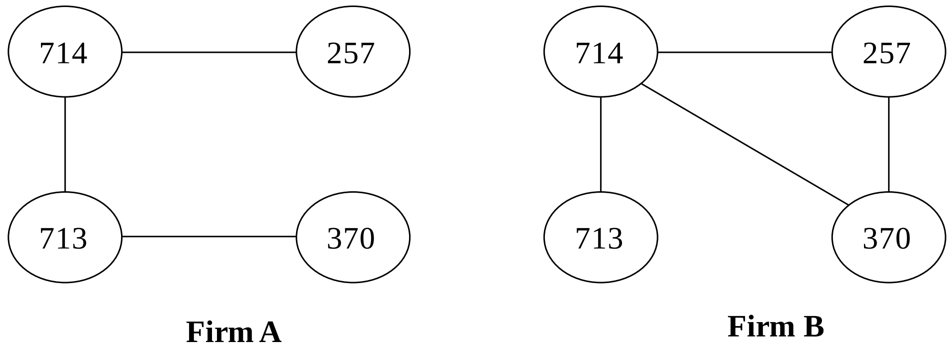
Figure 1 Technology class co-assignment relationship viewed as a network.



Note: Nodes represent technology classes. The 3-digit numbers in nodes are US patent class codes. Ties between nodes represent class co-assignment between technology classes. A pair of connected nodes represents a pair of coupled knowledge elements.

Table 1 Descriptive statistics

		Mean	Std	1	2	3	4	5	6
1	Innovative entry	57.48	53.22	1.00					
2	Patent	6858.17	8503.15	0.55	1.00				
3	Complexity	105.15	71.01	0.36	0.19	1.00			
4	Opportunity	0.47	0.07	-0.37	-0.59	0.23	1.00		
5	Cumulativeness	5.25	0.51	0.07	-0.15	-0.33	-0.13	1.00	
6	Appropriability	0.10	0.02	-0.23	-0.33	0.08	0.73	-0.04	1.00

Table 2 Results of Negative binomial regression

DV=Innovative entry			
	Coefficient	**P-0value**	
Constant	-5.30847	0.000	***
Patent	-9.23E-06	0.392	
Dummy(Semiconductor)	1.841088	0.000	***
Opportunity	0.0087113	0.000	***
Cumulativeness	-5.068855	0.004	***
Appropriability	-7.678357	0.057	*
Complexity	1.979414	0.000	***
Log likelihood	-283.669		
Pseudo R2	0.149		
Obs.	66		

*p<0.1;**p<0.05;***p<0.01