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Heterogeneous Combinations of Knowledge Elements: How the Knowledge Base Structure Impacts Knowledge-related Outcomes of a Firm*

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Heterogeneous Combinations of Knowledge Elements:

How the Knowledge Base Structure Impacts Knowledge-related Outcomes of a Firm[1]

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Abstract

Knowledge is the preeminent resource of a firm. Although many scholars have focused on the firm's knowledge base, few studies have examined the effects of the knowledge base structure—how knowledge elements are linked or separated from each other in clusters—on firm's knowledge-related outcomes. This study examines the knowledge base structure, and tests hypotheses about the effects of heterogeneous combinations of knowledge elements on the outcomes. Through an analysis of the patents related to LCD technology, (1) the usefulness of an organization's inventions correlates positively with the density of the knowledge links between technologically different knowledge components, (2) the average usefulness of a firm's inventions correlates positively with the density of the knowledge links between technologically disparate knowledge components, (3) the number of inventions correlates negatively with the density of the knowledge links between excessively disparate knowledge components.

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1. Introduction

For a company to gain competitive advantage, it must differentiate itself from its competitors. To this end, considerable research has been conducted, including examining difference from a resource-based view of the firm and, in more recent studies, employing a knowledge-based view of the firm (Grant 1996; Conner and Prahalad 1996). To date, various researchers have investigated how the characteristics of accumulated knowledge within organizations modulate the performance of knowledge creation activities of organizations, considering the effects of related dimensions and outcomes (Yayavaram and Ahuja 2008; Ahuja and Katila 2001).

Many scholars have focused on the quantitative aspect of the knowledge base. For example, the size of the knowledge base of the organization has positive effects on its outcomes (Henderson and Cockburn 1996; Pakes and Griliches 1984). Furthermore, the size of the knowledge base is also related to the success of mergers and acquisitions. When a company is acquired, there is a positive relationship between the size of the acquirer's knowledge base and the acquired company's subsequent output of innovation (Ahuja and Katila 2001). If an organization has a broad knowledge base, it also has greater ability to explore external knowledge (Brusoni et al. 2001; March 1991).

The knowledge base's qualitative aspect as well as its quantitative aspect has drawn the attention of researchers. For instance, recombination or refinement of familiar combinations of knowledge elements increases an invention's usefulness (Fleming 2001). The extent of a firm's absorption of technological capabilities from its alliance partners is positively related to its pre-alliance level of technological overlap with partner firms (Mowery et al. 1996). Lane and Lubatkin (1998) proposed that elements of a knowledge base can be classified into two categories: basic knowledge and specialized knowledge. The former refers to a general understanding of a discipline's underlying traditions and techniques. The latter includes all the remaining elements. According to these authors, in the case of a biotechnology company, the basic knowledge comprises things relevant to biochemistry, whereas the specialized knowledge is any other knowledge. The relevance of a student's basic knowledge of the firm to a teacher's knowledge base of the firm is positively associated with inter-organizational learning (Lane and Lubatkin 1998).

Most studies regarded the knowledge base of an organization as an aggregation of "knowledge components" (Grant 1996). Ahuja and Katila (2001) operationalized a company's knowledge base as the aggregation of patents earned and patents cited by a company. Patents are new intrinsic knowledge components, and they bring together past learning represented by patents cited to form an organization's knowledge base. Therefore, they are recognized as an aggregation of separate knowledge components (in the form of previous patents) that comprise the knowledge base. Fleming and Sorenson (2001) also argued that a knowledge base is an aggregation of knowledge components. Diversification of knowledge components increases the uncertainty surrounding the optimal combination of various components. Taylor and Greve (2006), who cited this assertion, considered the impact of diversity of an individual's and group's knowledge base on the creativity of the individual and group writing comic books.

In contrast to the research described above, a groundbreaking study by Yayavaram and Ahuja (2008) addressed the structural aspect of the knowledge base. The knowledge base structure links different knowledge elements or separates them in clusters. The point Yayavaram and Ahuja (2008) make is that even for organizations with knowledge bases composed of identical knowledge components, if the combination of the components is different, the results differ for knowledge bases. A study on the worldwide semiconductor industry revealed inter-organizational and inter-temporal differences in the organization knowledge structure, and proved that the level of the knowledge structure decomposability affects knowledge-related outcomes of the organization. More specifically, there exists an appropriate level of density of the total connections between the components of a knowledge base, and too high or too low a total density of the connections can negatively affect knowledge-related outcomes (Yayavaram and Ahuja 2008).

Various studies have focused on the quantitative and qualitative aspects of the knowledge base regarded as an aggregation of knowledge components. In contrast, Yayavaram and Ahuja (2008) analyzed the knowledge base structure. Because this was an epochal study, it warrants further research. In contrast to research on knowledge components, the qualitative aspects of knowledge structure is promising, and thus address the latter issue.

This paper is organized as follows. Section 2 poses hypotheses. In general, invention is a process of recombination of new or existing elements. Knowledge components of a firm's knowledge base are heterogeneous. Integration of knowledge components for invention can be more difficult when the components to be integrated are strongly heterogeneous. This study takes into account the effect of the heterogeneity of knowledge elements on the firm's knowledge-related outcomes. Section 3 describes the technological fields analyzed and the data retrieval method. Section 4 states the empirical results of the data analysis. Section 5 discusses the results, and concludes it.

2. Hypotheses

Innovation, an important determining factor in the continued maintenance of a corporation's competiveness, is the recombination of existing concepts, physical materials, and power, not simply a new combination of existing components of technology to invent new technology. Other forms of innovation include a new combination of technology and markets and the innovation of organizations (Nelson and Winter 1982; Schumpeter 1934). To simplify the discussion, we focus on the invention of a new technology.

Decomposability of Knowledge Structure and Outcomes

One representative view in the history of technology conceptualizes invention as a process of recombination (Fleming and Sorenson 2004; Fleming 2001). According to this perspective, the inventor is searching for a new combination of technology components (Weitzman 1996; Basalla 1988) and reconfiguring existing combinations (Henderson and Clark 1990). Here we refer to knowledge and basic bits of matter as technology components that the inventor uses during the invention process (Fleming and Sorenson 2004). The primary function of research and development (R&D) is to combine differing technology components to create new knowledge (Fleming 2001; Kogut and Zander 1992).

In order to invent, an organization must create and recombine technology components. When the variety of an organization's knowledge elements in its knowledge base increases, the number of potential recombinations also increases. The essence of organizational capability is the integration of specialized knowledge components (Grant 1996). An organization with a knowledge base comprising diverse knowledge components can invent things that yield greater value because of the greater number of possible combinations. Many researchers have analyzed the relationship between an organization's knowledge-related outcomes and the number of knowledge components (Ahuja and Katila 2001; Fleming 2001; Lane and Lubatkin 1998; Mowery et al. 1996).

Although most researchers have focused on the components that constitute knowledge bases, Yayavaram and Ahuja (2008) examined the impact of the knowledge base structure on knowledge-related outcomes. Their arguments are as follows.

The knowledge base structure links different knowledge elements or separates them in clusters. For example, consider the case of semiconductors. Viewing semiconductors as a combination of a material (silicon) and a given architecture (CMOS) is obvious, and the material and architecture for use can be decided separately. With two knowledge components, a person deciding on the solution to a problem either considers the two knowledge components as a combined single unit of knowledge or each knowledge element independently. Determining whether it is most appropriate to consider two knowledge components simultaneously involves an organization's reasoning process. The choice to consider two components simultaneously (link them in the knowledge base) does not depend on whether there is always a strong interdependence of technologies; rather, choosing whether to link both components together as a chunk depends on the organization's human decision-making characteristics (Simon 1996).

Organizational variations in coupling patterns between knowledge elements is reflected in a spectrum of the knowledge base structures, from non-decomposable through nearly decomposable to fully decomposable. The non-decomposable (integrated) structure is one with no emerging knowledge clusters, as the couplings are pervasively distributed. The nearly decomposable structure means that the knowledge clusters are discernible but connected through cross-cluster couplings. The fully decomposable structure refers to the knowledge base composed of distinct clusters of coupled knowledge elements with no significant link between clusters.

An organization can achieve significant outcomes by successfully combining deep knowledge in a particular field with broad knowledge (Macher and Boerner 2006; Katila and Ahuja 2002). Nearly decomposable knowledge bases permit both breadth and depth of search, and provide the benefits of exploration both within a cluster and across clusters. Therefore, the nearly decomposable knowledge structure provides the highest outcome of these three levels (Yayavaram and Ahuja 2008).

Heterogeneous Combinations of Knowledge Components and Outcomes

Past research about firms' knowledge bases can be classified into two categories. First, there are the studies on the variation of the knowledge components comprising the knowledge base. Second, many researchers have addressed component quality. The latter line of research has concentrated on the relatedness or similarity of knowledge elements with those of other organizations. Although the study by Yayavaram and Ahuja (2008) was groundbreaking in that they focused on the knowledge base structure, they had certain commonalities with the former line in that they did not consider the heterogeneity of the knowledge base elements. They operationalized the knowledge base structure by the density of links, which depends on the number of connections between knowledge components but regarded each component as faceless.

However, heterogeneity of the organization elements can affect its outcomes. For example, suppose that several organizations exist, one composed of Americans and Canadians and another composed of Taiwanese and Chinese, each obviously with less diversity than an organization composed of American, Canadian, Taiwanese, and Chinese. The first two organizations are more homogeneous than the third because members of the first two organizations have similar cultural backgrounds. It is safe to assume that harmonizing the members of the first two is much easier than the third, but the third organization's cultural diversity may make it more innovative than the first two.

Similarly, a knowledge base contains disparate knowledge components to achieve higher innovation potential.

An individual's learning is greatest when the new knowledge to be assimilated is related to the individual's existing knowledge structure (Lane and Lubatkin 1998; Bower and Hilgard 1981). Individuals who have the same basic knowledge can communicate and understand each other relatively easily. To understand new knowledge, individuals or firms must possess some amount of basic prior knowledge (Lane and Lubatkin 1998). Mastering the basic knowledge for an area facilitates understanding of the relevant more advanced knowledge components. Generally speaking, the wider the scope of knowledge being integrated (and thus the greater the diversity of individuals involved), the lower is the level of common knowledge, and the more inefficient the communication and integration of knowledge (Grant 1996). When considering the possibility for recombining knowledge components, if they are closely related technologies, it can be easier to evaluate the anticipated value of combining them, and there will be fewer obstacles to integrate them.

A firm's primary role, and the essence of organizational capability, is the integration of knowledge (Grant 1996); thus, the knowledge base's wealth of diversity leads to invention. However, diversity can also inhibit component integration for invention. In this complicated context, an invention borne out of the integration of highly diversified knowledge components enables firms to differentiate themselves from their competitors. On the one hand, in order to put the pieces together, if technologically different components are considered as a chunk, firms can make useful inventions. However, if the difference among components in a chunk is excessive, although the value of an invention increases, the number of inventions decreases. The foregoing discussion implies the following hypotheses.

Hypothesis 1a: The number of inventions is positively related to the density of knowledge links between different knowledge components.

Hypothesis 1b: The number of inventions is negatively related to the density of knowledge links between excessively different components.

Hypothesis 2a: The average usefulness of inventions is positively related to the density of knowledge links between different knowledge components.

Hypothesis 2b: The average usefulness of inventions is more strongly positively related to the density of knowledge links between excessively different knowledge components than to the density between moderately different components.

Given that the knowledge-related outcome of a firm is dependent on the quality and quantity of its inventions, the outcome will be higher when the knowledge base structure exhibits dense links among different components. However, when the degree of the difference between components to be linked is excessive, although the quality of the inventions will increase, the number of inventions will decrease. In that situation, the relationship between the density of the links between disparate components and the firm's knowledge-related outcome is unclear.

Hypothesis 3: The knowledge-related outcome of an organization is positively related to the density of links between different components, but when the difference between components to be linked is excessive, one cannot predict the explicit relationship between the density of links and the knowledge-related outcome.

3. Method

Empirical analysis focuses on the global liquid crystal display (LCD) industry for two reasons. The first reason is that LCDs have had various applications since the 1970s, such as their use in calculators, watches, laptop monitors, personal computer monitors, and televisions. The variety of applications continues to increase; thus, technology development in LCDs plays an important role in determining a company's competitiveness. The second reason is that manufacturing the LCD components requires a high level of technology, such as liquid crystal materials, thin film transistors (TFTs), drivers for LCDs, polarizers, color filters, glass, and backlights. Although LCD is a single product, it requires various types of technological elements, making it appropriate for testing the hypotheses of this study.

The data used in the empirical analysis are U. S. patents. While this study uses patent data filed since 1976, as described below, the structural indicator for knowledge bases for year *t* are composed of the sum of the prior three years (t-3 to t-1); thus, the outcomes analyzed are from 1979 onwards. In addition, considering the necessary time lag between patent filing and registration, patent filings up to the year 2002 were analyzed. There are various limitations in the information on patent citations (Jaffe and Trajtenberg 2002; Griliches 1990). For example, depending on the industry and products involved, the appropriability of innovations based on patents gained varies (Levin et al. 1987), and differences also exist in the patentability of technology and the ratio of citations (Hall et al. 2001). Because the following analysis is limited to specific technologies, these factors should not present a serious issue.

We extracted all patents registered with the USPTO for technology related to LCDs (search date July 13, 2011) using the Thomson Innovation database (Thomson

Reuters). A sample of how this technology category was extracted is the category use identified as “LCD technology-related” patents by the Derwent World Patent Index. The extraction retrieved 8,770 patents and from these, 2,419 patents were used for the analysis. The information provided in the database for each patent includes the name of the company (and the inventor’s name), filing date, registration date, the literature cited in the patent (patents, scientific literature), technical classification of the patent (U.S. classification, international classification), and other items. We used the international patent classification (IPC) to construct our key variables. In the rapidly evolving field of LCD technology, the acquisition of patents is extremely important for competitiveness (Spencer 2003); therefore, companies that have not acquired patents are not considered central players in the industry and are excluded from the analysis. In addition, this study limits its focus to manufacturers of LCDs, companies that have manufactured LCDs in the past, or companies that have established a subsidiary for the purpose of manufacturing LCDs; other companies, such as those specializing in technology development and acquiring patents for purposes thought to be different are excluded. We based this distinction on newspapers, magazines, and company annual reports.

Variables

Dependent variables. Three dependent variables are used in this study. The number of inventions in the year t by the firm j is measured by the number of patents. Patent citations are the key indicators used to measure the quality of the patents (Yayavaram and Ahuja 2008; Hall et al. 2001). If a patent has been cited by other patents many times, it indicates that the patent resulted in a change in technology and has had a significant impact on the society (Jaffe and Trajtenberg 2002). Here, as in many previous studies, the number of patent citations was used as a variable to represent the usefulness of an invention. The knowledge-related outcome of the firm j in the year t is measured by the number of times the patents has been cited by other patents in subsequent years. The average usefulness of the inventions in the year t by the firm j is measured by the citations' median.

Independent variables. In this study, a firm's knowledge base or patent portfolio at t is assumed to comprise all patents that the firm has accumulated from t-3 to t-1 years (Yayavaram and Ahuja 2008). For example, if the sample contains the knowledge creation outcomes of the firm j in the year t, this means that the firm j filed for one or more of the patents under consideration each year for four consecutive years (t-3 to t). There are repeated entries of new firms, exits of existing firms, and M&A in the LCD business. This study analyzed only companies performing stable R&D.

As an indication mark for later retrieval, each patent is given a unified international classification code indicating the related technology field, not classifications peculiar to individual countries. For international classifications, the hierarchical order is section, class, subclass, main group, and subgroup. This study uses the international classifications published in the January 2006 edition. Subclass, which is in the middle of the hierarchy, is used as the unit of analysis—knowledge components.

A patent is not limited to one classification alone; if a patent covers multiple fields of technology, it is allotted classification codes for each field. If two knowledge components are extracted for an organization, i.e., if an organization has been recognized to have combined two components, the organization must have produced an invention by combining the two components. Thus, it is possible to observe from their patent portfolio whether the company's knowledge base contains two knowledge components that have been combined (Yayavaram and Ahuja 2008). The technology classification of a patent can be determined from the past accumulated technology and by comparing the citations of past related patents by the inventor; the bias can be considered small (Yayavaram and Ahuja 2008). When a patent is given multiple subclasses, there exists a connection between each knowledge component, and thus the knowledge base technology classifications that are connected filings are considered to be knowledge links.

To derive the knowledge links, we used the association analysis data mining method. An application of association analysis is the retail point-of-sale data, which is used to extract information about products that tend to be bought at the same time. An association rule refers to the situation in which event B occurs whenever event A occurs. The greater the frequency of both event A and event B occurring together, the stronger the association rule. Three representative indicators are used to evaluate the association rule. The first is confidence, indicating the probability that B will occur when A occurs in the entire data set. The second is support, the probability of A occurring in the entire data set and the product of confidence. The third is lift, obtained by dividing the confidence by the probability of event B occurring, and representing the improvement that can be made in the predictability of event B occurring when it is examined in combination with the occurrence of event A compared with the independent occurrence of event B. In this study, the algorithm used to perform the analysis "apriori" (Agrawal et al. 1993) employs the R statistical environment data analysis package "arules"

(Hahsler et al. 2005), and derives the two knowledge components' association rules in the knowledge base of the firm *j* in the year *t*. Knowledge links for which the connection is extremely weak are considered exceptional cases; in order to exclude them, we employ commonly used statistical analysis metrics for determining significant levels: confidence of ≥0.01, level of support of ≥0.01, and rate of improvement of ≥1.

On the basis of the foregoing procedure, Figure 1 and Figure 2 display the organizational knowledge base structure in the year 2000 for Sharp and Samsung Electronics, respectively. The filings of the two companies between 1997 and 1999 appear on the vertical axis and horizontal axis, respectively. Among the subclass classification included in the technology categorization of the registered patents, the number of incidences was found to be at least 1% of the total number of the entire knowledge base for each company. The vertical and horizontal axes are the same subclass, and the diagonal line falling from the top left to the bottom right represents the symmetry of the matrix.

Our measure of revealed knowledge structure contains several characteristics. First, we measured knowledge structure directly at the firm level, not as an aggregation of individual knowledge structures. Second, precisely defined measure enables us to observe knowledge structures both cross-sectionally and intertemporally. These characteristics are the same as the Yayavaram and Ahuja measure (2008). Third, we can classify the extent of technological difference between knowledge components into three levels: intra-class, inter-class, and inter-section. From the technological standpoint of the patent classification, subclasses categorized in same class are closer than those categorized in different classes, and are much closer than those categorized in different sections. In Figures 1 and 2, subclasses in the same class appear in dashed boxes, and those in the same section appear in solid boxes.

Insert Figure 1 and Figure 2 here

The difference between Sharp and Samsung Electronics is that Sharp has more knowledge components than Samsung Electronics. Among these components is the technology related to section B "performing operations; transporting," B23K, B26F, B32B, B65D. These technologies are related to transporting large panels. The two figures suggest that Sharp was more enthusiastic than Samsung Electronics about inventions related to the production of large LCD panels. Further, the intersection of G02F with H01J has no knowledge link for Sharp, whereas Samsung Electronics has knowledge links at this intersection. Although these organizations conduct technology development at the same time in the same field, they exhibit differences in their knowledge links.

From the sum of squares in the figures, a diagonal line from upper left to bottom right is drawn through the number of squares (the number of the subclass types) dividing them into two, and we get the number of potential combinations of subclasses. On the basis of the metrics (evaluations criteria) of the association rules, pairs that occur beyond the defined frequency of occurrence (the shaded ones) are knowledge links. Independent variables are the ratio of the number of inter-class links to that of all links (interclass links ratio), and the ratio of the number of inter-section links to that of all links (intersection links ratio).

Control Variables. On the basis of the network theory, Yayavaram and Ahuja (2008) analyzed the effects of the knowledge base structure on the organization's knowledge-related outcome. They applied the concept of density to operationalize the knowledge base variable *level of decomposability*. Density refers to the proportion of links actually present in a network (Prell 2012). It is necessary to control this input measure. Decomposability of the knowledge base is measured as the rate of knowledge links within the number of potential combinations of two subclasses (density of links).

The number of citations may be different for each technology field. There may be more citations for technology in fields in which it is easy to patent technology or in fields on which attention is focused during the period under consideration. Therefore, it is necessary to consider the ease of citation for each technology field (Yayavaram and Ahuja 2008; Fleming and Sorenson 2001). Specifically, first, all the patents related to a single field, LCDs, are considered. Second, the averages for the year and class of the total number of citations are calculated. Third, all patent filing classes for the firm *j* in the year *t* are extracted, and the sum of the product of the average number of citations and occurrences for each class is calculated. Differences in trends in relation to the number of citations for each technology field are controlled (technology control). Because subclasses belonging to different classes are viewed as disparate elements in this study, technology control is calculated on a class basis.

In relation to an organization's technology development, the size of the knowledge base will vary—the greater the development, the larger the base. When there are greater technology development activities, more knowledge resources are invested in technology development, and there is a positive relationship between the magnitude of this investment and the outcomes, indicating that the size of the knowledge base (Ahuja and Katila 2001) based on a three-year patent portfolio.

If a significant amount of funds is invested in technology development, more resources can be devoted to the process of search and discovery, and better outcomes can be anticipated (Henderson and Cockburn 1996). Thus, controlling the differences in human resources and funds invested in the development of LCDs is necessary. However, many LCD manufacturers are diversified corporations, clouding the determination of the percentage of overall R&D spending devoted to LCDs. In addition, variation among the definitions of the LCD-related business units among these corporations makes comparing revenues across corporations difficult. Therefore, this study controls for differences in resources invested in R&D, using the number of inventors involved in related inventions. Specifically, patents for the firm j in the year t list the inventors, and using the full names of the inventors allows any duplication to be eliminated.

Control variables are also added to evaluate the number of classes in a knowledge base because the diversity of knowledge components in the knowledge base can have a positive effect on the knowledge-related outcome of the organization.

Statistical Analysis

The dependent variable is count data. Because the variance is approximately equal to the mean, Poisson regression analysis was performed. The result of the random effect model has been displayed in Table 2; the results were not significantly different, estimated by the fixed effect model.

Insert Table 1 here

4. Results

Table 2 presents the results of hypothesis testing for three types of dependent variables. Model 1, Model 4, and Model 7 display the results for the control variables. In Model 2, the interclass link ratio was inserted into Model 1. Thus, hypothesis 1a is not supported. In Model 3, the intersection link ratio is inserted into Model 1. The increase in the ratio of intersection links negatively influences the number of patents; thus, supporting hypothesis 1b. Next, the interclass link ratio in Model 4 was added to Model 5. The interclass link ratio has a positive influence on the median of citations; thus, supporting hypothesis 2a. The intersection link ratio in Model 4 was added to Model 6. The intersection link ratio positively influences the median of citations; thus, supporting hypothesis 2b. Further, the interclass link ratio in Model 7 was added to Model 8 and to Model 9. On one hand, the ratio of interclass links positively affects the number of citations, and the other, the ratio of intersection links positively affects the number of citations too. Consequently, hypothesis 3 is not supported.

Insert Table 2 here

5. Summary and Conclusion

New combination is the source of novelty. An invention can be defined as a new combination of components or a new relationship between previously combined technology components. Knowledge is a firm's critical resource, and organizational capability involves the integration of multiple knowledge components (Grant 1996). Therefore, an organization with a highly-diversified knowledge base can enhance its knowledge-related outcomes. Many researchers have focused on firms' knowledge base, particularly its elements. Yayavaram and Ahuja (2008) were the first to examine the structure by which different knowledge elements are linked or separated from each other in clusters. The present study examines the knowledge base structure considering the elements' heterogeneity.

Through an analysis of the patents related to LCD technology, we established three major findings. First, the usefulness of an organization's inventions correlates positively to the density of the knowledge links between technologically different knowledge components. Second, the average usefulness of a firm's inventions correlates positively to the density of the knowledge links between technologically disparate knowledge components. Third, however, the number of inventions correlates negatively to the density of the knowledge links between excessively disparate knowledge components.

These findings suggest a need for firms to choose a knowledge base creation strategy on the basis of industry or business domain. In industries such as pharmaceutical or bio-chemical, firms need little focus on the quantity of inventions because pharmaceutical firms can earn large profits from a single blockbuster patent and so should concentrate on improving the invention's quality. Therefore, incorporating many disparate elements into the knowledge base and connecting them is beneficial. However, in other industries, such as electronics and automobile, a single patent does not always strengthen the firm's competitiveness. In these industries, firms need a high quantity of inventions as well as high quality inventions. If improving an invention's quality decreases the quantity of patents, it harms firms in these industries. Thus, even though they incorporate disparate elements into the knowledge base, such firms should carefully examine how many disparate elements are added in the knowledge base and how densely they are linked.

Although the results of the statistical analysis are clear, we must interpret them carefully. This study focuses on LCD technology. LCDs comprise a complex combination of various elements. Deep knowledge about each of the technologies that comprise the product and the balance between this knowledge and the knowledge of how to combine them may have special importance for this technology. In contrast, for example, focusing on the combination of parts of a personal computer may lead to different results, and a comparative study involving such a product is clearly one of this study's limitations that has not yet been resolved. In addition, a difference may exist between industries regarding the level of knowledge link density and the level of knowledge component disparity at which the number of inventions decreases. These levels may affect the results of the test about hypothesis 3. Comparisons between industries and technologies are the challenges left for future research.

In this study, a degree of bias may exist as a result of the characteristics of the dataset. Here the subject of analysis was LCD manufacturers. These companies have at least the minimal knowledge required for LCD manufacture or related technology development. Companies that have not reached the stage of LCD production may not have the minimal knowledge required, and an analysis of such companies may produce different results. However, the presence of such a bias can be regarded as inevitable when using patent data sources. Patents are information about inventions resulting from successful technology development. To deal with this type of bias, a study must use other sources of data to complement the patent data in order to verify the results.

Most previous studies suggest that an organization's knowledge base is a collection of components. This study focused on the knowledge base structure and addressed the elements' heterogeneity and its implications for the firm's knowledge-related outcomes. Further research with this perspective may lead to additional productive results.

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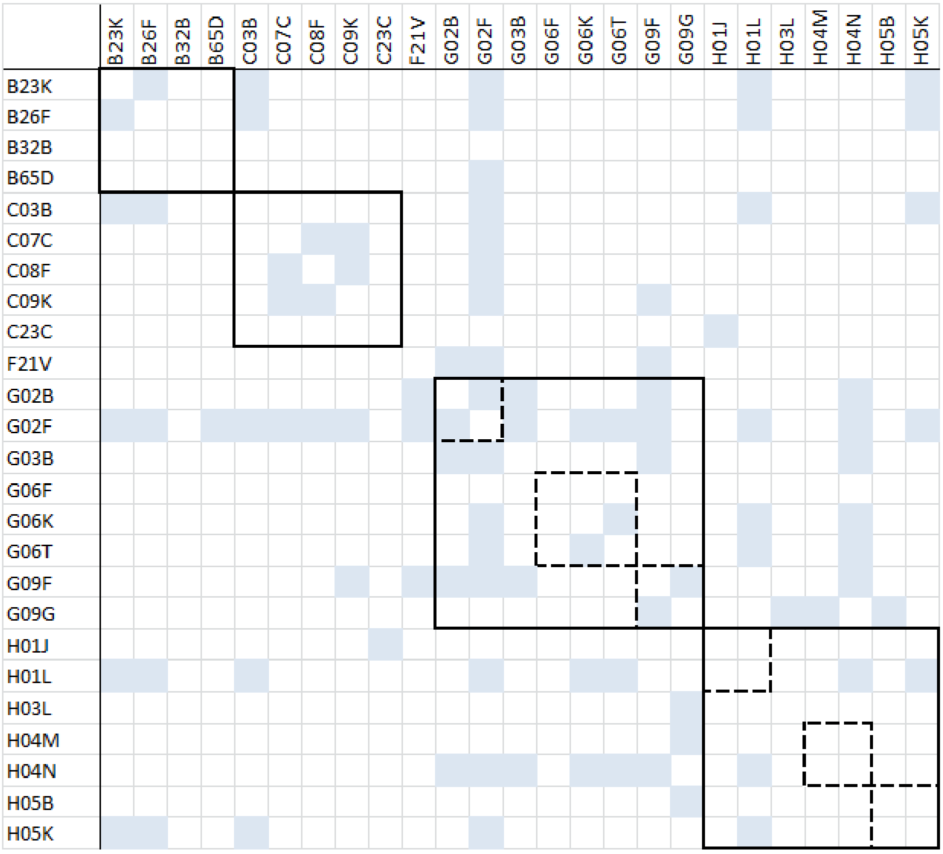

Figure 1: The Knowledge Base Structure (Sharp, 2000)

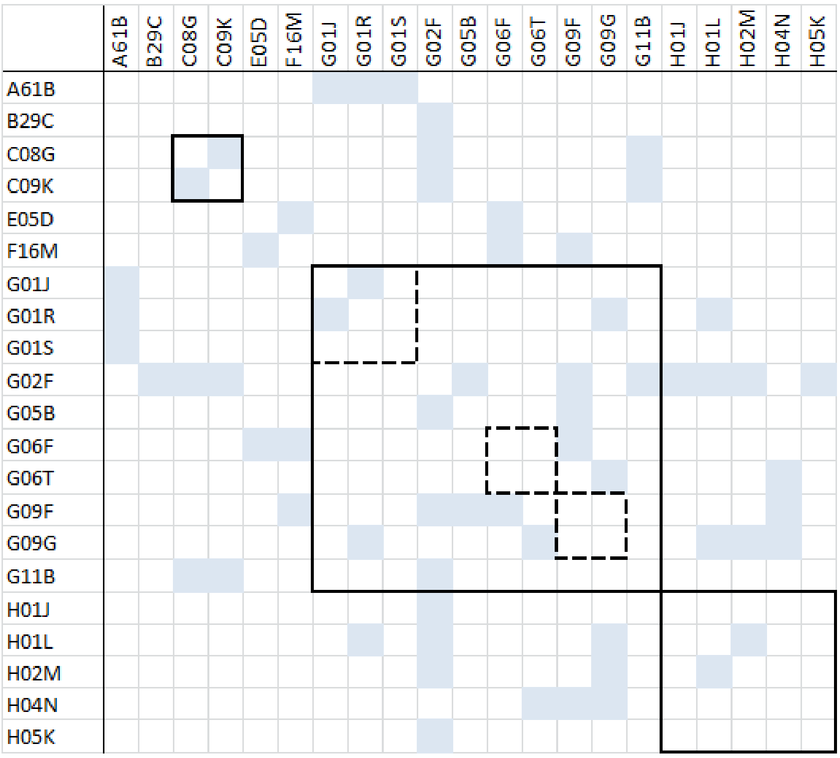

Figure 2: The Knowledge Base Structure (Samsung Electronics, 2000)

Table 1: Descriptive Statistics and Correlations

Variable	Obs	Mean	S. D.	Min	Max	1	2	3	4	5	6	7	8	9	10
1. # Citations	200	139.98	137.636	0	910	1									
2. M Citations	200	14.125	14.134	0	101.5	0.103	1								
3. # Patents	200	9.775	9.681	1	61	0.650	−0.286	1							
4. Interclass link ratio	199	0.911	0.086	0.5	1	0.137	0.098	0.082	1						
5. Intersection link ratio	199	0.543	0.173	0	1	0.093	0.036	0.162	0.209	1					
6. Density of links	200	0.318	0.168	0	1	−0.255	0.120	−0.354	−0.073	−0.190	1				
7. Technology control	200	290.147	261.324	5	1639.828	0.883	−0.061	0.717	0.139	0.066	−0.239	1			
8. Knowledge base size	200	167.94	156.508	12	852	0.473	−0.272	0.779	0.080	0.210	−0.435	0.476	1		
9. # Inventors	200	22.03	22.301	1	172	0.560	−0.264	0.849	0.046	0.161	−0.325	0.592	0.691	1	
10. # Classes	200	7.69	3.577	2	20	0.325	−0.275	0.657	0.063	0.208	−0.575	0.339	0.805	0.575	1

Table 2: Results of Poisson Regression Analysis

	Dependent variable = # Patents			Dependent variable = M Citations			Dependent variable = # Citations		
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9
Interclass link ratio		0.126			0.584**			0.957***	
		(0.746)			(0.034)			(0.000)	
Intersection link ratio			−0.389**			0.647***			0.130**
			(0.043)			(0.000)			(0.010)
Density of links	−0.913***	−0.864***	−0.899***	0.361**	0.307*	0.410**	−0.558***	−0.555***	−0.530***
	(0.000)	(0.001)	(0.001)	(0.034)	(0.076)	(0.019)	(0.000)	(0.000)	(0.000)
Technology control				0.001***	0.001***	0.001***	0.001***	0.001***	0.001***
				(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Knowledge base size	0.001***	0.001***	0.001***	−0.000	−0.000	−0.001*	0.000	0.000	−6.23e−07
	(0.002)	(0.002)	(0.001)	(0.235)	(0.220)	(0.092)	(0.485)	(0.383)	(0.993)
# Inventors	0.017***	0.017***	0.017***	−0.021***	−0.021***	−0.022***	0.005***	0.004***	0.004***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
# Classes	0.008	0.009	0.011	−0.035***	−0.037***	−0.027*	−0.024***	−0.024***	−0.022***
	(0.482)	(0.441)	(0.377)	(0.008)	(0.006)	(0.050)	(0.000)	(0.000)	(0.000)
# Observations	200	199	199	200	199	199	200	199	199
# Groups	23	23	23	23	23	23	23	23	23
Log likelihood	−540.763	−538.402	−536.416	−1035.154	−1030.181	−1019.403	−3676.376	−3631.381	−3669.699

Note: $*p<0.1$; $**p < 0.05$; $***p < 0.01$. All models include year dummies.