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Abstract

Given the increasing significance of knowledge spillovers in innovation, this study investigates and compares knowledge spillovers from arm's length firms in the industries (market) with those from other sister firms in the same business group (network). By dividing the knowledge pool into pools within and outside a sector to which a firm belongs, we re-examine the ongoing debate on the relative size of the intra- versus inter-sector spillovers, and address a new question on the relative size of spillovers from networks compared with those from markets. We find that although both intra- and inter-sector spillovers are significant, no evidence proves the dominance of either type of spillover, whether the spillover is from industries or from networks. More importantly, we find that spillovers from networks are greater than those from industries regardless of whether the comparison was made between intra- and intra-, inter- and inter-, intra- and inter, or inter- and intra-sector spillovers. Results imply that knowledge spillover is not automatic but subject to limitations related to the tacitness of knowledge, and that certain types of knowledge can be transferred only through direct interaction, which is more prevalent within a network organization such as a business group.

Keywords: knowledge spillover; network; business groups; productivity; inter-sector; intra-sector; innovation

JEL Codes: D22, D23, D24, D83, D85, L25

1. Introduction

Knowledge is a public good to a certain extent. Thus, an innovating firm cannot often prevent other firms from using its new product or process inventions, and other firms may achieve more innovations by exerting less effort (Jaffe, 1986; Medda and Piga, 2007). Other companies can use the knowledge of a firm at lower or zero costs because such knowledge is often shareable, inexhaustible, and reusable. Knowledge can spill over through various routes, including upstream and downstream linkages, learning by doing and observing, the movement of workers involved in research and development (R&D) activities, and various local networks between scientific and engineering personnel from different organizations (Hubert and Pain, 2001; Medda and Piga, 2007; Plunket, 2009; Dindaroglu, 2010; Desrochers and Leppälä, 2010). Firms located in a spatial neighborhood (i.e., in the same cluster) or in a conceptual neighborhood (i.e., in the same industry or network) benefit from the knowledge-creation activities of other firms.

Given its existence in diverse contexts and channels, knowledge spillover has been the subject of a large number of theoretical and empirical studies with difference foci. One of the early theoretical studies conducted is that of d'Aspremont and Jacquemin (1988), which finds that the optimal amount of R&D in cooperative R&D in a duopoly will be larger with knowledge spillover than without it. This research has led to several extensions.[1] Empirical studies on knowledge spillovers are well surveyed in the work of Griliches (1992), and defining the spillover pool, both domestic and international, has been a key issue in empirical literature. Jaffe (1986) constructs the potential spillover pool of an industry as the sum of the innovative activities of other firms in the industry. Empirical research confirms the effects of knowledge spillover from both domestic and international pools (Adams and Jaffe, 1996; Geroski, 1995; Coe and Helpman, 1995).

By examining further details of a spillover, one finds diverse results from empirical analyses. For instance, Wakelin (2001) finds that companies in the innovation-using sectors appear to benefit more from the R&D of other firms in the sector than from their own, whereas innovation-producing sectors do not appear to benefit from their own R&D expenditure or that of others. Given this situation, Kafouros and Buckley (2008) address an emerging issue, that is, the conditions under which firms benefit from spillovers. Although Kafouros and Buckley (2008) search for such conditions, such as firm size, technological

[1] For instance, Suzumura (1992) extends the case to an oligopoly.

opportunities, and competition, other reasons also exist. This study pays attention to the inherent tacitness of knowledge, which tends to restrict the degree of knowledge flows in terms of its transferability to and learning by other firms. One argument is that spillover and transfer among sister firms affiliated with the same business group or conglomerate may be less subject to such limitations. However, few studies analyze the spillover impact of a knowledge pool of a network consisting of affiliates in a business group, and compare them with spillover among arm's length firms in the industry.

Business groups, which consist of legally independent firms operating in multiple markets, are a common phenomenon in emerging markets and in several developed economies. This form of organization has attracted increasing interest in economic and business studies, as reviewed by an article in the *Journal of Economic Literature* (Khanna and Yishay, 2007). Earlier literature on business groups has focused on their emergence in an environment with market failures or institutional voids. Thus, a business group is perceived as an organizational device for internalizing transactions that are too costly to happen in the markets (Leff, 1978; Goto, 1982; Khanna and Palepu, 1997 and 2000). A resource-based view of the business group has stressed developing and sharing certain capabilities among firms affiliated with the group (Kock and Guillen, 2001). Chang and Hong (2000) confirm the positive profitability impacts of group-level resource variables, such as advertisement, intra-group transactions, and R&D expenditure. Resource (including knowledge) sharing among affiliates of a business group is more logical when certain resources are unavailable in the markets, or when the benefits from such sharing within a network are greater than the benefits from market transactions regardless of market failure (Cheong et al., 2010). Thus, the purpose of this study is to compare the size of spillover impacts from within-group (network) with that from industries (arm's length relationship).

This study focuses on the function of a business group as an effective organization for expanding the knowledge resources of a firm, and thereby boosting its productivity. We construct the knowledge pool of a business group (network) as an analogy to that of an industry, and then compare the relative size of these kinds of spillovers, namely, spillovers from networks and industries. We initially test the hypothesis that productivity impacts of knowledge spillover pools from business groups may be greater than those from industry spillover pools. Branstetter (2000) observes the vertical *keiretsu* of Japan as a valuable economic institution that internalizes knowledge spillovers, and verifies spillover impacts based on the weighted R&D expenditure of other firms as a knowledge pool available to a firm. However, Branstetter does not compare the relative size of the impacts from the network (within-group) and from the industry (outside-group). Assessing the impact of intra- and inter-sector spillovers both at the group and industry levels is the concern of the second hypothesis of this study. This issue is becoming more relevant in the current era characterized by an increasing trend of technology fusion, but is not addressed in literature on business groups.

With regard to inter- versus intra-sector spillovers, a number of scholars suggest that the former is more significant than the latter in explaining economic growth, social returns, or productivity (Hubert and Pain, 2001; Harris and Robinson, 2004; Kafouros and Buckley, 2008) for firms in highly competitive environments. Moreover, recent studies provide limited evidence on intra-sector technology spillovers, whereas significant inter-sector spillovers are often reported (van Stel and Nieuwenhuijsen, 2004; Javorcik, 2004; Bwalya, 2006; Kugler, 2006; Badinger and Egger, 2010). However, spillovers cannot be understood in a one-dimensional manner. A number of studies combine the geographical dimension with the sectoral dimension. Autant-Bernard (2011) analyzes the nature of intra- and inter-sector knowledge spillovers both within regions and between regions, and compares the relative size of spillover impacts. However, to our knowledge, no study has yet examined intra- versus inter-sector spillovers among firms affiliated with a business group. Thus, we test a hypothesis that affiliates in a business group will obtain more spillovers from sister firms in different sectors than from those in the same sector. This reasoning is consistent with the idea of technology fusion proposed by Kodama (1992) and Suzuki and Kodama (2004), that is, persistent technological diversification is necessary for the survival and long-term growth of a technology-based firm.

In the present study, we use sales per employee as a dependent variable, which is a definite and simple measure of productivity that is less subjected to data noise. Thus, this variable is used in existing literature, such as in the work of Kafouros and Buckley (2008). Then, we regress this variable on the variables measuring the sizes of knowledge pools in networks and arm's length industries, controlling other factors. Robustness tests are also conducted using total factor productivity (TFP).

The current study proceeds as follows. Section 2 reviews related literature and derives the two hypotheses on the relative sizes of knowledge spillovers, which an affiliate of a business group benefits from. Section 3 establishes the phenomenon of knowledge spillover in business groups within the context of Korean firms using patent citation data. Section 4 describes the methodology and data used in this study, and then section 5 presents the main results on the relationship between knowledge spillover and firm productivity. Section 6 concludes the study.

2. Literature and Hypotheses: Knowledge Spillovers and Business Groups

Knowledge can be used at a lower marginal cost or without any cost because it is reusable and non-exclusive. Consequently, knowledge accumulated by one firm can broaden the technology base of other firms without appropriate compensation for the former (Glaeser et al., 1992). Once developed by a firm, knowledge enhances the knowledge production of other firms because new knowledge can be built upon existing knowledge without exhaustion (Laursen and Meliciani, 2000). Knowledge has the inherent properties (at least in a partial sense) of non-excludability and non-rivalry. Thus, the production function of a firm depends on the level of knowledge available in the economy, as well as on its own inputs (Jaffe, 1986; Medda and Piga, 2007).[2]

According to the viewpoint of transaction cost economics, firms use internal capital or labor markets to reduce transaction costs resulting from market imperfections. An internal market is less costly than an external one in the presence of asymmetric information. Firms conduct their own R&D, and consequently, generate diverse technologies. Technology is one of the input factors of a firm that can be traded in the markets. Nevertheless, the tacitness of technological knowledge makes it difficult to transfer completely through markets. Therefore, a number of firms acquire technology from intra-firm markets. Conglomerates or business groups are good examples of internal markets. These organizations replace external markets, with trades or transfers occurring within the boundaries of related firms or business groups. The economic logic behind business groups can be a starting point for an argument regarding the positive benefits for group-affiliated firms resulting from the knowledge pool of the mother group. A rapidly changing business environment tends to lead firms toward requiring and promoting more cross-fertilization between technological areas. If a firm truly enjoys cross-fertilization among the technologies within its boundary, then spillovers will probably occur across firms within a business group (widened boundary of a firm). Branstetter (2000) argues that the vertical *keiretsu* of Japan is a valuable economic institution that internalizes knowledge spillovers.

[2] Although R&D spillovers spur the diffusion of new knowledge, they may also create disincentives for firms to undertake their own R&D investments (Bernstein, 2000).

Diversified business groups are common in emerging and developed economies (Khanna and Yishay, 2007). Based on the transaction cost perspective, when the cost of acquiring inputs through markets is extremely high, firms extend their boundaries and internalize rather than externalize their functions. During the early period of industrialization, markets for factors such as skilled labor, capital, or technology are nonexistent or incomplete. Under the circumstance of market imperfections, business groups replace poorly performing or nonexistent economic institutions such as banks and external labor markets (Ghemawat and Kanna, 1998; Chang and Hong, 2000). For example, in Korean business groups or chaebols, certain key activities (e.g., recruiting, training, and promoting employees; advertising; and R&D) have been conducted at the group level until recently. The labor mobility of scientists and engineers is a conduit for knowledge spillovers among firms (Dindaroglu, 2010; Kim and Marschke, 2005). The higher mobility of skilled labor among affiliates may facilitate the transfer of knowledge better within the business group than within the market.

Based on the perspective of resource-based theory of the firm, business groups can be effective organizations promoting the more efficient use of the knowledge resources of a firm. A resource-based view of a firm stresses sharing of resources among affiliates within the group (Chang and Hong, 2000). In particular, reusable and inexhaustible resources, such as technologies and managerial resources, are transferred to other affiliates to generate efficiency-enhancing results. More efficient resource utilization is possible by pooling resources at the business group level and sharing them among affiliates. Intra-group transactions among affiliates can offer lower prices because information asymmetry is less notable among firms affiliated with the same group. Obviously, the redistribution of profits from good to bad performers by the group headquarters can incur costs that are unique to business group affiliates (George et al., 2004).

Firms generally do not use technologies only for internal production purposes (Cesaroni, 2004). A number of underutilized technologies may exist even in firms that are highly diversified across product lines (Cheong et al., 2010). Cesaroni (2004) points out that the possibility of recovering the costs of R&D activities through in-house exploitation is drastically reduced when technological diversification is directed toward fields that are marginal to core technological competencies, and if the firm is not facing a sufficiently large demand. Nevertheless, the recovery of R&D costs at the group level is easier through intra-group technology transactions and transfers when confronted with an imperfect technology market.[3] The presence of business groups allows affiliates to more readily develop technologies that are marginal to their core competencies. In a technologically diversified group, the chances of finding affiliates within the group that are underutilizing their technologies would be higher. In addition, the potential for knowledge cross-fertilization will be better exploited within a business group than in a stand-alone firm. This reasoning is logical because knowledge is not exhausted but improved by the learning process through repeated use. Moreover, intra-group transfers of technologies are more efficient and faster than those between unrelated firms (Granstrand, 1999).

Therefore, we propose that knowledge pools at the group level affect the innovations of affiliated firms and their productivities. Given that member firms of a business group are closely interconnected, the influence of spillover pools from the network may be stronger than that of broader spillover pools from the market. Furthermore, the existence of cognition failure (Noteboom et al., 2007) resulting from the tacitness of knowledge will enable knowledge within a network to become more readily recognized, transferred, and utilized than knowledge at arm's length relations. That is, certain types of knowledge or the tacit dimension of knowledge can be transferred only through direct interaction and experience, which are more prevalent within a network organization, such as a business group. Thus, *the first hypothesis of this study is that productivity impacts of spillovers from firms affiliated with the same business group (network) are greater than those of spillovers from other firms in the industries (market).* To our knowledge, no research, except that of Branstetter (2000), focuses on spillovers from both an affiliated business group and an affiliated industry. However, Branstetter (2000), who uses weighted R&D expenditure rather than patent applications to measure knowledge pools, does not address the relative size of impacts arising from different types of spillover pools, such as networks (within a group) and industries (outside a group).

Our next hypothesis deals with comparing spillovers from the same and from different sectors. This issue has not been addressed in literature on business groups, but is becoming more significant, given the increasing trend toward technology fusion (Kodama, 1992). Ideas from a certain sector can induce new ideas in another sector.[4] This type of spillovers can emerge from the mobility of R&D employees, upstream (downstream) relationships with

[3]Technology transfer is different from knowledge spillover, which R&D practitioners cannot appropriate. However, the benefits from a business group do not only result from technology spillover per se but also from the speed and ease of technology transfer within the group. In fact, making a clear-cut distinction between the effects of knowledge spillovers and transfers is difficult.
[4]Los (2000) refers to this type of knowledge spillover as an "idea-creating" spillover.

suppliers (customers), and public information contained in patents, scientific journals, conferences, and so on (Los, 2000). In literature concerning the spillover effects of knowledge, a number of studies have addressed the issue of the relative size of inter- and intra-sector spillovers (Bernstein, 1988; Rouvinen, 2002; Kafouros and Buckley, 2008). However, no previous study has focused yet on the effects of inter- and intra-sector spillovers within a business group, and has compared spillovers from affiliates in different sectors and spillovers from affiliates in the same sector. Early research on spillovers has mainly focused on intra-sector effects, such as positive externalities from the subsidiaries of multinational corporations (MNCs) to domestic firms in the same sector. By contrast, the results of recent studies are not conclusive with regard to intra-sector spillovers (possibly because of the competition effect). This outcome has caused researchers to switch their attention from intra-sector to inter-sector spillovers (Sasidharan, 2006).

Table 1 summarizes studies on inter- or intra-sector spillovers from R&D or foreign direct investment. Hubert and Pain (2001) argue that spillovers across sectors should be considered in policy making as an additional channel of spillovers. Studies attempting to identify intra-sector spillovers may underestimate externalities from inward investment by foreign-owned companies (Hubert and Pain, 2001). Several recent studies suggest that inter-sector spillovers are more prevalent than intra-sector spillovers in explaining economic growth or social returns (Javorcik, 2004; Harris and Robinson, 2004; van Stel and Nieuwenhuijsen, 2004; Kugler, 2006; Jordaan, 2008; Badinger and Egger, 2010). Moreover, Bwalya (2006) finds limited evidence for intra-industry spillovers from foreign to local firms through horizontal channels, but cites significant evidence for inter-industry spillovers through backward and forward linkages. In this case, we can hypothesize that *a group-affiliated firm will obtain more spillovers from sister firms in different sectors than from those in the same sector within the business group*.

[Table 1]

The dominance of externalities across sectors over those within a sector can be explained as follows. Inter-sector spillovers occur through backward and forward linkages between buyers and sellers, whereas intra-sector spillovers occur through imitation, licensing, competition, or labor mobility (Harris and Robinson 2004). An innovative firm has an incentive to facilitate knowledge transfers to upstream or downstream firms, thus enabling recipients to produce intermediate inputs or equipment more efficiently. Therefore, adverse competition effects are more likely happening within a sector (Bwalya, 2006). Thus, knowledge spillovers within a sector may be counterbalanced by competition effects—a situation that leads to lack of intra-sector spillovers, according to several studies (Aitken and Harrison, 1999; Javorcik, 2004). By contrast, a greater potential for spillovers exists through forward and backward linkages, given that supplier-buyer relationships have grown stronger because of technological complexity (Kugler, 2006).

In summary, the discussion on the relative importance of intra- and inter-sector spillovers should consider the possible different impacts of specialization and diversity on productivity (van Stel and Nieuwenhuijsen, 2004). Although specialization facilitates spillovers among firms in the same sector either through direct contacts and the mobility of skilled labor, diversity fosters spillovers among firms in different sectors through cross-fertilization of ideas across different lines of work (van Stel and Nieuwenhuijsen, 2004; Plunket, 2009; Desrochers and Leppälä, 2010). Several studies indicate that industries in a region grow faster when the region is less specialized (Jacobs, 1969; Glaeser et al., 1992). The specialization viewpoint asserts that spillovers are more likely to occur among similar firms sharing common knowledge. By contrast, the diversification viewpoint emphasizes that cross-fertilization and complementarities among firms enhance knowledge spillovers (Autant-Bernard, 2011). Another stream of theoretical literature posits the idea of organizational and cognitive distance (Noteboom et al., 2007), and find that such distance has an inverted U shape with respect to the value of learning (Wuyts et al., 2005). This finding implies that spillover or learning effects are highest when a certain (optimal) level of distance exists.

Kodama (1992), who coined the term "technology fusion," observed that between 1980 and 1986, the Japanese textile industry spent 70% of its total R&D outside its principal products. In turn, the technologies developed by the sector gained potentials for other sectors. New fibers, for example, have been used in making building materials and filtration systems for kidney dialysis machines (Kodama, 1992). In Korea, Cheil Industries, the former leading textile company in the country, has evolved into a major chemical company by applying its fiber technologies to electronic materials and chemicals. Suzuki and Kodama (2004) argue that persistent technological diversification through fusion across internal or external technologies are necessary for the survival and long-term growth of technology-based firms. Kugler (2006) suggests that generic technology, which can be deployed easily in production across sectors, is more likely to be propagated and require fewer absorptive capacities than sector-specific technology.

The preceding discussion suggests that formulating a theoretical argument in favor of the dominance of either inter- or intra-sector spillovers will not be easy because it will depend on the relative importance of diversity compared with specialization. Thus, we do not assign any weight to the technical distance of patents from diverse sectors.

In summary, we consider the four sources of knowledge spillover pools presented in Table

2, and focus on the four main comparisons shown in Part 2 of the table, which can be generated by combining intra- and inter-sector dimensions with the dimension of network versus arm's length industries. We also partly deal with two more possible comparisons, as shown in Part 3 of the table. However, these possible comparisons are not the focus of this study.

Table 2. Four sources of spillover pools and their comparison combinations.

Part 1. Four sources of spillover pools

	Network	Arm's Length Industry
Intra-sector	A: Affiliated firms in the same sector	C: Arm's length firms in the same sector
Inter-Sector	B: Affiliated firms in a different sector	D: Arm's length firms in a different sector

Part 2. Four main comparisons

Across sectors within a network	Spillover from A is larger or smaller than B
Across boundaries within a sector	Spillover from A is larger or smaller than C
Across sectors within the industry	Spillover from C is larger or smaller than D
Across boundaries from different sectors	Spillover from B is larger or smaller than D

Part 3. Two more possible comparisons

Networked firms in the same sector versus other firms in a different sector	Spillover from A is larger or smaller than D
Networked firms in a different sector versus other firms in the same sector	Spillover from B is larger or smaller than C

3. Establishing the Case in the Context of Business Groups in Korea

Although the preceding section discusses the diverse impact of knowledge spillovers on productivity, one may think that the phenomenon of knowledge spillover should be established first before its productivity impacts are measured. This process can be conducted in two ways. We initially discuss the case of knowledge sharing in the more specific context of Korean business groups, and then, we provide technical evidence of the knowledge-sharing phenomenon in Korean firms. In essence, the planned analysis requires data on firms interacting within a network, and we find Korean firms affiliated with business groups to be a good choice. Korea is one of the few countries in the world where business groups are still extensively spread as a key form of firms in the national economy. The data on Korean firms, which clearly identify affiliates over time, are widely used in academic research published in international journals. Korea also fulfills another requirement, that is, the patent data for each affiliated firm should be available so that their knowledge spillover pools can be identified.

One institutional basis for knowledge spillover among affiliates in business groups is group-level or centralized personnel management, which includes hiring and training of new staff by the group headquarters rather than by each affiliate (Chang 2003: 93-94; Chang and Hong 2000). This practice has been in effect until the mid-1990s in the case of the oldest and largest business groups, although certain business groups, such as STX, still maintain such a system. For example, in the case of Samsung Group, one of the oldest business groups in Korea, group-level hiring of workers and their centralized training started as early as 1957, and had been maintained as late as 1994.[5] Group-level management of human resources includes, among others, group-level advertisement of recruitment and three to four weeks training of newly hired employees, during which they train, eat, and rest together. After this common training period, the newly recruited workers are assigned to different affiliates. Their job applications are not for specific affiliates but are considered for the entire group, and thus, they should not have any complaint on which affiliate they will be assigned to in their initial jobs.

Since the late 1990s, and particularly, the 2000s, typical business groups switched to decentralized staffing through which each affiliate announces job vacancies and hires its own staff. However, even after this decentralization move, a group still maintains group-level retraining sessions for newly promoted senior managers, and these officers, particularly the directors, are still rotated among affiliates and are subjected to group-level personnel management. Samsung maintains a group-level retraining organization called the Samsung Human Capital Development Center at the outskirts of Seoul City. This organization is responsible for training newly promoted senior managers from all affiliates (The LG Group

[5] Based on an interview (conducted on February 2013) with KT Chung, director general of the Samsung Economic Research Institute, who was formerly responsible for the personnel management system of the Samsung Group, and also with Mr. CH Lee, a section chief of LG Academy.

has a similar organization called the LG Academy). Similar to Samsung, each group has a special personnel management committee at its headquarters to make decisions regarding job rotation, promotion, and discipline of senior managers from all affiliates. This committee communicates directly with the group chairman or the controlling families. Although the practice of group-level or centralized recruitment of new staff has deceased, business groups still tend to form and manage task forces for specific matter, including R&D projects, entry into new business areas, and major overseas investments. These task forces are composed of the most talented or specialized employees from various affiliates.

The aforementioned facts suggest that the staff of Korean business groups tend to know one another from the beginning of their employment, and cross paths throughout their career regardless of their initial affiliation. They often work together and are rotated across boundaries of affiliates but within the boundary of the group. With regard to the spillover of technical knowledge, we have to examine the patent data of business groups. First, each affiliate applies and files patents in the name of each affiliate, which has been responsible for relevant R&D projects. Korean business groups are different from American-style conglomerates or MNCs which have clearly identified parent firm and affiliates. In Korean business groups, all affiliate firms are legally independent although they are under a common controlling family. Moreover, although there are several core-business companies, no clear distinction exists between parent and subsidiary firms because the equity ties among them are typically not in the shape of a pyramid but of a matrix (or a circle) shape (Choo et al. 2009; Chang 2003: Ch. 6). Each affiliate in a business group has its own R&D unit although in some groups, a group-level, independent R&D organization also exists, such as Samsung Advanced Technology Institute (Chang 2003: 87). However, this R&D institute focuses on basic or fundamental research, and is not concerned with short-term R&D applications, which is conducted by each affiliate for its own specific purposes.

Thus, for each R&D project, the affiliates that supervise a particular project are clearly identified. Each affiliate files patents in its name, and is responsible for the R&D outcomes of its work. Table 3A shows that in the case of Samsung Group affiliates, they file patents in their respective names; and then, the patents are distributed over several affiliates. One firm, SEC, is dominant in terms of the number of patents. Given that R&D outcomes, and hence, patents are among the main performance indicators, the chief executive officer (CEO) and senior manager of each affiliate are keen on filing more patents in the name of their companies.

[Table 3]

A technical method for establishing patterns of spillover use within business groups, compared with those of external spillovers is using patent citation data to estimate the degree of intra-group citations or group-level localization of patent citations following the method of Jaffe et al., (1993). Using patent citation data to estimate the degree of knowledge flow is reasonable because Jaffe et al. (2000) find through their survey of inventors that a significant number of citations reflect actual knowledge flow, although not necessarily accurately. To evaluate the geographic localization of patent citations for each country, Jaffe et al. (1993) suggest an approach comparing the 'probability of a patent matching the original patent by geographic area, which is conditional on the original patent, with the probability of a match that is not conditioned by a citation link.' The non-citation condition probability provides the baseline or reference value, vis-à-vis the proportion of matching citations. The basic insight offered by the approach proposed by Jaffe et al. (1993) is that the probability (or propensity) that the patents of country A will be cited by other patents can be compared to a similar probability defined according to a reasonably comparable reference patent (called control patent). In this study, we adopt a methodology similar to those of Jaffe et al. (1993) and Lee and Yoon (2009) to measure the degree of localization at the business group level and not at the country level.

In this case, we initially calculate the probability (A) that a patent by an affiliate (for example, ***x***) of a business group will cite a patent by a sister affiliate (for example, ***y***) as follows:

$$A = \frac{n_{xyt}}{n_{xt}}$$

where

n_{xyt} is the number of citations made to the patents of an affiliate ***y*** by the patents of another affiliate ***x*** in year ***t*** (In the calculation, we use a summation for all the combinations of ***x*** and ***y*** belonging to the same business group); and

n_{xt} is the number of citations made the patents of affiliate ***x*** in ***t*** year (In the calculation, we use a summation for all affiliates belonging to the same business group).

Simply put, formula A computes for the ratio of the total number of all inter-affiliate citations in each business group to all non-self citations made by all affiliates in a group. The next step is to select a comparable (called control patent in the study of Jaffe) patent for each original (for example, ***x***) patent by an affiliate of a business group. A control patent for each patent by an affiliate is selected randomly among a group of granted patents, which are of the same class (out of the 417 United States (US) Patent and Trademark Office classifications) and applied in the same year as the paired patent for a business group. Then, we calculate the probability (B) that a comparable (control) patent will cite a patent held by an affiliate (***y*** in A, except ***x***) in year ***t***, such that:

$$B = \frac{n_{cyt}}{n_{ct}},$$

where

n_{cyt} is the number of citations made to the patents of an affiliate ***y*** by a comparable patent ***c*** in ***t*** year (summation for all control patents; ***y*** can be any affiliate in a group, except ***x*** with which ***c*** is matched); and

n_{ct} is the number of all non-self citations made by a comparable patent ***c*** in year ***t*** (summation for all control patents).

Simply put, formula B computes for the ratio of the total number of citations made by control patents to patents held by all non-matching affiliates in each business group to all non-self citations made by all control patents.

Our objective is to show that patents by affiliates in a business group have a higher tendency to cite patents held by sister affiliates in the same business group than other patents. Ideally, conducting analysis for more business groups will be better, however, we limit our analysis to an exemplary business group, that is, the Samsung Group. One reason for this decision is that the Korean patent system does not require patent applicants to report citations when they file applications until recently, and thus, such data are not available. Therefore, we have no choice but to use the US patents filed by Korean firms. However, even large business groups tended not to have a sufficiently large number of US patents until recently. Table 3A shows that even for the Samsung Group, numerous affiliates have a considerably smaller number of US patents and a relatively large number of domestic (Korean) patents. Thus, we cannot repeat the same analysis for other business groups.

Table 3B presents the results of estimating the degree of group-level localization in the patent citations by the affiliates of Samsung Group. Part 1 of the table indicates the total number of citations and the number of intra-group citations. From 1995 to 1997, approximately 6.6% of the 22,211 citations are intra-group, and among these, the majority is accounted for by self-citations of each affiliate. Thus, citations made to patents held by sister affiliates in the Samsung Group account for only 2.1% of the total (Part 2 of the table). This figure is compared to a probability that other independent and comparable patents (called control patents by Jaffe) make citations to patents held by Samsung. Part 3 of the table indicates that the probability is only 0.43%. Then, the *t*-statistics in Part 4 show that the gap (1.67%) is significantly different from zero, thus implying that the probability (propensity) that Samsung affiliates will cite a patent of a sister affiliate is significantly higher than the probability that other patents will cite the patent of that affiliate.

In the following section, we now measure the productivity impact of such knowledge spillover within a business group.

4. Data and Research Method

1) Data

The Korean firm data used in this study consist of distinctive data sets from two different databases, namely, typical financial statement data and patent data of firms.

First, the financial data on Korean firms are obtained from Korean Information Service (KIS)-Value, the database of the KIS Company, which has been used in numerous empirical studies focusing on Korean firms (Chang and Hong, 2000; Choo et al., 2009; Cheong et al., 2010). The database covers all detailed items reported in financial statements, and includes firms listed in the Korea Stock Exchange (KSE), the Korea Securities Dealers Automated Quotation (KOSDAQ, the Korean version of the NASDAQ Stock Market), and all externally audited firms. The firms belonging to business groups are then identified. Information on business groups and their affiliates is obtained from the study of Choo et al. (2009). The definition of group used in this study is broader than that of the typical top 30 chaebols designated and monitored by the Korea Fair Trade Commission. The number of affiliates of a business group varies each year depending on the exits from and entries to the group. Therefore, the number of group affiliates in our sample is not fixed. For a group to be included in the sample, it should have more than two affiliates each year during the seven-year sampling period (1991 to 1997). In addition, an eligible group should have more than two patent applications, and should remain in the KIS data set throughout the sampling period. Otherwise, the group is excluded. Thus, the sample includes 79 groups and 417 firms. The number of firm-year observations is 2,242. Table 3 presents the names of the groups included in the sample and the number of affiliates of each group.

[Table 4]

The second data set consists of patent data of Korean firms. Patent data refer to the output of the innovation activities of a firm and serve as proxy for its technological capabilities. The current study uses patent applications filed with the Korean Intellectual Property Office (KIPO) from 1989 to 1997. Patent data can be downloaded from the Korea Intellectual Property Rights Information Service (http://www.kipris.or.kr), a publicly accessible Web-based patent database supported by KIPO. The information contained in a patent application includes the name of the applicants, renewal fee status, the final decision on patentability, International Patent Classification codes, inventors, and abstracts. We have downloaded approximately 10,000 text files and arranged them by variables using software such as SAS and Ultraedit. We then match applicants in the patent data with company names in the financial data. Table 5 shows the trend of patent applications filed at the KIPO. The table indicates that the technological capabilities of Korean firms, as represented by patent stocks, have been accumulated rapidly. The number of patent applications by local firms exceeded that of foreign applications in 1992. In 1993, domestic corporations overtook foreign firms in the number of applications. By 1997, the number of patent applications by domestic corporations reached 67,346, a sevenfold increase from only 9,082 in 1990. The number of applications by domestic corporations decreased by approximately 35% in 1998 as a result of the Asian financial crisis of 1997, and did not recover fully even in 2002.

[Table 5]

2) Variable Construction

The annual number of patent applications is susceptible to noise; thus, this study uses three year-cumulative sums of patent applications. Specifically, the study sums up the number of patents applied for in the periods T-2, T-1, and T to obtain a proxy for the knowledge base of a firm for year T. The concerned explanatory variables, such as group and industry patents, are then calculated based on these cumulative values. The firms and their patents are classified based on the standard industry classification (SIC) codes of the affiliated firms, which indicates that variations are at the sectoral level of the firms, and not at the underlying technological level.

In this study, we construct four variables representing the additional knowledge bases of a firm aside from its own patents, namely, intra- and inter-sector spillover pools outside the business group to which the firm belongs, and intra- and inter-sector spillover pools within the group.

The inter-sector-within-group spillover pool of a firm is represented by the three-year cumulative sum of the numbers of patents applied for by its sister firms in the same business group but from different sectors. That is, the inter-sector-within-group spillover pool of firm ***k*** is calculated by $Group\_Spillover_{inter} = \sum_{j \neq i} P_{gj}$, where ***g*** and ***i*** denote the group and the sector, respectively, with which firm ***k*** is affiliated, and P_{gj} denotes the three-year cumulative sum of the numbers of patents applied for by sister firms belonging to business group ***g*** and sector ***j***. The intra-sector-within-group spillover pool of firm ***k*** is $Group\_Spillover_{intra} = P_{gi} - p_k$. P_{gi} indicates the sum of the numbers of patent applications by other sister firms in sector ***i*** and business group ***g*** to which firm ***k*** belongs. p_k denotes the number of patents applied for by firm ***k***. Therefore, we simply sum up the numbers of patent applications by all sister firms in the sector under which firm ***k*** is classified, excluding the patent applications of firm ***k***. By contrast, the inter-sector spillover pool of a firm is proxied for by the sum of the numbers of patents that other firms (excluding its sister firms) in other sectors have applied for. The inter-sector spillover pool of firm ***k*** is calculated as follows:

$Industry\_Spillover_{inter} = \sum_{j \neq i} P_j - Group\_Spillover_{inter}$, where P_j denotes the sum of the numbers of patents that all other firms (including sister firms) in sector ***j*** have applied for, and ***i*** is the industry to which firm ***k*** belongs. The intra-sector spillover pool of firm ***k*** is calculated by $Industry\_Spillover_{intra} = P_i - Group\_Spillover_{intra}$, where P_i denotes the sum of the numbers of patents applied for by all other firms (including its sister firms) in sector ***i***.

We do not discount patents in different sectors in terms of technological distances.

Although several studies, such as that of Kafouros and Buckley (2008), adopt this type of weighting method, we have decided not to do so because whether long- or short-distance knowledge is more significant for a firm in raising productivity remains uncertain, as discussed in the preceding section. Instead, we attempt to measure the relative size of the impact itself.

We provide the following explanation for the actual variables used in the spillover regressions. Hereafter, all variables related to the patent counts are constructed based on the three-year cumulative sum as previously described.

Patent counts at the group level (group_patent): This number is the sum of patents applied for by affiliates in a business group. This study uses group patents as a proxy for group-level knowledge stock that can spill over to affiliates. In calculating the knowledge stock of a group that is available to a firm, we exclude the patents of the concerned firm (hereafter referred to as firm ***k***). To compare intra-industry spillover with inter-sector spillover, we divide group patents into patents within the sector (**group_patent(in)**) with which firm ***k*** is affiliated and patents outside the sector (**group_patent(out)**). Thus, group_patent(in) is the sum of the numbers of patents applied for by all other affiliates (excluding the firm itself) in the same business group and in the same sector that firm ***k*** belongs to. That is, group_patent(out) is $Group\_Spillover_{inter} = \sum_{j \neq i} P_{gj}$, and group_patent(in) is $Group\_Spillover_{intra} = P_{gi} - p_k$.

Patent counts in the industries are also divided into two parts as follows.

Industry_patent(in) refers to the patents applied for by all other firms in the same sector to which firm ***k*** belongs to, excluding those by firm ***k*** itself and other sister firms in the same business group with which firm ***k*** is affiliated. Specifically, industry_patent(in) is expressed as follows:

$$Industry\_Spillover_{intra} = P_i - Group\_Spillover_{intra} .$$

Industry_patent(out) refers to the patent applications by all firms in the other sectors, excluding those by other affiliates in the same business group with which firm ***k*** is affiliated. That is, industry_patent(out) denotes

$$Industry\_Spillover_{inter} = \sum_{j \neq i} P_j - Group\_Spillover_{inter} \ .$$

Age is the logarithm of the age of firm ***k***. The age of firm ***k*** is defined as (one plus) the number of years elapsed since the foundation of firm ***k***.

Market share is the ratio of the gross output of firm ***k*** to the gross output of the sector. The gross output of the sector is defined at the three-digit sectoral level.[6]

Export ratio[7] is the export to sales ratio, i.e., the share of exported output.

Table 6A presents the descriptive statistics for variables used in knowledge spillover estimations. This study uses labor productivity (defined as sales per employee) as a dependent variable. The mean of sales per employee in the sample is 232 million Korean won. The three-year cumulative sums of the numbers of patents within and beyond the industry to which a representative firm ***k*** belongs are respectively 5,593 and 67,790, on average. The average number of group patents within the sector with which firm ***k*** is affiliated is 486. The number of group patents outside the sector to which a firm belongs is approximately four times as large as the number within the same sector. Meanwhile, the inter-sector spillover pool is approximately 12 times larger than the intra-sector spillover pool. The maximum value of the export ratio is 99.6%, which means that several firms are fully oriented toward foreign markets. As shown in Table 6B, the correlations among variables are not high. Therefore, multicollinearity is not an issue for our data.[8]

[Table 6A] here

[Table 6B] here

3) Regression Models

The hypotheses investigated in this study are as follows. First, a group-affiliated firm enjoys higher spillover effects from the knowledge pools of the business group to which the

[6] The current study adds the outputs of all externally audited firms within a sector in the KIS database to calculate the sector output.

[7] KIS export data have missing values. This study fills up the missing values with data obtained from the TS2000 of the Korea Listed Companies Association.

[8] The correlation between the undivided group patents (group patent(in+out)) and group patent(out) is significantly high. However, these variables are not used together.

firm belongs than from the knowledge pools of non-affiliated firms. Second, a group-affiliated firm obtains more spillover benefits from sister (affiliated) firms in other sectors than those in the same sector. To explore the impact of knowledge spillovers on firm performance, we regress labor productivity and total factor productivity on the spillover measures from two distinct dimensions, namely, arm's length industry (or market) and network (business group), as well as other control variables. The coefficients of spillover pools imply whether the performance of a firm is affected by the knowledge available in the group or sector to which the firm belongs, or in other sectors. We include export ratio, market shares, and firm age as control variables, which are often referred to in literature as determinants of productivity.

To test the hypotheses, we adopt the following regression models: (3), (4), and (5). We use labor productivity as a productivity measure, which is defined as sales divided by the number of employees (that is, sales per employee).

$$\begin{aligned} productivity &= \alpha + \beta_1 * firm\_patent + \beta_2 * industry\_patent(in) \\ &+ \beta_3 * industry\_patent(out) + \delta * Z + \eta_i + u_{it} \end{aligned} , \quad (3)$$

where **Z** is the vector of other control variables, and firm_patent is the number of patents by a concerned firm itself.

$$\begin{aligned} productivity &= \alpha + \beta_1 * firm\_patent + \beta_2 * industry\_patent(in) \\ &+ \beta_3 * industry\_patent(out) + \beta_4 * group\_patent(in + out) + \delta * Z + \eta_i + u_{it} \end{aligned} , \quad (4)$$

$$\begin{aligned} productivity &= \alpha + \beta_1 * firm\_patent + \beta_2 * industry\_patent(in) \\ &+ \beta_3 * industry\_patent(out) + \beta_5 * group\_patent(in) \\ &+ \beta_6 * group\_patent(out) + \delta * Z + \eta_i + u_{it} \end{aligned} . \quad (5)$$

5. Regression Results: From Spillovers to Productivity

Using the previously described models, we first conduct the Hausman test to check the validity of the random effect models. Then, we report the result that is supported by the Hausman test for each specification. In the results, group patent is a proxy for the spillover pool from the business group, and industry patent is a proxy for the spillover pool from other firms in the same sector or in other sectors. Thus, the significant and positive coefficients of these variables confirm the spillover effects on an affiliated firm from the business groups or arm's length firms in an industry (from the same sector or other sectors).

Table 7 presents the baseline results using the firms' own patents, intra-sector, and inter-sector knowledge pools of a firm. Based on the baseline regressions, we reexamine the ongoing debate on the relative size of intra- versus inter-sector spillovers. Models 2 and 3 respectively demonstrate the results that intra-sector and inter-sector spillovers are existing and are both significant. Among the control variables, export ratio and market share exhibit significant positive effects, whereas age has a negative and insignificant effect throughout the models. When we place both variables in Model 4, the sizes of the two coefficients do not significantly differ. A test on the significance of the gap (reported in Table 10 along with the other test results) reveals that the two coefficients are not significantly different. That is, the results provide no evidence regarding the dominance of either intra- or inter-sector spillovers. Such results are different from those of existing literature which find dominance of either intra-sector (Bernstein, 1988; Rouvinen, 2002) or inter-sector spillovers (Harris and Robinson, 2004; van Stel and Nieuwenhuijsen, 2004; Javorcik, 2004; Bwalya, 2006; Kugler, 2006; Badinger and Egger, 2010; Autant-Bernard, 2011), but are in agreement with the perspective of Hubert and Pain (2001) and Medda and Piga (2007).

[Table 7]

Table 8 reports the results that compare the impact of within-group (network-based) knowledge pools and that of outside-group (industry-based) knowledge pools. In the regression shown in Table 8, we use the variable "group_patent (in+out)," which is the sum of the numbers of patents by all affiliates within a business group, excluding the patents of the concerned firm $\boldsymbol{k}$. This measure (coefficient) of the size of group-level knowledge spillovers is compared with those of intra- and inter-sector knowledge spillovers from an arm's length industry (Models 1, 2, and 4, respectively), and their combination (Model 3). The results of the four models all indicate that the coefficients of the within-group (network) spillovers are greater than the spillovers from industry (either from the same or different sector) and the sum of the intra- and inter-sector spillovers from the industry. The F-test results in Table 10 confirm that the differences are significant. Therefore, we can conclude that the impact of network-based spillovers is more powerful than that of arm's length relationship-based spillovers. This finding implies that group-affiliated firms obtain additional benefits from their sister firms in terms of spillovers. Model 5 in Table 8 aims to check the possibility of non-linearity by adding the square term of the group patent pool. As the table shows, the result is insignificant.

[Table 8]

Table 9 indicates the classification of network-based knowledge pools into those within and outside the sectors to which a firm belongs, namely, spillovers from affiliates in the same sector and those from affiliates in different sectors. We attempt several combinations to check for robustness. In Model 1, we investigate spillovers in the same sector, and compare the impact of sister firms and other firms in the same industry. The spillovers from the network are greater than those from the market (non-affiliated), which is consistent with the results in Table 8. In Model 2, we focus on spillovers from other sectors and compare the impact of sister firms and other firms in other industries. Again, the spillovers from the network are greater than those from the industry (non-affiliated firms).

Model 3 is a variation of Model 1, whereas Model 4 is a variation of Model 2. The results are consistent in that a stronger impact is observed from the network than from the arm's length industry regardless of the dimension of the sector (intra- or inter-). The final test is conducted on all intra- and inter-sector spillover variables, as reported in Model 5. All variables remain positive and significant, and the results are also consistent with regard to the relative impact of the network versus the industry. That is, spillovers from networks are greater than those from the industry in both intra- and inter-sector dimensions. The size of the spillover from the knowledge pool of a firm (own patents accumulated over time) tends to be similar to that of the spillover from the knowledge pools of affiliated firms in the same sector.

[Table 9]

Using the four coefficients of Model 5 in Table 9, we conduct significance tests on various pairwise combinations of these coefficients. The test results in Table 10 suggest that network spillovers tend to be larger than those from industries in all four possible combinations (intra- versus intra-, inter- versus inter-, intra- versus inter, and inter- versus intra-). All comparisons are significant at the 5% level, except inter- versus inter-, which is marginally significant at 12%. Thus, by considering all the results from Tables 8 and 9, we can conclude that spillovers from the network (within-group) are greater than those from the arm's length industries (outside-group).

Another consistent result is the relative size of intra- versus inter-sector spillovers. Significance tests in Table 10 regarding the relative size of the inter- versus intra-sector spillover from the industry (row 1 in columns 1, 2, and 3 of Table 10, using the coefficients from Tables 7, 8, and 9) consistently indicate no difference in size. Furthermore, the significance test on the relative size of the inter- versus intra-spillover from the network (from affiliated firms) also indicates no significant difference (Row 8 in Table 10). That is, no difference exists between inter- and intra-sector spillovers at both network and arm's length industry dimensions, whereas literature tends to compare spillovers only at the single dimension of the arm's length industry. This finding strongly supports the argument that intra- and inter- industry spillovers are both significant (Hubert and Pain, 2001; Medda and Piga, 2007).

The following discussion is on the magnitude of the spillover estimated from the regressions. Based on the coefficients from Model 5 in Table 9, an additional patent applied for by sister firms in the same sector to which a firm belongs results in an increase of approximately 6.58 US dollars (USD) in sales per employee for the firm affiliated with the same business group. By contrast, a firm will experience an increase of only 1.12 USD in labor productivity from one patent of an unrelated firm in the same sector.[9] Meanwhile, one more patent of affiliated firms in other sectors tends to increase sales per employee by 3.99 USD, whereas an additional patent in any unrelated firm in other sectors produces an increase of only 1.89 USD in the labor productivity of the concerned firm. Given that a firm in the sample hires an average of 1,753 employees, one more patent from sister firms in the same group of spillover pools results in a respective increase of 11,534 USD and 6,986 USD in sales for an average firm affiliated with a business group from intra- and inter-sector spillovers. From market spillover pools, an increase of 3,320 USD in sales is accrued to a firm from the inter-sector spillover, and an increase of 1,960 USD is accrued from the intra-sector spillover. By contrast, adding another patent in the knowledge pool of a firm results in an increase of 7.08 USD in labor productivity, and an increase of 12,417 USD in the sales of the firm.

However, the absolute sizes of industry spillover pools significantly outweigh those of

[9]The coefficients of spillover variables represent the impacts per patent in million Korean won; thus, we convert Korean won to US dollar by using the average exchange rate for 2010 (KRW/USD = 1,156.26). The constructed patent variables are based on the three-year cumulative sum of the numbers of patents. Therefore, the real impact of one patent is approximately three times as large as the value of each coefficient.

group spillover pools, as shown in Table 4. For example, the knowledge pool of sister firms in other sectors has only 1,974 patents, whereas the knowledge pool (market pool) of non-related firms in other sectors has 68,243 patents. The absolute size of the total effects of spillover pools at a given time is larger in the market than in the network (or affiliates). However, market spillover pools are not under the control of a firm. Thus, firms should pay more attention to the level and growth of spillover pools from the network. Moreover, most economic decisions are made based on the marginal effect rather than the total (or average) effect comparison.

[Tables 10, 11A, and 11B]

The following discussion presents the result of several robustness tests. The test is conducted using TFP rather than labor productivity as a dependent variable, and by conducting cross-section estimations rather than panel estimations. The results are reported in Table 11A (estimations) and Table 11B (tests of the differences in the coefficients). The results are basically consistent between Table 10 and 11. An additional insight from the cross-section results is that the coefficient of the intra-sectoral knowledge pool of other firms in the same sector is negative, which is logical because it clearly captures competition effects among firms in the same industry, which cannot be demonstrated by panel regressions.

One of the initial premises of this study is that knowledge spillover is not automatic but is subjected to limitations related to the tacitness of knowledge, thus giving rise to the advantage of business groups as they promote direct and indirect interactions among staff members across firm boundaries but within the boundary of business groups. Although we arrive at such an interpretation, we have not actually proven the importance of the tacitness of knowledge as an intervening factor. To address this issue, affiliated firms and their sectors are classified into either more tacit knowledge- or explicit (codified) knowledge-oriented sectors, and, simultaneously, knowledge pools are also classified into pools involving either more tacit or more explicit knowledge sectors. Thus, we have created four combinations using two types of knowledge pool sectors and two types of destination sectors. Then, we test whether a group affiliate belonging to a tacit (or codified) knowledge-oriented sector performs better in absorbing tacit (or codified) knowledge than codified (or tacit) knowledge.

In measuring the tacitness of knowledge across sectors, we have followed the method of Jung and Lee (2010), which use the number of patents per unit of R&D expenditure of a sector as a measure of inverse tacitness (explicitness) of the knowledge of a sector. The intuition is that codified (explicit) knowledge is easier to patent because it is easy to describe, and that companies in a sector that mostly uses explicit knowledge choose the patenting system as a defense mechanism, whereas companies in a sector that relies more on tacit knowledge tend to choose secrecy over patents (Nuria and Nieto–Antolín, 2007). Thus, for a given amount of R&D activities, a sector involving more explicit knowledge will generate more patents than other sectors. Actually, we find a systemic variation of this ratio over sectors similar to that presented in Jung and Lee (2010). For instance, the electronics sector has the highest ratio of 17.1 patents per billion won, whereas the apparel sector has the lowest ratio of 0.6 patents per billion won. Thus, we have classified the sectors into two groups: the first involves more tacit knowledge and the other involves more explicit knowledge. Firms are classified accordingly in terms of their sectoral affiliations.

Table 12 shows the results of the additional regressions. In Model 1, we compare only two groups, tacit versus explicit knowledge sectors. The coefficient of the knowledge pool from affiliated firms is shown to be larger in the tacit group. In Model 2, we test the two-by-two combinations. The impact on productivity in affiliated firms is found to be highest when firms in the tacit knowledge-oriented sector try to absorb tacit knowledge, compared with other combinations, such as tacit for explicit, explicit for tacit, or explicit for explicit. Obviously, these results should be considered with caution because the classifications of sectors are all relative, whereas firms in any sector involve both tacit and codified knowledge in different degrees. Model 3 uses a dummy for sectors that are more oriented toward tacit knowledge, as well as two types of knowledge pools and their interactions, to indicate that the tacit knowledge sector dummy is positive and significant, and that the interaction term of the tacit dummy and tacit knowledge pool is positive and significant, whereas interaction with the explicit knowledge pool is not significant. These results imply a larger impact of spillovers in cases involving more tacit than codified knowledge.

[Table 12]

6. Conclusion

Given the increasing significance of knowledge spillovers and technological fusion in innovations, this study investigates the productivity impacts of knowledge spillovers from firms in an arm's length relationship (or from the industry in general), and from a network consisting of other affiliates in the same business group. To shed light on the debate regarding the relative sizes of intra- and inter-sector spillovers, we have also divided knowledge pools into spillover pools within and outside a sector to which a firm belongs. This structure enables us to compare the sizes of spillovers over two-by-two combinations (between the industry and the network, and between the inter-sector and intra-sector).

This study finds that both intra- and inter-spillovers are significant channels of knowledge spillovers, but no evidence is found on the dominance of either intra- or inter-sector spillovers, regardless of whether the spillover is from an arm's length industry or from a network. This finding should be considered as a new contribution because literature tends to focus on spillovers from the arm's length industry, in general.

Second, and more significantly, we find that spillovers from networks (which consist of other affiliates) are greater than those from arm's length industries (which consist of unaffiliated firms in the industries) regardless of the comparison among intra- versus intra-, inter- versus inter-, intra- versus inter-, or inter- versus intra-sector spillovers.

Third, we have further classified firms and sectors into either more tacit knowledge- or more explicit knowledge-oriented sectors, and knowledge pools into pools involving more tacit or more explicit knowledge sectors. We discover that the impact on productivity among affiliated firms is highest when firms belonging to the tacit knowledge-oriented sector attempt to absorb tacit knowledge compared with other combinations, such as tacit for explicit, explicit for tacit, or explicit for explicit.

These results imply that knowledge spillover is not automatic but is subjected to limitations related to the tacitness of knowledge, and that certain types of knowledge can be transferred only through direct interaction and experience, which are more prevalent within a network organization, such as a business group. The knowledge of a firm is either available to, or more effectively exploited by, the affiliates of a concerned business group. In this sense, a business group is an effective organization for internalizing knowledge spillovers or for promoting more widespread knowledge diffusion among affiliates wherein the R&D activities undertaken by one firm benefits other firms in the same business group. The results are consistent with the finding on the resource-sharing advantage of business groups, as verified by Cheong et al. (2010) and Chang and Hong (2000). Given such benefit and all other things being equal, affiliated firms will find it more possible to expand their technological capabilities and to achieve a higher level of productivity. Finally, we have observed that higher spillover effects may be more specific to an environment with less inter-firm mobility of staff members, as experienced by Korea in the past, given that a higher inter-firm mobility of employees can be a substitute for intra-group knowledge spillover. Thus, future research topics may include the impact on intra-group knowledge spillover of alternative spillover channels, such as an increase in inter-firm employee mobility and the international ties of group-affiliated firms.

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[Table 1] Literature Comparing intra-sector (intra-industry) spillovers with inter-sector (inter-industry) spillovers

Studies	Results	Data	Types
Bernstein (1988)	Inter-industry spillover to the social return is virtually the same and small for all industries / Differentials between social and private returns and between social returns across industries depend on the extent of the intra-industry spillovers.	Canada	R&D spillovers
Hubert and Pain (2001)	There is evidence of significant intra-industry and inter-industry spillovers / Both intra- and inter industry effects are significant and although inter-industry spillovers are marginally larger than intra-industry spillovers, the hypothesis of common coefficients cannot be rejected.	UK	FDI spillovers
Harris and Robinson (2004)	Inter-industry spillovers are generally more prevalent than intra-industry spillovers.	UK	FDI spillovers
van Stel and Nieuwenhuijsen (2004)	No empirical evidence for a positive relationship between intra-industry spillovers and value added growth / evidence for positive relationships between inter-industry spillovers and value added growth.	Netherlands	Regional spillovers
Javorcik (2004)	No evidence of intra-industry spillovers / positive productivity spillovers from FDI taking place through contacts between foreign affiliates and their local suppliers in upstream sectors (evidence of inter-industry spillovers).	Lithuania	FDI spillovers
Bwalya (2006)	There is little evidence in support of intra-industry spillovers, but significant inter-industry spillovers.	Zambia	FDI spillovers
Kugler (2006)	knowledge spills over between but not within industries.	Colombia	FDI spillovers
Medda and Piga(2007)	Firms also benefit from spillovers originating from their own industries, as well as innovative upstream sectors(inter-industry spillovers).	Italy	R&D spillovers
Kafouros and Buckley(2008)	Both inter- and intra-industry spillovers are significant, but the magnitude of spillovers are higher for the R&D undertaken by intra-industry firms. / For firms in the environments of high competition, Inter-industry spillovers outweigh intra-industry spillovers.	UK	R&D spillovers
Jordaan(2008)	The presence of FDI creates negative externalities within industries and positive externalities between industries through backward linkages.	Mexico	FDI spillovers
Badinger and Egger(2010)	Inter-industry spillovers dominate intra-industry spillovers, which turn out much smaller and even insignificant in some specifications.	13 OECD countries	R&D spillovers
Autant-Bernard(2011)	The largest direct and indirect effects are associated with private R&D activity that spills across industry boundaries / But, Inter-industry spillovers decrease more drastically with distance than intra-industry spillovers.	France	Regional spillovers

[Table 3A] Samsung Affiliates' Patents filed in Korea (KR) and the US

Affiliates' Names	Country	1991	1992	1993	1994	1995	1996	1997	1991-94	1995-97
Cheil Industries	KR	50	60	62	52	57	82	90	224	229
Cheil Industries	US	3	3	1	1	3	3	0	8	6
Samsung Total	KR	1	8	34	25	36	30	44	68	110
Samsung Total	US	0	0	1	2	1	0	3	3	4
Samsung Petrochemical	KR	1	4	4	0	3	1	0	9	4
Samsung Petrochemical	US	0	0	0	1	0	0	0	1	0
Samsung Corning	KR	51	34	38	11	22	18	26	134	66
Samsung Corning	US	1	1	1	1	3	1	2	4	6
Samsung Heavy Industries	KR	33	56	72	145	188	178	180	306	546
Samsung Heavy Industries	US	7	7	1	21	28	15	11	36	54
Samsung SDI	KR	314	300	220	210	376	628	529	1,044	1,533
Samsung SDI	US	0	1	11	21	61	74	60	33	195
Samsung Electronics	KR	3,127	3,335	2,676	2,467	10,078	12,149	16,180	11,605	38,407
Samsung Electronics	US	366	381	394	455	613	1,320	1,008	1,596	2,941
Samsung Electro-Mechanics	KR	200	196	273	302	398	498	549	971	1,445
Samsung Electro-Mechanics	US	6	2	8	7	27	42	23	23	92
Samsung Techwin	KR	32	84	110	115	236	391	574	341	1,201
Samsung Techwin	US	0	4	9	17	19	42	26	30	87
Samsung C&T	KR	0	8	21	64	59	40	37	93	136
Samsung C&T	US	0	1	0	0	0	0	0	1	0
Samsung Engineering	KR	0	0	2	4	6	13	16	6	35
Samsung Engineering	US	0	0	0	0	0	1	0	0	1
Samsung Gwangju Electronics	KR	8	9	10	13	25	75	475	40	575
Samsung Gwangju Electronics	US	0	0	0	0	1	2	19	0	22
CJ (Cheil Jedang)	KR	86	77	80	49	86	107	68	292	261
CJ (Cheil Jedang)	US	0	4	2	4	2	6	3	10	11
Woongjin Chemical	KR	67	91	112	54	21	30	0	324	30
Woongjin Chemical	US	2	1	3	9	3	2	0	15	5
Hansol	KR	31	13	18	4	6	51	59	35	116
Hansol	US	1	0	0	1	0	1	0	2	1

Source: the authors; See the text for data sources

Notes: Affiliates include those which were separated from Samsung to be acquired by other business groups, such as CJ (1995), Woongjin Chemical (1996), and Hansol (1992).

[Table 3B] Relative Propensity of Inter-affiliates Citations in Samsung' Patents: Comparison using 'Control' Patents

	1991	1992	1993	1994	1995	1996	1997	1991-94	1995-97
Total No. of Samsung' patents	386	405	431	540	761	1509	1155	1762	3425
Total No. of citations	1927	2262	2401	2908	4543	9705	7963	9498	22211
No. of intra-group citations	67	91	97	137	295	604	567	392	1466
% of Total citations (A1)	3.48%	4.02%	4.04%	4.71%	6.49%	6.22%	7.12%	4.13%	6.60%
Part 1. Comparison with Citations by control patents									
% of citation to Samsung's patents (C1)	0.11%	0.15%	0.25%	0.67%	0.70%	0.35%	0.28%	0.34%	0.41%
Relative Propensity of Intra-Group Citation (A1-C1)	3.37%	3.87%	3.79%	4.05%	5.79%	5.88%	6.84%	3.79%	6.19%
t-statistics of (A1 - C1)	7.66	8.71	9.07	9.75	14.34	21.00	20.37	17.55	32.60
Part 2. Inter-Affiliate Citations within Samsung (excluding self-citations)									
No. of self-citations in Samsung	52	66	76	107	176	439	406	301	1021
% of Total citations	2.70%	2.92%	3.17%	3.68%	3.87%	4.52%	5.10%	3.17%	4.60%
No. of inter-affiliate citations	15	25	21	30	119	165	161	91	445
% of total citations	0.80%	1.14%	0.90%	1.07%	2.72%	1.78%	2.13%	0.99%	2.10%
Part 3. Citations by control patents excluding citations to paired Samsung affiliates									
% of citations to Samsung affiliates (C2)	0.11%	0.15%	0.26%	0.71%	0.74%	0.36%	0.30%	0.35%	0.43%
Part 4. Relative Propensity of Inter-affiliate Citation (A2-C2)	0.69%	0.98%	0.64%	0.36%	1.99%	1.42%	1.83%	0.64%	1.67%
t-statistics of (A2 - C2)	3.02	3.85	2.85	1.44	6.83	8.54	8.98	5.20	14.01

Notes: See the text for explanations and Lee and Yoon (2010). Citations by control patents in part 1 and 3 can be regarded as upper bounds because all control patents are randomly selected among Korean-held patents only which tended to have more citations to Samsung’s patents than non-Korean held patents which had very low incidence of citations to Samsung’s patents. Thus, here our estimates in part 4 of propensity of inter-affiliate citations, compared to that by control patens, are a ‘conservative’ estimates or lower bounds.

[Table 4] List of business groups included in the sample (as of 1997)

group name	no. of affiliates: manufacturing and externally audited firms[1)]	no. of affiliates: all [2)]	group name	no. of affiliates: manufacturing and externally audited firms[1)]	no. of affiliates: all [2)]
Samsung	24	60	Seah	4	11
Hyundai	17	52	Daenong	4	9
LG	15	43	DPI	4	8
Dongyang Chem.	13	18	Nongshim	4	8
Hanwha	11	32	Woonsan	4	7
Daewoo	10	28	Dongsung Chem.	4	6
Tongil	10	14	Hankook Elecronics	4	6
Lotte	9	29	Samyang Food	4	6
Posco	9	14	Samlip Food	4	4
Sinho	8	31	Byucksan	3	14
Daesang	8	26	Sambo Computer	3	13
Dongkuk Steel	8	16	Haitai	3	13
Hyosung	8	16	Kangwon Ind.	3	13
Hwaseung	8	13	Sungsin Cement	3	10
Kapul	8	12	Samchully	3	8
Aekyung	8	11	Woongjin	3	6
SK	7	42	Iljin	3	6
Ssangyong	7	26	Daewong Pharm.	3	5
Kia	7	26	Kirin	3	5
Kolon	7	23	Hwachun	3	4
Daesung	7	16	Ilshin	3	4
Koryeo	7	12	Poongsan	3	3
Pacific Corp.	7	11	Dongoh	3	3
Yuhan	7	9	Dongwon	2	9
Daelim	6	19	Taekwang	2	8
Samyang	6	7	Sindonga	2	6
Sungwoo	6	6	Hanil Cement	2	6
Doosan	5	24	Kyesung	2	5
Anam	5	19	Hite	2	4
Jinro	5	19	Taihan Electric Wire	2	3
Yoongpoong	5	18	Haesung	2	3
Halla	5	16	Rocket	2	2
Hanchang	5	9	Crown	2	2
Samwha	5	8	Choongbang	2	2
Kangnam	5	8	Samick	2	2
Chongkeundang	5	6	Kohap	1	13
Hanglas	5	5	Sammi	1	6
Daewon Steel	5	4	Sindoh	1	5
Kumho	4	26	Kookje Pharm.	1	3
Hanil	4	11			

Notes:

1) The figure includes only the firms that are under obligation to receive external auditing.
2) The number of affiliates for each group is counted using the list of business groups and affiliates from the Maekyoung Business Yearbook. The firms free from the burden of external auditing are also included in the figure.

[Table 5] Patent applications by applicant type and by year in Korea

year	All	Korean	Foreign	Externally audited
1985	10,587	2,703	7,884	978
1986	12,759	3,641	9,118	1,610
1987	17,062	4,871	12,191	2,312
1988	20,051	5,696	14,355	3,288
1989	23,315	7,021	16,294	4,880
1990	25,820	9,082	16,738	5,955
1991	28,132	13,253	14,879	9,210
1992	31,073	15,952	15,121	11,426
1993	36,491	21,459	15,032	15,259
1994	45,712	28,564	17,148	20,757
1995	78,499	59,236	19,263	49,488
1996	90,326	68,413	21,913	57,227
1997	92,734	67,346	25,388	54,105
1998	75,188	50,596	24,592	34,558
1999	80,642	55,970	24,672	33,528
2000	102,010	72,831	29,179	36,096
2001	104,612	73,714	30,898	39,688
2002	106,136	76,570	29,566	41,598

Notes:

1) Source: The Korean Intellectual Property Office

2) *"Externally audited"* (last column in the table) refers to the number of patents applied for by externally audited firms, which have generally more than seven billion won in total assets as of 2002. The number of patent applications in this column is obtained from the authors' own calculations after firm-applicant matching.

[Table 6A] Variables used in Analysis: Descriptive Statistics

Variables	Mean	Std. Dev.	Min	Max	Obs
sales_per_employee(million won)	232	172	37	1,682	2,242
firm patent	156	1,503	0	39,326	2,242
industry_patent(in)	5,593	13,310	0	88,690	2,242
industry_patent(out)	67,790	40,885	6,954	153,000	2,242
group_patent(in)	486	2,764	0	42,358	2,242
group_patent(out)	1,974	6,156	0	45,783	2,242
group_patent(in+out)	2,460	6,873	0	45,783	2,242
export_ratio(%)	18.4	27.5	0.0	99.6	2,242
market_share(%)	5.8	12.0	0.0	95.0	2,242
firm age	18.3	13.3	0.9	74.0	2,242

Notes:

1) Firm patents mean the number of patents applied for by each firm in the sample.
2) industry_patent(in) for each firm in this table and succeeding regression tables refers to the patents applied for by all firms in the same sector, except those by itself (each firm observation in the sample) and other affiliates in the same business group.
3) industry_patent(out) for each firm refers to the patents applied for by all firms in the other sectors than the sector to which a firm belongs, excluding those patents by other affiliates in the same business group.
4) group_patent(in) for each firm is the number of patents applied for by all affiliates in the same business group and the same sector, excluding those by itself (each firm observation in the sample).
5) group_patent(out) for each firm is the number of patents applied for by all of its sister firms in other sectors.
6) All variables using the number of patents are based on the cumulative sum of patents applied during the current year and the preceding two years, namely, years T, T-1, and T-2.

[Table 6B] Variables used in Analysis: Correlations

variables	sales_per_ employee	1	2	3	4	5	6	7	8
1. firm patent	0.03								
2. industry_patent(in)	-0.06	0.18							
3. industry_patent(out)	0.16	-0.04	-0.07						
4. group_patent(in)	-0.01	0.07	0.29	-0.03					
5. group_patent(out)	0.17	0.05	0.02	0.00	0.05				
6. group_patent(in+out)	0.15	0.07	0.13	-0.02	0.45	0.92			
7. export_ratio	0.10	0.08	0.19	-0.10	0.12	0.09	0.13		
8. market_share	0.09	0.31	-0.06	-0.08	0.03	0.23	0.22	0.17	
ln(firm_age)	0.00	0.06	-0.08	-0.07	-0.01	-0.10	-0.10	0.14	0.24

[Table 7] Comparing the impact of the intra- and inter- sector spillovers.

dependent var : sales per employee		model 1	model 2	model 3	model 4
		RE	RE	FE	FE
cons.	coef.	240.27	230.73	134.30	133.12
	t(z)-value	7.67	7.35	17.62	17.48
		***	***	***	***
firm patent	**coef.**	**52.92**	**28.99**	**39.19**	**29.08**
	t(z)-value	**3.03**	**1.65**	**2.41**	**1.76**
		***	*	**	*
industry_ patent(in)	**coef.**		**15.68**		**6.33**
	t(z)-value		**7.17**		**3.02**
			***		***
industry_ patent(out)	**coef.**			**7.90**	**7.62**
	t(z)-value			**20.54**	**19.25**
				***	***
export ratio	coef.	0.39	0.39	0.28	0.28
	t(z)-value	3.07	3.16	2.25	2.30
		***	***	**	**
market share	coef.	2.40	2.56	6.60	6.53
	t(z)-value	3.70	3.96	5.83	5.79
		***	***	***	***
firm age	coef.	-10.02	-7.52		
	t(z)-value	-1.41	-1.05		
industry dummies		yes	yes	no	no
R-sq.	within	0.015	0.042	0.201	0.205
	between	0.287	0.286	0.016	0.013
	overall	0.231	0.233	0.022	0.020
Hausman test		3.84(0.28)	4.17(0.38)	36.02(0.00)	32.81(0.00)

***Significant at 1% level; **Significant at 5% level; *Significant at 10% level

[Table 8] Comparison of the impact of the spillovers from the network and the industry

dependent var : sales per employee		model 1	model 2	model 3	model 4	model 5
		RE	FE	FE	FE	FE
cons.	coef.	222.20	133.53	132.88	132.70	132.73
	t(z)-value	7.18	17.61	17.53	17.50	17.40
		***	***	***	***	***
firm patent	**coef.**	**23.28**	**33.56**	**23.05**	**26.31**	**26.36**
	t(z)-value	**1.35**	**2.07**	**1.42**	**1.59**	**1.59**
			**			
group_ patent(in+out)	**coef.**	**35.11**	**19.53**	**17.21**	**17.80**	**17.42**
	t(z)-value	**8.27**	**4.51**	**3.95**	**4.05**	**1.57**
		***	***	***	***	
(group_ patent(in+out))^2	**coef.**					**0.09**
	t(z)-value					**0.04**
industry_ patent(in)	**coef.**	**12.16**			**4.86**	**4.87**
	t(z)-value	**5.54**			**2.29**	**2.28**
		***			**	**
industry_ patent(out)	**coef.**		**7.45**		**7.27**	**7.27**
	t(z)-value		**18.81**		**18.02**	**18.02**
			***		***	***
industry_ patent(in+out)	**coef.**			**7.11**		
	t(z)-value			**18.94**		
				***		
export ratio	coef.	0.36	0.26	0.27	0.27	0.27
	t(z)-value	2.93	2.16	2.23	2.20	2.20
		***	**	**	**	**
market share	coef.	2.27	6.49	6.41	6.45	6.45
	t(z)-value	3.56	5.77	5.71	5.74	5.74
		***	***	***	***	***
firm age	coef.	-4.84				
	t(z)-value	-0.69				
industry dummies		yes	no	no	no	no
R-sq.	within	0.070	0.210	0.212	0.212	0.212
	between	0.310	0.021	0.016	0.018	0.018
	overall	0.258	0.027	0.024	0.025	0.025
Hausman test		4.67(0.46)	34.41(0.00)	28.85(0.00)	34.47(0.00)	35.30(0.00)

*** Significant at 1% level; **Significant at 5% level; * Significant at 10% level

[Table 9] Spillovers from the affiliates in the same and different sectors

dependent var : sales per employee		model 1	model 2	model 3	model 4	model 5
		RE	FE	RE	FE	FE
cons.	coef.	231.35	134.48	221.40	132.91	132.39
	t(z)-value	7.36	17.69	7.16	17.51	17.44
		***	***	***	***	***
firm patent	**coef.**	**30.31**	**35.46**	**22.44**	**33.85**	**27.30**
	t(z)-value	**1.73**	**2.18**	**1.30**	**2.09**	**1.65**
		*	**		**	*
industry_ patent(in)	**coef.**	**13.54**		**12.67**		**4.31**
	t(z)-value	**5.94**		**5.62**		**1.96**
		***		***		**
industry_ patent(out)	**coef.**		**7.61**		**7.46**	**7.30**
	t(z)-value		**19.26**		**18.85**	**18.04**
			***		***	***
group_ patent(in)	**coef.**	**30.37**		**26.94**	**31.01**	**25.36**
	t(z)-value	**3.22**		**2.89**	**3.54**	**2.75**
		***		***	***	***
group_ patent(out)	**coef.**		**16.20**	**37.50**	**15.43**	**15.36**
	t(z)-value		**3.16**	**7.67**	**3.02**	**3.01**
			***	***	***	***
export ratio	coef.	0.40	0.26	0.36	0.27	0.27
	t(z)-value	3.18	2.15	2.91	2.20	2.22
		***	**	***	**	**
market share	coef.	2.60	6.41	2.23	6.61	6.53
	t(z)-value	4.02	5.68	3.50	5.86	5.80
		***	***	***	***	***
firm age	coef.	-7.76		-4.57		
	t(z)-value	-1.09		-0.65		
industry dummies		yes	no	yes	no	no
R-sq.	within	0.048	0.206	0.070	0.211	0.213
	between	0.286	0.021	0.312	0.018	0.017
	overall	0.235	0.027	0.259	0.025	0.024
Hausman test		5.01(0.42)	38.88(0.00)	5.80(0.45)	43.81(0.00)	38.99(0.00)

***Significant at 1% level; **Significant at 5% level; *Significant at 10% level

[Table 10] Test of the difference in the size of the estimated coefficients

Hypothesis tested	The model 4 in table 7	The model 4 in table 8	The model 5 in table 9
	F value (Prob.>F)	F value (Prob.>F)	F value (Prob.>F)
industry patent(in)=industry patent(out)	0.33(0.563)	1.17(0.280)	1.66(0.197)
industry patent(in) =group patent(in)			4.34(0.038)**
industry patent(in)=group patent(out)			3.93(0.048)**
industry patent(in)=group patent(in+out)		6.21(0.013)**	
industry patent(out)=group patent(in)			3.83(0.050)**
industry patent(out)=group patent(out)			2.39(0.122)+
industry patent(out)=group patent(in+out)		5.49(0.019)**	
group patent(in)=group patent(out)			0.87(0.350)
industry patent(in+out)=group patent(in+out) *(from model 3 in table8)*		5.09(0.024)**	

Notes:

1) H_0: $\beta_i = \beta_j$. The null hypothesis is that the regressors, X_i and X_j, have the same size as the coefficient.

The test statistic has the form, $\frac{(Rb-r)'[R(X'X)^{-1}R']^{-1}(Rb-r)/q}{e'e/(n-k)} \sim F(q,n-k)$, which has an F distribution under the null (see Johnston and Dinardo 1997).

2) Relative sizes among the estimated coefficients to be tested

A: From Model 5 in Table 9: group_patent(in) > group_patent(out) > industry_patent(out) > industry_patent(in)

B: From Model 4 in Table 8: group_patent(in+out) > industry_patent(out) >

industry_patent(in)

C: From Model 3 in Table 8: group_patent(in+out) > industry_patent(in+out)

3) **: Significant at 5% level: group_patent(in) > industry_patent(in)

group_patent(in) > industry patent(out)

group_patent(in+out) > industry_panten(in)

group_patent(in+out) > industry_panten(out)

group_patent(in+out) > industry_panten(in+out)

group_patent(out) > industry_panten(in)

+: Significant at 15% level: group patent(out) > industry patent(out)

Insignificant: industry patent(in)=industry patent(out)

group patent(in)=group patent(out)

[Table 11A] Robustness Test using TFP in both Panel and Cross-section Estimation

dependent var : TFP		panel regression			cross-sectional regression	
		specification1	specification2	specification3	1995 + 1996	1996 + 1997
cons.	coef.	-0.38	-0.38	-0.38	-0.07	-0.74
	t(z)-value	-13.96	-14.09	-14.10	-0.44	-4.18
		***	***	***		***
firm patent	**coef.**	**0.03**	**0.02**	**0.02**	**0.32**	**0.19**
	t(z)-value	**0.52**	**0.34**	**0.37**	**2.70**	**2.03**
					***	**
industry_ patent(in)	**coef.**	**0.04**	**0.03**	**0.03**	**-0.11**	**-0.03**
	t(z)-value	**5.01**	**4.20**	**3.90**	**-7.04**	**-2.49**
		***	***	***	***	**
industry_ patent(out)	**coef.**	**0.03**	**0.03**	**0.03**	**0.01**	**0.04**
	t(z)-value	**22.42**	**21.07**	**21.05**	**1.56**	**4.74**
		***	***	***	+	***
group_ patent(in)	**coef.**			**0.08**	**0.13**	**0.07**
	t(z)-value			**2.59**	**2.77**	**1.93**
				***	***	*
group_ patent(out)	**coef.**			**0.06**	**0.12**	**0.10**
	t(z)-value			**3.48**	**2.44**	**3.39**
				***	**	***
group_ patent(in+out)	**coef.**		**0.07**			
	t(z)-value		**4.39**			
			***			
export ratio	coef.	0.001	0.001	0.001	0.003	0.003
	t(z)-value	1.87	1.76	1.78	2.90	2.74
		*	*	*	***	***
market share	coef.	0.02	0.02	0.02	0.01	0.01
	t(z)-value	6.01	5.96	5.99	1.93	2.19
		***	***	***	*	**
R-sq.	within	0.262	0.027	0.270	0.201	0.203
	between	0.066	0.071	0.070		
	overall	0.100	0.107	0.107		

Notes: 1) TFP estimates used here are from Choo (2007) and the residuals from the fixed effect models, which we believe better than those from either LP method that suffers from non-monotonicity and perfect-collinearity or the GMM method that does not satisfy the criterion which a GMM specification should meet to be selected. Actually, we have checked all the three methods, and see Choo (2007) for more details.

2) Cross-section estimations using one year is subject to multi-collinearity problem owing to many observations with zero values for the number of patents, and thus we merged two most recent year observations into one cross section observation taking averages of the two year values to get these results in the last two columns.

[Table 11B] Hypotheses Test using the Results in Table 11A

Tested Hypotheses / models	panel regression			cross-sectional regression	
	specification1	specification2	specification3	1995 + 1996	1996 + 1997
	F value (Prob.>F)	F value (Prob.>F)	F value (Prob.>F)	F value (Prob.>F)	F value (Prob.>F)
industry patent(in) = industry patent(out)	0.53(0.466)	0.03(0.856)	0.00(0.980)	69.01(0.000)***	37.28(0.000)***
industry patent(in) = group patent(in)			2.28(0.132)+	19.86(0.000)***	6.20(0.013)**
industry patent(in) = group patent(out)			2.74(0.098)*	19.19(0.000)***	18.48(0.000)***
industry patent(in) = group patent(in+out)		3.99(0.046)**			
industry patent(out) = group patent(in)			2.75(0.097)*	6.19(0.013)**	0.84(0.361)
industry patent(out) = group patent(out)			3.17(0.075)*	4.86(0.028)**	5.18(0.024)**
industry patent(out) = group patent(in+out)		5.75(0.017)**			
group patent(in) = group patent(out)			0.32(0.574)	0.03(0.872)	0.55(0.461)

Note: See the notes in table 10.

[Table 12] Results with Firms and Knowledge Pools divided into Tacit vs. Explicit Knowledge Sectors

dependent var : sales per employee		model 1 (LSDV)			model 2(LSDV)				model 3 (LSDV) all sectors
		explicit knowledge sector	tacit knowledge sector	diff. test $\chi^2(1)$	explicit knowledge sector	diff. test $\chi^2(1)$	tacit knowledge sector	diff. test $\chi^2(1)$	
cons.	coef.	-155.40	639.52		-128.94		582.93		-443.42
	t(z)-value	-1.28	22.15		-1.05		18.04		-3.39
			***				***		***
firm patent	coef.	28.43	753.40		29.41		817.15		29.33
	t(z)-value	2.33	1.83		2.41		2.00		1.76
		**	*		**		**		*
industry patent (int+out)	coef.	5.73	7.47		5.85		7.11		6.75
	t(z)-value	10.02	11.59		10.12		11.00		14.58
		***	***		***		***		***
group patent (in+out)	coef.	**16.34**	**25.91**	**1.48**					
	t(z)-value	**3.40**	**3.46**	**(0.22)**					
		***	***						
group patent (explicit knowledge)	coef.				17.43		21.59		12.77
	t(z)-value				3.58		2.87		2.02
					***	**6.55**	***	**4.40**	**
group patent (tacit knowledge)	coef.				-264.16	**(0.01)**	1061.88	**(0.04)**	-242.01
	t(z)-value				-1.28		3.88		-0.87
							***		
tacit knowledge sector (dummy)	coef.								1031.96
	t(z)-value								7.71
									***
tacit dummy* explicit knowledge	coef.								9.79
	t(z)-value								1.09
tacit dummy*tacit knowledge	coef.								**1326.52**
	t(z)-value								**3.62**
									***
export ratio	coef.	-0.09	0.44		-0.11		0.41		0.25
	t(z)-value	-0.54	2.30		-0.69		2.15		1.83
		0.59	**				**		*
market share	coef.	2.86	11.67		2.80		11.65		6.13
	t(z)-value	2.21	4.72		2.16		4.75		4.50
		**	***		**		***		***
No. of observations		662	1,057		662		1,057		1,719
adjusted R^2		0.754	0.876		0.755		0.878		0.870

Notes: 1. The LSDV(Least Squares Dummy Variables) is equivalent to fixed effects as it is OLS with individual dummies for all cross-sectional units. We use this because Stata package allows easy test of the coefficient across samples.

2. The results of equality tests($\chi^2(1)$) between the coefficients of the same type of knowledge pool across 2 specifications in model 2 are as follows. $\chi^2(1)=0.27(0.61)$ for the explicit knowledge pool; $\chi^2(1)= 6.84(0.01)$ for the tacit knowledge pool.