ESTIMATION OF THE KNOWLEDGE SPILLOVER EFFECTS BETWEEN FIRMS IN BIO-RELATED INDUSTRIES*

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ABSTRACT

Knowledge spillover is a kind of externality originating from imperfect appropriation of R&D performances, which implies that the knowledge created by one agent could be transmitted to other related agents by affecting their R&D or other economic performances. For the estimation of knowledge spillover effects based on firm-level patent data between firms in bio-related industries, patents production function, as a proxy of knowledge production function, is formulated and estimated. Knowledge spillovers from some industries to other industries are observed and strong competition effects also seem to exist.

KEYWORDS: *knowledge spillover, patent, bio-related industries*

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I. INTRODUCTION

Knowledge spillover is a kind of externality originating from imperfect appropriation of R&D performances, which implies that the knowledge created by one agent could be transmitted to other related agents by affecting their R&D or other economic performances. Although the term of ‘knowledge spillover’ has been used as a synonym for the term of ‘R&D spillover’ in many literatures, Grilliches(1979) pointed out that R&D spillover consists of knowledge and rent spillover, which means that knowledge spillover is a part of R&D spillover.

The rent spillover is a kind of pecuniary externality transmitting through markets in the form of cost reduction, quality improvement, and productivity changes embodied into products by R&D activities. On the other hand, the knowledge spillover is the result of imperfect knowledge protection system. Knowledge created by one agent could be transmitted to other related agents through various means of knowledge transmission such as reverse engineering, human networks, etc. The knowledge spillover can affect the productivities of other firms or industries by reducing the existing technological restraints of the firms or industries. The knowledge spillover also can create new applied industrial areas by amalgamating some related knowledge together.

One of the most representative knowledge based industries is bio-industry which is highly based on biotechnology. The biotechnology has made remarkable progress in recent years and has been served as a knowledge foundation on which several bio-related industries are based and come into being. The industries which have been frequently taken as being high dependent on biotechnology include 'bio-industry', 'agriculture', 'food industry', 'chemical industry', 'health industry', and 'environmental industry'. These six industries are the sample cases under analysis in this study.

Firm-level micro data is employed in this study to estimate the effects of knowledge spillovers between firms in the six bio-related industries. In other words, this study identifies the direction and the magnitude of knowledge flows between firms in the bio-related industries, through which we can understand the technological relationships among those industries based on common knowledge.

For the purpose of this study, the knowledge needs to be measured. Although knowledge shares some common characteristics with ordinary commodities in terms of production, consumption and price-setting, it cannot be easily measured. For this reason, many alternative variables are used as proxies of knowledge in previous studies. Patent is one of them and employed in this study. Patent is a representative knowledge protection system for granting exclusive rights to the knowledge creator, but it also has good characteristics suitable for a proxy of knowledge especially in the knowledge spillover analysis. First, patent incorporates all the information about the new knowledge created and in general is subject to be released to the public after a certain term of license. Second, an IPC (International Patent Code) is given to each patent for the efficient management and reference of the patent data. The IPC enables researchers to easily identify the technological area of the patent. In this context, patent is used as a proxy of knowledge.

Specifically, the effects of knowledge spillovers are econometrically estimated using firm's knowledge stock. In this study, knowledge stock is formulated by using patents as the proxy of the knowledge. That is, the knowledge stock in each firm is measured by using the un-centered correlation technological distance and the number of patents. Finally, patents production function, as a proxy of knowledge production function, is formulated and econometrically estimated.

Several researches are observed in the field of knowledge spillovers. The researches are diversified according to how to construct the knowledge spillover variable. The magnitude or strength of knowledge spillover depends on the technological similarities between firms or industries. In general, the similarities are taken into account when spillover variables are constructed by considering some kinds of weights to reflect the similarities. With a few exceptions (Terleckyi(1974), Bernstein et al.(1989)), many researches incorporated appropriate weights into the variables. Terleckyi(1980), Mansfield(1980), Goto et al.(1989) introduced weights by considering input-output flows between industries. Jaffe (1986), Branstetter(2001), by calculating technological distance, and Fung et al.(2002), by patent citations.

II. ANALYTIC FRAMEWORK

The purpose of this paper is to estimate the magnitude of knowledge flows between firms which affects the endeavor of individual firm to innovate or create new knowledge. The individual firm's activity to innovate or create new knowledge is represented in the form of innovation production function (Branstetter et al.(1998); Branstetter(2001)).

$$(1) \quad n = f(I,\ K)$$

Here, newly created knowledge (n) is a function of the firm's innovative activities like R&D efforts (I) and the available knowledge stock (K). R&D efforts (I) are not easy to measure, so R&D expenditures are used as proxy. The available knowledge stock (K) can be divided into two, the inner knowledge stock which has been accumulated by the firm and outer knowledge stock which has been transferred from other firms. Furthermore, the outer knowledge stock can be decomposed by industry of origin and equation (1) is rewritten in the form of equation (2).

$$(2) \quad n_i \; = \; f(R_i,\; K_i,\; K_{ij}), \quad i = 1\cdots\cdots k, \quad j = 1\cdots\cdots L$$

R_i is the R&D expenditure of innovator i, K_{Ii}, the available inner knowledge stock, and K_{ij}, outer knowledge stock transferred from firm or industry j to i. Cobb-Douglas functional form is now applied to equation (2)

$$(3) \quad n_{it} \; = \; R_{it}^{\alpha} K_{Iit}^{\beta} \prod_{j=1}^{L} K_{ijt}^{\gamma_j} e^{\sum_{j=1}^{L} \delta_j D_{ij} + \varepsilon_{it}}$$

Here, n_{it} denotes new knowledge produced by firm i at time t and ε_{it} is the disturbance term. The dummy variable D_{ij} represents the industrial location of firm i and δ_j implies the differences in technological opportunity which exists in each industry. The log transformation of equation (3) yields equation (4).

$$(4) \quad \ln n_{it} = \alpha \ln R_{it} + \beta \ln K_{Iit} + \sum_{j=1}^{L} \gamma_j \ln K_{ijt} + \sum_{j=1}^{L} \delta_j D_{ij} + \varepsilon_{it}$$

The new knowledge (n_{it}) produced by innovation which cannot be measured directly requires proxy variable. Jaffe(1986) used the number of patents as the proxy of knowledge by noting that some portion of knowledge newly produced are applied for patents. In this study we think with Jaffe and use the number of patents as the proxy of knowledge. The number of patents applied (p_{it}) is expressed in the form of increasing function of knowledge newly produced.

$$(5) \quad p_{it} \; = \; e^{\sum_{j=1}^{L} \delta_j D_{ij}} \; e^{\xi_i} n_{it}$$

From equation (5), we can see that the ratio of the number of patents to the newly produced knowledge, the propensity of patent application ($\frac{p_{it}}{n_{it}}$), depends on dummy variables which imply the firm's industrial location and random firm-specific component. It reflects the fact that the propensity of patent application might vary from industry to industry because of the differences in technological opportunity in each industry. If the differences in the propensity of patent application by industries are significant, the significant differences in the values of δ_j will be expected. From equation (4) and (5), equation (6) is obtained.

$$(6) \quad \ln p_{it} = \alpha \ln R_{it} + \beta \ln K_{Iit} + \sum_{j=1}^{L} \gamma_j \ln K_{ijt} + \sum_{j=1}^{L} \delta_j D_{ij} + \eta_{it}$$

In this study, equation (6) is to be estimated and analytic focus will be given to the estimates of γ_j and δ_j. Equation (6) explains the individual firm's average propensity of patent application in all bio-related industries. However, we can also estimate the individual firm's average propensity of patent application in each industry by separating equation (6) into individual industries as in equation (7). Through equation (7), we can investigate the inter-industry knowledge spillover.

$$(7) \quad \ln p_{it} = \omega + \alpha \ln R_{it} + \beta \ln K_{Iit} + \sum_{j=1}^{L} \gamma_j \ln K_{ijt} + \eta_{it}$$

Considering that a panel data set will be applied to the estimation of equation (6) or (7) in this study, the disturbance term in equation (6) or (7) can be decomposed into cross sectional term and time serial term as in equation (8).

$$(8) \quad \eta_{it} = \zeta_i + \varepsilon_{it}$$

where ζ_i reflects the firm's individual variation and ε_{it} is the general white noise. The selection of estimation model between fixed and random effect models depends on whether ζ_i's are correlated with independent variables (regressors) or not. Branstetter(2001) took the position that there exist considerable correlation between the variable of firm's individual variation and firm's R&D scale (R&D expenditures) on the assumption of persistent differences in R&D productivity among firms mainly due to the different distribution of human capital. Based on Branstetter (2001), this study will estimate fixed effect model.

Now, note that the dependent variable of equation (6) or (7) is the yearly number of patent applied which is count data, nonnegative integers including zero. In this case, other estimation method rather than OLS estimation need to be considered. As we will see later, an estimation method based on the negative binominal distribution which is a generalized Poisson distribution in that it allows heterogeneous means and variances is selected through an appropriate hypothesis test. Moreover, the serial correlation problem attendant upon the estimation process based on the negative binominal distribution is considered by choosing conditional joint probability with respect to the sum of individual firm's variable during T years, $pr(P_{i1}, P_{i2}, \ldots\ldots, P_{iT} | \sum_{t=1}^{T} P_{it})$. The final estimation method selected is the maximum likelihood estimation of conditional fixed effect model.

III. DATA AND CONSTRUCTION OF VARIABLES

3.1 Data

Total 287 bio-related firms are included in the data set obtained from Korea Information Service(KIS), of which 285 are private firms and two are public bio-related research institutes (Korea Rural Development Administration, Korea Research Institute of Bioscience and Biotechnology). Total 6603 patent data for these firms and institutes are supplied by the Korea Institute of Patent Information. <Table 1> shows the distribution of 287 sample firms over six bio-related industries.

<Table 1> The Distribution of Sample Firms over Bio-related Industries

	Bio-Industry	Agriculture & Fisheries	Food & Beverage	Health	Chemistry	Environment	Total
Firms	44	29	58	66	65	25	287
Share (%)	15.3	10.1	20.2	23.0	22.6	8.7	100

3.2 R&D Expenditures

R&D expenditures are calculated based on the information in the balance sheet and income statement included in the data set obtained from KIS for the private firms while yearly R&D budget is used as R&D expenditure for the public research institutes which have accounting systems different from those of private firms. R&D expenditure is deflated using GDP deflator and lagged by one year according to the results of empirical study by Korea Industrial Technology Association (KOITA, 2000)

3.3 Inner Knowledge Stock

The inner knowledge stock is the knowledge stock which has been created and accumulated within the firm and has become available when producing new knowledge. As we mentioned before, the accumulation of patenting knowledge (the number of patents) is used as proxy. The number of patent is transformed to stock variable based on benchmark-year method by setting 1997 as benchmark year.

$$(9) \quad K_{It} = P_{t-\tau} + (1-\rho)K_{It-1}$$

K_{It} is the inner knowledge stock at time t, $p_{t-\tau}$ is the number of patents applied for at time t-τ, and ρ is the rate of obsolescence of existing knowledge. In this study the time lag (τ) is set as one year according to the results of empirical study by Korea Industrial Technology Association (KOITA, 2000), and the rates of obsolescence (ρ) by industries come from Sin et. al.(2002).

3.4 Outer Knowledge Stock

The concept of 'potential spillover pool' by Terleckyj(1974) is applied in this study to construct the outer knowledge stock.

$$(10) \quad S_i = \sum_{i \neq j} \omega_{ij} K_j$$

S_i, the potential spillover pool of firm i, is the weighted sum of knowledge of all firms which have some technological relations with firm i. The weight (ω) reflects the relative closeness of technological relations between firms. Although several approaches to calculating the weight are possible, here, un-centered correlation technological distance approach proposed by Jaffe (1986) is adopted. The approach captures the technological similarity between firms through the research area of common interests which can be measured by the correlation in R&D portfolio. The approach is based on the assumption that the more similar are the research areas between firms, the larger are the effects of knowledge spillovers between them. The flows of goods or services between industries revealed in the input-output table are often used to calculate the weights. However, the weights calculated by the flows of goods or services can be more appropriate in dealing with rent spillovers while the weights based on technological distance in dealing with knowledge spillovers (Branstetter(2001)).

In order to see the un-centered correlation technological distance approach, technological location vector of individual firm on the technology space needs to be introduced first.

$$(11) \quad F_i = (F_{i1,}, \cdots\cdots, F_{ik})$$

F_i is the technological location vector of firm i, F_{ik}, the R&D expenditures of firm i into k-th sub-technological area. But the data on R&D expenditures of an individual firm into several sub-technological areas are not easy to obtain. Here, the patent data of sub-technological areas which is regarded to be highly correlated with the R&D expenditures are used as proxy. Therefore, in this study, F_{ik} means the number of patents obtained by firm i in the k - th sub-technological area. We should note that the R&D portfolio rather than R&D record of individual firm matters to identify the technological location of individual firm. In this context, equation (11) is rewritten in the form of equation (12) which represents the technological location of firm i.

$$(12) \quad f_i = (f_{i1}, \cdots\cdots, f_{iL})$$

where f_{ik} implies the ratio of patents in k - th sub-technology area to total patents obtained by firm i and $\sum f_{ik} = 1$.

Finally, with the technological location vector in equation (12), the coefficient of un-centered correlation technological distance (ω_{ij}) can be defined as in equation (13).

$$(13) \quad \omega_{ij} = \frac{f_i \cdot f_j^{'}}{\|f_i\| \cdot \|f_j\|}$$

where $\|f\|$ means vector norm. If the location of firm i coincides with that of firm j on the technology space, ω_{ij} will become unity while if two firms have perfectly different R&D portfolio, that is, if they obtain patents from perfectly different sub-technology area, then ω_{ij} will become zero. The more similar are the R&D or technology areas between two firms, the closer to unity will be the value of ω_{ij}. With the ω_{ij}'s at hand now, the outer knowledge stock by industry can be obtained by equation (10).

IV. RESULTS OF THE ESTIMATION

<Table 2> shows the negative binomial estimation results of equation (6) over all 287 sample firms in bio-related industries while <Table 3> is the results of estimation over firms in each industry. The null hypothesis of equal means and variances of dependent variable is rejected by the likelihood ratio test for dispersion parameter α, which confirms that negative binominal distribution can approximate the distribution of dependent variable better than Poisson distribution implying that the distribution of dependent variable, patent, shows over-dispersion. Furthermore, another hypothesis test under the null hypothesis of no difference between the pooling data estimation and the conditional fixed effect estimation supports the fixed effect estimation which reflects the random firm-specific component.

From <Table 2>, individual firm's own R&D expenditures and inner knowledge stock have significant positive effects on patent production for the average firm in all bio-related industries. The elasticity of patent production with regard to inner knowledge stock is about 0.45, which is much larger than elasticity with regard to individual firm's own R&D expenditures, 0.02. The relatively higher elasticity of patent production with respect to inner knowledge stock compared with firm's own R&D expenditures is observed in all industries except environment industry from <Table 3>. The firm's own R&D expenditure reflects just one time experience of R&D investment while the inner knowledge stock reflects the accumulated results of R&D investment experiences. In this context, it would be reasonable that the elasticity of patent production with regard to inner knowledge stock is higher than that with regard to individual firm's own R&D expenditures.

From <Table 2> again, the patent production of average firm in all bio-related industries is negatively affected by outer knowledge stock especially coming from the firms in agriculture and bio-industry. Here, we need to note that we are using patent data as proxy of knowledge and so we are investigating the effects of outer knowledge stock on patent production instead of on knowledge production. In this case, we should pay attention to the function of patent as guaranteeing exclusive rights of knowledge. In general, keen competitions over R&D outcomes are to be expected between firms in technologically related industries. Under the environment that both keen competition over R&D outcomes between firms and patent system which guarantees exclusive rights for new created knowledge exist, competitions between firms over patent application within limited patenting opportunity for similar knowledge or technology are inevitable. Thus, a patent application of one firm becomes a barrier to patent applications of other competing firms, which implies that an increase of knowledge stock in technologically related industries might have negative effects on patent production of related firms. Therefore, some negative effects due to competitions over R&D outcomes between firms as well as pure positive knowledge spillover effects need to be considered together in estimating the effects of knowledge spillover on patent production as in this study (Jaffe(1986), Cohen et al.(1989), Branstetter(2001)). The final sign of estimated coefficient would depend on the relative magnitudes of pure knowledge spillover effects and competition effects.

The negative competition effects of knowledge spillover can be more clearly observed at the industrial level analysis in <Table 3>, where firms in each industry are affected negatively by the outer knowledge stock formed by other firms in the same industry. Since the industries under analysis in this study are classified based on technologies defined by the IPC (International Patent Code) which has been adopted by the Korean Patent Agency, the firms in the same industry would have relatively more homogeneity in the technological area. In this case, it is natural that the firms in the same industry should have higher competition over patent application and have negative knowledge spillover effects on other firms in the same industry. For the agriculture and bio-industry, the negative elasticity of patent production with respect to outer knowledge stock transferred from the firms in the same industry are -0.22 and -0.76 which are comparatively larger than for any other industries. The relatively strong negative effects of outer knowledge stock transferred from the firms in the same industry for the agriculture and bio-industry would mean that the firms in these two industries have larger overlapping, and hence higher competing area in R&D.

The industrial dummy variables are included in <Table 2> to capture the industrial differences in technological opportunity such as propensity of patent application and degree of guaranteeing exclusive rights etc. The estimated results indicate significant differences in technological opportunity in all industries.

Let's see the pattern of knowledge spillover at industrial level in more detail from <Table 3>. The numbers read by raw of <Table 3> indicate the effects of each variable on patent application of firms in each industry while the numbers read by column indicate absorbing effects of firms in each industry. First of all, the knowledge stock created by firms in agriculture has positive effects on the patent application of firms in all other industries especially with strong statistical significance on firms in bio-industry. All other outer knowledge stocks extended by firms in non-agricultural industries have positive or negative effects on firms in other industries. On the other hand the firms in agricultural industry absorb the knowledge stock from the firms in food and beverage industry and chemical industry. Firms in those two industries have statistically significant effects on the patent production of firms in agricultural industry with elasticity of 0.26 and 0.48 respectively. The firms in bio-industry absorb the knowledge stock from the firms in agricultural industry and health industry.

<Table 2> Maximum Likelihood Estimation for Firms in All Bio-related Industries

Parameters		Negative Binominal (Pooling data)	Negative Binominal (conditional fixed effect)
α	Own R&D Expenditures	0.0217 (2.15)*	0.0286 (3.39)***
β	Inner knowledge Stock	0.3692 (15.82)***	0.4572 (17.44)***
Outer Knowledge Stock			
γ_1	Agriculture	-0.0233 (-0.55)	-0.0311 (-1.08)
γ_2	Health	-0.0075 (-0.16)	0.0057 (0.17)
γ_3	Bio-Industry	-0.0158 (-0.36)	-0.0359 (-1.03)
γ_4	Food	0.1099 (2.69)**	0.1199 (3.75)***
γ_5	Chemistry	0.0588 (1.17)	0.0768 (1.80)
γ_6	Environment	0.0539 (1.56)	0.1265 (4.85)***
Dummy Variables			
δ_1	Agriculture	0.6363 (3.01)***	-0.7929 (-4.63)***
δ_2	Health	0.3640 (1.78)	-0.9711 (-5.66)***
δ_3	Bio-Industry	0.2599 (1.23)	-1.0571 (-6.12)***
δ_4	Food	-0.3876 (-1.95)	-1.5022 (-9.04)***
δ_5	Chemistry	0.1513 (0.76)	-1.2707 (-7.39)***
δ_6	Environment	0.1091 (0.49)	-1.2428 (-6.59)***
(Beta distribution parameter) a b			
Number of observations = 1148			
Log likelihood =		-2084.2475	-2080.7134
Wald		733.98	827.12
Prob >		0.000	0.000
Dispersion parameter for count data model(α) = 1.7068			
Likelihood ratio test of α=o : 2379.50 ; Prob > = 0.0000			

Dependent Variable: Patent
Likelihood ratio test vs. pooled: (01) = 117.29 Prob >(01) = 0.000
t-values are in ( )
***, **, * mean to be significant at 1%, 5%, 10% level respectively.

<Table 3> Maximum Likelihood Estimation for Firms in Each Industry (Conditional Fixed Effect Model)

		Agriculture	Health	Bio-Industry	Food	Chemistry	Environment
α	Own R&D Expenditures	-0.002 (-0.06)	-0.001 (-0.07)	0.053 (2.14)*	0.102 (2.77)**	0.054 (3.05)***	-0.008 (-0.28)
β	Inner knowledge Stock	0.344 (4.07)***	0.489 (8.98)***	0.382 (5.92)***	0.304 (4.24)***	0.433 (7.77)***	0.048 (0.45)
γ_1	Agriculture	-0.222 (-2.30)**	0.049 (0.72)	0.859 (3.15)***	0.102 (1.05)	0.061 (1.01)	0.177 (1.34)
γ_2	Health	-0.002 (-0.01)	-0.129 (-1.17)	0.167 (2.03)*	0.270 (1.32)	-0.044 (-0.63)	-0.235 (-1.85)
γ_3	Bio-industry	-0.144 (-1.16)	0.013 (0.10)	-0.760 (-3.52)***	-0.077 (-0.55)	0.007 (0.09)	0.201 (1.60)
γ_4	Food	0.265 (2.04)**	0.085 (0.94)	-0.040 (-0.36)	-0.150 (-0.85)	0.092 (1.71)	0.021 (0.17)
γ_5	Chemistry	0.489 (2.41)**	-0.059 (-0.30)	0.177 (1.16)	0.005 (0.03)	-0.016 (-0.23)	0.218 (0.89)
γ_6	Environment	0.191 (1.79)	0.009 (0.14)	0.071 (1.14)	-0.018 (-0.21)	0.135 (2.47)**	-0.019 (-0.13)
Con	Constant	-0.933 (-1.50)	-0.017 (-0.03)	-1.708 (-2.74)**	-1.859 (-3.05)***	-1.056 (-3.66)***	-0.442 (-0.58)
Log likelihood		-183.68	-517.42	-317.25	-319.55	-463.49	-130.75
Number of Obs.		116	264	176	232	260	100
Wald		129.540	104.300	230.550	53.010	169.060	17.240
Prob>		0.000	0.000	0.000	0.000	0.000	0.028

Dependent Variable: Patent
t-values are in ( )
***, **, * mean to be significant at 1%, 5%, 10% level respectively.

Firms in those two industries have statistically significant effects on the patent production of firms in bio-industry especially with very high elasticity of 0.86 with respect to firms in agricultural industry. Finally firms in chemical industry are affected significantly by the knowledge stock from firms in environmental industry. We cannot find other notable industrial relationships in knowledge spillover.

One of the most interesting findings in this study is that firms in agricultural industry have very strong positive spillover effects especially to the firms in bio-industry. Kim and Kim (2004) attributed the reason to the existence of public research institute (Korea Rural Development Administration; KRDA) in agricultural sector. They calculated the knowledge spillover propensity index based on patent data for all the sample firms in this study and concluded that public research institutes have dominating knowledge spillover propensity. Being at the early stage of development in biotechnology field, private firms are not willing to take over risks involved in R&D in the field of biotechnology. Thus, the industry which has a big public research institute funded by government would have the tendency of extending new knowledge to firms in other industry. Currently is reported that almost 30% of patents applied by KRDA are classified into the field of biotechnology. In this context, we may conclude that there are intimate interactions between the public research institute in agricultural sector which develop the biotechnology and the private firms in bio-industry.

V. SUMMARY AND CONCLUSION

The main purpose of this study is to investigate the pattern and effects of knowledge spillovers between firms in six bio-related industries. The six bio-related industries include agriculture, health, food & beverage, chemistry, environment, and bio-industry. These industries are classified on the basis of the technology defined by International Patent Code (IPC) adopted by Korea Patent Agency. We inferred the pattern and relative effects of knowledge spillover between firms through estimating the effects of knowledge stock created and accumulated by one industry on the knowledge production of other industry. Here, patent is used as a proxy of knowledge throughout this study. Patent is a good means of knowledge transmission as well as a good means to secure the exclusive rights of new invented knowledge. Thus, not only the effects of knowledge spillover but also the effects of competition over patent application within limited patenting opportunity in similar knowledge area are expected to appear in the study where patent is used as a proxy of knowledge like this study. Thus, a patent application of one firm becomes a barrier to patent applications of other competing firms, which implies that an increase of knowledge stock in technologically related industries might have negative effects on patent production of related firms. The results of this study fall into line with the results of some previous studies (Jaffe(1986), Cohen et al.(1989), Branstetter(2001)) in that negative effects of knowledge spillover on patent production are possible when the competition effects dominate the pure knowledge transmission effects. The strong effects of competition over patent application are still more confirmed in this study by the findings that knowledge stock measured by patents of all firms in an industry has negative effects on the knowledge (patent) production of other firms in the same industry.

Firms in agricultural sector tend to have positive knowledge spillover effects on the firms in all other industry especially with strong and statistically significant effects on the firms in bio-industry. The strong positive spillover propensity of firms in agricultural sector is explained by the existence of relatively large scaled public research institute. In Korea, being at the early stage of development in biotechnology, private firms are not willing to take over risks involved in R&D in the field of biotechnology. Thus, the industry which has a big public research institute funded by government would have the tendency of extending new knowledge to firms in other industry.

This study has several limits which come from the assumption that patent is the proxy of the knowledge. Patent is a part of knowledge and cannot explain the whole knowledge created. Papers, new products are good examples of knowledge. Moreover, knowledge spillover may have effects not only on patent application but also on productivity, profitability, quality of product, value of firm, production cost, and employment, etc. However, data availability forced us to stick to the assumption that patent is the proxy of the knowledge.

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