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Article

Factors Affecting the Outbound Open Innovation Strategies in Pharmaceutical Industry: Focus on Out-Licensing Deal

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Abstract: The pharmaceutical industry is a high-technology industry that requires a combination of in-depth knowledge from various fields. It is characterized by high cost, high risk and a long-term perspective due to the high level of regulation. In addition, it is known that research and development (R&D) productivity is deteriorating in the industry. Under these conditions, the importance of open innovation strategies has been emphasized. Under an open innovation system, it is essential for firms to develop several dynamic capabilities to effectively manage their resources both internally and externally. Using a systematic framework of dynamic capabilities suggested by previous studies, this study focuses on the determinants affecting firms' desorptive capacities, which are measured as the number of out-licensing deals, as an indicator for the performance of their outbound innovation. For the analysis, negative binomial regression is employed and inventive capacity and connective capacity are selected as the determinants of the licensors' desorptive capacity. The results of regression analysis reveal that inventive capacity does not have a significant effect on desorptive capacity and that only connective capacity has a significant positive effect on desorptive capacity.

Keywords: pharmaceutical industry; out-licensing; outbound open innovation; desorptive capacity; connective capacity

1. Introduction

The pharmaceutical industry is traditionally known as a knowledge-intensive industry in which various technologies are combined. It entails astronomical research and development (R&D) costs, and a long-time perspective attributed to the regulatory approval required for the production of new drugs. It is characterized by a technology-push model which depends on a complicated path of R&D breakthroughs with unsettled timing and hard-to-anticipate outcomes [1–3]. The extremely technology-driven, risky, costly and long drug development process used to be dominated by large pharmaceutical firms, sometimes referred to as the 'Blockbuster Model'. However, this traditional vertical model conducted by the large pharmaceutical firms has become increasingly hard to maintain since the 1980s. The large pharmaceutical firms have been faced with the (1) patent expiration of their main blockbuster drugs, and the overall pharmaceutical industry being in the situation of (2) lowering R&D productivity due to a reduction in the number of approved new molecular entities. This indicates that the strategy of sourcing the whole required knowledge and skills to develop a new drug within the firm is becoming hard to execute [2,4,5].

In order to overcome this situation, the cooperation and partnerships among the various actors have been increasing. In particular, the relationships among small biotech firms, which are research-intensive

institutes, and large pharmaceutical firms are getting stronger. Since the advent of the late 1980s, biotech firms have played an important role in providing innovative biomolecules through applied research. Most biotech firms are not able to perform the long development process of new drugs. This is because they lack the required downstream assets such as marketing capabilities, professional networks, and other resources to bring their own technologies to the market [6]. Thus, when they start their business, they consider exit strategies such as licensing, initial public offering (IPO), and the acquisition by large pharmaceutical firms. Large pharmaceutical firms not only perform in-licensing from biotech firms, they license out their products and technologies as well to supplement their financial resources and reorganize product lines. These industrial characteristics and the changing landscape are the reasons why open innovation strategies are so crucial to the pharmaceutical industry.

Under the open innovation paradigm, it is essential for firms to build up their dynamic capabilities to correspond with the kaleidoscopic environment. Conventionally, in the context of inbound innovation, studies mainly focused on the concept of the absorptive capacity, as suggested by [7]. However, as firms began to have increasing interest in selling their technologies as a way of outbound innovation, the research on open innovation has moved from mainly considering the inbound process to investigating the outbound process and stressing the need for empirical studies on knowledge capacities [8,9].

Reflecting these demands, numerous studies have been conducted and proved that the various capacities of firms have positive effects on the firms' performance [8,10,11]. However, with regard to the determinants affecting the out-licensing decision itself, only limited analysis exists. In spite of the growing importance of out-licensing activities, the hurdle for the firms to license out their technology as an outbound innovation strategy is quite steep. The success rate between the decision on out-licensing and the actual conclusion is less than 60% [12]. This is due to the complexities of these activities, which are mainly attributed to information asymmetry problems.

Under these circumstances, 'inventive capacity' and 'desorptive capacity' as dynamic capabilities of firms have been identified as main determinants of out-licensing propensity [8,13]. Inventive capacity refers to the firms' capabilities to internally generate new knowledge. This capacity is related to the prestige, noticeability, and visibility of the licensors to the potential licensees. Desorptive capacity is related to the firms' knowledge exploitation capabilities [8,10]. The capacities that firms should build up under the open innovation systems are systematically suggested by Lichtenthaler and Lichtenthaler [10] in their 'knowledge management capacities' framework. This mainstream framework does not include the knowledge retention capability, which is called 'connective capacity.' Connective capacity and how it affects the out-licensing decisions as a means of knowledge retention has received less scholarly attention.

This study focuses on connective capacity of the licensors as the determinant which affects desorptive capacity itself as an indicator of the performance of their outbound innovation. The research questions of the study are as follows: (1) Which capacities does a particular firm need to possess in order to actively out-license? (2) Does knowledge retention have an effect on the out-licensing decisions?

2. Literature Review

2.1. Outbound Open Innovation and Its Determinants

Out-licensing can play a crucial role in accessing the various sources of innovation during the R&D process in pharmaceutical industry [8,14]. As mentioned above, the overall pharmaceutical industry is in the crisis of cutting down of their R&D productivities. Firms seek to lower their total costs and risks of new drug development and shorten time to market through strategic alliances and licensing agreements [1,2,5,15]. In particular, the licensing agreements between pharmaceutical firms and research-intensive biotech firms are being active and strengthened.

For pharmaceutical firms, they try to secure their profits by purchasing technologies from biotech firms and other pharmaceutical firms to counter their declining R&D productivity. According to Kani and Motohashi [16], the wider the R&D pipelines of the pharmaceutical firms, the more likely they are to succeed at commercializing drug compounds. Furthermore, pharmaceutical firms are securing their profitability by licensing out their less important products or technologies to other firms as well.

However, the hurdle for the firms is that licensing out their technology as a strategy of outbound innovation is quite challenging. The attrition rate of conclusion of the deal is nearly below 40% due to the complexities of these activities [12]. Previous research regarding the outbound open innovation focused on 'inventive capacity' in the technology exchange markets and 'desoptive capacity' of the licensors, which were theoretically first suggested by Lichtenthaler and Lichtenthaler [10]. According to Lichtenthaler and Lichtenthaler [10], the "knowledge management capacity is defined as firm's ability to dynamically manage its knowledge base over time by reconfiguring and realigning the processes of knowledge exploration, retention, and exploitation inside and outside the organization". They built up a framework that supplements the existing notion of absorptive capacity and stressed the necessity of knowledge retention as well [7].

2.1.1. Inventive Capacity

Inventive Capacity is defined as "a firm's capability to create new knowledge inside the firm" [10]. The creation of new knowledge is generally the outcome of recognizing opportunity or unmet needs of the knowledge. Therefore, creating new knowledge is influenced by the existing knowledge base of the firm [8]. The new knowledge and technologies arising from the firms' knowledge bases is highly reflected in the patent characteristics of firms such as in forward citations and technological breadth.

Since the nature of technological knowledge is cognitive, intangible and tacit, technology licensing in technology-intensive environments is highly complex [13]. The process of licensing a contract and negotiating with partners is not an easy task due to the problem of information asymmetry [16].

Under this market condition, inventive capacity is related to the 'prestige' of the licensors and serves as a sign of the competencies in terms of the resources or capabilities firms possess. Gambardella et al. [12] listed the patent characteristics that affect a licensing contract as the generality of a technology, the spectrum of potential applications, the economic value of a technology, and patent breadth measured by the technology classes.

There are several reasons why the inventive capacity of licensors makes them more attractive to the potential licensees. First, the patent stock, or famous researchers of the licensors, act as a 'halo effect' that makes the licensee view the potential of the licensor's resource management capabilities or potentials. It provides the collective awareness of potential partners with trustworthiness and promising opportunities. This leads to the high 'noticeability' and 'visibility' of licensors to the licensees.

Second, licensees consider their own prestige to be higher by making transactions with licensors possessing stronger inventive capacities. Conducting a deal with licensors of high inventive capacities means that it is perceived as being an equal trust relationship from the standpoint of other firms. For example, biotech firms borrow prestige of well-known large pharmaceutical firms by forming partnerships [17]. In summary, licensors with a high inventive capacity will have a higher opportunity to out-license their technology due to the increase in noticeability, trustworthiness, and perceived benefits [18].

2.1.2. Desorptive Capacity

The second determinant is desorptive capacity, which is defined by Lichtenthaler and Lichtenthaler [10] as "an organization's ability to identify technology transfer opportunities based on a firm's outward technology transfer strategy and to facilitate the technology's application at the recipient". Desorptive capacity is related to the external knowledge exploitation that refers to the outbound knowledge transfer. It is a type of dynamic capabilities as well as it indicates that the firms

intentionally create, extend or modify their resource bases [19]. According to Teece [20], dynamic capabilities can be "disaggregated into sensing, seizing, and transforming capacity".

To build up a strong desorptive capacity, sufficient prior experience is required [21]. As mentioned above—as the information asymmetry is prevailing in the technology market—prior exposure to dealing with out-licensing can lower the transaction cost. Having experience in gathering information from prospective licensees or existing license negotiation or agreement will reduce the out-licensing cost of the licensors [3,15].

The method to build a strong desorptive capacity is learning from the firm's own technological trajectory [22]. Firms normally face their own problems in reacting to turbulent and competitive environments. According to Rosenberg [23], the innovation here can be defined as the cumulative and firm-specific process of problem defining and solving activities. The technological trajectories of a firm are distinctive and path-dependent since the nature of a firms learning experience are uniqueness and cumulativeness [24].

2.1.3. Connective Capacity

Firm's knowledge management processes are distinguished by knowledge exploration, knowledge exploitation, and knowledge retention [8,10,25]. Lichtenthaler and Lichtenthaler [10] proposed a framework of knowledge management capacities to provide guidance to the firms on how to manage their knowledge related capacities and embraced the standpoints of exploration, exploitation and retention.

Connective capacity refers to "a firm's ability to retain knowledge in interfirm relationships" [10]. It encompasses alliance and the relational capability of a firm. Unlike absorptive capacity, external knowledge retention does not assume transfer of internal knowledge. Instead, licensors are ensured privileged access to external knowledge without completely acquiring it. The more partners a firm has, the easier it is to manage relationships among partners and to benefit from external knowledge retention [8,10].

2.1.4. Other Determinants

Aside from this main classification, previous studies on out-licensing decisions, they have focused on other firm-level determinants. In this study, these determinants are added as control variables due to their well-established effects on the out-licensing process. First, the size of the licensor has been considered [16,26–29]. Firm size was used as an indicator of the degree of complementary assets held by the firms.

The second established determinant is 'R&D Intensity'. Basically, the innovative outputs stem from the R&D activities of firms [7,30–32] and the R&D intensity indicates the concentration of a biopharmaceutical firm's total R&D investments regarding their innovation process. For technology-based firms, the spending on internal R&D tends to promote inter-firm relationships and stimulate the firms' motivation to license out [17]. In summary, the licensor's R&D intensity is expected to have a positive effect on the out-licensing [3,16].

3. Research Framework and Hypothesis

3.1. Research Framework

Based on the above discussion, we developed a research framework with the licensor's desorptive capacity as the dependent variable and inventive capacity and connective capacity as the explanatory variables.

The dependent variable is the out-licensing number of each licensor (DC), which is the outcome of outbound innovation. Regarding inventive capacity—as it is related to internal knowledge exploration—it is reflected by the quality of the licensor's patents. In this study, inventive capacity is measured by the number of forward citations (FC) that represent the value of the patent and by

breadth (TB) corresponding to the qualitative information of the firm's patent stocks as well. Another independent variable—connective capacity—is the ability of knowledge retention resulting from the inter-firm relationships, which is measured by the number of R&D collaboration (NC) and the number of patent backward citation (BC). Additionally, we include firm size and R&D intensity as control variables.

3.2. Hypothesis

As licensing technologies are an act between the licensors and licensees, there will always be inefficiency and an information asymmetry problem. This is attributed to the cognitive, intangible and tacit nature of technological knowledge [13] which affects the licensing activity consisting of activities such as the evaluation of technologies and negotiation with the potential partners [33]. Limited transparency in the technology market impedes the identification of potential partners and leads to the 40% attrition rate with regard to the number of licensing decisions and the number of actually concluded contracts [12]. Under this market condition, inventive capacity is related to the 'prestige' of the licensors and serves as a signal of the quality in terms of the resources or capabilities possessed by the firms. As mentioned earlier, the prestige is deeply associated with the 'noticeability', 'visibility' and 'trustworthiness' of the licensors. In previous studies, it has been measured as the value of the firms' patents or technological breadth and was shown to have a positive effect on the out-licensing decisions.

Gambardella [12] listed patent characteristics such as economic value and the patent breadth of a technology effect on the licensing propensity. Hu et al. [13] have identified the licensors' prestige through forward citation and found that it enhances the licensing propensity. Ruckman and McCarthy [17] measured the determinants of out-licensing as well as the number of forward citations, technology depth and breadth.

First, the patent value is measured as the number of forward citations of the licensors' patents [12,13,17]. A larger number of forward citations implies the outstanding status in the knowledge domain, providing signals to potential licensees that the patents supporting the firm's out-licensing activities ensure generating more economic returns [13]. Therefore, firms with a high number of forward citations of their patents will have a larger number of out-licensing deals.

Hypothesis 1 (H1). *For licensors, the number of forward citations of their patents has a positive effect on the number of out-licensing deals.*

Regarding technological breadth, it is strongly related to the 'noticeability' of the licensors to the licensees. It is related to the variety and scope of technological areas the firms have dealt with [17,34]. Licensors with a broad technological knowledge base are more adept at disseminating their technologies to external parties. This can be interpreted as well as an increased attractiveness to the potential licensees.

Hypothesis 2 (H2). *For Licensors, the technological breadths of their patents have positive effects on the number of out-licensing deals.*

According to the Lichtenthaler and Lichtenthaler [10], the connective capacity implies external knowledge retention, i.e., the firms extending their knowledge bases by forming interfirm relationships. It is constituted as alliance capability and relational capability.

The mainstream of determinants of out-licensing have neglected this point of view. Firms not only conduct inbound knowledge transfer, they enter into various alliances with external parties as well to gain privileged access to their knowledge base. Therefore, by extending their knowledge through connective capacity, firms will be able to efficiently specialize in creating new knowledge [35]. In other words, the licensors with a stronger connective capacity are likely to show stronger desorptive capacity as well.

Previous studies related to the connective capacity measured it as the number of backward citations of the patents or the number of R&D collaborations [8,36,37].

Hypothesis 3 (H3). *For Licensors, the number of backward citations of their patents has a positive effect on the number of out-licensing deals.*

Hypothesis 4 (H4). *For Licensors, the number of R&D collaborations has a positive effect on the number of out-licensing deals.*

4. Methodology

4.1. Data

In this study, we used Medtrack, Gpass and the WRDS (Wharton Research Data Services) database to collect analytic samples. The final sample contains 1094 out-licensing cases conducted by 514 pharmaceutical firms in U.S. during 2009 to 2016.

The out-licensing and R&D collaboration data were derived from Medtrack database provided by INFORMA. Gpass database from LexisNexis was used to retrieve patent information of sample firms. Financial data of sample firms were derived from WRDS. Table 1 shows the descriptive statistics of the variables.

Table 1. Descriptive statistics of variables.

Variables	Observations	Mean	Standard Deviation	Min	Max
Dependent Variable					
Number of out-licensing	1094	1.641682	1.439712	1	13
Explanatory Variables					
FC (Forward Citation)	1094	68.00274	542.107	0	8774
TB (Technological Breadth)	1094	33.18282	210.6407	0	4024
BC (Backward Citation)	1094	9.13528	97.9298	0	2256
CN (R&D Collaboration)	1094	0.81444	1.1094	0	9
Control Variables					
FS (Firm Size)	1094	10,604.85	26,537.75	0	163,000
RND (R&D Intensity)	1094	0.17953	0.69722	0	9.266831

4.2. Empirical Model

Considering the dependent variable is a countable, nonnegative, and integer variable (the number of firm *i*'s out-licensing deals in a given year *t*), the conventional linear regression models are not appropriate for the analysis. As the sample mean is smaller than the sample variance in Table 1, the negative binomial model is specified in this study [38]. The more efficient estimator is used in the situation of overdispersion by adding a parameter that reflects unobserved heterogeneity among observations [27]. Therefore, we adopted the most general negative binomial model used in econometric applications with the mean function λ_i and variance function $\lambda_i + \alpha\lambda_i^2$ [39]:

$$f(y_{it}|\lambda_i,\ \alpha) = \frac{\Gamma\left(y_{it} + \alpha^{-1}\right)}{\Gamma\left(y_{it} + 1\right)\Gamma(\alpha^{-1})}\left(\frac{\alpha^{-1}}{\alpha^{-1} + \lambda_{it}}\right)^{\alpha^{-1}}\left(\frac{\lambda_{it}}{\alpha^{-1} + \lambda_{it}}\right)^{y_{it}} \quad (1)$$

Equation (1) is the model used in econometric applications with a mean function $\lambda_{it} = \exp(X_{it}'Q)$, where X_{it}' denotes a matrix of explanatory variables (FC, TB, CN, BC, FS, RND) and Q denotes a vector of unknown parameters. The estimation method is conducted through MLE.

4.3. Variables

4.3.1. Dependent Variable

The main interest of this study is to identify why some firms are more superior in successfully out-licensing than other firms—in spite of the fact that licensing activities are confronted with a high attrition rate. As this is related to the licensors' competencies to exploit their technology, it could be seen in the context of desorptive capacity. By definition, desorptive capacity refers to the capabilities of firms exploiting their resources to external partners [10] and features path-dependencies that stem from previous experiences. Previous studies have used the number of prior out-licensing deals [8,12,21,40] as a proxy for desorptive capacity.

In this study, it is measured by the number of out-licensing deals of licensors in a given year (DC). In addition, it is important that this study does not take into account the case of licensors with zero out-licensing.

4.3.2. Explanatory Variables

Inventive capacity in this study is measured by the forward citation number of granted patents (FC) and technological breadth (TB) of licensors. The inventive capacity is strongly related to the licensors' visibility, noticeability to the potential licensees and reflects the quality of their technologies [17]. Previous studies have measured the quality of patents in perspective of the number of forward citations [12,13] and technological breadth [12,16,17] of licensors.

In detail, as the number of citations qualifies the quantity of publications and patents [41], FC is computed as the sum of forward citations number of patents for the five-year period before the execution of the out-licensing deals. The TB is calculated as the number of different IPC classes. To measure this, this study followed the approach by Harhoff et al. [42] as the number of identical four-digit IPC classification codes in the granted patents. To be specific, TB is measured as the accumulative number of different four-digit IPC codes of patents in the five years before the execution of out-licensing deals.

According to Lichtenthaler and Lichtenthaler [10], connective capacity is the firms' ability to link with other external partners to facilitate the innovation process. It is associated with knowledge retention—which excludes the complete knowledge transfer. In previous studies, the number of R&D collaboration or the number of backward citations of patents are used to measure connective capacity [8,36,43]. Therefore, in accordance with these measurements, this study measures connective capacity in two ways; the number of R&D collaboration (CN) is defined as the sum of R&D collaborations in the five years before the execution of the out-licensing deals; and the number of backward citation (BC) is calculated as the sum of backward citations in the five years before the execution of the out-licensing deals.

4.3.3. Control Variables

This research includes two control variables; (1) firm size and (2) R&D intensity. Previous research has measured the firm size as the amount of sales or the number of employees. Since the dependent variable used in this study is a countable integer, firm size was measured as the number of employees in the intention to match the unit of measurement. There is the intention to avoid a duplication problem as well, because the R&D intensity is calculated as the R&D expenditure normalized by sales. The R&D intensity is normally measured as the R&D investment divided by the firm size [17]. It represents the concentration of the firms' innovation activities. Thus, the higher the R&D investment of pharmaceutical firms, the more likely they are to obtain technological innovation or financial outcome. In this context, the R&D intensity in this study is calculated as the R&D expenditure of each licensor in a given year normalized by its sales. Table 2 presents the specification of variables.

Table 2. Specification of variables.

Variable			Definition	Source of Data
Dependent Variable	Desorptive Capacity	Number of out-licensing (DC)	The number of out-licensing deals of each licensor in a given year	Medtrack
Explanatory Variable	Inventive Capacity	Number of forward citations (FC)	Accumulative number of the FC of each firm for five years before the execution of deal	Gpass
		Technological breath (TB)	Number of distinct IPC codes of each firm for five years before the execution of deals.	
	Connective Capacity	Number of backward citations (BC)	Accumulative number of the BC of each firm for five years before the execution of deal	Gpass
		Number of R&D collaborations (CN)	Accumulative number of R&D collaboration of each firm for five years before the execution of deal	Medtrack
Control Variable		Firm size (FS)	The number of employees of each licensor in a given year	WRDS
		R&D intensity (RND)	R&D Expenditure of each licensor in a given year/sales of each licensor in a given year	

5. Results

Table 3 reports the negative binomial regression results for the licensors' desorptive capacities. In order to examine the effect of each explanatory variable in detail, the regression is conducted in three ways; in Model 1, connective capacity is excluded; Model 2 is the result of analysis excluding inventive capacity; and Model 3 is the full model incorporating all variables.

First, in Model 1, FC, RND and FS of the licensors show a positive coefficient value, but only FS is statistically significant at the 1% significance level (0.00001). On the other hand, TB has negative signs but is not statistically significant.

In Model 2, both BC and CN, which represent the connective capacity of the licensors, show positive coefficients (BC: 0.00004, CN: 0.3885) at the 1% significance level. FS is positive as well at the 1% significance level (6.97×10^{-6}). RND shows a negative coefficient value but is not statistically significant.

Finally, the results of Model 3 are as follows: the coefficient values of the FC and TD—the inventive capacity of the licensors—are negative, but not statistically significant. On the other hand, BC and CN, which represent connective capacity, show positive coefficients (BC: 0.0008, CN: 0.3859) at the 1% significance level, which is the same as in Model 2. FS is positive as well at the significance level (7.08×10^{-6}). RND shows a positive coefficient value but is not statistically significant.

Looking at the results based on the variables, the coefficients of FC and TB—which represent the inventive capacity of the licensors—are showing inconsistent results and are statistically insignificant in both Model 1 and Model 3. This result implies that inventive capacity, with or without the influence of connective capacity, has no substantial effect on the desorptive capacity of licensors. Therefore Hypothesis 1, which stated that inventive capacity positively affects desorptive capacity, is not supported. This contradicts the results of previous studies which found that the inventive capacity of licensors positively affects the licensing propensity [12,13,16,17].

Concerning the connective capacities of the licensors, both CN and BC showed consistent results. Both coefficients are positive at the 1% significance level. In other words, the connective capacity of licensors has been proven to have a positive effect on their desorptive capacity. As licensors actively engage in R&D collaboration, they can share the R&D results of the partners, which in turn activate their backward citations and enrich their knowledge base. Consequently, out-licensing deals are conducted more actively [10].

Regarding the control variables, coefficients of FS are positive at the 1% significance level. This result follows Kim and Vonortas [27] and Kani and Motohashi [16] in that large licensors are more likely to license-out because they have a greater tendency to sell their non-core technologies in order to complement their revenue. This is attributed to the fact that large firms have larger patent portfolios than smaller firms. On the contrary, RND is found to not be statistically significant.

In summary, the results imply that existing licensors should strengthen their connective capacities rather than their inventive capacities to facilitate out-licensing activities. By forming collaborations, the firms could benefit from their partners' R&D outcomes and utilize these to further strengthen their knowledge base. Consequently, this facilitates active out-licensing. This suggests that different strategies are needed for out-licensing, depending on whether a firm is already conducting out-licensing or not.

Table 3. Negative binomial regression results.

Variables	Model 1	Model 2	Model 3
FC (Forward Citation)	0.00006 (0.00007)		−0.0001 (0.0001)
TB (Technological Breadth)	−0.0005 (0.00005)		−0.0001 (0.0004)
BC (Backward Citation)		0.00004 (0.00001) ***	0.0008 (0.0003) ***
CN (R&D Collaboration)		0.3885 (0.0399) ***	0.3859 (0.0399) ***
FS (Firm Size)	0.00001 (1.14×10^{-6}) ***	6.97×10^{-6} (1.15×10^{-6}) ***	7.08×10^{-6} (1.15×10^{-6}) ***
RND (R&D Intensity)	0.0306 (0.059)	0.0228 (0.0401)	0.0220476 (0.0404)
Log pseudolikelihood	−11,114.2593	−923.87547	−922.80171
Wald chi^2	261.75	499.75	623.50
Pseudo R^2	0.2282	0.3601	0.3608

1. *** indicates significance at <1%. 2. Number of observations: 1094. 3. Standard deviations are in parentheses.

6. Discussion and Conclusions

6.1. Theoretical Contribution

The pharmaceutical industry is a high technology industry that requires a combination of in-depth knowledge of various fields and is characterized by high cost, high risk and long-term perspectives due to high regulation. It faces the problem of deteriorating R&D productivity as well [1]. Under these conditions, the importance of open innovation strategies has been emphasized more than in any other industry, and, under the open innovation system, it is essential for firms to develop several dynamic capabilities to effectively manage their resources both internally and externally. Lichtenthaler and Lichtenthaler [10] suggested a systematic framework for such dynamic capabilities.

Among the capabilities, the absorptive capacities of firms related to the inbound process and external exploration have been a focus of research since the 1990s. As firms have shifted their focus to outbound innovation, several studies have been conducted on desorptive capacity [13], which is related to knowledge exploitation. The mainstream of the previous studies are studies on how these dynamic capabilities affect firm performance [8,11,40] and licensing propensities [13,16,26,27].

Therefore, the academic implications of this study are as follows: first, it differs from the previous studies, which have focused on the effects of dynamic capabilities on firm performance or licensing propensities. These studies have showed that the more capabilities firms build up, the higher performance they achieve. However, the desorptive capacity itself indicates that the performance of outbound innovation has received less attention as a dependent variable. Therefore, this research can be said to perform inter-capabilities analysis, which differs from the mainstream of dynamic capabilities research.

Second, previous studies dealing with the determinants of out-licensing propensity are limited to inventive capacity and desorptive capacity [13], which is related to knowledge exploration and exploitation. The perspective of knowledge retention was not considered as a determinant of out-licensing decisions. These days, it is not hard to see the landscape in which biotech firms' knowledge

is externally retained by pharmaceutical firms without immediate knowledge internalization. However, pharmaceutical firms have ensured exclusive access to the partners' R&D outcome by establishing partnership agreements [8]. In other words, the determinants of out-licensing have been more systematically organized and complemented in this research.

6.2. Managerial Contribution

This study identified competencies the licensors should build up in the pharmaceutical industry to actively conduct out-licensing deals. The important point here is that it focuses on the firms that have already been out-licensing. Thus, it does not cover the decision of whether or not to out-license, but rather focuses on existing licensors to investigate whether they are further promoting their out-licensing activities. Thus, as the determinants of out-licensing, inventive capacity and connective capacity of the licensors were measured by the characteristics of their knowledge such as patents and R&D-related activities.

The empirical results of this study provide important implications for firms engaged in the pharmaceutical industry. The inventive capacity of licensors are the core competencies for forming their knowledge base and reaching the licensees with signals. Previous studies have shown that this positively affects the out-licensing propensity [13,16,26,27].

However, according to the results of this study, inventive capacity does not have a significant effect on the licensors that are already out-licensing. On the contrary, connective capacity has a positive effect on desorptive capacity. Thus, in order to promote out-licensing activities of firms that are already out-licensing, additional efforts should be put into forming alliances or R&D collaborations with other external parties, rather than into internal R&D capacity improvement. In order to stimulate out-licensing activities, it is necessary for licensors to replenish their knowledge base through new innovations. However, there is no meaningful effect through the internal capabilities of the firms, and only the reconstruction of the knowledge base through the influx from inter-firm relationships has confirmed positive effects.

This can be explained in two ways: First, if the licensor is already engaged in out-licensing activities, this indicates that they have established some positioning in association with prestige, noticeability and technology fields related to the abilities to generate new knowledge internally. The next point is that the overall pharmaceutical industry is facing reduced R&D productivity. Increasingly stronger regulations on new drugs and developing treatments for most diseases are making it more difficult to maintain innovation [6]. Therefore, it is more efficient and time-saving for licensors to build up their knowledge base by sharing R&D outcome through various alliances or R&D collaboration with other partners, and actively citing the other partners' knowledge. In summary, as the desorptive capacity of licensor drives firms performance [8,11,40], the analysis on the determinants of desorptive capacity itself is meaningful for firms wanting to know how to best actively participate in the outbound process. This will provide licensors with some guidance for sustainability in dynamic open innovation ecosystems.

6.3. Limitations and Future Study

The limitation of this study is that the determinants of out-licensing are confined to the firm-level knowledge management capacities. It has been proven through several previous studies that the effects of industry-level characteristics affect out-licensing as well [16,21,26,27]. According to these studies, the licensors should consider not only their capabilities, but also the characteristics of the industry when out-licensing. Depending on how many competitors are in the market, the licensor's out-licensing incentive will vary with two effects; the revenue effect (the degree of profits they earn from out-licensing) and the rent dissipation effect (the extent to which market share is reduced by increasing competitors in the market).

In addition, another limitation of the study is that the interpretation of the analysis result is not rigorous because of the missing classification among the firms. As mentioned earlier, the pharmaceutical industry consists of large pharmaceutical firms and small and medium-sized biotech firms. They have

different incentives for out-licensing because they exhibit differences in the holdings of downstream assets. Large pharmaceutical firms tend to license out technologies that are less important to them, because they have a wealth of resources, marketing capabilities, and networking capabilities compared to biotech companies.

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