Special Section on Open Innovation

BerkeleyHaas
Haas School of Business
University of California Berkeley

Why Do Experts Solve Complex Problems Using Open Innovation?

Evidence from the U.S. Pharmaceutical Industry

Yeolan Lee[1], Eric Fong[1], Jay Bryan Barney[2], and Ashton Hawk[3]

California Management Review
2019, Vol. 62(1) 144–166

DOI: 10.1177/0008125619883617
journals.sagepub.com/home/cmr
SAGE

SUMMARY

This article investigates how project expertise and complexity jointly impact the decision to adopt open or closed innovation. It identifies four different types of open innovation models—crowdsourcing, coopetition, science-based, and network—and explores the varying conditions of project expertise and complexity under which firms tend to adopt a particular type. Using large data analysis from pharmaceutical drug development projects, the authors find that complexity moderates the relationship between project expertise and the choice of open or closed innovation and that levels of complexity and project expertise vary between different open innovation models.

KEYWORDS: open innovation, complexity, project expertise, new product development, absorptive capacity

As open innovation becomes more common, many managers face the question as to when their firms should adopt open innovation models for new product development (NPD). Inbound open innovation (OI) refers to the adoption of external knowledge, and closed innovation refers to the use of internal knowledge for a firm's NPD.[1] Prior literature shows that project expertise (defined as a firm's expertise and specialization in relation to a particular development project) and complexity (defined as interdependencies between components in the product development) are

[1]The University of Alabama in Huntsville, Huntsville, AL, USA
[2]The University of Utah, Salt Lake City, UT, USA
[3]University of Colorado Boulder, Boulder, CO, USA

two critical determinants of the decision to choose open or closed innovation.[2] However, while scholars generally agree that firms with relevant project expertise will use closed innovation and firms without such project expertise will use OI,[3] little agreement exists for complexity. Some scholars argue that closed innovation models are more efficient than OI models to integrate knowledge for complex projects, and, therefore, as complexity increases, firms should adopt closed innovation.[4] In contrast, other scholars highlight the fact that complex projects require the acquisition of diverse ideas and solutions from outsiders, and, thus, an OI approach may be better suited to deal with high complexity.[5]

These contradictory recommendations are partially attributed to scholars' emphasis on either knowledge integration (the process of integrating knowledge that resides in different individuals, functions, departments, or organizations) or knowledge divergence (the process of diversifying knowledge pools and problem-solving approaches or heuristics) in closed or open innovation environments. However, complex projects require *both* knowledge integration *and* knowledge divergence, and the choice of open or closed innovation can create trade-offs between knowledge integration and divergence. Put differently, neither open nor closed innovation models is inherently superior; the costs and benefits of these models depend upon the levels of project expertise and complexity that firms have when developing new products. The interaction between project expertise and complexity can influence the trade-offs and, thus, the choice of open or closed innovation.

Although prior literature recognizes that the joint effect of project expertise and complexity in the open and closed innovation choice may be important, little research examines both project expertise and complexity together, and the impact of their interaction on the choice of open or closed innovation has been largely ignored. Afuah and Tucci provide one of the few articles that include both project expertise and complexity, and they theoretically propose that high complexity and low project expertise can result in the choice of crowdsourcing (a particular type of OI model) over closed innovation.[6] In essence, their paper provides a theoretical explanation as to why firms that have little relevant project expertise adopt crowdsourcing to deal with complexity; however, their proposition on the joint role of complexity and project expertise has not been further explored nor empirically tested.

Our article adds to Afuah and Tucci's work by theoretically proposing, and empirically testing, the full moderating effect of complexity on the relationship between project expertise and OI adoption, in general. We also explore the relationships between project expertise, complexity, and a host of OI models: crowdsourcing, coopetition, science-based, and network. Regarding the moderating impact of complexity, we argue that complexity weakens the negative relationship between project expertise and OI adoption and, as a result, leads more firms with relatively high project expertise to adopt OI models. However, since not all OI models are the same, we then examine the individual OI models

and show differences in their use in relation to project expertise and complexity. For managers, we address two important questions: how does complexity moderate the relationship between project expertise and choice of open or closed innovation? Which OI model (crowdsourcing, coopetition, science-based, and network) is most often utilized when firms face certain levels of project expertise and complexity in a development project?

We use the U.S. pharmaceutical industry to study our research questions because firms in this industry face inherent complexity in NPD; they have widely adopted OI models to deal with complexity; different types of OI models exist in the industry, which provides the opportunity to examine how complexity and project expertise differ between these OI models; and implications learned from this industry are applicable to other complex industries such as aerospace, artificial intelligence, and semiconductor. Given that patents offer strong appropriability,[7] and firms prevalently use patent licenses to exchange knowledge in the industry,[8] we focus on OI models using patent licenses.

Theory Background

Complexity and NPD

To understand the role of complexity in NPD, managers need to understand that NPD is a process of recombinant search; new products are combinations of existing and/or new components, ideas, and processes.[9] For instance, the automobile is the combination of interchangeable parts including bicycles, internal combustion engines, and carriages.[10] The mobile phone is the combination of circuit boards, crystal displays, batteries, speakers, and keyboards. NPD is a solution search process in which firms identify a set of components and find ways to combine those components.[11]

Complexity arises in the NPD process because large numbers of components need to be integrated into a product and/or because there are interdependencies between those components.[12] According to Simon, as an NPD project combines a larger number of interacting components (i.e., NPD complexity increases), the search for a solution increasingly becomes more difficult; trials and errors go up and the probability of finding valuable products significantly goes down.[13]

Finding solutions to complex projects requires the creation of heuristics that guide solution search processes. Tacit knowledge (such as professional opinion, intuition, insight, and creativity), which is developed through project relevant expertise, creates heuristics that lead to successful solutions.[14] With such tacit knowledge, a firm is able to efficiently eliminate unsuccessful search paths and detect successful solutions in a complex project.

As knowledge becomes more sophisticated and evolves into narrowly defined subfields, NPD requires the combination of components from varying disciplinary and scientific areas.[15] As Leonard and Sensiper explain,

> We may have no choice about managing divergent viewpoints in the creation of today's complex systems of products and services . . . For instance, the first generation of cellular phones in the early 1980s, required only electrical engineering skills. By the mid-1990s, the third generation of these phones called for a knowledge of physics as well as electrical, mechanical, and computer engineering.[16]

In essence, in a complex system of innovation, NPD requires both knowledge integration and knowledge divergence.[17] Knowledge integration is important for solving complex problems because without integration, the creation of diverse ideas, viewpoints, and heuristics from different individuals or organizations will cause conflict and increase the costs of communication and coordination. At the same time, knowledge divergence is also critical in complex product development environments because without divergence, the integration of tacit knowledge from individuals that are governed by the same organizational culture and routines causes homogeneous thinking and limits viewpoints, which produce less innovation output.[18] In sum, complexity in NPD increases the need for both knowledge integration and knowledge divergence.

Knowledge Integration and Divergence in Open and Closed Innovation

Because firms need both knowledge integration and divergence in complex product development, managers are faced with a trade-off dilemma when choosing between open or closed innovation. Knowledge-Based View (KBV) research shows that closed innovation is more efficient than OI at integrating knowledge that resides in different individuals and functions because employees in the firm share the same vocabulary, organizing system, and principles.[19] Because complexity makes it difficult to break a product development project into several subtasks, when working with other organizations in complex development environments, the whole task is more likely to be shared with partners—and, accordingly, managers need to spend a lot of time and cognitive effort to communicate and integrate functions with the partners.[20] In a closed innovation environment, the time and cognitive effort is minimized because of the shared vocabulary, organizing systems, and principles.

In contrast, the OI literature highlights OI's advantage at collecting large knowledge pools in multiple disciplines, finding novel ideas, and diversifying problem-solving approaches.[21] Complex projects are characterized by the difficulty and uncertainty in anticipating technological feasibility and customer preference.[22] Inaccurate specification of user needs and the inability to fix errors in a timely manner can significantly increase complex project development costs and delay product testing and launch.[23] To overcome these issues, complex projects require collaborations with users, customers, and clients.

Almirall and Casadesus-Masanell found that complex projects require the matching of knowledge to reflect customers' preferences and their willingness to

pay, and OI is better suited to developing superior products in the eye of customers.[24] Jeppesen and Lakhani found that OI broadcast search (where a firm discloses the details of the problem at hand and invites others to solve the problem) brings novel perspectives and heuristics to the focal project and produces winning solutions based on the approaches that are native to the external problem solvers.[25] Terwiesch and Xu show that products developed through OI are always optimal in terms of technology performance and customer preference because OI brings together a diverse set of problem solvers.[26]

Theory on OI knowledge divergence benefits is deeply rooted in the organizational learning and absorptive capacity literature. Nelson and Winter view firms as a repository of routines, procedures, schema, and heuristics associated with their existing knowledge base, which accumulates over time and, thus, reflects their expertise.[27] In closed innovation environments, a firm's routines and existing expertise make it difficult to overcome incremental innovation trajectories, limit their knowledge pools, reinforce tendencies toward local search (the behavior to search in the neighborhood of its current expertise area), and often result in managerial decision-making biases, such as the "familiarity trap" (a situation where managers tend to focus on their specialty areas to develop deeper expertise).[28] Managerial bias and local search can limit both the number of viewpoints and size of knowledge pools available for development projects. Thus, the choice of closed innovation can dramatically increase knowledge divergence costs as the firm possesses more experience and established routines related to the focal development area.

Prior literature argues that absorptive capacity, defined as "a firm's ability to recognize the value of new, external information, assimilate it, and apply it to commercial ends," is related to the possession of prior knowledge stock in relevant knowledge fields (i.e., project expertise).[29] Firms with relevant project expertise and, thus, absorptive capacity are able to efficiently acquire diverse perspectives needed for complex projects through OI, and, therefore, knowledge divergence benefits in OI models can be magnified with higher levels of project expertise.[30]

This literature suggests that as complexity increases, high project expertise does not automatically lead to choosing closed innovation even though closed innovation offers distinct knowledge integration advantages given that firms can utilize various mechanisms to reduce knowledge integration costs. Rather, firms with high project expertise may choose OI models because of their inability to diversify their knowledge pools in closed innovation environments, and they have sufficient absorptive capacity to efficiently use external knowledge for complex projects.[31] This logic suggests that increasing complexity in NPD environments can moderate (weaken) the relationship between high project expertise and choice of open or closed innovation, and lead firms with relatively high project expertise to adopt OI.

Types of OI Models

Crowdsourcing OI

Crowdsourcing OI is defined as outsourcing a problem-solving task to the public.[32] Crowdsourcing OI can be in the form of broadcast search, intermediaries, communities, or platforms.[33] In this type of OI, firms broadcast the problem and individuals offer ideas, knowledge, or solutions to the problem, and this external knowledge is used in NPD. Crowdsourcing OI consists of several common elements, including a well-defined and articulated problem statement to be shared with the crowd, information on prizes to winners, evaluation methods, and time limits (i.e., some duration for the crowdsourcing contest).[34] The defining characteristic of crowdsourcing OI is the large number of problem solvers engaged in the innovation process, which ultimately can help the firm solve complex problems and enhance the quality of new products.

Researchers using modeling and theory argue that the participation of a large crowd in an innovation process always produces optimal outcomes when the focal firm lacks relevant project expertise.[35] A few empirical research studies support this proposition. Jeppesen and Lakhani's study on InnoCentive.com found that winning solutions were generated, through crowdsourcing OI, by external problem solvers who have the characteristic of "technical marginality" (defined as being distant from the focal problem in terms of technical expertise).[36] Shah studied open source software projects and reported that need-driven participants, who have highly diverse motivations and skills, account for many new software development ideas. She further argues that offering proper motivation mechanisms to different participants is the key to crowdsourcing OI success. Such motivation mechanisms include financial rewards, reputation, enjoyment, and intellectual stimulation.[37]

Although crowdsourcing OI provides benefits for dealing with complexity in NPD, overly complex crowdsourcing tasks can also discourage the crowd from joining the problem-solving contest and may reduce the benefits of crowdsourcing OI. This is because solving highly complex problems requires large investments of participants' time and skill, which may create negative reactions and reduce enjoyment and fun.[38] Thus, crowdsourcing OI is most suitable for dealing with moderate levels of complexity when the firm lacks relevant project expertise.

Coopetition OI

Coopetition OI is defined as OI created between firms in the same industry, and this type of OI entails the simultaneous pursuit of collaboration and competition.[39] Coopetition OI can occur between competing firms over different value chain functions or different phases of NPD.[40] For instance, competitors can collaborate for upstream activities, such as Research and Development (R&D), but compete in downstream activities, such as sales.[41]

Research shows that this type of OI is particularly useful for focal firms when they lack the required project expertise and can learn from rivals'

expertise.[42] The resource complementarity of firms in coopetition OI helps them jointly deal with complexity based on absorptive capacity because they share a common knowledge base regarding industry environments, product development processes, regulatory requirements, and general customer preferences.[43] Studying collaborations between Sony and Samsung, Gnyawali and Park conclude that "even a giant cannot go it alone given the technological trends."[44] Tether reports that when a firm heavily invests in acquired technologies to deal with complexity, it is likely to collaborate with competitors.[45]

Science-Based OI

Science-based OI is defined as collaborations between firms and research organizations including universities, government labs, and other research institutes, and it becomes an important source of scientific knowledge acquisition in NPD.[46] Scientific knowledge is different from other types of knowledge because it contains fundamental properties and underlying mechanisms of particular phenomena rather than merely describes what occurred.[47] Such scientific knowledge becomes more useful in complex NPD projects as it efficiently guides search processes on how to combine interconnected components. In the pharmaceutical industry, scientific knowledge originated from universities or government labs is an important source of new drugs and delivery systems.[48] Research shows that science-based OI allows firms access to cutting-edge scientific and specialist knowledge.[49]

However, firms using science-based OI face obstacles and significant challenges.[50] One of the challenges is related to transforming untested theory and raw science research into new products. High absorptive capacity is required to identify potential scientific knowledge that can be transformed into marketable products.[51] Cockburn and Henderson empirically show that absorptive capacity is the main determinant of the productivity of science-based OI.[52] Bishop, D'Este, and Neely found that the possession of relevant expertise can nurture the organization's absorptive capacity and increase the benefits of science-based OI.[53] In this regard, science-based OI is different from crowdsourcing and coopetition OI in that it requires the focal firm to possess relevant project expertise to utilize the external knowledge. When a firm has sufficient absorptive capacity, the science-based OI model can help the firm deal with high levels of complexity and create breakthrough innovations.

Network OI

OI can take the form of networks, ecosystems, or consortia, where multiple players participate in NPD.[54] Nambisan and Sawhney claim that network OI is a distinct form of OI in that it requires coordination processes between multiple organizations in the network.[55] Vanhaverbeke and Cloodt explain that the network OI model ("value constellations") is born to deal with increasing complexity in technological development.[56] Ritter and Gemunden state that networking OI can be used to deal with problems created by complex, interconnected technologies.[57]

Several empirical studies support the idea that network OI is the most efficient form for dealing with high levels of complexity. For instance, Olsen, Sofka, and Grimpe explain that network OI is formed to jointly solve "grand challenges," which are defined as the most significant complex and interdependent problems.[58] Kapoor and Adner explain that network OI helps organizations solve complex problems and enhance their learning opportunities.[59] Studying biopharmaceutical consortia, Allarakhia, Kilgour, and Fuller state that "consortia enable geographically separated researchers, facing the interconnectivity of large biological datasets, to develop tools to support complex upstream discovery research, and address the challenges associated with downstream product development."[60] Network OI models can be formed not only at the business level, but also at the regional, state, and national levels.[61]

Scholars report that network OI is strongly associated with participants' technological specialization and expertise in their knowledge fields.[62] This literature suggests that network OI can connect organizations that have specific project expertise in their fields and collectively solve highly complex problems.

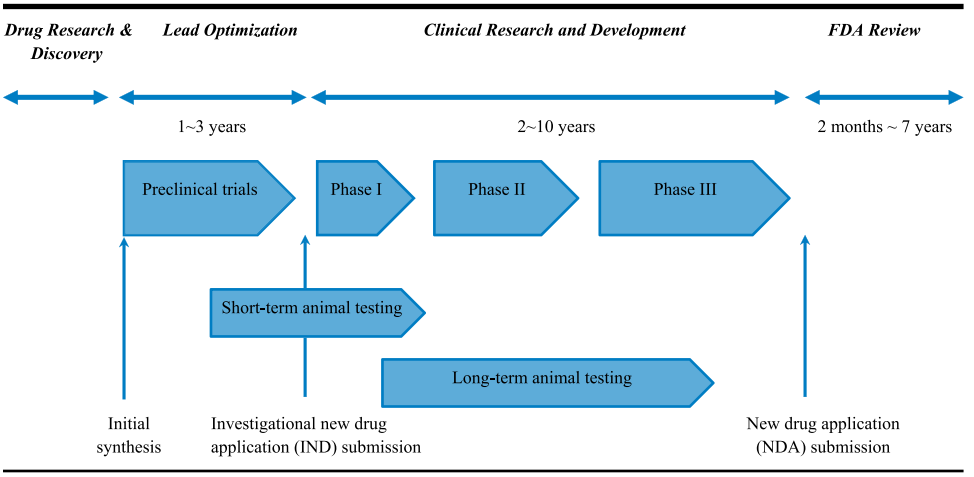
Research Design

The Pharmaceutical Industry

Pharmaceutical drug development is a multi-year, complex process starting from the discovery of compounds and ending with drug introduction. To introduce new drugs, pharmaceutical firms follow a similar process, as shown in Figure 1.[63] First, the firm conducts research to identify a drug target (molecules associated with particular diseases that can potentially produce desirable therapeutic effects) and the lead (the most promising compound). After the drug target and lead are identified, the firm assesses them using in vivo and in vitro models at the lead optimization stage. After animal testing results show positive signs and the commercial potential of a lead, the lead becomes a drug candidate. At this point, a firm files an investigational new drug (IND) application to the Food and Drug Administration (FDA) and initiates three phases of clinical trials. The firm tests the efficacy and toxicity of the drug candidate through these trials: Phase I includes 20 to 100 individuals with or without the disease, Phase II includes several hundred patients with the disease, and Phase III includes 300 to 3,000 patients that have the disease. After the firm collects sufficient evidence that shows the efficacy and safety of its drug candidate, it files a new drug application (NDA) for FDA review to obtain market approval.[64] The firm can sell the drug in market after approval.

Pharmaceutical NPD requires the understanding of basic science, human diseases, drug mechanisms, pharmacokinetics and pharmacodynamics profiles, clinical trial designs, and mass-manufacturing processes. Components used in drug development are also interdependent (i.e., change in one component requires changes in other components). For instance, a drug candidate may show sufficient efficacy to treat a target disease, but have undesirable side effects associated with

FIGURE 1. Pharmaceutical new product development process and timeline.



Source: M. Dickson and J.P. Gagnon, "Key Factors in the Rising Cost of New Drug Discovery and Development," *Nature Reviews Drug Discovery*, 3/5 (2004): 417-429; FDA website, https://www.fda.gov/forpatients/approvals/drugs/ucm405622.htm.
Note: FDA = Food and Drug Administration.

its drug delivery system. However, some components of the drug candidate only work with that particular delivery system and, thus, the firm cannot easily replace the delivery system. Such interdependencies between components in drug development require numerous iterations of development processes and create challenges for pharmaceutical firms.

Data Collection

We collected all prescription drugs approved during the period of 1990-2000 from the FDA database including the Orange Book. Although these data are publicly available, the FDA deletes expired patents related to drugs when it updates the electronic Orange Book. Therefore, we directly requested the data on all FDA-approved drugs and related patents through a Freedom of Information Act request and created our sample based on the FDA-provided data. Although the Orange Book offers information to match patents to the drug sample, it does not contain detailed information on the patents, specifically whether those patents were internally developed by focal organizations or externally sourced. Detailed information on patents is collected from the National Bureau of Economic Research[65] and the United States Patent and Trademark Office (USPTO). Firm-specific information such as R&D spending, firm age, and firm size were collected from Compustat. Information on marketing and sales executives was collected from the CorpTech Directory. Therapeutic market classes related to our drug sample are collected from the Physicians' Desk Reference. Project-specific information, such as therapeutic experience, priority reviewed, and orphan drug, was collected from the FDA database. Our final sample includes 309 prescription drugs developed by 59 firms. Because our main variables (project expertise and complexity) vary between projects within firms, we use project-level (drug development project) as our unit of analysis.

Variables

We created our main variables (choice of open vs. closed innovation, project expertise, and complexity) based on methods used in existing literature. Following Ceccagnoli et al., we created the variable, *open innovation choice*, to indicate whether the drug development project utilized internal or external patents.[66] If drug patents were originated from the drug developer, it means that the project utilized internal knowledge to develop the drug; therefore, it was coded as 0 (closed). If drug patents were originated from external entities, it means that the project utilized external knowledge to develop the drug, and, therefore, it was coded as 1 (open). We adopted Fleming and Sorenson's measure of *complexity*.[67] To capture *project expertise*, we count the number of previous patents that a focal organization had in the same technological fields (USPTO subclasses) as the focal drug patents seven years prior to the drug introduction. We took seven-year lags given the pharmaceutical development process takes between two and 17 years (on average seven years).[68] Table 1 summarizes our main and control variables.

Method

Because this research focuses on the choice between open and closed innovation, we use probit regression to examine our research questions. Given that the unit of our analysis is an NPD project and there are multiple projects within firms in our sample, we used probit regression with the robust standard errors clustered by firms.

Findings

We found that among the 309 prescription drugs in our sample, 211 drugs (68.28%) were developed through OI projects, and 98 drugs (31.72%) were developed through closed innovation projects. In OI projects, pharmaceutical and biotechnology companies accounted for 61.14% of all external knowledge sources, universities accounted for 5.21%, government organizations accounted for 3.79%, hospitals and research centers accounted for 5.69%, individual scientists accounted for 5.69%, and others accounted for 18.48%. Our data show that collaborations between pharmaceutical companies or between pharmaceutical and biotechnology companies are the most common form of OI models in this industry (coopetition OI).

We also found that multiple organizations collaborate for new drug development. For instance, AstraZeneca introduced the drug Atacand (treatment for hypertension and heart failure) in collaboration with Takeda Chemical and Nokia Mobile. In this drug development project, Takeda Chemical provided its compounds for treating hypertensive heart disease, and Nokia Mobile provided its power saving technologies in data transmission. Table 2 provides examples of these different OI models in our data.

How does complexity moderate the relationship between project expertise and choice of open/closed innovation? To test our proposition on the moderating effect of complexity, we first examine how project expertise affects the choice of open or

TABLE 1. Variable Description.

Variables	Description
Dependent variable	
Open vs. closed innovation choice	We adopted Ceccagnoli and colleagues' measure on the use of internal or external knowledge in pharmaceutical drug development projects.[a] If drug patents were originated from the drug developer, they were coded as 0 (closed). If drug patents were originated from external entities, they were coded as 1 (open).
Independent variables	
Complexity	We adopted Fleming and Sorenson's measure of complexity, which captures the degree of interdependency between drug components (patents).[b]
Project expertise	We measured the count of previous patents that a focal organization had in the same technological fields (United States Patent and Trademark Office subclasses) of the drug patents (listed on the Orange Book) seven years prior to the drug introduction.
Control variables	
Orphan drug	Orphan drug was coded as 1 and non-orphan drug was coded as 0.
Radical drug	New molecular entity was coded as 1 and otherwise 0.
Priority reviewed drugs	Priority reviewed drug was coded as 1 and standard reviewed drug was coded as 0.
Therapeutic market classes	Seven therapeutic market areas including Analgesic/Anesthetic, Anti-infective, Antineoplastic, Cardiovascular, Central Nervous System, Endocrine, and Others were identified, and six therapeutic dummies were included (with Others as our omitted reference group).
R&D expenses	The logged average R&D expenses of a firm during the past five years.
General technical capacity	A log of the firm's total patent counts over the past ten years.
Therapeutic experience	The number of a firm's new drug applications during the past 20 years.
Complementary assets	The possession of sales and marketing executive(s) at the time of drug approval was coded as 1 and otherwise 0.
Firm size	The logged average number of a firm's employees during the past five years.
Firm age	The number of years since a firm's founding.
Year dummies	Year dummies 1991-2000 (1990 is the omitted reference year).

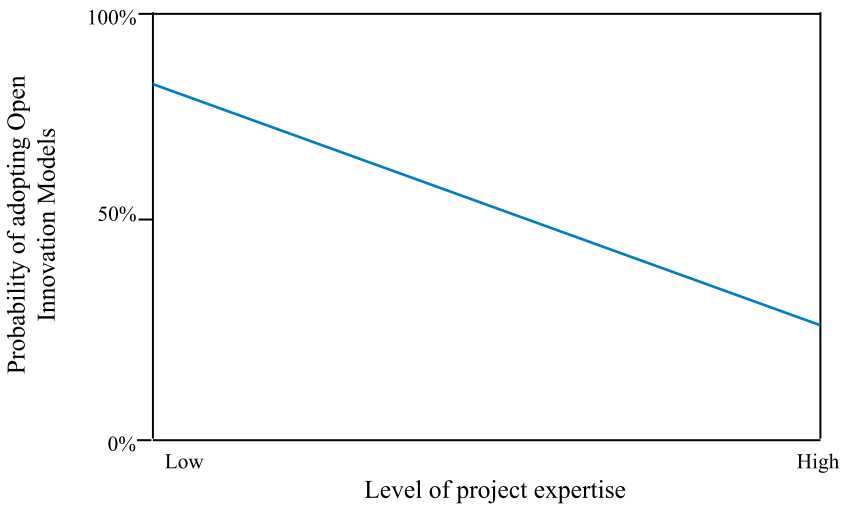
Note: R&D = Research and Development.
[a]M. Ceccagnoli, S.J. Graham, M.J. Higgins, and J. Lee, "Productivity and the Role of Complementary Assets in Firms' Demand for Technology Innovations," *Industrial and Corporate Change*, 19/3 (June 2010): 839-869.
[b]L. Fleming and O. Sorenson, "Science as a Map in Technological Search," *Strategic Management Journal*, 25/8-9 (August/September 2004): 909-928.

TABLE 2. Examples of Different Types of Open Innovation Models.

Types of OI	Drug Name	NDA Sponsor	Drug Patent Holder(s)	Licensed Patent(s)
1. Crowdsourcing OI	Mepron	GlaxoSmithKline	Victoria Latter (Beckenham, Kent, GB2), Winston Gutteridge (Beckenham, Kent, GB2)	A method and certain compositions
	Humalog	Lilly	Ronald Chance (Westfield, IN), Richard DiMarchi (Carmel, IN), Bruce Frank (Indianapolis, IN), James Shields (Noblesville, IN)	Insulin analogs modified
	Buphenyl	Medicis	Saul Brusilow (Baltimore, MD)	Process for waste nitrogen removal
2. Coopetition OI	Glyset	Pharmacia & Upjohn	Bayer Aktiengesellschaft	Compounds, methods for their preparation, compositions
	Famvir	Novartis	Beecham Group	Compounds of formula, compositions, and methods of treatment
	Prosom	Abbott	Upjohn Co.	Formula
3. Science-Based OI	Trusopt	Merck	University of Florida	Process for reducing intraocular pressure
	Zerit	Bristol Myers Squibb	Yale University School of Medicine	Method of therapeutic use
	Elmiron	Janssen Pharms	University of California	Method of treating
4. Network OI	Neutrexin	Medimmune Oncology	Warner Lambert	Salts and methods for producing salts
			U.S. Department of Health & Human Services	A method of treating infections
	Atacand	Astrazeneca	Takeda Chemical	Derivatives, compositions, and methods of pharmaceutical use
			Nokia Mobile Phones	Method and equipment for saving power in infrared data transmission
	Exosurf Neonatal	GlaxoSmithKline	University of California, Berkeley	Lung surfactant compositions
			Solus Ocean System	A system for installing

Note: OI = open innovation; NDA = new drug application.

FIGURE 2. Role of project expertise on open innovation adoption (without the consideration of complexity).



closed innovation without the consideration of complexity and its interaction with project expertise. Figure 2 displays graphic results of this relationship. These results confirm that project expertise is an important determinant of the decision to adopt open or closed innovation. When firms have relevant project expertise, closed innovation is preferred; and when firms lack project expertise, OI is adopted.

Next, we include the interaction effect between complexity and project expertise and examine how complexity moderates the relationship between project expertise and choice of open or closed innovation. Figure 3 shows the graphic result of how complexity affects the impact of project expertise on the choice of OI. The result shows that complexity weakens the negative tie between project expertise and the choice of OI. Specifically, at low levels of complexity, the negative relationship between project expertise and OI becomes more pronounced; however, as complexity in NPD increases, the negative tie between project expertise and OI diminishes, although a (weak) negative relationship still remains. These results support our proposition that complexity leads firms with higher levels of project expertise to adopt OI models.

Complexity and project expertise in different OI models. As noted, different OI types may be adopted under differing project expertise and complexity conditions. Table 3 shows mean differences in terms of complexity across the four different OI models. The average complexity is approximately 1.07 for coopetition OI projects, 1.06 for science-based OI projects, 0.59 for crowdsourcing OI projects, and 1.40 for networking OI projects. Among the four OI models, network OI is used most when projects deal with high levels of complexity, consistent with our theoretical explanation that network OI is the most efficient form for dealing

FIGURE 3. Role of project expertise on open innovation adoption under complexity.

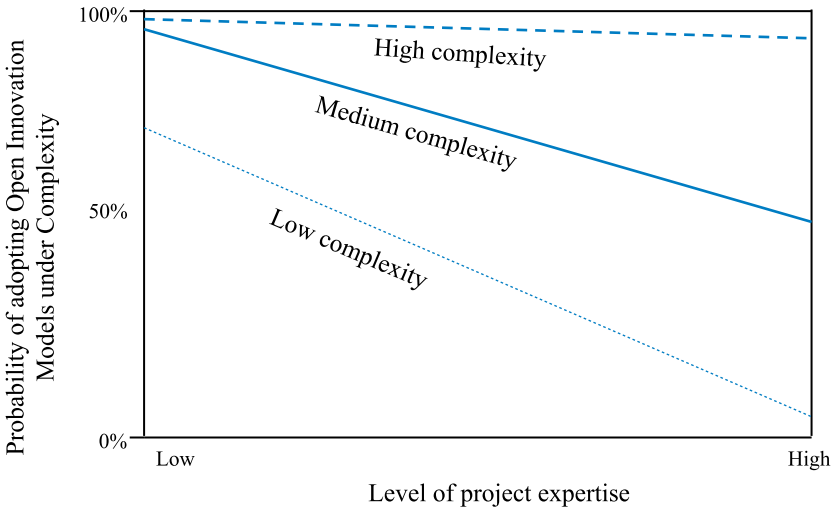


TABLE 3. Drug Development Complexity by Different Types of OI Models.

	#Observation	*M*	Minimum	Maximum
1. Coopetition OI Model	108	1.07	0	8.17
2. Science-Based OI Model	25	1.06	0	6.22
3. Crowdsourcing OI Model	9	0.59	0.25	1.69
4. Network OI Model	41	1.40	0	5.23

Note: Fleming and Sorenson's complexity measure was used in the table. OI = open innovation.

with high levels of complexity. This finding implies that network OI can become a more prevalent form of OI in the future as NPD complexity grows over time.

It is interesting to note that the average complexity of crowdsourcing OI is far below the means of the other OI models. This result suggests that crowdsourcing OI may be used most when firms need to deal with relatively low levels of complexity compared with other OI models. When a problem is identified and simplified, then the firm can broadcast the problem to the crowd without frequent knowledge transfer and communication, and crowdsourcing OI can quickly generate novel ideas and solutions. However, when a firm needs to frequently transfer knowledge to, and communicate with, the crowd (which occurs with increasing complexity), crowdsourcing OI models may significantly increase communication and knowledge integration costs. This is not only very costly for the focal firm, but also for the crowdsourcing participants because they need to devote a considerable amount of time and cognitive effort to communicate their ideas to the focal firm with little confidence that their proposed ideas will eventually be winning solutions. These communication burdens may reduce both the enjoyment and

TABLE 4. Levels of Project Expertise by Different Types of OI Models.

	#Observation	*M*	Minimum	Maximum
1. Coopetition OI Model	108	1.11	0	14
2. Science-Based OI Model	25	1.72	0	12
3. Crowdsourcing OI Model	9	0	0	0
4. Network OI Model	41	1.27	0	7

Note: OI = open innovation.

fun associated with engaging in crowdsourcing OI. Overly complex crowdsourcing tasks will reduce the performance of crowdsourcing OI by increasing communication burdens between the firm and the crowd.

Table 4 shows the average of project expertise for the different types of OI models. Coopetition OI projects possessed an average expertise of 1.11, science-based OI projects had an average expertise of 1.72, network OI projects had an average expertise of 1.27, and crowdsourcing OI had zero expertise (meaning that all crowdsourcing OI projects in the sample did not have any prior knowledge related to the drug development area). These results clearly highlight distinct differences between science-based OI and crowdsourcing OI. Consistent with the prior literature, our results show that crowdsourcing OI is beneficial when firms do not possess relevant project expertise.[69] In contrast, science-based OI is chosen by firms when they have relevant project expertise and, thus, absorptive capacity. These results not only confirm the prior OI literature's findings concerning the important role of relevant expertise as absorptive capacity in the science-based OI, but also provide evidence that the levels of project expertise required to efficiently utilize each OI model can be different.

Other Findings

We also found interesting results regarding firm size, R&D budgets, and market size. According to the U.S. Small Business Administration, small businesses in the pharmaceutical industry are defined as firms that hire less than 1,250 employees. We categorized firms in our sample into large and small businesses based on this definition of small businesses. Table 5 presents the differences in complexity between large and small firms choosing open and closed innovation models. For large companies, the average complexity of closed innovation projects is 0.57, and the average complexity of OI projects is 1.22. These results indicate that large firms choose OI models to deal with more complex projects.

However, small firms seem to do the opposite. Instead of adopting OI models, small firms choose closed innovation to deal with more complex projects. For small firms, the average complexity of closed innovation projects is 4.03, and the average complexity of OI projects is 0.46. This result shows that the trade-off

TABLE 5. Average of Complexity by Firm Size in Open and Closed Innovation Models.

Complexity in Drug Development	Large Firms	Small Firms
Closed Innovation Model	0.57	4.03
Open Innovation Model	1.22	0.46

Note: Small firms in the pharmaceutical industry are defined as firms that hire less than 1,250 employees (U.S. Small Business Administration definition).

between closed and open innovation in terms of knowledge integration and divergence can differ between large and small firms. In large firms, knowledge divergence through closed innovation can be challenging due to routines and procedures associated with the firm's existing knowledge and expertise. In contrast, small firms tend to possess flexible organizational structures, lack of routines, and existing expertise, which help them readily diversify knowledge and, thus, solve complex problems using closed innovation models.

With respect to knowledge integration, large firms have sufficient resources to redesign organizational structures in an attempt to mitigate high communication and coordination costs in OI environments. For instance, GlaxoSmithKline (GSK) plc, an expert in antibiotic drug research, redesigned its R&D departments by dividing them into six small Centers of Excellence in Drug Discovery (CEDD) and offered authority to make decisions on licensing-in compounds in each CEDD in an attempt to reduce knowledge integration costs (see the appendix for detailed information).[70] As our results show, knowledge divergence and integration costs can greatly differ between large and small firms.

In addition, our results found that projects with low R&D budgets are more likely to use OI models than projects with high R&D budgets. This finding is consistent with the OI literature, which argues that OI can be a useful avenue to share resources and costs.[71] We also show that orphan drug projects are more likely to adopt OI models than non-orphan drug projects. Orphan drugs are defined as pharmaceutical agents designed to prevent, diagnose, or treat rare diseases and disorders that generally affect fewer than 200,000 people in the United States. Traditionally, the small market size of orphan drugs discouraged pharmaceutical companies from developing the drugs in-house. Our results show that when pharmaceutical companies develop orphan drugs, they are more likely to adopt OI models. This finding is consistent with the logic for R&D budgets; that is, firms likely adopt OI for orphan drugs to share in the costs and risks of NPD.

Discussion

Scholarly Implications

In a recent comprehensive review of the OI literature, Bogers and colleagues highlight that theory development should be the center for the advancement of the OI literature, and our research is in alignment with the position.

We have presented a theory framework with important constructs, including complexity, project expertise, and OI adoption, and have offered explanations regarding why increasing complexity is a driver for the rapid adoption of the OI phenomenon.[72]

Furthermore, we have contributed to the link between the OI literature on complex systems and KBV and propose a theoretical framework utilizing knowledge divergence and knowledge integration in complex problem solving. Although the OI literature significantly draws from KBV, particularly utilizing the concept of absorptive capacity,[73] this prior literature focuses on OI performance.[74] Here, we have focused on the adoption of open versus closed innovation and, thus, utilize KBV to explain why open and closed innovation choices entail both costs and benefits (trade-offs) in regard to knowledge divergence and integration. A firm's absorptive capacity not only impacts OI performance, as suggested in prior research, but our theory and results show it also impacts the firm's decision to select OI.

In addition, Bogers and colleagues state that "research on OI predominantly addresses the firm as the unit of analysis" and, therefore, more research using different levels of analysis is necessary.[75] This observation is logical, since many firms have multiple projects of varying complexity and in areas where they have varying levels of expertise; thus, firm-level analysis may not efficiently capture these differences at the project level. They also point out that prior OI literature heavily utilizes case studies, and, therefore, research such as ours using large quantitative data analysis can offer important empirical contributions.

Practical Implications

We have described the dilemma that managers face in complex NPD environments and linked the dilemma to the choice of OI or closed innovation models. Primarily, NPD in complex environments requires diverse knowledge, and OI approaches provide the benefit of access to diverse knowledge. The adoption of OI models also comes with costs; specifically, they can generate increasing communication and coordination requirements with external partners. The adoption of OI for knowledge divergence also requires firms' deliberate efforts to minimize increased communication and coordination costs.

The varying circumstances that firms face influence the trade-off between open and closed innovation; these circumstances include not only project expertise and complexity, but also firm size, R&D budget, and market size. Our results show that small and large firms handle complexity differently by choosing different organizational methods (open or closed innovation). In addition, firms predominantly adopt OI models when they have low R&D budgets or when they develop new products that have a small market size. When new products are expected to require high R&D budgets or have limited profit potentials due to small market size, managers may give up on these product development opportunities. OI models can capitalize on such product development opportunities while minimizing the use of a firm's resources in those projects.

TABLE 6. Our Recommendations for Large Firms.

		Complexity	
		High	**Low**
Project Expertise	High	Open innovation (Science-based OI/Network OI)	Closed innovation
	Low	Open innovation (Coopetition OI)	Open innovation (Crowdsourcing OI)

Note: OI = open innovation.

There are multiple OI models, and, thus, managers have options when making the decision to utilize OI. Four different types of OI models were examined here: crowdsourcing, coopetition, science-based, and network. Managers' selection of certain types of OI models is dependent upon the level of complexity they face in development projects and the level of project expertise required. In other words, firm's unique circumstances such as complexity and project expertise influence not only *whether* managers choose open or closed innovation, but also *which type of OI model* they tend to adopt.

Table 6 summarizes our recommendations based on our findings for large companies. Network OI models (collaborations with multiple partners) or science-based OI models (collaborations with research institutes) are utilized most often when firms attempt to conduct complex projects; however, such OI models also require high levels of project expertise as absorptive capacity. In contrast, crowdsourcing OI models (collaborations with individual scientists) are selected most often when a firm attempts to conduct relatively less complex projects (when compared with other OI models) and lacks relevant project expertise in the development area. When a firm does not possess relevant expertise and the development project requires common knowledge on markets and customers with the OI partner, coopetition OI (collaborations with rivals) is selected most often. Using the coopetition OI model, firms and their partners can improve joint problem-solving skills with their shared knowledge on markets and customers and share costs and risks associated with complex NPD projects.

Appendix

GSK's Centers of Excellence in Drug Discovery

> With the rise of resistance to the most widely used treatments and few new antibiotics in development, experts have warned of a return to a pre-antibiotic era, where medical procedures will no longer be able to take place, and patients may routinely die from seemingly minor infections. (GSK website)[76]

GSK was created through a merger between two British companies—Glaxo Wellcome and SmithKline Beecham in 2000. These pre-merger companies were

also formed by a merger between Beecham and SmithKline in 1989 and a merger between Glaxo and Wellcome in 1995. GSK has been a leader in the antibacterial market over the past few decades. The company is committed to antibacterial research and has both significant experience and resources on antibacterial drugs.

Between 1995 and 2001, GSK (previously, SmithKline Beecham) ran high-throughput screening (HTS) campaigns on antibacterial targets using its large chemical library. HTS is an automated drug discovery process that has been widely used in the pharmaceutical industry.[77] HTS robots allowed corporate scientists to test up to 100,000 compounds per day against (antibacterial) targets.[78] Using their extensive chemical compound collection, GSK scientists, through HTS campaigns, were able to identify 16 "hits," of which five became leads, but most of those leads did not become drug candidates. GSK managers explained that the lack of success in their antibacterial HTS campaigns was due to insufficiency in the molecular diversity of their compound library.[79]

Pre-merger, both Glaxo Wellcome and SmithKline Beecham had centralized decision-making processes on new product development projects. A single committee, which consisted of senior executives from different functional areas, reported the progress of development projects to the head of Research and Development (R&D), who eventually made decisions regarding whether to advance the projects to the next stages. The committee members were not chosen based on their expertise in each therapeutic market, but based on their ability to evaluate the firm's entire drug development portfolio.[80]

The merger between Glaxo Wellcome and SmithKline Beecham offered the new organization, GSK, a substantial presence in various therapeutic areas and numerous R&D pipelines. The merged company also realized that controlling all drug development projects using a centralized R&D structure was too time-consuming and inefficient because their scientists had to spend a significant amount of time reporting discoveries to the committee and the head of R&D. In addition, the merger brought together roughly 1,900 drug discovery scientists in the company's R&D departments.[81] It was very difficult for two individual scientists in the same department to have day-to-day communication. Furthermore, collaborations with external partners in this centralized R&D organization created complex communication and reporting requirements for scientists and committee members.

In response to those challenges, GSK redesigned its R&D departments by dividing them into six small Centers of Excellence in Drug Discovery (CEDD) and adopted an open innovation (OI) model. Each CEDD was given authority to make decisions regarding licensing-in compounds from external partners.[82] They also encouraged their scientists to seek out new scientific discoveries and create partnerships with outside organizations and scientists.

In 2002, GSK evaluated its antibacterial drug research to improve low R&D productivity and integrated the research program into CEDD. The adoption of OI for antibacterial drug research brought a visible increase in R&D productivity

within a few years. GSK was able to identify six antibacterial drug candidates through CEDD, more than the number of candidates they discovered in the past 20 years. Payne and colleagues described this OI process at GSK, "Hits and leads have been transferred to our alliance partner, who is responsible for producing development candidates that are then taken back by GSK for further development."[83]

The company also validated the value of external knowledge prior to bringing candidates to the development stages by replicating experiments in-house. With external knowledge and their large chemical compound library on antibacterial drugs, GSK found more combinatory opportunities, which helped them find new antibiotic candidates using OI. At the same time, through redesigning their organizational structure (the creation of decentralized and flexible small R&D units), GSK was able to offset the increased communication costs associated with collaborations with external partners at CEDD.

Author Biographies

Yeolan Lee is an Assistant Professor of Management in the College of Business at the University of Alabama in Huntsville (yeolan.lee@uah.edu).

Eric Fong is an Associate Professor of Management in the College of Business at the University of Alabama in Huntsville (eric.fong@uah.edu).

Jay Bryan Barney is the Presidential Professor of Strategic Management and holds the Pierre Lassonde Chair in Social Entrepreneurship at the David Eccles School of Business at The University of Utah (jay.barney@eccles.utah.edu).

Ashton Hawk is an Assistant Professor of Strategy and Entrepreneurship in the Leeds School of Business at the University of Colorado Boulder (Ashton.Hawk@colorado.edu).

Notes

1. H. Chesbrough, *Open Innovation: The New Imperative for Creating and Profiting from Technology* (Boston, MA: Harvard Business Press, 2003); H. Chesbrough and M. Bogers, "Explicating Open Innovation: Clarifying an Emerging Paradigm for Understanding Innovation," in *New Frontiers in Open Innovation*, ed. H. Chesbrough, W. Vanhaverbeke, and J. West (Oxford, UK: Oxford University Press, 2014), pp. 3-28.
2. A. Afuah and C.L. Tucci, "Crowdsourcing as a Solution to Distant Search," *Academy of Management Review*, 37/3 (July 2012): 355-375.
3. J. Barney, "Firm Resources and Sustained Competitive Advantage," *Journal of Management*, 17/1 (March 1991): 99-120; D. Teece, "Competition, Cooperation, and Innovation: Organizational Arrangements for Regimes of Rapid Technological Progress," *Journal of Economic Behavior & Organization*, 18/1 (June 1992): 1-25.
4. J.A. Nickerson and T.R. Zenger, "A Knowledge-Based Theory of the Firm—The Problem-Solving Perspective," *Organization Science*, 15/6 (November/December 2004): 617-632.
5. Afuah and Tucci (2012), op. cit.
6. Afuah and Tucci (2012), op. cit.
7. R.C. Levin, A.K. Klevorick, R.R. Nelson, and S.G. Winter, "Appropriating the Returns from Industrial Research and Development," *Brookings Papers on Economic Activity*, 3 (1987): 783-820.
8. Chesbrough (2003), op. cit.

9. L. Fleming, "Recombinant Uncertainty in Technological Search," *Management Science*, 47/1 (January 2001): 117-132; L. Fleming and O. Sorenson, "Technology as a Complex Adaptive System: Evidence from Patent Data," *Research Policy*, 30/7 (August 2001): 1019-1039.
10. Fleming (2001), op. cit.
11. Nickerson and Zenger (2004), op. cit.
12. H.A. Simon, "The Architecture of Complexity," *Proceedings of the American Philosophical Society*, 106/6 (December 1962): 467-482.
13. Ibid.
14. H.A. Simon, "Artificial Intelligence: An Empirical Science," *Artificial Intelligence*, 77/1 (August 1995): 95-127.
15. A. Spithoven, W. Vanhaverbeke, and N. Roijakkers, "Open Innovation Practices in SMEs and Large Enterprises," *Small Business Economics*, 41/3 (October 2013): 537-562.
16. D. Leonard and S. Sensiper, "The Role of Tacit Knowledge in Group Innovation," *California Management Review*, 40/3 (Spring 1998): 112-132.
17. Ibid.
18. Ibid.
19. B. Kogut and U. Zander, "Knowledge of the Firm, Combinative Capabilities, and the Replication of Technology," Organization Science, 3/3 (August 1992): 383-397.
20. Nickerson and Zenger (2004), op. cit.; T. Felin and T.R. Zenger, "Closed or Open Innovation? Problem Solving and the Governance Choice," *Research Policy*, 43/5 (June 2014): 914-925.
21. L.B. Jeppesen and K.R. Lakhani, "Marginality and Problem-Solving Effectiveness in Broadcast Search," *Organization Science*, 21/5 (September/October 2010): 1016-1033.
22. C.Y. Baldwin and K.B. Clark, *Design Rules: The Power of Modularity*, vol. 1 (Cambridge, MA: MIT Press, 2000).
23. E. Von Hippel, "Innovation by User Communities: Learning from Open-Source Software," *MIT Sloan Management Review*, 42/4 (Summer 2001): 82-86.
24. E. Almirall and R. Casadesus-Masanell, "Open versus Closed Innovation: A Model of Discovery and Divergence," *Academy of Management Review*, 35/1 (January 2010): 27-47.
25. Jeppesen and Lakhani (2010), op. cit.
26. C. Terwiesch and Y. Xu, "Innovation Contests, Open Innovation, and Multiagent Problem Solving," *Management Science*, 54/9 (September 2008): 1529-1543.
27. R.R. Nelson and S.G. Winter, *An Evolutionary Theory of Economic Change* (Cambridge, MA: The Belknap Press of Harvard University Press, 1982).
28. L. Rosenkopf and P. Almeida, "Overcoming Local Search through Alliances and Mobility," *Management Science*, 49/6 (June 2003): 751-766; G. Ahuja and C.M. Lampert, "Entrepreneurship in the Large Corporation: A Longitudinal Study of How Established Firms Create Breakthrough Inventions," *Strategic Management Journal*, 22/6-7 (June/July 2001): 521-543.
29. W.M. Cohen and D.A. Levinthal, "Absorptive Capacity: A New Perspective on Learning and Innovation," *Administrative Science Quarterly*, 35/1 (March 1990): 128-152, at p. 128; A. Spithoven, B. Clarysse, and M. Knockaert, "Building Absorptive Capacity to Organise Inbound Open Innovation in Traditional Industries," *Technovation*, 30/2 (February 2010): 130-141.
30. T.O. Salge, T. Farchi, M.I. Barrett, and S. Dopson, "When Does Search Openness Really Matter? A Contingency Study of Health-Care Innovation Projects," *Journal of Product Innovation Management*, 30/4 (July 2013): 659-676; A. Zobel, "Benefiting from Open Innovation: A Multidimensional Model of Absorptive Capacity," *Journal of Product Innovation Management*, 34/3 (May 2017): 269-288.
31. Chesbrough (2003), op. cit., p. 53.
32. J. Howe, *Crowdsourcing: Why the Power of the Crowd Is Driving the Future of Business* (New York, NY: Crown Business, 2008).
33. Jeppesen and Lakhani (2010), op. cit.; K. Boudreau and K. Lakhani, "How to Manage Outside Innovation," *MIT Sloan Management Review*, 50/4 (Summer 2009): 69-75.
34. J. Bentzien, R. Bharadwaj, and D.C. Thompson, "Crowdsourcing in Pharma: A Strategic Framework," *Drug Discovery Today*, 20/7 (July 2015): 874-883.
35. Terwiesch and Xu (2008), op. cit.; Afuah and Tucci (2012), op. cit.
36. Jeppesen and Lakhani (2010), op. cit.
37. Boudreau and Lakhani (2009), op. cit.
38. S. Djelassi and I. Decoopman, "Customers' Participation in Product Development through Crowdsourcing: Issues and Implications," *Industrial Marketing Management*, 42/5 (July 2013): 683-692.

39. A.M. Brandenburger and B.J. Nalebuff, *Co-opetition* (New York, NY: Currency Doubleday, 1996); M. Bengtsson and S. Kock, "'Coopetition' in Business Networks—To Cooperate and Compete Simultaneously," *Industrial Marketing Management*, 29/5 (September 2000): 411-426; R.B. Bouncken, J. Gast, S. Kraus, and M. Bogers, "Coopetition: A Systematic Review, Synthesis, and Future Research Directions," *Review of Managerial Science*, 9/3 (July 2015): 577-601.
40. R. Rusko, "Mapping the Perspectives of Coopetition and Technology-Based Strategic Networks: A Case of Smartphones," *Industrial Marketing Management*, 43/5 (July 2014): 801-812.
41. Bengtsson and Kock (2000), op. cit.
42. Teece (1992), op. cit.; G. Hamel, Y.L. Doz, and C.K. Prahalad, "Collaborate with Your Competitors—and Win," *Harvard Business Review*, 67/1 (January/February 1989): 133-139.
43. P. Ritala, P. Hurmelinna, and K. Blomqvist, "Tug of War in Innovation—Coopetitive Service Development," *International Journal of Services Technology and Management*, 12/3 (May 2009): 255-272; Teece (1992), op. cit.
44. D.R. Gnyawali and B. Park, "Co-opetition between Giants: Collaboration with Competitors for Technological Innovation," *Research Policy*, 40/5 (June 2011): 650-663, at p. 658.
45. B.S. Tether, "Who Co-operates for Innovation, and Why: An Empirical Analysis," *Research Policy*, 31/6 (August 2002): 947-967.
46. K.R. Fabrizio, "Absorptive Capacity and the Search for Innovation," *Research Policy*, 38/2 (March 2009): 255-267.
47. L. Fleming and O. Sorenson, "Science as a Map in Technological Search," *Strategic Management Journal*, 25/8-9 (August/September 2004): 909-928.
48. Fabrizio (2009), op. cit.
49. J. Du, B. Leten, and W. Vanhaverbeke, "Managing Open Innovation Projects with Science-Based and Market-Based Partners," *Research Policy*, 43/5 (June 2014): 828-840.
50. J. Bruneel, P. D'Este, and A. Salter, "Investigating the Factors That Diminish the Barriers to University-Industry Collaboration," *Research Policy*, 39/7 (September 2010): 858-868.
51. R. Veugelers and B. Cassiman, "R&D Cooperation between Firms and Universities. Some Empirical Evidence from Belgian Manufacturing," *International Journal of Industrial Organization*, 23/5-6 (June 2005): 355-379.
52. I. Cockburn and R. Henderson, "Absorptive Capacity, Coauthoring Behavior, and the Organization of Research in Drug Discovery," *Journal of Industrial Economics*, 46/2 (June 1998): 157-182.
53. K. Bishop, P. D'Este, and A. Neely, "Gaining from Interactions with Universities: Multiple Methods for Nurturing Absorptive Capacity," *Research Policy*, 40/1 (February 2011): 30-40.
54. W. Vanhaverbeke and M. Cloodt, "Open Innovation in Value Networks," in *Open Innovation: Researching a New Paradigm*, ed. H. Chesbrough and W.P.M. Vanhaverbeke (Oxford, UK: Oxford University, 2006), pp. 258-281.
55. S. Nambisan and M. Sawhney, "Orchestration Processes in Network-Centric Innovation: Evidence from the Field," *Academy of Management Perspectives*, 25/3 (August 2011): 40-57.
56. Vanhaverbeke and Cloodt (2006), op. cit.
57. T. Ritter and H.G. Gemünden, "Network Competence: Its Impact on Innovation Success and Its Antecedents," *Journal of Business Research*, 56/9 (September 2003): 745-755.
58. A.O. Olsen, W. Sofka, and C. Grimpe, "Coordinated Exploration for Grand Challenges: The Role of Advocacy Groups in Search Consortia," *Academy of Management Journal*, 59/6 (December 2016): 2232-2255.
59. R. Kapoor and R. Adner, "What Firms Make vs. What They Know: How Firms' Production and Knowledge Boundaries Affect Competitive Advantage in the Face of Technological Change," *Organization Science*, 23/5 (March 2012): 1227-1248.
60. M. Allarakhia, D.M. Kilgour, and J.D. Fuller, "Modelling the Incentive to Participate in Open Source Biopharmaceutical Innovation," *R&D Management*, 40/1 (January 2010): 50-66, at p. 59.
61. Y. Lee and E.A. Fong, "The Impact of Diversifying and *De Novo* Firms on Regional Innovation Performance in an Emerging Industry: A Longitudinal Study of the U.S. Ethanol Industry," *Industry and Innovation*, 26/7 (2019): 769-794.
62. Olsen et al. (2016), op. cit.
63. This figure is created based on Dickson and Gagnon (2004) and FDA information found at https://www.fda.gov/forpatients/approvals/drugs/ucm405622.htm; M. Dickson and J.P. Gagnon, "Key Factors in the Rising Cost of New Drug Discovery and Development," *Nature Reviews Drug Discovery*, 3/5 (2004): 417-429.

64. J.A. DiMasi, H.G. Grabowski, and J. Vernon, "R&D Costs, Innovative Output and Firm Size in the Pharmaceutical Industry," *International Journal of the Economics of Business*, 2/2 (1995): 201-219.
65. B.H. Hall, A.B. Jaffe, and M. Trajtenberg, "The NBER Patent Citation Data File: Lessons, Insights and Methodological Tools" (NBER working paper 8498, National Bureau of Economic Research, 2001, https://www.nber.org/papers/w8498).
66. M. Ceccagnoli, S.J. Graham, M.J. Higgins, and J. Lee, "Productivity and the Role of Complementary Assets in Firms' Demand for Technology Innovations," *Industrial and Corporate Change*, 19/3 (June 2010): 839-869.
67. Fleming and Sorenson (2001), op. cit.
68. Dickson and Gagnon (2004), op. cit.
69. Jeppesen and Lakhani (2010), op. cit.
70. Detailed information regarding Centers of Excellence in Drug Discovery (CEDD) can be found in GlaxoSmithKline (GSK) 2002 and 2003 annual reports.
71. J. Hunter and S. Stephens, "Is Open Innovation the Way Forward for Big Pharma?," Nature Reviews Drug Discovery, 9/2 (February 2010): 87-88.
72. M. Bogers, A.K. Zobel, A. Afuah, E. Almirall, S. Brunswicker, L. Dahlander, L. Frederiksen, A. Gawer, M. Gruber, S. Haefliger, J. Hagedoorn, D. Hilgers, K. Laursen, M.G. Magnusson, A. Majchrzak, I.P. McCarthy, K.M. Moeslein, S. Nambisan, F.T. Piller, A. Radziwon, C. Rossi-Lamastra, J. Sims, and A.L.J. Ter Wal, "The Open Innovation Research Landscape: Established Perspectives and Emerging Themes across Different Levels of Analysis," *Industry and Innovation*, 24/1 (2017): 8-40.
73. K. Randhawa, R. Wilden, and J. Hohberger, "A Bibliometric Review of Open Innovation: Setting a Research Agenda," *Journal of Product Innovation Management*, 33/6 (November 2016): 750-772.
74. Salge et al. (2013), op. cit.; Zobel (2017), op. cit.
75. Bogers et al. (2017), op. cit., at p. 11.
76. https://www.gsk.com/en-gb/research/what-we-are-working-on/antibiotics-research/.
77. D.J. Payne, M.N. Gwynn, D.J. Holmes, and D.L. Pompliano, "Drugs for Bad Bugs: Confronting the Challenges of Antibacterial Discovery," *Nature Reviews Drug Discovery*, 6/1 (2007): 29-40.
78. I. Caraus, A.A. Alsuwailem, R. Nadon, and V. Makarenkov, "Detecting and Overcoming Systematic Bias in High-Throughput Screening Technologies: A Comprehensive Review of Practical Issues and Methodological Solutions," *Briefings in Bioinformatics*, 16/6 (2015): 974-986.
79. Payne et al. (2007), op. cit.
80. R.S. Huckman and E. Strick, "GlaxoSmithKline: Reorganizing Drug Discovery (A)," Harvard Business School Case #605-074, May 2005.
81. Huckman and Strick (2005), op. cit.
82. Detailed information regarding CEDD can be found in GSK 2002 and 2003 annual reports.
83. Payne et al. (2007), op. cit., p. 38.