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Public Knowledge, Private Gain: The Effect of Spillover Networks on Firms' Innovative Performance

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Complementing received research on the role of collaboration networks in fostering interorganizational learning and innovation, the authors focus on the importance of learning from other firms' public knowledge. To this end they introduce the concept of spillover network—the network of "source" firms whose public knowledge a "recipient" firm is able to readily absorb and use as innovation input. Using patent-based data on a panel of semiconductor firms between 1976 and 2002, the authors demonstrate that firms' innovative performance tends to be higher when their spillover network is either munificent or rich in structural holes. However, being exposed to a spillover network that is both munificent and rich in structural holes is generally counterproductive. Consistent with the insight that the value of external knowledge inputs depends on the firm-level resources with which it can be bundled, furthermore, the authors argue that the extent to which firms benefit from their spillover network hinges on specific intraorganizational factors—their scientific intensity and degree of downstream integration.

Keywords: *innovation; knowledge spillovers; interorganizational learning; science intensity; downstream integration; semiconductor industry*

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Extant research has demonstrated the importance of interorganizational collaboration networks as a means to absorb technological knowledge from other firms (Ahuja, 2000; Lane & Lubatkin, 1998; Powell, Koput, & Smith-Doerr, 1996). Collaboration networks are useful because they stimulate face-to-face "interactive" learning (Lane & Lubatkin, 1998) and joint problem solving among firms (Hamel, 1991). As a result, they make it possible to capture externally generated knowledge even when this is tacit, that is, uncodified, socially situated, and organizationally embedded (Baden-Fuller & Grant, 2004; Kogut, 1988: 323). Supporting this line of argument, several prior studies showed that interorganizational collaboration networks are an important source of learning and innovation (Kogut, 1988: 323; Powell et al., 1996), particularly for firms endowed with dedicated resources for managing partners' tacit knowledge (Lieberskind, 1996; Mowery, Oxley, & Silverman, 1996; Rowley, Behrens, & Krackhardt, 2000).

Based on this rich body of received theory and evidence, there remains little doubt that absorbing the tacit knowledge held by a firm's collaboration partners is an important form of interorganizational learning driving systematic differences in firms' innovative performance (Ahuja, 2000; Baum, Calabrese, & Silverman, 2000; Powell et al., 1996). But is this the only—or perhaps even the most important—source of interorganizational learning through which firms can gain an innovation advantage? This question is meaningful because as notable economic historians have argued (e.g., Mokyr, 2002), the key distinguishing trait of the so-called knowledge-based economy is that a large share of the technological knowledge firms generate is *not* tacit. Rather, it is codified and made publically accessible through scientific articles, patents, technical publications, and conference presentations (Appleyard, 1996; Arora & Gambardella, 1994; Carnabuci & Bruggeman, 2009; Lim, 2010; Romer, 1986). Thus, in addition to the tacit knowledge captured through a firm's external collaboration ties, it seems important to investigate an aspect of interorganizational learning that prior research has only scantly examined: How does learning from the *public* technological knowledge generated by other firms affect a firm's innovative performance?

Although economists have widely recognized the economy-wide benefits of firms' public technological knowledge (Griliches, 1992; Jaffe, Trajtenberg, & Henderson, 1993), management scholars have tended to deemphasize its firm-level strategic value on the grounds that it has the characteristics of a "public good" (Arrow, 1962), that is, it can be appropriated by all firms at negligible costs (Lane & Lubatkin, 1998). Premised on this view, the competitive advantage that a firm might derive from capturing other firms' public knowledge has generally been assumed to be negligible or short lived, especially when compared to that stemming from tacit knowledge (Leonard-Barton, 1995; Powell et al., 1996). This assumption, however, might deserve further examination as it seems incongruent with two well-established insights on the nature of knowledge as a firm-level resource. On one hand, research on absorptive capacity has demonstrated that the cost of capturing spillovers even from the most clearly codified knowledge sources is *not* negligible (Somaya, Williamson, & Zhang, 2007), and in fact it becomes inaccessibly large when a firm lacks sufficient prior related experience (Jensen & Szulanski, 2007; Yang, Phelps, & Steensma, 2010). On the other hand, a key insight of the resource-based view of the firm is that the firm-level value of a resource (e.g., knowledge) does not primarily depend on how unique the resource itself is but, rather, on the extent to which the firm has the organizational capabilities needed to "bundle" it with complementary elements of its idiosyncratic resource base (Penrose, 1959; Rumelt, 1974; Somaya et al., 2007: 923). Thus, according to this latter line of thinking, absorbing public knowledge *will* lead to a sustainable innovation advantage insofar as the firm has the organizational capabilities needed to combine that knowledge with complementary firm-level resources.

Taken together, these arguments suggest that the technological knowledge made public by other firms might provide a more important source of interorganizational learning than previous research has recognized and, what is most relevant to the present article, one that contributes to explaining why certain firms are systematically more innovative than others. Providing support to this argument, recent studies showed that firms vary widely in their ability to absorb the public knowledge of other firms even in the same technological sector and that these differences have an impact on their technological capabilities (Brown & Duguid, 2002: 141-142). Lim (2010: 1261), for example, showed that AMD, Motorola, and Applied Materials—but not other semiconductor firms—were able to deal with a radical technological shift by scrupulously tracking, analyzing, and building on IBM's patented innovations. Pushing further this argument, Yang et al. (2010) analyzed firms' "spillover knowledge pool" (the pool of externally generated patents that build on a focal firm's own patents) to show that learning from another firm's public knowledge may trigger even a self-reinforcing interorganizational learning cycle, benefitting the innovative performance of both "recipient" and "source" firms.

In this article, we extend this recent line of inquiry in an attempt to elucidate how learning from the public technological knowledge generated by other firms affects a firm's innovative performance. Following prior studies, we focus on what is by far the most important form of public technological knowledge in the knowledge-based economy, that is, patents (Griliches, 1990; Jaffe et al., 1993). To examine why some firms learn more than others from the pool of patented knowledge generated by other firms, we introduce the concept of *spillover network*, which we define as the network of "source" firms whose patented technological knowledge a "recipient" firm has the ability to readily absorb and use as innovation input. Received research on interorganizational collaboration networks has argued that firms' absorptive capacity is inherently relational (Lane & Lubatkin, 1998). Analogously, our proposed concept of spillover network rests on the assumption that a firm's ability to learn from the patents generated by other firms varies depending on the level of prior experience the "recipient" firm has developed about each "source" firm (Hoang & Rothaermel, 2005; Lane & Lubatkin, 1998). Thus, if a "recipient" firm has accumulated limited prior experience about the innovation trajectory of a "source" firm, capturing valuable knowledge inputs from its patented innovations is going to be challenging. However, the greater the level of prior experience accumulated about a given "source" firm, the easier it should be to understand its patented knowledge and use it as an innovation input.

As the experience a firm accumulates about other firms depends on the time and resources invested in monitoring their idiosyncratic innovation trajectory, over time firms are likely to develop different levels of experience about distinct pools of "source" firms, resulting in different spillover networks. The overarching argument of the present article is that the spillover network to which a firm is exposed at any point in time affects the flow of public knowledge that it is able to absorb and, hence, its ability to generate innovations. From this general argument we derive two sets of testable hypotheses. The first set explicates which characteristics of the spillover network affect firms' innovative performance. In particular, we argue that firms' innovative performance tends to be higher when their spillover network is either munificent or rich in structural holes (Baum et al., 2000; Burt, 1992; Zaheer & Bell, 2005); however, being exposed to a spillover network that is *both* munificent *and* rich in structural holes is generally counterproductive. Consistent with the insight that the value of external knowledge inputs depends on the firm-level resources with which it can be bundled (Penrose, 1959; Rumelt, 1974; Somaya et al., 2007) furthermore, the second set of hypotheses examines the organizational factors and capabilities influencing firms' ability to fully take stock of their spillover network. In particular, we focus on two aspects of a firm's internal organization—its scientific intensity and its degree of downstream integration—to argue that certain firms are systematically better than others at converting the abstract and general knowledge articulated in patent documents into actual innovations.

We test our hypotheses using a sample of firms in the global semiconductor industry between 1976 and 2002—an empirical setting wherein patents provide a major repository of technological knowledge and, we suspect, an important source of interorganizational learning. Extending the concept of "spillover knowledge pool" introduced by Yang et al. (2010), we empirically track each firm's spillover network over time using historical patent citation data (Griliches, 1990; Hall, Jaffe, & Trajtenberg, 2001). Furthermore, we complement patent data with archival firm-level data to model key aspects of a firm's internal organization as well as to control for possible alternative explanations of our findings. Our empirical analyses provide support for our argument and hypotheses.

The article proceeds as follows. We begin by introducing the concept of spillover network and the distinctive learning mechanisms involved in capturing spillovers from the public knowledge of other firms. We then develop our hypotheses, discuss the data and method, and present the results of our analyses. We conclude by elaborating on the implications of the study and by suggesting ways in which the concept of spillover network could be applied in future research.

Theory and Hypotheses

Interorganizational Learning in Spillover Networks

As interorganizational learning is a key source of innovation for the firm (Baden-Fuller & Grant, 2004; Lane & Lubatkin, 1998; Powell et al., 1996), management scholars have gone to great depths to identify the factors and mechanisms that promote it. One general conclusion of this research is that which specific mechanisms are conducive to interorganizational learning essentially depends on characteristics of the knowledge the firm is trying to absorb (Hamel, 1991; Machlup, 1962). A key distinction in this respect is whether the interorganizational learning process involves knowledge that is tacit (i.e., uncodified, socially situated, and/or organizationally embedded) or public (i.e., codified and publicly observable; Baden-Fuller & Grant, 2004; Kogut, 1988: 323; Lane & Lubatkin, 1998). Although the literature agrees that absorbing these two types of knowledge entails very different interorganizational learning processes, however, scholarly attention has been almost exclusively directed toward unveiling what favors the absorption of tacit knowledge. As a result, our understanding of the factors and mechanisms favoring the absorption of other firms' *public* knowledge is still remarkably limited.

Because interorganizational learning processes vary depending on the type of knowledge to be absorbed, the learning mechanisms favoring the absorption of tacit knowledge may not necessarily be effective in the case of public knowledge. For example, the literature concurs that absorbing another firm's tacit knowledge requires engaging in "interactive learning" and joint problem solving with the firm (Hamel, 1991; Lane & Lubatkin, 1998). However, what is distinctive about public knowledge as a source of interorganizational learning is precisely that firms may absorb valuable innovation inputs even *without* any direct interaction or collaboration with the source of that knowledge (Griliches, 1992; Yang et al., 2010). Thus, although interactive learning and joint problem solving favor innovation through the process of concurrently "working together" on a common problem situation (Hamel, 1991), absorbing another firm's public knowledge is essentially a sequential learning process (Katila & Chen, 2008) whereby the observable innovation output of a "source" firm (e.g., a patent) is used as an innovation input by a "recipient" firm (Haunschild & Miner, 1997; McGahan & Silverman, 2006).

Although the importance of monitoring the innovation output of other firms has been recognized by prior research, the majority of existing studies focused on this particular form of interorganizational learning to explain how, by examining the performance outcomes of a few selected competitors, firms draw inferences about their own competitive position and the factors and strategies that might improve it (Denrell, 2003; Greve, 2003; Miner & Mezias, 1996). To the extent that firms' innovation outputs are clearly codified and made publicly available, however, monitoring such outputs might also lead to a form of interorganizational learning that more directly impinges on firms' innovativeness. For example, in industries characterized by a high propensity to patent such as semiconductors (Di Biaggio, 2007), biotechnology (Owen-Smith & Powell, 2004), and robotics (Katila & Chen, 2008), research has shown that firms learn from the patents granted to other firms to improve their own innovations (Katila & Chen, 2008), discover new technological opportunities (Lim, 2010), and monitor how their own innovations are being developed by other firms (Yang et al., 2010). It is therefore important to investigate whether this form of interorganizational learning contributes to explaining why some firms are systematically more innovative than others.

Although economists have traditionally assumed the knowledge codified in a patent to flow unconstrained among all firms (Arrow, 1962), research on absorptive capacity has demonstrated that learning from even the most clearly codified knowledge is generally very difficult if a firm lacks sufficient related knowledge (Hoang & Rothaermel, 2005; Yang et al., 2010). Consistent with this argument, we suggest that the more prior experience a "recipient" firm has accumulated about the innovation trajectory of a given "source" firm, the easier it should be to draw from the public knowledge it generates. Repeatedly drawing knowledge from a given "source" firm is important because it increases a "recipient" firm's mastery of the scientific and engineering knowledge on which that "source" firm builds its innovations (Brusoni, Prencipe, & Pavitt, 2001), resulting in a more profound understanding of the causal links and technological interdependencies on which its innovations are based, a deeper comprehension of the ideas, solutions, and processes described in its patents, and a greater ability to discern useful knowledge inputs from dead ends (Fleming, Mingo, & Chen, 2007; Patel & Pavitt, 1997; Yayavaram & Ahuja, 2008).

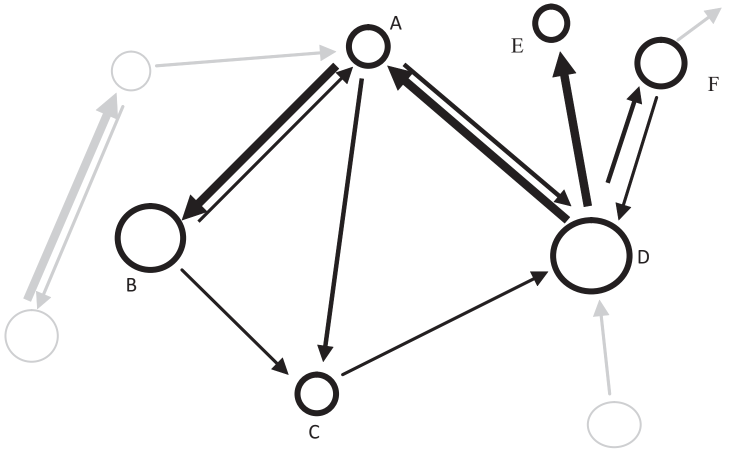
Because the experience a firm accumulates about other firms depends on the time and resources invested in monitoring their idiosyncratic innovation trajectories, over time firms are likely to develop different levels of experience about different "source" firms. Consequently, the pool of "source" firms whose public knowledge firms are equipped to absorb—that is, their spillover network—might be widely different even among firms belonging to the same technological sector. The overarching thesis of the present article is that such differences systematically affect firms' innovative performance. To elaborate the concept of spillover network in a more granular fashion, and to derive empirically testable hypotheses about its effects, let us begin with a visual example.

Figure 1 represents the spillover network of a hypothetical "recipient" firm A at time *t*. A's spillover network comprises: A's "source" firms (B, C, and D), the ties between A and its "source" firms, and the ties among A's "source" firms. Tie values indicate the experience firms have accumulated up to time *t* vis-à-vis each of their "source" firms, which reflects their ability to capture spillovers from the public knowledge those firms generate during *t*. Last, the size of the nodes represents their technological productivity, that is, the number of innovations they generate during time *t*. For example, prior to *t* firm A has accumulated substantial experience about the innovation trajectory developed by "source" firm B, making it possible for A to capture a great deal of spillovers from the patents B generates during *t*. Conversely, A's experience with C and D is relatively small, resulting in a limited capacity to benefit from the patents they come up with at *t*. Note that the absence of ties is as informative as their presence in our model, signaling which firms *do not* have enough experience to benefit from the public knowledge generated by other firms. In Figure 1 for example, B is highly unlikely to understand the technological knowledge made public by D during *t*. Finally, note that our model allows *asymmetric* ties: For instance, A's capacity to capture spillovers from B is much larger than B's capacity vis-à-vis A.

Spillover Networks and Firms' Innovative Performance

The concept of spillover network outlined above suggests that not all spillover networks are necessarily equally munificent. For example, a firm that over the years has accumulated experience about a pool of "source" firms that today are highly innovative is exposed to a more munificent spillover network than one whose "source" firms currently are producing few innovations. A straightforward testable implication of this argument is that firms exposed to a more munificent spillover network should generally display a higher innovative performance. One reason is that the larger the number of innovations generated by a firm's "sources," the greater the volume of knowledge inputs a "recipient" firm can screen, process, and select from to boost its innovation projects (Fleming, 2001; McGahan & Silverman, 2006). A second related reason is that "source" firms may be technologically prolific because they have identified new valuable veins of technological development, or, similarly, they

Figure 1
Example of Knowledge Combinative Patterns Across Firms



may have triggered what economic historian Nathan Rosenberg called "compulsive sequences" of solutions to technical bottlenecks (Rosenberg, 1977). In that case, having already accumulated source-specific experience increases the likelihood of capturing spillovers during the early phases of such compulsive sequences, providing the "recipient" firm with a distinctive advantage over other firms. We therefore advance the following hypothesis:

Hypothesis 1: The more technologically munificent a firm's spillover network, the higher the firm's innovative performance.

Received research has shown that firms tend to be more innovative when their network is rich in structural holes (Baum et al., 2000; Zaheer & Bell, 2005). The reason is that firms with a network rich in structural holes have access to more *diverse* knowledge inputs compared to firms whose contacts are themselves mutually connected (e.g., Ahuja, 2000; Burt, 1992). As a result, they are more likely to envision novel connections and elaborate syntheses between apparently disparate and unrelated knowledge inputs, eliciting knowledge brokerage processes that boost their innovative performance (Hargadon & Sutton, 1997; McEvily & Zaheer, 1999; Zaheer & Bell, 2005). Although extant research has focused on the structural holes inherent in a firm's collaboration network, the underlying causal mechanism responsible for the innovation-enhancing effect of structural holes—access to diverse knowledge inputs—should be at work also in the case of firms' spillover networks. Accordingly, we hypothesize that a firm's innovative performance will also benefit from the structural holes inherent in its spillover network.

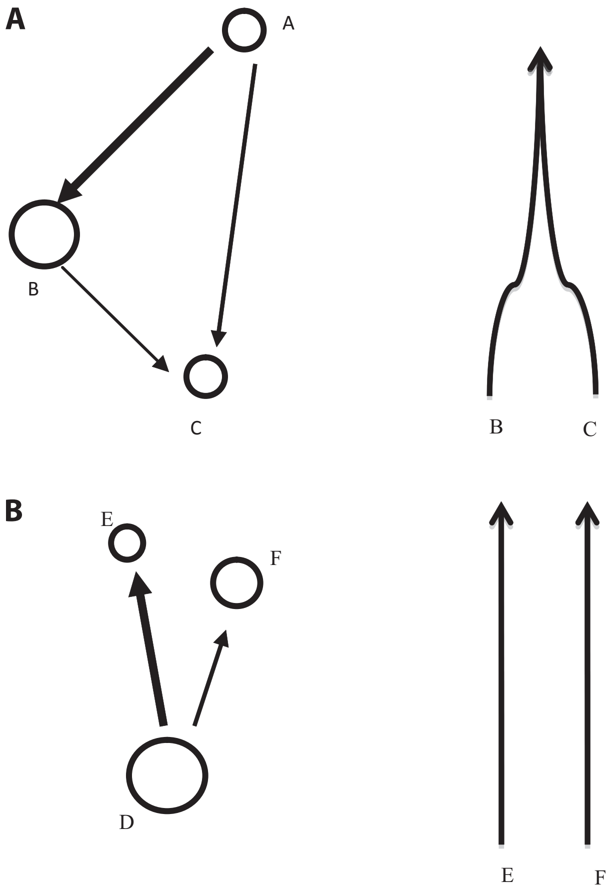
In a spillover network, dense clusters correspond to pockets of firms whose accumulated experience is focused on each other's innovation trajectories, allowing them to extensively draw from each other's patents. Accordingly, the knowledge inputs circulating within a spillover network lacking structural holes are generated by firms whose innovation trajectories are by definition mutually interwoven. For example in Figure 1, firm A has accumulated substantial experience about "source" firms B, C, and D. Because B and C also have often extensively used each other's knowledge in the past, their innovation trajectories are intertwined and largely overlapping (Figure 2a).

Conversely, a firm is exposed to a hole-rich spillover network insofar as its "source" firms have limited or no accumulated experience about each other's innovation trajectories. Going back to Figure 1, consider the case of "recipient" firm D and its "source" firms A, E, and F. Because E and F have accumulated no mutual experience in the past, their innovation trajectories are likely to have developed in a largely independent fashion (Figure 2b). As firm D is exposed to knowledge inputs generated by firms whose innovation trajectories have grown independent of each other, the likelihood of being exposed to diverse knowledge inputs is higher. As a result, D should more easily envision and synthesize unusual combinations among diverse and previously unrelated knowledge inputs, which should increase its innovative performance. Thus, we hypothesize,

Hypothesis 2: The more a firm is exposed to a spillover network rich in structural holes, the higher its innovative performance.

Our third hypothesis brings together our previous two hypotheses, proposing that the benefits of munificent and hole-rich spillover networks are less than additive. Although each of these learning environments is in itself beneficial, we argue that combining both dramatically increases the capability requirements and coordination costs needed to take full stock of the spillover network (Cohen & Levinthal, 1989, 1990; Zahra & George, 2002). The reason is that munificent and hole-rich spillover networks involve fundamentally different learning processes. To take full advantage of a munificent spillover network, a firm needs to efficiently screen and select from a large and fast-changing stream of knowledge those ideas, methods, and technologies that promise to be most useful for its current or future innovation projects (Yang et al., 2010; Zahra & George, 2002). In a hole-rich spillover network, conversely, envisioning combinations and elaborating syntheses among dissimilar knowledge inputs requires exploring unknown and complex interdependencies at the interface between previously unrelated innovation trajectories (Brusoni et al., 2001; Yayavaram & Ahuja, 2008). As it appears, the capabilities required to innovate under these two distinct learning modes are substantially different; hence, concurrently developing both of them is likely to yield less than additive returns. Furthermore, effectively carrying out both learning processes within the same firm is likely to add substantial coordination problems. For example, when a firm is exposed to a spillover network that is both munificent and rich in structural holes, many unexpected interdependencies may arise (because of the fact that many diverse knowledge inputs are combined) and their rate of occurrence may be hard to predict (because of the fact that those combinations have never been explored before), which significantly increases the coordination costs faced by the firm (Brusoni et al., 2001; Brusoni & Prencipe, 2001). Building on these arguments, our third hypothesis reads as follows:

Figure 2
Structural Holes and "Source" Firms' Technological Trajectories



Hypothesis 3: The innovation benefits of munificent and hole-rich spillover networks are less than additive; hence, the more munificent a spillover network, the less the presence of structural holes increases a firm's innovative performance.

Organizational Factors

Prior research has posited that the value of any resource input depends on the way in which it is bundled within the firm's idiosyncratic resource base. In a recent study, for example, Somaya et al. (2007) showed that firms that bundle their R&D inputs with an internally developed legal capability tend to be systematically more innovative (in terms of patenting output) than those that do not have an internal legal capability. Analogously, we hypothesize that a firm's ability to benefit from its spillover network increases if the firm has the capabilities needed to convert the abstract and general knowledge accruing to them through the spillover network into valuable innovations. In particular, we focus on two organizational factors directly impinging on firms' ability to manage this type of knowledge and combine it in productive ways: its degree of scientific intensity and whether or not it is downstream integrated.

Scientific intensity. We define a firm's scientific intensity as the extent to which a firm's inventors build on scientific knowledge while searching for new technologies (Fleming & Sorenson, 2004; Tijssen, 2001). In-depth accounts of notable inventions suggest that corporate engineers routinely consult the scientific literature to resolve technological difficulties (Allen, 1977; Gibbons & Johnston, 1974). We expect a solid scientific knowledge base to increase the benefits of spillover networks in multiple ways. In particular, firms characterized by strong scientific capabilities may be better equipped to screen, make sense of, select, and apply innovations that are codified in abstract and general terms, such as the innovations described in a patent. The reason is that a distinguishing aspect of scientific knowledge is that new concepts, ideas, and discoveries are systematically communicated by means of codified knowledge representations that, just like patents, are inherently abstract and general (Arora & Gambardella, 1994; Mokyr, 2002). Thus, being able to screen and understand such abstract and general technological knowledge and turn it into situation-specific actionable solutions is a capability that science-based firms can be expected to have more than other firms. Moreover, science provides a useful means for predicting the results of untried experiments and to assess "off-line" the context-specific value of abstract and general knowledge, which is essential to avoid dead ends (Lippman & McCall, 1976). Thus, particularly in munificent spillover networks, firms characterized by a high degree of scientific intensity should be better than others at selecting promising knowledge inputs from the voluminous stream of public knowledge accruing to them, and at converting those inputs into valuable innovations.

Hypothesis 4a: The greater a firm's scientific intensity, the more being located in a technologically prolific spillover network increases the firm's innovative performance.

A high degree of scientific intensity may also provide a deeper understanding of the interdependences existing between other firms' innovation trajectories, helping firms in the task of synthesizing diverse and previously unrelated knowledge inputs (Fleming & Sorenson, 2004; Fleming, Sorenson, & Rivkin, 2006). In line with this view, prior research has shown that science acts as a map guiding firms as they navigate poorly understood and unexplored technological interdependencies, "leading them more directly to useful combinations, eliminating fruitless paths of research, and motivating them to continue even in the face of negative feedback" (Fleming & Sorenson, 2004: 909). As taking stock of hole-rich spillover networks requires envisioning useful syntheses between unrelated innovation trajectories and making sense of the technological interdependencies that exist among them, we contend that firms endowed with internal scientific capabilities should be more effective than others at learning from hole-rich spillover networks.

Hypothesis 4b: The greater a firm's scientific intensity, the more being exposed to a hole-rich spillover network increases the firm's innovative performance.

Downstream integration. A relevant consequence of the increased codification of technological knowledge in general and abstract terms is the possibility for a division of innovative labor (Arora & Gambardella, 1994: 523), leading some firms to specialize in the production of technological knowledge to be used downstream by other firms. This trend fundamentally changed the organizational structure of many knowledge-based industries. Staying within the empirical contest of the present study, for example, the semiconductor industry is populated by two quite distinct organizational forms: vertically integrated device manufacturers, which engage in the design, commercialization, and production of semiconductor devices, and fabless firms, which are exclusively specialized in the production of technological knowledge (Langlois & Steinmueller, 1999). Prior research has shown that which of these organizational forms a firm adopts has far-reaching strategic implications (e.g., Brusoni & Prencipe, 2001; Monteverde, 1995).

We contend that whether a firm is vertically integrated or not also has an impact on its ability to learn from the spillover network. In particular, we argue that integrated firms are systematically less capable than non-vertically-integrated ones to take stock of munificent spillover networks. As said, firms positioned within a munificent spillover network are continuously exposed to a voluminous stream of patented (i.e., abstract and general) knowledge that they need to efficiently screen, and from which they need to select those inputs that promise to be most fruitful for the firm. Because their core business is producing and selling general and abstract technological knowledge in the "market for technology" (Arora & Gambardella, 1994; Di Biaggio, 2007; Langlois & Steinmueller, 1999), nonintegrated firms are more likely to have the organizational capabilities and skills needed to effectively manage this type of knowledge. In addition, not having to coordinate the production of technological knowledge with the manufacturing of downstream products makes nonintegrated firms extraordinarily lean from an organizational standpoint, allowing them to more flexibly switch to more appealing knowledge inputs and innovation opportunities whenever they arise. By contrast, integrated firms are typically characterized by complex interdependencies among organizational processes that severely reduce their organizational flexibility (Macher, 2006; Thompson, 1967), as well as by an increased reliance on embedded knowledge and unstructured technical dialogue (Monteverde, 1995: 1628). Hence, their ability to efficiently screen a large stream of abstract and general knowledge inputs, and flexibly integrate them into the firm's existing innovation projects, is likely limited.

Hypothesis 5a: The more a firm is downstream integrated, the more being located in a munificent spillover network decreases the firm's innovative performance.

Although vertically integrated firms tend to be organizationally less flexible than nonintegrated ones, prior research suggests that their ability to combine diverse knowledge inputs across a firm's internal organizational and knowledge boundaries provides them with a distinctive advantage. In his account of vertically integrated semiconductor firms, for example, Monteverde (1995) argues that research and development scientists and dedicated manufacturing engineers routinely engage in thick knowledge exchanges to anticipate the technical and organizational interdependencies that might arise at the junction of their respective competence domains. Similarly, the presence of heavyweight organizational mechanisms linking the firm's internal processes and structures in a more interdependent fashion provides for an organizational context where combinations of diverse knowledge inputs are more likely to be envisioned, understood, and turned into valuable innovations (Hargadon & Sutton, 1997; Yayavaram & Ahuja, 2008). Conversely, the lean organizational structure of nonintegrated firms is typically designed to minimize such interdependencies (Macher, 2006; Macher & Mowery, 2004), which might reduce their ability to broker knowledge across the firm's internal organizational and competence boundaries. Hence, their ability to envision combinations and synthesize inputs stemming from diverse innovation trajectories should be relatively limited.

Hypothesis 5b: The more a firm is downstream integrated, the more being exposed to a hole-rich spillover network increases the firm's innovative performance.

Method

Data and Measures

To test our hypotheses, we focus on a comprehensive sample of global semiconductor device firms between 1976 and 2002. This setting lends itself to analyzing how spillover networks affect firms' innovative performance for three main reasons. First, firms' ability to innovate is crucial to command a competitive advantage in this industry (Hall & Ziedonis, 2001). Second, public technological knowledge is widely recognized as important both to the innovative performance of individual firms and of the industry as a whole (Langlois & Steinmueller, 1999; Lim, 2010). Third, all relevant players in this industry routinely patent their innovations at the U.S. Patent and Trademarks Office (USPTO; Hall & Ziedonis, 2001).

Industry accounts suggest that the inclusion of non-U.S. firms is crucial to understand innovation in the semiconductor field since the growth of the industry "would no doubt have been smaller if the technological leadership of the United States had not come under challenge by the emergence of international competition" (Langlois & Steinmueller, 1999: 19). To accurately capture firms' spillover networks, we therefore consider all U.S., European, and Asian firms that patented their inventions at the USPTO. To select our sample, we used the following procedure. We first consulted historical company profiles of authoritative specialized market data providers (such as Integrated Circuit Engineering Corporation, Gartner Research, and the Semiconductor Industry Association) to identify a list of semiconductor firms active between 1976 and 2002. We then used the Directory of Corporate Affiliation to detect the subsidiaries of each firm in the initial list. Financial data about these firms and their subsidiaries were retrieved from COMPUSTAT North America, annual reports, and SEC filings for U.S. firms and from COMPUSTAT Global, Osiris, and the Japan Company handbook for non-U.S. firms. Furthermore, we consulted business directories (*Hoovers Premium*, *Who Owns Whom US, UK, and Asia*), industry sources (ICE—Intellectual Circuit Engineering Corporation—manuals annual volumes), and prior research (Hall & Ziedonis, 2001) to identify each firm's founding date and to establish whether a firm should be categorized as (a) "original equipment manufacturers," which produce semiconductor devices primarily to incorporate them in other products; (b) "integrated device manufacturer" (IDM), that is, firms specialized in the design, manufacturing, and commercialization of semiconductors; (c) "fabless," that is, firms specialized exclusively in designing semiconductor devices; or (d) "others," that is, semiconductor service providers.

To collect patent information on this sample of firms, we used three independent data sets: the National Bureau of Economic Research Patent and Patent Citations Data Set (Hall et al., 2001), the National University of Singapore's Patent Data Set (Lim, 2004), and the Harvard Business School Patent Network Dataverse (Lai, D'Amour, & Fleming, 2009). Using patent data from a single country is a standard practice in prior research (e.g., Ahuja, 2000; Katila & Chen, 2008; McGahan & Silverman, 2006; Yayavaram & Ahuja, 2008), as this practice guarantees consistency, reliability, and comparability (Griliches, 1990). To identify semiconductor-related patents, we used the list of USPTO subclasses developed by Macher (2006). Namely, we counted the number of patents granted in any of the listed subclasses to each of the identified firms and subsidiaries, and we selected those firms that had at least one patent between 1976 and 2002. Although we have data until 2008, we ended the observation period by 2002 to guarantee a 5-year citation window across the whole sample. We thus generated an unbalanced panel of 214 firms over the period 1976–2002.

Modeling Spillover Networks

The present study follows a large body of prior research that has employed patent data to model knowledge spillovers (see, among others, Cockburn & Henderson, 1998; Griliches, 1992; Jaffe et al., 1993; Yang et al., 2010). Patent data have become popular among researchers because they provide detailed large-scale information about both innovations and the knowledge connections among them, and they offer complete coverage over long time periods. Prior research has used a patent's *backward citations* (the list of existing patents on which a focal patent builds) to trace the knowledge inputs from which it drew. We use patents' backward citations with the more modest ambition to longitudinally reconstruct firms' spillover networks. Thus, we analyze the aggregate pattern of cross-firm patent citations to infer how much experience each firm has accumulated, up to any given time point, about the innovations developed by other semiconductor firms (Cockburn & Henderson, 1998; Lim, 2010; Zahra & George, 2002: 199).

To explicate our operationalization of firms' spillover networks,[1] let us consider the spillover network of firm A (Figure 1). The spillover network of firm A comprises all "source" firms whose public knowledge has been used up to t by firm A as a knowledge input: firm B, firm C, and firm D. Node values indicate the number of patented innovations each firm generated during t. The thick arrow from A to B indicates that firm A has accumulated substantial experience about the innovation trajectory developed by "source" firm B prior to t, making it possible for A to capture a great deal of spillovers from the knowledge B generates during t. Conversely, A's experience with C and D is relatively small, resulting in a limited capacity to benefit from the patents they generate at t.

We follow a multistep procedure to operationalize tie weights. First, we build for each time t a firm-to-firm citation network, where a tie v_{ijt} indicates the sum of postgrant citations that firm i has made to firm j's patents from 1976 up to t.[2] As said, we assume that firm i's capacity to capture spillovers from a "source" firm j is a function of the experience accumulated by firm i about the innovation trajectory developed by j (e.g., Lane & Lubatkin, 1998). Second, we apply a decay function and discount citations based on the years elapsed between the time of citation and t (Burt, 2000),[3] to account for organizational forgetting (de Holan, Phillips, & Lawrence, 2004). Third, we row-normalize (i.e., divide each cell by the sum of each row) the firm-to-firm citation matrix, as is common practice in network research (e.g., Burt, 1992). This ensures that ties are comparable across both large and small firms, and it minimizes the risk that ties may reflect exogenous shocks in patenting activity, such as generalized increases in the patent citation rate. Thus, each tie v_{ijt} is transformed into a proportional tie w_{ijt}, expressing the share of citations that firm i makes during t to patents generated by firm j, over the total number of citations made by i. Hence, $w_{ijt} \in [0, 1]$.

To exemplify this procedure, let us go back to Figure 1 and assume that we want to measure the experience that firm A has accumulated up to 1979 about B, C, and D, respectively. Also assume that in 1976, firm A made 20 citations to patents generated by firm B, 30 citations in 1977, and 20 citations in 1978. Furthermore, in 1976 firm A made 12 citations to patents generated by firm C, no citations in 1977, and 4 citations in 1978. Finally, in 1978 firm A made 10 citations to patents generated by firm D. To obtain tie weights, we first sum the citations, using a discount factor to give more weight to recent citations than to old ones, so that

$$v_{AB1978} = \frac{1}{2}\times 20 + \frac{1}{3}\times 30 + \frac{1}{4}\times 20 = 25,\ v_{AC1978} = \frac{1}{2}\times 4 + \frac{1}{3}\times 0 + \frac{1}{4}\times 12 = 5.,\ \text{and}\ v_{AD1978} = \frac{1}{2}\times 10 = 5\ .$$

We then row-normalize tie weights, that is, divide each cell of the citation matrix by the total of its row. Thus, in 1979 w_{AB} = 25/35 = 0.714, w_{AC} = 5/35 = 0.143, and w_{AD} = 5/35 = 0.143.

In reconstructing firms' spillover networks, we allow a minimum of 3 years of patent history to be able to estimate prior experience. As our data start in 1976, we begin modeling firms' spillover networks in 1978. Also, since our dependent variable is observed until 2002 and all our predictors are lagged by one year in the econometric models, firms' spillover networks are traced until 2001.

Dependent Variable

Following a standard practice (e.g., Yayavaram & Ahuja, 2008), we measure *firms' innovative performance* by counting the number of patents granted to a firm,[4] weighed by the number of *forward citations* each of these patents received within a given time (5-year) interval. Citation-based counts are considered a reliable and externally validated measure of innovative performance (Griliches, 1990; Yayavaram & Ahuja, 2008) and correlate with both the economic and the social value of a firm's innovations (Harhoff, Narin, Scherer, & Vopel, 1999) and a firm's ability to generate new products (Comanor & Scherer, 1969) and science-based inventions (Basberg, 1982). To reduce truncation bias, we counted the number of forward citations received by each of a firm's patents within 5 years from the patent's application date.[5] Thus, for example, a firm's innovative performance in 1996 counts the number of successful patent applications filed by the firm in 1996, weighed by the number of forward citations received by those patents until 2001.

Independent Variables

Our first explanatory variable is labeled *spillover network munificence* and aims to capture how munificent is a firm's spillover network. To this end, we count the number of patented innovations each "source" firm generates during t, weighed by the level of experience the "recipient" firm has accumulated prior to t about each source. This indicates a "recipient" firm's ability to capture spillovers from its sources. Adapting a well-known model of "network autocorrelation" (Doreian, Teuter, & Wang, 1984; Leenders, 2002), this variable is computed as follows,

$$\textit{Spillover Network Munificence}_{it} = \sum_{\substack{i=1 \\ i \neq j}} w_{ijt} \times \textit{Patent Count}_{jt},$$

where $\textit{Patent Count}_{jt}$ is a vector indicating the number of successful patent applications filed by each of i's "source" firms j and w_{ijt} is a weight reflecting i's accumulated experience about j in the years prior to t, as described earlier. Let us go back one more time to the example in Figure 1 to see how this works. Let 70, 35, and 140 be the number of patented innovations generated in 1978 by B, C, and D, respectively. Then, the *spillover network munificence* of C is computed as follows: $\textit{spillover network munificence}_{C\ 1978} = 0.714 \times 70 + 0.142 \times 35 + 0.142 \times 140 = 75$.

The second explanatory variable employed in our study, labeled *structural holes*, measures the degree of connectivity (or the lack of it) between a firm's "source" firms (Burt, 1992). A "recipient" firm's spillover network is rich in structural holes if its "source" firms are mutually disconnected, implying that their innovation trajectories have developed independently and hence do not overlap (see Figure 2b). By contrast, when there are few structural holes in a firm's spillover network, all of a firm's "source" firms are tightly connected. Therefore, their innovation trajectories overlap to a large extent (Figure 2a). To compute the *structural holes* measure we follow the literature and take the additive inverse of Burt's well-known measure of "constraint" (Burt, 1992: 54-55). The network constraint index begins with the extent to which a "recipient" firm i has directly or indirectly invested in accumulating experience about each of its "source" firms j. Formally this is captured by the following formula, $c_{ijt} = (p_{ijt} + \sum_q p_{iqt}\, p_{qjt})$, where $q \neq i \neq j$, where p_{ijt} is the proportion of firm i's experience in "source" firm j, and $\sum_q p_{iqt} p_{qjt}$ is the extent to which each "source" firm j has experience about other firms belonging to firm i's spillover network. The sum of squared proportions, $\sum_j C_{ijt}$, is the network constraint measure C_{it}. We measure structural holes as the additive inverse of the constraint index: $\textit{Structural Holes}_{it} = 1 - C_{it}$.

Consistent with our definition of spillover network and with our focus on the experience developed by *i* with the innovation trajectory developed by *j*, our measure of *structural holes* is based on outgoing ties only—that is, we consider only the experience that *i* has accumulated about *j*, but not the other way round. The *structural holes* measure goes from 0 to 1, with larger values indicating more structural holes.[6] When all the sources of a "recipient" firm are directly or indirectly connected in the spillover network (e.g., Figure 2a), the *structural holes* measure takes a value close to 0, whereas the measure is close to 1 when a firm's sources are mutually disconnected (e.g., Figure 2b). All network measures were computed with UCINET VI (Borgatti, Everett, & Freeman, 2002).

Our first organizational moderator, *scientific intensity*, refers to the extent to which a firm uses scientific knowledge to generate its technological innovations. Following a well-established practice (Fleming & Sorenson, 2004; Tijssen, 2001), we measure scientific intensity as the relative propensity of a firm to cite scientific articles as opposed to patent documents in their *prior art*. Our second organizational moderator, *downstream integration*, captures whether a firm engages in the integration of its technological knowledge in manufactured products (Monteverde, 1995). To construct this variable, we construct a dummy variable that is coded 1 if the firm is an *IDM* or an original equipment manufactures, and 0 if it is a fabless firm (*Fabless*; Langlois & Steinmueller, 1999; Macher, 2006).

Control Variables

We control for a comprehensive set of factors that may affect firms' innovative performance. Following prior literature, we use the number of patents granted to a firm in each time window to control for the effects of firms' *knowledge base size* (Yayavaram & Ahuja, 2008). A firm that produces general technologies, that is, technologies that may be applied in several application sectors, is more likely to be cited than a technological specialist (Hall et al., 2001). To control for the degree of *technology generality* of a firm's knowledge base, we used Hall et al.'s (2001) generality index. Forward citation frequencies may vary across technological sectors and subsectors independently of firm-specific factors. For example, some technological areas may have inherently higher growth potential than others (Patel & Pavitt, 1997). To control for these effects we use a *technological fertility* variable, defined as the average performance of each technology class in which a firm has patents in a given year, weighed by the number of patents the firm is granted in that technology class in that year. This is then summed over all technology classes for each firm (Ahuja, 2000). Technologically diversified firms may be more innovative (Garcia-Vega, 2006) and better able to absorb external knowledge (Cohen & Levinthal, 1990). Following Yang and colleagues (2010) we measure firms' technological diversity using Hall's (2002) adjusted Herfindahl index, based on the three-digit USPTO patent classes in which firms are granted patents. Firms vary in the extent to which they innovate by building on their own previous knowledge, as opposed to drawing from innovations generated by other firms. As this may affect their innovative performance, we compute for each firm in each time interval the ratio of backward self-citations to total citations (*self-citation ratio*). Prior research has shown that firms' innovative performance is influenced by whether they cumulatively build on a body of existing knowledge or, conversely, experiment with pioneering technologies. We follow previous studies in modeling this effect by counting the average number of *backward citations* a firm's patents make to previous patents (Katila & Ahuja, 2002). Firm *size* may affect both the scope and the scale of its technological activities, whereas *age* may affect a firm's innovative performance because older firms tend to be more inert than younger ones (Cyert & March, 1963). We measure firm size as the natural logarithm of a firm's assets and *age* as the number of years elapsed between the firm incorporation and the middle year of each time window. *R&D intensity* has often been used as a measure of input in the process of technological generation (Ahuja, 2000; Hall & Ziedonis, 2001). We compute *R&D intensity* as the ratio between a firm's R&D expenditure and employment.[7] Previous studies hypothesized that the economic performance of a firm may have both positive (Katila & Ahuja, 2002) and negative (Cyert & March, 1963) effects on its subsequent innovative performance. We measure a firm's economic performance by its *ROI.* Finally, since differences may exist across countries in patenting propensity, our models include a dummy variable, *US*, which is set to 1 if a firm's country is the United States, and 0 otherwise. We also introduce a set of *time dummies* to control for possible exogenous shocks and other time-varying factors.

Results

The unit of analysis in our study is the firm-period, and the data have an unbalanced panel structure. The dependent variable is a count variable that takes on only nonnegative values. Linear regression models are inadequate under these conditions because the distribution of residuals will be heteroscedastic and nonnormal. In addition, a likelihood ratio test showed that our data were significantly overdispersed, violating the assumption that the conditional mean of outcome is the same as the conditional variance. Thus, a negative binomial panel specification was preferred over a Poisson model. The negative binomial model is a generalization of the Poisson model and allows for overdispersion by incorporating an individual unobserved effect into the conditional mean (Hausman, Hall, & Griliches, 1984). The Hausman (1978) test rejected the unbiasedness of the random-effect estimator (p = .251). Hence, we estimated a panel fixed effects negative binomial model. Following a well-established approach, we standardized all variables before entering them in the model and creating their cross-products to reduce collinearity and interpret the results in a meaningful manner (Aiken, West, & Reno, 1991; Rothaermel & Hess, 2007). We use Stata 11 to estimate all equations.

We report summary statistics and correlations in Table 1. To assess potential problems of multicollinearity, we calculate variance inflation factors (VIFs) based on the pooled data. VIF values for the full model range from 1.02 to 6.67 (M = 1.87), whereas conventionally VIFs are regarded as indicative of multicollinearity problems when they exceed the value of 10 (Wooldridge, 2002). Thus, multicollinearity is not an issue in our data. For 22 firms we have data for no more than one year. In addition, 7 firms in our sample were granted patents that received no forward citations in the following 5 years, thus engendering all zero outcomes in our variables. In our fixed effects estimations, these firms are automatically

Table 1
Descriptive Statistics and Bivariate Correlation Matrix

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
1. Firms' innovative performance	1																		
2. Spillover network munificence	.22	1																	
3. Structural holes	.18	–.18	1																
4. Scientific intensity	–.01	–.16	.01	1															
5. Downstream integration	.12	–.01	.15	.02	1														
6. Knowledge base size	.75	.32	.20	–.03	.18	1													
7. Technology generality	.05	–.02	–.10	.14	.08	.01	1												
8. Technological fertility	.33	.56	–.11	–.11	.01	.32	.09	1											
9. Technological diversity	.14	.15	.14	.02	.24	.20	.35	.12	1										
10. Self-citation ratio	.19	.13	.07	.06	.02	.23	.10	.07	.21	1									
11. Backward citations	.08	.26	–.10	–.07	–.12	.05	.20	.31	.12	.11	1								
12. ROI	.00	–.01	.01	.04	.02	.00	.02	.00	.04	.02	–.01	1							
13. Age	.11	.08	.19	.00	.40	.20	.04	.03	.28	.18	–.10	.01	1						
14. R&D intensity	–.02	–.04	.03	–.01	–.07	–.03	–.03	–.04	–.05	–.04	–.01	–.12	–.05	1					
15. Assets	.23	.13	.15	.07	.21	.32	.02	.08	.17	.13	–.04	.00	.35	–.03	1				
16. US	–.01	–.11	–.02	.04	–.24	–.08	.01	–.14	–.14	–.02	.07	–.04	–.36	.05	–.14	1			
17. IDM	.04	–.04	.03	–.03	.53	.03	–.01	–.01	–.01	–.13	–.01	–.02	–.26	–.01	–.19	.18	1		
18. Fabless	–.12	.00	–.11	–.09	–.74	–.16	–.06	–.06	–.16	–.12	.14	–.02	–.33	.10	–.17	.28	–.39	1	
19. Other	–.05	.03	–.10	.07	–.39	–.07	–.05	.12	–.16	.11	.01	–.01	–.16	–.03	–.12	.01	–.31	–.23	1
M	220.29	118.85	0.71	0.44	0.66	33.37	0.38	6429.04	0.53	0.12	7.52	0.03	30.67	0.27	5438.071	0.63	0.35	0.22	0.15
SD	707.37	129.67	0.24	0.78	0.47	87.97	0.22	7407.38	0.4	0.16	9.39	2.55	30.99	2.41	16349.58	0.47	0.48	0.41	0.36
Min	0	0	0	0	0	0	0	0	0	0	0	–27.29	0	0	0	0	0	0	0
Max	11135	1023	1	16	1	1063	1	35431	2	1	119.57	117.9	155	67.28	242223	1	1	1	1

Note: $N = 2{,}064$. All positive and negative correlations greater than .07 are significant at $p < .05$.

dropped because mean deviations cannot be computed. Last, for 174 firm-year data points we were able to gather information about firms' patented innovations, but not about their financial data (e.g., assets, R&D expenditure, and employment). This is because those firms were technologically active but not yet publicly traded. Given that these observations did not meet the requirements for imputation, we decided to drop them as well. As a consequence of these choices, our econometric analyses are based on an unbalanced panel of 185 firms, yielding a total of 2,064 firm-period observations for the fixed effects models.

In Table 2, we report the results of our analyses. Model 1 is a baseline model including only control variables. Of these, firms' *age*, *knowledge base size*, *technological diversity*, and *self-citation ratio* have a significant positive effect on firms' innovative performance. In line with prior research, *technological fertility* has a positive and significant effect, indicating that firms' innovative performance is enhanced by the rate of progress of their area of specialization. All other variables show little association with our dependent variable.

In Model 2, we introduce our first explanatory variable, *spillover network munificence*, which as expected has a positive and significant effect. Corroborating Hypothesis 1, firms' innovative performance is enhanced by the technological productivity of their spillover network ($\beta = .049$, $p < .05$).[8] Model 3 introduces the *structural holes* variable. In line with Hypothesis 2, the effect of *structural holes* is positive and significant ($\beta = .404$, $p < .001$), indicating that firms whose spillover network is rich in structural holes tend to be more innovative. Model 4 introduces the interaction term between *structural holes* and *spillover network munificence*. Hypothesis 3 predicted that the positive effect of *spillover network munificence* would be lower for firms whose spillover network is rich in structural holes. And by the same token, the innovation-enhancing effect of *structural holes* would be diminished at higher levels of *spillover network munificence*. The coefficient of the interaction term is negative and statistically significant ($\beta = -.055$, $p < .01$), providing support for this hypothesis. Based on the estimates provided by Model 4, for a firm with an average value of both *spillover network munificence* and *structural holes*, a one standard deviation increase in *structural holes* leads to a remarkable 53.3% increase in the firm's innovative performance. Yet for a firm with a munificent spillover network (i.e., one standard deviation above the mean), a one standard deviation increase in *structural holes* reduces innovation by 5.3%.

Moving now to examine how organizational factors affect firms' ability to convert the patented knowledge of other firms into innovative performance differentials, Model 5 and Model 6 explore how *scientific intensity* moderates the effect of *spillover network munificence* and *structural holes* on *innovative performance*. Supporting Hypothesis 4b, the interaction between *structural holes* and *scientific intensity* is positive and statistically significant ($\beta = .127$, $p < .001$), suggesting that science-based firms are better at elaborating syntheses of diverse the innovation trajectories characterizing hole-rich spillover networks. Hypotheses 4a predicted that firms with a strong science base would be better equipped to exploit the learning potential inherent in munificent spillover networks. Although the sign of the coefficient of the interaction term is positive as expected ($\beta = .056$), the coefficient is not statistically significant a 5%. To conclude, Model 7 and Model 8 test our last two hypotheses. Hypotheses 5a and 5b predicted that *downstream integration* would reduce the positive effect of *spillover network munificence* and would increase the positive effect of *structural holes*. Our results seem to support our theoretical expectations: The interaction term between

Table 2
Results of Fixed Effects Panel Negative Binomial Predicting Innovative Performance

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10	Model 11
Spillover network munificence		0.049*	0.127**	0.066*	0.070*	0.093**	0.154**	0.136**	0.113**	0.126**	0.087†
		(0.023)	(0.025)	(0.030)	(0.032)	(0.032)	(0.040)	(0.042)	(0.044)	(0.043)	(0.050)
Structural holes			0.404**	0.449**	0.450**	0.442**	0.437**	0.345**	0.344**	0.353**	0.267**
			(0.034)	(0.037)	(0.037)	(0.036)	(0.036)	(0.051)	(0.054)	(0.054)	(0.059)
Spillover network munificence × structural holes				–0.055**	–0.055**	–0.044**	–0.034*	–0.033*	–0.046**	–0.042*	–0.066**
				(0.014)	(0.014)	(0.015)	(0.015)	(0.016)	(0.017)	(0.017)	(0.020)
Spillover network munificence × scientific intensity					0.013	0.056	0.057	0.054	0.049	0.050	0.040
					(0.035)	(0.040)	(0.040)	(0.040)	(0.042)	(0.042)	(0.042)
Structural holes × scientific intensity						0.127**	0.126**	0.119**	0.120**	0.128**	0.081*
						(0.034)	(0.034)	(0.034)	(0.037)	(0.037)	(0.035)
Spillover network munificence × downstream integration							–0.083*	–0.059†	–0.075*	–0.085*	–0.027
							(0.034)	(0.036)	(0.037)	(0.037)	(0.041)
Structural holes × downstream integration								0.154*	0.130†	0.124†	0.261**
								(0.063)	(0.067)	(0.068)	(0.075)
Collaboration structural holes									0.073**		
									(0.022)		
Collaboration ties										0.019	
										(0.025)	
Internal patent law expertise											0.012
											(0.013)
Scientific intensity	0.029	0.031	0.039†	0.039†	0.035	0.105**	0.103**	0.101**	0.099**	0.106**	0.107**
	(0.023)	(0.023)	(0.023)	(0.023)	(0.026)	(0.031)	(0.031)	(0.031)	(0.037)	(0.037)	(0.032)
Downstream integration	–0.009	0.013	–0.007	0.000	–0.002	–0.001	0.062	0.135	0.159	0.171	0.270*
	(0.084)	(0.085)	(0.084)	(0.084)	(0.085)	(0.085)	(0.089)	(0.094)	(0.104)	(0.104)	(0.107)
Knowledge base size	0.125**	0.125**	0.107**	0.116**	0.116**	0.117**	0.118**	0.117**	0.110**	0.113**	0.115**
	(0.009)	(0.010)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.010)	(0.010)	(0.010)
Technology generality	–0.054†	–0.038	0.014	0.025	0.025	0.024	0.020	0.019	–0.001	0.007	–0.034
	(0.029)	(0.029)	(0.030)	(0.030)	(0.030)	(0.030)	(0.030)	(0.030)	(0.035)	(0.035)	(0.038)

(continued)

Table 2 (continued)

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10	Model 11
Technological fertility	0.158**	0.131**	0.225**	0.241**	0.241**	0.239**	0.241**	0.242**	0.230**	0.223**	0.230**
	(0.031)	(0.032)	(0.033)	(0.033)	(0.033)	(0.033)	(0.032)	(0.032)	(0.034)	(0.034)	(0.039)
Technological diversity	0.267**	0.257**	0.228**	0.231**	0.231**	0.228**	0.228**	0.225**	0.198**	0.207**	0.183**
	(0.027)	(0.027)	(0.028)	(0.028)	(0.028)	(0.028)	(0.028)	(0.028)	(0.031)	(0.031)	(0.030)
Self-citation ratio	0.073**	0.080**	0.067**	0.061*	0.060*	0.052*	0.048†	0.046†	0.001	0.006	0.032
	(0.025)	(0.025)	(0.026)	(0.026)	(0.026)	(0.026)	(0.026)	(0.026)	(0.032)	(0.032)	(0.029)
Backward citations	–0.024	–0.040	–0.038	–0.055†	–0.054†	–0.058*	–0.058*	–0.056†	–0.051†	–0.052†	–0.105**
	(0.026)	(0.027)	(0.027)	(0.028)	(0.028)	(0.029)	(0.029)	(0.029)	(0.030)	(0.029)	(0.035)
ROI	0.007	0.007	0.005	0.005	0.005	0.003	0.003	0.003	0.004	0.001	0.002
	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)
Age	0.148**	0.141**	0.088**	0.100**	0.101**	0.096**	0.097**	0.091**	0.049	0.061†	0.090**
	(0.030)	(0.030)	(0.030)	(0.030)	(0.030)	(0.030)	(0.030)	(0.030)	(0.035)	(0.035)	(0.031)
R&D intensity	–0.055†	–0.055	–0.055	–0.054	–0.054	–0.056	–0.053	–0.051	–0.154*	–0.156*	–0.232†
	(0.033)	(0.033)	(0.035)	(0.035)	(0.035)	(0.035)	(0.035)	(0.034)	(0.079)	(0.078)	(0.119)
Assets	0.034	0.025	0.005	0.020	0.019	0.019	0.023	0.019	–0.038	–0.027	0.009
	(0.023)	(0.024)	(0.024)	(0.024)	(0.024)	(0.024)	(0.024)	(0.024)	(0.029)	(0.032)	(0.028)
US	0.145†	0.164*	0.078	0.094	0.094	0.105	0.115	0.096	–0.033	–0.019	0.121
	(0.078)	(0.078)	(0.077)	(0.078)	(0.078)	(0.078)	(0.078)	(0.078)	(0.088)	(0.088)	(0.084)
Firm type dummies	included	included	included	included	included	included	included	included	included	included	included
Time dummies	included	included	included	included	included	included	included	included	included	included	included
Constant	–0.979**	–1.442**	–0.997**	–1.009**	–1.007**	–1.000**	–1.054**	–1.082**	–0.659**	–0.641**	–1.153**
	(0.116)	(0.206)	(0.205)	(0.205)	(0.205)	(0.205)	(0.206)	(0.206)	(0.135)	(0.134)	(0.222)
Log likelihood	–8413.77	–8409.3	–8327.1	–8320.57	–8320.51	–8312.79	–8309.78	–8306.83	–6782.97	–6776.14	–7375.62
$\Delta\chi^2$		4.30*	138.24**	14.85**	0.13	13.83**	6.09*	5.93*			
Observations	2,064	2,064	2,064	2,064	2,064	2,064	2,064	2,064	1,584	1,584	1,698
Number of firms	185	185	185	185	185	185	185	185	166	166	152

Note: Standard errors in parentheses.
†$p < .1$. *$p < .05$. **$p < .01$.

downstream integration and *spillover network munificence* is positive, though weakly significant ($\beta = -.059$, $p < .10$), and the interaction between *downstream integration* and *structural holes* is positive and significant. The chi-square tests show that each model, except Model 5, indicates a statistically significant improvement in fit vis-à-vis each previous model.

Contrasting Spillover Networks and Collaboration Networks

The relevance of our theory is ultimately based on the presumption that spillover networks and collaboration networks funnel distinct streams of knowledge spillovers, implying that their effect on firms' innovative performance should be at least in part independent. It is therefore important to show that our results hold even when controlling for the effects of collaboration networks. To this end, we use data on firms' R&D collaboration (Ahuja, 2000; Baum et al., 2000; Powell et al., 1996). Following prior research (Schilling, 2009), the data were collected from the Federal Register of the U.S. Department of Justice, in which all R&D alliances based in the United States must be reported under the National Cooperative Research Act (NCRA).[9] In this way, we retrieved information on the R&D alliances formed between 1986 and 2002 by a subset of firms in our data set (i.e., all U.S.-based firms and all international companies having at least one collaborative tie with a U.S. partner). The data report the initiation date of all collaborations, whereas the termination date is reported for only one fourth of the data. To construct firms' R&D collaboration networks, we assumed each tie to last 3 years, which is very close to the average duration observed for the collaborations for which we have termination dates (2.8 years), and it is a standard assumption in previous studies (e.g., Ahuja, 2000). Based on the resulting networks, for each firm in each period we calculated the additive inverse of Burt's structural holes measure—a variable we labeled *collaboration structural holes* and the count of *collaboration ties* that a firm maintains in a given window. Because we were unable to collect R&D collaboration data for our full sample, we report the results in separate models. Confirming the results of prior studies (Baum et al., 2000; Zaheer & Bell, 2005), Model 9 shows that the effect of *collaboration structural holes* on *innovative performance* is positive and significant ($\beta = .073$, $p < .01$). Model 10 shows that the number of *collaboration ties* maintained by a firm has a positive effect on *innovative performance*, albeit not statistically significant. Importantly, these results indicate that a firm's spillover network yields additional advantages that are not explained by the properties of a firm's collaboration network, corroborating the view that spillover and collaboration networks entail distinct interorganizational learning processes and that the spillover network has an effect on firms' innovative performance over and above that exerted by their collaboration network.

Alternative Model Specifications

Following the prevalent approach in modeling patent counts (e.g., Ahuja, 2000; Katila & Ahuja, 2002; Rothaermel & Hess, 2007; Yayavaram & Ahuja, 2008), and in line with the result of the Hausman test and of a likelihood ratio test for overdispersion, we presented a set of results based on a conditional fixed effects negative binomial panel specification (Hausman et al., 1984). As said, all variables were standardized prior to entering them in the regression model. Although we believe this to be the most appropriate econometric approach in the context of our analyses, we reestimated our full model under several distinct econometric models to evaluate the robustness of our empirical results. In an attempt to be as conservative as possible, we reproduced all modeling approaches (that we are aware of) used by other studies in the context of count models (Hausman et al., 1984; Hall & Ziedonis, 2001; Somaya et al., 2007). We thus estimated (a) a random effect panel negative binomial model with a presample dependent variable, to take into account firm-specific unobserved heterogeneity (Hall et al., 1984); (b) a negative binomial, fixed effects model with log transformation of all size dependent variables, where all other variables are nonstandardized; (c) a fixed effects panel ordinary least squares regression, where the dependent variable (*innovation performance*) is log transformed; (d) a generalized estimating equations technique using a Poisson specification and an AR(1) correlation structure (as proposed by Somaya et al., 2007); and (e) a quasi-maximum-likelihood Poisson regression with firm fixed effects with robust standard errors and log transformation of all size dependent variables.[10] The rationale for using the latter set of models is that some studies have argued that Poisson estimators may produce consistent estimates of the parameters in an unobserved components multiplicative panel data model even if the underlying distribution in the data is not truly Poisson (Gouriéroux, Monfort, & Trognon, 1984; Wooldridge, 2002).

For space reasons Table 3 summarizes only the results concerning our hypotheses, whereas the full models are available from the authors on request. The table shows that our first three hypotheses remain strongly supported under all model specifications. Turning now to the moderation hypotheses, all the models appear to support the idea that *downstream integration* and *scientific intensity* positively affect a firm's ability to benefit from a hole-rich spillover network. With respect to how organizational factors affect firms' ability to benefit from *spillover network munificence*, results are in line with our expectations but less consistent. In sum, we interpret these robustness analyses as providing broad support to our argument and hypotheses.

Concerns Related to the Use of Patent Citations

Using patent data to both reconstruct a firm's spillover network and gauge firms' innovative performance engenders two sets of concerns. On one hand, one may argue that patent citations may not accurately reflect interorganizational learning from other firms' public knowledge, as in some instances citations may signal strategic behavior or depend on factors that are external to the firm. As already said, our usage of patent citations is rather modest compared to previous studies. Although previous research has taken individual patent citations as indicative of instances of knowledge spillovers (e.g., Cockburn & Henderson, 1998; Jaffe et al., 1993; Yang et al., 2010), we look at historically aggregated patterns of interfirm citations to infer firms' accumulated experience. Nevertheless, also our measure suffers from a well-known problem of citation-based indicators: Although citing all

Table 3
Robustness Checks

	Panel Negative Binomial (Fixed Effects)	Panel Negative Binomial (Random Effects With Presample Dependent Variable)	Panel Negative Binomial (Fixed Effects, Logged Size Dependent Predictors)	Fixed Effects OLS Panel Regression	Fixed Effects AR(1) Panel Poisson (Logged Size Dependent Predictors)	Fixed Effects Quasi Maximum Likelihood Panel Poisson (Logged Size Dependent Predictors)
H1	+**	+**	+**	+*	+**	+*
H2	+**	+**	+**	+**	+**	+*
H3	–*	–†	–**	–	–**	–**
H4a	+	+	+†	+†	+*	–
H4b	+**	+**	+*	+*	–**	+
H5a	–†	–*	+	–	+	+
H5b	+*	+*	+**	+	+**	+†

†$p < .10$. *$p < .05$. **$p < .01$.

relevant prior art is a legal obligation for a patent applicant, "inventors, their employers, attorneys, and patent examiners all have input to the citation process" (Miller, Fern, & Cardinal, 2007: 314). As a consequence, using citation patterns to measure how much experience a firm has accumulated about another may yield both Type I and Type II errors (Alcacer & Gittelman, 2006). To gauge the magnitude of this problem in the context of our measure, we exploit data from 2001, which disentangle the patent citations made by an inventor from those added during the patent examination process. Based on these data, we can compare the network of interfirm citations constructed on the basis of inventor citations only, with the one obtained using all citations.[11] Results show that the similarity in the citation patterns between the two networks is remarkably high (r = .832) and higher than that reported in studies in which this check was made (Alcacer & Gittelman, 2006; Criscuolo & Verspagen, 2008). Therefore, we feel confident to use patent citation data to operationalize learning in spillover networks.

On the other hand, because we use patent data to construct both our dependent and our independent variable, our results may be biased because of unobserved heterogeneity in firm's propensity to patent. In addition, firms in similar technology areas, and hence citing each other's patents, may be affected by common shocks in patent production. Indeed, using patent data to construct both predictors and outcome variables is by now a widely accepted practice, especially if the lag structure guarantees that temporally distinct patent sets are used to construct the variables. However, to further ensure that our results are not biased, we tried to enrich our model by taking into account one factor that according to previous research may drive systematic differences in firms' patenting activity (Somaya et al., 2007): firm's *internal patent law expertise*. This variable captures the extent to which a firm has in-house law expertise. Model 11 shows that our results hold even after controlling for *internal patent* *law expertise*. In unreported analyses, we also controlled for other factors reflecting technology-specific factors driving patenting propensity (Ahuja, 2000). Results were unaltered.

Conclusions

A key distinguishing trait of the knowledge-based economy is that in addition to the tacit knowledge absorbed through interfirm collaborations, a significant portion of interorganizational learning occurs through the absorption of codified, publicly available knowledge (Brown & Duguid, 2002: 141-142; Mokyr, 2002; Yang et al., 2010). Inspired by this consideration, the present article investigated whether, and under which conditions, this form of interorganizational learning provides firms with a sustainable competitive advantage in the technological race. To this end we introduced the concept of *spillover network*, defined as the network of "source" firms whose public knowledge a "recipient" firm is able to readily absorb and use as innovation input. Based on a longitudinal panel of global semiconductor firms between 1976 and 2002, our study demonstrated two sets of results. First, we found that differences in the properties and structure of firms' spillover networks result in systematic and sizeable differences in firms' innovative performance. Importantly, these results hold after controlling for the characteristics of firms external collaboration network. In particular, we showed that being positioned within a munificent spillover network significantly enhances firms' innovative performance. Testifying to the generality of structural holes theory (Burt, 1992, 2000), furthermore, we showed innovative performance to be higher for firms whose spillover network is rich in structural holes. Last, our analyses indicated that because the benefits of hole-rich and munificent spillover networks are less than additive, being positioned in a spillover network that is both munificent and hole rich is generally counterproductive.

Our analyses also demonstrated that the extent to which a firm is able to reap the benefits inherent in its spillover network depends on specific intraorganizational factors impinging on the firm's ability to manage knowledge that is represented in an abstract and general form, such as in patents. We argued that having a solid scientific base helps firms efficiently selecting knowledge inputs in munificent, fast-growing spillover networks (Fleming & Sorenson, 2004), and it guides them as they attempt to synthesize knowledge from previously unrelated innovation trajectories. Consistent with this argument, we predicted and found that the advantage of being exposed to a munificent spillover network is greatest for firms characterized by a high degree of scientific intensity, as it is the advantage of being exposed to a hole-rich spillover network. Furthermore, we argued that vertically integrated firms are better at internally brokering knowledge (Monteverde, 1995), which we predicted to result in a greater ability to envision connections between diverse knowledge inputs. As a result, we hypothesized and showed that downstream integration increases firms' ability to seize the knowledge-diversity benefits inherent in hole-rich spillover networks. At the same time, however, we also argued that vertically integrated firms are too organizationally rigid, and too reliant on unstructured and embedded knowledge, to be able to fully exploit the fast-growing stream of abstract and general knowledge characteristic of munificent spillover networks.

Limitations of the Study

The study has some noteworthy limitations, which in turn suggest potentially fruitful research opportunities. First, we used patent citations to proxy the experience accumulated by a "recipient" firm vis-à-vis its "source" firms and to compute our measures of innovative performance. Although we did our best to make sure that our results were not affected by endogeneity problems, we would like to acknowledge that we cannot entirely exclude this possibility. In particular, a question that may be raised is whether exogenous shocks may concurrently affect "source" firms and "recipient" firms propensity to patent. In addition, by using patent citations to measure prior experience we abstracted away from the micro processes underlying such experience accumulation. This leaves open several potentially important questions, which our study did not directly address. For example, how do firms select their "source" firms? And how do strategic considerations, path dependence, and unplanned organizational dynamics influence such selection process? Furthermore, practitioners and the popular managerial press report that specialized knowledge intermediaries have emerged that help firms scan and monitor the public knowledge of other firms (Rivette & Kline, 2000). This is an interesting phenomenon that speaks to the importance of public, codified knowledge as a source of interorganizational learning, and which raises another theoretically relevant question that our study did not address. Should firms necessarily develop the ability to screen and monitor other firms' innovation trajectories internally, or might it be enough for them to outsource this service?

Second, our study looked at only one specific aspect of firms' innovative performance, that is, their ability to generate new valuable technological knowledge. However, equally important is the ability to turn technological knowledge into commercially valuable processes or products (Brusoni et al., 2001; Katila & Ahuja, 2002). As we have not observed these aspects of technological innovation in the present study, we currently do not know if and to what extent our arguments can be extended to explain them. Our understanding of the workings of spillover networks, and of the scope of their effects, could certainly be improved by expanding consideration to this matter. Similarly, we did not disentangle, either theoretically or empirically, innovation output from innovation impact. However, it is possible that the spillover network affects each of these two components of a firm's innovative performance in different ways. For example, a spillover network rich in structural holes may reduce the number of innovations a firm generates, while at the same time increasing their impact. Recent research has shown the importance of disentangling these two aspects in the context of collaboration networks (Fleming et al., 2007), and much could be learned about spillover networks too.

A third, related limitation is that our arguments abstract away from the *content* of knowledge that firms capture through their spillover network. For example, firms may be more likely to generate public technological knowledge about product innovations, whereas the knowledge pertaining to process innovations tends to remain embodied in organizational routines and artifacts (Jensen & Szulanski, 2007). Similarly, prior research suggests that the public knowledge firms absorb from the environment consists primarily of *component* knowledge, whereas firms' *architectural* knowledge more often remains confined with firms' boundaries (Henderson & Clark, 1990). Investigating which types of knowledge firms access through their spillover network may help us to both enrich and qualify our theoretical arguments.

Finally, we focused exclusively on one industry wherein the propensity to codify knowledge is high. Because industries vary greatly in the extent to which technological knowledge is codified and made publicly available, learning through the spillover network may be important in only some settings, whereas in others interorganizational learning may mostly occur through face-to-face, interactive processes. For example, Katila and Chen (2008: 603) point out that whereas automobile companies routinely make reciprocal agreements to exchange private tacit information, robotics companies rely on public information such as scanning of competitors' patents. Exploring industry-level factors that affect the relative benefits of interorganizational learning through collaboration or through spillovers from public sources would help us better define both the theoretical scope and the practical relevance of our research.

Contribution and Implications

This article makes important contributions to interorganizational learning research. Although prior studies in this area have almost exclusively focused on the innovation benefits associated to the absorption of tacit knowledge through collaboration ties (Ahuja, 2000; Owen-Smith & Powell, 2004; Powell et al., 1996), this study extends recent attempts to expand consideration to the knowledge spillovers firms capture when other firms codify their technological knowledge and make it available in the public domain (Yang et al., 2010). In particular, we complement Yang and colleagues' (2010) inquiry into how firms' innovative performance is driven by their differential access to public knowledge. Introducing the concept of "knowledge spillover pool," the authors showed that a firm often benefits from having its public knowledge absorbed and recombined by other firms. The reason is that by using a focal firm's knowledge, these firms generate a pool of new related public knowledge which may in part flow back to the focal firm, enhancing its innovativeness. Rather than focusing on the benefits of knowledge spillovers for either the "recipient" (Cohen & Levinthal, 1990; Griliches, 1992) or the "source" firm (McGahan & Silverman, 2006; Yang et al., 2010), this study extends this line of inquiry by analyzing under what conditions the broader spillover network in which a firm is embedded represents a source of sustainable innovative advantage. By showing how the characteristics of spillover networks affect the munificence and diversity of knowledge inputs available to the firm, and how the internal organizational capabilities of a firm in turn affects its ability to turn such inputs into an actual innovation advantage, we began to illuminate the distinctive mechanisms underpinning spillover learning from collaboration-based learning.

Taken together, Yang et al.'s and our findings also cast some doubts over the oft-heard view that the only source of sustainable innovation performance differentials lies in firms' tacit knowledge. This view rests on the premise that innovations are valuable insofar as they are hard to imitate. Since tacit knowledge is by definition hard to imitate, tacit knowledge is crucial for innovation. By contrast, our article was premised on the view that even knowledge inputs that are perfectly codified and publicly available can make a firm's innovations valuable and hard to imitate, granted that they are bundled in unique ways with complementary firm-level resources, process, and capabilities (Penrose, 1959; Rumelt, 1974; Somaya et al., 2007). Analogous to research showing that firm-level organizational factors increase firms' ability to benefit from interorganizational collaboration (e.g., Singh, Kale, & Dyer, 2002; Zaheer & Bell, 2005), our article illuminates how organizational characteristics, such as scientific intensity and downstream integration, affect the firm's ability to take stock of the knowledge made public by other firms.

Finally, our study contributes to the literature on the role of knowledge brokerage in interorganizational learning. This line of inquiry has witnessed a long-lasting debate both in the innovation (e.g., Hargadon & Sutton, 1997) and in the network tradition (e.g., Ahuja, 2000; Baum et al., 2000; Rowley et al., 2000; Zaheer & Bell, 2005) on the putative benefits of knowledge brokerage. Several studies (Baum et al., 2000; Zaheer & Bell, 2005) found that brokerage opportunities inherent in networks rich in structural holes boost innovation. Yet a few scholars have argued that firms' innovative performance is enhanced when firms build cumulatively on each other's innovation trajectory, thereby deepening their understanding of common knowledge inputs and mutually reinforcing each other's research directions (Ahuja, 2000; Rowley et al., 2000). Partly reconciling these apparently conflicting findings, the present article contributes to this debate by identifying boundary conditions to the innovation-enhancing effect of knowledge brokerage. Namely, we show that firms are better able to benefit from diverse knowledge inputs insofar as their sources generate knowledge at a relatively low pace; however, being embedded in a closed network facilitates the absorption and recombination of knowledge spillovers when a firm's sources are highly prolific. Future research should verify if this explanation holds true in the context of collaboration-based knowledge brokerage.

The key insight of the article—that firms can gain a sustainable innovation advantage by learning from other firms' public knowledge—is also relevant from the perspective of managerial practice. Our findings suggest that firms may deploy two alternative strategies to take stock of the public knowledge generated by other firms. One strategy, ideal for firms located in a munificent spillover network, is to invest in basic research and science and in the development of adequate tools to monitor codified knowledge. By so doing, the focal firm may better monitor and make sense of the innovation trajectories developed by its "source" firms, taking advantage of the fact that such trajectories are developing rapidly. This strategy resonates in a quote of an R&D manager interviewed by Yang and colleagues:

> We have, of course, a whole group in Library Science that does nothing but review the adequacy of our information search tools and similarly our scientists are always trying to push form . . . and others are inventing other ways to search for information. (Yang et al., 2010: 386)

In doing so, firms need to carefully leverage their degree of downstream integration to be able to monitor several rapidly evolving trajectories by competitors, very much as many semiconductor firms are adopting so called "asset-light" business models. An alternative strategy is to develop an ability to envision connections between the innovation trajectories of unrelated "source" firms, thereby creating and exploiting brokerage opportunities in the spillover network. Toward this end, firms may greatly benefit from internal brokerage structures that create an interface between a firm's internal knowledge and organizational boundaries, such as manufacturing and research and development (Brusoni et al., 2001; Lim, 2010). Clearly, each of these strategies entails both risks and costs. How to strike a balance between them stands out as an interesting question for both practitioners and researchers.

Notes

1. Let us formalize the illustration provided in Figure 1 as a network model. We define a firm's spillover network N_t at time t as an ego network, $N_t = (I_t, J_t, L_t, V_t, A_t)$, consisting of a focal node $I_t = \{y\}$; a finite set of contact nodes, $J_t = \{i,\ldots,k,q,\ldots,j\}$; a finite set of arcs (i.e., directed ties) between the focal node and its contact nodes, as well as among the contact nodes, $L_t = \{l_{ik,t}, \ldots, l_{qj,t}\}$; a function $V_t(.)$ mapping arcs on pertaining arc values, w; and a function $A_t(.)$ mapping nodes on node values for each contact node. We then model for each year in which a semiconductor firm is technologically active a weighted and directed ego network, allowing us to trace the firm's spillover network over time.

2. Following prior research, citations are assigned to each year based on the application year of the citing patent (Griliches, 1990; Katila & Ahuja, 2002; Yayavaram & Ahuja, 2008).

3. Formally, $v_{ijT} = \sum_{t=1976}^{T} \frac{1}{T-t+1} v_{ij}$, where weights decrease with time at a decreasing rate. To make sure that our results do not depend on this specific modeling choice, we inspect two "extreme" alternative specifications. First, we assume historical experience to depreciate instantaneously after 3 years (i.e., for a spillover network measured at t, ties reflect only the patent citations the "recipient" firm has made between t-3 and t-1). Second, we assume that past knowledge does not depreciate at all (i.e., for a spillover network measured at t, ties reflect the patent citations the "recipient" firm has made between 1976 and t-1). Results, available from the authors, are in line with those presented in the article.

4. Innovation performance encompasses two dimensions: number of innovations generated by a firm and impact of those innovations.

5. The number of forward citations received throughout the entire period by each firm is highly correlated with the forward citations obtained with the first 5 years (Spearman's rho correlation of the rank orders turned out to be as high as .982). This indicates that stopping citation counts after 5 years from application does not significantly reduce the quality of the measure.

6. Bruggeman (2008) showed that because of a mathematical loophole, Burt's model of constraint yields values slightly larger than 1 for a handful of network configurations. Because conceptually all such configurations correspond to maximally constrained networks, we recoded these cases to 1 (i.e., *structural holes* = 0).

7. When R&D, sales, or employment data are not available, we use imputation techniques to estimate the value based on existing data using Stata *ice* function. A total of 74 values are imputed.

8. It is still possible that firms are overwhelmed when their spillover network is "too" munificent. To examine this empirical question, we ran a set of additional analyses including the squared term of *spillover network munificence*. Unreported results show that the sign of the squared term is negative but the effect is not significant. Most importantly, the inflection point, based on a linear approximation of the model presented above, corresponds to 4 standard deviations about the mean. These results suggest that at least for the firms in our sample, it is highly unlikely that a spillover network becomes so munificent to have an innovation-dampening effect.

9. Our R&D alliance data are therefore similar to those reported in the CORE database (Schilling, 2009), in that both are drawn from filings reported in the Federal Register. However, unlike the CORE database, we have obtained and tracked membership in the various research joint ventures at the firm and arrangement level. However, each filing is made by a distinct organizational entity and does not conform to a common standard for naming its members. This leads to an inconsistency in naming of organizational members across Federal Register filings. Therefore, we limit our analysis to publicly traded firms in the United States, for which we have identified a unique standard identifier: the CUSIP number, used in the S&P Compustat database. We are grateful to James Hayton for letting us use the data.

10. To implement this in Stata we use the xtqmlp procedure originally developed by Tim Simcoe and available at (http://scripts.mit.edu/~pazoulay/docs/xtqmlp.ado).

11. We randomly sampled 10% of the patents granted to each firm in our study population in 2001. This resulted in a subsample of 540 patents, accounting for 2,285 citations to patents generated by the firms in our population. To check if this subsample was representative of the patents in our sample in the same year, we performed a t test of both the mean number of backward citations and the number of claims made per patent. Neither variable differed

across the two groups. We then coded each citation in the subsample to indicate whether the examiner added it or, conversely, the inventor reported it. On this basis, we built two separate networks. One network was constructed based on all citations; the other network was based on the citations made by the patent's inventor(s) only. We used a quadratic assignment procedure to assess the degree of similarity (or difference) between the two resulting networks (Simpson, 2001).

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