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Knowledge Maturity and the Scientific Value of Innovations: The Roles of Knowledge Distance and Adoption

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How does the scientific value of innovations vary with the maturity of the knowledge that underlies them? We reconcile conflicting views in the innovation literature by introducing a contingency perspective that underscores the role of knowledge distance along technological and geographical domains. We predict an inverted U-shaped effect of knowledge maturity on the scientific value of new innovations. We further suggest that incorporating geographically distant knowledge can enhance the value contribution of knowledge maturity, whereas incorporating technologically distant knowledge or waiting for the adoption of knowledge in the industry mitigates this value. Our analysis of 5,575 biotechnology patented innovations offers support for our conjectures. We thus advance research on knowledge management and innovation by underscoring the temporal aspect of innovation and its interplay with technological and geographical distances.

Keywords: *innovation; knowledge maturity; technological distance; geographical distance; knowledge adoption*

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> He took the paper and held it over the wastebasket and said, "what do you want me to do with it?" Then he dropped it in. That was 20 years ago, and ever since, Dr. Bissell and a few others have struggled for acceptance of what seemed a radical idea: Gene mutations are part of the process of cancer, but mutations alone are not enough. Cancer involves an interaction between rogue cells and surrounding tissue. The idea seemed messy and unduly complicated, and cancer genes seemed comparatively clear-cut. So it was often ignored or dismissed. Now, though, more and more researchers are plunging into those murky depths. Some researchers are taking a fresh look at ideas that were dismissed.
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> —*International Herald Tribune* (2009: 7)

Introduction

Management research on knowledge management and innovation has underscored the conditions that facilitate technological innovation and the factors that enable firms to appropriate value from it, such as firms' complementary assets (e.g., James, Leiblein, & Lu, 2013; Teece, 1986). Whereas early research considered the implications for firms' innovative output (e.g., Henderson & Cockburn, 1994), more recent work has paid attention to the value of innovations (Hess & Rothaermel, 2011; Phene, Fladmoe-Lindquist, & Marsh, 2006). A distinction can be made between the financial returns that a firm can derive from its commercialized innovations and the scientific value of these innovations, which relates to their impact on subsequent innovations. The scientific value of an innovation depends on industry conditions, such as the institutional environment (Mueller, Rosenbusch, & Bausch, 2013), the innovative efforts of competitors (Katila & Chen, 2008), and the geographic proximity of inventors (Audretsch & Feldman, 1996; Jaffe, Trajtenberg, & Henderson, 1993). This value is further driven by organizational characteristics, such as the firm's absorptive capacity (Cohen & Levinthal, 1990) and combinative capability (Kogut & Zander, 1992), as well as by the behavior of individual inventors (Felin & Hesterly, 2007; Zucker, Darby, & Brewer, 1998).

Besides environmental, organizational, and individual mechanisms, the value of an innovation for the scientific community is associated with the attributes of knowledge elements that underlie the innovation. The knowledge management literature has underscored the organizational processes and capabilities that support the integration, transfer, and combination of knowledge elements (Grant, 1996), but has paid less attention to the properties of knowledge that drive the value of particular innovations. One exception has been research on the tacit versus explicit nature of knowledge (Kogut & Zander, 1992). Here we focus on the maturity of knowledge elements that can shape the scientific value of innovations.

Studying the knowledge elements incorporated in particular innovations calls for shifting the unit of analysis from the firm to the single innovation. In an effort to shed light on the association between the scientific value of an innovation and its underlying knowledge elements, we study how the maturity of the knowledge embedded in that innovation drives its scientific value. Nevertheless, because we study innovations in the context of commercial firms, we also account for relevant organizational aspects that can affect the innovations' scientific value.

We advance management research that has underscored the importance of the temporal dimension in knowledge recombination (Katila, 2002; Liebowitz & Margolis, 1995; Nelson

& Winter, 1982). This research has debated the merits of relying on mature versus recent knowledge and has offered conflicting perspectives on the innovative implications of knowledge maturity. More recent research calls for a contingency approach to uncover the circumstances under which knowledge maturity enhances the scientific value of innovations (Nerkar, 2003). We contribute to this stream of research by demonstrating that the complex implications of knowledge maturity are contingent on distinct types of knowledge distance and on the extent to which this knowledge has been adopted in the industry. In light of these contingencies, inventors can improve their approaches to incorporating prior knowledge elements in their innovations, and enhance the scientific value of those innovations.

An innovation can be defined as “a new idea, which may be a recombination of old ideas, a scheme that challenges the present order, a formula, or a unique approach” (Van de Ven, 1986: 591). Accordingly, an innovation often embeds knowledge elements that have been developed in the past (Arthur, 2009; Kogut & Zander, 1992; Nelson & Winter, 1982). To capture knowledge maturity, we examine the time elapsed between the original discovery of knowledge and when it is incorporated in an innovation.

Scholars have debated the merits of relying on recent versus mature knowledge in developing innovations. Some have argued that building on recent knowledge enables a firm to adapt its innovations to changing requirements (Eisenhardt, 1989; Sørensen & Stuart, 2000) and introduce novel innovations. Thus, mature knowledge tends to become obsolete, since it is subject to core rigidities that limit adaptation (Leonard-Barton, 1992). Accordingly, this research suggests that the value of knowledge for the scientific community appreciates with its recency. Others have instead suggested that successful innovations often incorporate mature knowledge that has been already tested in use, which can eliminate some costly errors in the innovation process (Nerkar, 2003) and enhance the reliability of the firm’s new products (Katila, 2002). Mature knowledge can also support radical innovation, as demonstrated in Corning’s development of fiber optics, which is considered a new application for a mature technology (Cattani, 2006). Hence, an inventor can successfully employ mature knowledge in certain niches where that knowledge had not been used in the past (Abernathy & Clark, 1985; Adner & Snow, 2010). In addition, the benefits of incorporating new knowledge can be offset by technological uncertainty and limited application experience (Heeley & Jacobson, 2008). In sum, prior research has offered inconsistent arguments and evidence about the implications of knowledge maturity for the scientific value of innovations.

Few studies have attempted to reconcile these opposing views. Katila’s (2002) study of the robotics industry revealed that mature intraindustry knowledge undermines product development, whereas mature extraindustry knowledge promotes it. However, her study examined the effect of knowledge maturity on how many new products a firm produced, rather than on the scientific value of innovations. In addition, Nerkar (2003) reported that mature knowledge may be fruitful, especially if the inventor combines it with more recent knowledge, so that the value of an innovation increases in decreasing rates with knowledge maturity. But although his study contributes to the understanding of knowledge maturity, it did not consider contingencies that can shape its effects. Finally, Heeley and Jacobson (2008) revealed an S-shaped association between knowledge recency and a firm’s stock market performance. They concluded that intermediate levels of knowledge maturity can both improve and undermine performance. But because their study focused on firm-level performance rather than on the value of particular innovations, it disregarded the heterogeneity of knowledge maturity across the firm’s various innovations. Studying the implications of knowledge maturity for a firm's productivity and economic return limits understanding of the mechanisms that drive the innovation process and the conditions under which knowledge maturity enhances the scientific value of innovations. In sum, prior research has offered mixed views and evidence on the implications of knowledge maturity, thus leaving open the question of how knowledge maturity affects the scientific value of a particular innovation. Such an effect may be nonlinear and contingent on various characteristics of the underlying knowledge elements.

To better understand the implications of knowledge maturity, we shift attention from the firm to the innovation as the unit of analysis. We seek to reconcile the conflicting perspectives on knowledge maturity by studying its curvilinear effect on innovation value. We further examine the interplay of knowledge maturity with contingencies relating to technological and geographical distances from the inventor's knowledge base as well as to the extent to which this knowledge has been adopted in the industry. These domains of knowledge distance and the mechanism of knowledge adoption have been central to research on innovation (e.g., Phene et al., 2006; Rothaermel & Alexandre, 2009), yet their interplay with knowledge maturity has been thus far ignored.

We contribute to innovation research by revealing the curvilinear effect of knowledge maturity on innovation value and positing that it is contingent on different types of knowledge distance. We contend that inventors can enhance the value of an innovation to the extent that they incorporate moderately recent knowledge. As knowledge begins to mature, it becomes more reliable and applicable, thus enhancing the scientific value of innovations. Yet, beyond a certain threshold, overly mature knowledge may become obsolete or at least more difficult to retrieve, understand, and apply, characteristics that undermine the value of innovations. We further advance management research by elucidating the contingent value of knowledge maturity. Specifically, we argue that technological distance attenuates the benefits of knowledge maturity, since limited familiarity undermines the reliable use of mature knowledge while making it more difficult to retrieve and apply. In turn, geographical distance reinforces the benefits of mature knowledge by contributing to its novelty and delaying its obsolescence. Finally, we claim that the broader the adoption of mature knowledge in the firm's industry the more its value contribution is undermined.

Our analysis of 5,575 patents issued to 283 biotechnology firms between 1985 and 2002 grants support for the inverted U-shaped effect of knowledge maturity on innovation value as well as for the knowledge adoption contingency and the disparate effects of knowledge distance. By examining knowledge distance along temporal, technological, and geographical domains, and by studying the implications of knowledge adoption in the industry, we offer insights into the mechanisms underlying the scientific value of innovations. Hence, we contribute to the literature on knowledge management and innovation by underscoring the temporal dimension of knowledge search, revealing the contingent value of knowledge maturity, and shifting focus from the commercial to the scientific value of innovations.

Theory and Hypotheses

Knowledge Maturity and the Scientific Value of Innovations

Innovation often entails searching for and combining knowledge elements that have been developed in the past. Some innovations integrate knowledge elements that were developed at different periods (Fleming, 2001). For instance, mechatronics emerged in the late 1970s from the fusion of mature mechanical technologies with the embryonic electronics technologies (Freddi, 2009). The maturity of knowledge refers to the time elapsed between the original discovery of that knowledge and its incorporation in a new innovation. This time interval can affect the scientific value of the innovation. We focus on the value of an innovation with respect to its quality and its potential impact on subsequent innovation efforts of the scientific community (Phene et al., 2006; Sorenson, Rivkin, & Fleming, 2006) rather than on its commercial value for the firm. This allows us to leave out considerations of value appropriation and commercialization. We conjecture an inverted U-shaped association between knowledge maturity and the scientific value of an innovation, so that moderately mature knowledge is expected to be the most valuable.

Although the most recent knowledge tends to be novel, embedding it in innovations may limit their scientific value because of inexperience in use and limited technological applicability. As knowledge begins to mature, it enhances the scientific value of innovations that embed it by increasing their reliability and applicability.

First, an innovation relying on increasingly mature knowledge is more reliable, since that knowledge is likely to have already been put into practice. Even if an inventor is not familiar with that knowledge, greater information on its nature and usage is available in the industry, which makes it easier for the inventor to learn it. By incorporating sufficiently mature knowledge, the inventor can generate temporally consistent patterns of innovation that enhance subsequent innovation ability (Turner, Mitchell, & Bettis, 2013). Since knowledge maturity initially facilitates the knowledge's codification and experience in use, the inventor can better understand it. Relying on relatively mature knowledge enables the inventor to more effectively assess the merits of knowledge and thus produce useful and more reliable innovations that rely only on knowledge that has been tested and proved useful in the past. Furthermore, sufficiently mature knowledge can be subjected to validation over time, so incorporating it in an innovation enables the inventor to reduce the likelihood of errors and improper application. For example, despite the numerous benefits arising from adopting the diesel engine in the rail industry, its use presented a number of technical problems in the first few years after its introduction; engines incorporating this technology experienced low power output density, reduced maximum rotating speed, and high combustion noise. The reliability of an innovation is likely to increase with the maturity of knowledge in decreasing rates (Nerkar, 2003), since after inventors gain sufficient experience with particular knowledge, the innovation's reliability can be only marginally improved.

Second, an innovation incorporating the most recent knowledge is likely to suffer from limited technological applicability, especially when the industry is nascent and users of the innovation need to be educated about the technology before they can apply it. As knowledge begins to mature, innovations that embed it are likely to have been applied in various ways. For example, the scientific value of the touch-screen technology used in the iPhone smartphone increases with the number of touch-screen applications that software firms develop over time. Therefore, as inventors retrieve increasingly mature knowledge, the more likely their innovations are to generate valuable applications (Nerkar, 2003). This is also typical when industry conditions have changed since the original knowledge was developed—for instance, if complementary assets or enabling technologies gradually become available and support the innovation. In the example of common rail technology, 60% of the performance of the diesel engine depends on the injection system, which reached maturity only in 1994 following the shift from mechanical to electronic components. This complementary technology helped maintain a consistent injection pressure that reduces exhaust emissions, makes fuel cleaner, lessens engine combustion noise, and enables higher-power output density. Until that time, electronics were considered unsafe and unreliable. Furthermore, as knowledge begins to mature, new applications may emerge that can enable firms to leverage an innovation in ways unknown before. Accordingly, a successful innovation may result from the redeployment of mature knowledge in different domains (Adner & Levinthal, 2002; Cattani, 2005). Hence, as knowledge begins to mature, it is likely to initially enhance the value of an innovation. Yet, eventually, as it continues to mature, its marginal contribution diminishes, because its reliability has been already established and most of its technological applications have been already explored, thus constraining the discovery of new applications for the innovation.

Beyond a certain threshold, relying on increasingly mature knowledge can be detrimental to the value of an innovation because of its possible obsolescence and impediments associated with its retrieval and application. Specifically, the novelty of knowledge is likely to diminish over time as new discoveries advance the knowledge frontier, so that overly mature knowledge can become obsolete (Tushman & Anderson, 1986). Thus, an innovation embedding overly mature knowledge may fail to meet current user requirements if it incorporates knowledge that is no longer relevant or is subject to historical problems that transpire in new ways (Leonard-Barton, 1992). Consequently, as knowledge becomes overly mature, its obsolescence can limit an innovation's scientific value.

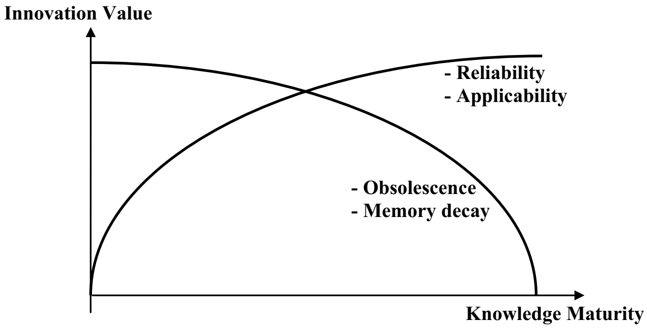
Besides its obsolescence, overly mature knowledge may be difficult to retrieve and apply. As knowledge becomes overly mature, forgotten practices, lost records, and turnover of R&D personnel (Argote, 1999) may facilitate memory decay, which in turn reduces the inventor's ability to correctly recall, retrieve, and apply overly mature knowledge in an innovation. Consequently, the innovation may necessitate increasing effort to retrieve overly mature knowledge. Moreover, inventors are likely to lack the training and expertise needed to apply overly mature knowledge, since the personnel involved in the innovation process may be better trained with recent, more commonly used technologies than with outdated ones. Thus, memory decay may lead the inventor to misapply overly mature knowledge or to experience impediments with its application (Sørensen & Stuart, 2000). Incorporating overly mature knowledge can therefore result in less valuable innovation.

Overall, the reliability and applicability of knowledge are likely to enhance the value of an innovation at decreasing rates as the knowledge begins to mature. In turn, knowledge obsolescence and impediments associated with memory decay are likely to diminish the value of the innovation at increasing rates as knowledge further matures (Figure 1). Moderately mature knowledge is thus likely to contribute the most to the value of the innovation. The scientific value of the innovation is likely to initially increase, but beyond a certain threshold, we expect it to decline as a result of the maturation of knowledge incorporated in that innovation.

> *Hypothesis 1:* Knowledge maturity will exhibit an inverted U-shaped effect on the scientific value of the resulting innovation, so that this value first increases and then decreases as its underlying knowledge base matures.

The distance between the inventor's knowledge base and the knowledge incorporated in the new innovation can shape the effect of knowledge maturity on the scientific value of that

Figure 1
Mechanisms Driving the Association Between Knowledge Maturity and Innovation Value



innovation. According to prior research (e.g., Phene et al., 2006), an inventor can seek proximate versus distant knowledge in the technological and geographical domains. Together with knowledge maturity, these domains shape the outcome of the innovation process by influencing both the novelty of the acquired knowledge and its absorption. Previous studies have underscored some of the main effects of knowledge distance on innovation value along these dimensions (Rosenkopf & Nerkar, 2001; Rothaermel & Alexandre, 2009; Stuart & Podolny, 1996), but we provide a more nuanced account of their implications by considering their interplay with knowledge maturity. We focus on the technological and geographical distances of knowledge (Phene et al., 2006) to study how they shape the value of an innovation that embeds mature knowledge. We consider knowledge to be technologically proximate if it originates from within the inventor's industry, and distant if it originates from outside that industry (Katila, 2002). Geographical distance is defined as the distance between the home countries of the knowledge developers and the inventors using that knowledge.

Knowledge Distance and the Scientific Value of Innovations

An inventor that embeds technologically distant knowledge in an innovation is likely to limit the reliability of mature knowledge and facilitate its obsolescence, while exacerbating retrieval and application impediments associated with its use, which in turn reduce the maturity level at which innovation value is maximized. First, when the inventor incorporates mature knowledge beyond its familiar technological domain, the necessary expertise for assessing such knowledge may be lacking (Cohen & Levinthal, 1990), thus making mature knowledge even less accessible. Distance from the technological domain reinforces the inventor's inability to correctly assess the merits of mature knowledge, and that inability restricts the reliable use of the mature knowledge in the innovation. The reliability of knowledge suffers when the inventor's technological expertise is exceeded, because of limited familiarity and experience with mature knowledge. Thus, even though mature knowledge is typically reliable, the extension of technological distance makes it difficult to ensure the reliable use of that knowledge, thus further reducing the scientific value of the innovation that relies on it.

Second, embedding knowledge that rests beyond the current technological domain exacerbates the challenges of retrieving, interpreting, and applying mature knowledge in the innovation, given that such knowledge becomes distant both temporally and technologically. As a result, it becomes more difficult, costly, and time-consuming for the inventor to recognize, evaluate, and retrieve mature knowledge that is also technologically distant (Cohen & Levinthal, 1990; Wang & Li, 2008). In addition, the complementary expertise needed to leverage such mature knowledge is likely to be lacking, which hinders its successful application in the innovation. Acquiring unrelated knowledge elements may cause information overload, confusion, and diseconomies of scope (Ahuja & Lampert, 2001), since the innovation entails both noncurrent and heterogeneous knowledge. This lack of coherence may prevent the inventor from leveraging a restricted bundle of close-knit skills, thus undermining the use of mature knowledge in the innovation (Nesta & Saviotti, 2005; Perez & Soete, 1988). Developing such competencies entails restricting knowledge exploration so that it remains in proximity to the current knowledge base. Relying on technologically distant knowledge for which the inventor's available knowledge base is insufficient may thus further limit experience and familiarity with mature knowledge. Limited expertise and possible misapplication of mature knowledge can in turn impair the scientific value of the innovation.

Finally, technological distance exacerbates the risk of obsolescence inherent in the use of mature knowledge in the innovation. Lack of familiarity with knowledge that is distant from the current technological domain makes it more difficult to identify possible alternative combinations and uses for mature knowledge in the innovation (Kogut & Zander, 1992). Consequently, it may be impossible to extend the productive lifespan of an innovation that relies on such knowledge. In sum, the technological distance of knowledge is expected to limit the scientific value of the innovation incorporating mature knowledge, so that maximum innovation value is reached for more recent knowledge elements.

> *Hypothesis 2:* Reliance on more technologically distant knowledge will decrease the linear effect of knowledge maturity on the scientific value of the innovation resulting from that knowledge.

Technological distance can undermine the relevance and usefulness of mature knowledge because of limits to absorptive capacity and the need for technological compatibility or even complementarity with the current knowledge base. In contrast, geographical distance does not preclude successful recombination of knowledge and is less likely to impose impediments on knowledge transfer and internalization. In fact, whereas technological distance can limit the contribution of knowledge maturity to the value of an innovation, we expect geographical distance to improve that contribution, thus extending the maturity of knowledge at which innovation value is maximized. By incorporating geographically distant knowledge, the inventor can enhance the novelty of an innovation that relies on mature knowledge and reduce the likelihood of its obsolescence.

Because of the localized nature of knowledge and the ensuing geographically bounded nature of knowledge externalities that are reinforced by cross-national institutional and cultural differences (Audretsch & Feldman, 1996; Jaffe et al., 1993; Mueller et al., 2013; Phene & Tallman, 2002), geographical distance can limit the accessibility of knowledge (Freel, 2003; Oerlemans & Meeus, 2005). Hence, knowledge that is common in its country of origin may be perceived as novel when applied in an innovation that is introduced in a distant country (Cantwell, 1989). Increasing geographical distance of embedded knowledge can thus enable the inventor to revitalize mature knowledge and enhance the scientific value of the innovation.

The fact that mature knowledge is newly applied in a certain geographical region contributes to its novelty in that region under the assumption that knowledge originating from a different country is likely to be distinctive. Indeed, research on national innovation systems has demonstrated that different nations develop distinctive technological competencies by leveraging unique knowledge bases. Consequently, the geographical distance of knowledge is often associated with its distinctiveness (Frost, 2001). Cross-national differences in knowledge characteristics have been ascribed to distinctive national cultures (Hofstede, 1980), different regulatory systems, country-specific practices and rules, unique national resource endowments, and distinctive industry structures that direct innovation in unique paths (Porter, 1990). Such cross-national differences can influence both the type of knowledge created and the process by which it is created. For instance, cross-national differences may explain a tendency to expand abroad in search of knowledge that is not available in the home country (Florida, 1997; Serapio & Dalton, 1999). Therefore, by seeking geographically distant knowledge, the inventor can enhance the perceived uniqueness of mature knowledge that is incorporated in the innovation.

Moreover, incorporating mature knowledge in an innovation that is developed in distant locations reduces the likelihood that it will become obsolete in its country of application even if it has already been overexploited in its country of origin. Therefore, seeking geographically distant knowledge reduces the hazard of mature knowledge becoming obsolete (Leonard-Barton, 1992). Overall, geographical distance is expected to enhance the value of an innovation incorporating mature knowledge, so that maximum innovation value is reached for more mature knowledge elements.

Hypothesis 3: Reliance on more geographically distant knowledge will increase the linear effect of knowledge maturity on the scientific value of the innovation resulting from that knowledge.

Industry Adoption of Knowledge and the Scientific Value of Innovations

The scientific value of an innovation relying on mature knowledge derives in part from the relative novelty of such knowledge, which in turn depends on the extent to which it has been adopted in the industry. Scholars have considered the prior use of knowledge (e.g., Katila & Ahuja, 2002), but have paid less attention to the extent to which such knowledge has been used in various innovations. We contend that the use of mature knowledge in multiple innovations can limit the prospects of new applications while facilitating knowledge obsolescence and undermining the novelty of an innovation that relies on that knowledge.

Whereas knowledge maturity increases the applicability of innovations that leverage that knowledge, the adoption of mature knowledge in the industry counters this process by limiting the number of remaining applications. An innovation that incorporates well-received industry knowledge can support related innovations (Marinova, 2004) and contribute to the emergence of industry standards (Gawer & Cusumano, 2002). However, the adoption of knowledge in the industry may limit the value of any innovation whose perceived value is already reduced as a result of its reliance on mature knowledge. The availability of possible applications for an innovation is eventually exhausted not only because of the prolonged time that has passed since the corresponding knowledge was first introduced, but also because of the popular use of that knowledge by multiple firms, which limits the potential for discovering novel applications that leverage that knowledge. Thus, the adoption of mature knowledge in the industry reduces the scientific value of the corresponding innovation.

As knowledge is adopted and becomes widely available in the industry, its distinctiveness is limited (Ahuja & Katila, 2004; Rothaermel & Boeker, 2008), and its potential contribution to the value of the innovation incorporating it is reduced (James et al., 2013). The value of a particular innovation may decline over time as the inventor faces greater challenges in generating novel combinations of adopted knowledge elements (Kogut & Zander, 1992; Messeni Petruzzelli & Savino, 2012). Assuming a limited number of possible knowledge recombinations, the adoption of knowledge in the industry facilitates exploitation. Hence, the wide adoption of mature knowledge diminishes the value of an innovation relying on that knowledge more rapidly as it becomes outdated. Moreover, because the knowledge dissemination is time-consuming, as mature knowledge is adopted by many firms in the industry it becomes susceptible to the hazard of leaking to competing innovations. To the extent that it is commonly used in a large number of innovations, over time, the adopted knowledge becomes more transparent and codified (Zander & Kogut, 1995), thus progressing on the learning cycle associated with established knowledge (Zollo & Winter, 2002). Specifically, the increased codification of mature knowledge that becomes widely adopted in the industry facilitates imitation, thus limiting the uniqueness of any innovation that incorporates mature knowledge. As the number of innovations using mature knowledge increases, the scientific value of an innovation that incorporates such knowledge diminishes because of potential substitution by related innovations. In sum, the adoption of mature knowledge in the industry limits its uniqueness while facilitating its obsolescence, so that maximum innovation value is reached for more recent knowledge elements.

Hypothesis 4: Reliance on widely adopted knowledge will decrease the linear effect of knowledge maturity on the scientific value of the innovation resulting from that knowledge.

Research Method

Research Setting and Data

The U.S. biotechnology industry serves as the setting for testing our hypotheses. This setting is suitable for several reasons. First, biotechnology has revolutionized the process by which drugs are discovered and developed, so that it leverages a combination of mature and recent knowledge and expertise (Rothaermel & Boeker, 2008). Second, this industry relies on multiple technologies, involving molecular biology, immunology, genetics, combinatorial chemistry, and bioinformatics (Sørensen & Stuart, 2000), underscoring the need to search for knowledge across technological domains (Phene et al., 2006). Third, besides its technological diversity, the biotechnology industry exhibits geographical diversity, as shown by differences across national systems of biotechnology innovation (Bartholomew, 1997). Fourth, because patents are an effective means for protecting intellectual property in the biotechnology industry (Albert, Avery, Narin, & McAllister, 1991; Hoang & Rothaermel, 2010; Phene et al., 2006; Rothaermel & Boeker, 2008), prior research supports our reliance on patent-based measures for studying the scientific value of innovations in this setting (Somaya, 2012). Finally, because the biotechnology industry originated in the United States and since U.S. firms typically file for domestic patents (Phene & Almeida, 2008), our focus on U.S. firms ensures the representativeness of our sample.

Our sample corresponds to the innovations of 283 U.S. firms, both public and private, listed in the BioScan database, that filed for at least one biotechnology patent with the U.S. Patent and Trademark Office (USPTO) between 1985 and 2002.[1] The cited patents cover the full history of modern biotechnology since Cohen and Boyer's invention involving recombinant DNA in 1973. We focused on patents issued in the United States because it is almost compulsory to first patent there, in the largest market for biotechnology. The final sample included 5,575 patents (focal patents) filed by the 283 firms. For this set of focal patents, we identified 51,151 cited patents (previously issued patents cited by the focal patents) that served for assessing the knowledge incorporated in innovations. We also collected data on the 57,503 subsequent patents that cite the focal patents, to measure the value of the resulting innovation. We gathered firm-level data from multiple sources, including SEC filings for publicly traded firms, press releases, and corporate websites. Missing values (0.2% of the observations) were treated with listwise deletion (Allison, 2000).

Variables

Dependent variable. The scientific value of an innovation refers to its quality (Phene et al., 2006), impact (Nerkar, 2003), and potential contribution to further technology development from the standpoint of the scientific community (e.g., Albert et al., 1991; Sorenson et al., 2006; Trajtenberg, 1990). Thus, the value of an innovation (*InnovationValue*) was measured by the number of forward citations received by a focal patent until 2009 (e.g., Cattani, 2005; Singh, 2008). Forward citations to a patent serve as an appropriate proxy for the value of an innovation as captured by industry awards, as perceived by technology experts, and with respect to its social value (Trajtenberg, 1990). Patent citations are assumed to furnish essential technological and economic information. First, patented innovations are for the most part the result of costly R&D conducted by profit-seeking firms. Thus, when they invest in an innovation disclosed in a prior patent, the resulting (citing) patents signify that the cited innovation is valuable. Second, citations often occur over an extended period, which allows for dissipation of the uncertainty regarding the cited patent's technological viability and commercial use. Therefore, citations that are observed years after the cited patent was granted indicate the impact of the patented innovation (Nerkar, 2003).[2] To capture the value of an innovation, we incorporated information on all citing patents, including non-biotechnology patent classes. Since patents from different years have different "windows of opportunity" to be cited in our data set, directly comparing patent citations across patents from different years would be inappropriate. To overcome this, we include year fixed effects and patent age in our models, so that systematic intertemporal differences are accounted for (Jaffe & Trajtenberg, 2002).

Independent variable. Following prior research (Katila, 2002; Rosenkopf & Nerkar, 2001; Sørensen & Stuart, 2000), for each focal patent we measured the average maturity of patents cited by that patent. The maturity of knowledge (*KnowMaturity*) was measured as the average number of years elapsed since the filing date of patents cited in the focal patent document. The maximum value of knowledge maturity observed for a single cited patent was 34 years. Backward citations to patents describe technical information relating to the knowledge upon which the focal patent is based (Walker, 1995). Prior research has validated the use of patent citations for capturing knowledge search activities (e.g., Albert et al., 1991; Trajtenberg, 1990). Hence, patent citations can serve for measuring the maturity of knowledge elements incorporated by the focal patent.

Moderating variables. We operationalized moderating variables based on information on backward citations listed in each patent document. Information on patent classes served for determining technological distance. The assignee's country of origin served for calculating geographical distance, and the number of cited patents served for calculating knowledge adoption. Specifically, for each focal patent, the technological distance of knowledge (*TechDist*) was measured as the ratio of the number of backward citations assigned to patent classes that are not associated with the biotechnology industry to the total number of backward citations (Phene et al., 2006). For each focal patent, the geographical distance (*GeoDist*) of knowledge was measured as the distance in thousands of miles from the home country of the focal patent's assignee to the home countries of the inventors associated with the cited patents. To calculate this measure, we considered the firm's subsidiary in which the innovation took place rather than its headquarters location and averaged the distance across all inventors listed for a patent. The resultant value was further averaged across all patents cited by the focal patent. This approach is preferable to relying only on the location of the first inventor (e.g., Phene et al., 2006; Singh, 2005) since, unlike in scientific publications, where the first author typically takes the lead in conducting the research, in patent applications the first inventor listed often plays a formal role as principal investigator or owner of the research center or laboratory that conducts the research. Finally, for each focal patent, we followed Huang and Murray (2009) and Ziedonis (2004) in measuring the adoption of knowledge in the industry *(KnowAdoption)* as $\frac{1}{n}\sum_{i=1}^{n}\frac{NASSCITED_i}{NCITED_i}$, where $NASSCITED_i$ indicates the number of different firms that have previously cited patent i, which is cited by the focal patent, while $NCITED_i$ indicates the count of all patents that have previously cited that patent. This measure takes into account the relative concentration of the citing patents, thus capturing the number of distinctive innovations relying on a particular knowledge element. Knowledge adoption and the technological and geographical distances of knowledge search served as moderators of the relationship between the scientific value of an innovation and knowledge maturity.

Control variables. The main effects of our moderators served as control variables. In addition, we incorporated several control variables considered by prior research that may affect the value of innovations. For each focal patent, we controlled for the age of patent (*PatentAge*) by counting the number of years elapsed since the filing date of a focal patent until the year 2009, thus accounting for right censoring, that is, the risk that an older patent may receive a greater number of forward citations because it can accumulate citations for a longer time. We also took into account the diversity of knowledge maturity (*KnowMaturityDiversity*), measured by the standard deviation in the number of years elapsed since the filing date of patents cited by the focal patent (Katila, 2002). As this time spread increases, knowledge recombination may become more challenging yet fruitful (Nerkar, 2003). Next, we controlled for interorganizational collaboration (*InterOrgCollab*) in the innovation process by counting the number of applicants to which the patent was assigned. In addition, we considered the effects exerted by the different dimensions of search. Following Capaldo and Messeni Petruzzelli (2011), we measured search span (*SearchSpan*) as the number of different three-digit patent classes assigned to a patent by the USPTO. Search depth and search scope were evaluated based on the measures proposed by Katila and Ahuja (2002). Specifically, search depth (*SearchDepth*) was measured for each focal patent as the average number of times a patent was repeatedly cited during the past 5 years. In turn, search scope (*SearchScope*) was measured for each patent as the share of citations that could not be found in the list of patents cited in the prior 5 years. In addition, we controlled for the number of claims per patent (*Claims*) (Lanjouw & Schankerman, 2004), references to scientific knowledge (*SciKnowledge*) measured by the number of nonpatent references each focal patent cited (Narin, Hamilton, & Olivastro, 1997), and number of forward self-citations (*SelfCitations*).

Besides controls at the innovation level, we controlled for relevant organizational attributes by considering the firm's patent stock (*PatentStock*) as a proxy for its expertise, capability, or propensity to innovate (e.g., Hall, Jaffe, & Trajtenberg, 2005). Firms with greater patent stocks are more likely to successfully finalize the patenting process, so this variable controls for possible survivor bias (see also Nooteboom, Vanhaverbeke, Duysters, Gilsing, & van den Oord, 2007). The firm's patent stock was measured as the natural logarithm of the number of patents that the firm filed with the USPTO during the 5 years preceding the filing date of a focal patent. We also controlled for the firm's innovation performance (Ahuja & Lampert, 2001; Nerkar, 2003) by counting the number of thousands of forward citations received by the firm prior to the filing of the focal patent (*InnovationPerformance*). We further accounted for such performance by measuring the firm's proportion of patent applications that were not approved by the USPTO (*InnovationFailure*). High values of this measure indicate inability to innovate successfully. In addition, we controlled for the firm's size, which may affect its innovation ability, by computing the natural logarithm of the average number of firm employees during the 5 years prior to the filing date of each sampled patent (*FirmSize*). This proxy is suitable for measuring firm size in the biotechnology industry, because many of these firms do not yet generate revenue, while their assets are mainly intangible (e.g., Rothaermel & Boeker, 2008). Moreover, the size of the team involved in knowledge development may affect the value of the resulting innovation as a result of economies of specialization. In fact, large teams may have access to a wide pool of knowledge (Singh, 2008). Therefore, we controlled for team size (*TeamSize*), measured as the number of inventors associated with each patent. We also controlled for the firm's public status (*PublicFirm*) using a dummy variable that receives a value of one if the firm is publicly traded at the filing date of its focal patents, and zero otherwise. Also, we controlled for business diversification (*BusDiversification*), which may affect innovation (Hitt, Hoskisson, & Kim, 1997), by counting the number of different SIC codes assigned to the firm.

Next, we controlled for the firm's age (*FirmAge*) by computing the difference between a firm's year of incorporation and the filing year of a focal patent. The firm's age reflects experience with organizational routines that may enhance the efficiency of innovation. However, in rapidly changing environments, such experience may undermine the firm's ability to adapt using innovative capabilities (Sørensen & Stuart, 2000). Furthermore, the firm's strategies for knowledge search may also vary with its particular biotechnology domain, so we included dummies to control for assigned patent classes 424 (drug, bio-affecting, and body treating compositions), 435 (chemistry: molecular biology and microbiology), 514 (drug, bio-affecting and body treating compositions others), 530 (chemistry: natural resins or derivatives; peptides or proteins; lignins or reaction products thereof), and 800 (multicellular living organisms and unmodified parts thereof and related processes), with remaining classes that together account for less than 10% of the total number of patents serving as the omitted category. We also controlled for government support (*GovInterest*), using a dummy variable that receives a value of one if the patent has been funded by the U.S. government, and zero otherwise. This variable indicates whether the innovation is socially relevant. In addition, we controlled for the technological evolution of the industry (Audretsch, 1995; Klepper, 1997), using the natural logarithm of the accumulated number of USPTO patents issued in biotechnology patent classes at the time of the focal patent's filing (*IndustryEvolution*). Thus, our findings cannot be simply ascribed to the trajectory of evolution of the biotechnology industry. Finally, we incorporated year dummies (*Year*) to capture temporal trends. Overall, our extensive battery of controls can effectively limit unobserved heterogeneity at the innovation and firm levels.

Analysis

The focal patent served as the unit of analysis. Since the dependent variable is a nonnegative integer count variable, the negative binomial model is appropriate for estimating it. The Poisson model assumes equity between the mean and the variance. But patent data typically feature overdispersion, as evident by the coefficient of variation (standard deviation/mean) that equals 2.11 in our case. The negative binomial model that corrects for such overdispersion is more suitable, since it allows for the variance to differ from the mean (Gourieroux, Monfort, & Trognon, 1984; Hausman, Hall, & Griliches, 1984). We used hierarchical models, with Model 1 serving as the baseline model that includes only the control variables, Models 2 to 5 serving as partial models that introduce the independent variable and each of the moderating variables, and Model 6 serving as the full model that incorporates all variables. We relied on the partial models for testing our hypotheses, since tests for potential multicollinearity indicated that the maximum variance inflation factor (VIF) index in the full model exceeds the critical value of 10 (Kleinbaum, Lawrence, Muller, & Nizam, 1998). The high VIF values can be ascribed to the multiple inclusions of the main effects in the interaction terms. No symptoms of multicollinearity were observed, as coefficients and levels of significance remain consistent across models.

Results

Table 1 reports descriptive statistics and pairwise correlations, showing relatively low correlations except for those measured across *PatentStock* and *FirmSize*, and *PatentAge* and *IndustryEvolution*. To avoid concerns about multicollinearity, we excluded the controls for firm size and industry evolution from our reported models. The results of the negative binomial models are reported in Table 2, showing a good statistical fit to the data. Consistent with prior research, Model 1 reveals that while controlling for self-citations to the firm's patents ($ß = 0.10$, $p < .001$), innovation value improves with the firm's public status ($ß = 0.10$, $p <$

Table 1
Bivariate Correlation Matrix (N = 5,575)

Variable	*Mean*	*SD*	Min	Max	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1. InnovationValue	11.19	23.60	0.00	518.00														
2. KnowMaturity	5.96	4.25	0.00	34.00	.00													
3. TechDist	0.08	0.19	0.00	1.00	.08***	.22***												
4. GeoDist	2.69	5.54	0.00	87.28	−.00	.23***	.12***											
5. KnowAdoption	6.19	9.62	0.00	299.00	.06***	.07***	.07***	−.01										
6. KnowMaturityDiversity	2.81	2.28	0.00	17.00	.03	.50***	.26***	.19***	.13***									
7. PatentStock	3.71	1.82	0.00	6.19	−.10***	.00	−.18***	−.29***	.02	−.12***								
8. FirmSize	6.78	2.39	0.00	11.98	.02	−.02	−.14***	−.21***	.04**	−.12***	.64***							
9. TeamSize	3.02	2.02	1.00	27.00	.01	.03*	.04**	.06***	.02	.06***	−.01	−.02†						
10. PublicFirm	0.61	0.49	0.00	1.00	.04**	−.02*	.05***	.09***	.03*	.02	−.17***	−.10***	.11***					
11. BusDiversification	2.66	1.22	0.00	15.00	−.02	.01	−.03**	−.06***	.00	−.05***	.21***	.27***	−.02	.23***				
12. FirmAge	19.63	21.41	0.00	137.00	−.07***	−.03*	−.14***	−.16***	−.12***	−.08***	.41***	.36***	−.15***	−.48***	.15***			
13. InterOrgCollab	1.10	0.32	1.00	3.00	−.00	−.03*	−.00	−.03*	−.01	−.02	−.01	−.01	.21***	.06***	−.01	−.06***		
14. Claims	20.19	21.86	0.00	683.00	.04**	.00	.03*	.04***	.01	.04**	.01	−.08***	.12***	.08***	.06***	−.08***	.01	
15. SciKnowledge	31.55	48.81	0.00	438.00	.05***	.18***	.03*	.00	.19***	.13***	.07***	.02†	.08***	.11***	.08***	−.09***	.04**	.10***
16. GovInterest	0.03	0.18	0.00	1.00	.06***	−.01	.05***	−.00	.05***	−.02	−.07***	−.09***	.09***	.04***	−.03**	−.08***	.13***	.01
17. PatentAge	11.56	3.86	7.00	24.00	.26***	−.01***	−.08***	−.08***	−.02	−.20***	−.12***	.21***	−.12***	−.06***	−.00	−.08***	−.01	−.14***
18. SelfCitations	0.87	1.91	0.00	23.00	.06***	.13***	.08***	.01	.06***	.15***	.05***	−.01	.06***	.09***	−.01	−.02	.05***	.04**
19. SearchSpan	2.26	0.99	1.00	8.00	.07***	.01	.14***	−.03*	.05***	.05***	.08***	.04**	.07***	−.00	−.01	.02	.03**	.06***
20. SearchDepth	2.64	9.47	0.00	106.00	−.03***	.18***	−.03*	−.08***	.04***	−.08***	.20***	.10***	−.11***	−.15***	.03*	.34***	−.05***	.00
21. SearchScope	0.49	0.43	0.00	1.00	.02	.16***	.13***	.20***	−.00	−.03†	−.16***	−.11***	.06***	−.02	−.04***	−.13***	.03*	.05***
22. 435PatentClass	0.39	0.49	0.00	1.00	−.01	−.07***	−.06***	−.07***	.04**	−.09***	−.04**	−.01	−.00	−.01	.05***	−.20***	−.02†	.02*
23. 514PatentClass	0.18	0.38	0.00	1.00	−.01	.08***	.09***	.14***	.01	.11***	−.12***	−.11***	.07***	.21***	−.07***	−.17***	.03*	.02
24. 530PatentClass	0.08	0.28	0.00	1.00	−.03	−.04**	−.10***	−.05***	.01	−.07**	.10***	.06***	.04*	.12***	.05***	−.08***	.00	−.04**
25. 424PatentClass	0.14	0.34	0.00	1.00	.02	.09***	−.04*	.06***	.03*	.06***	−.06***	−.04**	−.01	.08***	−.03*	−.11***	.04**	−.02
26. 800PatentClass	0.11	0.31	0.00	1.00	−.03*	−.10***	−.12***	−.14***	−.13***	−.12***	.27***	.22***	−.17***	−.41***	.08***	.79***	−.07***	−.02†
27. OtherPatentClass	0.23	0.42	0.00	1.00	.11***	−.44***	.21***	.10***	.06***	.12***	−.22***	−.18***	.04*	.10***	−.06***	−.18***	.02†	.01
28. InnovationPerformance	0.54	1.00	0.00	7.46	−.07***	−.02	−.11***	−.13***	.04**	−.02	.45***	.42***	.08***	.09***	.22***	.15***	.01	−.07***
29. InnovationFailure	0.03	0.15	0.00	0.99	−.05***	.04*	.05**	.01	.02	.02	.06***	−.00	.10***	.07***	.02†	−.05	.04*	.04**
30. IndustryEvolution	11.73	0.37	10.45	12.36	−.26***	.10***	.09***	.08***	.02	.19***	.12***	−.21***	.12***	.05***	.01	.09***	.01	.14***

(continued)

Table 1 (continued)

Variable	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29
16. GovInterest	.01														
17. PatentAge	−.05***	−.01													
18. SelfCitations	.25***	−.03*	−.12***												
19. SearchSpan	.06***	.01	−.01	.01											
20. SearchDepth	.03**	−.01	−.15***	.10***	.01										
21. SearchScope	−.12***	−.00	.12***	−.11***	−.00	−.24***									
22. 435PatentClass	.00	.03*	.09***	−.06***	−.09***	−.10***	−.01								
23. 514PatentClass	.00	.01	−.11***	−.01	−.04**	−.06***	.07***	−.28***							
24. 530PatentClass	.01	.01	.02	−.02†	−.08***	−.05***	−.02	−.17***	−.10***						
25. 424PatentClass	.02	.00	.03*	.03	.07***	−.07***	.05**	−.22***	−.12***	−.12***					
26. 800PatentClass	−.09***	−.06***	−.06***	.05**	.04**	.40***	−.14***	−.28***	−.16***	−.11***	−.14***				
27. OtherPatentClass	.04*	.05**	−.01	.13***	.09***	−.05***	.06***	−.44***	−.25***	−.05***	−.17***	−.17***			
28. InnovationPerformance	.12***	−.04*	−.19***	.14***	.04*	.05**	−.13***	−.02*	.00	.10***	.02†	−.02	−.05***		
29. InnovationFailure	−.01	.03	−.27***	.02	.03	−.00	−.06***	−.02†	.04*	.01	.01	−.04*	.00	.21***	
30. IndustryEvolution	.05***	.01	−.99***	.12***	.01	.15***	−.12***	−.09***	.10***	−.02	−.03†	.06***	.01	.19***	.26***

†$p < .10$.
*$p < .05$.
**$p < .01$.
***$p < .001$.

Table 2
Negative Binomial Regression Models

Dependent Variable: InnovationValue	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
KnowMaturity		0.03*** (0.01)	0.03*** (0.01)	0.04*** (0.01)	0.03*** (0.01)	0.04*** (0.01)
KnowMaturity^2		−0.003*** (0.00)	−0.003*** (0.00)	−0.004*** (0.00)	−0.002*** (0.00)	−0.004*** (0.00)
KnowMaturity × TechDist			−0.05** (0.02)			−0.06** (0.02)
KnowMaturity × GeoDist				0.003*** (0.00)		0.003*** (0.00)
KnowMaturity × KnowAdoption					−0.001** (0.00)	−0.0004** (0.00)
TechDist	1.01*** (0.10)	1.01*** (0.10)	1.43*** (0.23)	1.01*** (0.10)	0.99*** (0.10)	1.43*** (0.23)
GeoDist	−0.02** (0.01)	−0.01** (0.00)	−0.01** (0.00)	−0.02** (0.01)	−0.01** (0.00)	−0.02** (0.01)
KnowAdoption	0.01*** (0.00)	0.01*** (0.00)	0.01*** (0.00)	0.01*** (0.00)	0.03*** (0.01)	0.02*** (0.000)
KnowMaturityDiversity	0.04*** (0.00)	0.03*** (0.00)	0.03*** (0.00)	0.04*** (0.00)	0.03*** (0.00)	0.03*** (0.00)
SelfCitations	0.10*** (0.01)	0.10*** (0.01)	0.10*** (0.01)	0.10*** (0.01)	0.10*** (0.01)	0.10*** (0.01)
Claims	0.01*** (0.00)	0.01*** (0.00)	0.01*** (0.00)	0.01*** (0.00)	0.01*** (0.00)	0.01*** (0.00)
GovInterest	0.48*** (0.09)	0.47*** (0.09)	0.46*** (0.09)	0.47*** (0.09)	0.45*** (0.09)	0.45*** (0.09)
SciKnowledge	0.001*** (0.00)	0.001*** (0.00)	0.001*** (0.00)	0.001*** (0.00)	0.001*** (0.00)	0.001*** (0.00)
InterOrgCollab	−0.12† (0.05)	−0.12† (0.05)	−0.10† (0.05)	−0.12† (0.05)	−0.11† (0.05)	−0.09† (0.05)
TeamSize	0.04***(0.01)	0.04***(0.01)	0.04***(0.01)	0.04***(0.01)	0.04*** (0.01)	0.04***(0.01)
PatentAge	0.15*** (0.02)	0.15*** (0.02)	0.15*** (0.02)	0.14*** (0.02)	0.15*** (0.02)	0.14** (0.02)
PublicFirm	0.10** (0.04)	0.10** (0.04)	0.10** (0.04)	0.10** (0.04)	0.10** (0.04)	0.10*** (0.04)
BusDiversification	−0.01† (0.01)	−0.02† (0.01)	−0.02† (0.01)	−0.01† (0.01)	−0.01† (0.01)	−0.02† (0.01)
FirmAge	−0.01*** (0.00)	−0.01*** (.000)	−0.01*** (0.00)	−0.01*** (0.00)	−0.01*** (0.00)	−0.01*** (0.00)
PatentStock	−0.07*** (0.01)	−0.07*** (0.01)	−0.07*** (0.01)	−0.07*** (0.01)	−0.07*** (0.01)	−0.07*** (0.01)
SearchSpan	0.06** (0.02)	0.06** (0.02)	0.04** (0.02)	0.05** (0.02)	0.05** (0.02)	0.04** (0.02)
SearchDepth	0.01** (0.00)	0.01** (0.00)	0.01** (0.00)	0.01** (0.00)	0.01** (0.01)	0.01** (0.06)
SearchDepth^2	−0.0003** (0.00)	−0.0002** (0.00)	−0.0002** (0.00)	−0.0002** (0.00)	−0.0002** (0.00)	−0.0002** (0.00)
SearchScope	−0.15* (0.06)	−0.14* (0.06)	−0.12* (0.06)	−0.14* (0.06)	−0.14* (0.06)	−0.10* (0.05)
InnovationPerformance	0.05** (0.02)	0.05** (0.02)	0.06** (0.02)	0.05** (0.02)	0.05** (0.02)	0.06** (0.02)
InnovationFailure	−0.09 (0.17)	−0.09 (0.17)	−0.07 (0.17)	−0.02 (0.17)	−0.09 (0.17)	−0.13 (0.12)
424PatentClass	0.08† (0.05)	0.08† (0.05)	0.09† (0.05)	0.07† (0.05)	0.08† (0.05)	0.08† (0.05)
435PatentClass	−0.09* (0.04)	−0.10* (0.04)	−0.10* (0.04)	−0.10* (0.04)	−0.10* (0.04)	−0.10* (0.04)
514PatentClass	0.05 (0.04)	0.05 (0.05)	0.05 (0.05)	0.05 (0.05)	0.04 (0.05)	0.05 (0.05)
530PatentClass	−0.07 (0.06)	−0.07 (0.07)	−0.05 (0.07)	−0.08 (0.07)	−0.07 (0.07)	−0.06 (0.06)
800PatentClass	0.48*** (0.10)	0.48*** (0.11)	0.55*** (0.11)	0.46*** (0.11)	0.48*** (0.11)	0.56*** (0.11)
Year dummies	Included	Included	Included	Included	Included	Included
Likelihood ratio test (χ^2)	−16700.17***	−16692.02***	−16689.76***	−16684.95***	−16690.84***	−16682.16***
Improvement in fit over base model ($\Delta\chi^2$)		8.15	10.41	15.22	9.33	18.01
Observations	5,575	5,575	5,575	5,575	5,575	5,575

Note: Huber–White robust standard errors are reported in parentheses.
†$p < .10$.
*$p < .05$.
**$p < .01$.
***$p < .001$.

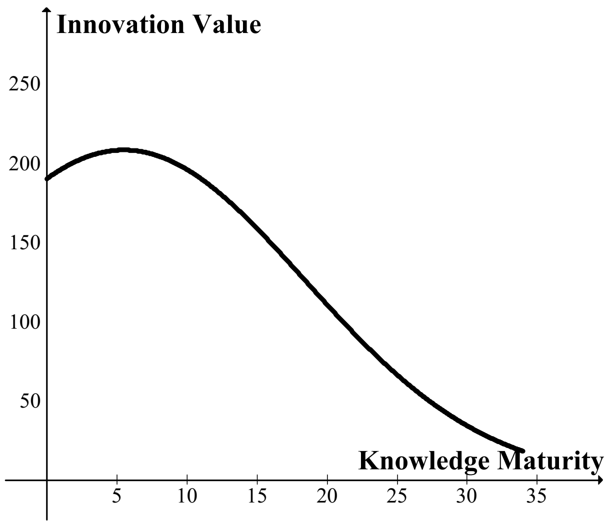
.01) (Cohen & Levin, 1989), the size of the inventor team (ß = 0.04, $p < .001$) (Singh, 2008), the number of patent claims (ß = 0.01, $p < .001$) (Lanjouw & Schankerman, 2004), the support of the U.S. government (ß = 0.48, $p < .001$), the age of the patent (ß = 0.15, $p < .001$) (Reitzig, 2004), the scientific knowledge referred to by the patent (ß = 0.001, $p < .001$) (Fleming & Sorenson, 2004), and the firm's innovation performance as captured by its accumulated number of patent citations (ß = 0.05, $p < .01$) (Ahuja & Lampert, 2001). In turn, increases in firm age (ß = −0.01, $p < .001$) (Sørensen & Stuart, 2000), interorganizational collaborations (ß = −0.12, $p < .1$) (Koput, 1997), business diversification (ß = −0.01, $p < .1$) (Hitt et al., 1997), and patent stock (ß = −0.07, $p < .001$) (Arora, Gambardella, Magazzini, & Pammolli, 2009) negatively affect the development of valuable innovations.

The time spread captured by the diversity of knowledge maturity (ß = 0.04, $p < .001$) indicates the merits of combining old knowledge with new knowledge (Nerkar, 2003). Search depth generates an inverted U-shaped effect on the value of innovations ($ß_1$ = 0.01, $ß_2$ = −0.0003, $p < .01$) (Katila & Ahuja, 2002), and search span produces a positive effect (ß = 0.06, $p < .01$) (Capaldo & Messeni Petruzzelli, 2011), while the effect of search scope (ß = −0.15, $p < .05$) is negative (Laursen & Salter, 2006). We tested the nonlinear effects of both search span and search scope, finding no significant effects of their quadratic terms on the value of innovations. Finally, innovations are less valuable in the molecular biology and microbiology field (ß = −0.09, $p < .05$) as defined by patent class 435, with higher value observed in the fields of bio-affecting and body treating compositions (ß = 0.08, $p < .1$) and multicellular living organisms (ß = 0.48, $p < .001$), as indicated by patent classes 424 and 800, respectively. In addition, technological distance enhances innovation (ß = 1.01, $p < .001$), whereas geographical distance is detrimental to innovation (ß = −0.02, $p < .01$). Hence, the value of an innovation improves when the inventor spans technological boundaries while also restricting the geographical scope of knowledge search (Phene et al., 2006). Finally, the adoption of knowledge in the industry contributes to the value of an innovation (ß = 0.01, $p < .001$), probably by enhancing its legitimacy and applicability.

Per Model 2, knowledge maturity generates an inverted U-shaped effect on innovation value, in support of Hypothesis 1. Specifically, the linear term of *KnowMaturity* is positive (ß = 0.03, $p < .001$), whereas its squared term is negative (ß = −0.003, $p < .001$). Thus, beyond a certain threshold, knowledge maturity becomes detrimental to the value of innovations. According to Model 3, Hypothesis 2 gains support, as evidenced by the negative interaction effect of knowledge maturity and technological distance (ß = −0.05, $p < .01$). Similarly, Hypothesis 3 gains support in Model 4, based on the significant positive interaction of knowledge maturity and geographical distance (ß = 0.003, $p < .001$). Finally, per Model 5, Hypothesis 4 gains support, as indicated by the negative interaction effect of knowledge maturity and knowledge adoption (ß = −0.001, $p < .01$). These effects persist in the full model (Model 6), to which they are introduced simultaneously.

Figure 2 depicts the predicted value of an innovation as a function of knowledge maturity, showing that when knowledge matures beyond 5.5 years, the costs of its maturity outweigh the benefits. Hence, there is a relatively short period during which the value of the innovation increases, followed by an extended period of substantial decline in value. This inverted U-shaped pattern suggests that the effect of knowledge maturity on the scientific value of an innovation is not merely increasing at decreasing rates (Nerkar, 2003), but in fact declines after a certain threshold. To gain further insight into the interaction effects predicted by Hypotheses 2, 3, and 4, we decompose the interaction terms and conduct simple slope

Figure 2
Knowledge Maturity and Innovation Value



analysis (Ai & Norton, 2003; Aiken & West, 1991; Hoetker, 2007) as shown in Figures 3 to 5. For each of the three hypotheses, we consider two levels of the moderating variables—low (one standard deviation below the mean) and high (one standard deviation above the mean)—and estimate the effect of knowledge maturity on innovation value for both levels (Poppo, Zhou, & Zenger, 2008). Figure 3 reveals the negative moderating effect of technological distance on the association between knowledge maturity and innovation value. This figure shows how the value of the innovation reaches a maximum after 3.5 years of knowledge maturity at high technological distance, as opposed to 5.8 years at low technological distance. Figure 4 shows how geographical distance defers the threshold levels beyond which knowledge maturity undermines innovation value. In this case, maximum innovation value is reached after 8.4 years for high geographical distance as opposed to 5.2 years for low geographical distance. Finally, Figure 5 depicts the moderating effect of knowledge adoption on the association between knowledge maturity and innovation value. The value of the innovation appreciates as knowledge matures for up to 8 years under the low adoption condition, yet in the high adoption condition the value of the innovation peaks at 4 years and declines as knowledge further matures. All of the inflection points fall within range (0 to 34 years).

Robustness Tests

To test the robustness of our findings, we conducted several auxiliary analyses using alternative operationalizations of our variables and alternative model specifications.

First, in accordance with prior research (e.g., Ahuja, 2000; Hess & Rothaermel, 2011; Nooteboom et al., 2007; Rosenkopf & Nerkar, 2001), we considered alternative measures of

Figure 3
The Moderating Effect of Technological Distance

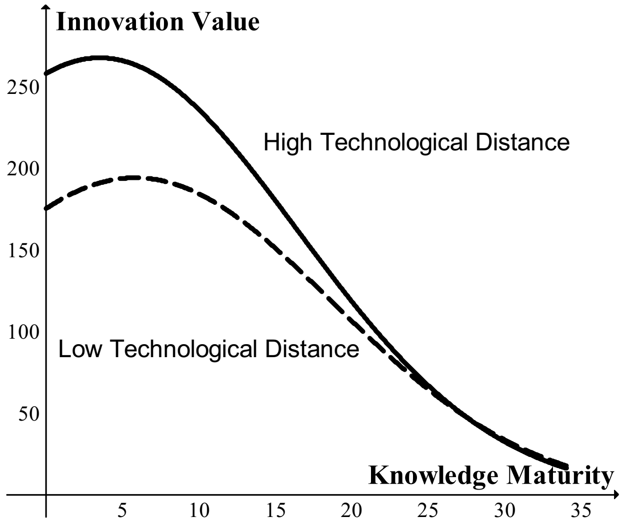


Figure 4
The Moderating Effect of Geographical Distance

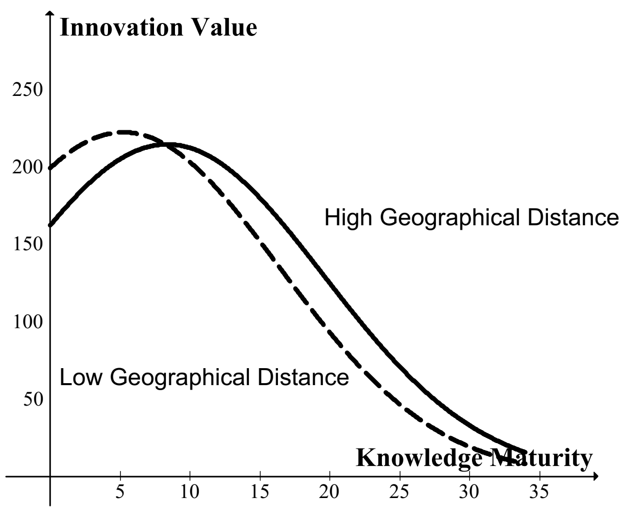
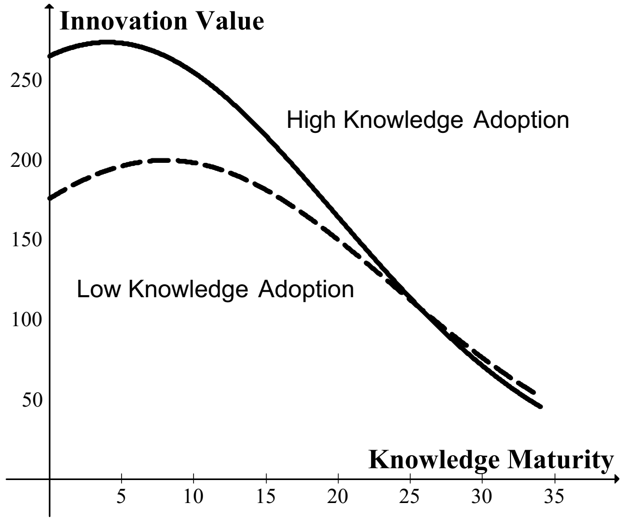


Figure 5
The Moderating Effect of Knowledge Adoption



innovation value. First, we excluded self-citations from the count of forward citations and dropped the corresponding control variable, still finding support for our hypotheses. Next, we divided the count of forward citations by patent age, instead of including patent age as a separate control variable. With this alternative specification, Hypotheses 1, 2, and 4 gained support, but the interaction term corresponding to Hypothesis 3 lost significance. Furthermore, we controlled for the risk that an old patent may be more frequently cited by using a 7-year window when counting forward citations to a focal patent instead of relying on the patent age control. This alternative specification offered support for our hypotheses. Overall, controlling for self-citations and patent age with separate variables better isolates their independent effects. Finally, we operationalized our dependent variable as the number of citations received by patents in the biotechnology field, while controlling for citing patents in other patent classes, still finding support for our hypotheses.

Second, we considered alternative measures of knowledge maturity. In particular, instead of measuring the time elapsed since application for a cited patent, we measured knowledge maturity with the average number of years elapsed since the last citation of the same patent by the same firm. The four hypotheses gained support with this alternative measure, suggesting that the effect of knowledge maturity on innovation value holds when considering both the scientific community's and the firm's perspectives as well as with respect to both the first and last use of knowledge. In addition, we operationalized knowledge maturity as the average number of times the patents cited by a focal patent were cited in the past by the same firm, assuming that knowledge matures with repeated use of knowledge rather than over time. Corresponding findings grant support to Hypotheses 1 and 3 on the effect of knowledge maturity and the moderating effect of geographical distance.

Third, we incorporated interactions of the squared term of knowledge maturity with the three moderating variables (*TechDist*, *GeoDist*, and *KnowAdoption*). These interactions generated consistent results, suggesting that technological distance, geographical distance, and knowledge adoption influence mostly the linear trajectory of the knowledge maturity effect. Yet these results may suffer from potential multicollinearity, as indicated by the high VIF indexes (maximum VIF = 22.65), which led us to exclude these terms from the models.

Fourth, to account for selection bias in the decision to rely on mature knowledge, we ran a two-stage model (Heckman, 1979). The first stage assessed the likelihood that an innovation would incorporate mature knowledge, as indicated by a dummy variable receiving a value of one when the maximum maturity of cited patents is greater than the mean value of knowledge maturity. For exclusion restriction we used the mean number of years elapsed since the publication date of nonpatent references cited by the focal patent. The inverse Mills ratio estimates were incorporated in the second-stage model, with no material change in results. To further account for selection bias, we controlled for the risk that the inventor decides to incorporate certain knowledge elements while disregarding others, by adding a control variable that measures the value of innovations citing noncited biotechnology patents applied for in the same year as the cited patent. Although this control was marginally significant ($p < .1$), it did not affect our reported findings. Finally, we ran piecewise exponential models by splitting knowledge maturity into three time intervals using corresponding dummy variables, finding further support for our hypotheses.

Fifth, we considered alternative measures of technological distance. We first measured technological distance by calculating the ratio of the number of non-biotechnological classes to the total number of technological classes for each cited patent and then averaged this ratio across the total number of backward citations for each focal patent. With this operationalization, the interaction of *KnowMaturity* and *TechDist* was negative, but insignificant. Next, we calculated an alternative measure that captures proximity of the patents' technological classes (Jaffe, 1986). We then considered another variant of this measure based on Euclidean distance (Ahuja, 2000; Benner & Waldfogel, 2008; Rosenkopf & Almeida, 2003). Finally, we employed a measure of technological distance based on the number of matching patent class digits (Trajtenberg, Henderson, & Jaffe, 1997). With these three alternative operationalizations, Hypothesis 2 gained marginal support, as the interaction of *KnowMaturity* and *TechDist* was negative yet insignificant. The fact that the distinction between intra- and extraindustry knowledge matters more than technological distance, as captured by refined measures of technological domains, may suggest that inventors possess sufficient absorptive capacity to internalize external knowledge as long as it does not rest beyond the boundaries of the biotechnology industry.

Sixth, we measured *GeoDist* as the natural logarithm of the distance between the countries of the first inventors listed in the focal and cited patents (Singh, 2008), averaged across all backward citations of a focal patent. With this alternative measure, the interaction of *KnowMaturity* and *GeoDist* was positive yet insignificant. We next measured *GeoDist* as the ratio of the number of backward citations whose first inventor's home country was not the United States to the total number of backward citations (Phene et al., 2006). We also considered an alternative measure based on the ratio of the number of backward citations for which more than 50% of the inventors resided outside the United States to the total number of backward citations. In both cases, Hypothesis 3 gained support. Finally, we replaced the geographical distance measure with a measure of cultural distance between the United States and the country of origin of the first inventor of a cited patent. We used Kogut and Singh's (1988) composite index of the Hofstede (1980) cultural dimensions. This auxiliary analysis revealed a positive interaction effect of knowledge maturity with cultural distance, suggesting that the enhanced value of mature knowledge is partially due to national cultural differences between the original inventor and the user of knowledge.

Seventh, we replaced our measure of knowledge adoption with a measure of the average number of times each cited patent has been previously cited by other firms, excluding self-citations (Miller, Fern, & Cardinal, 2007), finding consistent results for Hypothesis 4. This unweighted measure better captures the number of prior uses as opposed to the number of prior users of knowledge components.

Eighth, we accounted for knowledge embedded in scientific publications other than patents by operationalizing our independent variable and moderators using data on nonpatent references. In this case, no support was found for our hypotheses, but when these variables and their corresponding interactions were introduced as control variables in addition to our reported patent-based models, our findings remained consistent. Since we focus on the innovations of firms rather than the innovations of universities, perhaps patents are more relevant than nonpatent references as proxies for knowledge creation.

Ninth, we considered an alternative measure of *PatentStock* based on the cumulative number of all patents that a firm filed with the USPTO until the year preceding the filing year of the focal patent ($t-1$) (Furman, Porter, & Stern, 2002). We also replaced *PatentStock* with *FirmSize*, and *PatentAge* with *IndustryEvolution* as alternative control variables. In all these cases, the results supported our hypotheses. Tenth, we added *FirmSize* and *FirmAge* as moderators of the knowledge maturity effect, which did not weaken the significance of our reported moderators. Eleventh, we ran alternative models using clustering with robust standard errors to account for the potential nonindependence of observations pertaining to the same cited patent and to different patents involving the same inventor (Singh & Agrawal, 2011). Finally, we ran Poisson regression models (Wooldridge, 1999), zero-inflated negative binomial models that account for excess zero values in the dependent variable, and models with bootstrapping. Under all these alternative model specifications, we found some support for our hypotheses. Overall, these auxiliary analyses bestow confidence in our findings.

Discussion and Implications

We study how the scientific value of an innovation varies with knowledge maturity and its contingencies on technological and geographical distances, while accounting for the degree of adoption of this knowledge in the industry. We find that, up to a point, the scientific value of an innovation increases with the maturity of knowledge upon which it is based, but that beyond that point the value declines. We ascribe the initial appreciation in value to the time needed for knowledge to prove valuable and reliable. Employing mature knowledge may also make it possible to uncover new applications that have not been pursued in the past for lack of enabling technologies or complementary assets. The appreciation in the value of an innovation with knowledge maturity is in line with Nerkar's (2003) study of the pharmaceutical industry. Yet as knowledge matures beyond a certain threshold, memory decay can exacerbate the challenges of retrieving, interpreting, and applying that knowledge, so that eventually it may be rendered obsolete, thus diminishing the value of corresponding innovations. Therefore, our findings suggest that moderately mature knowledge is most desirable for enhancing the scientific value of resulting innovations.

Our findings further indicate that the desirable level of knowledge maturity is contingent upon the distance of that knowledge from the industry's technological domain. The more distant the knowledge from the current domain of expertise in the industry, the more difficult it is to generate value from maturing knowledge. An inventor's unfamiliarity with distant knowledge and increasing difficulties in searching, internalizing, and leveraging that knowledge can limit its recombination opportunities and depreciate the value of innovations. However, these impediments can be offset by seeking geographically distant knowledge that can rejuvenate mature knowledge and enhance the scientific value of innovations that incorporate it. We ascribe this effect to the relative novelty of mature knowledge that is used remotely from its geographical origin.

Finally, we suggest that, as mature knowledge is being incorporated in an increasing number of innovations, they lose their novelty. Therefore, inventors are better off leveraging that knowledge before it is adopted by many firms in their industry. This entails monitoring the pace of knowledge adoption in the industry. Consideration of the distance and adoption contingencies can clarify whether inventors should adopt external knowledge as soon as it becomes available or instead wait until its value appreciates as a result of enhanced reliability.

Implications for Theory

Our study contributes to management research and to the literature on innovation by revealing the contingent value of knowledge maturity. We investigate the interplay of the maturity of the knowledge elements underlying innovations with the technological and geographical distances of that knowledge. Unlike prior research that has concentrated on firms' commercial gains from innovations, we study how knowledge maturity shapes the value of innovations for the scientific community in terms of recognition by peer inventors and technological impact on subsequent innovations. We show that the scientific value of knowledge maturity can be better assessed when considering its technological and geographical distances. Hence, firms may need to trace the technological and geographical origins of knowledge and consider the extent of its adoption in their industry.

We conclude that there is an optimal level of maturity beyond which the value of an innovation depreciates. However, relatively mature knowledge can enhance the value of an innovation to the extent that it has been sourced from a distant country. Thus, the value of innovations incorporating mature knowledge varies by country of origin, so that firms that are late to introduce innovations can still increase the contribution of their innovations to the scientific community by extending the international scope of their knowledge search. Additional heterogeneity is ascribed to the distance of the incorporated knowledge from the industry's technological domain. Such distance limits the relevance of the inventor's technological expertise, thus diminishing the scientific value of an innovation that relies on mature knowledge. Finally, we uncover a boundary condition, overlooked by prior research, relating to the adoption of mature knowledge in the industry. We demonstrate that because innovation does not occur in a vacuum, its scientific value depreciates faster with knowledge maturity if a larger number of innovations incorporate such knowledge.

Our study further advances innovation research by shedding new light on the temporal aspect of innovation. Prior innovation research has mostly paid attention to other issues, such as a firm's tendencies to rely on internal versus external knowledge (Laursen & Salter, 2006), engage in distant versus local search for technological competencies (Katila & Ahuja, 2002; Rosenkopf & Nerkar, 2001), and span multiple knowledge domains (Capaldo & Messeni Petruzzelli, 2011). Less attention has been paid to knowledge maturity, with only a few studies that show mixed findings. Our study reconciles this mixed evidence by revealing that mature knowledge enhances innovation value up to a certain threshold. However, unlike prior research that suggested that the value of an innovation increases at a decreasing rate (Nerkar, 2003), we show that, beyond a certain level of knowledge maturity, this value actually diminishes. We also reveal that the added value of mature knowledge depends on its distance, with some conflicting implications depending on whether reach is extended in the technological domain or geographical domain. The distance of knowledge seems to influence both its novelty and the ability to absorb it (Phene et al., 2006), whereas the rate of adoption of knowledge in the industry affects mostly the ability to benefit from knowledge application.

In addition, our study informs research on balancing exploration and exploitation (Capaldo, 2007; Gupta, Smith, & Shalley, 2006; Lavie, Stettner, & Tushman, 2010; March, 1991) by showing how such balance can be achieved when searching for knowledge over time. Counter to the temporal separation approach to balance (Brown & Eisenhardt, 1997) that calls for focusing on either exploration or exploitation at a given time, we advocate reliance on intermediately mature knowledge. In line with the domain separation approach (Lavie, Kang, & Rosenkopf, 2011; Lavie & Rosenkopf, 2006) and the ambidexterity literature (He & Wong, 2004; O'Reilly & Tushman, 2004; Rothaermel & Alexandre, 2009), we call for balance across the technological and geographical domains. Firms are advised to seek technologically proximate knowledge while spanning geographical boundaries. Thus, we call for balancing geographical exploration with technological exploitation when seeking mature knowledge.

Finally, our study informs research on absorptive capacity (Ben-Oz & Greve, 2015; Cohen & Levinthal, 1990; Lane, Koka, & Pathak, 2006; Zahra & George, 2002) by noting the limitations of relying on external knowledge that differs from the internal knowledge base. Specifically, our findings suggest that even if external knowledge is well established in the market, its absorption remains challenging if the inventors lack a related knowledge base. The challenges of incorporating and applying mature knowledge are ascribed to misinterpretation, misunderstanding, and misapplication of such knowledge, problems that grow with the technological distance between such external knowledge and the inventors' domain of expertise. In fact, our findings reveal that when innovations incorporate mature knowledge beyond the current technological domain, the value of those innovations quickly diminishes.

Managerial Implications

By demonstrating how mature knowledge can enhance the value of innovations, we encourage managers to consider not only the type of knowledge used in innovations but also its birth date and birthplace. Mature knowledge is not necessarily less valuable, but its value depends on how distant it is from the current knowledge base and country of origin. To innovate effectively, firms need to assess the distance of knowledge sources and their adoption in the industry. We expect mature knowledge to be most valuable when it is related to the industry's technological domain, yet geographically distant. Hence, our findings depart from prior research on absorptive capacity (Phene et al., 2006) that underscored the value of proximity irrespective of the type of distance. Furthermore, our findings underscore the need to balance exploration and exploitation across domains (Lavie & Rosenkopf, 2006), since the value of an innovation is maximized when seeking distant knowledge in the geographical domain (i.e., exploration) while investing in local search in the technological domain (i.e., exploitation). Managers do not typically consider the origin of knowledge in their decisions to incorporate mature knowledge in new innovations, but they should pay more attention to it when considering how to leverage such knowledge in their firms' innovations.

Limitations and Directions for Future Research

Our study contributes to the innovation literature while leaving room for future research. First, using patents as indicators of innovation may raise potential methodological concerns. Although patent citations enable the tracking of knowledge flows among innovations, several citations are often added by examiners and thus may not reflect an actual knowledge flow (Alcacer & Gittelman, 2006). In addition, real knowledge flows generally occur through complex interactions involving written and oral communication, learning, face-to-face interactions, chance meetings, and close working relationships, which may be difficult to track using patent citations (Singh, 2005). Moreover, patents are often treated as homogenous in cross-sectional studies despite the fact that they significantly differ across firms, industries, and technology fields (Gittelman, 2008). Finally, not all innovations are patentable, and not all patents represent innovations (Giuri et al., 2007), with some firms relying on alternative means for protecting their knowledge resources (de Faria & Sofka, 2010). Hence, despite the popularity of patent data in the innovation literature, patents cannot fully capture an innovation's value. Patents represent only a subset of firms' technologies that corresponds primarily to codified knowledge. In addition, not all patent citations reflect genuine incorporation of prior knowledge. Path-breaking innovations may not involve extensive citations to historical patents. We handle some of these limitations by including relevant control variables and applying scrutiny when interpreting our results. Furthermore, we considered nonpatent sources of knowledge in our robustness tests. Despite the above limitations, patents are still the most commonly used proxy for innovations (e.g., Cattani, 2005; Miller et al., 2007; Rosenkopf & Nerkar, 2001; Singh, 2008), since patent data are readily available in most countries; the comprehensiveness of patent data supports both cross-sectional and longitudinal analysis; and patent data contain detailed useful information, such as technological fields, assignees, inventors, and some other market features (Ratanawaraha & Polenske, 2007), thus making patent citations the most robust measure for capturing the scientific value of an innovation.

Second, future research can reexamine how mature knowledge contributes to firms' financial and market performance (Heeley & Jacobson, 2008), perhaps by distinguishing the implications of value creation mechanisms from those of value appropriation mechanisms. Third, we focused on the technological and geographic distances of knowledge, but future research may consider additional types of distance, such as that relating to organizational differences between inventors. Fourth, whereas we focused on the implications of competition by studying the adoption of knowledge in the industry, future research may study the effects of collaboration in driving knowledge creation and application (Lavie & Drori, 2012). Fifth, scholars can focus on the mechanisms that enable effective integration of mature knowledge in innovations. Perhaps the value of an innovation depends on the effectiveness of these processes irrespective of the distance of knowledge. Finally, our sample is limited to the innovations of U.S.-based biotechnology firms that may exhibit particular patterns of patenting. Future research may assess the generalizability of our findings by extending our inquiry to other industries and countries, such as those in which patents do not serve as an essential element of the appropriability regime. Our findings are mostly applicable in technology-driven industries in which knowledge and innovation are paramount.

Notes

1. The USPTO assigns the following patent classes to the biotechnology domain: 424 (drug, bio-affecting, and body treating compositions), 435 (chemistry: molecular biology and microbiology), 436 (chemistry: analytical and immunological testing), 514 (drug, bio-affecting, and body treating compositions [different subclasses]), 530 (chemistry: natural resins or derivatives; peptides or proteins; lignins or reaction products thereof), 536 (organic compounds), 800 (multicellular living organisms and unmodified parts thereof and related processes), 930 (peptide or protein sequence), and PLT (plants) (Rothaermel & Thursby, 2007).
2. The use of forward citations is particularly suitable for our study, since citations added by examiners do not represent a critical issue. First, the share of examiner citations for biotechnology patents is the lowest compared to all other technological fields. In fact, only 25% of drug and medical patents contain examiner citations (Alcacer, Gittelman, & Sampat, 2009), and assignees withhold only 5% to 7% of the relevant citations (Lampe, 2012). Second, we rely on patents granted by the USPTO to U.S. firms, hence further reducing the share of examiner citations, which is especially high for foreign firms (Alcacer et al., 2009). As a result, the share of examiners' citations in our sample of patents accounts for only 402 patents granted after 2000, corresponding to about 20% of the overall number of forward citations.

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