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A QUEST IN TIME: THE VALUE OF INNOVATION AND THE AGE, ORIGIN, AND POPULARITY OF KNOWLEDGE

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Abstract

Prior research has examined how a firm?s knowledge stock contributes to the value of its innovations, yet revealed mixed findings. We seek to reconcile this inconsistent evidence by studying how the age, origin, and popularity of knowledge affect the value of innovations. We claim that the age of knowledge which the firm incorporates exerts an inverted U-shaped effect on the value of innovations. However, this effect is moderated by the origin of knowledge. Specifically, relying on knowledge from distant technological domains attenuates the value of old knowledge, whereas incorporating geographically distant knowledge enhances the value of such knowledge. Finally, as the firm?s old knowledge base becomes more popular, its value to the firm diminishes. Analysis of the patent citations contained in

5,571 USPTO patents issued to 284 biotechnology firms operating in the U.S. between 1985 and 2002 supports these conjectures. Our study advances innovation research and contributes to the learning literature by underscoring the contingent value of knowledge age.

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ABSTRACT

Prior research has examined how a firm's knowledge stock contributes to the value of its innovations, yet revealed mixed findings. We seek to reconcile this inconsistent evidence by studying how the age, origin, and popularity of knowledge affect the value of innovations. We claim that the age of knowledge which the firm incorporates exerts an inverted U-shaped effect on the value of innovations. However, this effect is moderated by the origin of knowledge. Specifically, relying on knowledge from distant technological domains attenuates the value of old knowledge, whereas incorporating geographically distant knowledge enhances the value of such knowledge. Finally, as the firm's old knowledge base becomes more popular, its value to the firm diminishes. Analysis of the patent citations contained in 5,571 USPTO patents issued to 284 biotechnology firms operating in the U.S. between 1985 and 2002 supports these conjectures. Our study advances innovation research and contributes to the learning literature by underscoring the contingent value of knowledge age.

Keywords: search; innovation; knowledge age; knowledge origin; knowledge popularity

INTRODUCTION

Innovation is a search process aimed at creating new knowledge (Nelson and Winter, 1982; March, 1991). Innovation often results from novel combinations of existing knowledge that a firm has obtained from various internal and external sources (Schumpeter, 1934; Kogut and Zander, 1992; Galunic and Rodan, 1998; Fleming, 2001). The absorptive capacity literature has discussed the process by which the firm incorporates external knowledge, assimilates, and leverages it when carrying out research and development (Cohen and Levinthal, 1990; Lane, Koka, and Pathak, 2006). Related research has concentrated on the means by which firms search for external knowledge, distinguishing among three main dimensions, namely search scope (Stuart and Podolny, 1996), search depth (Katila and Ahuja, 2002), and search span (Capaldo and Messeni Petruzzelli, forthcoming). An emerging theme in innovation research has identified the age of knowledge as a factor that can influence the outcomes of the search process. Nevertheless, this literature is divided concerning the merits of relying on old versus new knowledge. In particular, some scholars have argued that firms should build on recent knowledge to constantly adapt their knowledge base to current environmental needs and expectations (Eisenhardt, 1989; Sorenson and Stuart, 2000), while others suggested that established knowledge can be valuable to the innovation process as it increases reliability and reduces the intensity of competition (Katila, 2002).

Few studies have begun to empirically examine the impact of knowledge age on innovation. In an attempt to reconcile the conflicting expectations concerning the implications of old knowledge, a prior study has revealed that innovativeness favours search for old knowledge across industries (Katila, 2002). Another study has suggested that successful innovations entail combining current knowledge with knowledge accumulated over long time spans (Nerkar, 2003). A more recent study found that firms that leverage intermediately aged knowledge inputs experience high returns (Heeley and Jacobson, 2008).

We seek to contribute to this emerging research stream by contending that the effect of old knowledge may vary with certain characteristics of that knowledge, which in turn may make it more or less useful when incorporated in innovations. Hence, we advance innovation research by elucidating the contingent value of knowledge age.

Specifically, we theorize that the value of old knowledge may depend on its origin and popularity. Following prior research (Phene, Fladmoe-Lindquist, and Marsh, 2006), we distinguish between the technological and geographical origins of knowledge, and consider whether firms reach beyond their technological and geographical boundaries. We further consider the popularity of the firm's knowledge in an attempt to examine the implications of its diffusion in the industry. These contingencies, so we argue, can influence the value of established knowledge.

Drawing on a sample of 5,667 USPTO patents issued to 347 biotechnology firms between 1979 and 2002, our findings reveal that knowledge age has an inverted U-shaped effect on innovation value. Additionally, we find that integrating technologically distant knowledge attenuates the benefits of old knowledge, whereas incorporating knowledge originating from distant geographical locations reinforces its benefits. Finally, the popularity of knowledge undermines the value of old knowledge. Our study offers a nuanced account of the merits of incorporating established knowledge in innovations, thus informing innovation and learning research as well as related literatures on absorptive capacity and on balancing exploration and exploitation endeavors.

THEORETICAL BACKGROUND AND HYPOTHESES

Innovation as a Search and Recombination Process

The recombinant perspective of innovation (Gilfillan, 1935) suggests that 'innovation combines factors in a new way, or that it consists in carrying out new combinations'

(Schumpeter, 1939: 88). According to this perspective, developing novel solutions entails recombining existing conceptual and physical elements (Nelson and Winter, 1982). For example, the computer workstation may be considered a novel combination of existing components including the CPU, motherboard, virtual storage and memory units, a display, graphics processor, and systems and applications software (Fleming and Sorenson, 2004). Similarly, the emerging field of nanotechnology combines knowledge and techniques originating in the semiconductor, mechanical and biotechnology industries. Hence, innovation can be conceptualized as a process of problem solving and decision making (Gavetti and Levinthal, 2000; Rivkin, 2001), where the inventor searches the technological landscape (Rivkin, 2000; Fleming and Sorenson, 2004) and selects distinctive pieces of knowledge in order to discover the most useful components as well as the best approach for combining them (Henderson and Clark, 1990).

Based on this conceptualization of the knowledge recombination process, March (1991) underscored the tension between exploration of new opportunities and exploitation of prior experience. Exploration involves learning via experimentation and adopting new knowledge, whereas exploitation refers to learning by means of refinement and reuse of existing routines that leverage established knowledge (Benner and Tushman, 2002; He and Wong, 2004; Gupta, Smith, and Shalley, 2006). Therefore, exploration enriches a firm's knowledge base by facilitating acquisition of novel components that serve in the development of innovative solutions. Nevertheless, given the cumulative nature of learning, recombination typically involves components that are salient, proximal, and available to the inventors (Fleming, 2001) that tend to concentrate their exploration efforts in areas where they have encountered prior success (Cyert and March, 1963).

Effective innovation entails nurturing an absorptive capacity (Cohen and Levinthal, 1990), which is essential for assessing knowledge sources, as well as for assimilating and applying them. Absorptive capacity enables a firm to identify and acquire externally generated knowledge that is critical to its operations (Kim, 1997), to analyze, interpret, and comprehend external information (Szulanski, 1996), to combine the newly acquired knowledge with its existing knowledge (Zahra and George, 2002), and to commercially apply that knowledge (Cohen and Levinthal, 1990). Absorptive capacity is path-dependent and derives from the firm's experience and accumulated knowledge. Hence, a firm's absorptive capacity shapes the search process by which it acquires and assimilates new knowledge.

Extant research describes innovation as a search process, i.e., the process by which organizations seek new knowledge (Nelson and Winter, 1982; Rosenkopf and Almeida, 2003; Fleming and Sorenson, 2004; Katila and Chen, 2008). This research refers to several dimensions of search and to distinctive search strategies, that have been shown to differentially affect a firm's innovation output (Katila and Ahuja, 2002; Laursen and Salter, 2006; Miller, Fern, and Cardinal, 2007). Studying the innovation process in the context of new product development, Katila and Ahuja (2002) followed March's (1991) distinction between exploration and exploitation, identifying depth and scope as two primary dimensions of search. Search depth refers to the degree to which a firm repeatedly exploits its existing knowledge, whereas search scope describes the extent to which a firm explores by incorporating previously unused knowledge. The extant literature on innovation typically focuses on search scope and discusses local versus distant search. Local search refers to the innate tendency of firms to search for solutions in the neighborhood of their existing knowledge base (March and Simon, 1958; Nelson and Winter, 1982). Such tendency has been empirically demonstrated in a number of contexts (Stuart and Podolny, 1996; Benner and Tushman, 2002). Boundary-spanning or distant search occurs when a firm searches for knowledge distant from its current knowledge base (Ahuja and Lampert, 2001; Rosenkopf and Nerkar, 2001; Rosenkopf and Almeida, 2003). Hence, the search depth versus scope framing is consistent with the exploitation-exploration perspective (Levinthal and March, 1993) which defines search with respect to a firm's existing knowledge. Another relevant dimension of search concerns its span (Capaldo and Messeni Petruzzelli, forthcoming). Search span captures the extent to which a firm's search encompasses different knowledge domains, irrespective of whether these domains rest beyond a firm's existing knowledge base and of the extent to which they are distant from it.

Several studies have empirically investigated the impact that the aforementioned dimensions of search on innovation. Katila and Ahuja (2002) found an inverted U-shape association relating the depth and scope of search to the number of new products introduced to the market. Similarly, Laursen and Salter (2006) report that searching widely and deeply is curvilinearly related to innovation performance. In turn, Rosenkopf and Nerkar (2001) showed that searching across both technological and organizational boundaries positively affects a firm's patenting activity in the optical disk industry. Rothaermel and Alexandre (2008) underscored the merits of balancing local and distant search to achieve desirable innovation and economic outcomes. Finally, Capaldo and Messeni Petruzzelli (forthcoming) demonstrated that in R&D alliances, search span generates an inverted U-shaped effect on value creation while positively influencing value appropriability. Overall, this stream of research sheds some light on the complex association between search processes and innovation.

The Temporal Dimension of Knowledge Search

As noted by Katila (2002), most prior research suggests that in order to successfully innovate a firm should incorporate the most recent knowledge and solutions. The underlying assumption is that, as knowledge ages, it tends to become obsolete and may fail to fit current environmental needs and expectations. Yet, some recent studies have argued that old knowledge contributes to innovation (Adner and Snow, 2010). Specifically, the reliability of old knowledge may allow a firm to successfully develop new solutions by decreasing the likelihood of failures and costly errors (Katila, 2002). In fact, in line with earlier research on knowledge recombination, many modern innovations rely on integration of knowledge paradigms which have been developed at different time periods (Fleming, 2001). For instance, mechatronics emerged at the late 1970s from the fusion of old mechanical technologies with the embryonic field of electronics (Freddi, 2009).

Despite the fertile debate on the merits of old versus new knowledge, there is little empirical evidence on the effect of knowledge age on innovation. There are, however, a few notable exceptions. Specifically, Katila (2002) investigated how firms search over time to introduce new product innovation, analyzing the innovation approaches of 131 robotics firms from 1985 to 1997. Her findings revealed that employing old solutions is not always beneficial, instead depending on whether a firm limits its search to its industry boundaries. Accordingly, old intra-industry knowledge undermines innovation whereas old extra-industry knowledge promotes it. In subsequent work, Nerkar (2003) studied the impact of temporal exploration and exploitation on future knowledge creation. In particular, he defined temporal exploitation as the recombination of recently created knowledge, and temporal exploration as the recombination of older knowledge. Adopting a path-dependent evolutionary framework, Nerkar advanced that both current and historical knowledge matter for innovation. Based on the analysis of the patents of pharmaceuticals firms, he found that adopting old technologies may be fruitful, especially if they are employed together with new and more recent knowledge. Recently, Heeley and Jacobson (2008) found that the relationship between the recency of technological inputs and a firm's financial performance is non-monotonic. Specifically, their analysis of US manufacturing firms revealed three regimes, in which different associations prevail between the age of technology and the firm's stock return. For firms whose new patents rely on knowledge in the mid-range of the technology recency distribution, the relationship is positive. Instead, for firms whose new patents make use of either nascent or very mature technological inputs, the relationship is negative. Finally, van de Vrande, Vanhaverbeke and Duysters (forthcoming) found that the newness of the technological portfolios of the partnering firms influences differently the impact of different external technology sourcing modes on the creation of radical innovations. Their analysis of a sample of 153 firms active in the pharmaceutical industry shows that employing older knowledge strengthens the positive influence of corporate venture capital investments and non-equity alliances on the generation of pioneering technologies, while the newness of the technology a firm invests in attenuates the negative effect of M&As on the creation of pioneering technologies. Thus, the discrepancy in the findings concerning the implications of knowledge age merits further attention.

To shed more light on the effect of the temporal dimension of search, we investigate how the age of knowledge affects the value of innovations. We examine how this effect may depend on the origin of knowledge. To do so, we focus on two additional dimensions of search, namely, the technological and geographic distances of knowledge used in the firm's current innovations. Additionally, we further enhance understanding of the relationships between knowledge age and innovation by considering the diffusion of knowledge in the firm's industry, suggesting that the value of temporal search may depend on the popularity of knowledge. Thus, we account for both value creation and value appropriation in studying how the age of knowledge affects innovation.

Knowledge Age and Innovation Value

Following prior research, relying on old knowledge can potentially enhance innovation (Katila, 2002). First, knowledge that has been prevalent in the market for a long period of time is considered more reliable, thus increasing the likelihood of generating successful innovations. In fact, old knowledge can be subjected to more extensive validation over time. Consequently, a firm may better realize the costs and benefits of using it, which decreases the likelihood of errors and failures. Second, Levinthal and March (1993) have argued that a recency bias affects organizations, which therefore tend to focus on, and ascribe more importance to, recent rather than distant ideas and circumstances. A possible consequence is that competitors will react more severely to the use of more recent knowledge. Thus, building on older knowledge is likely to be associated with less competitive intensity, which in turn positively impact firms' ability to extract value from their innovative endeavours. Third, firms tend to build on recent knowledge also because this is more easily available. In fact, as new knowledge is created, it is typically promoted and disseminated in an attempt to reach prospective markets, which simplifies and speeds the search process. Conversely, old knowledge may be less commonly sponsored and more difficult for actual or potential competitors to find and build upon (Argote, 1999). Therefore, it may constitute a distinctive resource for the firm that employs it. In addition, looking back across broad time periods may allow firms uncover valuable knowledge 'that is forgotten or whose time has not come' (Nerkar, 2003: 215), e.g., promising technologies whose innovative potential has not yet been (fully) exploited from the time of their launch due to the lack of adequate complementary assets. Based on the above, the value of innovation is expected to initially increase with the age of knowledge.

Nevertheless, beyond a certain threshold, relying on increasingly older knowledge may be detrimental to the value of innovation. First, as knowledge matures, multiple or incomplete interpretations of such knowledge may emerge. A firm may need to invest more in knowledge retrieval and in reconciling conflicting interpretations of that knowledge in an attempt to achieve an adequate level of coherence in knowledge use. Second, competency traps (Levinthal and March, 1993) may lead to misapplication of old knowledge, thereby undermining firms' innovation efforts. In particular, a firm that builds heavily on its established knowledge base often foregoes the prospects of gaining experience with more recent, and potentially more rewarding, knowledge (Sorensen and Stuart, 2000). Third, as knowledge ages, it may become obsolete. This would turn it from a potential source of competitive advantage into a core rigidity (Leonard-Barton, 1992) that limits the firm's competitiveness, especially if competitors rely instead on new knowledge. Finally, patents expire after a certain number of years and no legal protection may be available to enforce appropriation of value. Accordingly, we expect the value of innovation first to increase and then decrease with increases in the age of knowledge that the firm incorporates in its innovations.

> *H1. The age of knowledge will exhibit an inverted U-shaped effect on the value of innovation resulting from that knowledge.*

The Origin of Knowledge and Innovation Value

Innovation entails combining knowledge derived from multiple different sources (Stuart and Podolny, 1996; Rosenkopf and Nerkar 2001; Rothaermel and Alexandre, 2009), so that heterogeneous knowledge inputs are transformed into outputs (Katz and Kahn, 1996). The technological and geographical origins of knowledge inputs may shape the value of old knowledge as it becomes embedded in innovations. Following previous research (Phene, Fladmoe Linquist, and Marsh, 2006), we consider knowledge as technologically proximate or distant based on whether it originates from within or outside the firm's industry, whereas the geographical origin refers to whether the knowledge emanates from the firm's home country versus other countries.

Leveraging technologically distant knowledge is likely to limit some of the benefits while exacerbating some of the impediments associated with using old knowledge. First, when a firm searches for previous knowledge outside its technological domain it may lack the necessary expertise for assessing such knowledge (Cohen and Levinthal, 1990). Inability to correctly assess the costs and benefits associated with old and technologically distant knowledge may reduce its reliability. Hence, reaching beyond the firm's technological boundaries is likely to limit the value of established knowledge as the firm encounters greater challenges with its incorporation given its limited familiarity and unavailability of recent experience. An example of such challenges is evident in the difficulties software firms experienced in developing technologies for facing the year 2000 computer crisis. In this case, firms were forced to develop new expertise using archaic software languages for which there was limited current expertise (Hilson and Khurana, 1999). Thus, even though old knowledge is typically considered reliable, when firms extend the boundaries of their technological search they may be unable to ensure its reliability, which in turn reduces the value of innovations built upon such knowledge.

Second, previous research has shown that technologically distant knowledge is conducive to more breakthrough or radical inventions (Ahuja and Lampert, 2001; Phene, Fladmoe-Lindquist, and Marsh, 2006), which in turn have been proved to exert a dramatic impact on economic and innovation performance (Achilladelis, Schwarzkopf and Cines, 1999; Zhou, Yim and Tse, 2005). This suggests that, when a firm embeds technologically distant knowledge in its innovations, severe reactions by competitors are to be expected. Accordingly, the positive effect that the use of established knowledge exerts on innovation value due to limited competitive intensity is likely to be attenuated when the employed knowledge is also distant from the firm's technological domain, as a consequence of strong competitive reactions.

Third, although old knowledge is difficult to find for competitors, old knowledge that is technologically distant may be difficult to locate and to learn for the firm due to a lack of absorptive capacity. Thus, technological distance may reduce the positive impact that the use of established knowledge tends to exert on the firm's competitiveness. This may also be due to the fact that old and technologically distant knowledge is less likely to become a distinctive resource for the firm that employs it. Indeed, strategic management literature suggests that firms should develop their knowledge base and build their strategy around restricted bundles of familiar 'core' competencies (Prahalad and Hamel, 1990; Teece, Pisano, and Shuen, 1997) i.e., without exploring too much beyond their existing knowledge base.

Moreover, when a firm searches for knowledge outside its technological domain, the challenges of retrieving, and of interpreting and applying old knowledge may be amplified given that such knowledge becomes remote both temporally and technologically. Due to a lack of absorptive capacity (Cohen and Levinthal, 1990), the firm will find it more difficult, costly, and time-consuming to recognize, evaluate, and retrieve old knowledge that is also far from its knowledge domain. In addition, it may also lack the complementary expertise needed for leveraging old knowledge, which may hinder its successful application (Levinthal and March, 1993). Acquiring unrelated knowledge components may cause information overload, confusion, and diseconomies of scope (Ahuja and Lampert, 2001) since the firm is forced to develop recombinant capabilities using heterogeneous knowledge. Lacking coherent capabilities may limit the innovative use of old knowledge since the firm may be unable to gain by sharing that knowledge across innovations (Perez and Soete, 1988; Nesta and Saviotti, 2005). In fact, acquiring technologically distant knowledge in the U.S. biotechnology industry constrained innovation because of the lack of common knowledge base and inexperience or unfamiliarity with the technology (Phene, Fladmoe-Linquist, and Marsh, 2006). To the extent that the firm relies on old knowledge, it faces even further inexperience and unfamiliarity, which impair innovation as a result of possible misapplication of that knowledge.

Also, technological distance exacerbates the negative effects of the risk of obsolescence inherent in the use of older knowledge. Indeed, the lack of familiarity with distant knowledge will render it more difficult for the firm to search for and find possible alternative uses and combinations that may help to extract all the value potential of aging knowledge and, by doing so, attenuate the overall negative effects that employing older knowledge exerts on the value of innovation. In sum, incorporating technologically distant knowledge is expected to further limit the value of aging knowledge which the firm uses in its innovation efforts.

H2. Reliance on more technologically distant knowledge will linearly decrease the positive effect of the age of knowledge on the value of innovation resulting from that knowledge.

Seeking geographically distant knowledge enables a firm to generate more value from aging knowledge and overcome some of the impediments associated with its use. First, geographical distance tends to enhance the reliability of established knowledge. Since knowledge tend to be first used near to its origin (Jaffe, Trajtenberg, and Henderson, 1993), established knowledge that is also geographically distant is even more likely to have been largely used previously and therefore to have undergone extensive scrutiny.

Second, given that competitors are less likely to import knowledge that is both geographically distant and old, the firm may be further able to mitigate competitive intensity and enhance value creation and appropriation associated with its innovation. Searching for established knowledge across countries decreases the risk of retaliation because competitors may be less likely to introduce across different geographical locations competing innovations that leverage old knowledge.

Third, by incorporating knowledge which is geographically distant, the firm can enhance the uniqueness and distinctiveness of established knowledge, especially if used outside the region from which it originated. While an innovation based on old knowledge is considered less valuable when developed in its country of origin, in other countries such innovation could still be valuable given that the underlying knowledge may be considered relatively novel (Cantwell, 1989). Thus, geographical distance can revitalize old knowledge and enhance its value. Knowledge that is considered common in the country of origin may be perceived as unique when applied in a distant location. Therefore, the fact that established knowledge is new to the region may increase the benefits arising from its incorporation in the firm's innovations. The underlying assumption is that knowledge originating from different countries is distinctive. Research on national innovation systems has demonstrated that different nations develop distinctive technological competencies by leveraging unique knowledge accumulation patterns (Cantwell, 1989). Such specialization derives from the localized nature of knowledge (Jaffe, Trajtenberg, and Henderson., 1993; Audretsch and Feldman, 1996) as well as from firms' tendencies to engage in geographically local search for new knowledge (Rosenkopf and Almeida, 2003). Consequently, the national origin of knowledge is often associated with its distinctive nature (Frost, 2001). Cross-national differences in knowledge characteristics result from distinctive national cultures (Hofstede, 1980), different regulatory systems, peculiar practices and rules, specific national resource endowments, and distinctive industry structure (Porter, 1990). Such cross-national differences can influence both the type of knowledge created and the process by which it is created. Specifically, the cross-national diversity of knowledge has been documented in the biotechnology industry, where firms seek to enrich their knowledge base by expanding abroad in search of knowledge that is not available in their home countries (Florida, 1997; Serapio and Dalton, 1999). In sum, by seeking geographically distant knowledge the firm can enhance the uniqueness of old knowledge that serves in its innovation process. This may be also due to the fact that old knowledge coming from distant countries tend to be more difficult to reproduce because competitors will find such knowledge even more difficult to be found and built upon

Finally, since knowledge is more likely to be first used near to its origin (Jaffe, Trajtenberg, and Henderson, 1993), it is less likely to become obsolete when used in remote distance, thus reducing the risk that building upon established knowledge that turns into core rigidity (Leonard-Barton, 1992) and becomes exposed to competency traps (Levitt and March, 1988). Overall, geographical distance is expected to enhance the value of innovations incorporating established knowledge.

H3. Reliance on more geographically distant knowledge will linearly increase the positive effect of the age of knowledge on the value of innovation resulting from that knowledge.

The Popularity of Knowledge and Innovation Value

Prior research has considered whether the firm has previously used certain knowledge (Katila and Ahuja, 2002) but paid less attention to the extent to which such knowledge has been used by the firm's competitors. The extent to which the knowledge used by the firm has been disseminated and widely used in the firm's industry may have ambivalent effect on the value of the innovations the firm builds on that knowledge. On the one hand, the popularity of knowledge may facilitate the use of related innovations given their market acceptance (Marinova, 2004). On the other hand, this may limit the firm's ability to appropriate value from its innovation as competition that leverages said technology becomes more intense. This negative effect is particularly prevalent when the knowledge is not only popular but also old. As old knowledge disseminates and becomes popular, impediments associated with its possible obsolescence intensify. Given its wide dissemination, the value of innovations relying on that knowledge declines more rapidly as it becomes out-dated. In addition, knowledge that is more diffused tends to be widely available, which declines its distinctiveness thereby reducing its potential contribution to a firm's innovativeness and sustained competitive advantage (Barney, 1991).

Moreover, a firm may face challenges in generating novel combinations of popular knowledge components over time, thus decreasing the value of its innovations (Kogut and Zander, 1992). In fact, following the recombinant view (Schumpeter, 1934; Henderson and Clark, 1990; Galunic and Rodan, 1998; Fleming, 2001), a firm that relies on popular knowledge that is also employed by its competitors is likely to encounter competing innovations which would restrict its ability to appropriate value from its own innovations (Teece, 1986; Winter, 2006; Ceccagnoli, 2009). Naturally, the dissemination of knowledge takes time, so that old and popular knowledge is more susceptible to the hazard of misappropriation by competitors. A firm that incorporates new knowledge gains an early mover advantage whereas a firm that relies on aging knowledge diminishes its ability to benefit from it as the number of firms using that knowledge increases. Thus, the firm may not be able to enjoy the mitigated competitive intensity associated with innovations based on old knowledge.

Finally, popular knowledge contributes to product observability (Zander and Kogut, 1995), since its use is common to a large network of industry competitors. As part of the dissemination process, popular knowledge becomes codified and more explicit, which reinforces the learning cycle associated with established knowledge (Zollo and Winter, 2002). The increased codifiability of old knowledge makes it less difficult to imitate, so that a firm that incorporates popular knowledge in its innovations makes old knowledge less valuable. In sum, the popularity of old knowledge limits it uniqueness and novelty, and thus reduces the overall value of innovations based on that knowledge.

H4. Reliance on more popular knowledge will linearly decrease the positive effect of the age of knowledge on the value of innovation resulting from that knowledge.

METHODS

Research Setting and Data Sample

The U.S. biotechnology industry served as the setting for testing the hypotheses. This industry had its origins in the discovery of the double helix structure of DNA by Watson and Crick in 1953, whereas the foundations of the contemporary biotechnology industry can be traced to a subsequent development 20 years later, with Cohen and Boyer's breakthrough finding on recombinant DNA in 1973. This setting is suitable for our research for several reasons. First, the emergence of biotechnology is considered a radical innovation with respect to the process by which drugs are discovered and developed (Stuart, Hoang, Hybels, 1999). Specifically, it leverages a combination of old and new knowledge and expertise (Rothaermel and Boeker, 2008). Second, this industry relies on multiple technologies, such as molecular biology, immunology, genetics, combinatorial chemistry, and bioinformatics (Sorensen and Stuart, 2000), underscoring the need for searching knowledge across technological domains in order to innovate (Phene, Fladmoe-Lindquist, and Marsh, 2006). Third, besides the technological diversity, the biotechnology industry exhibits geographical diversity, as shown by differences across national systems of biotechnology innovation (Bartholomew, 1997). Finally, previous research has demonstrated that patents are effective means for protecting firms' intellectual property in the biotechnology industry (Albert, Avery, Narin, and McAllister, 1991; Phene Fladmoe-Lindquist, and Marsh, 2006; Rothaermel and Boeker, 2008; Hoang and Rothaermel 2010). This prior research supports our choice to rely on patent-based measures to study the value of innovations.

The data encompasses 358 U.S. firms, both public and private, identified in the BioScan database in 2010. From this population of 358 firms we constructed our sample which included every firm that filed for at least one biotechnology patent at the U.S. Patent and Trademark Office (USPTO) from 1985 to 2002[1].We focused on patents obtained in the U.S. because it represents the largest market for biotechnology worldwide, and thus it is almost compulsory for firms to first patent in the U.S.. The final sample included 284 firms that filed for 5,571 patents (focal patents). The focal patent served as the unit of analysis. For each of the 5,571 focal patents, we identified the cited patents (previously issued patents cited by the focal patents). The total of 51,509 cited patents served for measuring the characteristics of the knowledge that was used for innovation. We also collected data on the 57,470 subsequent patents that cite the focal patents, in order to measure the value of the resulting innovation. We gathered firm level data from multiple sources, including Goliath Company Profiles, World'Vest Base, press releases, and company web sites.

Variables

Dependent variable.

The value of innovation (*InnovationValue*) was measured by the number of forward citations received by a firm's patent until 2009, excluding self-citations (e.g., Cattani, 2005; Singh, 2008). It is important to recognize that, since patents from different years have different 'windows of opportunity' to be cited in our dataset, a direct comparison of patent citations across patents from different years would be inappropriate. To overcome this issue, we follow Jaffe and Trajtenberg (2002) in including year fixed effects and patent age in all regressions, so that systematic cross-year differences are accounted for. Forward citations to a patent serve as a proxy for the value of a specific innovation as captured by industry awards,

[1] The USPTO has assigned the following patent classes to the biotechnology domain: 424 [Drug, bio-affecting and body treating compositions (different sub-classes)], 435 [Chemistry: Molecular biology and microbiology], 436 [Chemistry: Analytical and immunological testing], 514 [Drug, bio-affecting and body treating compositions (different sub-classes)], 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 and Thursby, 2007).

as perceived by technology experts and with respect to its social value (Trajtenberg, 1990). Highly cited patents are also associated with higher profits (Hall, Jaffe, and Trajtenberg, 2005).[2] Two main reasons allow us to believe that citations convey not just technological but also economically significant information. First, patented innovations are for the most part the result of costly R&D conducted by profit seeking organizations. Thus, if firms invest in further developing an innovation disclosed in a previous patent, then the resulting (citing) patents presumably signify that the cited innovation is economically valuable. Second, citations typically keep coming over the long run, thus giving plenty of time to dissipate the original uncertainty regarding both the technological viability and the commercial worth of the cited innovation. Thereby, citations are observed years after the grant of the cited patent, it must be that the latter had indeed proven to be valuable.

Independent variable.

Following Katila (2002), we measured the average age of patents cited by each of the firm's patents, under the assumption that a firm that cites relatively old patents searches for more

[2] Using patents as indicators of innovation may present some methodological problems that need to be considered. First, although patent citations allow tracking knowledge flows among inventions, given that a patent is a complex legal document, several citations are often added by examiners, and thus may not reflect an actual knowledge flow (Alcacer and Gittleman, 2006). Second, real knowledge flows generally occur through a complex interactions involving written and oral communication, teaching, learning, face-to-face interaction, chance meetings, and close working relationships, which may be difficult to track using patent citations (Singh, 2005). Third, 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)). Despite these limitations, patents are still the most commonly used proxy for innovations (e.g. Rosenkopf and Nerkar, 2001; Cattani, 2005; Miller, Fern, and Cardinal, 2007; Singh, 2008), and by including relevant control variables and applying scrutiny in the interpretation of results, we handle some of these limitations. Despite the above limitations, several factors can explain the intensive use of patents (Ratanawaraha and Polenske, 2007). First, patent data are readily available in most countries. Second, the extensiveness of patent data enables researchers to conduct both cross-sectional and longitudinal analysis. Third, patent data contain detailed useful information, such as technological fields, assignees, inventors, and some other market features.

established knowledge. For each patent, the age of searched knowledge (*KnowAge*) was measured as the average number of years elapsed since the filing date of patents cited in the focal patent document. Such backward citations to patents describe technical information or knowledge upon which the focal patent is based (Walker, 1995). Prior research has validated the use of patent citations for capturing firms' knowledge search activities (e.g. Trajtenberg, 1990; Albert, Avery, Narin, and McAllister, 1991). The use of patent citations for measuring the age of searched knowledge is appropriate since citations to prior patents indicate the age of knowledge components incorporated by the focal patent. Furthermore, we take into account the diversity in the knowledge age searched by firms (*KnowAgeDiversity*), measured as the variance in knowledge age for each focal patent (Katila, 2002).

Moderating variables.

We measured moderating variables based on information on backward citations listed in each patent document. Information about 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 popularity. 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, Fladmoe-Lindquist, and Marsh, 2006). Similarly, for each focal patent, the geographical distance (*GeoDist*) of knowledge was measured as the ratio of the number of backward citations whose first inventor's home country was outside the U.S. over the total number of backward citations (Phene, Fladmoe-Lindquist, and Marsh, 2006). Finally, for each focal patent, knowledge popularity (*KnowPopularity*) was measured as the average number of times each cited patent had been previously cited by other firms, excluding self citations (Miller, Fern, and Cardinal, 2007). The technological and geographical distances of knowledge search and knowledge popularity served as moderators of the relationship between the value of innovation and knowledge age.

Control variables.

We incorporated several control variables that may explain the value of the resulting innovations. We controlled for a firm's patent stock (*PatentStock*), which represents the firm's expertise, capability, or propensity to innovate (e.g. Nooteboom, Van Haverbeke, Duysters, Gilsing, and van den Oord, 2007). The firm's patent stock was measured as the number of patents the firm filed with the USPTO during the five years preceding the filing date of a focal patent. In addition, we controlled for the firm's size, which may affect its innovative capability, by computing the natural logarithm of the average number of employees a firm employed during the five years prior to the filing date of each sampled patent (*FirmSize*). This proxy is suitable to describe the firm's size in the biotechnology industry since many firms are yet to show revenues and since their assets are mainly intangible (e.g. Rothaermel and Boeker, 2008). Moreover, the size of the team involved in knowledge development may affect the value of the resulting innovation due to economies of specialization. In fact, larger teams may have access to a wider 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 public status of the firm (*PublicFirm*) using a dummy variable that receives a value of one if the firm is publicly traded in the filing date of its focal patents, zero otherwise. Additionally, we controlled for the firm's business diversification (*BusDiversification*) by counting the number of different time variant SIC codes assigned to the firm at the time of patent filing. Business diversification may indeed impact the firm's ability to innovate (e.g. Hitt, Hoskisson, and Kim, 1994). Next, we controlled for firm age (*FirmAge*) by computing the difference between a firm's year of incorporation and the filing year of a focal patent. Firm age reflects experience with organizational routines that may enhance the efficiency of the innovation process. However, in rapidly changing environments such experience may influence the firm's ability to adapt by nurturing innovative capabilities (Sorensen and Stuart, 2000). Furthermore, we controlled for the firm's innovation experience (*PatentExperience*) (Rothaermel and Boeker, 2008) by counting the number of years elapsed since the firm's first patent was filled with the USPTO until the year 2008. We also controlled for inter-organizational collaboration (*InterOrgCollab*) in the innovations process by counting the number of co-applicants to which the patent was assigned. In addition, we considered also the effects exerted by the different dimensions of search investigated in the literature. As proposed by Capaldo and Messeni Petruzzelli (forthcoming), we measured search span (*SearchSpan*) as the number of different three-digit patent classes assigned to a patent by the U.S.PTO. Search depth and search scope were evaluated adopting the proxies proposed by Katila and Ahuja (2002). Specifically, search depth (*SearchDepth*) was created by calculating, for each focal patent, the number of times that, on the average, each citation in year *t—1* was repeatedly used during the past five years by the firm granted the focal patent. Differently, search scope (*SearchScope*) referred, for each focal patent, to the share of citations that could not be found in the previous five years' list of citations by the firm granted the focal patent. In addition, we controlled for two main variables that are associated with patent value, namely the number of claims per patent (*Claims*) (Lanjouw and Schankerman, 2001) and references to scientific knowledge (*SciKnowledge*), measured by the number of scientific non-patent references each focal patent cites (Narin, Hamilton, and Olivastro, 1997). Still, we controlled for the government's support of the innovation process (*GovInterest*), using a dummy variable that takes a value of one if the patent has been funded by the US government, zero otherwise. This variable indicates whether the innovation is socially relevant. In addition, we measured the age of patents (*PatentAge*) by counting the number of years elapsed since filing a focal patent until the year 2008, thus controlling for the risk that older patent may receive a greater number of forward citations.. Finally, we incorporated year dummies (*Year*) to capture temporal trends.

Analysis

We used a firm's patent as the unit of analysis. Since the dependent variable is a non-negative integer count variable, the negative binomial model is appropriate for estimate it. Unlike the Poisson model which assumes equity between the mean and the variance, patent data typically feature over-dispersion, as evident by the coefficient of variation (standard deviation/mean) that equaled 2.28 in our case. Therefore, the negative binomial model that corrects for such over-dispersion is more suitable since it allows for the variance to differ from the mean (Gourieroux, Monfort, and Trognon, 1984; Hausman, Hall, and Griliches, 1984). We incorporated hierarchical models with Model 1 serving as the baseline model that includes only the control variables, models 2-5 serving as partial models that introduce the independent and each of the moderating variables, and finally, Model 6 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 (Model 6) exceeds the critical value of 10 (Kleinbaum, Lawrence, Muller, and Nizam, 1998). The high VIF values were ascribed to the multiple inclusions of the main effects in the interaction terms and the full model was reported for reference only. No symptoms of multicollinearity were observed given that coefficients and levels of significance remain consistent and stable across models. Missing data were treated with list wise deletion.

<Insert Tables 1-2 about here>

RESULTS

Table 1 reports descriptive statistics and the pairwise correlations across all variables, showing relatively low values, except for *PatentExperience*, *PatentStock*, and *FirmSize*, which are highly correlated. Thereby, in order to avoid multicollinearity concerns, we included in our analysis only the size of biotechnology firms. The results of the negative binomial models are reported in Table 2. Overall, the models suggest a good fit of the negative binomial model to the data. Consistently with prior research, we found that innovation value improves with the age of firm (β=0.002, p<0.01) (Sorensen and Stuart, 2000), its public status (β=0.138, p<0.01), the size of the team of inventors (β=0.032, p<0.001) (Singh, 2008), the number of patent claims (β=0.008, p<0.001) (Lanjouw and Schankerman, 2004), the support of US government (β=0.464, p<0.001), the age of patent (β=0.134, p<0.001) (Reitzig, 2004), and the scientific knowledge referred in the focal patent (β=0.002, p<0.001) (Fleming and Sorenson, 2004). In turn, business diversification (β=-0.044, p<0.01) and patent stock (β=-0.001, p<0.001) (Phene, Fladmoe-Linquist, and Marsh, 2006) negatively affect the development of valuable innovative solutions. Finally, regarding the effects of the different dimensions of search on innovation value, search depth presents an inverted U-shape impact (Katila and Ahuja, 2002), whereas search scope turns to be negative and insignificant, and search span shows a positive relationship (β=0.063, p<0.001) (Lerner, 1994).

Considering the main effects in Model 2, the results reveal that knowledge age has an inverted U-shaped effect on innovation value, in support of Hypothesis 1. Specifically, the linear term *KnowAge* is positive (β=0.055, p<0.001), whereas its squared term is negative (β=-0.003, p<0.001). Thus, beyond a certain threshold, aging knowledge becomes detrimental to the value of a firm's innovations. In addition, Hypothesis 2 gained support as evident by the negative interaction effect of knowledge age and technological distance (β=-

0.057, p<0.01) in Model 3. Similarly, Hypothesis 3 gained some support based on the marginally significant positive interaction of knowledge age and geographical distance (β=0.027, p<0.1), as revealed in Model 4. Finally, referring to Model 5, Hypothesis 4 gained support as indicated by the negative interaction effect of knowledge age and knowledge popularity (β=-2.4e-4, $p < 0.1$).

Figure 1 depicts the predicted innovation value as a function of knowledge age, showing that when knowledge is older than 9.2 years, the costs of using old knowledge outweigh its benefits. Hence, there is a relatively short period in which the value of knowledge increases a bit, followed by a long period of substantial decline in value. This result is in line with prior research that revealed an inverted U-shaped effect of knowledge age on innovation (Katila, 2002; Nerkar, 2003). Figures 2-4 show simple slope analyses using minimum and maximum levels of the moderating variables. Figure 2 reveals the negative moderating effect of technological distance on the relationship between knowledge age and innovation value. This figure shows how at maximum technological distance the value of knowledge diminishes monotonically with its age as opposed to the value of knowledge at minimum technological distance which reaches a maximum at the age of 14.5 years. Figure 3 shows how geographical distance defers the threshold levels beyond which knowledge age undermines innovation value. In this case, maximum innovation value is reached at the age of 14.2 years for maximum geographical distance. Finally, Figure 4 depicts the moderating effect of knowledge popularity on knowledge age. Whereas the value of knowledge appreciates with age up to a threshold level of 12.5 years under the minimum popularity condition, in the maximum popularity condition, the value of knowledge only decreases with age quite rapidly.

<Insert Figures 1-4 about here>

We conducted several auxiliary analyses to test the robustness of our findings by considering alternative operationalizations of our variables and implementing alternative model specifications. First, we included in the models the interactions between the squared term of knowledge age and the three moderating variables (*TechDist*, *GeoDist*, and *KnowPopularity*). These interactions turned out insignificant, suggesting that technological distance, geographical distance, and knowledge popularity affect only the linear trajectory of the function without changing the shape of the association between innovation value and knowledge age. We did not include these terms in the reported tables to avoid potential multicollinearity. Second, we provided alternative measures of both *TechDist* and *GeoDist*. The former was measured taking into account the number of non-bio technological classes over the total number of technological classes for each cited patent. Then, we evaluated an average value over the total number of backward citations for each focal patent. Following this operationalization, Hypothesis 1 found only partial support, since the interaction term between *KnowAge* and *TechDist* was negative but not significant. The latter was measured as the natural logarithm of the distance (in miles) between points of geographic origin (defined as the address of the first inventor) (Singh, 2008) for each pair of focal and cited patent. Then, we calculated the average distance over the total number of backward citations for each focal patent. In this case, Hypothesis 2 remained confirmed (β=0.038, $p < 0.1$). Third, we investigated the impact exerted by the cultural dimension of geographical origin on the relationship between knowledge age and innovation value. Specifically, for each focal patent, we computed the average cultural distance (*CultDist*) between U.S. and the country of origin of each first inventor of corresponding backward citations using Kogut and Singh's (1988) composite index of Hofstede (1980). Results show that the interaction between *KnowAge* and *CultDist* is positive and significant (β=0.012, $p < 0.1$). Fourth, we included as control *PatentStock* and *PatentExperience* instead of *FirmSize*, separately. In both the cases, hypotheses are supported. Finally, we incorporated firm fixed effects to account for remaining unobserved heterogeneity. Overall, these auxiliary analyses allow us to be confident in our reported findings.

DISCUSSION AND IMPLICATIONS

This study offers theory and evidence on the contingent value of knowledge age, thus reconciling some mixed findings in prior research. Our findings suggest that the value of innovation increases with the age of knowledge upon which it is based up to threshold level following which it declines. The initial appreciation in value is ascribed to the time needed for knowledge to prove useful and valuable as its development and refinement may enhances its reliability. As knowledge matures, this also limits the intensity of competition since competitors may adopt new knowledge instead. Furthermore, the difficulty of finding and incorporate old knowledge may enhance its distinctiveness and hence the value of innovation incorporating such knowledge. Nevertheless, as knowledge continues to age beyond a certain level, it may become obsolete and diminish the value of corresponding innovations. The challenges of retrieving, comprehending, and applying old knowledge become exorbitant and the firm may face misappropriation problems. Hence, an optimal timing exists for incorporating knowledge in order to enhance the value of innovations.

Our findings further indicate that the desirable age of knowledge is contingent on a variety of factors such as its origin and popularity. Specifically, the more remote the knowledge from the firm's domain of technological expertise, the more difficult it is for the firm to extract value from relatively old knowledge. Limited absorptive capacity (Cohen and Levinthal, 1990) and increasing impediments of searching, internalizing, and leveraging such knowledge depreciate its value. However, the firm can offset this cost by seeking geographically distant knowledge that can rejuvenate old knowledge and enhance the firm's ability to appropriate value from innovations based on relatively established knowledge. This effect is ascribed to the diffusion of knowledge away from origin, so that it is considered relatively novel in the firm’s target markets. Finally, our findings suggest that as knowledge becomes diffused and incorporated by many firms, it loses its uniqueness and novelty, thus undermining the value of old knowledge. Hence, as knowledge becomes popular, firms are advised to promptly leverage it instead of witnessing its dissemination. The above contingencies suggest that firms should determine the timing of adopting external knowledge based on its technological and geographical origins as well as on the pace of its adoption in their industry. Careful consideration of these contingencies should allow the firm to decide whether to adopt external knowledge as soon as it becomes publicly available or rather wait until its value is enhanced, it gains reliability, and faces limited competition.

Implications for Theory and Research

Our study contributes to the knowledge management literature by offering a comprehensive account of the value of temporal search. Complementing research on the innovation process (Kogut and Zander, 1992; Fleming, 2001) and knowledge search (Rosenkopf and Nerkar, 2001; Katila and Ahuja, 2002), we reveal the contingent value of search in time. We demonstrate that the value of temporal search can be assessed only when considering the type of knowledge sourced (Katila, 2002). To assess the value of old knowledge, one needs to trace its technological and geographical origins and consider its diffusion in the industry. There is an optimal age beyond which the value of knowledge depreciates, but that age is lower when the firm searches in remote technological fields. Conversely, a firm can rejuvenate old knowledge and enhance the value of innovation to the extent that it imports it from remote countries. Therefore, the age of knowledge has different value creation potential in different locations, so that firms that are late to market with their innovation can still appropriate value to the extent that they extend the international search for knowledge sources. Further interfirm heterogeneity is ascribed to the distinctive knowledge bases of firms as evident by the technological distance contingency that diminishes the value of old knowledge for which the firm cannot effectively leverage its existing expertise. Finally, our study uncovers the important boundary condition of competition, which has been often overlooked in prior research. We demonstrate that the firm's innovation efforts do not occur in a vacuum and that the value of knowledge depreciates faster with age to the extent that larger numbers of firms incorporate such knowledge in their innovations. When competition intensifies, the innovative potential of knowledge declines much faster and firms are advised to invest in new knowledge creation rather than in recombination of old knowledge.

Our study contributes to the emerging literature on knowledge search by shedding new light on the association between temporal search and innovation. Prior research has paid attention mostly to other dimensions of search, such as a firm's tendency to rely on internal versus external knowledge (e.g. Laursen and Salter, 2005), engage in distant versus local search for technological competences (e.g. Rosenkopf and Nerkar, 2001; Katila and Ahuja, 2002), and to the tendency to span across multiple knowledge domains (Capaldo and Messeni Petruzzelli, forthcoming). Less attention has been paid to the temporal dimension of the search process, with the few relevant studies showing mixed findings. Our study reconciles these mixed findings by underscoring the contingent value of knowledge. In accordance with prior research we show that old knowledge enhances innovativeness up to a certain threshold beyond which its value diminishes (Katila, 2002; Nerkar, 2003; Heeley and Jacobson, 2008). However,, we also add that the value of old knowledge depends on its origin and popularity, with some conflicting implications depending on whether the firm outreaches on the technological versus geographical dimensions of search. The origins of knowledge matter for both the novelty of knowledge and the firm's ability to absorb it (e.g. Phene, Fladmoe-Lindquist, and Marsh, 2006). In turn, the popularity of knowledge affects its uniqueness and the firm's ability to appropriate value from its innovations.

Our study also informs research on balancing exploration and exploitation (March, 1991; Gupta, Smith, and Shalley, 2006) by demonstrating how such balance can be achieved when firms search for knowledge over time. Counter to the temporal separation approach for balance (Brown and Eisenhardt, 1997) that calls for focusing on either exploration or exploitation at a given time, our findings advocate the reliance on intermediately aged knowledge that corresponds to balance in the temporal dimension. Furthermore, in line with the domain separation approach (Lavie and Rosenkopf, 2006; Lavie, Kang, and Rosenkopf, forthcoming) and the ambidexterity literature (He and Wong, 2004; O'Reilly and Tushman, 2007; Rothaermel and Alexandre, 2009), our study calls for balance across the technological and geographical domains, since a firm is advised to search proximately in the technological domain and span boundaries in the geographical dimension. In this sense, our study calls for balancing geographical exploration with technological exploitation as the firm searches for old knowledge.

Finally, our study advances research on absorptive capacity (Cohen and Levinthal, 1990; Zahra and George, 2002; Lane, Koka, and Pathak, 2006) by noting the limitations of relying on external knowledge that differs from the firm's own knowledge base. Specifically, we demonstrate that even if external knowledge is well established in the market its absorption remains challenging to the extent that the firm lacks a related knowledge base. These challenges of incorporating and applying old knowledge are ascribed to misinterpretation, misunderstanding, and misapplication of such knowledge that amount with the technological distance between such external knowledge and the firm's domain of expertise. In fact, our findings reveal that when the firm moves beyond its technological domain in search for established knowledge, the value of such knowledge quickly diminishes.

Managerial Implications

Our study offers several practical implications. By examining how old knowledge enhances the value of innovation, we encourage managers to consider not only the type of knowledge that they use but also its birthdate and birthplace. Old knowledge is not necessarily less valuable, yet its value depends on how remote it is from the firm's current knowledge base and country of origin. To innovate effectively, managers need to assess the origin of knowledge and how diffused it is. Investing in search for knowledge pays off only if one carefully designs its search strategy. Old knowledge is most valuable when it is technically close to the firm's expertise but geographically remote from where it originated. In this sense, our findings depart from traditional research on absorptive capacity (Lundvall and Johnson, 1994; Phene, Fladmoe-Linquist, and Marsh, 2006) that underscored the value of proximity irrespective of the search dimension. Furthermore, our findings reveal that it is necessary to balance exploration and exploitation since the value of innovation is maximized when the firm engages in distant search in the geographical domain (i.e., exploration) while investing in local search in the technological domain (i.e., exploitation).

Future Research Directions

Our study makes important strides in advancing the learning and innovation literature, yet leaves room for future research. First, even though patent data have been used extensively in the innovation literature, they cannot fully capture an innovation's value. Patents represent only a subset of a firm's technologies and capabilities employed in the innovation process. Some knowledge is not patentable or a firm may rely on alternative means for protecting its knowledge (de Faria and Sofka, 2010). In addition, not all patent citations suggest desirable incorporation of prior knowledge. In some cases a firm may resort to established knowledge instead of generating new knowledge. Indeed, pathbreaking innovations may not involve extensive citations to historical patents. Furthermore, the decision to cite a patent may be made by the examiner rather than by the firm, so the extent to which such knowledge indeed informs the firm's innovation is questionable (e.g. Gittelman, 2008). Still, patent citations are the most robust measure available for capturing the value of innovation. Future research may identify alternative proxies that shed more light on some other innovation outcomes such contribution to society. It may also be interesting to examine the contribution of knowledge not only to the value of innovation but also to firms' productivity. Given the gap between knowledge creation and application, future research may examine how innovations lead to product development. In addition, we focused on the technological and geographic origins of knowledge, but future research may consider additional dimensions of search. Whereas we focused on the implications of competition by studying the popularity of knowledge, future research may as well incorporate the effects of collaboration in driving knowledge creation and application (Lavie and Drori, forthcoming). Scholars may also focus on the mechanisms that enable firms to effectively integrate old knowledge in their innovation efforts. Perhaps the value of innovation depends on the effectiveness of these processes irrespective of the origin of knowledge. Finally, future research may assess the generalizability of our findings by extending our inquiry to other industries and countries.

REFERENCES

Achilladelis, B., Schwarzkopf, A., Cines, M. 1999. The dynamics of technological innovation: The case of the chemical industry. *Research Policy*, **19**: 1-34

Adner, R., Snow, D. 2010. Old technology responses to new technology threats: Demand heterogeneity and technology retreats. *Industrial and Corporate Change*, **19**: 1655-1675.

Ahuja, G., Lampert, C. M. 2001. Entrepreneurship in the large corporation: A longitudinal study of how established firms create breakthrough inventions. *Strategic Management Journal*, **22**: 521-543.

Albert, M.B., Avery, D., Narin, F., McAllister, P. 1991. Direct validation of citation counts as indicators of industrially important patents. *Research Policy*, **20**: 251–259.

Alcacer, J., Gittleman, M., 2006. How do I know what you know? Patent examiners and the generation of patent citations. *Review of Economics and Statistics*, **88**: 774–779.

Argote, L. 1999. *Organizational learning: Creating, retaining and transferring knowledge*. Boston: Kluwer.

Audretsch, D.B., Feldman, M.P., 1996. R&D spillovers and the geography of innovation and production. *American Economic Review*, **86**: 630-640.

Barney, J. 1991. Firm resources and sustained competitive advantage. *Journal of Management*, **17:** 99-121.

Bartholomew, S. 1997. National systems of biotechnology innovation: Complex interdependence in the global system. *Journal of International Business Studies* **28**: 241-266.

Benner, M.J., Tushman, M. 2002. Process management and technological innovation: A longitudinal study of the photography and paint industries. Administrative Science Quarterly **47**: 676-706.

Brown, S.L., Eisenhardt, K.M. 1997. The art of continuous change: Linking complexity theory and timepaced evolution in relentlessly shifting organizations. *Administrative Science Quarterly*, **42**: 1–35.

Cantwell, J. 1989. *Technological Innovations and Multinational Corporations*. Blackwell, Cambridge.

Cantwell, J., Janne, O. 1999. Technological globalization and innovative centres: the role of corporate technological leadership and locational hierarchy. *Research Policy*, **28**: 119–144.

Capaldo, A., Messeni Petruzzelli, A. 2011. forthcoming. In search of alliance-level relational capabilities. Balancing innovation value creation and appropriability in R&D alliances. *Scandinavian Journal of Management*, forthcoming.

Cattani, G. 2005. Preadaptation, firm heterogeneity, and technological performance: a study on the evolution of fiber optics, 1970–1995. *Organization Science*, **16**: 563-580.

Ceccagnoli, M. 2009. Appropriability, preemption, and firm performance. *Strategic Management Journal*, **30**:81-98.

Chung, W., Alcacer, J. 2002. Knowledge seeking and locational choice of foreign direct investment in the United States. *Management Science,* **48**: 1534–1554.

Cohen, W., and Levinthal, D. 1990. Absorptive capacity: a new perspective on learning and innovation. *Administrative Science Quarterly,* **35**: 128-152.

Cyert, R.M., March, J.G. 1963. *A Behavioral Theory of the Firm*. Prentice Hall: Englewood Cliffs.

de Faria P., Sofka, W. 2010. Knowledge protection strategies of multinational firms—A cross-country comparison. *Research Policy*, **39**: 956-968.

Eisenhardt, K. 1989. Making fast strategic decisions in high-velocity environments. *Academy of Management Journal*, **32**: 543-576.

Fleming, L. 2001. Recombinant uncertainty in technological search. *Management Science*, **47**: 117-132.

Fleming, L., Sorenson, O. 2004. Science as a map in technological search. *Strategic Management Journal*, **25**, 909–928.

Florida, R. 1997. The globalization of R&D: results of a survey of foreign-affiliated R&D laboratories in the USA. *Research Policy,* 26: 85–103.

Freddi, D. 2009. The integration of old and new technological paradigms in low- and medium-tech sectors: the case of mechatronics. *Research Policy* **38**: 548-558.

Frost, T. 2001. The geographic sources of foreign subsidiaries innovations. *Strategic Management Journal*, **22**: 101–123.

Galunic, D., Rodan, S. 1998. Resources recombinations in the firm: knowledge structure and the potential for Schumpeterian innovation. *Strategic Management Journal* **19**: 1193-1201.

Gavetti, G. Levinthal, D. 2000. Looking forward and looking backward: Cognitive and experiential search. *Administrative Science Quarterly*, **45**: 113-137.

Gilfillan, S.C.. 1935. *Inventing the Ship*. Follett Publishing, Chicago.

Gittelman, M. 2008. A note on the value of patents as indicators of innovation: Implications for management research. *Academy of Management Perspectives*, **22**: 21–27.

Giuri, P., Mariani, M., Brusconi, S., Crespi, G., Francoz, D., Gambardella, A., Garcia-Fontes, W., Geuna, A., Gonzales, R., Harhoff, D., Hoisl, K., Le Bas, C., Luzzi, A., Magazzini, M., Nesta, L., Nomaler, O., Palomersa, N., Patel, P., Romanelli, M., Verspagen, B. 2007.

Inventors and invention processes in Europe: results from the PatVal-EU survey. *Research Policy*, **36**: 1107-1127.

Gourieroux, C., Monfort, A., Trognon, A. 1984. Pseudo maximum likelihood methods: theory. *Econometrica*, **52**: 681–700.

Grimpe, C., Sofka, W. 2009. Search patterns and absorptive capacity: Low and high-technology sectors in European countries. *Research Policy* **38**: 495-506.

Gupta, A.K., Smith, K.G., Shalley, C.E. 2006. The interplay between exploration and exploitation. *Academy of Management Journal*, **49**: 693-706.

Hagedoorn, J. 2002. Inter-firm R&D partnerships: an overview of major trends and patterns since 1960. *Research Policy*, **31**, 477-492.

Hall, B.H., Jaffe, A.B., and Trajtenberg, M. 2005. Market value and patent citations. *RAND Journal of Economics*, **36**: 16-38.

Harhoff, D., Scherer, F.M., Vopel, K. 2003. Citations, family size, opposition and the value of patent rights. Research Policy, **32**: 1343-1363.

Hausman, J., Hall, B., Griliches, Z. 1984. Econometric models for count data with an application to the patents-R&D relationship. *Econometrica* **52**: 909-938.

He, Z., Wong, P. 2004. Exploration vs. exploitation: An empirical test of the ambidexterity hypothesis. *Organization Science*, **15**: 481-494.

Heeley, M.B., and Jacobson, R. 2008. The recency of technological inputs and financial performance. *Strategic Management Journal*, **29**: 723-744.

Henderson, R.M., Clark, K.B. 1990. Architectural innovation: the reconfiguration of existing product technologies and the failure of established firms. *Administrative Science Quarterly*, **35**: 9-30.

Hilson, G., Khurana R. Environmental control systems and Y2K. *Journal of Cleaner Production*, **7**: 359-364.

Hitt, M.A., Hoskisson, R.E., Kim,H. 1997. International diversification: effects on innovation and firm performance in product-diversified firms. *Academy of Management Journal*, **40**: 767-798.

Hoang, H., Rothaermel, F.T. 2010. Leveraging internal and external experience: Exploration, exploitation, and R&D project performance. *Strategic Management Journal*, **31**: 734-758. Hofstede, G. 1980. *Culture's Consequences: International Differences in Work-related Values*. Beverly Hills, CA: Sage.

Hofstede, G. 1980. *Culture's Consequences_ International Differences in Work-Related Value*. Sage Publications, Beverly Hills, CA.

Jaffe, A.B., Trajtenberg M. 2002. Patents, citations, and innovations: a window on the knowledge economy. MIT Press: Cambridge.

Jaffe, A.B., Trajtenberg, M., Henderson, R. 1993. Geographic localization and knowledge spillovers as evidenced by patent citations. *Quarterly Journal of Economics*, **108**: pp. 577-598.

Katila, R. 2002. New product search over time: past ideas in their prime? *Academy of Management Journal*, **45**: 995-1010.

Katila, R., Ahuja, G. 2002. Something old, something new: A longitudinal study of search behavior and new product introduction. *Academy of Management Journal*, 45, 1183-1194.

Katila, R., and Chen, E.L. 2008. Effects of search timing on innovation: the value of not being in sync with rivals. *Administrative Science Quarterly,* **53**: 593-625.

Katz, D., Kahn, R. 1996. *The Social Psychology of Organizations.* New York: Wiley.

Kim, L. 1997. The dynamics of Samsung's technological learning in semiconductors. *California Managament Review*, **39**: 86-100.

Kleinbaum, D. G., L. K. Lawrence, K. E. Muller, A. Nizam. 1998. *Applied Regression Analysis and Other Multivariable Methods*. Brooks/Cole: Pacific Grove, CA.

Kogut, B., H. Singh. 1988. The effect of national culture on the choice of entry mode. *Journal of International Business Studies,* **19**:411–432.

Kogut, B., Zander, U. 1992. Knowledge of the firm, combinative capabilities, and the replication of technology. *Organization Science*, **3**: 383-397.

Lane, P.J., Koka, B.R., Pathak, S. 2006. The reification of absorptive capacity: a critical review and rejuvenation of the construct. *Academy of Management Review*, **31**: 833-863.

Lanjouw, J.O., Schankerman, M. 2004. Patent quality and research productivity: measuring innovation with multiple indicators. *The Economic Journal,* **114**: 441-465.

Laursen, K., and Salter, A. 2006. Open for innovation: the role of openness in explaining innovation performance among U.K. manufacturing firms. *Strategic Management Journal,* **27**: 131-150.

Lavie, D., Drori, I. Forthcoming. Collaborating for knowledge creation and application: the case of nanotechnology research centers, *Organization Science.*

Lavie, D., Kang, J., Rosenkopf, L. Forthcoming. Balance within and across domains: the performance implications of exploration and exploitation in alliances, *Organization Science*.

Lavie, D., Rosenkopf., L. 2006. Balancing exploration and exploitation in alliance formation. *Academy of Management Journal*, **49**: 797-818.

Leonard-Barton, D. 1992. Core capabilities and core rigidities: A paradox in managing new product development. *Strategic Management Journal*, **13**: 111-125.

Levinthal, D., March, J. 1993, The myopia of learning. *Strategic Management Journal*, **14**: 95-113.

Levitt, B., March, J. 1988, Organizational learning. In J., Blake and J. Hagan (Eds.), *Annual review of sociology*. Greenwich, GT: JAI Press.

March, J., 1991. Exploration and exploitation in organizational learning. *Organization Science,* **2***:* 71-87.

March, J., Simon, H.A. 1958. *Organizations*. Wiley, New York.

March, J., Sproull, S.,, Tamuz, M. 1991. Learning from samples of one and fewer. *Organization Science,* **2***:* 1-13.

Marinova, D. 2004. Actualizing innovation effort: The impact of market knowledge diffusion in a dynamic system of competition. *Journal of Marketing*, **68**: 1-20.

Miller, D.J., Fern, M. J., Cardinal, L.B. 2007. The use of knowledge for technological innovation within diversified firms. *Academy of Management Journal*, **50**: 307-326

Narin, F., Hamilton, K.S., Olivastro, D. 1997. The increasing linkage between U.S. technology and public science. *Research Policy*, **26**: 313-330.

Nelson, R., Winter, S. 1982. *An Evolutionary Theory of Economic Change*. Harvard University Press, Cambridge.

Nerkar, A. 2003. Old is gold? The value of temporal exploration in the creation of new knowledge. *Management Science* **49**: 211-229.

Nesta, L., Saviotti, P.P. 2005. Coherence of the knowledge base and the firm’s innovative performance: evidence from the U.S. pharmaceutical industry. *Journal of Industrial Economics*, **53**: 123-142.

Nooteboom, B., Van Haverbeke, W., Duysters, G., Gilsing, V., and van den Oord, A. 2007. Optimal cognitive distance and absorptive capacity. *Research Policy*, **36**: 1016-1034.

O’Reilly III, C.A., Tushman, M.L. 2004. The ambidextrous organization. *Harvard Business Review*, **82**: 74–81.

Perez, C, Soete, L. 1988. Catching up in technology: entry barriers and windows of opportunity. In: Dosi, G. *et al*. (eds) Technical change and economic theory. Pinter: London, pp 458-479.

Phene A, Fladmoe-Lindquist K, Marsh L. 2006. Breakthrough innovations in the U.S. biotechnology industry: the effects of technological space and geographic origin. *Strategic Management Journal* **27**: 369-388.

Porter, M.E. 1990. *The Competitive Advantage of Nations*. Free Press: New York.

Prahalad, C.K., Hamel, G. 1990. The core competence of the corporation. *Harvard Business Review* **68**: 79-91.

Ratanawaraha, A., Polenske, K.R. 2007. Measuring the geography of innovation: a literature review. In Polenske, K.P. (ed.) *The Economic Geography of Innovation.* Cambridge, UK, Cambridge University Press.

Reitzig, M. 2004. Improving patent valuations for management purposes—validating new indicators by analyzing application rationales. *Research Policy*, **33**: 939-957.

Rivkin, J.W. 2001. Reproducing knowledge: replication without imitation at moderate complexity. *Organization Science*, **12**: 274-293.

Rivkin, J.W., 2000. Imitation of complex strategies. *Management Science* **46**: 824-844.

Rosenkopf L., Nerkar A. 2001. Beyond local search: boundary-spanning, exploration, and impact in the optical disc industry. *Strategic Management Journal* **22**: 287-306.

Rosenkopf, L., Almeida, P. 2003. Overcoming local search through alliances and mobility. *Management Science*, **49**: 751-766.

Rotahermel, F., Alexandre, M.T. 2009. Ambidexterity in technology sourcing: the moderating role of absorptive capacity. *Organization Science*, **20**: 759-780.

Rothaermel, F.T., Boeker, W. 2008. Old technology meets new technology: complementarities, similarities, and alliance formation. *Strategic Management Journal*, **29**: 47-77.

Schumpeter, J. 1934. *Theory of Economic Development*. Harvard University Press, Cambridge.

Serapio, M.G., Dalton, D.H. 1999. Globalization of industrial R&D: an examination of foreign direct investments in R&D in the United States. *Research Policy*, **28**: 303–316.

Singh, J. 2005. Collaborative networks as determinants of knowledge diffusion patterns. *Management Science*, **51**: 756-770.

Singh, J. 2008. Distributed R&D, cross-regional knowledge integration and quality of innovative output. *Research Policy*, **37**: 77-96.

Smith, K., Grimm, G., Gannon, M., Ghen, M.-J. 1991. Organizational information processing, competitive responses, and performance in the U.S. domestic airline industry. *Academy of Management Journal*, **34**: 60-85.

Sorensen, J., Stuart, T. 2000. Aging, obsolescence, and organizational innovation. *Administrative Science Quarterly*, **45**: 81-112.

Stuart T. E. and Podolny J. M. 1996. Local search and the evolution of technological capabilities. *Strategic Management Journal* **17**: 21-38.

Stuart TE, Hoang H, Hybels RC. 1999. Interorganizational endorsements and the performance of entrepreneurial ventures. *Administrative Science Quarterly*, **44**: 315–349.

Szulanski, G. 1996. Exploring internal stickiness: Impediments to the transfer of best practices within the firm. *Strategic Management Journal*, **17** Winter Special Issue: 27-44.

Teece, D.J. 1986. Profiting from technological innovation: Implications for integration, collaboration, licensing and public policy. *Research Policy,* **15**: 285–305.

Teece, D.J., Pisano, G., Shuen, A. 1997. Dynamic capabilities and strategic management. *Strategic Management Journal*, **18**: 509-533.

Trajtenberg, M. 1990. A penny for your quotes: patent citations and the value of innovations. *RAND Journal of Economics,* **21**: 172-187.

van de Vrande, V., Vanhaverbeke, W. and Duysters, GM. Forthcoming. Technology in-sourcing and the creation of pioneering technologies. *The Journal of Product Innovation Management*..

Walker, R. 1995. *Patents as scientific and technical literature.* Metunchen, NJ: Scarecrow Press.

Watson, J.D., Crick, F. 1953. Molecular structure of nucleic acids: A structure for deoxyribose nucleic acid. *Nature*, **171**: 737-738.

Winter, S.G. 2006. The logic of appropriability: from Schumpeter to Arrow to Teece. *Research Policy* **35**: 1100-1106.

Zahra, S.A., George, G. 2002. Absorptive capacity: a review, reconceptualization, and extension. *Academy of Management Review*, **27**: 185-203.

Zander, U., Kogut, B. 1995. Knowledge and the speed of the transfer and imitation of organizational capabilities: An empirical test. *Organization Science,* **6**: 76-92.

Zhou, K.Z., Yim, C.K., Tse, D.K. 2005. The effects of strategic orientations on technology- and market-based breakthrough innovations. *Journal of Marketing***, 69**: 42-60.

Zollo, M., Winter, S.G. 2002. Deliberate learning and the evolution of dynamic capabilities. *Organization Science*, **13**: 339-351.

TABLES AND FIGURES

Table 1. Descriptive statistics and bivariate correlation matrix (*n* = 5,571).

Variables	Mean	St.Dev.	Min	Max	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
1. InnovationValue	10.308	23.539	0	518	1.00																			
2. KnowAge	5.959	4.246	0	34	-.006	1.00																		
3. TechDist	.085	.188	0	1	.077*	.223*	1.00																	
4. GeoDist	.183	.256	0	1	.014	.310*	.124*	1.00																
5. KnowPopularity	16.589	34.622	0	1141	.003	.333*	.047*	-.037*	1.00															
6. PatentStock	111.673	131.653	0	531	-.134*	.029*	-.188*	-.067*	.060*	1.00														
7. FirmSize	6.782	2.395	0	11.983	.028	-.017	-.134*	-.005	.031*	.495*	1.00													
8. TeamSize	3.017	2.024	1	27	.009	.028*	.037*	.073*	-.021	.005	-.028*	1.00												
9. PubFirm	.615	.491	0	1	.036*	-.026*	.049*	.023	-.043*	-.175*	-.104*	.115*	1.00											
10. BusDiversification	2.663	1.220	1	15	-.022	.010	-.030*	.017	.038*	.151*	.271*	-.019	.234*	1.00										
11. FirmAge	19.635	21.414	0	137	-.073*	-.034*	-.141*	-.114*	.038*	.447*	-.114*	-.146*	-.480*	.150*	1.00									
12. PatentExperience	9.249	5.963	0	26	-.131*	.066*	-.201*	-.053*	.039*	.772*	.612*	-.038*	-.212*	.155*	.550*	1.00								
13. InterOrgCollab	1.099	.316	0	1	-.003	-.032*	-.003	.002	-.034*	-.017	-.006	.216*	.062*	-.014	-.066*	-.019	1.00							
14. Claims	20.189	21.862	0	683	.037*	.001	.028	.021	.024	.000	-.083*	.117*	.086*	.059*	-.082*	-.125*	.011	1.00						
15. ScieKnowledge	31.552	48.808	0	438	.028*	.179*	.031*	.049*	.148*	.067*	.025	.077*	.107*	.007	-.089*	.032*	.041*	.104*	1.00					
16. GovInterest	.033	.179	0	1	.064*	-.016	.056*	-.013*	.035*	-.067*	-.085*	.104*	.044*	-.035*	-.082*	-.092*	.170*	.012	.019	1.00				
17. PatentAge	11.563	3.862	5	23	.269*	-.015*	-.090*	.010	-.105*	-.269*	.210*	-.125*	-.060*	-.004	-.085*	-.166*	-.008	-.144*	-.053*	-.012	1.00			
18. SearchSpan	2.265	.994	1	8	.075*	.009	.138*	.026	.028*	.050*	.046*	.071*	-.003	-.011	.021	.022	.032*	.062*	.058*	.012	-.005	1.00		
19. SearchDepth	2.640	9.475	0	106	-.044*	.180*	-.028*	-.100	.356*	.235*	.098*	-.110*	-.151*	.033*	.344*	.187*	-.049*	.005	.035*	-.008	-.144*	.011	1.00	
20. SearchScope	.478	.428	0	1	.028*	.151*	.122*	.232*	-.064*	-.181*	-.108*	.057*	-.021	-.044*	-.126*	-.184*	.032*	.048*	-.114*	-.003	.115*	-.006	-.235*	1.00

*$p < 0.05$.

Table 2. Negative binomial regression models.

Dependent variable: InnovationValue	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
KnowAge		.055*** (.011)	.054*** (.012)	.058*** (.012)	.050*** (.012)	.053*** (.012)
KnowAge^2		-.003*** (.001)	-.002*** (.000)	-.003*** (.000)	-.002*** (.000)	-.003*** (.000)
KnowAge x TechDist			-.057** (.026)			-.056** (.025)
KnowAge x GeoDist				.027† (.017)		.022† (.011)
KnowAge x KnowPopularity					-2.4e-4† (.000)	-1.8e-4† (.000)
TechDist	.892*** (.113)	.827*** (.114)	1.258*** (.235)	.826*** (.114)	.818 (.111)***	1.250*** (.235)
GeoDist	-.049† (.022)	-.113† (.079)	-.112† (.076)	-.295* (.145)	-.118† (.079)	-.269† (.147)
KnowPopularity	.002† (.000)	.002† (.000)	.002† (.000)	.002† (.000)	.003* (.002)	.003† (.002)
KnowAgeDiversity	-	.003*** (.001)	.003*** (.001)	.003*** (.001)	.003*** (.001)	.003*** (.0011)
Claims	.008*** (.001)	.008*** (.001)	.008*** (.001)	.008*** (.001)	.008*** (.001)	.008*** (.001)
GovInterest	.464*** (.098)	.465*** (.098)	.449*** (.098)	.466*** (.098)	.454*** (.098)	.443*** (.098)
SciKnowledge	.002*** (.000)	.002*** (.000)	.002*** (.000)	.002*** (.000)	.002*** (.000)	.002*** (.000)
InterOrgCollab	-.095 (.058)	-.094 (.058)	-.096 (.058)	-.095 (.058)	-.092 (.058)	-.097 (.058)
TeamSize	.032***(.009)	.032***(.009)	.032***(.009)	.032***(.009)	.032*** (.009)	.033***(.009)
PatentAge	.134*** (.030)	.138 (.030)***	.140*** (.030)	.140*** (.030)	.138*** (.030)	.141*** (.030)
PubFirm	.138** (.044)	.141** (.044)	141** (.044)	.138** (.044)	.141** (.044)	.138** (.044)
BusDiversification	-.044** (.015)	-0.46** (.015)	-.045** (.015)	-.045*** (.015)	-.045*** (.015)	-.043** (.015)
FirmAge	.002** (.001)	.003** (.001)	.003** (.001)	.003** (.001)	.003** (.001)	.003** (.001)
FirmSize	.047*** (.011)	.049*** (.011)	.049*** (.011)	.048*** (.011)	.048*** (.011)	.048*** (.011)
SearchSpan	.063*** (.018)	.063*** (.018)	.064*** (.018)	.064*** (.018)	.063*** (.018)	.064*** (.018)
SearchDepth	.021*** (.006)	.014*** (.006)	.014*** (.006)	.015*** (.006)	.013*** (.006)	.014*** (.006)
SearchDepth^2	-.0003*** (.000)	-.0002*** (.000)	-.0002*** (.000)	-.0002*** (.000)	-.0002*** (.000)	-.0002*** (.000)
SearchScope	-.042 (.048)	-.042 (.048)	-.046 (.048)	-.037 (.048)	-.043 (.048)	-.043 (.048)
Years	Included	Included	Included	Included	Included	Included
Likelihood ratio test (χ2)	1448.43***	1469.51***	1474.48***	1471.70***	1472.81***	1478.65***
Improvment over base model ($\Delta\chi$2)		21.08***	26.05***	23.27	24.38	30.22
No. of Obs.	5,571	5,571	5,571	5,571	5,571	5,571

Huber-White robust standard errors are reported in parentheses.

*†< 0.1; *p < 0.05; **p < 0.01; ***p < 0.001.*

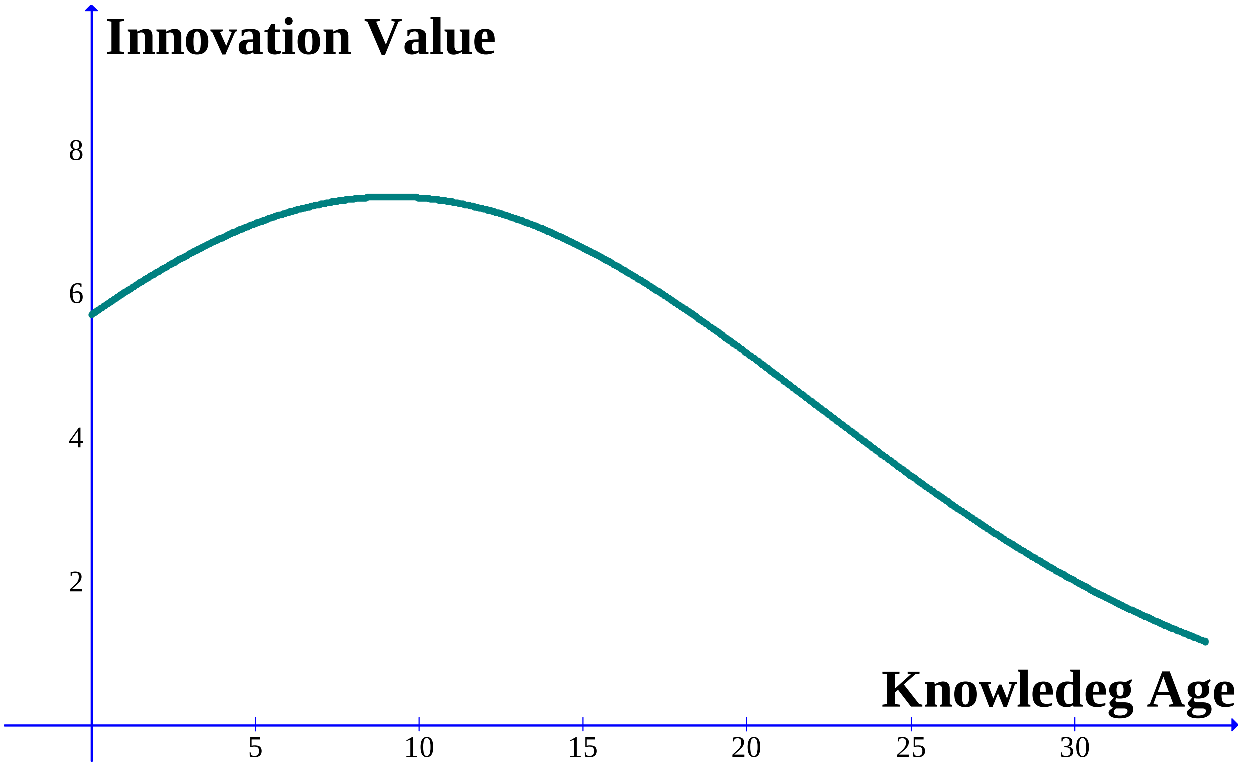

Figure 1. Knowledge age and innovation value.

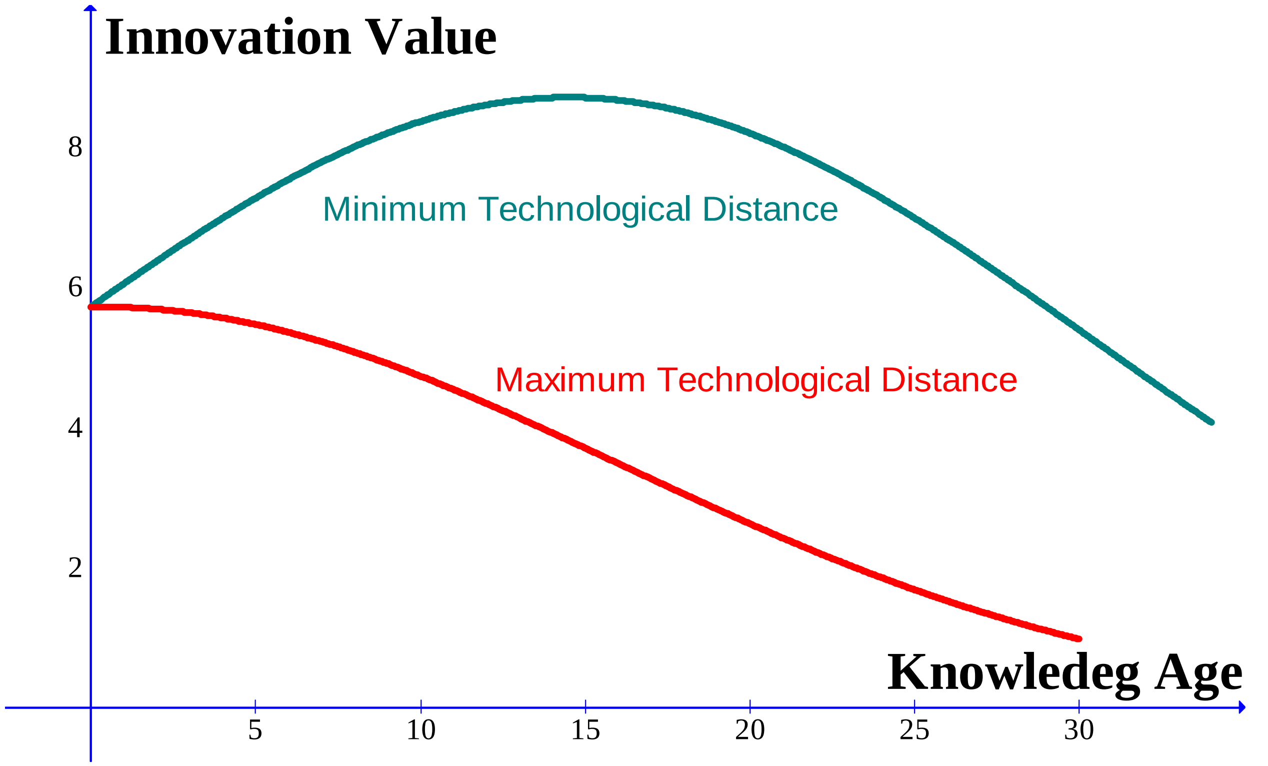

Figure 2. The moderating effect of technological distance on the relationship between knowledge age and innovation value.

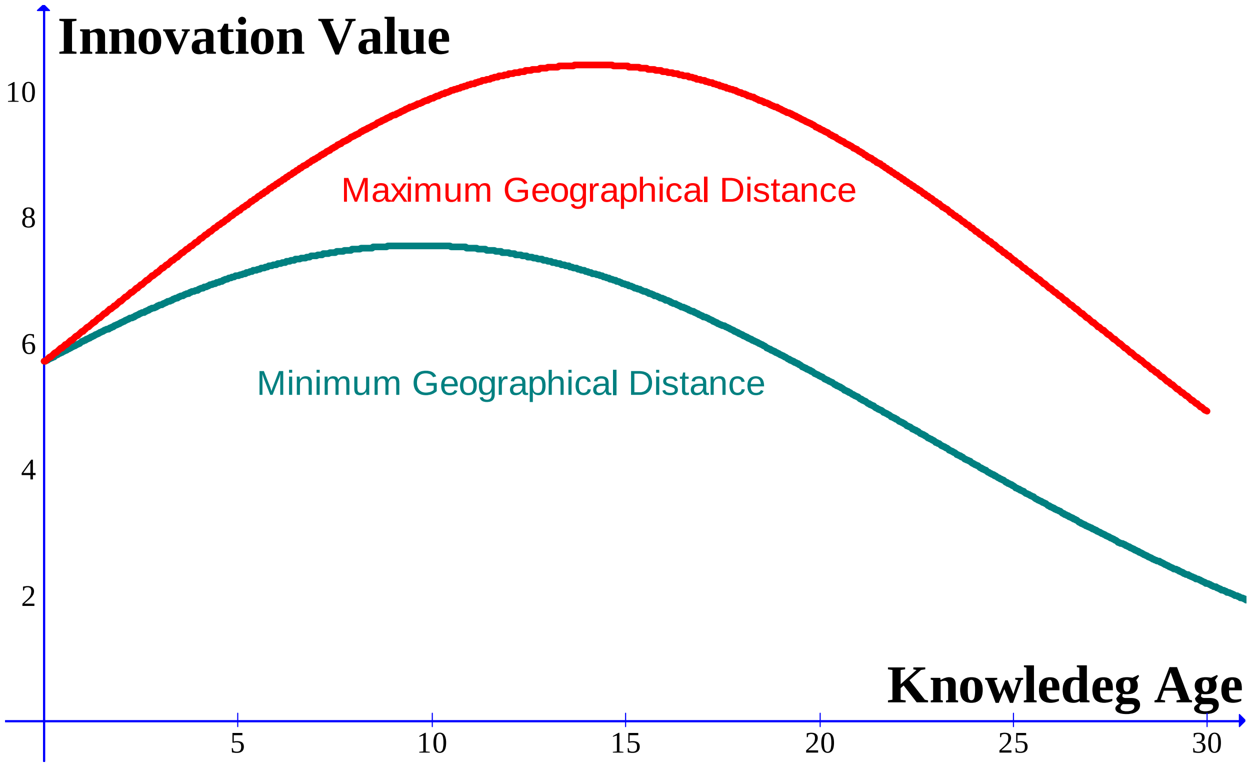

Figure 3. The moderating effect of geographical distance on the relationship between knowledge age and innovation value.

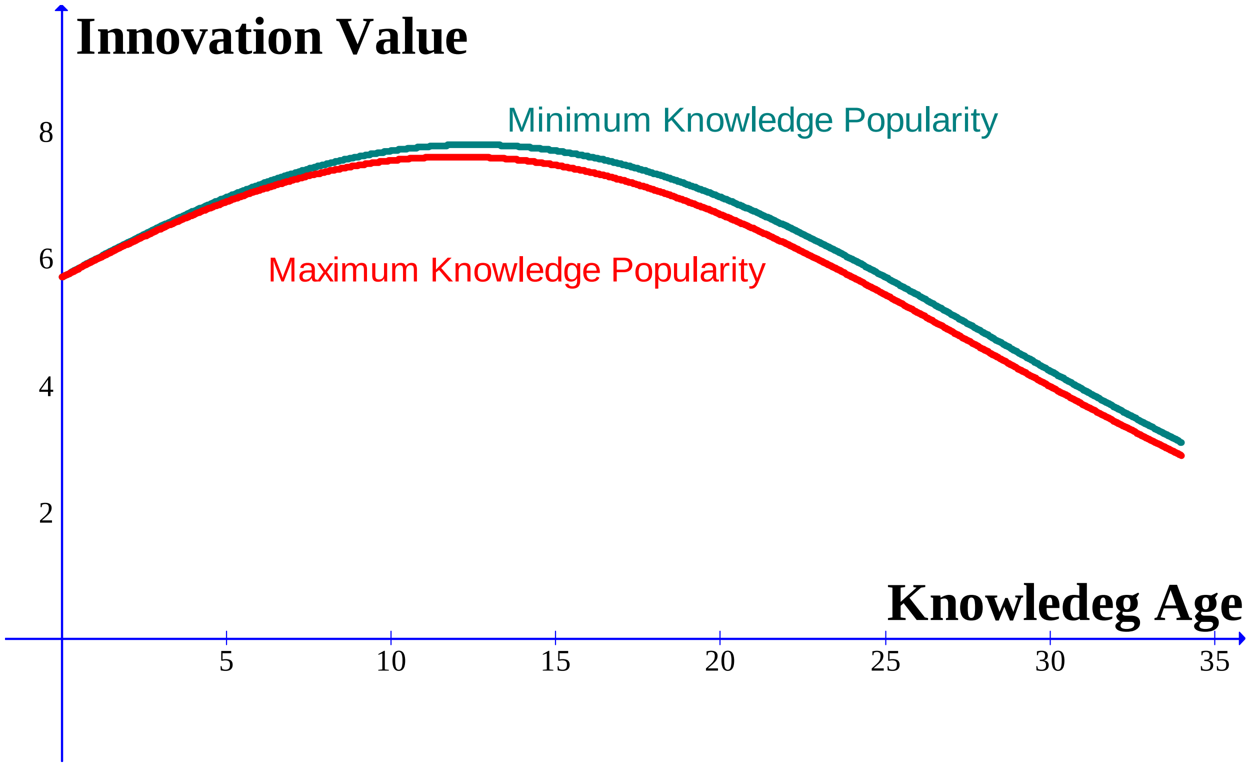

Figure 4. The moderating effect of knowledge popularity on the relationship between knowledge age and innovation value.