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Timing of Search and Innovation. The Moderating Effect of Firm Age and Size

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Abstract

This paper investigates the relationship between the age of knowledge inputs upon which an innovation is built and its value, as well as how this relationship strongly depends on specific firms? characteristics, as age and size. Following previous empirical evidences, we argue that the age of knowledge depicts an inverted U-shaped effect on the value of innovation, since firms exploiting middle-aged inputs exhibit greater returns than those using both nascent and mature knowledge. Nevertheless, we seek to advance the existing literature by revealing how the successful use of knowledge inputs of different age is strictly related to both the age and size of inventing firms. Specifically, we state that older firms outperform younger ones when employ mature knowledge, while young firms are able to better exploit nascent and middle-aged knowledge. In terms of size, we expect that larger firms present a greater capability to innovate by using both nascent and mature knowledge, while smaller firms develop more valuable innovative solutions when build upon middle-aged knowledge inputs. These ideas are empirically tested on a sample of biotechnology patented inventions and the results offer support for the hypotheses developed in this paper.

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THE MODERATING EFFECT OF FIRM AGE AND SIZE

This paper investigates the relationship between the age of knowledge inputs upon which an innovation is built and its value, as well as how this relationship strongly depends on specific firms' characteristics, as age and size. Following previous empirical evidences, we argue that the age of knowledge depicts an inverted U-shaped effect on the value of innovation, since firms exploiting middle-aged inputs exhibit greater returns than those using both nascent and mature knowledge. Nevertheless, we seek to advance the existing literature by revealing how the successful use of knowledge inputs of different age is strictly related to both the age and size of inventing firms. Specifically, we state that older firms outperform younger ones when employ mature knowledge, while young firms are able to better exploit nascent and middle-aged knowledge. In terms of size, we expect that larger firms present a greater capability to innovate by using both nascent and mature knowledge, while smaller firms develop more valuable innovative solutions when build upon middle-aged knowledge inputs. These ideas are empirically tested on a sample of biotechnology patented inventions and the results offer support for the hypotheses developed in the paper.

Key words: age of knowledge inputs; search; innovation; firm age; firm size

INTRODUCTION

Innovation is generally conceived as the engine of firms' competitiveness (Arroniz, Wolcott and Sawhney, 2006; Birkinshaw, Hamel, and Mol, 2008), and seen as the combination of existing knowledge inputs in novel ways (Schumpeter, 1934). By following this re-conceptualization of the innovation process, scholars have paid noteworthy attention to identify the main characteristics of knowledge inputs, seen as important predictors of innovation success. For example, the origins of knowledge inputs (Rosenkpof and Nerkar, 2001; Phene, Fladmoe-Lindquist, and Marsh, 2006), the uncertainty of their recombination (Altschuler, 1998; Fleming, 2001), as well as the degree of relatedness among inputs (Kogut and Zander, 1992; Ahuja and Katila, 2004) have been proved to significantly influence the innovative outcome, playing thus a strategic role for firms' innovation strategy.

Recently, among the different issues investigated by the literature, the age of knowledge inputs has been recognized as a key factor. Innovations in fact may result as the combination of knowledge from different ages, as nascent inputs, that stay in the forefront, or more mature ones, that exist from a longer time and whose characteristics are well known (Arthur, 2009). Scholars have debated about the necessity to find a balance between the employment of current knowledge and knowledge available across large time spans, discussing its implications for firm performance (Katila, 2002; Nerkar, 2003; Heeley and Jacobson, 2008). Nevertheless, despite previous contributions, the relationship between knowledge age and innovation remains still unclear. Therefore, the present study aims at shedding further light to this emerging debate, by providing further empirical evidence on the costs and benefits of recombining aged knowledge inputs to develop valuable innovations. Furthermore, while prior research has concentrated on the origin of this knowledge (Katila, 2002; Albino, Messeni Petruzzelli, and Rotolo, 2012), a better understanding of which factors make firms more or less able to leverage knowledge across time is needed. Accordingly, we investigate how an effective search for and adoption of knowledge inputs of different time depend on specific firms' characteristics, as age and size, which have proved to significantly influence firm's innovative capability (e.g. Schumpeter, 1934; Acs and Audretsch, 1990; Damanpour, 1992; Sorenson and Stuart, 2000; Balasubramanian and Lee, 2008).

By conducting an extensive study on a sample of 5,575 biotechnology patented inventions, we reveal an inverted U-shaped relationship between the age of knowledge inputs and the value of the resulting innovations, and further advance the existing literature by showing that firm's experience and routines, as well as the availability of resources contingent this relationship in a nonlinear way. Older firms in fact outperform younger ones when employ mature knowledge, while larger firms present a greater capability to innovate by using both nascent and mature knowledge. This paper contributes to the literature on the search and recombinant perspective of innovation by jointly investigating the influence of knowledge and firm's characteristics on the value of resulting innovative solutions. The remainder of the paper is organized as follows. In the next section, we develop a set of testable hypotheses concerning the influence of knowledge age and the moderating effect of firm' characteristics. Then, we present the research methodology employed and the empirical results. Finally, we discuss our findings, outline their implications for both theory and practice, and acknowledge the limitations of the study.

THEORY AND HYPOTHESES

The Age of Knowledge Inputs and the Value of Innovation

A central idea in the innovation management literature is that innovation results from a process of search and recombination (Schumpeter, 1939; Nelson and Winter, 1982; Fleming, 2001), where heterogeneous knowledge inputs are transformed into final innovative solutions. These inputs may be generally characterized by a different geographical, technological, and organization origin, as the outcome of a process of search that may involve multiple landscapes (Rosenkopf and Almeida, 2003; Phene et al., 2006; Rothaermel and Alexandre, 2009). Within these contexts, scholars have largely debated about local versus distant search (Stuart and Podolny, 1996; Rosenkopf and Nerkar, 2001), as the former referring to the innate tendency of firms to search for solutions in the neighbourhood of their existing knowledge base, while the latter occurring when a firm searches for knowledge distant from its current knowledge base (Ahuja and Lampert, 2001; Rosenkopf and Nerkar, 2001; Katila and Ahuja, 2002). Furthermore, more recently, the dimension of time has received an increasing attention, as revealed by the number of empirical studies discussing the relationship between innovation and the age of knowledge inputs upon which it is built (Katila, 2002; Nerkar, 2003; Heeley and Jacobson, 2008). Specifically, the studies have found similar results, irrespective of the industries under analysis, thus demonstrating that the choice to rely upon mature or nascent knowledge inputs present both costs and benefits. As knowledge ages, in fact, it tends to become more reliable (Fleming, 2001), hence reducing uncertainty as well as both viability development and utilization costs (Heeley and Jacobson, 2008), since it its extensive validation over time decreases the likelihood of technical errors and improper applications. Moreover, using aged knowledge inputs may allow to discover valuable applications whose time has not yet come (Nerkar, 2003; Cattani, 2006) due to a lack of enabling technologies or complementary assets. As pointed out by Vinton Cerf, Internet co-inventor, “Leonardo da Vinci had many inventions that really could not be built effectively in the 15th or 16th century because of a lack of suitable materials...The latest technologies often produce opportunities to reapply earlier ideas more effectively” (Standage, 2005: 131). This phenomenon has been also explained by Hughes, a historian of technology, in terms of “reverse salients”, which refers to solutions that have fallen behind or are out of phase with the others. However, building upon mature knowledge inputs may have harmful consequences on the development of valuable innovations. First, embedding mature knowledge may result into obsolete innovative solutions that do not fit with customers’ current needs and expectations (Tushman and Anderson, 1986). Second, knowledge maturity implies also increasing learning difficulties, as reflected in the complexity of its interpretation and application, which is in turn associated with the decay of organizational memory (Argote, 1999; Katila, 2002). Third, in contrast to more recent knowledge, mature knowledge inputs may suffer from a lack of recombinant opportunity (Heeley and Jacobson, 2008), since many of the potential combinations may be already employed, hence leaving few room to the development of valuable solutions, while enhancing the risk of imitation. Finally, firms combining aged knowledge resources may fail in the race towards scarce resources, hence lagging behind their competitors (Lieberman and Montgomery, 1998). In fact, if resources related to a specific technology are scarce, first adopters may capture these resources at the expenses of the followers, which may fall into a disadvantage position. Overall, the above reasoning seems to suggest a non-monotonic relationship between the age of knowledge inputs and the value of the resulting innovations. Thereby, we expect that:

H1. The age of knowledge inputs presents an inverted U-shaped effect on the value of innovation. In other words, building upon middle-aged knowledge inputs present greater benefits in terms of innovation value than relying on both nascent and mature ones.

The Moderating Effect of Firm Age

The role of firm age has been a long standing theme in the scientific literature, which finds its roots in a number of studies conducted by organizational ecologists on the consequence of aging on organizations' survive (Hannan, 1998), distinguishing between both positive and negative effects as the result of two competing perspectives, namely the liability of newness (Strinchcombe, 1965; Hannan and Freeman, 1984) and the liability of senescence (Barron, West, and Hannan, 1994). In the context of innovation studies, Sorensen and Stuart (2000) have been among the first to analyze the influence of firm age and have showed that although old and experienced firms generate more innovations, these are generally incremental and of lower quality. In turn, this strongly depends on a more rigid and bureaucratic structure, ossified within established routines and practices, which may lead older firms to fall into competency traps (Levinthal and March, 1993) and core rigidities (Leonard-Burton, 1992), hence preventing them from successfully innovate. This increasing institutionalization over time may exacerbate the costs of building upon nascent knowledge inputs, since older firms face more difficulties than younger ones to explore and learn new technological opportunities (Abernathy and Utterback, 1978; Anderson and Tushman, 1990). In fact, being entrenched within existing cognitive frameworks and cultural norms, older firms are less likely to effectively acquire and apply newer knowledge inputs that break industry norms and paradigms, while tend to search especially internally (Gopalakrishnan and Bierly, 2006) and in the neighborly of their competencies and expertise (Cyert and March, 1963; Nelson and Winter, 1982; Tushman and Anderson, 1986). This tendency narrows firms' knowledge base and reduces the scope of recombination (Katila and Ahuja, 2002; Laursen and Salter, 2006), as the number of potential new solutions and ideas that may be developed by employing the same set of knowledge inputs. Thereby, older firms may encounter more difficulties to effectively exploit new knowledge inputs and find valuable applications, given their limited capability to recombine them in new and useful ways and developing innovative architectural solutions (Henderson and Clark, 1990).

Furthermore, firm age tends to reduce organization-environment fit (Hannan and Freeman, 1984; Sorenson and Stuart, 2000), by augmenting the gap between organizational competencies and environmental demands, and hence turning into obsolescence (Barron et al., 1994). This is particularly true in high dynamic and technology active contexts, where older firms often fail to own all the required knowledge and skills imposed by the continuous scientific and technological developments (Ranger-Moore, 1997; Henderson, 1999; Giarratana, 2004; Balasubramanian and Lee, 2008). Older firms in fact may risk to be trapped into established routines and practices that have sustained business activities over time, hence limiting their capability to adapt to market changes and developing innovative solutions that may become "mismatched with current environmental demands and irrelevant to the innovative activities of the other firms in the technological community" (Sorenson and Stuart, 2000: 88). With this regard, age and experience may become a disadvantage when compared with inexperience and youth, as the negative influence of firm age in responding to current customers' needs and expectations may reduce the benefits going along with the employment of newer knowledge inputs, by making firms less able to fully exploit their potential and translate them into commercial products, while amplifying the risk of uselessness of the resulting outcomes. In fact, established conventions expose older firms to a myopia of learning (Levithal and March, 1993), which may in turn lead them to not be able to understand and appreciate new knowledge, which is not consistent with existing cognitive frameworks, and hence give rise to poor innovative solutions.

Nevertheless, as knowledge exceeds a certain temporal threshold, older firms may be more able to exploit the benefits of knowledge age than younger ones, as dependent on their established information-processing routines (Nelson and Winter, 1982; Henderson, 1993; Sorenson and Stuart, 2000; Kotha, Zheng, and George, 2011). First, one of the key impediment in using mature knowledge inputs is related to the difficulties of their correct interpretation. However, older firms are more likely to have experienced workforce as well as a long lasting organizational memory (Weick, 1979; Walsh and Ungson, 1991; Gopalakrishnan and Bierly, 2006; Arora, Gambardella, Magazzini, and Pammolli, 2009), which increase the accuracy of their search and selection process over time by enhancing the reliability of mature knowledge inputs and reducing the likelihood of their misapplications. Older firms may in fact benefit from greater experience and learning economies, which provide informational advantages through the perceived legitimacy or past success of repetition (Baum, Li, and Usher, 2000). Second, older firms present a greater learning continuity to the past that makes them more familiar with components that stay on the market from a longer time, thus enhancing the reliability of the mature knowledge they employ (Fleming, 2001). Taken together, these arguments lead to the formulation of the following hypothesis:

H2. The age of firms moderates the relationship between the age of knowledge inputs and the value of innovation in such a fashion that younger firms are able to better exploit nascent and middle-aged knowledge inputs, while older firms benefit more from building upon mature ones.

The Moderating Effect of Firm Size

Studies on the relationship between firm size and innovation can be traced back at least as far as Schumpeter (1942), who proposed a polarization between the so called creative destruction view, where innovation results from smaller dynamic firms, and then the cumulative perspective, which emphasizes the idea that larger firms enjoy a relative advantage in the development of innovation over smaller ones. This two competing views find justification in the costs and benefits going along with an increasing of organizational dimension, as reflected into a lack of flexibility and adaptability (e.g. Kimberly and Evanisko, 1981; Acs and Audrtetsch, 1990; Hitt, Hoskisson, and Ireland, 1990), as well as into a greater availability of resources (e.g. Teece, 1986; Acs and Audretsch, 1988), respectively. However, although smaller firms may avoid “bureaucratic inertia” and more easily adapt to changes into markets (Gilder, 1988), a larger size may set firms in a better position to innovate by building upon both nascent and mature knowledge inputs. In fact, larger firms may exploit economies of scale in R&D activities (e.g. Acs and Audtretsch, 1988; Macher and Boerner, 2006). In turn, this allows them to accumulate technological knowledge and competences (Damanpour, 1992), which favor the absorption of novel discoveries (Cohen and Levinthal, 1990), by reducing the likelihood of errors in their adoption and enhancing the capability to build upon them. Furthermore, the employment of newer knowledge inputs is generally a more risky and uncertain process, leading to an increase of research and development costs (Dewar and Dutton, 1986). Nevertheless, larger firms are also expected to be advantaged in terms of financial resources, since size is one of the most strongest predictor of rapidly accessible and stable flows of internal funding (Cohen and Levin, 1989; Veugelers, 1997). Hence, larger firms may better withstand financial stress and potential new product failure (Ettlie and Rubenstain, 1987). Finally, a larger firm may enjoy from widespread marketing and distribution facilities (Cohen, 1995; Corsino, Espa, and Micciolo, 2011) that, together with a deep knowledge of customers (Freeman, 1982), an higher reputation (Teece, 1986), and a wide set of strategic alliances and supply relationships

(Gulati, 1999), may ease the market penetration of radical products embodying recent knowledge resources by facing customers' resistance.

The benefits of size may outweigh its costs also when firms rely upon mature knowledge inputs. Larger organizations in fact may employ a larger R&D staff as well as may attract and support specialized scientific personnel (Macher and Boerner, 2006), which are more likely to recognize the value of previously unexploited knowledge opportunities (Kamien and Schwartz, 1982), hence reducing the likelihood to encounter fruitless and obsolete discoveries (Stock, Greis and Fischer, 2002). In addition, previous research has shown that the value of older knowledge often depends on the availability of complementary assets and enabling technologies (Cattani, 2006), which is one of the key advantage of larger firms (Teece, 1986). In fact, they may exploit scope economies (e.g. Henderson and Cockburn, 1996; Arora et al., 2009) by integrating a wide set of heterogeneous technologies across related products and processes (Fai and von Tunzelmann, 2001), also as the result of complementarities between R&D and other internal activities (Cohen, 1995), which in turn enhance their recombinative capability. Thereby, the opportunity to find new and useful links among components decreases the risk to turn mature knowledge from a potential source of value into core rigidity (Leonard-Barton, 1992) and competency traps (Levinthal and March, 1993), as well as that the resulting innovations fail to meet current market needs.

However, being large is expected to be less effective when firms use middle-aged knowledge inputs, since in this case innovation is a less uncertain and risky process. Hence, smaller firms result more free of resource constraints, such as research capabilities, financial funds, and marketing facilities, and are in a better condition for exploiting the advantages derived from their reduced dimension (Katila and Shane, 2005). Specifically, as suggested by Rothwell and Dogson (1994), smaller firms may benefit from a behavioral advantage, which stays in an entrepreneurial orientation and a rapid decision-making process, which allow them to grab technological and market opportunities (Corsino et al., 2011). Thereby, when embodying knowledge resources that stay slightly behind the technology frontier, smaller firms may get along without the material advantages characterizing larger organizations by focusing on the higher creativity of their technical personnel (Acs and Audrtesch, 1990), as well as on their greater capability to be flexible and to adapt to environmental changes (Gopalakrishnan and Bierly, 2006). Indeed, smaller organization may result more innovative efficient than larger ones (e.g. Hage, 1980; Ettlie and Rubenstein, 1987; Graves and Langowitz, 1993) and hence able to develop more valuable innovative outcomes. Accordingly, following the above discussion, we hypothesize that:

H3. The size of firms moderates the relationship between the age of knowledge inputs and the value of innovation in such a fashion that smaller firms are able to better exploit middle-aged knowledge inputs, while larger firms benefit more from building upon nascent and mature ones.

METHODS

Setting and Data

The hypotheses are tested on a sample of patented inventions granted by 298 U.S. biotechnology firms at the U.S.P.T.O... The biotechnology industry finds its roots in the discovery of the double helix structure of DNA by Watson and Crick in 1953, and the following results on DNA's recombinant by Cohen and Boyer in 1973. It is originated in the U.S. market and dominated by a small number of big companies, as Genentech, Amgen, and Chiron. Furthermore, the industry is characterized by a large R&D expenditures ($125–250 million per drug), long commercialization cycles, and very complicated and often lengthy regulatory (FDA) approval procedures (Shan, Walker, and Kogut,1994). A number of considerations motivated the choice of biotechnology as the setting of the study. Innovations are more discrete in terms of products fragmentation and may be covered by a small number of patents. Hence, biotechnology firms tend to expend more effort on writing strong and valuable patents, thus assuring a certain confidence in using patents as an innovation output (e.g. Shan and Song, 1997; Phene, et al., 2006: Rothaermel and Thursby, 2007). Since biotechnology results as a combination of multiple scientific and technological disciplines, (Russell, 1999; Sorenson and Stuart, 2000), searching and recombining knowledge across different dimensions, as the temporal one, assume fundamental role in leading innovation. Finally, firms in the industry vary significantly in terms of both age and size (Gopalakrishnan and Bierly, 2006; Rothaermel and Boeker, 2008), thus making this sector as a suitable choice for testing the influence of the above two characteristics on knowledge sourcing strategies. For example, the industry includes more established firms, such as Ortho-Clinical Diagnostics and Purdue Pharma, that are over 100 years old, and others younger companies, such as Curis and Questcor Pharmaceuticals, that stay on the market from less than 15 years. Moreover, in the biotechnology sector operates larger firms, such as Amgen and Genentech with more than ten thousands employees, and also the smaller ones, such as Access Pharmaceuticals and NitroMed with less than ten employees.

Biotechnology firms have been selected from BioScan, a biotech industry reporting service, where a sample of 298 U.S. companies, both public and private, filing for at least one biotechnology patent at the U.S. PTO. between 1895 and 2002[1] have been identified. For each patent, information on forward and backward citations, as well as on assignee, inventor(s), technological classes, and claims have been collected. Thus, the final patent sample is composed by 5,575 focal patents filed by the 294 firms, 51,151 cited patents, and 57,503 subsequent patents that cite the focal patents. Other firm information have been gathered from multiple sources, such as SEC filings for publicly traded firms, press releases and company websites.

Variables

Dependent variable. The value of innovation (*Innovation Value*) was measured by counting the number of forward citations received by focal patents until 2009, excluding self-citations. The use of forward citations as a proxy of the importance of patents is a common and widely accepted practice in the literature, since it has been demonstrated to be positively related to consumer-surplus generated, expert evaluation, patent renewal rates, and firm profit (Trajtenberg, 1990; Hall, Jaffe,

[1] The U.S.P.T.O.. defines the boundaries of the biotechnology domain according to the following three-digit U.S. technological clasess: 424, 435, 436, 514, 530, 536, 800, 930, and PLT (Rothaermel and Thursby, 2007).

and Trajtenberg, 2005). To account for the fact that older patents are more exposed to the risk of being cited, year fixed effects are included in all regressions, hence reducing this "truncation bias" (Jaffe and Trajtenberg, 2002; Singh, 2008). Furthermore, the use of forward citation to measure patent value is often criticized because citations may be added by the examiners (Alacacer and Gittleman, 2006). Nevertheless, in this context this issue is less relevant for at least two reasons. First, in the biotechnology industry, the share of applicants citations is on average greater than 70% (Alcacer, Gittleman, and Sampat, 2009) and assignees strategically withhold only 5–7% of citations (Lampe, 2011). Second, the study is based on patents granted by the U.S.P.T.O. to local firms, hence further reducing the share of examiner citations, which has been proven to be especially high among foreign firms (Alcacer et al., 2009).

Independent variable. To account for the age of knowledge inputs (*Knowledge Inputs Age*) we used information included in the patent backward citations, which describe the existing knowledge upon which the focal patent builds. Specifically, in line with previous studies (Sorenson and Stuart, 2000; Katila, 2002), we measured the mean time lag between the cited patents and the focal one. The sample includes focal patents based on different knowledge inputs' ages. In fact, these rely on both more nascent knowledge inputs, as the "immunoreactive polypeptide compositions" (patent 5,670,152) developed by Chiron with an average age of inputs equal to 1.5 years, and more mature ones, as the "compounds and methods for increasing endogenous levels of corticotropin-releasing factor" (patent 6,133,276) assigned to Neurocrine Biosciences with an average age of inputs equal to 33 years.

Moderating variables. We measured the age of firms (*Firm Age*) as the natural logarithm of the difference between the firms year foundation and the focal patent application date (e.g. Sorenson and Stuart, 2000). We proxied firm size through the natural logarithm of the number of employees for each biotechnology firm (*Firm Size*). The number of employees is a suitable proxy in this industry because many firms possess only intangible assets and had very unstable revenues (e.g.

Powell, Koput, and Smith-Doerr, 1996; Rothaermel and Deeds, 2004; Rothaermel and Boeker, 2008).

Control variables. We included several variables to control for alternative factors that may explain differences across patent value. Specifically, we controlled for the number of backward citations (*Backward Citations*), claims per patent (*Claims*) (Lanjouw and Schankerman, 2001), references to scientific knowledge (*Scientific Knowledge*), as the number of non-patent references each patent cites (Narin et al., 1997), team size (*Team Size*), as the number of inventors associated with each patent (e.g. Singh, 2008), age of patents (*Patent Age*), as the number of years elapsed since filing a focal patent until the year 2009, government's support (*Government Support*), as a dummy variable that takes a value of one if the patent has been funded by the U.S. government, scope of patent (*Patent Scope*), as the number of different three-digit patent classes assigned to a patent by the U.S.P.T.O.. (Lerner, 1994), the number of co-applicants to which the patent was assigned (*Co-Applicants*), and the diversity of knowledge inputs' age (*Diversity*), measured as the variance in the number of years elapsed since the filing date of patents cited by the focal patent (Katila 2002). Furthermore, we distinguished if the patent assignee is a public or private firm, by introducing a dummy variable (*Public Firm*) that receives a value of one if the firm is publicly traded at the filing date of the patent, and zero otherwise. Finally, we included year dummies and the "Year 1985" was the relative omitted category.

Estimation Procedure

The dependent variable is a non-negative integer count variable with a coefficient of variation (standard deviation/mean) equals to 2.28. Hence, we used negative binomial regression analysis (Cameron and Trivedi, 1998), which allows for the variance to differ from the mean and, consequently, to correct for over-dispersion (Gourieroux, Monfort, and Trognon, 1984; Hausman, Hall, and Griliches, 1984). Although firms' age and size represent the moderating variables, they have been included in all regression models. This approach makes moderated regression a conservative method for examining interaction effects (Jaccard, Wan, and Turrisi, 1990). In addition, we employed a Huber-White sandwich estimator, which corrects for heteroscedasticity and provides robust standard errors. Finally, variance inflation factor (VIF) index has been included in the analysis. Accordingly, the three hypotheses have been tested on the partial models, since the VIF index in the full model exceeds the critical value of 10 (Kleinbaum, Lawrence, Muller, and Nizam, 1998).

<Insert Tables 1-2 about here>

RESULTS

Table 1 presents the descriptive statistics and the correlation values for all variables, which are relatively low. Table 2 presents the coefficient estimates for the negative binomial regression models (Models 1 to 4). Model 1 is the baseline model and includes controls and moderating variables. In particular, it emerges that firm's size ($\beta = 0.011$, $p < 0.01$), number of backward citations ($\beta = 0.016$, $p < 0.001$), size of inventors' team ($\beta = 0.037$, $p < 0.01$), number of claims ($\beta = 0.007$, $p < 0.001$), U.S. government support ($\beta = 0.502$, $p < 0.001$), patent age ($\beta = 0.170$, $p < 0.001$), scope of patent ($\beta = 0.086$, $p < 0.001$), and diversity of knowledge input's age ($\beta = 0.006$, $p < 0.001$) positively influence the innovation value. On the contrary, the age of the biotechnology firms ($\beta = -0.076$, $p < 0.01$) and the number of non-patent references ($\beta = -0.001$, $p < 0.001$) exert a negative impact. In Models 2, 3, and 4 the independent and the two moderating variables are included and serve for testing the three hypotheses, respectively. Model 2 shows the results after entering the independent variable. The coefficients of *Knowledge Inputs Age* ($\beta = 0.034$, $p < 0.01$) and its squared term ($\beta = -0.002$, $p < 0.01$) are significant and in the expected direction, hence providing support for Hypothesis 1. Thereby, findings reveal that building upon middle-aged knowledge inputs provide greater benefits than relying on both nascent or mature ones. Specifically, Figure 1 depicts that innovation value reaches its maximum value when knowledge is about nine years old and after this short period the value tends to quickly diminish.

Model 3 shows the results after entering the first moderating variable, firm age. The coefficients of *Knowledge Inputs Age x Firm Age* (β = -0.080, p <0.001) *Knowledge Inputs Age*^{2} *x Firm Age* (β = 0.003, p <0.01) are significant and reveal that the contribution of aged knowledge resources declines with firm's age. However, it is necessary to gain more insights into the interaction effects in order to verify the extent to which they support Hypothesis 2. By following the procedure of Aiken and West (1991) to decompose the interaction terms, two levels of the moderating variable, as low (one standard deviation below the mean) and high (one standard deviation above the mean) are considered. Accordingly, Figure 2 shows that biotechnology firms' age negatively moderates the relationship between the age of knowledge inputs and the value of the resulting innovations. In particular, younger firms outperform older ones when employ both nascent or middle-aged knowledge, while older firms are more able to exploit mature knowledge (i.e. over about 30 years). Hence, this provides strong confirmation for the second hypothesis.

Model 4 presents the results after including the second moderating variable, firm size. As in the previous case, the coefficients of *Knowledge Inputs Age x Firm Size* (β = -0.027, p <0.001) *Knowledge Inputs Age*^{2} *x Firm Size* (β = 0.001, p <0.01) predict the existence of decreasing returns going along with the employment of aged knowledge as firm's size increases. Nevertheless, it is necessary to graphically analyze the effect of firm size for testing its fit with Hypothesis 3 (Aiken and West, 1991). Figure 3 reveals that biotechnology firms' size negatively moderates the relationship between the age of knowledge inputs and the innovations' value. Specifically, larger firms outperform smaller ones when embody both nascent (up to about six years) and mature (over about 23 years) knowledge, while smaller firms benefit more from using middle-aged knowledge inputs.

We tested the robustness of the results by conducting several auxiliary analyses. First, we further controlled for the risk that an older patent may be more cited, by using a five-years time window to account for the forward citations received by each focal patent (e.g. Griliches, 1979; Ahuja, 2000; Hess and Rothaermel, 2011). Hypotheses 1 and 3 remain strongly confirmed, while Hypothesis 2 is only partially supported, since the interaction coefficient is in the expected direction but loses significance. Second, we retained self citations in the measurement of the dependent variable and controlled for the number of self citations. Under this specification, all the three hypotheses are strongly supported. Third, we considered an alternative measure of firm age based on patenting experience, measured as the time elapsed between the first patent filled at the U.S.P.T.O. and the focal patent, which confirms the second prediction. Fourth, we replaced firm size in terms of employees with the patent stock of biotechnology firms calculated as the natural logarithm of the number of patents the firm filed with the U.S.P.T.O.. during the five years preceding the filing date of a focal patent (Mowery, Sampat, and Ziedonis, 2002; Owen-Smith and Powell, 2003; Nooteboom, van Haverbeke, Duysters, Gilsing, and van den Oord, 2007; Rothaermel and Boeker, 2008). Also by adopting this operationalization, Hypothesis 3 is supported. Fourth, to account for the excess of zeros in the dependent variable, we run the analysis by using a zero-inflated negative binomial regression. Also under this specification, results remain confirmed. Fifth, we run fixed effects Poisson regression (Wooldridge, 1999) and found the hypotheses supported. Finally, we incorporated firm fixed effects to account for remaining unobserved heterogeneity. All these additional analyses confirmed that the results are robust to measurement issues and alternative model specifications.

<Insert Figures 1-3 about here>

CONCLUSIONS

Key Findings

Focusing on the biotechnology industry, the present study advances the existing literature on search and recombination, by revealing the contingent value of knowledge age upon two specific firm’s characteristics, as its age and size. Results show that recombining both nascent and mature knowledge inputs presents costs and benefits, hence calling for a trade-off in the search for knowledge over time between the necessity to both operate near the technological frontier and reduce risks and uncertainty by relying upon more established resources. In fact, innovations resulting from the combination of very nascent or mature knowledge inputs are characterized by a lower value than innovations built on middle-aged inputs.

However, the returns of using knowledge inputs from different ages are strongly dependent on the characteristics of firms, allowing them to leverage knowledge at the right time. Specifically, it emerges that older firms may better exploit mature knowledge inputs since their greater learning experience allow them to more effectively scrutinize and recombine knowledge over larger time spans. On the contrary, younger firms seem more likely to appreciate and apply nascent knowledge inputs that challenges industry norms and rules, as well as middle-aged resources, since they tend to be less constrained by past inertial pressure. In terms of firm’ size, findings show that larger firms may better innovate by employing nascent or mature knowledge inputs, given the greater availability of resources, which in turn reduces the risks and uncertainty to built upon newer knowledge, as well as amplifies the opportunities to create value from more aged and established knowledge. Instead, smaller firms may better exploit the benefits of their greater flexibility and adaptation when the innovation process is mainly based on the recombination of middle-aged knowledge inputs, being hence less subject to resource limitations.

Implications for Theory

The present study advances the existing literature on search and recombination by jointly investigating the effect exerted by knowledge and firm’s characteristics on the innovation process. While previous research has mainly paid attention to where (Phene et al., 2006; Rothaermel and Alexamdre, 2009) and how (Stuart and Podolny, 1996; Rosenkof and Nerkar, 2001) firms search for knowledge resources, as well as to the mechanisms of their recombination (Fleming, 2001), we demonstrate that the value of innovative solutions resulting from recombination is influenced not only by the knowledge resources firms employ, but also by the distinctive traits of the firms. In particular, by focusing on the role played by the age of knowledge inputs, we confirm the existence of a trade-off in using knowledge of different ages (see also Heeley and Jacobson, 2008), hence suggesting that employing middle-aged knowledge inputs provide greater benefits than recombining both nascent and mature knowledge. Furthermore, we reveal that the effective use of inputs of different recency strongly depends on the nature of the firms, which may influence the success of temporal search strategies, by making the right time to leverage knowledge as different as for older or younger firms, as well as for larger or smaller ones.

We also contribute to the long standing studies on the relevance of firms' ages and size to innovative effort. Generally, scholars have mainly debated about the benefits and costs of both age (Hannan and Freeman, 1984; Barron et al., 1994; Sorenson and Stuart, 2000), in terms of experience vs. ossified routines and practices, and size (Schumpeter, 1934; Teece, 1986; Acs and Audrtetsch, 1990), in terms of availability of resources vs. lack of flexibility, paying however less attention to how these trade-offs may be affected by the search strategies firms perform. Specifically, our work reveals that both the advantages and disadvantages of age and size need to be carefully evaluated according to the specific knowledge inputs that are recombined. In fact, by investigating the temporal dimension of knowledge search, we show that age becomes a resource when employing mature knowledge, while size allows firms to create valuable innovations by leveraging both nascent and mature knowledge inputs.

Finally, previous studies have more or less explicitly advanced the existence of a positive relationship between the use of young and novel knowledge inputs and innovation (e.g. Lee, Smith, Grimm, and Schomburg, 2000; Ahuja and Lampert, 2001; Shane, 2001). In fact, it is assumed that these contribute to increase the likelihood of developing radical innovations, hence enhancing firms' innovative capabilities and competitiveness. Nevertheless, we question this view, by demonstrating that the advantages of nascent knowledge are strictly dependent on the firm exploiting them. Specifically, our study reveals that younger and larger firms seem to be in a better position to benefit from the recombination of knowledge inputs staying on the edge of the frontier.

Implications for Practice

The study provides interesting strategic implications for the sourcing and management of technological knowledge. Our results highlight the existence of both costs and benefits going along with the employment of knowledge inputs of different ages, revealing that using nascent or mature knowledge presents negative returns in terms of innovative outcomes, while the recombination of middle-aged inputs allows firms to exploit the advantages of both novelty and reliability, and reduce the risk of uncertainty and obsolescence. However, we show that the relationship between the age of knowledge inputs and the resulting innovation is strongly dependent on specific characteristics of firms making use of that knowledge. Specifically, by comparing innovative solutions developed by older and younger firms, as well as by larger and smaller ones, we find that different firms have different capabilities to search and recombine knowledge over time. In fact, younger companies seem to benefit more from the adoption of nascent and middle-aged knowledge, while older firms may better understand and apply mature knowledge. Instead, larger companies may better face the difficulties of building upon both nascent and mature inputs, while smaller firms may fully exploit their flexibility and responsiveness when innovate on middle-aged knowledge. Thereby, managers should carefully evaluate how age and size interact with the use of knowledge resources, in order to design and implement effective innovation strategies.

Limitations and Directions for Future Research

Despite the contribution the study provides to the existing literature on knowledge management and innovation, it presents several limitations, which leave room for future researches. First, we rely on patent data to measure knowledge inputs and innovative outcomes. Nevertheless, despite their extensive use, patent data have been often criticized (e.g. Gittleman, 2008) since these capture only a subset of firms' innovative dynamics and mainly focus on technology inventions, while neglecting other competencies and capabilities, whose investigation may require studies conducted with different research approaches, such as survey and case study, and analyzing innovation at the product and process level. Second, we contingent the effect of knowledge age upon two specific firm's characteristics, as its age and size. Nevertheless, other features may be considered, as science-based nature (e.g. Gittleman, 2007), explorative vs. exploitative orientation (e.g. Katila and Ahuja, 2002), and relational capital (e.g. Powell, Koput, and Smith-Doerr, 1996), which has been proved to influence how firms search for and manage knowledge resources. Third, scholars may extend our line of inquiry by investigating the moderating effect of the environment where firms operate (e.g. Klevorick, Levin, Nelson, and Winter, 1995), hence accounting for competitive intensity, dynamisms, and technology evolution. Finally, other industries and countries may be analyzed in order to verify the generalizability of our findings.

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TABLES AND FIGURES

TABLE 1. Bivariate correlation matrix (*n* = 5,575).

Variables	Mean	Std. Dev.	Min	Max	1	2	3	4	5	6	7	8	9	10	11	12	13
1. Innovation Value	11.19	23.60	0	518													
2. Knowledge Inputs Age	5.96	4.25	0	34	-0.01												
3. Firm Age	2.54	0.95	0	4.92	-0.09***	0.04***											
4. Firm Size	6.89	2.25	0	11.98	0.02†	-0.02	0.51***										
5. Backward Citations	9.17	19.76	0	259	0.07***	0.25***	-0.19***	-0.15***									
6. Claims	20.19	21.86	0	683	0.03**	0.00	-0.14***	-0.09***	0.13***								
7. Scientific Knowledge	31.55	48.81	0	438	0.03*	0.18***	-0.06***	0.29*	0.53***	0.10***							
8. Team Size	3.02	2.02	1	27	0.01	0.03*	-0.12***	-0.29*	0.07***	0.12***	0.08***						
9. Patent Age	11.56	3.86	7	24	0.27***	-0.11***	-0.04**	0.22***	-0.14***	-0.14***	-0.05***	-0.12***					
10. Government Support	0.03	0.18	0	1	0.06***	-0.01	-0.10***	-0.10***	0.00	0.01	0.01	0.09***	-0.01				
11. Patent Scope	2.26	0.99	1	8	0.07***	0.01	-0.00	0.06***	0.09***	0.06***	0.06***	0.07***	-0.01	0.01			
12. Co-Applicants	1.10	0.32	1	3	-0.00	-0.03*	-0.04***	-0.01	-0.01	0.01	0.04**	0.21***	-0.01	0.13***	0.03*		
13. Diversity	2.81	2.28	0	17.06	0.01	0.50***	-0.07***	-0.12***	0.30***	0.04**	0.13***	0.06***	-0.20***	-0.02	0.01	-0.02	
14. Public Firm	0.61	0.49	0	1	0.03**	-0.03*	-0.43***	-0.11***	0.11***	0.08***	0.11***	0.11***	-0.06***	0.04***	-0.00	0.06***	0.02

† *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
Knowledge Inputs Age		.034** (.008)	.253** (.044)	.220** (.034)	.301** (.048)
Knowledge Inputs Age^{2}		-.002** (.001)	-.010** (.002)	-.009** (.002)	-.012** (.003)
Knowledge Inputs Age x Firm Age			-.080*** (.019)		-.071*** (.019)
Knowledge Inputs Age^{2} x Firm Age			.003** (.001)		.003** (.001)
Knowledge Inputs Age x Firm Size				-.027*** (.006)	-.010*** (.000)
Knowledge Inputs Age^{2} x Firm Size				.001** (.000)	.001** (.000)
Firm Age	-.076* (.039)	-.072* (.040)	-.183* (.078)	-.105* (.037)	.137* (.082)
Firm Size	.011* (.005)	.010* (.005)	.018* (.010)	.068** (.024)	.063** (.023)
Backward Citations	.016*** (.001)	.015*** (.002)	.013*** (.001)	.014*** (.001)	.013*** (.001)
Claims	.007*** (.001)	.007*** (.001)	.007*** (.001)	.007*** (.001)	.007*** (.001)
Scientific Knowledge	-.001*** (.000)	-.001*** (.000)	-.001*** (.000)	-.001*** (.000)	-.001*** (.000)
Team Size	.037*** (.012)	.034*** (.011)	.037*** (.011)	.034*** (.011)	.037*** (.011)
Patent Age	.170*** (.025)	.170*** (.025)	.173*** (.025)	.167*** (.024)	.171*** (.023)
Government Support	.502*** (.128)	.500*** (.127)	.454*** (.119)	.503*** (.124)	.461*** (.119)
Patent Scope	.086*** (.025)	.086*** (.025)	.076*** (.022)	.086*** (.024)	.077*** (.022)
Co-Applicants	-.032 (.067)	-.032 (.066)	-.017 (.065)	-.033 (.066)	-.019 (.065)
Diversity	.006***(.001)	.006***(.001)	.006***(.001)	.006***(.001)	.006***(.001)
Public Firm	.076 (.047)	.076 (.047)	.084 (.046)	.078 (.047)	.082 (.046)
Year dummies	Included	Included	Included	Included	Included
Likelihood ratio test (χ^2)	-17088.561***	-17083.709***	-17034.223***	-17059.622***	-17031.573***
Improvement in fit ($\Delta\chi^2$)		4.852	54.338	28.939	56.988
Number of observations (n)	5,575	5,575	5,575	5,575	5,575

Huber-White robust standard errors are reported in parentheses. † *p <.10;* **p <.05;* ***p < .01;* ****p <.001.*

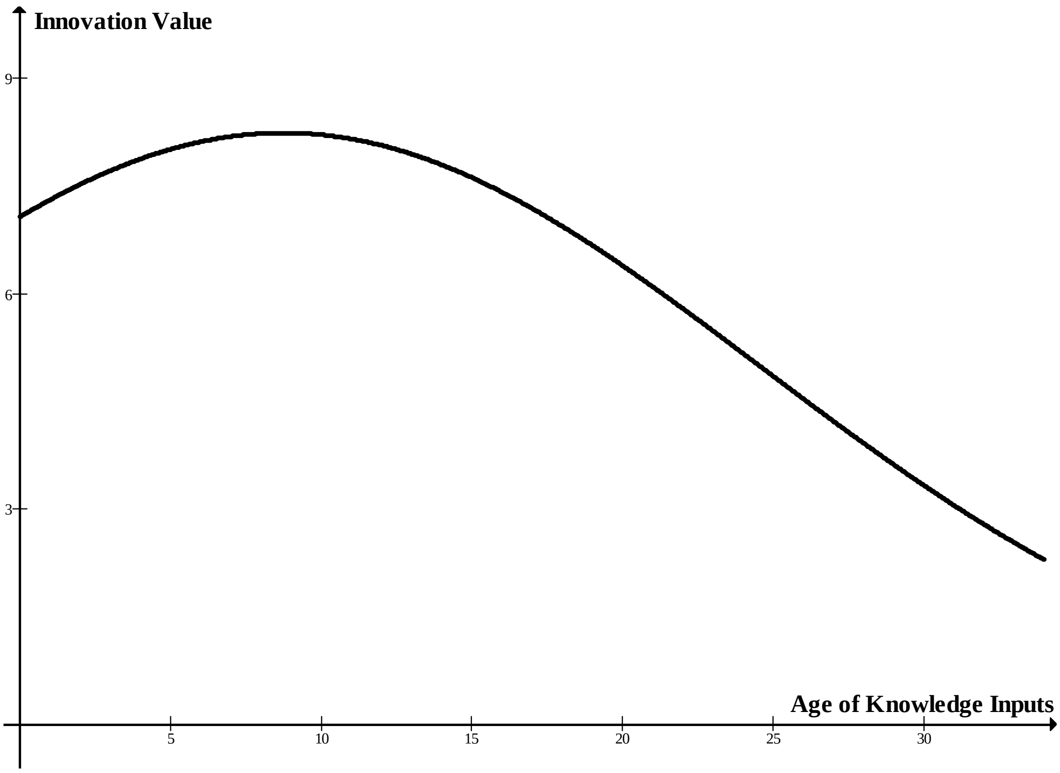

FIGURE 1. The age of knowledge inputs and innovation value.

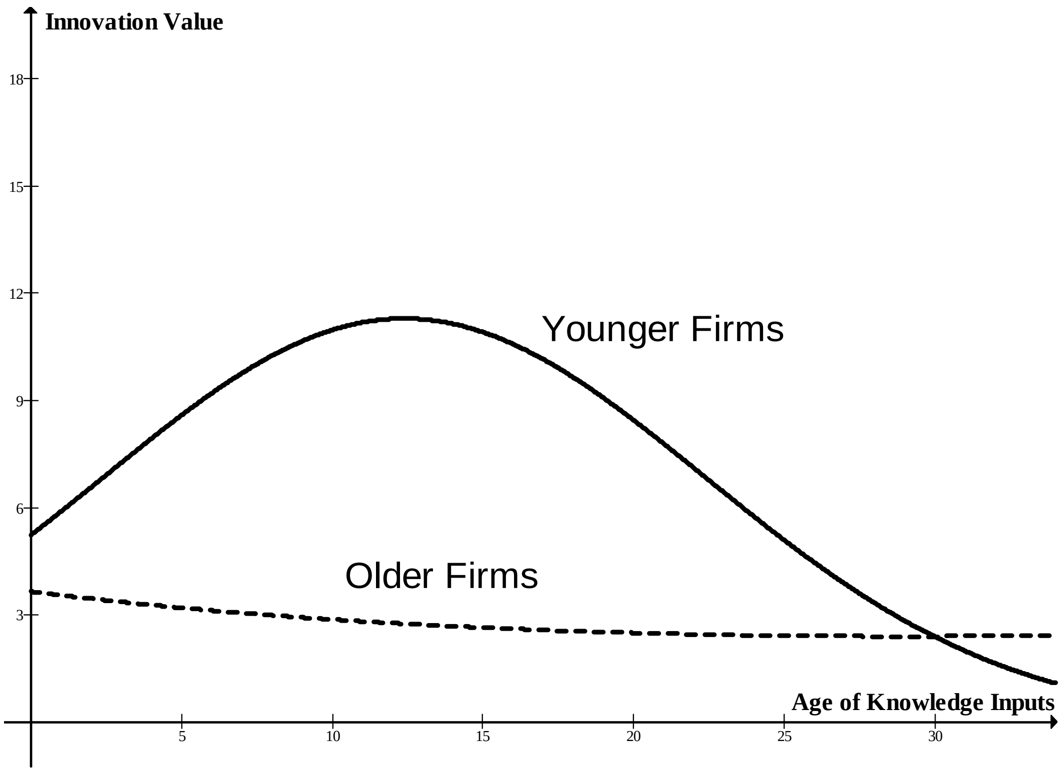

FIGURE 2. The moderating effect of firm age.

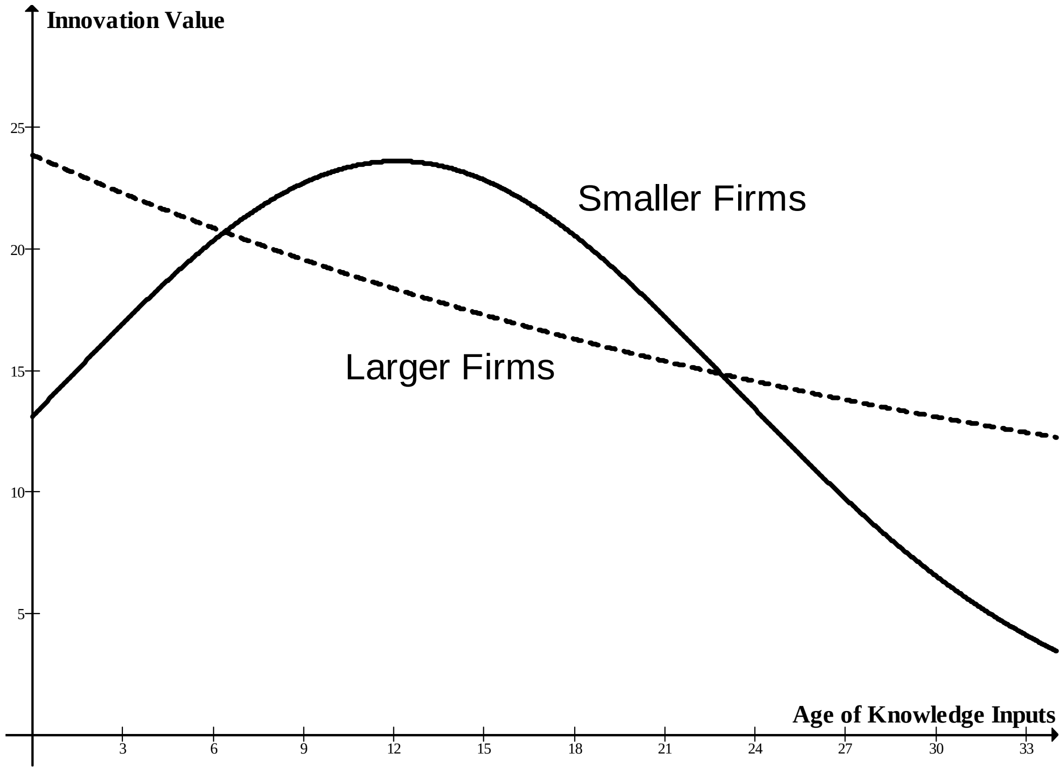

FIGURE 3. The moderating effect of firm size.