Old Is Gold? The Value of Temporal Exploration in the Creation of New Knowledge

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Atul Nerkar
Graduate School of Business, Columbia University, 721 Uris Hall, 3022 Broadway, New York, New York 10027
aan19@columbia.edu

In this paper, knowledge creation is considered as a path-dependent evolutionary process that involves recombining knowledge spread over time. The findings of the paper suggest that a balance in combining current knowledge with the knowledge available across large time spans is an important factor that explains the impact of new knowledge. These ideas are empirically tested using patent data from the pharmaceutical industry. Results from the analysis offer support for the hypotheses developed in the paper.
(*Innovation; Knowledge Creation; Temporal Search*)

Introduction

Knowledge creation has fascinated scholars from different disciplines and different fields for many years (Grant 1996, Garud and Karnoe 2001). Economists have studied the issue of knowledge creation under the broad heading of technical change (Rosenberg 1982), while sociologists have examined the social forces and environments that lead to the creation of new knowledge (Merton 1972). Recent research in the field of strategic management and entrepreneurship has examined issues in new knowledge creation that are relevant to firm performance and entrepreneurial activity (Helfat 2000, Shane and Venkataraman 2000). Such increased interest has led researchers to examine the antecedents and the consequences of knowledge creation. Empirical research in the area of strategy has examined the drivers of new knowledge creation (Ahuja and Lampert 2001), while entrepreneurship research has explored when new knowledge is exploited for entrepreneurial ends (Shane 2001). This emerging research has studied varied aspects of knowledge creation and its consequences. However, the temporal dimension of knowledge creation remains relatively unexplored (exceptions include Helfat 1994a and Katila 2002).

By examining the temporal dimension in the creation of new knowledge, this paper makes three contributions to the field of research in R&D and innovation. First, it reconciles two competing views on technological evolution: one that values recently created knowledge through temporal exploitation and the other that values older knowledge via temporal exploration by suggesting that both contribute to the creation of new knowledge. Second, it empirically tests propositions that emerge from these views in a setting (the pharmaceutical industry) where knowledge creation is considered crucial for success. Finally, by examining the temporal dimension, it explores the recombinant process of knowledge creation and creates an agenda for future empirical research whereby the interaction of different dimensions, such as geographic, technological, organizational, and temporal dimensions, can be systematically examined.

The paper is structured as follows: I first develop an argument for knowledge creation as a recombinant process. Based on this I then discuss the importance of temporal dimension in the knowledge creation pro-

0025-1909/03/4902/0211$5.00
1526-5501 electronic ISSN

cess. In the next section, based on different theoretical perspectives, I develop a series of hypotheses linking recency, use of recent knowledge, and time spread, use of spread-out knowledge, in knowledge creation. In the fourth section, I empirically test these hypotheses using patent data from the pharmaceutical industry. Finally, I present conclusions and directions for future research.

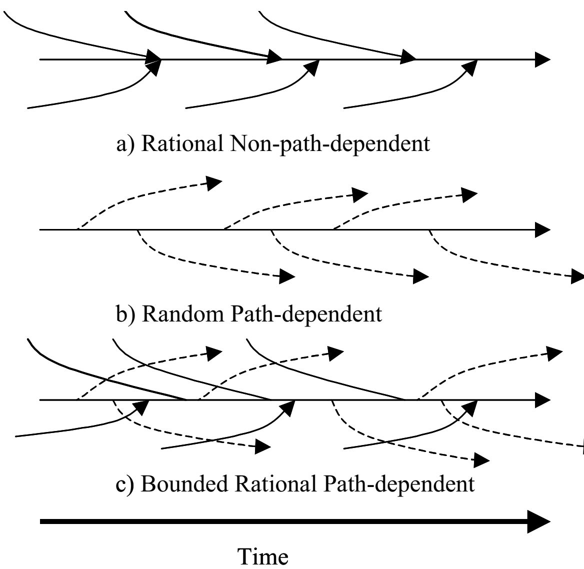
Theoretical Development

Role of Time in Knowledge Creation

Recent research has considered knowledge creation as a recombinant process that involves the coming together of different streams of knowledge (Fleming 2001). Knowledge creation as recombination is associated with the fabrication of a new product, process, or market by combining existing bits of knowledge (Kogut and Zander 1992). New knowledge embodied in such inventive recombination provides temporary Schumpeterian rents to the extent that such knowledge is valued by customers and remains inimitable (Winter 1995). Competitive advantage derived from knowledge created through the recombinant process is sustainable, as the underlying capabilities required are in many cases tacit, systemic, complex, and unobservable even if the knowledge chosen for recombination is codified and observable (Winter 1987, Kogut and Zander 1992). For the purposes of this paper, I consider new knowledge creation as a recombinant process that involves search, discovery, and use of existing, codified, and observable knowledge (Schumpeter 1934, Henderson and Clark 1990, Kogut and Zander 1992).

If the new knowledge creation process is a recombinant one that involves recombining codified knowledge, what determines the creation and the impact of new knowledge? Most scholars studying technological change agree that history and temporal dimension matter but disagree with respect to the nature of its impact on future outcomes (Liebowitz and Margolis 1995). Past research suggests different explanations for how technology and knowledge evolve over time (Nelson and Winter 1982). These different approaches to knowledge evolution can be split into three broad models that are depicted in Figure 1.

Figure 1 Models of Knowledge Creation and Evolution



The first model draws on neoclassical economics and assumes perfect information and complete rationality on the part of the firms and the inventors involved in the creation process. Under this explanation, the new knowledge creation act is an act of optimization along a production function (Pardey 1989). Knowledge evolves through exogenous random variations or shocks that lead to recombinations of existing bits of knowledge at the *current point of time* through an optimization process (Elster 1983). In the first stream of Figure 1, knowledge is shown to evolve as a result of different streams coming together. Inventors choose among alternative streams and include the best choices in their recombination process, leading to an optimal outcome.

The second model, which is based on random walks and chaos theory, suggests that knowledge and technology change through a purely stochastic path-dependent process. The outcomes that emerge are a result of a process that is devoid of rationality on part of the inventor and firms (Arthur 1989, David 1988). Thus the outcomes at time period t_n influence the outcomes of time period t_{n+1}, and these then influence outcomes at t_{n+2}. The sequence in which these outcomes arise is important, as any firm or inventor wanting to arrive at the same outcome needs to follow the same path or sequence. The purely stochastic random nature of the process can lead to suboptimal outcomes. This model is shown in the second stream of Figure 1 where knowledge evolves as result of arbitrary choices made between different paths that present themselves to inventors and firms. Inventors, by ignoring certain paths, change the evolution of technologies. Under this model, multiple suboptimal and optimal outcomes are possible. Such outcomes have been shown to emerge in mathematical models (Arthur et al. 1987) though their actual observance has been disputed (Liebowitz and Margolis 1995).

A third perspective that is also path-dependent considers inventors as bounded rational individuals who lack complete information and who satisfice as opposed to optimize in their knowledge creation efforts (March and Simon 1958, Winter 2000). Knowledge evolves as a result of conscious variations on the part of inventors over time (Nelson and Winter 1982). Some of these variations are selected by the environment and retained over time. The variation and selection process is a willful act on the part of inventors but not necessarily driven by efficiency (Campbell 1965). This "satisficing" model is shown in the third stream of Figure 1, where bounded rational inventors choose between technologies on the basis of limited information. Such decisions can lead to outcomes that are not necessarily optimal.

The three explanations described have led to research on when history matters with respect to market outcomes. In the first explanation the temporal dimension is not considered relevant for the creative act, while in the second and third explanations the temporal dimension forms the core of the argument underlying knowledge creation. In this paper, I take the stance that history matters whereby knowledge creation is neither completely random nor completely rational. While I use all the models to develop hypotheses, the intention of this paper is to offer the bounded rational model as a reconciliation of the first and second model. The process by which knowledge evolves has elements of the rational choice (though bounded) as well as the random walk model, both of which are relevant for the specific hypotheses developed later in this paper.

This historical aspect of knowledge creation has important implications for competitive advantage derived by firms through R&D. Cohen and Levinthal (1990) suggest that the absorptive capacity of a firm helps it to access, synthesize, and commercialize knowledge. Past research on absorptive capacity suggests that R&D investments increase a firm's absorptive capacity. Such research has examined different dimensions along which R&D takes place and has led to the creation of absorptive capacity (Saxenian 1990, Rosenkopf and Nerkar 2001). However, this emphasis on other dimensions has left the role of time relatively unexplored. In the next section, I build a series of hypotheses that examine the role of time and the tension between temporal exploration and exploitation. Specifically, I examine two aspects of the temporal dimension: recency and time spread. Recency is the extent to which history does not matter in knowledge creation. Temporal exploitation is the creation of new knowledge through a recombinant process that emphasizes recency. Time spread measures the extent to which history matters in the process of knowledge creation. Temporal exploration is the creation of new knowledge through recombination of older knowledge obtained by examining a wider time spread.

Hypotheses Development

The Positive Role of Recency in New Knowledge Creation

Understanding the positive role of recency, i.e., use of recently created knowledge, in knowledge creation efforts requires a detailed explanation of the sources of benefits accruing from such choices. Drawing on the three models of technological evolution discussed earlier, I offer three reasons for the positive role of recency in knowledge creation.

The rational choice approach to knowledge creation and evolution implies that knowledge creation is an optimization problem defined by a knowledge production function (Elster 1983). At any stage during the evolution of knowledge, inventors are aware of the nature of the problem they are working on and the knowledge that is to be recombined. Knowledge evolves because of exogenous shocks that lead to reoptimization of the production function. Given these assumptions, it is in the interest of the firm and its inventors to direct their recombinant effort on bits of knowledge that are currently available because such knowledge is representative of the best alternatives that have emerged. For instance, the invention of the steam engine by James Watt has been traced back to the Newcomen engine and to other historical inventions, leading Basalla (1988) to conclude that the actual emergence of the steam engine came about through a series of incremental inventions that were better than the preceding inventions. Thus an inventor, by using knowledge that is in use and currently available, is more likely to have a greater impact on future knowledge creation efforts.

The second reason for using recent knowledge is the advantages accruing from "temporal local search." Past research has documented the tendency of firms and individuals within firms to conduct local search, i.e., search for solutions to problems in the neighborhood of their current expertise (Nelson and Winter 1982, Martin and Mitchell 1998). For instance, Almeida and Kogut (1999) find that knowledge spillovers in the semiconductor area are localized within geographic regions. The use of recent knowledge in the context of new knowledge creation is partly a result of the above logic. The organizational memory of firms is embodied in the routines of the firm and represents the capability of a firm, i.e., activities that define the competence of a firm. These routines help firms maintain continuity. By focusing on recency in knowledge creation, firms use embedded routines and are less likely to make errors and, consequently, produce knowledge with fewer problems and greater value. Such knowledge is likely to have a bigger impact than knowledge that emerges through a trial-and-error process of broad temporal search. The above has been modeled as a first-order Markov process in evolutionary analyses of innovation and knowledge creation (Nelson and Winter 1982). Helfat (1994b) finds empirical evidence of local search in the petroleum industry in which firms tend to persist in their lines of R&D over time.

The third reason for valuing recency in knowledge creation is linked to the cognitive and institutional processes at play during and after knowledge creation. Research on organizational learning finds that past successes and failures lead individuals within firms to develop cognitive frameworks that affect their interpretation of future events (Lant et al. 1992). In particular, Martins and Kambil (1999) find empirical evidence that prior success leads managers to develop cognitive frameworks that produce a favorable outlook toward future events. Bandwagon and institutional effects can also cause firms to use recently created knowledge in their recombinant efforts. Abrahamson (1996) shows that fads and fashions contribute to the creation of theories in the management area. By incorporating latest technology, firms expect to have legitimacy amongst stakeholders and influence on future innovation. This "cutting edge" societal norm causes firms to value knowledge that is recently created and also legitimizes the use of such knowledge by other firms in the future. Thus:

Hypothesis 1. *All other things being equal, the greater the temporal exploitation, i.e., recency in recombination, the greater is the impact of such recombination on knowledge creation.*

The Positive Role of Time Spread in New Knowledge Creation

The earlier discussion suggests that recency in knowledge creation efforts leads to a greater impact on knowledge creation as it enables inventors within firms to pick up the best solutions that have emerged over time, to leverage their competence, and to conform to institutional pressures. However, recent recombined knowledge may not be the technologically superior solution that has emerged (David 1988). In addition, by leveraging competence, the firm and its inventors may actually be reinforcing "rigidities" as opposed to using competencies (Leonard-Barton 1992). Finally, fads and fashions are short lived causing conformity in knowledge creation to have little impact on future knowledge creation (Abrahamson 1996).

The third model of knowledge creation, i.e. path-dependent evolutionary, assumes that inventors are bounded rational, lack complete information, and satisfice as opposed to maximize. Technologies and knowledge evolve through trial-and-error processes, which leads to outcomes that are not necessarily optimal (March 1991). While recombining knowledge, inventors search and choose from knowledge that is "locally available," ignoring potentially far more fruitful paths that exist or that could emerge in the future (Levinthal 1997).

Two possibilities exist for the neglect of such paths. The first is linked to the notion of bounded rationality on part of individuals and firms involved in the search process and leads to choices that are close to the neighborhood of their current expertise (Cyert and March 1992, Leonard-Barton 1992). For instance, the choice of the tire market for the launch of Kevlar in 1974, a new material developed by DuPont, in the face of neutral market research data, was dictated by their competence in that market at that time. After many failures, in 1987 the company revisited the decision to launch Kevlar in the tire market and chose a range of niche markets that were far more receptive to Kevlar (Christensen 1998). By conducting broader temporal explorations, firms and inventors can help to uncover decisions made in history by other inventors that were a result of bounded rationality. By looking back, inventors are likely to find such decisions leading to creation of more valuable knowledge and consequently an increase in impact.

The second reason for the lack of exploration and use of potentially useful knowledge is associated with coevolution of complementary knowledge, institutions, or standards that are necessary for employing a potentially useful piece of knowledge. Coevolutionary processes imply direct or indirect association between the phenomena being observed (Baum and Singh 1994, Rosenkopf and Tushman 1998). Firms and inventors are forced to choose second-best alternatives for lack of complementary knowledge and assets (Teece 1986). Helfat and Raubitschek (2000) present a conceptual model of coevolution that links organizational knowledge, capabilities, and products to competitive advantage and innovation. For instance, automobile designers in the 1950s designed the aerodynamic cars that we see on the roads today. However, these designs were not implemented until the 1980s, as the press tool technology required to build the shapes and forms required of these cars did not exist in the 1950s. Even when such complementary knowledge is available, corresponding choices are not revisited due to switching costs (David and Bunn 1988, Arthur 1989). Different rates of coevolution can cause potentially useful technologies to lie fallow for many years. These paths could have led to significantly different outcomes for technologies and firms. Inventors who look back across broad time periods are likely to find such potentially useful technologies. This suggests that recombining knowledge from broad time periods is relevant as it can uncover valuable knowledge that is forgotten or whose time has not come.

Hypothesis 2. *All other things being equal, the greater the temporal exploration, i.e., time spread in recombination, greater is the impact of such recombination on knowledge creation.*

Dangers of Excessive Temporal Exploration and Exploitation

Being current in knowledge recombination through temporal exploitation is valuable for future knowledge creation activities because of efficiency and societal norms while combining knowledge across a wider expanse of time through temporal exploration helps to uncover useful knowledge that has not been exploited because of the lack of complementary knowledge. However, knowledge recombinations that use only recent knowledge or try to combine only across wide time spreads run the dangers of excessive exploration and exploitation that are similar to those suggested by March (1991).

Recombinations that make use of only current knowledge may have temporary novelty that is lost due to the appearance of similar recombinations. Recent knowledge is more likely to be discovered and used by competitors who have followed similar technological paths, thus leading to multiple occurrences of the same invention at the same time (Merton 1972). One of the most popular examples is the simultaneous development of calculus by Newton and Leibnitz. In the case of inventions that provide competitive advantage, simultaneously occurring multiple inventions arising from temporal exploitation can lead to a contest for the rights to the innovation through litigation and consequently a reduction in impact. A second danger of focus on recency is the lack of novelty in the resultant recombination. Such a lack of novelty may result from imitation by competitors who also have access to recent knowledge. This is typically reflected in imitative strategies that do not differentiate between the pioneer and the follower on any competitive aspect.[1] For instance, a large number of e-commerce ventures, also known as business-to-consumer businesses, are failures as they have been unable to differentiate themselves from other firms on any competitive dimension. Resorting to excessive temporal exploitation can lead to new knowledge that is shallow and does not have any impact on other creation efforts. Hence:

Hypothesis 3a. *All other things being equal, there will be decreasing returns to temporal exploitation, i.e., recency will have a curvilinear relationship with impact on knowledge creation.*

By recombining knowledge spread across wide time spans, instead of using recently created knowledge, firms may be intent on uncovering useful knowledge that has been ignored but may instead follow old redundant paths that do not offer better solutions than those offered through temporal local search. Firms searching for valuable ideas in the past may actually recombine knowledge that is no longer relevant. Older technologies may be in an era of decline making them obsolete (Tushman and Anderson 1986). Also, old knowledge depreciates unless it is maintained as in the case of Sony's miniaturization competence, which though old has been maintained by continuous application in different product markets (Helfat and Raubitschek 2000). Excessive temporal exploration may lead to the creation of knowledge that incorporates old problems, though in a new form.

Hypothesis 3b. *All other things being equal, there will be decreasing returns to temporal exploration, i.e., time spread will have a curvilinear relationship with impact on knowledge creation.*

Balancing Across the Temporal Dimension of Knowledge

While using only recently created knowledge can lead to poor derivative ideas that have no impact, searching only in the distant past can lead to failure in producing anything new. This suggests that knowledge creation strategies be balanced between the past and the present to effect the future.

Being current in knowledge recombination leads to the use of accepted knowledge and creates status for the new knowledge (Podolny and Stuart 1995) in the network of current competitors and collaborators, while the ability to hunt out pathways unexplored in history allows the firm to create new value from old knowledge by exploiting useful untapped knowledge. This recombination of old and new knowledge may have additional dimensions to it such as technological, market, or geographic. Examples of combinations that use both current and older knowledge can be found in the pharmaceutical sector. "Neem," an herb from India whose healing powers have long been known but not exploited, was developed into a commercial drug in the United States by W R Grace, a chemical company after a recent surge of interest in herbal cures (Gray 2000). Age-old knowledge combined with recent knowledge of consumer preferences has led to the introduction of new drugs and products. This new knowledge thus has a substantial influence on future creation efforts.

However, this balancing across the temporal dimension involves trade-offs (March 1991). Emphasizing one activity to the exclusion of other can lead to a reduction of benefits that emerge from the other. Temporal exploration, like other exploratory activities while increasing the variance of the performance distribution can reduce the increase in mean performance that emerges from temporal exploitation. This is because the ability to recombine recent knowledge is markedly different from that required to recombine across time spans. Figure 1(c) helps in understanding the dilemma firms face trying to balance between temporal exploitation and exploration. Exploitation at time any time t requires a firm to stay abreast of different knowledge streams represented by the solid lines, while exploration at the same time requires a firm to keep track of the knowledge streams not chosen in the past and represented by the dotted lines. The ability to explore long stretches of time periods requires the active maintenance of archives

[1] In some cases a follower or imitative strategy may actually help the firm. See Teece (1986) for a more detailed explanation of such situations.

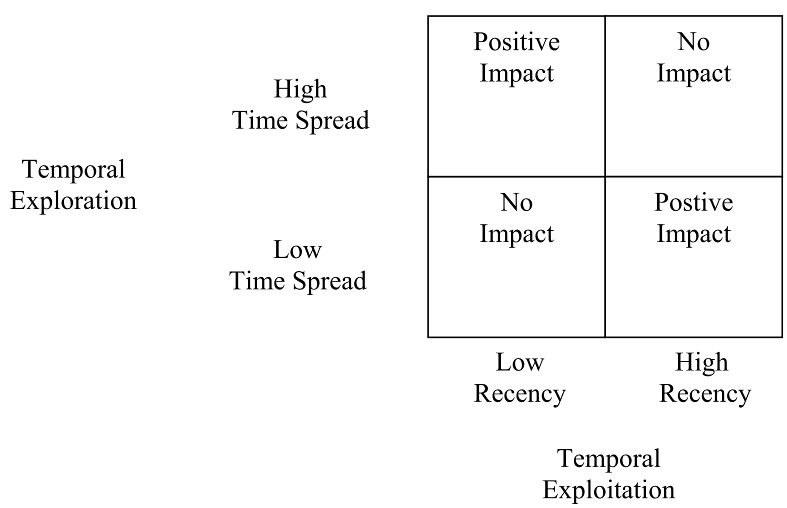
of such unexplored knowledge streams. Such knowledge archives may be explicit in the form of databases or implicit in the form of higher-order search routines or a combination of both. Further, such maintenance is of little use unless the ability to synthesize the knowledge is also present (Garud and Nayyar 1994). This maintenance and synthesis of old knowledge is antithetical to the activities involved in temporal exploitation that require an understanding of current developments.

An example of such a trade-off is seen in the problem faced by financial institutions in the year 2000. Most computer systems used by financial institutions in the United States were developed in the early seventies using COBOL, a computer language with few features. COBOL has given way to more efficient languages such as C and C++ and, as a result, firms lost their ability to program in COBOL. This led to huge problems when firms had to make their computers Y2K (ready for the year 2000) compliant as this required an understanding of COBOL, and most firms did not have programming capabilities in COBOL. Firms from other countries such as Russia and India who had access to such knowledge to provided the programming capabilities to American firms at exorbitant prices (Greenmeier 2002). Given their limited resources firms typically allocate support to knowledge creation activities that are cutting edge, i.e., built on the latest technology. Those firms that can do both temporal exploration and temporal exploitation are able reap the benefits of such balance. However, such simultaneous temporal exploration and exploitation may not always lead to benefits for the firm given the curvilinear relationships suggested in the Hypotheses 3a and 3b, respectively. This is depicted in the 2×2 matrix shown in Figure 1.

The lower left quadrant (2) suggests that inventors and firms that do not conduct either temporal exploration or temporal exploitation will have no impact or negative impact on knowledge creation as they are unable to capture benefits of recency or time spread in their recombinant activity. Correspondingly, the upper right-hand quadrant (4) suggests that firms and inventors who conduct both temporal exploration and exploitation excessively will have a negative or little impact on knowledge creation because of the decreasing returns discussed in Hypothesis 3.

In contrast, firms that do a little of temporal exploration or exploitation will find value in moving from corresponding lower levels of temporal exploitation or exploration to higher levels of temporal exploration (quadrant 3) and exploitation (quadrant 1), respectively, as this move helps to balance across the temporal dimension by letting firms garner some of the benefits from such activity. For instance, inventors and firms that are on the cutting edge of technology are more likely to find success by creating new knowledge through recombination of this knowledge with

Figure 2 Balancing Temporal Exploration and Exploitation



older knowledge obtained by examining a wider time spread. Similarly, firms that are extremely competent in searching across time spans will benefit from using recent knowledge. Hence:

Hypothesis 4. *All other things being equal, temporal exploitation (recency of knowledge) will interact with the temporal exploration (time spread of knowledge) in its relationship with impact on knowledge creation.*

Research Methods

Data and Research Site

To examine the creation of new knowledge within a firm and its impact on future creation, I use patents as proxy indicators of knowledge creation efforts. The emphasis in this paper is on codified knowledge, and patents provide an excellent paper trail of such codified knowledge (Jaffe et al. 1993). This follows the research efforts of several other scholars who have used patents as a measure of knowledge held by the firm (Ahuja and Lampert 2001, Henderson and Cockburn 1994).

I am interested in analyzing the effect of temporal explorations and exploitations by a firm during the creation of new knowledge on future R&D activities. Hence, the unit of analysis is the patent, while the level of analysis is the firm. Each patent within a firm represents a knowledge creation effort on part of the firm. The sources for this information include the U.S. Patent Office and online databases. I selected my sample from the pharmaceutical industry. Prior research clearly indicates that patenting activity is an important source of technological advantage in the pharmaceutical industry (Levin et al. 1987), whereas patents may not necessarily mean much as knowledge indicators in other technical areas. Based on SIC code 2834, pharmaceuticals, I collected a data set consisting of 15,345 patents for a period of seven years (1981 to 1987) for 33 firms.[2]

Even though my hypotheses are at the knowledge level, I chose to sample on the basis of firms in SIC 2834 instead of looking at broad pharmaceutical classes for two reasons. One of the primary motivations of this paper has been to understand the evolution of knowledge from the context of new knowledge capability development within firms. By including these 33 firms, I account for more than 70% of the drug development and patenting in the pharmaceutical sector. I am able to explore the capability development within firms that matter for new knowledge creation. A second reason is that the large number of patents generated by using the entire population of pharmaceutical patents makes data collection and analysis difficult if not infeasible. The emphasis on these 33 firms can lead to problems of generalizability and sample selection bias. However, the firms represented in this dataset account for majority of R&D activity taking place in the pharmaceutical sector. In the section on research methods, I discuss empirical solutions to sample selection bias (if any exists) in the dataset. Finally, there are a considerable variety of firms with different size pharmaceutical firms being represented in the sample.

[2] The entire list of firms along with patent distributions is available from the author on request.

Measurement

Dependent Variable. Patent citations have been considered to be an excellent measure for technological impact and performance (Albert et al. 1991). It is the responsibility of the inventor to cite appropriate prior art (patents granted earlier that are relevant to the invention). But such citation or reference to other patents needs the approval of the patent examiner. This approval removes inventor bias to a considerable extent from citation behavior.

Impact: I use the total number of citations a patent receives from the time it is granted till the end of 1996 as an indicator of impact on future knowledge creation. These citations are received from the entire universe of patents that includes the sample of 15,345 patents used in this paper.

Independent Variables. Each patent contains references to other patents and scientific literature. These references are known as prior art and are analogous to the bibliography or references in an academic research paper. Both the primary independent variables are derived from the prior art cited on the front page of the patent.

Temporal Exploitation: This measure was operationalized by computing a "recency" measure as follows: I first measured the median age as the median difference between the grant date of a patent and that of the U.S. patents referenced in the patent (Sorensen and Stuart 2000). I then examined the distribution of this variable and found that the oldest patent cited in the sample was granted in the early part of the 20th century, i.e., 1914. Based on this examination, I transformed the median age to reflect the recency of knowledge by subtracting from 100 the median age. The minimum value of this variable is 0 years, which represents the oldest possible knowledge, while the maximum value is 100 years, which represents the most recent knowledge. The age variable obtained from the patent data has a negative relationship with impact. By subtracting 100 from the median age, I transformed the variable allowing me to conduct a test of the positive relation between recency and impact.

Temporal Exploration: This was constructed by computing a "time spread" measure based on patents cited. This was measured as the interquartile range of knowledge used in a patent and is computed as the difference between the grant dates of the lower quartile and the upper quartile of the age distribution of the cited patents. I ran alternate regression models with measures such as standard deviation, variance, and range. The results are similar to and consistent with those obtained with the range construct. However, these alternate measures are more strongly correlated than the range measures with the median age of knowledge.

Control Variables. I used seven control variables that are considered by other researchers to influence number of citations received by a patent. First, by including a variable that counts the number of inventors on a patent, *Inventor Diversity,* I control for creative diversity that influences knowledge creation and can lead to differentials in future citation patterns of patents (Reagans and Zuckerman 2001). Second, I include two variables to measure *Technological Diversity.* These are essentially controls for the technological scope of the patent and are measured as the number of technological classes and subclasses assigned to a patent (Silverman 1999). Third, I include a variable, *Geographic Diversity*, which controls for diversity arising from geographic scope because of different locations of inventors on the patent (Cantwell and Odile 1999). This is measured as the number of unique geographic inventor locations or cities on a patent. Fourth, by including a variable, *Patent Type,* I control for the nature of the patent. Specifically, this variable is a dichotomous variable that is coded as 0 when the patent was explicitly designated as part of a pharmaceutical class (Penner-Hahn 1998). Fifth, I control for the tendency of firms to self-cite by including a variable, *Self-Citations,* a count of the number of patents in the prior art that are self-citations (Sorensen and Stuart 2000). Sixth, I control for the time that the patent was under review before being granted by including a variable, *Application Time*. This is measured as the time taken in years by the patent office to grant the patent application. Finally, I also include a variable, *Technological Value,* which controls for the ex ante value of the patent by measuring the number of claims made by it (Tong and Frame 1994). I also control for fixed-year effects by including dummy variable. The omitted year is 1987.

The temporal spread and the median age of knowledge are two variables that measure different aspects of knowledge creation. These variables are distinct in their construction. Patents that do not cite other patents have zero recency and time spread. I exclude these patents from my data collection and analysis.

Analytical Techniques

Researchers in the past (e.g., Hausman et al. 1984) have modeled citation rates using poisson regression. The dependent variable in the regression is the number of citations that takes only discrete nonnegative integer values while the regression takes the form

$$E(y_i/x_i) = e^{xit-1\beta}, \tag{1}$$

where "y_i" are the number of citations received by a patent filed in year "i" at the end of 1996, and X_i is a vector of independent variables such as age, time spread, and other control variables affecting the mean of citations. I examined the summary statistics and find that the Poisson estimates may be biased as they suffer from over-dispersion (Cameron and Trivedi 1986). Hence, I use negative binomial regression models to correct for overdispersion. I include the logarithmic transformation of the time elapsed for citation for each patent since its grant to alleviate the problem of truncation because of varying citation periods of patents. I force the value of its parameter to be 1, allowing comparison of patents granted at different periods of time in the dataset.[3]

As mentioned earlier, my sample uses 33 firms in the pharmaceutical industry that account for bulk of the R&D in the area. I examine the patenting activity of these 33 firms. I consider each patent as a knowledge creation effort. However, these knowledge creation efforts within a firm are not independent of one another. To address the problem of repeated observations for the same firm, I estimate the negative binomial model using the GEE (generalized estimating equations) approach (Liang and Zeger 1986). The negative binomial model described above does not account for unobserved heterogeneity. To address this problem, I follow Ahuja and Lampert (2001) who use a presample panel approach based on Blundell et al. (1995). I include prior capabilities and prior performance or impact in the regression model to capture the effect of pre-existing conditions on future knowledge creation. I measured prior capabilities as the stock of patents (number of successful knowledge creation efforts) in the time period between 1977–1980 and prior performance resulting from these knowledge creation efforts as the average citations received by these patents. I control for differences in the capability and performance differentials resulting from such capabilities before the observation period began (1981) by including these variables. In addition, I also report all results with significance levels based on robust or empirical standard errors to control for residual heteroscadasticity (White 1980).

Results

Patent-level descriptive statistics along with a correlation matrix for the sample are presented in Table 1.

The median recency of knowledge recombined across all the patents was 91.08 years while the average interquartile time spread of knowledge across all patents was 6.86 years. The average impact measured as the number of citations received from other firms by a patent was 3.97. The correlation coefficients between the dependent variable (total citations) and the independent variables (median age of knowledge and time spread of knowledge) are significant and in the direction hypothesized. Further, the highest correlation between any two independent variables is 0.48, between time spread and recency. This number drops to 0.36 when the partial correlation matrix is computed with fixed effects for years and firms. This level of correlation does indicate that problems of multicollinearity are substantially alleviated even if not completed ruled out. The highest correlation coefficient between control variables between scope (number of classes) and subscope (number of subclasses) is $r = 0.6$. I ignore this correlation as these two variables measures similar constructs. Dropping either of them did not change the results for the main effects. In the next section, I test the hypothesized relationships in a series of multivariate analyses.

Negative Binomial Regressions

Table 2 presents results for the negative binomial regression models of impact measured as future citations on the explanatory variables of recency and time spread. All hypotheses were supported except Hypothesis 3a that received only partial support. Recency and time spread of knowledge recombination has a positive relationship with future citations. However this relationship is curvilinear for time spread and linear for recency. Further, recency and time spread interact with each other in their relation with impact.

Model I in Table 2 presents the results for the control variables. Model II adds the variables for Hypotheses 1 and 2, respectively, with no squared terms. Model III and IV add the squared terms for each hypothesized effect while controlling for the other effect. Model V includes both the hypothesized effects and the squared terms. To test for the interaction effects, I ran a series of models that are presented in Models VI through X.

The results from Models I through V offer strong support for Hypotheses 1, 2, and 3b but no support for Hypothesis 3a. Most of the control variables in Model 1 are significant and in directions that are consistent with findings from prior research

[3] I ran regression models in LIMDEP and SAS. Both provided similar and consistent results.

Table 1 Summary Statistics and Correlation Matrix

	Variable	Mean	SD	Min	Max	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
(1)	Impact	3.968	6.260	0	203	1.000											
(2)	Recency	91.079	7.371	14.923	100	0.034	1.000										
(3)	Time spread	6.864	8.420	0	78	0.041	−0.483	1.000									
(4)	Prior capabilities	631.928	452.247	0	1470	−0.052	−0.088	0.063	1.000								
(5)	Prior performance	3.774	1.161	1.978	11.593	0.205	−0.017	0.053	−0.138	1.000							
(6)	Technological value	11.884	12.110	1	263	0.125	0.058	−0.035	−0.060	0.044	1.000						
(7)	Tech. diversity (class)	2.171	1.235	1	13	0.079	0.048	−0.031	0.023	−0.046	0.095	1.000					
(8)	Inventor diversity	2.210	1.234	1	8	−0.004	0.040	−0.055	−0.041	−0.137	−0.037	0.054	1.000				
(9)	Geographic diversity	1.128	0.355	1	4	0.007	−0.005	−0.002	0.076	−0.006	−0.012	0.006	0.346	1.000			
(10)	Application time	1.944	0.882	0	12.195	0.027	−0.062	0.007	−0.005	0.018	0.062	0.050	0.006	−0.003	1.000		
(11)	Tech. diversity	5.481	4.980	1	29	0.098	0.036	−0.008	0.093	−0.046	0.132	0.611	0.042	−0.004	0.062	1.000	
(12)	Self citations	1.151	3.122	0	102	0.307	0.067	−0.042	0.007	0.179	0.100	0.090	0.027	−0.006	−0.015	0.092	1.000
(13)	Type of patent	0.313	0.464	0	1	−0.019	0.115	−0.149	−0.236	−0.005	0.113	0.185	0.108	0.013	0.031	0.087	0.056

Note. All correlation coefficients above 0.01 are significant at $p < 0.05$.

Table 2 GEE Negative Binomial Regression Models of Impact

Variable(s)	I	II	III	IV	V
Intercept	−7.9288****	−7.9344****	−7.9246****	−7.8827****	−7.8865****
	(0.2172)	(0.2138)	(0.2128)	(0.2123)	(0.2118)
Recency		0.0114****	0.0085****	0.0115****	0.0131****
		(0.0015)	(0.0024)	(0.0015)	(0.0023)
Time spread		0.0153****	0.0148****	0.0274****	0.0281****
		(0.0025)	(0.0024)	(0.0042)	(0.0040)
Recency^2			−0.0001^t		0.0001
			(0.0001)		(0.0001)
Time spread^2				−0.0006****	−0.0006****
				(0.0001)	(0.0001)
Prior capabilities	−0.0002^t	−0.0002^t	−0.0002^t	−0.0002^t	−0.0002^t
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Prior performance	0.1637****	0.1587****	0.1583****	0.1539****	0.1539****
	(0.0439)	(0.0432)	(0.0431)	(0.0427)	(0.0427)
Technological value	0.0132****	0.0130****	0.0130****	0.0129****	0.0129****
	(0.0015)	(0.0015)	(0.0015)	(0.0015)	(0.0015)
Tech. diversity (classes)	0.0260	0.0249	0.0247	0.0232	0.0232
	(0.0159)	(0.0155)	(0.0155)	(0.0153)	(0.0153)
Inventor diversity	−0.0052	−0.0026	−0.0023	−0.0015	−0.0016
	(0.0180)	(0.0183)	(0.0184)	(0.0181)	(0.0181)
Geographic diversity	0.0367	0.0310	0.0302	0.0314	0.0319
	(0.0513)	(0.0481)	(0.0481)	(0.0476)	(0.0475)
Application time	0.0382**	0.0440**	0.0426***	0.0436***	0.0444***
	(0.0152)	(0.0157)	(0.0156)	(0.0159)	(0.0159)
Tech. diversity	0.0208****	0.0209****	0.0209****	0.0209****	0.0209****
	(0.0038)	(0.0037)	(0.0037)	(0.0036)	(0.0036)
Self citations	0.1006****	0.1012****	0.1015****	0.1011****	0.1009****
	(0.0050)	(0.0051)	(0.0051)	(0.0052)	(0.0052)
Type of patent	−0.1666**	−0.1469**	−0.1470**	−0.1360*	−0.1355*
	(0.0617)	(0.0605)	(0.0604)	(0.0591)	(0.0592)
Year 1981	−0.4416****	−0.4353****	−0.4330****	−0.4266****	−0.4276****
	(0.0852)	(0.0797)	(0.0798)	(0.0811)	(0.0811)
Year 1982	−0.3126****	−0.3137****	−0.3112****	−0.3047****	−0.3058****
	(0.0620)	(0.0586)	(0.0584)	(0.0593)	(0.0591)
Year 1983	−0.2979****	−0.2873****	−0.2855****	−0.2791****	−0.2797****
	(0.0509)	(0.0501)	(0.0506)	(0.0496)	(0.0498)
Year 1984	−0.1791**	−0.1728**	−0.1712**	−0.1671**	−0.1677**
	(0.0587)	(0.0559)	(0.0556)	(0.0550)	(0.0547)
Year 1985	−0.2499****	−0.2447****	−0.2437****	−0.2409****	−0.2414****
	(0.0505)	(0.0470)	(0.0473)	(0.0483)	(0.0482)
Year 1986	−0.0014	0.0012	0.0034	0.0063	0.0053
	(0.0479)	(0.0447)	(0.0448)	(0.0441)	(0.0440)
Log likelihood	50278.49	50348.22	50350.78	50390.96	50391.29
Improvement		69.7347	2.5557	42.7350	0.3359
Comparison		I	II	II	IV

Note. Values in parentheses are standard errors. All tests are one-tailed except for control variables.
$^{****}p < 0.0001$, $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, $^{t}p < 0.1$.

($\beta_{\text{Prior Capabilities}} = -0.0002$, $p < 0.1$; $\beta_{\text{Prior Performance}} = 0.1637$, $p < 0.0001$; $\beta_{\text{Technological Value}} = 0.0132$, $p < 0.0001$; $\beta_{\text{Self-Citation}} = 0.1006$, $p < 0.0001$). Model II is significant and offers strong support for Hypotheses 1 and 2. The parameter coefficients for time spread are positive and statistically significant, offering strong support for Hypotheses 1 and 2, respectively ($\beta_{\text{Recency}} = 0.0114$, $p < 0.0001$; $\beta_{\text{Timespread}} = 0.0153$; $p < 0.0001$). The addition of the squared term of recency in Model 3 does not improve the fit of the model as compared with Model 2. Although the coefficient is negative, it is insignificant and provides only partial support for Hypothesis 3a. In comparison to this result, the addition of the squared term of the time spread variable in Model 4 improves the fit of the model as compared with Model 2 (Improvement in log likelihood = 42.735). Also, the coefficient for the time spread squared variable is negative and significant as hypothesized ($\beta_{\text{Timespread}\times\text{Timespread}} = -0.0006$, $p < 0.0001$). This result supports Hypothesis 3b. Model 5 includes squared terms for both recency and time spread. The increase in Log-likelihood as compared to Model 4 is insignificant. The coefficient for the squared term of time spread continues to be negative and significant ($\beta_{\text{Timespread}\times\text{Timespread}} = -0.0002$, $p < 0.0001$) while the coefficient for the squared term of recency is positive and insignificant ($\beta_{\text{Recency}\times\text{recency}} = 0.0001$). These results continue to offer support for Hypothesis 3b but not for Hypothesis 3a.

I hypothesized an interaction effect between recency and time spread in their relation with impact. Both these variables are hypothesized to have curvilinear relations with impact. Following Aiken and West (1991), I analyzed a series of models that lead to the hypothesized interaction effect of Hypothesis 4:

$$\text{Impact} = \alpha + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_1^2 + \beta_4 x_2^2 + \beta_5 x_1 x_2 + \beta_6 x_1^2 x_2 + \beta_7 x_1 x_2^2 + \beta_8 x_1^2 x_2^2 + \xi \quad (1)$$

where x_1 = Recency and x_2 = Time Spread, α is the intercept and ξ the error term.

In Table 3, I present results of the negative binomial regressions of impact (measured as citations) on the variables time spread and recency and their interaction with each other. Model VI includes the first-order interaction effect between time spread and recency to the full model tested in Model V. Model VII adds the interaction term between the squared term of recency and time spread, while Model VIII examines the interaction between the squared term of time spread and recency. Model IX includes all the variables mentioned in Equation (1). Of all the four models analyzed, the best fitting model is Model VIII, which provides support for a curvilinear relation between time spread and impact and a linear relation between recency and impact, respectively. In this model the parameters of the interaction between the squared effects of time spread and recency, that is, the quadratic relation between time spread and impact varies in form as a function of the value of recency, or conversely the relation between recency and impact varies in form as a function of time spread ($\beta_{\text{Timespread}\times\text{Timespread}\times\text{Recncy}} = 0.00001$, $p < 0.0001$; $\beta_{\text{Timespread}\times\text{Recncy}} = 0.0007$, $p < 0.0001$).

As a robustness check, I further analyzed a model that includes performance of the last patent successfully granted to the firm as a control variable. By doing this I control for unobserved heterogeneity (Heckman and Borjas 1980). These results are reported in Model X. The relations continue to remain significant offering support for all hypotheses except Hypothesis 3(a).

Discussion

A principal purpose of this research was to explore the impact of temporal exploration and exploitation on future knowledge creation. Using a path-dependent evolutionary framework, I developed the argument that both current knowledge and historical knowledge matter for future creation of new knowledge. Further, I hypothesized that current knowledge and historical knowledge interact with each other in their relation with impact. The results from the empirical analyses generally support the above argument with one exception. Temporal exploitation measured as recency in recombination has a strong positive linear relation with impact while temporal exploration measured as the time spread in recombination has a positive curvilinear relation with impact. The findings of this paper offer support for the bounded rational approach to technological evolution, whereby rationality as well as luck are both given due credence.

Table 3 GEE Negative Binomial Regression Models of Impact

Variable(s)	VI	VII	VIII	IX	X
Intercept	−7.8860****	−7.9058****	−7.8563****	−7.8539****	−7.8599****
	(0.2118)	(0.2131)	(0.2136)	(0.2139)	(0.2098)
Recency	0.0131****	0.0090****	0.0137****	0.0147****	0.0148****
	(0.0023)	(0.0024)	(0.0015)	(0.0026)	(0.0027)
Time spread	0.0281****	0.0187****	0.0312****	0.0317****	0.0317****
	(0.0040)	(0.0032)	(0.0042)	(0.0043)	(0.0043)
Recency^2	0.0001	0.0000		0.0000	0.0000
	(0.0001)	(0.0001)		(0.0001)	(0.0001)
Time spread^2	−0.0006****		−0.0008****	−0.0008****	−0.0008****
	(0.0001)		(0.0001)	(0.0001)	(0.0001)
Recency × time spread	−0.0001	0.0009****	0.0007***	0.0008*	0.0008*
	(0.0002)	(0.0002)	(0.0003)	(0.0005)	(0.0005)
Recency^2 × time spread		0.0000***		0.0000	0.0000
		(0.0000)		(0.0000)	(0.0000)
Time spread^2 × recency			0.0000***	0.0000**	0.0000***
			(0.0000)	(0.0000)	(0.0000)
Recency^2 × time spread^2				0.0000	0.0000
				(0.0000)	(0.0000)
Prior capabilities	−0.0002^t	−0.0002^t	−0.0002^t	−0.0002^t	−0.0002^t
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Prior performance	0.1538****	0.1567****	0.1519****	0.1518****	0.1446****
	(0.0427)	(0.0430)	(0.0426)	(0.0426)	(0.0417)
Recent performance					0.0070****
					(0.0016)
Technological value	0.0129****	0.0129****	0.0128****	0.0128****	0.0127****
	(0.0014)	(0.0015)	(0.0014)	(0.0014)	(0.0014)
Tech. diversity	0.0231	0.0252	0.0228	0.0228	0.0229
	(0.0153)	(0.0155)	(0.0153)	(0.0152)	(0.0154)
Inventor diversity	−0.0017	−0.0012	−0.0008	−0.0008	−0.0014
	(0.0181)	(0.0183)	(0.0179)	(0.0179)	(0.0177)
Geographic diversity	0.0324	0.0273	0.0302	0.0302	0.0321
	(0.0470)	(0.0470)	(0.0465)	(0.0465)	(0.0462)
Application time	0.0443***	0.0430***	0.0446***	0.0448***	0.0452***
	(0.0159)	(0.0158)	(0.0159)	(0.0160)	(0.0161)
Tech. diversity	0.0209****	0.0210****	0.0211****	0.0210****	0.0209****
	(0.0036)	(0.0037)	(0.0036)	(0.0036)	(0.0037)
Self citations	0.1009****	0.1016****	0.1011****	0.1010****	0.1006****
	(0.0052)	(0.0051)	(0.0052)	(0.0052)	(0.0052)
Type of patent	−0.1355*	−0.1430**	−0.1335*	−0.1334*	−0.1319**
	(0.0592)	(0.0595)	(0.0586)	(0.0585)	(0.0584)
Year 1981	−0.4279****	−0.4275****	−0.4233****	−0.4236****	−0.4219****
	(0.0807)	(0.0783)	(0.0805)	(0.0807)	(0.0790)
Year 1982	−0.3060****	−0.3075****	−0.3024****	−0.3020****	−0.3017****
	(0.0591)	(0.0578)	(0.0589)	(0.0588)	(0.0568)
Year 1983	−0.2801****	−0.2800****	−0.2761****	−0.2767****	−0.2768****
	(0.0498)	(0.0496)	(0.0489)	(0.0490)	(0.0477)
Year 1984	−0.1679**	−0.1675**	−0.1666**	−0.1679**	−0.1690****
	(0.0547)	(0.0545)	(0.0546)	(0.0544)	(0.0527)

Table 3 Continued

Variable(s)	VI	VII	VIII	IX	X
Year 1985	-0.2414^{****}	-0.2418^{****}	-0.2408^{****}	-0.2417^{****}	-0.2406^{****}
	(0.0483)	(0.0469)	(0.0485)	(0.0488)	(0.0469)
Year 1986	0.0051	0.0047	0.0027	0.0016	0.0015
	(0.0440)	(0.0440)	(0.0439)	(0.0441)	(0.0431)
Log likelihood	50391.38	50363.89	50403.89	50405.32	50420.68
Improvement	0.08	−27.49	12.60	14.02	29.39
Comparison	V	V	V	V	V

Note. Values in parentheses are standard errors. All tests are one-tailed except for control variables. Models have been analyzed after mean-centering the predictor variables to reduce problems of multicollinearity.

$^{****}p < 0.0001$, $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, $^{t}p < 0.1$.

These results are consistent with a broader stream of research which suggests that firms benefit from both exploration and exploitation but in tightly competitive situations it is exploration that leads to dramatic improvements in performance (March 1991).

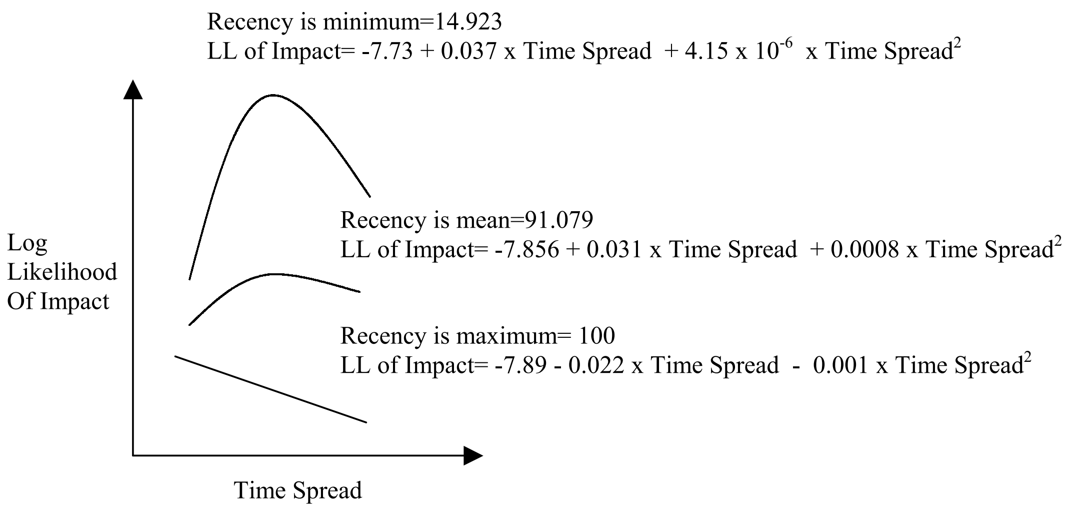
Two nonresults deserve further discussion. First is the lack of support for excessive temporal exploitation and its negative association with impact. This further leads to the lack for support for the interaction between the squared terms of time spread and recency, respectively. The relation that is supported is the interaction between the squared term of time spread and recency as shown graphically in Figure 3. At low levels of recency, that is, at the minimum value, the curvilinear relation is positive and accentuated, while at high levels, that is, maximum value, the relation is negative and linear. This provides support for the 2×2 matrix described earlier in Figure 2. In particular, Figure 3(a) provides evidence supporting outcomes in quadrants (3) and (4) where temporal exploration is high, while temporal exploitation varies between low and high. Correspondingly, Figure 3(b) suggests that at high levels of time spread, that is, the maximum value, increases in recency lead to more increases in impact than at low levels of time spread, that is, the minimum value. These results provide support for outcomes in quadrants (1) and (2) where temporal exploration is low and temporal exploitation varies between low and high. However, this result suggests that once temporal exploration is at a maximum, there are no disadvantages to excessive focus on temporal exploitation. This does not support the hypothesized outcome of quadrant 4.

Current research on exploration and exploitation offers a few reasons for the lack of evidence of negative impact. First, firms typically are involved in exploration along other dimensions apart from the temporal one, i.e., technological, organizational, and geographic. Firms that excessively emphasize recent technological changes may compensate for lack of novelty arising from such exploitation by accessing knowledge that is outside firm boundaries or is far from their technological expertise. A second reason are the short-run profits resulting from inventions building only on recent knowledge even though such inventions may not provide sustainable competitive advantage. One approach to reconcile this result with the hypothesized relationship is to look at the nature of impact. By measuring impact as the number of commercially successful products it may be possible to untangle cognitive, technological, and institutional explanations from temporal explanations. The current dataset does not permit a deeper empirical exploration of this nonresult though recent research has begun using such variables (Katila 2002, Katila and Ahuja 2002).

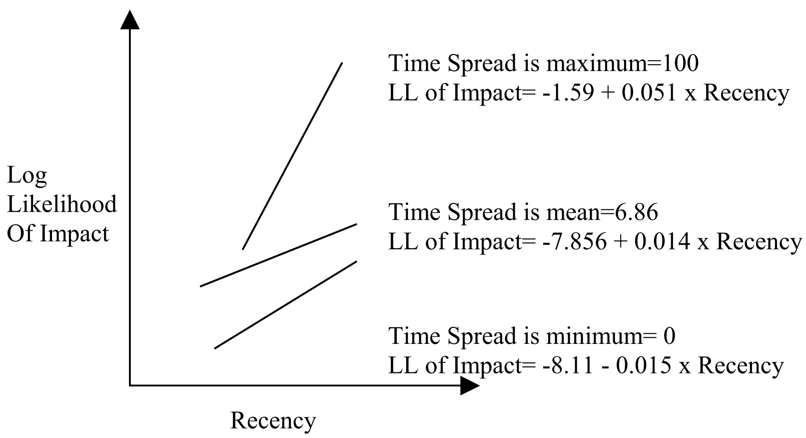
Finally, the control variables introduced in the form of the number of claims, prior performance, prior capabilities, technological diversity, application time, patent type, and self-citations are significant and in a direction consistent with past research in the area.

The use of patent data, while very useful in developing different knowledge trajectories has been considered to have several limitations. First, patents are not measures of all the knowledge held by the firm. The distinction between tacit and codified knowledge

Figure 3



(a)



(b)

is very important. Patents and patent citations are excellent indicators of codified knowledge but not necessarily for tacit knowledge (Winter 1987). This is especially true in the case of service industries (Levin et al. 1987). Second, my sampling strategy of using SIC code 2834 favors the larger public firms with budgets that can afford many patent applications, and who therefore file "thickets" of related patents. Third, patent citations can in some cases be negative citations in which the patent citing the patent instead of using knowledge embodied in the cited patent is negating it. I use patents cited in the prior art as a proxy for knowledge recombination. However, cited patents are not the only knowledge recombined. Ahuja and Lampert (2001) shows that patents that do not cite any other patents are breakthrough or pioneering patents and are more likely to be cited by other patents in the future. It would be useful to conduct a couple of case studies in this industry to check whether these results are supported by qualitative analysis.

Implications and Future Research

The findings of this paper provide an agenda for understanding the evolution of knowledge and creation of technological capabilities within the firm. The role of path dependence in knowledge creation highlights the importance of what Cohen and Levinthal

(1994) call "fortune favoring the prepared." Future research can conduct several extensions of the present research. First, the study should be replicated in other settings, perhaps in different industries with different time frames to test the theory and further the findings. Second, in this paper I examined only the temporal dimension and controlled for the technological, organizational, and geographic dimensions of knowledge combinations. It may be fruitful to examine the interactions of different dimensions of knowledge combinations. For instance, is it better to combine across different technologies but in a particular geographic location as compared to combining across locations but in the same technological area? Research on such questions would need to address the nested nature of these effects. Third, the nature of the impact in this paper is measured simply as the number of citations received by a particular patent. It may be useful to explore the role of different knowledge combinations on different types of impact. Are there other dimensions to search behavior? Research done by Zucker et al. (1998) suggests that star scientists play a key role in the evolution of technology. Such scientists could form another dimension of knowledge recombination, for instance, personnel networks.

From a managerial perspective, this paper offers important insights into the knowledge creation process. Firms and inventors, by recombining knowledge across time spans can create new paths as opposed to becoming prisoners of path-dependent processes (Garud and Karnoe 2001). Many firms are increasingly resorting to computerized approaches such as "data mining" to understand what the past may hold for them. Firms need to build this ability maintaining, activating and synthesizing historical knowledge. Recent research has suggested a real options approach to new knowledge creation (McGrath 1997). By taking out options on inventions firms can have the luxury of waiting and watching as more information about past knowledge is revealed. Further, the complementary knowledge required for exploiting old useful underutilized knowledge can be created. Another approach is to license knowledge created in the past that is valuable. This knowledge cannot be exploited within the firm as either the firm does not possesses the complementary assets or the technology does not form a key part of the strategy developed by the firm. More companies are actively adopting a licensing strategy for old valuable knowledge while simultaneously trying to combine old knowledge with new knowledge with the objective of obtaining successful product and process innovations (Rivette and Kline 1999). However, this effort is not widespread and still is regarded as a novel approach to innovation.

In conclusion, the role of time is considered as self-evident and important in most social sciences research but only recently has been explored independently. The differences in the states of knowledge created at different times and their use influence the future trajectories of knowledge creation (Dosi 1982). In the context of knowledge creation and use history plays a particularly important role as it shapes the present and constrains the future. This paper by emphasizing knowledge creation along the temporal dimension suggests that new insights can be obtained by incorporating this dimension into future research on knowledge creation.

Acknowledgments
The author gratefully acknowledges research assistance provided by Michal Levi and Srikanth Paruchuri. Conversations with Asim Ansari, Ray Horton, Paul Ingram, Ian C. MacMillan, and S. Venkatarman were extremely useful.

References
Abrahamson, E. 1996. Management fashion. *Acad. Management Rev.* **21**(1) 254–286.

Ahuja, G., C. M. Lampert. 2001. Entrepreneurship in the large corporation: A longitudinal study of how established firms create breakthrough inventions. *Strategic Management J.* **22**(6/7) 521–543.

Aiken, L. S., S. G. West. 1991. *Multiple Regression: Testing and Interpreting Interactions*. Sage Publications, New York.

Albert, M. B., D. Avery, F. Narin, P. McAllister. 1991. Direct validation of citation counts as indicators of industrially important patents. *Res. Policy* **20**(3) 251–260.

Almeida, P., B. Kogut. 1999. Localization of knowledge and the mobility of engineers in regional networks. *Management Sci.* **45**(7) 905–917.

Arthur, W. B. 1989. Competing technologies, increasing returns, and lock-in by historical events. *Econom. J.* **99**(394) 116–132.

——, Y. M. Ermoliev, Y. M. Kaniovski. 1987. Path dependent processes and the emergence of macrostructure. *Eur. J. Oper. Res.* **30** 294–303.

Basalla, G. 1988. *The Evolution of Technology*. Cambridge University Press, Cambridge, U.K.

Baum, J. A. C, J. V. Singh. 1994. Organization-enviroment coevolution. J. A. C. Baum, Jitendra V. Singh, eds. *Evolutionary Dynamics of Organizations*. Oxford University Press, New York, 379–402.

Blundell, R., R. Griffith, J. V. Reenen. 1995. Dynamic count data models of technological innovation. *Econom. J.* **105**(429) 333–344.

Cameron, C. A., P. K. Trivedi. 1986. Econometric models based on count data: Comparisons and applications of some estimators and tests. *J. Appl. Econometrics* **1** 29–53

Campbell, D. T. 1965. Variation and selective retention in sociocultural evolution. H. R. Barringer, G. I. Blanksten, R. W. Mack, eds. *Social Change in Developing Areas: A Reinterpretation of Evolutionary Theory*. Schnkman, Cambridge, MA, 19–48.

Cantwell, J., J. Odile. 1999 Technological globalisation and innovative centres: The role of corporate technological leadership and locational hierarchy. *Res. Policy* **28**(3) 119–144.

Christensen, C. 1998. Du Pont Kevlar Aramid industrial fiber (abridged). HBS Case 698079, Harvard Business School Press, Cambridge, MA.

Cohen, W. M., D. A. Levinthal. 1990. Absorptive capacity: A new perspective on learning and innovation. *Admin. Sci. Quart.* **35**(1) 128–153.

——, ——. 1994. Fortune favors the prepared firm. *Management Sci.* **40**(2) 227–251.

Cusumano, M. A., Y. Mylonadis, R. S. Rosenbloom. 1992. Strategic maneuvering and mass-market dynamics: The triumph of VHS over Beta. *Bus. History Rev.* **66**(1) 51–95.

Cyert, R., J. G. March. 1992. *A Behavioral Theory of the Firm*. Prentice Hall, Englewood Cliffs. NJ.

David, P. A. 1988. Path dependence: Putting the past into the future of economics. Working paper. Stanford University, Stanford, CA.

——, J. A. Bunn. 1988. The economics of Gateway Technologies and network evolution: Lessons from electricity supply history. *Inform. Econom. Policy* **3**(2) 165–203.

Dosi, G. 1982. Technological paradigms and technological trajectories: A suggested interpretation of the determinants and directions of technical change. *Res. Policy* **11**(3) 147–163.

Elster, J. 1983. *Explaining Technical Change: A Case Study in the Philosophy of Science.* Cambridge University Press, New York.

Fleming, L. 2001. Recombinant uncertainty in technological search. *Management Sci.* **47**(1) 117–132.

Garud R., P. Karnoe. 2001. Path creation as a process of mindful deviation. R. Garud, P. Karnoe, eds. *Path Dependence and Creation.* Lawrence Erlbaum Associates, Mahwah, NJ, 1–38.

——, P. Nayyar. 1994. Transformative capacity: Continual structuring by inter-temporal technology transfer. *Strategic Management J.* **15** 365–385.

Grant, R. M. 1996. Prospering in dynamically-competitive environments: Organizational capability as knowledge integration. *Organ. Sci.* **7**(4) 375–387.

Gray, C. 2000. Neem tree freed. *Multinational Monitor* **21**(6) 4.

Greenmeier, L. 2002. Offshore outsourcing grows to global proportions—U.S. companies extend their search beyond India for IT help overseas. *InformationWeek* (February 11) 56.

Hausman, J., B. H. Hall, Z. Griliches. 1984. Econometric models for count data with an application to the patents—R & D relationship. *Econometrica* **52**(4) 909–938.

Heckman, J. J., G. J. Borjas. 1980. Does unemployment cause future unemployment? Definitions, questions and answers from a continuous time model of heterogeneity and state dependence. *Economica* **47**(187) 247–283.

Helfat, C. E. 1994a. Evolutionary trajectories in petroleum firm R&D. *Management Sci.* **40**(12) 1720–1747.

——. 1994b. Firm-specificity in corporate applied R&D. *Organ. Sci.* **5**(2) 173–184.

——. 2000. Guest editor's introduction to the special issue: The evolution of firm capabilities. *Strategic Management J.* **21** 955–959.

——, R. S. Raubitschek. 2000. Product sequencing: co-evolution of knowledge, capabilities and products. *Strategic Management J.* **21**(10/11) 961–979.

Henderson, R. M., K. B. Clark. 1990. Architectural innovation: The reconfiguration of existing product technologies and the failure of established firms. *Admin. Sci. Quart.* **35**(1) 9–30.

——, I. Cockburn. 1994. Measuring competence? Exploring firm effects in pharmaceutical research. *Strategic Management J.* **5** 63–84.

Jaffe, A. B., M. Trajtenberg, R. Henderson. 1993. Geographic localization of knowledge spillovers as evidenced by patent citations. *Quart. J. Econom.* **108**(3) 577–675.

Katila, R. 2002. New product search over time: Past ideas in their prime. *Acad. Management J.* **45**(5) 995–1010.

——, G. Ahuja. 2002. Something old, something new: A longitudinal study of search behavior and new product introduction. *Acad. Management J.* Forthcoming.

Kogut, B., U. Zander. 1992. Knowledge of the firm, combinative capabilities, and the replication of technology. *Organ. Sci.* **3**(3) 383–397.

Kirzner, I. 1985. *Discovery and the Capitalist Process*. University of Chicago Press, Chicago, IL.

Lant, T. K., F. J. Milliken, B. Batra. 1992. The role of managerial learning and interpretation in strategic persistence and reorientation: An empirical exploration. *Strategic Management J.* **3** 585–608.

Liebowitz, S. J., Margolis, S. E. 1995. Path dependence, lock-in and history. *J. Law, Econom. Organ.* **11** 205–226.

Leonard-Barton, D. 1992. Core capabilities and core rigidities: A paradox in managing new product development. *Strategic Management J.* **13** 111–126.

Levin, R. C., A. K. Klevorick, R. R. Nelson, S. G. Winter. 1987. Appropriating the returns from industrial research and development. *Brookings Papers Econom. Activity* **3** 783–831.

Levinthal, D. A. 1997. Adaptation on rugged landscapes. *Management Sci.* **43** 934–950.

Liang, K. Y., S. L. Zeger. 1986. Longitudinal data analysis using generalized linear models. *Biometrika* **73**(1) 13–22.

Liebowitz, S. J., S. E. Margolis. 1995. Path dependence, lock-in and history. *J. Law, Econom. Organ.* **11** 205–226.

March, J. G. 1991. Exploration and exploitation in organizational learning. *Organ. Sci.* **2**(1) 71–87.

——, H. Simon. 1958. *Organizations.* Wiley, New York.

Martin, X., W. Mitchell. 1998. The influence of local search and performance heuristics on new design introduction in a new product market. *Res. Policy* **26**(7) 753–771.

Martins, L. L., A. Kambil. 1999. Looking back and thinking ahead: Effects of prior success on managers interpretations of new information technologies. *Acad. Management J.* **42**(6) 652–661.

McGrath, R. G. 1997. A real options logic for initiating technology positioning investments. *Acad. Management Rev.* **22**(4) 974–997.

Merton, R. K. 1972. *The Sociology of Science*. University of Chicago Press, Chicago, IL.

Nelson, R. R., S. G. Winter. 1982. *An Evolutionary Theory of Economic Change.* Belknap Harvard, Cambridge, MA.

Pardey, P. G. 1989. The agricultural knowledge production function: An empirical look. *Rev. Econom. Statist.* **71**(3) 453–461.

Penner-Hahn, J. 1998. Firm and environmental influences on the mode and sequence of foreign research and development activities. *Strategic Management J.* **19**(2) 149–168.

Podolny, J. M., T. E. Stuart. 1995. A role-based ecology of technological change. *Amer. J. Sociology* **100** 1224–1260.

Reagans, R., E. Zuckerman. 2001. Networks, diversity, and productivity: The social capital of corporate R&D teams. *Organ. Sci.* **12**(4) 502–517.

Rivette, K. G., D. Kline. 1999. *Rembrandts in the Attic: Unlocking the Hidden Value of Patents.* Havard Business School Press, Cambridge, MA.

Rosenberg, N. 1982. *Inside the Black Box: Technology and Economics*. Cambridge University Press, Cambridge, U.K.

Rosenkopf, L., A. Nerkar. 2001. Beyond local search: Boundary spanning, exploration, and impact in the optical disc industry. *Strategic Management J.* **22**(3) 287–306.

——, M. Tushman. 1998. The coevolution of community networks and technology: Lessons from the flight simulator industry. *Indust. Corporate Change* **7**(2) 311–346.

Saxenian, A. L. 1990. Regional networks and the resurgence of Silicon Valley. *California Management Rev.* **33**(1) 89–113

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

Shane, S. 2001. Technological opportunities and new firm creation. *Management Sci.* **47**(2) 205–220.

——, S. Venkataraman. 2000. The promise of entrepreneurship as a field of research. *Acad. Management Rev.* **25**(1) 217–226.

Silverman, B. 1999. Technological resources and the direction of corporate diversification: Toward an integration of the resource-based view and transaction cost economics. *Management Sci.* **45**(8) 1109–1124.

Sorensen, J. B., T. E. Stuart. 2000. Aging, obsolescence and organizational innovation. *Admin. Sci. Quart.* **45**(1) 81–112.

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

Teece, D. J. 1986. Profiting from technological innovation: Integration, strategic partnering, and licensing decisions. *Res. Policy* **15**(6) 285–306.

Tong, X., D. J. Frame. 1994. Measuring national technological performance with patent claims data. *Res. Policy.* **23**(2) 133–142.

Tushman, M. J., P. Anderson. 1986. Technological discontinuities and organizational environments. *Admin. Sci. Quart.* **31** 439–465.

Winter, S. G. 1987. Knowledge and competence as strategic assets. D. J. Teece, ed. *The Competitive Challenge: Strategies for Innovation and Renewal*. Ballinger Publishing Company, Cambridge, MA, 186–219.

——. 1995. Four Rs for profitability: Rents, resources, routines and replication. C. A. Montgomery, ed. *Resource-Based and Evolutionary Theories of the Firm: Towards a Synthesis*. Kluwer, Norwell MA, 147–178.

——. 2000. The satisficing principle in capability learning. *Strategic Management J.* **21**(10/11) 981–996.

White, H. A. 1980. A heteroskedasticity—Consistent covariance matrix estimator and a direct test for heteroskedasticity. *Econometrica* **48** 817–838.

Zucker, L. G., M. R. Darby, M. B. Brewer. 1998. Intellectual human capital and the birth of U.S. biotechnology enterprises. *Amer. Econom. Rev.* **88** 290–306.

Accepted by Ralph Katz; received June 2001. This paper was with the authors 11 months for 3 revisions.