

Preadaptation, Firm Heterogeneity, and Technological Performance: A Study on the Evolution of Fiber Optics, 1970–1995

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Strategy research typically traces stable performance differences among firms to a priori heterogeneity in initial resource endowments or in expected flows of resources. The objective of this paper is to explore how this heterogeneity is created and how it affects firm technological performance. Within the framework of an evolutionary view of technological change, we develop the notion of technological *preadaptation* to describe that part of a firm's prior experience that is accumulated without anticipation of subsequent uses. In particular, we hypothesize that (technological) performance differences are positively related to (1) firms' stock of relevant skills and knowledge potentially available for applications other than those for which they were originally developed and (2) the extent to which firms actually build on these skills and knowledge in new domains. The empirical setting is fiber optics technology as it evolved for use in long-distance communications between 1970 and 1995. We find that "preadapted" firms that consistently leveraged their prior experience achieved higher levels of performance than did firms that did not leverage that experience or did not have prior experience. The study illustrates the importance of preadaptation in capability development and technological competition.

Key words: prior experience; preadaptation; initial conditions; technological performance

1. Introduction

The problem of sustaining competitive advantage in the face of technological change is especially critical in technology-intensive industries, where superior performance depends on consistent innovation (Nelson 1991, Teece et al. 1997). Strategy research, which typically traces the ability to innovate consistently to heterogeneity in initial resource endowments (Rumelt 1984, Barney 1991, Peteraf 1993), has shied away from establishing whether differences in resource endowments result from strategic foresight or historical accidents. Yet, while determining the role chance plays in human activity is fraught with conceptual ambiguity, any attempt to derive normative implications of existing strategy research requires that the question of strategic foresight be properly addressed.

Strategy researchers have recently begun to investigate more systematically whether firm heterogeneity is the result of luck or strategic foresight (e.g., Barney 1986, 1997; Garud et al. 1997; Cockburn et al. 2000; Holbrook et al. 2000; Denrell 2004). A few empirical studies have likewise examined the origin of differences in initial conditions among firms. In particular, these studies have highlighted the positive impact of prior experience, that is, existing skills and knowledge, on innovation and firm performance, especially when firms redeploy that experience across new markets and/or industries (e.g., Carroll et al. 1996, Holbrook et al. 2000, Klepper and Simons 2000, Klepper 2002).

Building on this existing research, we examine the extent to which firms that create new technological domains leverage skills and knowledge from other domains (see Abernathy and Clark 1985, Levinthal 1998). Our empirical setting is the fiber optics technology industry as it evolved from 1970—the year when the possibility of using optical glass fibers for long-distance telecommunications applications was demonstrated for the first time—to 1995.

In examining the factors that lead to differential performance, we follow Cockburn et al.'s (2000) suggestion that empirical strategy research should "not only identify those factors that are correlated with superior performance but also attempt to explore the origins and the dynamics of their adoption." We concern ourselves with exploring whether the skills and knowledge firms use to develop a new technology—and even initiate a new technological trajectory (Dosi 1982, Nelson and Winter 1982)—are created in anticipation of this technology or were developed in the past for other applications.

Because our objective is to study the potential value of preexisting skills and knowledge for the creation of new technological domains, we chart technological entry (e.g., Malerba and Orsenigo 1999), defined as innovation in a new technological domain, as distinct from market entry, which refers to initial production of a product or provision of a service (Helfat and Lieberman 2002, p. 726). Since patent data provide a detailed and consistent chronology of when certain skills and knowledge

were originally created (Katila and Ahuja 2002), we use them along with other sources (field interview data, industry and company reports, specialized books, and business press articles) to measure technological entry.

Our period of study spans from the inception of fiber optics technology to the advent of the Internet, so it is well suited to investigation of the performance implications of prior experience. Fiber optics was originally applied in the long-distance telecommunications market and subsequently in short-distance markets; over time it has grown into an industry in its own right. The research design is intended to capture the transition from the phase when firms accumulate skills and knowledge without anticipating their future use for other applications to the phase when firms begin to apply those skills and knowledge in a new technological domain. In fiber optics, the first phase lasted until 1966, the year the theoretical possibility arose of using glass for data transmission. Initial lab experiments were conducted between 1966 and 1970, the year when producing fibers that could be used in long-distance applications became a practical possibility. The application phase began in 1970 and lasted until the present.

A firm's history endows it with knowledge for reasons that are unrelated to that knowledge's application in new areas of opportunity. Borrowing terminology from evolutionary biology, we develop the notion of technological *preadaptation* to describe the firm's accumulation, without anticipation or foresight of subsequent uses, of skills and knowledge. In biology, preadaptation refers to cases when the feature of an organism proves by chance to be useful, or *preadapted*, for performing a function other than the one for which it developed or was originally selected (Bock 1959, Gould and Vrba 1982). This formulation implicitly acknowledges that skills and knowledge might exist prior to full consideration of their possible uses.

Our dependent variable measures a firm's technological performance by gauging the quality of its patenting activity, that is, the number of citations its patents receive from subsequent patents filed by other firms. We then estimate the contribution each sample firm made to the development of fiber optics by looking at the extent to which other firms build on its R&D activity. We chose to measure performance with patent data rather than revenue data both because the dataset was more complete and because patents report performance in the R&D phase as well as the market phase. Sales data for the industry proved less precise than patents; in the case of some diversified firms, sales relevant to fiber optics are impossible to isolate. Using patents enables us to establish backward citation patterns and form direct links between a firm's prior experience and its technological performance. While patents represent the best performance data that was available to us (their shortcomings are discussed in §4), in technology-intensive industries

technological performance measures tend to be positively correlated to financial and market-based performance measures (e.g., Trajtenberg 1990a, b; Hall 2000). In many industries patent data measure the knowledge embodied in a new technology accurately (see Hall et al. 2001). Qualitative evidence from our field work (including interviews with executives of Corning and data from the Freedonia Group) and extensive research of the industry further support our empirical results.

Our goal with this paper is to make three contributions to strategy and innovation research. First, in response to existing studies that assert the detrimental effect of established firms' experience on their ability to innovate within an existing domain (for a review see Methe et al. 1997, Hill and Rothaermel 2003), we introduce the idea that when creating new technologies, prior experience can become a source of competitive advantage rather than a constraint. Second, on the premise that firms differ both with respect to their prior skills and knowledge and to their ability to properly leverage their skills and knowledge, we seek to separate the potential for innovation from the achievement of innovation. We distinguish between having and using preadaptation by using backward citations, which reveal when a firm declines to build on its own research that is cited by other firms. Third, instead of attributing firm heterogeneity to initial conditions defined a priori (e.g., Stinchcombe 1965, Porter 1991), we seek to unpack sources of firm heterogeneity by first tracing differences in initial conditions to differences in the stock of (potentially) transferable skills and knowledge and then by examining to what extent firms actually use them in developing a new technological domain.

The paper is organized as follows. In the next section (§2), we review briefly the strategy and innovation literature that studies the link between prior experience and firm (technological) performance, develop the notion of technological preadaptation, and present the hypotheses. We then describe the empirical setting (§3) and the data (§4) and consider the dependent (§5), independent (§6), and control variables (§7). We continue by presenting the model and method (§8) and the results of the analyses (§9). We conclude with a discussion of the main implications of our findings and the identification of important topics for future research (§10).

2. Theory

Multiple studies have expounded the potential pitfalls of preentry experience. The dominant design theory, for instance, argues that preentry experience is disadvantageous when it wedds firms to technologies made obsolete by the emergence of a new dominant design (see Christensen et al. 1998). When searching locally, firms target technologies that are within the boundaries of what they have done, create incremental innovations, and

become more expert in their current domain. However, as established firms become “increasingly removed from other bases of experience and knowledge and more vulnerable to change in their environments” (Levinthal and March 1993, p. 102), they risk falling into competency traps (Levitt and March 1988) or becoming hampered by their core rigidities (Leonard-Barton 1992). Several empirical studies have shown how local search without exploration may jeopardize innovation and performance at the firm level (e.g., Helfat 1994, Stuart and Podolny 1996, Martin and Mitchell 1998, Rosenkopf and Nerkar 2001).

Firms can avoid the pitfalls of local search by partnering with other firms (e.g., forming alliances, joint ventures) to gain access to and/or create novel technologies (e.g., Stuart and Podolny 1996, Nagarajan and Mitchell 1998). They can also build the absorptive capacity required to recognize the value of new, external information, assimilate it, and apply it to commercial ends (Cohen and Levinthal 1990). But absorptive capacity is also path dependent and domain specific: As the argument goes, firms can enhance their ability to innovate by expanding their base of experience in an existing domain. These two alternatives have been extensively investigated.

The case in which a firm explores a new domain, with customers’ needs and performance requirements different from the domains in which it is already competing, has received relatively less attention (see Methe et al. 1997). Using an evolutionary framework, *technological speciation* theory has recently argued that new technological lineages may result from redeploying existing knowledge across different domains (Levinthal 1998, Adner and Levinthal 2002). Technological speciation originates from “transplanting the existing technological know-how to a new application domain where it evolves in new directions” (Adner and Levinthal 2002, p. 51). The process of adapting to a new selection environment ultimately triggers novel (rather than path-dependent) evolutionary patterns, without requiring the firm to overhaul its knowledge base.

Previous studies have recognized the value of deliberately redeploying existing technology in new domains. Abernathy and Clark (1985), for instance, showed how old technologies can be used to create new market niches. As a result, the body of knowledge that is a source of competency traps in an existing domain might enable a firm to create new competitive advantages in a different domain.

Current research on firm heterogeneity and industry evolution has further delved into this issue by focusing on the conditions favoring the fit between prior experience and new market applications. In their analysis of the relationship between market entry decisions and firm prehistory, Helfat and Lieberman (2002) emphasize the importance of the similarity effect, the idea that the

degree of similarity between a firm’s preentry resources and capabilities and those required in a new domain positively affects not only the decision to enter the new domain, but also the ability to innovate and then prosper in it. Several longitudinal studies provide supporting evidence for the similarity effect. Carroll et al. (1996), for instance, found that firms entering the American automobile industry from related industries survived longer than newly founded firms or firms from unrelated industries. Klepper and Simons (2000) showed how firms experienced in the manufacturing of radios were more likely to enter the TV industry, were more innovative, achieved greater market share, and survived longer in the TV industry than firms with no radio production experience. Other studies found consistent results in additional industries (e.g., Holbrook et al. 2000, King and Tucci 2002, Klepper 2002). This stream of research has significantly enhanced our understanding of the relationship between prior experience, innovation, and firm performance and has shed light on why prior experience can be viewed as a critical source of variation in initial conditions.

However, what is not entirely clear in these studies is to what extent the ability to innovate can be understood as a consequence of a firm’s prior experience in other domains. In other words, do firms innovate because they anticipate which skills and knowledge will be needed, or does the environment select those firms whose skills and knowledge randomly match the requirements of a new domain? To analyze this question of intentionality, two issues surrounding the redeployment of technology must be addressed more thoroughly.

First, if prior experience is a critical source of differences in initial conditions and possesses implications for firm performance, R&D efforts made in exploration of a new domain should be separated from those conducted without foreknowledge of any potential redeployment. Identifying a firm’s prior experience (its preentry resources and capabilities) means clarifying what constitutes “entry.” If entry “refers to initial production of a product or provision of a service” (Helfat and Lieberman 2002, p. 726), then prior experience consists of both skills and knowledge created for other applications and skills and knowledge originating from deliberate efforts to adapt to a new application domain. The notion of “technological entry” (e.g., Malerba and Orsenigo 1999)—marked by innovation in a new area, regardless of whether a market exists—allows for a more accurate characterization of two conceptually and chronologically distinct adaptive processes. Time, often years, may elapse between technological entry and market entry, the production or provision of a new product or service. During this interval, firms typically carry out the first lab experiments to develop a new technology—a process of adaptation rather than preadaptation. R&D efforts between the technological and market entries could

enhance the degree of similarity between a firm's existing knowledge base and that required in a new domain; therefore, R&D efforts must be separated according to when in the innovation timeline they occurred.

Moreover, because previous studies typically establish an indirect link between prior experience on the one hand and firm innovation and performance in a new domain on the other, it is not always entirely clear which part of that experience retains its value and is then selected for new uses (e.g., Mokyr 2000). As a result, the question of whether firms anticipate new applications as they accumulate skills and knowledge within an existing domain is not explicitly addressed. The next section seeks to tackle these two issues by developing the notion of technological preadaptation.

2.1. Preadaptation in Evolutionary Biology and Technology

In biology, preadaptation refers to the case where “by chance, an organ that works well in one function turns out to work well in another function after relatively little adjustment” (Ridley 1999, p. 347).¹ The concept of preadaptation assigns no role to foresight. An organ or a feature of an organism did not evolve in anticipation of its new function; it happened to be adaptable to it (Futuyma 1998). It was then selected for this new function. The observed function of an existing feature does not always coincide with the use for which it developed or was originally selected, but it is often a by-product of adapting to novel, unanticipated conditions.² It is the nature of the selection forces that are associated with the new function to allow a preadapted feature to execute this function (Bock 1959, p. 201).

Biological preadaptation has technological analogues. Each invention or innovation offers a spectrum of opportunities, only a few of which will ever be developed during its lifetime (Basalla 1988). A firm might be endowed by its past history with skills and knowledge for reasons that are unrelated to their application in a new opportunity. This body of knowledge frequently exists prior to full consideration of its possible uses. For example, in the early 1960s, Corning invested in the new field of integrated circuits despite the fact that it was essentially a specialty glass manufacturer. Eventually, Corning divested, but a few years later the knowledge they had gathered as a result of this investment happened to be useful to fiber optics. Fiber optics' synergetic combination of glass manufacturing and semiconductors meant that Corning's past experiences made it particularly preadapted to the new industry (Cattani 2004).

Firms can learn more about applications for which they are potentially preadapted as new information emerges. Past, even antiquated, technologies might in fact find novel, unanticipated applications in new environmental conditions.³ As a result, firms with a long-standing tradition in R&D very often already have

in-house solutions to new problems (see Garud and Nayyar 1994). Moreover, as the notion of technological speciation implies, a firm's knowledge base can spur the emergence of new technological fields when it taps into unexploited market niches, so long as the corresponding market needs and performance standards differ significantly from those faced in other application domains. This further implies that even prior experience that has become a competency trap, that is, a “stable suboptimal solution” (March 1994, p. 96), in its current application might turn out to be a source of adaptation when the firm uses it in a distinct application domain.

Previous research has argued that the ease with which knowledge can be transferred across domains depends on the degree of similarity between them (e.g., Helfat and Lieberman 2002). Technological preadaptation, while embracing the similarity effect, is less restrictive about the designation of similarity. The same body of knowledge can in fact enhance the ability to generate (economically valuable) innovations in domains with similar technological roots that appear entirely distinct from a user's perspective. Significant variations in the market space do not necessarily command comparable variations in the technology space (e.g., Adner and Levinthal 2002). This is especially true when firms create a new technological field and the only available knowledge they can readily rely on is their own. Technological preadaptation represents a vantage point from where significant innovations but also new evolutionary patterns can be generated.

HYPOTHESIS 1. Technological performance in a new domain of application is positively related to a firm's level of relevant technological preadaptation, which serves as a potential source of competitive advantage.

The emphasis placed on preadaptation might unwittingly convey the impression of underestimating the significance of purposive behavior. As Cockburn et al. (2002, p. 1,124) observed, if performance heterogeneity “arises from the degree to which a firm's resources and/or strategy ‘match’ the competitive environment, and if resources are randomly distributed at ‘birth’ . . . then performance heterogeneity simply reflects the fact that the realized competitive environment favors some strategies and some resource bundles over others.” However, even firms that are similar in all accounts (including resource endowment) may still differ in their ability to take advantage of the same environmental conditions. Far from implying a deterministic view of innovation and technological performance, and thus discarding any meaningful role for strategy, preadaptation allows for variation in the observed behavior of preadapted firms.

As we noted earlier, the degree of similarity between a firm's knowledge base and that required in a new

domain increases the probability of entering, innovating, and prospering in that domain. However, even firms originating from the same industry (and thereby possessing similar market/technology experience) are likely to exhibit a differential ability to leverage their experience. While many technological innovations arise from the recombination and novel application of existing knowledge, established firms often fail to capitalize on their past R&D (e.g., Garud and Nayyar 1994). One of the challenges facing these firms is to make better use of their knowledge base. There is in fact an important distinction between having a pool of “relevant specialized transferable skills and knowledge” (Carroll et al. 1996) potentially available for other applications than the original ones and being able to leverage relevant skills and knowledge to generate innovations.⁴

We believe that keeping the potential for innovation distinct from innovation itself is crucial to properly estimate whether the effects of prior experience “dissipate or persist over time and exactly how the backgrounds of entrants condition their performance...” (Klepper and Simons 2000, p. 998). Equally preadapted firms can display a differential ability to take advantage of solutions, which they have already in-house, to new problems. Because the range of possible applications of a firm’s technological knowledge base is typically wider than its current applications, firms can capitalize on previous technological investments, a capability that Garud and Nayyar (1994) call “transformative capacity.” For instance, firms that have over time developed routines to store, transform, and retrieve knowledge (e.g., Garud and Nayyar 1994, Hargadon and Sutton 1997) stand a better chance of realizing new syntheses and attaining higher levels of technological performance. This implies that “having” preadaptation (i.e., availability of relevant skills and knowledge) is distinct from “using” preadaptation. Even though performance (as measured by patent impact) of firms that continue to build on their prior knowledge within an existing domain is likely to decline (e.g., Sørensen and Stuart 2000, Rosenkopf and Nerkar 2001), knowledge that becomes less valuable in its current application might be of greater value for other applications.

HYPOTHESIS 2. Technological performance in a new domain of application is positively related to the extent to which firms draw upon their technological preadaptation.

To test these hypotheses, we study the emergence and evolution of fiber optics technology. Since we trace its evolution virtually from its inception, we can identify the experience accumulated before the development of fiber optics and estimate to what extent firms actually acted on their accumulated experience in their subsequent innovative efforts.

3. Empirical Setting: Evolution of Fiber Optics

This analysis focuses on the emergence and evolution of fiber optics between 1970 and 1995. An optical communications system comprises several interdependent components, including a light-emitting device that converts an electric signal to light, a light-transmission medium (optical fiber) through which light is transmitted, and a light-receiving device that decodes the optical signal and converts it back to electricity. Optical (glass) fibers are the core component in long-distance communications.

The notion of preadaptation implies that in the course of technological evolution it is sometimes possible to identify a “dividing line” or “watershed event.” Before this event, during the preadaptation phase, a firm accumulates skills and knowledge without anticipating their subsequent application. After the event, higher levels of foresight allegedly guide that firm’s search behavior as it incorporates market feedback. The role for foresight, and hence strategy, is especially critical during the transition between these two phases because this transition is when a firm begins to realize the possibility of redeploying its preexisting skills and knowledge into a new domain.

Because identifying such a dividing line is central to the variables of theoretical interest as well as the statistical analyses, we offer a succinct narrative of these events below. Besides drawing from multiple sources of information (books, newspaper articles, academic papers, case studies, annual financial reports, and industry reports), we gathered additional data and information from three rounds of semistructured interviews with R&D managers from Corning (some of whom experienced the development of the fiber optics industry) and an interview with one expert in the field of optical communications. These interviews let us discuss some of the key facts, double-check our interpretation of the information, and reduce the risk that we would impose meaning on historical events from knowledge of the outcomes (Aldrich 2000).

The Industry

The possibility of using low-loss optical glass fibers over long distances was first shown in 1970, when Corning produced the low-loss optical glass fiber. However, the theoretical possibility of using light for communications purposes had been envisioned four years earlier by two researchers, Charles K. Kao and George Hockham, from the Standard Telecommunications Laboratories (STL), the British subsidiary of ITT.

The company had formed a research team to study the properties of optical waveguides to satisfy the needs of the British Post Office, which at the time operated the British telephone network and was trying to improve the national telecommunications infrastructure. The British

Post Office was concerned with “a better technology to send signals between local switching centers that typically were a few miles apart...” and in particular with “...something easy and inexpensive to install in heavily developed areas, not high-priced-capacity systems to span vast distances” (Hecht 1999a, p. 111). At the Institution of Electrical Engineers meeting held in London in 1966, Kao and Hockham (1966) presented a paper in which they argued that optical fibers would be a suitable transmission medium for long-distance communications if attenuation could be kept under 20 dB/km. This implied that 1% of the light entering a waveguide would remain after traveling one kilometer. By setting this threshold Kao and Hockham laid out a concrete methodology, spurring the first wave of large-scale laboratory experiments.

Corning’s invention of the first optical glass fiber with attenuation below 20 dB/km in 1970 and its subsequent refinements during the early 1970s fundamentally shaped the evolution of optical communications by demonstrating for the first time optical fiber’s commercial viability for long-distance telephone networks (see Trajtenberg et al. 1997). Concurrent advances in semiconductor laser technology at AT&T Bell Laboratories also proved critical (Hecht 1999a). The commercial success of fiber optics remained incomplete until the early 1980s, when the U.S. government first deregulated the telecommunications industry (1982) and forced AT&T to split up (1984). By injecting more competition into the long-distance telephone market, AT&T’s divestiture opened new investment opportunities and fostered the rapid growth of fiber optics. Moreover, in mid-1982, MCI decided to build the first long-distance telephone network in the United States using single-mode optical fibers, which then became the new market standard. Since single-mode fibers have a smaller core than multi-mode fibers, they possess superior transmission qualities in terms of speed, capacity, and attenuation level (see Hecht 1999a, b).

To summarize, the evolution of optical communications had three main phases. Until 1966, light-transmission over long distances was confined to the “realm of wishes.” This is a period marked by no foresight with respect to this new application. After 1966, Kao and Hockham’s paper fostered the first wave of laboratory experiments to meet the 20 dB/km threshold. Also, the British Post Office’s intention to replace copper fibers with optical glass fibers signaled the existence of a potentially profitable market. After Corning demonstrated the commercial feasibility of fiber optics in 1970, market feedback provided an increasingly clear sense of direction.

Because preadaptation implies that success in a market is determined largely by circumstances established before anyone knew this market would exist, only skills and knowledge accumulated before 1966 represent

preadaptation for later stages. Thus, 1966 is an ideal dividing line or “watershed event” between the period when foresight was not a factor and the period when a higher level of foresight was more explicitly at work.⁵ Available sources on the history of fiber optics (e.g., Hecht 1999a, b) as well as our field interviews confirmed that 1966 was indeed a turning point in the evolution of fiber optics. This dividing line shaped the overall research design, how we collected data, and how we created the variable of theoretical interest.

4. Data

In the analysis we used patent data. We chose 1970 as the beginning of the observation period because the first key patents that laid the foundations for the practical implementation of fiber optics were filed in that year. In 1970, Robert Maurer, Donald Keck, and Peter Schultz from Corning developed the first low-loss optical glass fiber. The two key patents, *Fused Silica Optical Waveguide* (No. 3659915) and *Method of Producing Optical Waveguide Fibers* (No. 3711262), were filed on May 11, 1970. For the period 1966–1970, we could not collect patent data, as they are not fully available electronically. We thus manually collected data on pre-1970 patents, but only when these patents were cited by a post-1970 patent.

While patents do not measure all relevant knowledge held by a firm, research has increasingly employed them as a measure of firm knowledge (e.g., Henderson and Cockburn 1994, Jaffe et al. 1993, Albert et al. 1991, Narin et al. 1987) and as an indicator of technological capabilities (e.g., Jaffe 1986, Patel and Pavitt 1994, Stuart and Podolny 1996, Silverman 1999, Fleming and Sorenson 2001). Unlike R&D expenditures, patents offer information on a firm’s specific strengths. Furthermore, in fiber optics, firms display a high propensity to patent (Levin et al. 1987, Hall et al. 2001).

To identify the technology underlying optical fibers, we conducted the analysis at the patent subclass level. The classes and subclasses we identified as relevant are listed in Table 1. Instead of using a three-digit, primary technological field classification in determining the

Table 1 Patent Primary Classes and Subclasses

Patent primary classes	Patent subclasses
65 Glass manufacturing	17.1–35, 60.1–65, 102–121, 134.1–137, 157–192, 268–301, 335, 346, 348–362, 370.1, 374.1–540
356 Optics: Measuring and testing	73.1, 139, 141, 153, 335–338, 342
385 Optical waveguides	All subclasses
427 Coating processes	162, 163.2
501 Compositions: Ceramic	11–79

degree of technological relatedness of patents falling into different classes, we captured technological similarity by using a classification up to the nine-digit, subclass level. Doing so allowed us to define the relevant fiber optics technical fields as accurately as possible. To ensure precise and comprehensive coverage of the relevant technical fields, we double-checked our identification of the relevant patent primary classes and subclasses with two firms in the sample. We also validated our interpretation of the data with these two firms.

For the period 1970–1995, we collected patent data from the National Bureau for Economic Research (NBER) (see Hall et al. 2001), the U.S. Patent and Trademark Office (USPTO), and the UPSTO Cassis databases. We traced backward citations from patents filed subsequently using Micropatents. We obtained financial data from Compustat. Detailed information about patents filed before 1970 is not available electronically. However, the creation of the variables of theoretical interest requires detailed information such as assignee, filing year, and patent class for all backward citations made by the focal patents to previous patents, regardless of when they were granted. We thus retrieved relevant citation information manually from the USPTO's official website for all backward citations referring to patents for which that information was not available electronically. As a result, our database is distinctive because it captures as accurately as possible all prior work relevant to the development of fiber optics.

The research sample was drawn from the population of firms patenting in the patent classes and subclasses that define the fiber optics technical fields (Table 1). We included a firm in the sample if it filed at least one patent in one of the relevant subclasses. Unfortunately, using patent data means that potentially preadapted firms that never filed a patent in fiber optics for telecommunications applications are not included in the final sample. A very interesting case in this regard is American Optical Company. During the 1950s it contributed to the development of the fiberscope, an image-transmitting device that used the first practical all-glass fiber and was primarily employed for medical applications such as the endoscope. Although its patents were widely cited by subsequent patents in fiber optics for communications applications, it never entered the telecommunications market.

As we noted in §2, in the paper we use notion of “technological entry” (Malerba and Orsenigo 1999), which is distinct from the case in which a product or service is actually brought to market (Helfat and Lieberman 2002). Our choice of technological versus market entry was motivated by the following reasons. First, as outlined in §2, we are concerned with the technological lineage of the firms that came to establish a new field (fiber optics), not simply their decisions to create or enter a new or existing market. Second, though firms often file

patents they never use for commercial applications, evidence from other industries' firms indicates that not all such patents are purely exploratory; sometimes firms prefer to license their patents without directly participating in the production stage. For instance, in the semiconductor industry many patents are granted to firms (also known as fabless firms) that only design (never produce) chips but profit from collecting patent license fees. Their involvement with the downstream market where those patents are actually used is only indirect. Third, product-level data were not available. While this is clearly a limitation of the study, many of the firms that in our sample appear as technology leaders, filing more patents that were also more widely cited, became market leaders later on.⁶ The final list of firms is comprehensive: As Table 2 indicates, the number of patents filed by the sample firms represents a significant proportion of all patents falling in the relevant classes and subclasses, thus ensuring that we are not sampling on the dependent variable.

The NBER database provides both the name of the firm to which the patent was assigned and the name of the parent company. A firm with several subsidiaries and divisions can, therefore, have a single entry in Compustat but several assignee names in the NBER database. We thus treated every assignee name as part of the same corporation whenever the latter held more than 50% of that assignee. Availability of yearly data on the

Table 2 Sample Firm Patents vs. Total Patents in Fiber Optics, 1970–1995

Year	Total patents (a)	Focal firm patents (b)	% (b/a)
1970	162	107	0.66
1971	193	131	0.68
1972	227	144	0.63
1973	227	134	0.59
1974	241	146	0.61
1975	261	174	0.67
1976	284	177	0.62
1977	301	180	0.60
1978	264	156	0.59
1979	286	178	0.62
1980	344	242	0.70
1981	339	218	0.64
1982	314	205	0.65
1983	304	185	0.61
1984	337	192	0.57
1985	427	216	0.51
1986	397	192	0.48
1987	444	209	0.47
1988	466	222	0.48
1989	491	236	0.48
1990	537	266	0.50
1991	615	283	0.46
1992	598	265	0.44
1993	465	210	0.45
1994	531	246	0.46
1995	563	268	0.48

control variables reduced the final sample to 206 public firms patenting in the United States and traded on U.S. stock markets, for a total of 1,209 firm years. Private firms, academic institutions, and public research labs for which R&D and firm size data are not available are not included. Nevertheless, the composition of the sample ensures enough variety on most of the key variables. For instance, firms vary in their size, with the largest firms having more than 70,000 employees and the smallest fewer than 100 employees; their age, with some firms (e.g., Corning, General Electric) being founded more than 100 years ago and others relatively recently (e.g., during the observation period); and the volume of their patenting activity in fiber optics, with some firms filing only a few patents and others more than 100 patents per year. Moreover, as we explain in §9, we ran the analysis including all firms—not merely firms patenting in the United States and traded on U.S. stock markets—and found the results to be qualitatively similar to those reported here.

The final sample is an unbalanced panel. Over the study period, the sample firms filed 5,067 patents, comprising more than 50% of all the 9,618 patents that other firms (private or traded on foreign stock markets), research labs, individual inventors, or academic institutions filed in any of the technological fields corresponding to the selected classes and subclasses.

5. Dependent Variable

We measured firm performance in technological terms by using patent citations to the focal firm from other firms to estimate the value of a firm's innovative output. We preferred this measure to the number of patents each firm filed in a given year because we are interested in each firm's actual contribution to the creation of a new technological field (i.e., fiber optics). The use of patent counts can be questioned on several grounds: Firms differ in their propensity to patent; not all inventions are eventually patented; and not all patented inventions are turned into commercial applications (see Hall et al. 2001, Hall and Ham-Ziedonis 2001). Also, many patents have little value and do not reflect any truly distinctive or significant innovation. As such, although a patent count indicates a firm's R&D productivity, it is a poor proxy for the value of its patents (e.g., Griliches et al. 1987, Scherer 1965, Hall 2000).

Especially in R&D-intensive industries, the number of citations a patent receives from other patents is a more precise measure of technological performance and a better estimate of the focal patent's true value (e.g., Griliches 1981, 1990; Trajtenberg 1990a, b). Such citations indicate “that the cited patents opened the way to a technologically successful line of innovation. . . . Thus, if citations keep coming, it must be that the innovation originating in the cited patent had indeed proven

to be valuable” (Trajtenberg 1990a, p. 174). Patents that firms report as more valuable are typically more heavily cited in subsequent patents (Harhoff et al. 1999). Previous studies have found a positive relation between firm market value and patent citations (Shane and Klock 1997, Hall 2000, Hall et al. 2001). Strong citation indicators also tend to be positively correlated with firm sales, profits, and stock prices (see Narin et al. 2001). Strategy research has focused increasingly on the number of future citations on the premise that they are a better estimate of true value of a patent and a more informative signal of success (e.g., Ahuja and Lampert 2001, Bierly and Chakrabarti 1996, DeCarolis and Deeds 1999, Rosenkopf and Nerkar 2001). Indeed, highly cited patents “cover innovations that experts in a technological area perceive to have been the most important inventions in that area” (Sørensen and Stuart 2000, p. 93).

For all patents the sample firms filed over the study period (1970–1995) we collected future citations up to April 2004 from Micropatents. Because patents filed in earlier years are exposed to the risk of being cited by subsequent patents for a longer period, we compared patents only to those filed during the same year. All the focal patents were issued before February 1996; as a result, they have remained at risk of being cited for at least eight years. For each patent, we counted all future citations received until April 2004, net of a firm's self-citations. While self-citations measure the extent to which a firm builds on its previous R&D efforts, citations from other firms more objectively estimate the actual relevance of a firm's patents.

Following Trajtenberg (1990a, b), the dependent variable estimating the impact of a firm's patenting activity is computed as an index of weighted citation counts as follows:

$$\text{Weighted Citation Index}_{it} = \sum_{j=1}^m (1 + C),$$

where C is the number of future citations that patent j ($1, \dots, m$) filed by (and then granted to) firm i ($1, \dots, n$) in year t (1970, . . . , 1996) received in subsequent years (until year 2004) from patents filed in fiber optics by other firms. The results of the analysis do not vary if we compute the index including citations also coming from patents filed in other classes/subclasses than those defining fiber optics.

6. Independent Variables

To test Hypothesis 1, we created the variable *preadaptation*, which measures a firm's stock of relevant transferable skills and knowledge potentially available for new uses. The creation of a more fine-grained variable would require defining the profile of each firm by reconstructing its historical background. Since some of the firms in the sample have roots in industries other than

telecommunications, one approach would be to trace their complete past patenting activity. Unfortunately, patents prior to 1970 are not available in an electronic format.

We thus followed a different approach. We used patent backward citations to identify technological knowledge each firm accumulated before 1966. Interestingly, even though firms typically build on their prior R&D efforts, very often they fail to do so fully, whether by design or by oversight. For instance, several sample firms never cited some of their early (up to 1966) patents in their subsequent fiber optics patents, even though those same early patents were cited by other firms. In total, the sample firms filed 1,234 fiber optics patents in 1966 or before that were subsequently cited by other patents. Of those 1,234 patents, 997 were cited only in patents filed by firms other than the original assignee, and 237 were cited at least once by the original assignee. Thus, the pool of relevant skills and knowledge available to each firm was larger than the set of skills and knowledge they actually used.

We considered each firm's pool of pre-1966 patents to reflect its level of preadaptation with respect to the new technology (fiber optics), regardless of whether the sample firms actually leveraged (cited) their prior experience (the stock of pre-1966 patents) in subsequent innovative efforts (new patents). This way of estimating technological preadaptation accounts for a firm's knowledge by looking only at its patenting activity and thereby does not consider manifestations (such as inventors' scientific papers) of knowledge that existed without having led to patents. Nevertheless, it represents a good approximation. If it is true that citation-based measures are noisy indicators of technological linkages, several studies have validated their use in identifying the technologies on which other innovations build (e.g., Jaffe and Trajtenberg 2002).

Overall, 63 of the 206 sample firms were preadapted, to varying degrees. Twenty six had accumulated experience in *glass manufacturing*, four in *optics: measuring and testing*, eight in *optical waveguides*, two in *coating processes*, and 24 in *compositions: ceramic* (see Table 1 for the patent classes and subclasses defining the corresponding technical fields). While several firms (e.g., AT&T, Corning, General Electric, ITT) were also operating in technical fields other than glass, prior experience in glass manufacturing was clearly an important vantage point.

In the analysis we do not distinguish between different types of prior experience or preadaptation to establish how closely previous applications were related to fiber optics. This would require a precise identification of all technical fields in which the sample firms were operating based on their primary patent classes. The technical background of the sample firms is quite heterogeneous (as the number of distinct primary classes

of the cited patents clearly indicates). Distinguishing between different types of technological preadaptation represents an interesting avenue for future research but goes beyond the purpose of this study. We entered the variable *preadaptation* into the final model after applying a logarithmic transformation. Since for several firms the variable is equal to 0, we added the value 1 to be able to take the log. The results do not change appreciably by using different values.

To test Hypothesis 2, we captured the extent to which firms build on their prior experience into a different domain by using backward self-citations. As future patents build on previous patents, a firm that cites its patents is leveraging its stock of skills and knowledge (Jaffe et al. 1993). Because the theoretical groundwork for the development of fiber optics dates back to 1966, we chose this year as the dividing line; only skills and knowledge available in 1966 or before represent preadaptation for future applications. A careful examination of the content of the patents cited by the focal patents, along with our interviews with managers from Corning and an industry expert, further supports our choice. Among the cited patents, those filed before 1966 did not mention telecommunications as a possible application for optical fibers. Accordingly, the variable consists only of backward self-citations that refer to patents filed until 1966.

Several years may elapse between a patent application and its publication date. One might thus fail to correctly identify when prior R&D efforts were first conducted by simply looking at the year in which a cited patent was granted. The choice of the filing year for backward self-citations thus traces more closely the timing of the process of accumulating skills and knowledge. An example may clarify this point. Suppose patent A granted in 1975 cites patent B, which was granted in 1970 but filed in 1966. The efforts that eventually led to patent B allegedly date back to 1966 or before. If a firm's future patents build on its previous patents, the filing year, rather than the publication year, of previous patents more accurately captures the time when the relevant skills and knowledge were first created (see Hall et al. 2001). In other words, such skills and knowledge were available in-house earlier than the publication year would suggest otherwise. Following this reasoning, the variable *leverage* is given by the following ratio:

$$\text{Leverage}_{it} = \frac{\text{total backward self-citations until 1966}}{\text{total backward citations}},$$

where the numerator, *total backward self-citations until 1966*, is the number of citations that all patents filed by firm i ($1, \dots, n$) made in year t to patents filed by firm i in 1966 or before. The denominator, *total backward citations*, is the sum of all backward citations—self-citations and citations of patents filed by other firms—made by the patents firm i filed in year t . The variable measures

the extent to which firms actually leverage their prior experience in a different domain. It takes on the value 0 when one of the following three conditions is fulfilled: (1) a preadapted firm did not leverage its prior experience; (2) a firm in existence before the beginning of the observation period had no prior relevant knowledge; and (3) a firm was founded after 1966.

7. Control Variables

To account for possible competing hypotheses, we included several control variables in the model specification.

Technology Cycle. The value of prior experience is likely to decay over time (see Argote et al. 1990, Baum and Ingram 1998). This implies that firms that build on older technologies might undermine their ability to innovate in the future. Following previous research (e.g., Rosenkopf and Nerkar 2001), we controlled for this possibility by creating a variable, *technology cycle*, that measures the average age of the patents cited by the patents a firm filed in a given year. More specifically, we first computed the difference between the year in which the (focal) citing patent was filed and the filing year of all cited patents. We did the same for all patents each firm filed in a given year. We then calculated the average age of all cited patents.

Firm Fiber Optics Patents. The number of patents a firm files in a given year is likely to be affected by its prior patenting activity. We should then expect future citation counts to grow with the number of patents being filed. Controlling for the total number of patents previously applied for allows capturing differences between firms in their quality threshold for patenting (Sørensen and Stuart 2000). We thus created the *firm fiber optics patents* variable by counting the number of patents a firm filed in fiber optics in the previous year. We entered the variable with one-year lag to avoid simultaneity problems with the dependent variable.

R&D Expenditures. Several studies have documented the relation between a firm's patenting activity and R&D expenditures (Griliches 1981, 1990; Hausman et al. 1984). We used the log of yearly R&D, expressed in 1996 constant dollars, as a proxy for a firm's total R&D inputs to the innovation process. We obtained data from Compustat. For the few observations where R&D was not reported, we created a dummy so the R&D coefficient would not be biased (Ham-Ziedonis 2004).

External Knowledge. Firms can accumulate skills and knowledge in a new domain by learning from direct experience or the experience of others (Levitt and March 1988). Firms that cite patents filed by other firms are more likely to access external knowledge and expand their base of experience than are firms that continually

cite their own patents. Prior research has shown that exploration that spans firm boundaries influences technological evolution in a given domain more than exploration that does not span firm boundaries (Rosenkopf and Nerkar 2001). Firms can partly offset the disadvantage of not having relevant transferable specialized skills and knowledge through "vicarious interorganizational learning" during their lifetimes (Baum and Ingram 1998, p. 1,002). We then created the variable *external knowledge*, which denotes the ratio of the number of backward citations made to patents filed by other firms to the sum of all backward citations in a given year.

Firm Size. Literature in economics has shown that large firms are responsible for a disproportionate quantity of innovation as measured by the number of patents filed (Cohen et al. 1987, Cohen and Klepper 1996). On the other hand, since large organizations "are often more bureaucratic and less entrepreneurial than small enterprises... [size might] have a negative effect on the importance of firms' innovations" (Sørensen and Stuart 2000, p. 94). To control for the effect of size, we used the log of the number of employees. We also tried a firm's total assets (in 1996 constant dollars) but found no difference. Data were obtained from Compustat.

Firm Age. Older firms are more likely to have accumulated experience in different domains and as such to have a larger stock of relevant transferable skills and knowledge. Older firms create more innovations, though these innovations often have less impact. Firm age should also increase the frequency of issuing self-citing patents (Sørensen and Stuart 2000). But older firms might also be less innovative due to inertial forces, core rigidities, or existing customers. To control for these possibilities we created a time-varying variable, *firm age*, measuring the years elapsed since the firm was founded, or, if the foundation year was not available, the difference between the current year and the year the focal firm first filed a patent in fiber optics.

Total Fiber Optics Patents. The number of patents each firm filed in a given year and the number of future citations received by them might also depend on the overall patenting activity in the relevant fiber optics patent classes. As the number of patents grows, the focal patents are more likely to be cited by subsequent patents. On the other hand, over time, future citations will be increasingly spread out over a larger number of patents. We then created a measure of patent density, *total fiber optics patents*, to control for all fiber optics patents filed by any economic actors—not just the sample firms—in a given year. We also created a quadratic term but it turned out to be nonsignificant. Alternatively, we could have included a calendar time trend (e.g., year) in all models to account for the fact that the overall patenting activity volume increases over time, but also because

“the actual composition of organizational innovation is likely to change as a consequence of the maturation of the industrial context” (Sørensen and Stuart 2000, p. 94). Because the variable was highly correlated with the patent density measure and the results did not vary appreciably, we decided to enter only the latter into the model.

Average Patent Impact. Regardless of their quality, on average recent patents are less frequently cited than older patents simply because they have been exposed to the risk of being cited for a shorter period. For each year, we thus estimated the average number of citations—*average patent impact*—fiber optics patents received from other patents in subsequent years. We computed this measure including all patents filed in the relevant classes/subclasses by any type of assignee (whether public or private firms, academic institutions, or an individual inventor), not just the sample firms. We also ran the analysis using different citations windows by computing the citation index with future citations within five to seven years after the focal patent was issued, but the results did not change significantly. We used the former approach in our final analysis.

8. Model

To test the previous hypotheses, we estimated a random-intercept model. The model has the following basic form:

$$y_{it} = \mu_t + \beta x_{it} + \gamma z_i + a_i + \varepsilon_{it}. \quad (1)$$

The random-effects model is related most closely to the fixed-effects model. However, instead of assuming that a_i represents a set of fixed parameters, we suppose that each a_i is a random variable with a specified probability distribution. Typically, it is assumed that a_i has a normal distribution with a mean of 0 and constant variance and that it is independent of x_{it} , z_i , and ε_{it} .

Because the dependent variable *weighted citation index* can take on only nonnegative integer values, a Poisson or a negative binomial specification is recommended (Hausman et al. 1984). In the Poisson distribution, both the mean and the variance are equal to the single parameter λ , which is a function of the explanatory variables—that is, $E[Y] = \text{var}[Y] = \lambda$ (Allison 1999). However, in the presence of overdispersion—as in our data—the variance tends to be greater than the mean. While overdispersion does not bias the coefficient estimates, standard errors might be underestimated and chi-square value statistics overestimated. We thus included the stochastic component ε_{it} that allows for the effect of omitted explanatory variables to correct for this problem as follows:

$$E[Y_{it}] = \lambda_{it} = \exp(y_{it} = \mu_t + \beta x_{it} + \gamma z_i + a_i + \varepsilon_{it}), \quad (2)$$

where $\exp(\varepsilon_{it}) \sim \Gamma[1, \alpha]$; that is, it is assumed to have a gamma distribution. The subscripts i and t indicate

that the parameter λ is allowed to vary across firms ($i = 1, \dots, n$) and time ($t = 1, \dots, m$). In this formulation of the negative binomial model, the parameter α is estimated directly from the data and captures overdispersion. Because λ (*weighted citation index*) cannot be less than 0, it is generally expressed as a log-linear function of the covariates as follows.

In the analysis, we report significance levels based on Huber-White robust standard errors to control for any residual heteroscedasticity across panels. We obtained our estimates using PROC NLMIXED and PROC GENMOD in SAS (version 9.1) for the random intercept and the fixed-effects negative binomial regression models, respectively.

9. Results

Table 3 presents the descriptive statistics and the correlation values for all variables. The correlation values are relatively low, except for R&D and firm size. In analyses not reported here, we entered these two variables separately into the model but found no difference in the results. We thus decided to include only the variable R&D.

Table 4 presents the coefficient estimates for the random intercept negative binomial regression model (Models 1 to 3). Model 1 is the baseline model and includes all controls, which are statistically significant and in the expected direction, except for external knowledge, which is not significant. The positive coefficient of the average patent impact variable suggests that a firm's fiber optics patents tend to have greater impact in years when patents filed in the same technical field are more widely cited. This is especially true for older patents that have been exposed to the chance of being cited for a longer period. Moreover, patents filed by older firms (firm age), which also filed more patents in the previous year (firm fiber optics patents), have a higher chance of being cited in the future. In contrast, firms that build on older technologies, that is, that cite older patents (technology cycle), are more likely to generate innovations with less impact.

Model 2 shows the results after we entered the first variable of theoretical interest, preadaptation, to test Hypothesis 1. The coefficient is significant and in the expected direction, providing support for the hypothesis. In line with our theory, technological preadaptation represents a vantage point from where firms can eventually generate new, often very significant, innovations—as the improvement in the overall fit of the model indicates.

Model 3 presents the results after we included the second variable of theoretical interest, leverage, to test Hypothesis 2. The coefficient is statistically significant and in the expected direction. Firms leveraging their pre-1966 pool of relevant skills and knowledge in developing fiber optics are, *ceteris paribus*, more likely to achieve

Table 3 Means, Standard Deviations, and Correlations

Variables	Mean	Std dev	Min	Max	1	2	3	4	5	6	7	8	9	10	11
1. Weighted citation index	67.98	117.76	1	1,174	1										
2. Average patent impact	12.55	1.57	7.36	15.12	0.05	1									
3. Total fiber optics patents*	6.27	0.48	5.25	7.28	0.10	−0.07	1								
4. Technology cycle	7.83	5.51	0	45.33	−0.09	0.05	0.002	1							
5. R&D*	12.40	9.34	0.01	22.87	−0.06	0.05	0.04	−0.05	1						
6. Firm size*	7.16	5.17	0.04	13.68	−0.08	0.04	−0.06	−0.04	0.94	1					
7. Firm fiber optics patents*†	0.94	1.02	0	4.13	0.62	−0.03	0.11	−0.03	0.05	0.04	1				
8. Firm age	55.85	35.83	0	152	0.27	−0.05	0.04	0.03	−0.07	−0.07	0.35	1			
9. External knowledge	0.88	0.17	0	1	−0.26	0.01	−0.01	0.05	−0.01	−0.02	−0.30	−0.20	1		
10. Preadaptation*	1.50	1.53	0	6.88	0.02	−0.04	−0.13	−0.03	0.21	0.22	0.18	0.24	−0.21	1	
11. Leverage	0.02	0.06	0	0.45	0.09	−0.11	−0.27	0.10	0.02	0.05	0.12	0.10	−0.36	0.46	1

*Variables are logged.

†Variable with one-year lag.

Table 4 Determinants of Patent Impact

Variables	Model 1 Random effects	Model 2 Random effects	Model 3 Random effects	Model 4 Fixed effects
Intercept	−0.529 (0.534)	−0.810 (0.547)	−1.717 (0.587)	—
Average patent impact	0.079*** (0.019)	0.081*** (0.019)	0.097*** (0.019)	0.084*** (0.022)
Total fiber optics patents (log)	0.397*** (0.065)	0.424*** (0.066)	0.503*** (0.069)	0.576*** (0.092)
Technology cycle	−0.029*** (0.007)	−0.028*** (0.007)	−0.030*** (0.007)	−0.020** (0.008)
R&D (log)	0.009* (0.005)	0.007 (0.005)	0.006 (0.005)	0.018* (0.009)
Firm fiber optics patents (log)†	0.364*** (0.044)	0.361*** (0.044)	0.373*** (0.044)	0.220*** (0.048)
Firm age	0.004** (0.001)	0.003** (0.001)	0.003** (0.001)	0.001 (0.004)
External knowledge	0.090 (0.225)	0.130 (0.224)	0.377* (0.227)	0.624** (0.255)
Preadaptation (log)		0.104** (0.046)	0.077* (0.046)	
Leverage			3.172*** (0.864)	3.108** (0.955)
Variance parameter	0.269 (0.055)	0.264 (0.053)	0.260 (0.052)	
theta	1.573 (0.077)	1.580 (0.077)	1.602 (0.078)	
−2 Log likelihood	9,252	9,247	9,232	
Likelihood ratio test (vs. baseline)		5***	20***	

Notes. Random intercept and fixed-effect regression models dependent variable = weighted citation index, 1,209 observations. Sample includes firms publicly traded in the United States. The method of estimation is maximum likelihood for a negative binomial specification. Standard errors (in parentheses) are heteroskedastic consistent ("robust"). Although not shown, a dummy was included in the model when R&D was not reported. Two-tailed tests for all variables.

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.001$.

†One-year lag.

higher levels of technological performance. The variable preadaptation is now significant at the 10% level. While the availability of transferable skills and knowledge might enhance the ability to innovate in a new technological field, firms that actually take advantage of their past R&D efforts have a better chance of innovating in the new field as well as a better chance of creating innovations of greater impact. The inclusion of the two variables significantly improves the overall fit of the model as compared to the baseline model. Taken together, the results support the two hypotheses.

Robustness Tests. We tested the robustness of the results against alternative model specifications. First, we compared them with those for the fixed-effects model (see Model 4 in Table 4) to verify whether unobserved heterogeneity might be a problem in our analysis. Because the variable preadaptation is time invariant, we excluded it from the model. Following Allison and Waterman (2002), we estimated a fixed-effects negative binomial regression model by using unconditional maximum likelihood to control for all stable covariates (easily accomplished in SAS with PROC GENMOD in version 9.1). Allison and Waterman showed that the negative binomial model of Hausman et al. (1984), and its associated conditional likelihood estimator, does not accomplish what is usually desired in a fixed-effects method, namely to control for all stable covariates. The reason is that the model is based on a regression decomposition of the overdispersion parameter rather than the usual regression decomposition of the mean. The coefficient estimates for the fixed-effects regression model are qualitatively similar to those obtained using the random-intercept model. Also the standard errors are not too different, though bigger for the fixed-effects model. In line with previous research estimating a fixed-effect negative binomial model (Rosenkopf and Nerkar 2001), the only noticeable difference is that the coefficient for the variable external knowledge is now statistically significant. However, after controlling for the size effect by looking at the standardized coefficients, we saw that the impact of the variable external knowledge on the dependent variable is smaller than that of the leverage variable.

For several firms in the sample the preadaptation and leverage variables are equal to 0 over the entire study period. Apart from firms founded after 1966 (for which the variable is obviously equal to 0), the variable is equal to 0 when these firms did not have or did not leverage prior relevant skills and knowledge. To further check the robustness of the results, we excluded from the analysis those firms for which the two variables are always 0. This led to a subsample of 34 firms for a total of 487 firm years. Though not reported here, we found similar results to those presented in the paper.

We further controlled whether sample selection bias might affect our results. In particular, we ran the analysis by including all assignees—that is, public firms not

traded on U.S. stock markets, private firms, research labs, and academic institutions—that filed patents in any of the selected subclasses defining the fiber optics technological field (for a similar approach see Sørensen and Stuart 2000). Although we could not obtain data on R&D and size for those assignees, we nevertheless believe that the variable firm fiber optics patents, which measures their overall patenting activity in fiber optics, can be used as a “reasonably good” proxy for them, on the premise that larger firms invest more in R&D and thereby are more likely to patent. The results, which are available from the authors upon request, did not vary appreciably from those reported here, suggesting that sample selection bias may not be an issue in our analysis.

Because previous studies have controlled for differences in citation rates across technological domains by including dummies for the main patent classes (e.g., Sørensen and Stuart 2000), we checked whether the propensity to patent varied across the relevant technical fields. While we found the propensity to patent higher for the classes 65 and 385 (and related subclasses), where most fiber optics patents were filed, the results are essentially the same with respect to the variables of theoretical interest. We also ran additional analyses by (1) including R&D and firm size in the same model, (2) replacing yearly R&D with a moving average of 3–5 years for R&D, and (3) substituting R&D intensity (R&D divided by sales) for R&D expenditures. All these tests supported the main results and are consistent with research showing that R&D spending is correlated to patent counts but not necessarily patent quality (Narin et al. 2001).

Since the combined number of patents filed by Corning and AT&T in optical fibers over the study period amounts to almost 26% of the overall number of patents filed by the firms in the sample (1,317 of 5,067), in a separate set of analyses we excluded these two firms. But again we found no significant difference from the results presented in the paper. Finally, we ran the analysis using patent counts as the dependent variable. Although not reported, the results are qualitatively similar to those reported here.

10. Discussion and Conclusions

The main objective of this paper was to explore how heterogeneity in technological knowledge affects (technological) performance differences among firms. Using the concept of biological preadaptation, we investigated how the availability and exploitation of “relevant transferable skills and knowledge” relate to technological performance differences among firms. Extant research emphasizes how a firm’s prior experience in its current application domain might become a constraint and jeopardize the firm’s ability to innovate in that

domain. In this paper, on the contrary, we examined the case when the very same firm redeploys that experience across different domains. Firms are often endowed with skills and knowledge for reasons unrelated to the demands of a new opportunity. As a result, they have the possibility of creating new competitive advantages as they leverage their existing skills and knowledge into a different domain of application. We situated our analysis in the context of fiber optics, tracing the emergence and evolution of this new technology virtually from its inception. We identified relevant transferable skills and knowledge using patent data and backward citation patterns.

Firm (technological) preadaptation was found to have a positive effect on technological performance. Preadaptation does not imply a deterministic view of innovation, discarding any meaningful role for strategy. If the availability of a pool of skills and knowledge potentially available for other applications is an important source of firm heterogeneity, so too is firms' differential inclination to leverage skills and knowledge to generate (economically) valuable innovations. Since we estimated the extent to which firms actually leverage their existing base of experience, the paper establishes a direct link between prior experience and technological performance.

The results of the analysis seem to be inconsistent with previous research showing how the overall quality of a firm's patenting activity declines when firms repeatedly cite their own patents (e.g., Sørensen and Stuart 2000, Rosenkopf and Nerkar 2001). However, this apparent inconsistency can be explained by the fact that these studies do not distinguish between knowledge that predates the emergence of a new technological domain (what we define as preadaptation) and knowledge that firms accumulate after a new domain emerges. Moreover, those studies focus on firm (technological) performance within an existing domain rather than creation of new technological domains.

We believe our findings contribute to the ongoing debate in strategy on the determinants of competitive advantage, especially with respect to R&D-intensive industries, where superior performance rests on consistent innovation. One side of the debate argues that if superior performance results mainly from differences in resources that are distributed randomly "at birth," then some firms will outperform others "merely because the environment happens to change in such a way that it favors their particular resource environment" (Henderson 2000, p. 286). The other argument is that competitive advantage can be the result of "any kind of managerial foresight or strategic insight" (Henderson 2000, p. 289). Realistically, probably both luck and foresight play a role; the challenge is to clarify when each of these two forces is more likely to be at work.

The identification of a clear watershed event helped us delineate more accurately the role of foresight and

test whether (technological) performance differences were attributable to circumstances established before the emergence of the new technology (i.e., fiber optics). While firms cannot determine *ex ante* whether their prior experience will ever become useful in a new domain, the spectrum of possible applications for a firm's base of experience is often not confined to current applications. The strategic implication is that firms can increase their returns from previous technological investments by transferring skills and knowledge already available in-house, instead of creating new resources from scratch (Garud and Nayyar 1994).

One challenge of using analogies from evolutionary biology is justifying their significance in a different field. Innovations are not exactly analogous to random biological mutations (Alchian 1950), but rather result from firms' attempts to adapt to and at times even alter their own environment (Penrose 1952, Garud et al. 1997). Although we emphasize preadaptation, we do not want to downplay the significance of purposive behavior. For instance, several firms in our sample had prior experience in glass manufacturing—a clear vantage point for producing optical glass fibers. However, even firms from the same origin industries exhibit a differential ability to take advantage of their prior experience across different domains, which clearly reflects purposive behavior. Equally preadapted firms can thus differ not only with respect to their ability to leverage preexisting skills and knowledge, but also with respect to when and/or how quickly they decide to do so.⁷

A central assumption in the evolutionary theory of the firm is that of "local search"—a firm's R&D activity is closely related to its previous R&D activity (March and Simon 1958, Nelson and Winter 1982, Helfat 1994). While firms typically search locally, within the boundaries of their existing knowledge domain, some of them display a higher propensity to search beyond such boundaries (e.g., Rosenkopf and Nerkar 2001). As research on learning has pointed out, firms have "to cope with confusing experience and the complicated problem of balancing the competing goals of developing new knowledge (i.e., exploration) and exploiting current competencies in the face of dynamic tendencies to emphasize one or the other" (Levinthal and March 1993, p. 95). However, both processes can coexist when firms leverage their base of experience across different domains. These new applications can in fact be very different with respect to the market needs and performance requirements that must be satisfied. As such, even though they may not imply a major shift in a firm's technological knowledge base, they might require that a firm engage in exploration.

In this paper, we concerned ourselves with the performance implications of being preadapted in the technology space. However, the analysis could be further expanded to embrace "complementary assets" (Teece

et al. 1994, Helfat and Lieberman 2002). A firm, for instance, is more likely to enter a new market or industry if it also “possesses a broad base of assets required for successful commercialization of the new goods...” (Mitchell 1989, p. 208). While our data do not lend themselves to properly measure complimentary assets and gauge their importance relative to prior (technological) experience, we surmise that the results would not change even after controlling for their effect. The two explanations are not in fact mutually exclusive. Furthermore, in our empirical setting, patents are a key success factor. What the results suggest is that technological preadaptation, especially if combined with the ability to leverage it, positively affects (technological) performance, regardless of whether complementary assets retain their value in a new domain.

There are some obvious limitations to the study. First, whenever an analysis focuses on only one technology, it is unclear whether findings can be generalized. Future research comparing and contrasting the evolution of different technologies will verify whether the same dynamics can be detected in technological settings other than fiber optics. More specifically, notwithstanding the continuity underlying technological evolution, the challenge is to identify a clear dividing line to discriminate between the preadaptation and adaptation phases as accurately as possible.

Second, we could not compare technological performance with other market-based or financial measures (though in R&D-intensive industries technological performance measures are reasonably good proxies for firm performance). Third, since we do not have product-level data, we could not establish which firms actually entered the fiber optics market and which firms just filed patents in this new field. Given our interest in each firm’s contribution to the creation of a new technological field, however, focusing on the impact of its patenting activity is consistent with the original purpose of this study.

In conclusion, we would like to emphasize that despite their many useful applications, patent data exhibit some shortcomings as well. While patents have been increasingly used as a measure of firm knowledge, they do not fully measure a firm’s overall base of experience. For instance, even though reference to prior art—that is, citations to patents by other patents—has been a core methodology in research on social, organizational, and geographic pathways of knowledge flows, citations made by patent examiners have not been separated from citations made by inventors (Alcacer and Gittelman 2004). Focusing on a single industry, as we did in this paper, where patents are important for appropriating returns to R&D, might significantly reduce the effect of this problem, which is on the contrary compounded in studies comparing knowledge flows across very different industries. Of course, similar problems afflict most empirical

measures, especially those measuring intangibles such as skills and knowledge.

Looking at inventors’ patenting and publication records might be a complimentary way of capturing how prior experience spanning several technological domains is embodied in technologies applied in other domains. The focus on inventors is consistent with the argument that, though organizational memory does not necessarily coincide with individual memory, inventors are often “the sole storage point of knowledge that is both idiosyncratic and of great importance to the organization” (Nelson and Winter 1982, p. 115). Indeed, inventors play a key role in facilitating the diffusion and recombination of skills and knowledge accumulated in otherwise distinct technological domains. Future research should explore this issue more deeply.

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Endnotes

¹There is some disagreement on how expansive the concept of preadaptation should be. Bock (1959) does not distinguish between features that have changed and those that have retained their original function. In contrast, for Gould and Vrba (1982) preadaptation refers solely to features that promote fitness and were built by selection to perform the same function for which they originally evolved, while features that evolved for other usages or for no function at all and that were coopted for their current role at a later point in time are “exaptations.” Yet the usefulness of establishing whether existing features were from the outset “optimally designed by natural selection for their functions” (Gould and Lewontin 1979, p. 585) is questionable. As Reeve and Sherman (1993) point out, the original roles of many observable features are virtually impossible to identify because the phylogenetic and ecological information needed to infer such roles is unavailable or incomplete.

²The evolution of *tetrapod limbs* is an example. A structure that was effective at locomotion in water was also good at locomotion over land with relatively few changes. Bird feathers are another example of a preadaptation: The first feathers were for heat insulation rather than an adaptation for flight (see Ridley 1999).

³Intel's first microprocessor was a chip set designed to perform advanced calculator functions, not to be used in a computer (Burgelman 1994).

⁴For instance, distinction between *de alio* and *de novo* firms Carroll et al. (1996), and the finding that firms from origin industries with relevant specialized transferable skills and knowledge have lower death rates than newly founded firms and/or firms without similar skills and knowledge clearly sheds light on sources of firm heterogeneity within an organizational population. However, a critical strategy question—what might be driving performance differences among firms within each group—is not properly accounted for.

⁵For instance, while it laid out the foundations for the practical implementation of fiber optics with the invention of the first low-loss optical glass fiber in September 1970, Corning initiated the first lab experiments as early as 1966, when it began to leverage its prior experience in specialty glass, quantum optics, and electronics (see Figure 1). A correct identification of Corning's preentry resources and capabilities, therefore, should trace them back to the period before 1966. While subsequent efforts by Corning to develop new resources and capabilities before a market for optical fibers materialized spanned several years, those efforts were made already knowing the new application (i.e., telecommunications). Therefore, they represent adaptation to this new application, but not preadaptation, or adaptation to other application(s).

⁶We extracted what information about market share we could from the annual financial reports of some of the sample firms and also by looking at the company list provided by the Freedomia Group, a leading international business research company that publishes industry (including fiber optics) research studies annually.

⁷For instance, despite its monopoly within the long-distance telecommunications industry, AT&T failed to take the lead in the development of fiber optics and lost it to Corning. For Corning, fiber optics was a new technology that opened up a new market with high growth potential, while for AT&T it was a substitute technology bound to replace an existing telecommunications network in which traditional (copper based) technologies were still in use. The incentives to invest in the new technology and accelerate its large-scale adoption were obviously quite different (Cattani 2004). In contrast, ITT entered the market for optical fibers relatively late, although its engineers had done most of the theoretical groundwork for fiber optics.

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