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ABSTRACT

A central issue in strategy concerns how established firms survive and sustain their competitive advantage in the face of technological change. In line with the evolutionary view of technological change, I explore how firms that leverage their prior experience across different domains (i.e., markets/industries) stand a higher chance of embracing and even initiating a new technological trajectory.

INTRODUCTION

A core strategy question is how established firms can sustain their competitive advantage in the face of technological change. This question is even more salient in technology intensive industries where superior performance critically rests on the ability to innovate consistently (e.g., Teece et al. 1997). While strategy research typically traces this ability to a priori heterogeneity in initial stocks or in expected flows of resources, whether such differences result from strategic foresight or historical accidents is unclear. The precise role of chance and foresight in any human activity is difficult to estimate. Yet any evaluation of the normative implications of existing strategy research requires this question to be properly addressed. For example, the principle of ‘leveraging idiosyncratic assets’ is frequently affirmed, particularly in the resource-based view. This formulation implicitly acknowledges that key assets may exist prior to full consideration of their possible uses.

To sharpen this “leveraging” prescription, it is important to examine in detail what strategy is like in a context involving a large and complex endowment of specific resources and the gradual emergence of new information about the possible uses of those resources. With a few exceptions, to date there has been little work on this subject (e.g., Garud et al. 1997; Cockburn et al. 2000; Hoolbrook et al. 2000). A few empirical studies have started to tackle this issue by examining how differences in initial conditions and the ability to accumulate resources across markets and/or industries developed (e.g., Carroll et al. 1996, Helfat & Lieberman 2002, Klepper & Simons 2000). Building on this strand of research, I show how established firms create new competitive advantages by leveraging their experience across different domains (i.e., markets or industries). To this end, I develop the notion of technological pre-adaptation. I hypothesize that firms that can leverage skills and knowledge into applications for which they are potentially pre-adapted tend to outperform those that lack such competencies and experience.

THEORY

Much research in strategy and innovation emphasizes that prior experience hinders technological advancement (e.g., Henderson & Clark 1990). The dominant design theory, for example, argues that pre-entry experience is disadvantageous when it weds firms to technologies...
made obsolete by the emergence of a new dominant design (see Christensen et al. 1998). Conversely, recent research on industry dynamics has pointed out that prior experience positively affects new market entry decisions, firm performance, and the evolution of market structure, especially when firms leverage their prior experience in a different domain. Carroll et al. (1996), for example, found that firms entering the American automobile industry from related industries attained higher levels of performance than new firms did. Similarly, Klepper and Simons (2000) showed how firms experienced in the manufacture of radios were more likely to enter the TV industry, were more innovative, achieved greater market share, and survived longer within the TV industry than were firms with no experience in radio production.

However, this stream of research must address several issues more thoroughly. In particular, what is not clear in these studies is the extent to which a firm’s ability to generate new technologies can be understood as a consequence of prior experience in other domains. Is this ability the result of luck or foresight? 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 match the requirements of a new domain of application?

To address these questions I develop the notion of technological pre-adaptation to describe that part of prior experience that is accumulated without anticipation (foresight) of subsequent uses. In biology, pre-adaptation refers to the case when “by chance, an organ that works well in one function turns out to work well in another function after relatively little adjustment” (Ridley 1999: 347). An organ or a feature of an organism did not evolve in anticipation of its new function, it happened to be adaptable to it. It was then selected for this new function.

Pre-adaptation also has non-biological analogues. Corning’s pioneering work in fiber optics for long-distance communications was largely an outgrowth of its long-standing experience with specialty glass – though used for different applications (Cattani and Winter, 2003; for other examples see Basalla, 1988). Firms can create new competitive advantages by discovering how to apply their technological expertise to new applications. Prior experience may enhance a firm’s ability to promptly identify the emergence of a new technology and to cope with the challenges of developing this technology. Since accurate foresight is rare, firms can learn more about applications for which they are potentially pre-adapted by relying on market feedback. The nature of the selection forces to which a firm becomes (intentionally) exposed can steer that firm’s R&D in totally different directions and even initiate distinct evolutionary patterns.

The notion of pre-adaptation also suggests that in the course of technological evolution it is sometimes possible to identify a “dividing line” or “watershed event.” Before this event, during the pre-adaptation 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 pre-existing skills and knowledge.

**EMPIRICAL ANALYSIS**

**Industry**

The analysis focuses on the emergence and evolution of fiber optics technology and its use within the telecommunications industry, between 1970 and 1995. The possibility of using low-
loss optical glass fibers over long-distances was first shown in 1970 when Corning produced the first glass fiber with attenuation below 20 dB/km. Charles K. Kao and George Hockham from Standard Telecommunications Laboratories (STL) had envisioned the theoretical possibility of using light for communications purposes a few years earlier: in 1966 they published 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 paper spurred the first wave of large-scale laboratory experiments. Thus, year 1966 is an ideal ‘dividing line’ between the period when foresight was not a factor and the period when a higher level of foresight was more explicitly at work. This dividing line shaped the overall research design, the data collection and the creation of the variable of theoretical interest.

Data

I studied the performance implications of technological pre-adaptation by using patent data. I collected patent data from the National Bureau for Economic Research and the US Patent and Trademark Office Cassis databases for the period 1970-1995, and financial data from Compustat. I included a firm in the sample if it filed at least one patent in one of the relevant classes and subclasses. The final sample is an unbalanced panel that comprises 204 public firms, for a total of 1179 firm-years, all patenting in the US and traded on US stock markets, for a total of 4760 patents.

Dependent Variable

Following Trajtenberg (1990), the dependent variable estimates the impact of a firm’s patenting activity and is computed as a weighted citation index of the number of future citations received from other firms in subsequent years.

Independent Variable

Since the theoretical groundwork for the development of fiber optics dates to 1966, only skills and knowledge available in 1966 or before represent pre-adaptation for future applications. Accordingly, for each year the variable – Leverage – is the ratio between backward self-citations that refer to patents the focal firm filed in any year before 1966 (included) and the sum of all backward citations. The variable measures the extent to which firms actually take advantage of their level of technological pre-adaptation in a new domain.

Control Variables

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

\textit{Patent Stock}. The number of patents a firm files in a given year is likely to be affected by its prior patenting activity. Specifically, Patent Stock$_{t} = 0.80 \times$ Patent Stock$_{t-1} +$ New Patents$_{t}$. To avoid simultaneity problems, I lagged the variable by one year.

\textit{R&D Stock}. Since patents filed in a given year may reflect past R&D efforts, I added the cumulative number of R&D expenditures (in 1996 constant dollars) in previous years to current R&D after applying a 15 percent depreciation rate.

\textit{External Knowledge}. 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 keep citing their own patents. The variable is the ratio of the number of backward citations of patents filed by other firms to the sum of all backward citations in a given year.
Firm Size. The effect of size is controlled using the value of a firm’s total assets expressed in 1996 constant dollars.

RESULTS

Table 1 presents the results for the fixed-effects negative binomial regression model by using unconditional maximum likelihood to control for all stable covariates (see Allison and Waterman, 2002). I report significance levels based on Huber–White robust standard errors. I also included year dummies control for macroeconomic trends that might affect a firm’s patenting activity.

Table 1 about here

Since R&D Stock and Total Assets are highly correlated, I entered them separately. Model 1 includes all controls, R&D Stock, Patent Stock, and External Knowledge, that were significant and in the expected direction. In Model 2, I substituted Total Assets for R&D Stock (the variables are highly correlated): the results are not noticeably different from the results in Model 1. Taken together, these variables indicate a positive relation between the creation of ‘absorptive capacity’ in a new domain and the impact of a firm’s patenting activity. To check for any residual serial correlation within panels, in Model 3 I also included the dependent variable, Weighted Citation Index, with a one-year lag. Model 4 shows the results after I entered the variable of theoretical interest, Leverage. The coefficient is statistically significant and in the expected direction. This result suggests that firms leveraging their level of technological pre-adaptation, are, ceteris paribus, likely to outperform firms that rely only on skills and knowledge not developed internally.

While not reported here, the results are robust to alternative model specifications, such as the random effects and the OLS regression models. To conclude, the results confirm a positive link between firm pre-adaptation and performance as measured by the impact of its patenting activity in a new domain of application.

DISCUSSION AND CONCLUSIONS

Pre-adaptation implies that success in a market can be attributed to circumstances established before the emergence of such a market. In line with the notion of pre-adaptation, the study clarifies the role of luck and foresight in the development of resource differences among firms. To this end, the research design attempted to capture the transition from the phase when firms accumulate resources without anticipating their future use to the phase when they leverage them into a totally different domain. It is during this second phase when firms start receiving feedback from the market that higher levels of foresight presumably guide firms’ R&D. Despite their shortcomings, patent data and backward citation patterns provide a detailed and consistent chronology of when certain resources were originally created. Thus, I used them to establish as accurately as possible when foresight most likely influenced the development of a new technology (i.e., fiber optics), and to further explore differences in firm characteristics and resource endowments, rather than attribute them to initial conditions defined a priori. The study should then be regarded as an attempt to unpack some of the key determinants of firm heterogeneity.
The paper has also important implications for organization learning research. Several studies emphasize how firms are confronted with the need to strike a balance between exploration and exploitation (e.g., Levinthal and March 1993). Firms differ in their propensity to engage in either type of search behavior. However, both processes can co-exist when firms leverage their base of experience across different domains of application. Indeed, while leveraging their base of experience into a new selection environment firms must also learn about new market needs and performance requirements – and then engage in exploration while exploiting their base of experience.

REFERENCES


**Table 1**
**Determinants of Patent Impact. Fixed-Effects Negative Binomial Regression.**
*Dependent Variable = Weighted Citation Index, 1179 Observations*

<table>
<thead>
<tr>
<th>Variables</th>
<th>Model 1</th>
<th>Model 2</th>
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† The variable is expressed in thousands  
* p < 0.05, ** p < 0.01, *** p < 0.001
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