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ENTREPRENEURSHIP IN THE LARGE CORPORATION: A LONGITUDINAL STUDY OF HOW ESTABLISHED FIRMS CREATE BREAKTHROUGH INVENTIONS

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We present a model that explains how established firms create breakthrough inventions. We identify three organizational pathologies that inhibit breakthrough inventions: the familiarity trap – favoring the familiar; the maturity trap – favoring the mature; and the propinquity trap – favoring search for solutions near to existing solutions. We argue that by experimenting with novel (i.e., technologies in which the firm lacks prior experience), emerging (technologies that are recent or newly developed in the industry), and pioneering (technologies that do not build on any existing technologies) technologies firms can overcome these traps and create breakthrough inventions. Empirical evidence from the chemicals industry supports our model.

INTRODUCTION

Radical or 'breakthrough' inventions lie at the core of entrepreneurial activity and wealth creation (Kirchhoff, 1991; Schumpeter, 1975). Such inventions serve as the basis of new technological trajectories and paradigms and are an important part of the process of creative destruction in which extant techniques and approaches are replaced by new technologies and products. Most academic studies, as well as reports in the popular press, have focused on the role of new firms in the creation of such breakthroughs (Methe *et al.*, 1997). This focus is understandable since several studies show that breakthrough inventions are often likely to originate with entrants rather than incumbents (Cooper and Schendel, 1976; Foster, 1986). However, recent research suggests that established firms may actually be contributing to breakthrough inventions to a far greater extent than is generally recognized, and, in some industries, may even dominate this process (Methe *et al.*, 1997). Thus, contrary to common perceptions, it appears that at least some large firms are able to establish routines that enable them to generate significant technological breakthroughs, and reinvent themselves and retain technological leadership in their industry. In this study we examine the issue of how established firms create such breakthrough inventions.

Understanding how large, established firms create breakthrough inventions has rich theoretical and practical implications from the perspectives of entrepreneurship, technology strategy and organizational learning. As Venkataraman (1997) notes, 'Entrepreneurship as a scholarly field seeks to understand how opportunities to bring into existence "future" goods and services are discovered, created and exploited, by whom and with what consequence.' Further, he elaborates, true entrepreneurship entails the creation of both private wealth and social benefit (Schumpeter, 1975; Venkataraman, 1997). Breakthrough inventions of the kind that are studied here possess all three of these

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concomitants. Almost by definition breakthrough inventions serve as the basis of 'future' technologies, products and services. Further, research finds that breakthrough inventions are related to the creation of private wealth and the generation of streams of Schumpeterian rents for their inventors (Harhoff *et al.*, 1999), while also enhancing social welfare (Trajtenberg, 1990a, 1990b).

Examining the nexus between such breakthrough inventions and large established corporations also provides insights into the processes of corporate entrepreneurship. Although the stereotype of the solitary inventor toiling in a garage adds a memorably heroic dimension to the breakthrough invention story, the fact remains that a very large proportion of R&D resources continue to be expended by established, publicly held corporations. Identifying strategies that can help such corporations to improve their record of breakthrough inventions can potentially create significant private and social value. Further, beyond simply wealth creation, for established corporations technological breakthroughs can serve as internally generated opportunities for corporate reinvention, business growth, and new business development (Burgelman, 1983). Research suggests that the routines of the large established firm that ensure reliable throughput and output also entail formalization and bureaucratization, and sometimes even obsolescence and death, as the organization's fit with a changing environment deteriorates (Hannan and Freeman, 1989; Sorensen and Stuart, 2000). Studying entrepreneurial behavior in large corporations can present important insights for corporate rejuvenation (Covin and Miles, 1999).

Exploring the determinants of breakthrough inventions is also of importance from the perspective of technology strategy and organizational learning. Breakthrough inventions represent rare, valuable, and potentially inimitable sources of competitive advantage (Barney, 1991). Understanding how large corporations create technological breakthroughs and sustain their preeminence in an industry is of fundamental concern to strategy theorists trying to explain durable or sustained superior performance. Relatedly, organizational learning theorists have argued that learning creates its own traps: as organizations develop capabilities that improve immediate performance they often simultaneously reduce competence with respect to new paradigms that may hold the key to future performance (Levinthal and March, 1993). Identifying the kinds of corporate activities that help firms escape such *learning traps* is then of significant importance.

In the sections that follow we integrate the entrepreneurship and organizational learning literatures to develop a theoretical model that explains how established firms create fundamental technological breakthroughs. Our model has the following key features. First, from the entrepreneurial literature we draw on the notion that diversity and experimentation within the large corporation are central to successful entrepreneurial activity (Burgelman, 1983; Lant and Mezias, 1990; McGrath and MacMillan, 2000; Mezias and Glynn, 1993). Second, from the organizational learning literature we draw on the idea that the dynamics of established organizations make the provision of such diversity difficult, leading organizations into learning traps that favor specialization and inhibit experimentation (Levinthal and March, 1993; March, 1991). Thus, we argue that the essential constraints to the ability of large firms to create breakthrough inventions stem in large part from practices that are both necessary and efficient for them. Third, we suggest that in the context of breakthrough inventions such learning traps are manifested in three types of organizational pathologies: a tendency to favor the familiar over the unfamiliar; a tendency to prefer the mature over the nascent; and a tendency to search for solutions that are near to existing solutions rather than search for completely de novo solutions. We call these three pathologies the *familiarity trap*, the *maturity trap*, and the *propinquity trap*, respectively, and argue that each of these is grounded in significant immediate benefits for firms, but eventually constrains their ability to create breakthrough inventions that hold the key to future performance. Finally, by expanding and elaborating the notion of learning traps in this fashion, we identify specific strategies that organizations can use to counter these pathologies. Specifically, we suggest that by experimenting with *novel*, *emerging*, and *pioneering* technologies firms can overcome the liabilities of these traps and successfully create breakthrough inventions.[1]

[1] Learning traps (Levinthal and March, 1993) are closely related to another, more familiar construct: competency traps (Levitt and March, 1988: 322). Competency traps are defined

Novel technologies are technologies that are new or unfamiliar to the firm (i.e., they are technologies in which the firm lacks prior experience), even though they possibly have existed in the industry before. *Emerging* technologies are leading-edge technologies that are recent or new to the entire industry (as distinct from older, mature technologies). *Pioneering* technologies are technologies that have no technological antecedents (i.e., they represent technologies that do not build on any existing technologies). We test our arguments with longitudinal data on the invention output of the leading firms in the chemical industry to demonstrate that these strategies are predictive of a firm's record of breakthrough invention.[2]

THEORY AND HYPOTHESES

The distinction between invention and innovation is an important one. Invention refers to the development of a new idea or an act of creation; innovation refers to the commercializing of the invention (Hitt, Hoskisson, and Nixon, 1993: 162; Schumpeter, 1934). In this study, for clarity and focus we restrict our attention to the creation of the actual inventions rather than their subsequent commercialization. Breakthrough inventions can provide a unique competitive advantage and attendant rents to the inventing organization (Achilladelis, Schwarzkopf, and Cines, 1990; Harhoff *et al.*, 1999). Further, the capacity to create breakthrough or radical inventions can itself be regarded as a form of meta-learning or dynamic core competence (Lei *et al.*, 1996; Prahalad and Hamel, 1990) reflecting a firm's unique and specialized problem-solving capabilities. Thus, from both practical and theoretical perspectives, understanding the determinants of breakthrough inventions at the firm level is important.

Radical or breakthrough inventions can be defined along different dimensions. At a very basic level a distinction can be made between inventions that are radical from a technological perspective vs. inventions that are radical from a user or market perspective. In this research we focus on the technological importance of an invention in classifying it as breakthrough or radical (Trajtenberg, 1990a, 1990b; Podolny and Stuart, 1995; Rosenkopf and Nerkar, 2001), and accordingly define breakthrough inventions as those foundational inventions that serve as the basis for many subsequent technological developments (Trajtenberg, 1990a, 1990b). The technological importance of inventions can vary significantly. While some inventions open new paths of technological progress and spawn many subsequent inventions, others are technological dead ends (Dosi, 1988; Fleming, 1999; Podolny and Stuart, 1995; Sahal, 1985). Inventions that serve as the source of many subsequent inventions can be regarded as breakthrough or radical because they have demonstrated their utility on the path of technological progress (Achilladelis *et al.*, 1990; Fleming, 1999). Past research suggests that such inventions that open the door to many subsequent inventions have considerable technological and economic value (Trajtenberg, 1990a; Rosenkopf and Nerkar, 2001). Although technologically important inventions can also be radical inventions from the perspective of a user, neither our theory nor our data permit us to extend our arguments to a user-based concept of radicality. Accordingly, we limit the domain of our theory and empirical claims to inventions that are technologically important.

Prior research on corporate entrepreneurship and breakthrough inventions

Recent research has compellingly argued that corporate entrepreneurship adds value not only

to occur 'when favorable performance with an inferior procedure leads an organization to accumulate more experience with it, thus keeping experience with a superior procedure inadequate to make it rewarding to use' (Levitt and March, 1988: 322). Learning traps, on the other hand, embody the conflict between routines that enable the organization to perform well in the short run but may position the organization unfavorably for the future. Thus, while competency traps entail choices between two procedures or routines targeted towards the same outcome, the learning traps we discuss here are about the implications of the same routines for two different outcomes such as reliable and predictable outputs that are necessary for immediate or short-run performance, and breakthrough inventions that may form the basis of superior performance in the future.

[2] A relevant issue is whether these three strategies represent actions to overcome learning traps, or a more complex global 'ability to learn.' From our perspective a firm's *ability to learn* is a broad construct that is likely to subsume many forms of learning (see, for instance, Huber, 1991; Lei, Hitt, and Bettis, 1996). In this study we focus on the firm's ability to overcome three specific forms of weaknesses or traps. Although the overcoming of these traps is probably just one facet of a firm's overall ability to learn, we believe that this specific characterization is useful in identifying specific countering strategies. The identification of these countering strategies would not be possible or at least not as easy if we focused on the broader, but less tangible, construct of a global ability to learn.

by utilizing resources in new ways but also, perhaps more importantly, by creating new resources (Zahra, Jennings, and Kuratko, 1999; Floyd and Wooldridge, 1999; Greene, Brush, and Hart, 1999). Prominent among these created resources are knowledge and the various knowledge outcomes of the corporate entrepreneurship process (Zahra *et al.*, 1999; Hitt *et al.*, 1999). Consistent with this theme several recent studies have looked at knowledge-related outcomes of corporate entrepreneurship. However, the focus of many of these studies is on innovation, in the form of new product development, rather than invention, the act of creating a technological breakthrough. For instance, Hitt *et al.* (1999) have examined the role of cross-functional teams in the design and development of new products, finding that elements of team context such as top management team support and organizational politics have a more significant influence on team success than internal team characteristics. Similarly, Koberg, Uhlenbruck, and Sarason (1996) examine the moderating effect of the life cycle stage of a venture on the organizational and environmental determinants of product innovation. Relatively little research has examined *inventions* as the outcome variable of the entrepreneurial process. Yet, technologically radical inventions can be regarded as opportunities or options that are subsequently exploited through new ventures or commercialization within the existing businesses. Thus, research on the determinants of breakthrough inventions complements the above studies that focus on the exploitation of opportunities, by trying to establish an understanding of the *creation* of opportunities. Indeed, to the extent that without inventions there are no innovations, improving our understanding of the strategies that lead to breakthrough inventions is critical.

Large-sample studies of breakthrough *inventions* are relatively rare even in the technology area. In common with the literature on corporate entrepreneurship, studies that have examined the issue of radical technological breakthroughs have more often focused on the commercialization of inventions or the introduction of new products rather than on the actual inventions themselves (Anderson and Tushman, 1990; Mitchell, 1989; Tushman and Anderson, 1986). For instance, a common objective across many of these studies has been the identification of the relative importance and likelihood of incumbents and entrants as sources of successful innovations (Cooper and Schendel, 1976; Foster, 1986; Henderson, 1993; Methe *et al.*, 1997; Tushman and Anderson, 1986; Utterback, 1994). The few studies examining the corporate creation of breakthrough inventions have focused on the impact of such inventions rather than their creation (for instance, Achilladelis *et al.*, 1990; Trajtenberg, 1990b). Similarly, in-depth case studies of breakthrough inventions (Foster, 1986; Kusunoki, 1997; Nayak and Ketteringham, 1986) or of corporate practices fostering such inventions (Brown, 1991) have provided wonderfully rich and insightful characterizations of the invention process; however, the task of synthesizing these individual findings into a formal model of breakthrough invention in large corporations remains. In this research we attempt to address this gap.

Established firms and breakthrough inventions

The failure of large firms to create breakthrough inventions can be understood through either their lack of motivation (the economic perspective) or their lack of ability (the organizational perspective) (Henderson, 1993). In this study we control for economic motivations such as the profitability of firms in our empirical work but focus our theory development largely on the organizational question of why large firms may fail to create breakthrough inventions. We use the most influential patents (defined in greater detail later) in the chemicals industry over an 8-year period as our indicators of breakthrough invention and develop a framework to explain the strategies that led to the creation of such inventions. We focus especially on why the very nature of being an established firm creates tensions with regard to the generation of breakthrough inventions.

Our model of breakthrough inventions in established firms begins with three basic premises drawn from the organizational learning literature. First, we presume that organizational behavior is based on routines (Nelson and Winter, 1982; Levitt and March, 1988). Second, we presume that routines are oriented to targeted outcomes (Levitt and March, 1988; Simon, 1955). Each organization is subject to a set of external and internal objectives, and routines are oriented to the accomplishment of these objectives. Third, we assume that in successful or established organizations, i.e., those organizations that survive and mature in the organizational ecology, organizational routines and actions are path-dependent and therefore based on interpretations and outcomes of past actions (Lei *et al.*, 1996; Levitt and March, 1988). Routines that are associated with success in a situation are replicated and perpetuated, while those associated with failure are discarded or modified. Over time this process of winnowing of unproductive routines and replication of successful ones, combined with the second premise identified above, ensures that in established organizations routines are specialized towards very specific outcomes.

A firm's survival and success are eventually based on its ability to meet at least three sets of objectives. First, it must satisfy some market demands or needs. Without an external demand for its outputs, the firm must eventually die. Second, in a competitive environment, to succeed a firm must attempt to develop a competitive advantage over other firms seeking to offer products to the same markets. Third, a firm needs to establish an internally consistent set of throughput processes that ensure that the above output and competitive advantage demands are met. Established firms, or firms that emerge as leaders or survivors in an industry, are those that have met these three objectives in at least a minimal fashion.

Although a firm must meet several requirements to satisfy market demands, its ability to provide reliable high-quality outputs in an efficient and predictable fashion is likely to be key to its success and survival (Hannan and Freeman, 1989). Similarly, from the perspective of obtaining a competitive advantage, a firm needs to develop a distinctive competence, a unique capability housed in the organization that differentiates it from its competitors (Hitt and Ireland, 1985). Finally, from the perspective of internal consistency it is important that a firm's structure and systems conform to its strategy (Burgelman, 1985; Dess, Lumpkin, and McGee, 1999). The greater the effectiveness with which a firm can accomplish these three objectives, the higher the likelihood of its survival, at least in the context of a stable environment.

By developing and refining a competence, by providing reliable outputs, and by operating a set of internal controls and processes that ensure the first two outcomes, a firm can enjoy the benefits of external and internal consistency. Interestingly, these very attributes can also serve to limit the firm's effectiveness at breakthrough invention. In a set of processes that we describe in greater detail slightly later, we note that each of these performance-enhancing attributes that enable a corporation to survive and establish itself also potentially entail a significant dark side. The impetus to provide reliable and predictable solutions focuses a firm's attention on mature technologies (Christensen and Rosenbloom, 1995; Sorensen and Stuart, 2000). The impetus to develop a competitive advantage favors the retention of routines that lead to distinctive competence and specialization, rather than experimentation (Levinthal and March, 1993). Finally, the necessity of establishing control to accomplish the first two objectives leads to bureaucratic procedures and structures that favor searching proximate domains of technology, rather than its unknown nether regions that may hold eventually more effective, but *ex ante* more uncertain and unknown, solutions. As we argue below, this focus on the familiar, the mature, and the proximate may serve to limit the likelihood of creating a truly breakthrough invention.

The above, prognosis however, presumes the dominance of single-loop learning among organizations (Argyris, 1983). The retention of routines that enhance reliability, specialization, and control may enable an organization to prosper in a steady state. However, the reality of business indicates that significant innovation is likely to be an important dimension of firm performance for many firms. In such situations, the possibility of double-loop learning suggests a second dynamic that may be operative on at least some firms (Lei *et al.*, 1996). Recognizing that the above-described routines lead to significant deficiencies in their capabilities to create breakthrough inventions, some firms may consider a second loop of activity that enables them to counter this dysfunctional outcome of the primary loop. Accordingly, instead of seeking to develop just a primary set of competencies at producing output, firms may target the development of more dynamic capabilities (Lei *et al.*, 1996; Deeds, DeCarolis, and Coombs, 1999). Prominent among such capabilities is the development of heuristics and insights to define and solve complex technological problems, problems of the kind that can lead to technological breakthroughs (Lei *et al.*, 1996). The integration of these second-order capabilities of problem definition and solution, with the primary capabilities at output generation described earlier, can serve as a form of meta-learning for these firms and provide a basis for even more significant and durable competitive advantages (Lei *et al.*, 1996; Prahalad and Bettis, 1986). This incentive, of developing a highly tenable competitive position, can serve as a basis for the reevaluation of the firm's existing routines and help the firm to identify strategies to counter these deficiencies. In the sections that follow we investigate in some detail both these deficiencies and the strategies firms may follow to overcome them.

The familiarity trap and novel technologies

Received research suggests that increasing returns to experience, or mutual positive feedback between experience and competence, make the refinement of familiar technologies preferable to the exploration of new ones (Levinthal and March, 1993; March, 1991). Experience with a technology leads to enhanced absorptive capacity and increased competence with the technology (Cohen and Levinthal, 1990). Greater competence with a technology fosters increased usage, and hence increases experience with the technology (Cohen and Levinthal, 1990). This cycle of experience and competence is rewarding in terms of enabling the organization to build a specialized competence. However, the increased ease of learning and problem solving in specific directions made possible by enhanced absorptive capacity and competence in those areas makes the adoption of alternate directions of development less attractive and potentially less rewarding. Since developing deeper expertise with familiar knowledge bases yields more immediate and likely returns, it is preferred to investing in unfamiliar technologies (Cohen and Levinthal, 1990; Levinthal and March, 1993). Unfortunately, this path dependence increases the risks of the organization falling into a *familiarity* trap.

As experience and competence in a specific set of technologies accumulate, knowledge architectures reify (Henderson and Clark, 1990). Cognitive maps become increasingly rigid and existing, dominant, paradigmatic solutions are applied to all problems (Leonard-Barton, 1992; March, 1991). The reduction in experimentation and the invocation of a dominant and familiar paradigm to address all problems reduces the probability that a distinct, radically different approach to solving a given problem will emerge (Fiol and Lyles, 1985; Lei *et al.*, 1996). However, a given set of routines and competencies can address only so many problems in an effective fashion. The likelihood that the optimal, or even a highly effective, solution to a problem will be discovered diminishes as the range of problems addressed with a given set of competencies is increased. Concurrently, the likelihood that some principles will be inappropriately applied rises as a constrained set of competencies is applied to more and varied technological problems. Without exposure to novel technologies and the novel modes of reasoning and variation in cause–effect understandings that are associated with such exposure, breakthrough solutions become increasingly unlikely. Thus, although the firm uses familiar, well-understood technologies with great competence, the absence of novelty and experimentation that are likely to help the firm craft breakthrough solutions to upcoming problems limits the firm's capacity for breakthrough invention.

Exploring *novel technologies*, i.e., *technologies that are new to the organization*, even though they may have been in existence earlier, are an important mechanism by which firms can avoid familiarity traps. Exploring realms of knowledge that an organization has hitherto not explored provides the organization with multiple benefits from the perspective of generating new, breakthrough solutions. First, it provides the organization with the benefit of heterogeneity in its problem-solving arsenal (Amabile, 1988). Novel technologies may differ in their modes of reasoning and problem formulation and solution. Exposure to these different approaches adds to the repertoire that the organization can bring to bear on any new problem that it faces. Newly learnt or observed perspectives may reflect better, more effective solutions to a given problem. Second, as new technologies are observed and studied, the stability of existing cognitive structures and cause–effect relationships is challenged (Lei *et al.*, 1996). New world-views have to be developed that account for both the known as well as the unfamiliar, and this process can lead to additional insights and profundity. Metaphorically speaking, the irritant of new, imperfectly understood streams of knowledge can foster the pearls of insight that encompass both old and new knowledge. The enhanced repertoire and deeper understanding that are the consequence of exploration of new technologies can provide the basis for breakthrough inventions.

Even though exposure to new technologies is likely to be beneficial up to a point, excessive exploration of new technologies must eventually be harmful (Levinthal and March, 1993). In moderate quantities, the novelties that new technologies draw attention to spark renewed examination of causes and effects, improve understanding and insight, and lead to breakthrough inventions. In excess, the same novelties can become a source of confusion and information overload. As organizations are reduced to 'frenzies of experimentation' performance suffers (Levinthal and March, 1993). Further, expending resources on multiple new technologies simultaneously may eventually imply diseconomies of scale within the individual technologies. These arguments suggest that:

Hypothesis 1: A firm's creation of breakthrough inventions is related to its exploration of novel *technologies in a curvilinear (inverted-U shaped) manner.*

The maturity trap and emerging technologies

Closely related but conceptually distinguishable from the tendency to favor familiar technologies is the tendency to favor mature technologies. Mature technologies are technologies that have been in existence for some time and are relatively well known and understood in the industry. In contrast, *emerging* technologies are technologies that are new in chronological terms. They represent the leading edge of technology and have only recently been developed.

Mature technologies are closely tied to the advantages and characteristics of the established firm. First, mature technologies are usually well understood and offer greater reliability relative to more recently developed and less tested approaches. For the established firm, providing reliable performance to its constituencies is a critical element of its competitive repertoire (Hannan and Freeman, 1989). Second, mature technologies are likely to have highly developed value networks and organizational and extra-organizational assets that are co-specialized with these technologies (Christensen and Rosenbloom, 1995). These co-specialized assets and networks make subsequent innovations on these existing technologies easier, but may impede experimentation with nascent technologies that require different sets of assets, inputs, and complements. Third, mature technologies being well known in the industry offer the benefits of legitimacy; even if new technologies hold the promise of superior performance, convincing customers to trust unproven technologies may be difficult and expensive. For all these reasons, the established firm may prefer to exercise its innovative efforts in well-developed, mature technologies while choosing to forgo more current alternatives. This failure to explore emerging technologies may, however, lead the firm into a *maturity* trap. The organization's assets and commitments favor the further development of mature technologies; however, lack of exposure to immature technologies may reduce the likelihood of creating a breakthrough invention.

Experimenting with nascent or *emerging* technologies can be a mechanism by which firms can increase their likelihood of creating a breakthrough invention and circumvent the maturity trap. Emerging technologies are likely to differ from mature technologies in terms of the nature of technical problems they pose as well as the possibilities of technical solutions that they present. On both these accounts they offer a greater potential for breakthrough invention. We examine these two mechanisms in some detail below.

Research suggests that the character of invention and innovation changes across the life cycle of a technology (Abernathy and Utterback, 1978; Tushman and Anderson, 1986). In its earliest period a technology poses many significant problems as its basic concepts are reduced to practice. Although these problems raise the uncertainties associated with a technology, they also represent significant opportunity for early entrants into this technology. Solution of the fundamental problems of a technology can often be of a path-breaking character (Dosi, 1988). In contrast, as a technology matures, fewer major problems remain to be solved. Thus, the opportunity to make fundamental breakthroughs is higher in emerging technologies.

The theory of recombinant invention provides a second argument for the increased likelihood of breakthrough invention with an emerging technology (Fleming, 1999; Utterback, 1994). According to this theory inventions are very commonly the result of combining or recombining existing elements of knowledge into new syntheses (Henderson and Clark, 1990; Kogut and Zander, 1992; Tushman and Rosenkopf, 1992; Fleming 1999). Every new technology that is invented adds a new set of knowledge elements to the existing universe of knowledge elements. These new knowledge elements can themselves be recombined in various ways and thus serve as the basis for further inventions (Fleming, 1999).

The recombination potential of any set of knowledge elements is, however, finite in that there are only so many ways that existing elements of knowledge can be fruitfully recombined. As technologies mature, the likelihood that high-utility combinations of the technology's elements have not yet been tried or exploited already must eventually decline. Conversely, emerging technologies, technologies whose constituent elements are relatively new, offer significantly higher potential for breakthrough recombinations. Since the elements in these technologies have been in existence for a relatively short period, experimenting with such technologies can enrich the set of underexploited technological factors or primitives available to the organization and increase the potential for breakthrough inventions. Thus, from both the perspective of unsolved problems as well as the prospect of recombinatory solutions, emerging technologies present a higher likelihood of breakthrough invention.

Eventually, the logic of diminishing returns must apply to the exploration of emerging technologies too. Working on emerging technologies is likely to demand more focus, attention, and resources. These technologies are likely to be relatively poorly understood given their recency. Further, even the infrastructure for research in these technologies may be underdeveloped relative to that of more mature technologies. Research inputs and materials that are routinely available for older technologies may need to be developed afresh for these technologies. Further, the pathways to successful innovation are more uncertain in such technologies (Sahal, 1985). Experimenting with many emerging technologies at the same time may fragment the organization's efforts and resources and may well undermine its efforts to recharge its invention potential. As with novel technologies, the pursuit of emerging technologies is likely to be most rewarding when conducted in moderation. Without access to new and underexploited technological elements, the organization's ability to create breakthrough recombinations may be affected. With excessive exploration of emerging technologies the organization's focus and resources may be challenged. Accordingly, we propose:

Hypothesis 2: A firm's creation of breakthrough inventions is related to its exploration of emerging *technologies in a curvilinear (inverted-U shaped) manner.*

The propinquity trap and pioneering technologies

A third dynamic that is likely to characterize the problem-solving behavior of established organizations is their propensity to search for solutions in the neighborhood of existing solutions (Helfat, 1994; Martin and Mitchell, 1998; Nelson and Winter, 1982; Stuart and Podolny, 1996). Attempting to solve technological problems is an enterprise fraught with uncertainty. In ambiguous and uncertain environments, reliance upon historical experience is often the norm (March, 1988). Previously used solutions provide a base of familiarity from which the problem solver can move forward. Further, using elements or approaches that are known to have succeeded in past searches provides some assurance to the problem solver that the endeavor will not be a complete failure (Fleming, 1999). Thus, from a corporate innovation champion's perspective an effort that builds on technological antecedents is less risky than one that attempts a *de novo* solution to a problem (Hoskisson, Hitt, and Hill, 1993; Hoskisson, Hitt, and Ireland, 1994). Similarly, adaptation of existing solutions to new problems conserves cognitive effort and resources, both scarce inputs.

The impulse to build on existing foundations is therefore likely to be strong in the context of inventions in general. In the context of an established organization this impulse is likely to be heightened by the organization's need to ensure organizational order (Burgelman, 1983; Mezias and Glynn, 1993). In large corporations, organizational size and complexity demand that a structured approach be used to regulate organizational activity (Burgelman, 1983). Resource allocation must follow established norms, controls, and procedures (Hitt *et al.*, 1996). Projects that build on clearly specified antecedents are likely to be more easily justifiable before a rule-bound decision-maker than projects that rely on completely new principles.

Although risk aversion, organizational routines, and bureaucratic convenience all mandate a priority for projects that look for new solutions near old solutions, these factors also predispose the organization towards falling into the *propinquity* or nearness trap. If the organization searches extensively and almost universally for new solutions in the neighborhood of old solutions, then large areas in the solution domain remain unexplored. Yet, the history of science suggests that many remarkable inventions eventually emerge from precisely these hitherto unexplored domains (Utterback, 1994). Actors from unrelated contexts, unfettered by the need to build on existing precedents, introduce new solutions or define problems in new ways that facilitate completely unprecedented and discontinuous solutions (Foster, 1986; Brown, 1991).

Experimentation with *pioneering* technologies may provide one mechanism for incumbents to circumvent the dangers of the propinquity trap and preempt such attackers (Brown, 1991). Pioneering technologies build on no existing technologies. Instead of trying to modify an available solution, pioneering technologies focus on completely *de novo* solutions. Indeed, the directive to researchers from a pioneering technology perspective is often to ignore all available solutions, focus instead on basic problems and their root causes, and step into the complete unknown in search of a fundamental solution. Such a path is very aptly captured in the following missive from the Director of the Xerox Palo Alto Research Center (PARC) to an incoming employee (Brown, 1991):

> Our approach to research is 'radical' in the sense conveyed by the word's original Greek meaning: 'to the root'. At PARC we attempt to pose and answer basic questions that can lead to fundamental breakthroughs … If you come to work here there will be no plotted path. The problems you work on will be the ones that you help to invent. When you embark on a project, you will have to be prepared to go in directions you couldn't have predicted at the outset … That's why following your instinct is so important. Only by having deep intuitions, being able to trust them and knowing how to run with them will you be able to keep your bearings and guide yourself through uncharted territory. The ability to do research that gets to the root is what separates merely good researchers from world class ones. The former are reacting to a predictable future; the latter are enacting a qualitatively new one.

In more abstract form, the role of pioneering strategies in fostering radical inventions can be understood in terms of the research on technological progress and technological trajectories. Researchers have often described technological progress as a series of continuous improvements in fitness (a composite of all relevant performance attributes of a technology) along a technology trajectory, with occasional discontinuities that emerge because of jumps to a different technology trajectory (Dosi, 1988; Foster, 1986; Sahal, 1985). If we consider the fitness of a technology as a function defined on a technological space, then technology trajectories can be represented as the mapping of elements of the technology space onto several distinct, continuous functions. The individual distinct functions represent different trajectories, and thus have discontinuous or very different ranges of fitness values, but within a trajectory there is continuity as fitness values of a given technology are closely related to fitness values of proximate technologies. In such a situation, solutions that build on existing solutions are likely to map onto the same technological trajectory and consequently yield very similar fitness values to the ones already obtained by other solutions. A pioneering technology is an attempt to jump to a distinct trajectory in the hope that the range of fitness values embodied in the new trajectory is radically higher. Such an attempt is, of course, risky. There is no guarantee that the new trajectory will yield a higher range of fitness values, and indeed may yield extremely low ranges of fitness. However, increasing the number of experiments with such pioneering technologies should eventually yield at least some breakthrough inventions. Other things being equal, the larger the number of such pioneering attempts the greater the likelihood that at least some of them are successful.

The implications of increased experimentation with pioneering technologies for breakthrough inventions are not as clear as those of experimenting excessively with novel and emerging technologies. Both novel and emerging technologies directly challenge the cognitive capabilities and research resources of the organization. For instance, we noted earlier that excessive exploration of novel or emerging technologies can lead to information overload and diseconomies of scale, and a consequent reduction in breakthrough inventions as the organization tries to develop and integrate too many unfamiliar or nascent and underdeveloped streams of knowledge. With respect to pioneering technologies this effect is not as clearly specified. On the one hand pioneering technologies may imply an even greater cognitive task as the organization grapples with deep and fundamental problems. On the other hand pioneering technologies may result from simply ignoring conventional wisdom or from using broad-based creativity from people not directly involved in the field. For instance, Exxon's 'Wish' program entailed the involvement of a large set of interested people who were not directly involved in the subject field to come up with radical inventions (Berkowitz, 1996). Since such pioneering efforts may involve only an unconventional approach to a problem, rather than complicated integration of disparate or novel knowledge bases, their costs may be reflected not in terms of cognitive overload but rather simply in greater financial outlays or organizational expenditures. Thus, their negative consequences may show up in financial figures rather than through a decline in the number of breakthrough inventions. *A priori*, this suggests two possible outcomes, the first consistent with a cognitive overload interpretation, while the second would suggest that the negative consequences of excessive experimentation with pioneering technologies may be reflected on dimensions other than the output of breakthrough inventions:

> *Hypothesis 3a: A firm's creation of breakthrough inventions is related to its exploration of* pioneering *technologies in a curvilinear (inverted-U shaped) manner.*

> *Hypothesis 3b: A firm's creation of breakthrough inventions is positively related to its exploration of* pioneering *technologies.*

It would be useful at this stage to clarify the differences between the three traps/strategies identified above. Although a firm can simultaneously fall into all three traps there are nevertheless important conceptual distinctions between them. The familiarity trap arises on account of lack of variety in the firm's conceptual repertoire. The remedy is to introduce variety in the form of unfamiliar or novel technologies. In contrast, the maturity trap arises as a consequence of the opportunity (or the lack of it) in the technology itself – the inventive potential of the technologies being used by the firm has been diminished over time. The remedy is to be active in more leading-edge or emerging technologies. Finally, the propinquity trap arises as a function of the search approach adopted—whether the firm attempts *de novo* solutions or uses existing solutions as a starting point for defining and addressing technical problems. It is thus a condition relating to the *originality* of the solution approach used. The remedy is to move away from existing solutions and explore the possibilities of a radically different solution. This original approach could be applied to emerging or mature technologies, or familiar or novel ones.

Table 1 provides a set of illustrative cases of firms that fall into each of these traps. Although the table highlights the cases of three pure types, in reality firms are likely to fall along a continuum on each of these dimensions. Further, while there can be overlaps between novel, emerging, and pioneering technologies (for instance, an *emerging* technology can also be *novel* to the firm), the constructs do not perfectly subsume each other. They work through distinct mechanisms and the occurrence of one does not necessarily imply the occurrence of the others.

RESEARCH DESIGN

Sample and data selection

Since longitudinal data on all inventions in an industry are not generally available, in prior studies scholars have been forced to examine only the cases of inventions that proved to be radical. The methodology of this research attempts to overcome this problem of sampling on the dependent variable and its attendant threats to internal and external validity (Berk, 1983). Specifically, we study a sample of firms irrespective of whether or not they have created breakthrough inventions. By obtaining measures of the strategies followed by them and incorporating a history

Table 1. The three traps

Firm description	Familiarity trap	Maturity trap	Propinquity trap
Firm works in a single technology, not exploring any others. However, in that single technology it usually works on the leading edge and often uses a very original approach in terms of addressing the problems in that technology.	Yes	No	No
Firm explores several technologies but usually works on mature technologies. Within these mature technologies it sometimes adopts a very original approach to addressing the problems in that technology.	No	Yes	No
Firm explores several technologies but usually works on leading-edge technologies. Within these leading-edge technologies it usually adopts an unoriginal approach, preferring to work on problems and solutions that have well established precedents.	No	No	Yes

of all their inventions, breakthrough or otherwise, we are able to present a relatively unbiased picture of the association between firm strategies and breakthrough inventions.

We tested the hypotheses on a longitudinal data set on the patenting activities of the global chemicals industry over the period 1980–95. We used patent citation counts to identify breakthrough inventions. Several studies have shown that patent citation counts are important indicators of the technical importance of an innovation (Albert *et al.*, 1991; Narin, Noma, and Perry, 1987). Further, highly cited patents represent critical or path-breaking inventions (Trajtenberg, 1990a, 1990b). We selected the chemicals industry as the setting for this research because patents are widely regarded as a meaningful indicator of invention in this industry (Levin *et al.*, 1987; Arundel and Kabla, 1998).

The data collection consisted of two phases. In the first phase we identified the most highly cited patents in the chemicals industry for each year between 1980 and 1989. For each successful chemical patent application between these years, we computed the number of citations received by the patent. Thereafter, for every year we sorted the patents applied for in that year on the basis of their citation weights and identified the top 1 percent of patents for that year as breakthrough inventions. This procedure ensures that each patent is compared in its importance only to other patents of the same year. Since the duration for which a patent is at risk of being cited varies for patents of different vintages, it is important to compare patents only with their own cohort. A similar procedure has been used in past research (Trajtenberg, 1990a, 1990b). A benefit of this approach is that breakthrough inventions are identified from a universe of all inventions. Hence, sampling on the dependent variable is avoided.

In the second phase of the data collection our task was to identify and obtain data on the established firms in the industry. To accomplish this we consulted the leading trade journals (*Chemical Week* and *C&E News*) that provide annual listings of the largest chemicals firms. In the lists published by these journals, subsidiaries were often listed separately from parent firms. From an original sample of approximately 120 firms, after including subsidiaries with parent firms, a sample of 107 firms remained. For 10 of these firms either patent data or covariate data could not be reliably obtained and they were dropped from the analysis. For the remaining firms in the sample we obtained yearly patenting histories identifying each patent that they had created over the study period. We then used the list of breakthrough inventions in the chemicals industry to identify the breakthrough inventions created by these firms. Note that with this approach, since the sampling on firms is independent of whether or not they created breakthrough inventions, there are many firms in the sample that do not create any breakthrough inventions in a given year. This approach now enables us to have a panel data set with each firm's complete history of breakthrough inventions across the study period.

Patents applied for in later years have a smaller window for getting cited. Although our procedure for counting citations only compares patents with other patents applied for in the same year, and thus keeps the 'at risk of being cited' period consistent for all compared patents, and we use year dummy variables as suggested in the literature (Trajtenberg, 1990a, 1990b), there is still the concern that the citation patterns for the most recent patents might not be representative of their final worth given the shorter period they were available for being cited. Accordingly, we omitted all observations for years after 1989. Construction of some of the independent variables entailed lags too, and the final panel used for regression analysis covers 8 years. The panel is unbalanced as some of the firms were acquired by other firms or restructured in a fashion that made comparison difficult beyond a particular year. Even though the sample was focused on the largest firms in the chemicals industry the inclusion of 97 firms provides significant depth to the sample and ensures that there is considerable variety on all key variables. For instance, the number of employees for firms in the sample varies from a minimum of 1100 to a maximum of more than 181,000. Financial figures and personnel data on these firms were obtained from Compustat, Worldscope, Japan Company Handbooks, Daiwa Institute Research Guides, and trade publications and company annual reports. For all firms, financial data were converted to constant (1985) U.S. dollars to ensure standardization within the sample. A full list of the sample firms is available from the authors.

We used U.S. patent data for all firms, including the foreign firms in the sample. This was necessary to maintain consistency, reliability, and comparability, as patenting systems across nations differ in their application of standards, system of granting patents, and value of protection granted. The United States represents one of the largest markets for chemicals, and firms desirous of commercializing their inventions typically patent in the United States. Prior research using patent data on international samples (e.g., Stuart and Podolny, 1996; Patel and Pavitt, 1997), including studies of the global chemicals industry (Achilladelis *et al.*, 1990), have followed a similar strategy of using U.S. patent data for international firms.

Variable definitions

Dependent variable

Breakthrough inventions. This was computed as the number of breakthrough patents in the chemical industry in any year that were created by the focal firm. As noted earlier, for every year we sorted the patents applied for in that year on the basis of their citation weights and identified the top 1 percent of patents for that year as breakthrough patents. Note that the dependent variable is computed based on citations in patents that are issued *after* the breakthrough invention. These patents are therefore different from the patents on which the independent variables are based. The independent variables, described below, are based on the focal firm's patenting history in the period *before* the breakthrough invention. Thus, even though both the dependent and some of the independent variables are based on patent data, the actual patents on which they are based are different.

Our choice of identifying the top 1 percent of patents (based on the number of citations received by the patents) as breakthrough inventions was based on the following rationale. Prior research suggests that (a) the most heavily cited patents are the most valuable (Trajtenberg, 1990b), and (b) the value distribution of patents is very highly skewed, a few patents are very valuable, while most patents have relatively low values (Griliches, 1990; Harhoff *et al.*, 1999). Studies using citations suggest that the distribution of citations to a patent drops off pretty sharply, but does not provide an indication of an exact cut-off point that can be used to classify truly breakthrough inventions (Trajtenberg, 1990b). Therefore, we examined the actual pattern of citations received by the top 1 percent, top 2 percent, and top 5 percent of patents. These indicated a fairly sharp drop-off in average number of citations received between these three categories of patents. For instance, of all chemicals patents applied for in 1981, the top 1 percent received 37 citations on average, the top 2 percent received 30 citations on average, while the top 5 percent received 22 citations on average. Since our interest is in identifying truly path-breaking inventions we decided to use the top 1 percent as our indicators of breakthrough inventions. However, for sensitivity we also repeated the analyses using the top 2 percent (as we report in the Results section, the findings are substantively the same with either measure).

Independent variables

Novel technologies. For this variable we needed to develop a measure that taps into the degree to which a firm experiments with technologies that it has not used previously. We computed this variable using the technology classification provided by the U.S. patent system. The U.S. patent system classifies the technology domain into 400 broad classes and several hundred thousand subclasses nested within the classes. Based on a firm's prior patenting history we computed this variable as the number of new technology classes that were entered by a firm in the previous 3 years. A firm was considered to have entered a new technology class when it first applies for a patent in a class in which it had not patented in the previous 4 years. The presumption is that if a firm has not patented in a technology in the previous 4 years, then that technology represents an unfamiliar technology for the firm. For robustness, we also computed this measure using a 5-year interval instead of a 4-year interval. Since technical knowledge tends to depreciate or obsolesce over time, not participating in a technology for an extended period of time is likely to significantly reduce a firm's stock of viable knowledge in that technology. Prior research in technology-intensive industries has used a 4- to 5-year window as the appropriate time frame for assessing the validity of a knowledge base in a given technology (Stuart and Podolny, 1996; Ahuja, 2000). The choice of a 4- to 5-year period for knowledge relevance is also consistent with studies of R&D depreciation (Griliches, 1984).

Emerging technologies. For this variable we needed a measure that would capture the degree to which a firm experiments with leading-edge or nascent technologies. We based this measure on the average age of the patents cited by a firm. Every patent is required by law to disclose all prior art, the previous patents that served as the foundation for the current patent. If a firm is working primarily on old technologies then the average age of the patents it cites is likely to be high. On the other hand, if a firm cites very recent patents then it can be said to be working on very current technologies. We computed the variable as the number of a firm's patents that cite technology that is on average less than 3 years old. As an alternate measure (for robustness), we also computed this variable as the number of a firm's patents that cite technology that is on average less than 2 years old. The choice of a 2- to 3-year time period to signify an emerging technology was related to the currency of knowledge issue raised in the context of the previous variable. Since prior research has used a 4- to 5-year period as one representing the most viable life of a technology, the earlier part of this period would be appropriate for measuring emerging technologies. Hence, we use 2- and 3-year cut-offs.

Pioneering technologies. For this variable we needed a measure that would capture the degree to which a firm experiments with technologies that build on no prior technologies. We computed this variable as the number of a firm's patents that cite no other patents. As noted earlier, patents must indicate their prior technological lineage by citing all patents that they build on (Podolny and Stuart, 1995; Stuart and Podolny, 1996; Jaffe, Trajtenberg, and Henderson, 1993; Trajtenberg, Henderson, and Jaffe, 1992). Patents that cite no other patents indicate that they have no discernible technological antecedents. Past research has used the relative lack of prior art citations in a patent as an indicator of the *originality* and *creativity* of that patent (Trajtenberg *et al.*, 1992). Accordingly, we suggest that the creation of many such patents by a firm reflects its willingness to adopt a pioneering or unprecedented approach in its innovation strategy. Thus, firms that create many patents that cite no other patents are firms that can be regarded as willing to explore technology spaces that have not been explored before.

Control variables. Prior research suggests that the incentives of a firm to introduce breakthrough inventions may vary with its profitability (Henderson, 1993). Accordingly, we included the variable Net Income as a control variable. We also included several other control variables including R&D expenditures (R&D), firm size as measured by natural log of number of employees

(Logemployees), and firm diversification (Diversification/Entropy) as calculated using the entropy measure (Palepu, 1985). In all models we included the unobserved heterogeneity control variable Prior Breakthrough Inventions (the sum of breakthrough inventions created by a firm in the 3 years prior to the firm's entry into the sample) and dummy variables for firm nationality (U.S. and Japanese–European being the base category) and calendar year. Finally, it is possible that the frequency of patenting or citations or breakthrough inventions varies across the United States Patent Office (USPTO) technology classes (Trajtenberg *et al.*, 1992). To account for the possibility of technology class effects we created a set of 80 dummy variables to reflect the 81 classes that cover the chemicals sector. The most commonly occurring class (Class 428) was treated as the omitted category. For each observation these dummy variables reflect a firm's participation or nonparticipation in that particular technology class in that year.

Model specification and econometric issues

The dependent variable of the study, Breakthrough Inventions, is a count variable and takes only nonnegative integer values. A Poisson regression approach is appropriate for such data (Hausman, Hall, and Griliches, 1984; Henderson and Cockburn, 1996). Accordingly, we specified the following Poisson regression model:

$$P_{it} = e^{X_{it\text{-}1}\gamma + A_{it\text{-}1}\beta} \qquad (1)$$

where P_{it} is the number of breakthrough inventions obtained by firm i in year t, $X_{it\text{-}1}$ is a vector of control variables affecting P_{it}, and $A_{it\text{-}1}$ is a vector of variables representing the hypothesized effects.

The above specification does not account for unobserved heterogeneity, the possibility that observationally equivalent firms may differ on unmeasured characteristics. For instance, firms may enter the sample with inherently different breakthrough invention-generating capabilities (Ahuja and Katila, 2001). To address this possibility we used the Presample Panel Poisson approach (Blundell, Griffith, and Van Reenen, 1995) and included the Presample variable described earlier, Prior Breakthrough Inventions, as a measure of the unobserved differences between the sample firms in their ability to create breakthrough inventions.

The presample approach presumes that the influences valid in the presample period continue to be valid in the study period. To ensure that our results were robust to this assumption we did two things. First, as an alternate measure we used lagged values of the dependent variable as an alternate measure of unobserved heterogeneity. Second, in addition to using conventional Poisson estimation of the Presample Panel Poisson model (Blundell *et al.*, 1995) we also estimated the models using the GEE (General Estimating Equation) approach for modeling longitudinal Poisson data (Liang and Zeger, 1986). Since unobserved heterogeneity that is affecting the dependent variable should be reflected in correlation between the residuals of the same firm, using an approach that models serial correlation into the estimation procedure accounts for any remaining correlation. Finally, we report all results with 'robust' or empirical standard errors (SAS, 1997). In case of model misspecification or overdispersion, the model-based standard errors for a Poisson regression can be incorrect. Using robust standard errors guards against this possibility.

RESULTS

Table 2 provides descriptive statistics and correlations for all variables. Table 3 presents the results of the hypothesis testing. We originally attempted to run the GEE regressions with the full set of 80 USPTO class dummies. However, the full models with 80 class dummies and 21 other covariates proved to be nonestimable using GEE methodology. Accordingly, we first estimated a series of regular Presample Poisson models with all 80 dummies. From these estimations we identified all USPTO classes that indicated a significant class effect. To be conservative we included all classes that were significant even at $p < 0.10$. Then, we estimated the GEE models with this smaller subset of 38 class dummies, treating the remaining classes as a single class. The results of these estimations are reported in the GEE Models 1–8 in Table 3.

Model 1 in Table 3 presents the results for the control variables. Model 2 adds the variables for the three hypothesized effects, with no squared terms. Model 3 adds all three squared terms for

Table 2. Descriptive statistics and zero-order correlations

	Variable	Mean	S.D.	Min.	Max.	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
1	Breakthrough Inventions	0.42	1.11	0	9	1.00																	
2	Novel Technologies$_{it-1}$	6.89	3.59	0	27	0.03	1.00																
3	Emerging Technologies$_{it-1}$	7.39	11.64	0	79	0.54	0.05	1.00															
4	Pioneering Technologies$_{it-1}$	1.64	3.44	0	24	0.39	0.02	0.82	1.00														
5	R&D$_{it-1}$	86.53	166.36	0.10	1081.2	0.60	0.04	0.82	0.72	1.00													
6	Firm Size (LogEmployees)$_{it-1}$	2.40	1.22	0.09	5.20	0.44	0.12	0.60	0.53	0.66	1.00												
7	Net Income$_{it-1}$	120.12	254.39	−647	2312.4	0.64	0.10	0.58	0.48	0.81	0.59	1.00											
8	Diversification-Entropy$_{it-1}$	1.30	0.34	0.20	2.19	0.23	0.05	0.40	0.40	0.41	0.46	0.30	1.00										
9	Prior Breakthrough Inventions$_{it-1}$	1.32	2.54	0	16	0.53	0.02	0.64	0.49	0.62	0.53	0.53	0.24	1.00									
10	U.S.A.	0.26	0.44	0	1	0.26	0.04	0.06	−0.04	0.12	0.26	0.24	−0.12	0.24	1.00								
11	Japan	0.43	0.50	0	1	−0.19	−0.03	−0.20	−0.19	−0.32	−0.68	−0.32	−0.14	−0.21	−0.52	1.00							
12	Year 1982	0.13	0.33	0	1	0.01	−0.06	−0.01	−0.02	−0.05	0.00	−0.12	0.02	0.00	−0.01	−0.00	1.00						
13	Year 1983	0.13	0.33	0	1	−0.02	−0.02	−0.04	−0.02	−0.04	0.00	−0.07	0.01	0.00	0.00	−0.00	−0.14	1.00					
14	Year 1984	0.13	0.33	0	1	0.01	−0.03	−0.03	−0.01	−0.04	−0.01	−0.01	−0.01	−0.00	0.01	−0.01	−0.15	−0.15	1.00				
15	Year 1985	0.13	0.34	0	1	−0.02	−0.01	−0.02	−0.01	−0.02	0.01	−0.08	−0.00	−0.00	0.00	−0.01	−0.15	−0.15	−0.15	1.00			
16	Year 1986	0.13	0.33	0	1	0.00	0.01	−0.02	0.02	0.03	0.00	0.01	0.00	−0.01	−0.00	−0.01	−0.15	−0.15	−0.15	−0.15	1.00		
17	Year 1987	0.12	0.33	0	1	−0.01	0.08	0.03	0.00	0.07	−0.01	0.10	−0.01	−0.00	−0.00	0.00	−0.14	−0.14	−0.14	−0.14	−0.14	1.00	
18	Year 1988	0.12	0.33	0	1	0.04	0.10	0.06	0.07	0.10	−0.01	0.18	−0.02	0.00	−0.00	0.00	−0.14	−0.14	−0.14	−0.14	−0.14	−0.14	1.00

N = 721 observations
All correlations with magnitude > |0.07| are significant at the 0.05 level

Table 3. GEE/Poisson regressions of the impact of novel technologies, emerging technologies and pioneering technologies on breakthrough inventions

Variable	Model 1 GEE	Model 2 GEE	Model 3 GEE	Model 4 GEE	Model 5 GEE	Model 6 GEE	Model 7 GEE	Model 8 GEE (2%)	Model 9 Poisson	Model 10 Poisson (2%)
Constant	–4.7787*** [0.6869]	–4.8255*** [0.7129]	–5.1820*** [0.7109]	4.7206*** [0.7133]	–5.2875*** [0.7092]	–5.1613*** [0.7110]	–5.0607*** [0.7159]	–3.3905*** (0.5247]	–5.7640*** [0.6299]	–3.7188*** [0.4808]
Novel Technologies$_{it-1}$		0.0059 [0.0216]	0.2074*** [0.0618]	0.0147 [0.0208]	0.1993*** [0.0633]	0.2057*** [0.0609]	0.2053*** [0.0620]	0.1603*** [0.0417]	0.1974** [0.0694]	0.1642** [0.0535]
Novel Technologies Squared$_{it-1}$			–0.0105*** [0.0032]		–0.0104*** [0.0033]	–0.0105*** [0.0032]	–0.0103*** [0.0032]	–0.0074*** [0.0020]	–0.0104** [0.0038]	–0.0075** [0.0028]
Emerging Technologies$_{it-1}$		0.0078 [0.0086]	0.0440* [0.0240]	0.0399+ [0.0247]	0.0106 [0.0084]	0.0465* [0.0238]	0.0447* [0.0241]	0.0582*** [0.0168]	0.0358+ [0.0232]	0.0456* [0.0184]
Emerging Technologies Squared$_{it-1}$			–0.0005* [0.0003]	–0.0004+ [0.0003]		–0.0005* [0.0003]	–0.0005* [0.0003]	–0.0006** [0.0002]	–0.0004+ [0.0003]	–0.0005* [0.0002]
Pioneering Technologies$_{it-1}$		0.0279* [0.0151]	0.0659* [0.0327]	0.0586* [0.0333]	0.0811* [0.0353]	0.0425** [0.0144]	0.0399** [0.0139]	0.0403** [0.0141]	0.0430* [0.0222]	0.0423* [0.0180]
Pioneering Technologies Squared$_{it-1}$			–0.0012 [0.0016]	–0.0012 [0.0015]	–0.0024+ [0.0017]					
R&D$_{it-1}$	–0.0000 [0.0006]	–0.0005 [0.0007]	–0.0003 [0.0007]	–0.0003 [0.0007]	–0.0004 [0.0007]	–0.0003 [0.0007]	–0.0005 [0.0007]	–0.0004 [0.0004]	0.0000 [0.0008]	–0.0002 [0.0007]
Firm Size (LogEmployees)$_{it-1}$	0.3145* [0.1410]	0.2717+ [0.1395]	0.1583 [0.1372]	0.2190 [0.1453]	0.2173 [0.1342]	0.1521 [0.1377]	0.1081 [0.1432]	0.1768+ [0.0990]	0.2200+ [0.1467]	0.1573 [0.1179]
Net Income$_{it-1}$	0.0010** [0.0003]	0.0012** [0.0004]	0.0012** [0.0004]	0.0011** [0.0004]	0.0012*** [0.0004]	0.0012*** [0.0003]	0.0012*** [0.0003]	0.0007*** [0.0002]	0.0013*** [0.0003]	0.0008*** [0.0002]
Diversification-Entropy$_{it-1}$	–0.0776 [0.3180]	–0.0945 [0.3114]	–0.1134 [0.3042]	–0.0911 [0.3155]	–0.1230 [0.3007]	–0.1136 [0.3049]	–0.0330 [0.3056]	–0.4857* [0.2309]	–0.0153 [0.2759]	–0.4419* [0.2054]
Prior Breakthrough Inventions$_{it-1}$	–0.0259 [0.0224]	–0.0286 [0.0213]	0.0313 [0.0206]	–0.0293 [0.0207]	–0.0291 [0.0205]	–0.0319 [0.0206]		0.0086 [0.0106]	–0.0362 [0.0345]	–0.0013 [0.0167]

Table 3. Continued

Variable	Model 1 GEE	Model 2 GEE	Model 3 GEE	Model 4 GEE	Model 5 GEE	Model 6 GEE	Model 7 GEE	Model 8 GEE (2%)	Model 9 Poisson	Model 10 Poisson (2%)
Lagged Breakthrough Inventions							0.0335			
							[0.0332]			
U.S.A.	1.1246***	1.2424***	1.2515***	1.2773***	1.2182***	1.2450***	1.1409***	1.0461***	1.5072***	1.1267***
	[0.2172]	[0.2200]	[0.2041]	[0.2050]	[0.2084]	[0.2067]	[0.1979]	[0.1723]	[0.2593]	[0.1982]
Japan	1.1954**	1.2207**	0.9629**	1.1386**	1.0429**	0.9547**	0.8076*	0.8276***	1.3003***	0.9166***
	[0.3793]	[0.3888]	[0.3590]	[0.3805]	[0.3649]	[0.3627]	[0.3534]	[0.2370]	[0.3575]	[0.2774]
Year 1982	0.3778	0.4729^{+}	0.4616^{+}	0.4567	0.4867^{+}	0.4580^{+}	0.4727	0.0954	0.4087^{+}	0.1328
	[0.2564]	[0.2797]	[0.2801]	[0.2808]	[0.2818]	[0.2780]	[0.2940]	[0.1587]	[0.2405]	[0.2014]
Year 1983	–0.0014	0.0635	–0.0033	0.0081	0.0209	0.0085	–0.0122	–0.0339	0.1127	0.0640
	[0.2742]	[0.3029]	[0.3007]	[0.3025]	[0.3049]	[0.2982]	[0.3134]	[0.1871]	[0.2724]	[0.2188]
Year 1984	0.3036	0.3602	0.3071*	0.3459	0.2935	0.3175	0.3221	0.3174^{+}	0.3255	0.4223*
	[0.2785]	[0.2951]	[0.2790]	[0.2923]	[0.2812]	[0.2801]	[0.2781]	[0.1691]	[0.2399]	[0.1926]
Year 1985	0.0589	0.1380	0.1093	0.1354	0.1023	0.1138	0.1330	0.0336	–0.0590	–0.0777
	[0.2963]	[0.3236]	[0.3142]	[0.3225]	[0.3162]	[0.3134]	[0.3257]	[0.1901]	[0.2549]	[0.2071]
Year 1986	–0.2935	–0.2289	–0.3095	–0.2549	–0.3158	–0.2950	–0.2288	–0.0635	–0.2646	–0.0581
	[0.2842]	[0.2988]	[0.2878]	[0.3009]	[0.2906]	[0.2857]	[0.2915]	[0.1867]	[0.2664]	[0.2098]
Year 1987	–0.5115	–0.4397	–0.5562^{+}	–0.4568	–0.5636^{+}	–0.5449	–0.5197	–0.1925	–0.4703^{+}	–0.0800
	[0.3270]	[0.3394]	[0.3330]	[0.3430]	[0.3300]	[0.3330]	[0.3637]	[0.1896]	[0.2818]	[0.2154]
Year 1988	–0.5332	–0.4968	–0.6499	–0.4935	–0.6607*	–0.6451*	–0.5687^{+}	–0.3316	–0.7269*	–0.3818^{+}
	[0.3296]	[0.3400]	[0.3262*]	[0.3426]	[0.3269]	[0.3260]	[0.3280]	[0.2094]	[0.2941]	[0.2302]
USPTO technology class dummies	38 dummies	38 dummies	38 dummies	38 dummies	38 dummies	38 dummies	38 dummies	38 dummies	80 dummies	80 dummies
Scale	0.7492	0.7476	0.7379	0.7461	0.7395	0.7375	0.7383	0.9161	0.7366	0.9187
N	721	721	721	721	721	721	721	721	721	721
Deviance	374.98	371.72	360.42	369.04	362.56	360.62	361.36	556.39	336.94	524.16

$^{+}p < 0.10$; $^{*}p < 0.05$; $^{**}p<0.01$; $^{***}p < 0.001$
Note: Single-tailed *t*-tests have been used for all hypothesized variables; two-tailed *t*-tests have been used for all control variables.

the three hypothesized effects to account for the possibility of curvilinearity. Model 3 indicates that the coefficients for Novel Technologies, Novel Technologies Squared, Emerging Technologies and Emerging Technologies Squared, and Pioneering Technologies are statistically significant with the predicted sign. However, the coefficient for Pioneering Technologies Squared, while negative, is not statistically significant. We also ran a series of models (Models 4, 5, and 6) omitting the squared terms for each of the three hypothesized effects, one at a time. The deviance statistics, which indicate overall model fit, confirm the same results as they indicate that omitting the square term for either Novel or Emerging Technologies leads to a worsening of model fit (although for Emerging Technologies the worsening was only marginally statistically significant, $p < 0.10$), but omitting the Pioneering Technologies Squared term does not worsen the model fit. Thus, Model 6 that omits the Pioneering Technologies Squared term is the best-fitting specification.

Model 6 indicates some support for all three hypotheses. In Hypothesis 1 we had predicted that experimenting with Novel Technologies should increase the likelihood of breakthrough inventions up to a point and then lead to a diminution (an inverted U). The coefficient of Novel Technologies is positive and statistically significant, while the coefficient of its squared term is negative and statistically significant, indicating support for the prediction. In Hypothesis 2 we had predicted that experimenting with Emerging Technologies should increase the likelihood of breakthrough inventions up to a point and then lead to a diminution (an inverted U). The coefficient of Emerging Technologies is positive and statistically significant, while the coefficient of its squared term is negative and statistically significant, again indicating support for Hypothesis 2. The estimated coefficients for these variables indicate that the turning point of the curve lies well within the observed range of data for both these variables (for Novel Technologies the point of inflection is at $0.2057/(2*0.0105) = 10$, where the observed range is 0–27, and for Emerging Technologies it occurs at $0.0465/(2*0.0005) = 46.5$, where the observed range is 0–79), thus further confirming the downward component of the curve. In the case of Hypothesis 3 we had developed two competing predictions. Hypothesis 3a predicted an inverted U relationship between Pioneering Technologies and Breakthrough Inventions, while Hypothesis 3b predicted a positive effect of Pioneering Technologies on Breakthrough Inventions. The coefficient of the Pioneering Technologies variable was positive and statistically significant, but the coefficient for its squared term was not statistically significant, and indeed was dropped from the final model. Thus, the results do not support Hypothesis 3a, but do support the competing hypothesis, Hypothesis 3b. It appears that Pioneering Technologies have a positive impact on breakthrough inventions but the diminishing returns to experimentation evident with the strategies of Novel and Emerging Technologies are not statistically visible with Pioneering Technologies. We explore this issue in the Discussion section.

Since the Emerging and Pioneering Technologies variables were highly correlated (0.82) a danger of multicollinearity arises. In general, the symptoms of multicollinearity include (a) very large standard errors for the affected variables and therefore even true effects show up as nonsignificant or (b) extreme sensitivity of results such that coefficients flip signs after even minor changes in the specification or sample size and omitting even a few observations affects the results materially (Greene, 1997). In the context of the reported results, neither of these symptoms was observed. Indeed, the results are very robust and stable across many changes in specification, sample, dependent variables, independent variables, and estimation method. We reran the analyses with a one-period lagged value of the dependent variable Breakthrough Inventions as a regressor in place of the presample variable Prior Breakthrough Inventions (Model 7). We also reestimated the models after defining our dependent variable Breakthrough Inventions as including all patents in the top 2 percent of cited patents (rather than top 1%) (Model 8). Finally, we estimated the models using regular Poisson maximum likelihood estimation instead of the GEE approach and included all 80 class dummies, for both the top 1 percent and the top 2 percent definitions of the dependent variable (Models 9 and 10 respectively). The results are again consistent with the overall pattern though the Emerging Technologies coefficients in Model 9 are only marginally statistically significant ($p < 0.07$ and $p < 0.06$, for the variable and its squared term, respectively). Among other sensitivity tests, not presented here but for which results are available directly from the authors, we used alternate definitions of Novel Technologies (we recomputed the variable after defining novel technologies as technologies in which the firm had not patented in, in the previous 5 years instead of 4) and Emerging Technologies (we recomputed the variable as the number of patents citing technology less than 2 years old instead of 3 years old). Finally, as another alternate estimation approach we aggregated all 34 patent classes that were involved in less than 10 percent of the observations into a single class and estimated a GEE model using the resulting 46 class dummies. The results were robust to these and many other specifications of these models.

DISCUSSION AND CONCLUSIONS

Researchers have suggested that the pursuit of corporate entrepreneurship requires established companies to strike a delicate balance between engaging in activities that use what they already know, while at the same time challenging themselves to embark upon new activities and opportunities to rejuvenate themselves (Floyd and Wooldridge, 1999; Hannan and Freeman, 1989; Huff, Huff, and Thomas, 1992). Leonard-Barton has aptly termed this conflict as a 'capability–rigidity paradox, where existing capabilities provide the basis for a firm's current competitive position, [but] without renewal, these same capabilities become rigidities constraining the firm's future ability to compete' (Leonard-Barton, 1992). Interest in resolving this apparent paradox has led researchers to examine the processes by which corporations have attempted to 'redefine, renew and remake themselves' (Covin and Slevin, 1991; Guth and Ginsberg, 1990; Zahra, Jennings, and Kuratko, 1999). In this study we explored this capability–rigidity paradox in the context of one mechanism through which established firms can initiate the process of renewal: breakthrough inventions. After identifying three organizational pathologies that could hinder the creation of breakthrough inventions in established corporations we suggested three strategies that could help firms to counter these problems. Our empirical results provided support for our arguments that experimenting with novel, emerging, and pioneering technologies may be ways for organizations to overcome the traps of familiarity, maturity, and propinquity. Specifically, we found that exploration of novel and emerging technologies is curvilinearly associated with subsequent breakthrough inventions, first increasing and then decreasing a firm's likelihood of creating a breakthrough invention. However, the downward sloping part of the curve was not identifiable in the case of pioneering technologies.

Two possibilities could be consistent with this nonfinding. First, as we argued in the hypothesis development for Hypothesis 3b, it could be that Pioneering Technologies differ in their cognitive demands and likelihood of information overload from both Novel Technologies and Emerging Technologies. Entry into Novel and Emerging Technologies entails study of new areas from the firm's perspective and the absorption of a body of knowledge already in existence or being created. Pioneering Technologies on the other hand can often imply an attempt to move away from existing bodies of knowledge and give rein to creative solutions. Thus, it is not so much the possibility of information overload that is problematic but simply that the attempted solution may yield no results. In such a circumstance, although excessive experimentation with pioneering technologies will have significant costs, these costs may not be eventually reflected in a decline in breakthrough invention; instead they would appear as larger resource outlays or monetary costs. Another explanation for this finding could be that not enough firms reached the level of experimentation on this variable that was sufficiently high for the negative effects of resource fragmentation to become statistically significant. These two explanations are not mutually exclusive; however, future research may help to further clarify this matter. We now briefly touch upon the implications of our study for theory, research, and practice.

Implications for theory, research, and practice

Theoretically, the arguments and conclusions of this study make contributions to the literature on entrepreneurship, strategy, and organizational learning. From the perspective of organizational learning this study's identification of three traps that hinder breakthrough invention in the large corporation is important in and of itself; however, it is also important in terms of drawing attention to the fact that the constraints to breakthrough invention in the established firm do not necessarily stem from some dysfunctional traits of the organization, but emerge as a very natural consequence of some fairly functional traits. As our model argues, emphasizing the familiar and mature, and building on existing developments, are all efficient responses from the standpoint of the large firm. They may, however, not be effective when the outcome variable of interest is breakthrough invention. Characterizing the problem in this fashion is useful when compared with a potential alternative characterization: that large corporations fail at breakthrough inventions because they are inept or incompetent. There is no antidote to incompetence. However, the dynamics we identify can be productively arrested as our identification of three countering strategies demonstrates.

In drawing the relationship between rational strategies and unintended negative consequences we follow the lead of organizational theorists that have argued for more refined analyses of organizational processes accounting for both first-order and second-order effects (March, 1991; Levinthal and March, 1993). However, we also take their work a few steps further. Prior theorizing suggests that firms often get caught in *learning traps* (Levinthal and March, 1993). Here we build on the learning trap arguments in three ways. First, we suggest that in the context of breakthrough inventions learning traps are manifested in three types of organizational pathologies: traps of familiarity, traps of maturity, and traps of propinquity. Factoring learning traps in this fashion permits us to identify specific strategies that organizations can use to counter these pathologies. Second, we extend the learning trap arguments by including the possibility of second-order or double-loop learning (Argyris, 1983; Huber, 1991). Double-loop learning requires the reexamination and change of the governing values of the organization from the perspective of long-range outcomes (Argyris, 1983; Huber, 1991). If firms regard breakthrough inventions as important to their future, organizational routines that fail to produce such inventions are likely to be the subject of reappraisal and reformulation (Huber, 1991). Thus, by incorporating the possibility that firms will counteract such pathologies we deepen and condition the learning trap arguments from a conceptual standpoint. Finally, we provide empirical evidence in support of our arguments and thus contribute to filling what has been identified as a significant gap in the organizational learning literature – the absence of systematic large-sample empirical studies to supplement the rich but potentially idiosyncratic case studies (Huber, 1991).

This study found that firms varied in their use of entrepreneurial strategies and that using these entrepreneurial strategies led to superior invention performance. However, the variation in firms' strategies on the three exploration variables and the identification of a statistically discernible impact of these variations on the firm's output of breakthrough inventions raises a natural question: why do firms vary in their adoption of entrepreneurial strategies? Why do some firms pursue novel, emerging, and pioneering technologies more than others? Although this variation across the entrepreneurial behavior of firms has been noted earlier (Lant and Mezias, 1990; Mezias and Glynn, 1993), less research explains why this variation occurs.

We believe that our work, when contrasted with prior contributions in the entrepreneurship literature, draws attention to one possible explanation of this variation that could be addressed in future research: the existence of a 'virtuous circle of corporate entrepreneurship.' The virtuous circle argument would suggest that although many firms would like to pursue such strategies they are unable to do so. This inability stems from their exclusion from a virtuous cycle in which (a) the pursuit of novel, emerging, and pioneering technologies leads to breakthrough inventions, (b) breakthrough inventions when they occur, create wealth and surplus resources, and (c) these surplus resources fund the next cycle of entrepreneurial experimentation, which in turn leads to more breakthrough inventions. Although the full investigation of this virtuous circle goes beyond the scope of this study, prior research and the theory developed in this study provide at least some evidence in support of this explanation. This study's results provide direct support for the first leg of this cycle.

However, the study also provides some indications in support of the second leg. For instance, the descriptions of the three forms of exploration identified here suggest that the pursuit of novel, emerging, and pioneering technologies is likely to require considerable slack resources. To go off in search of the unknown (a.k.a. pioneering) or experiment with novel technologies is likely to demand extensive resources. Without slack, these strategies may be attractive but beyond reach. Indeed, both prior theory (Burgelman, 1983) and anecdotal evidence suggest that cash-rich corporations can far more easily afford certain kinds of speculative and experimental ventures (Styros, 1997). Similarly, in support of the third leg of the cycle, prior research on the wealth-creating impact of breakthrough inventions suggests that technologically important inventions can generate very significant returns (Hall, Jaffe, and Trajtenberg, 1998; Harhoff *et al.*, 1999). For instance, Harhoff *et al.* (1999) find that the most valuable patents in their sample are worth tens of millions of dollars. In general, specifying the theoretical models underlying the second and third legs of this cycle may be a fruitful task for further research on corporate entrepreneurship and wealth creation.

The paper also makes a contribution towards managerial practice. From a practitioner standpoint, explaining the determinants of breakthrough inventions is of significant importance given the economic stakes associated with them. Additionally, the concepts of the three traps and counteracting strategies have practical utility. Prior research has identified three basic strategies for entrepreneurship in large firms (Lant and Mezias, 1990): fixed (nonentrepreneurial), imitative (searching domains new to the firm), and adaptive (searching domains new to the population). Through this study we provide managerially actionable variants of the imitative (novel) and adaptive (emerging) strategies in the context of technology and identify an additional new strategy (pioneering) that large corporations can use to reinvent themselves.

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