

Innovative product portfolios by navigating markets and technology

Riitta Katila

Department of Management Science and Engineering
Stanford University

Working paper. 2005

Abstract

This paper compares systematically the two theoretical models of adaptation, ecological and evolutionary. Using notions from innovation, learning, and balanced change, the two models are contrasted in the context of 73 European, Japanese, and U.S. industrial robotics firms that introduced new robotics products in 1984-1997. A hybrid of ecological and evolutionary views is found to predict innovativeness of these companies best. When organizations use new, uncertain knowledge to create new products, ecological view is relevant. When they use existing, predictable knowledge to create new products, evolutionary view is appropriate. These findings suggest a redefinition of balance in organizational adaptation, and explain how established firms can change through product innovation.

Key words: product innovation; search; adaptation and change.

How organizations adapt to their environments is one of the fundamental questions in organization research. Authors from several research perspectives have argued that such adaptation is most successful if it balances variation and stability (March & Simon, 1958; Thompson, 1967). For example, the ecological view concludes that punctuated change efforts that alternate with long periods of stability improve adaptation (Miller & Friesen, 1980; Tushman & Romanelli, 1985). The evolutionary view, similarly, argues that organizations should balance path-creating (variation) and path-deepening (recombination) efforts to change (Holland, 1975; Nelson & Winter, 1982; Rosenkopf & Nerkar, 2001). While both views stress the importance of balance of variation and stability, they differ in how such a balance is defined and implemented. In this study, I compare and contrast the ecological and evolutionary views in the context of firm's adaptation through innovative product portfolios. I find that both views provide partial and complementary explanations for organizational adaptation. A hybrid, that is, a redefined balance, of ecological and evolutionary views is found to predict innovativeness best.

Product innovation is one of the most visible ways in which organizations adapt to their environments. Through introducing new products, organizations create and move to new markets, and introduce new technologies (Burgelman, 1991; Fligstein & Dauber, 1989). Product innovation is “a critical means by which members of organizations diversify, adapt, and even reinvent their firms” (Brown & Eisenhardt, 1995: 344). In this study I examine organizational adaptation in the context of industrial robotics companies that adapt to the environment by introducing innovative products. The critical importance of maintaining an innovative product portfolio—that is, introducing innovative products that satisfy customer needs better than existing products—has been shown in several prior studies. Organizations that introduce innovative products live longer (Banbury & Mitchell, 1995), win market share (Chaney &

Devinney, 1992), and perform better financially (Myers & Marquis, 1969; Roberts, 1999). I also chose innovativeness as the dependent variable because of its similarities to and differences from product development time, an often studied outcome of product development (e.g., Clark, Chew, & Fujimoto, 1987; Eisenhardt & Tabrizi, 1995). While finishing a project fast is an important internal measure of project performance, in most industries the product's innovativeness, that is, its value to customers is a critical external measure of product success. For example, Abernathy and Utterback (1978) found that competitive advantage was based on superior functional performance rather than low cost, and that superior product performance tended to offer high unit profit margins.

But how do firms create innovative product portfolios? Two streams of research provide answers. Authors in the first, ecological stream propose that innovation builds on discontinuity, and occurs through a punctuated equilibrium. For example, young and entrant firms often introduce innovative products while old and incumbent firms let the opportunity slip by (Kamien & Schwartz, 1982). For example, Mansfield's (1972) study on important pharmaceutical preparations suggested that young firms introduce the most innovative products. Similarly, Gersick (1989, 1994) found that the most effective of the teams that were asked to develop a creative product, alternated between long periods of inertia and short bursts of drastic change. During change, the teams "made dramatic progress by adopting new perspectives on their work, often influenced by renewed contact with outside stakeholders. The choices made during transitions shaped new approaches to groups' tasks, which carried them through their next phase of activity" (Gersick, 1994: 12). In each of these studies, innovative products were introduced through a major transformation in an existing firm, or by a new organization. These studies also

share the view that successful change hinges on coordination and structure, rather than learning or improved ability.

A second, evolutionary stream, in contrast, argues that innovative products grow out of existing knowledge and build on continuity. Organizations that create new innovations store knowledge over time, use it in new combinations, and learn from previous experiments (Garud & Nayyar, 1992). Several authors have suggested that learning (Methe, Swaminathan, & Mitchell, 1996; Pisano, 1994) and the ability to share resources (Cohen & Levin, 1989; Henderson & Cockburn, 1996) promote innovativeness. General Electric, for instance, was able to bring to bear high-powered mathematical analysis used in its military research division to the development of innovative computerized tomography (CT) products in its medical equipment division (Rutenberg, 1986). At the same time, researchers emphasize that to avoid competency traps, successful evolutionary strategy also balances existing knowledge with small amounts of new variation (Rosenkopf & Nerkar, 2001). Process-level studies provide support for these findings, suggesting that cross-functional communication (Ettlie et al., 1984; Kusunoki, 1997), information flows (Moorman & Miner, 1997) and gatekeepers (Allen, 1977) improve innovativeness of product introductions. A synthesis of this second stream suggests that a continuous stream of iterative learning, ability to mix and match previous experiences and small amounts of variation are major determinants of product innovativeness. Thus, successful change hinges on learning and improved ability, rather than coordination or structure.

Taken together, these two streams portray the product development process from two distinct perspectives: either as a process where innovative new products are a result of periodical compact transformations, or, in contrast as a process where firms that gradually accumulate, manipulate, and integrate existing knowledge introduce the most innovative product portfolios.

In this study, I build two models, one based on the first, ecological model of product innovation, and the other based on the second, evolutionary view. I compare and contrast these two models systematically using a sample of 73 European, Japanese, and U.S. firms that create new products in the industrial robotics industry in 1984-1997. During this time period, the robotics industry is characterized by a diverse set of innovation approaches partly due to lack of emergence of a dominant design (Schlesinger & Imany, 1986), and a large number of highly differentiated new robot designs (Dahlin, 1993; Fleck, 1988), making it an especially appropriate setting to compare the two views. The results show that both ecological and evolutionary views partly explain how firms create innovative product portfolios. However, the best approach depends on the type of knowledge. When organizations use new, uncertain knowledge to create new products, ecological view is relevant. When they use existing, predictable knowledge to create new products, evolutionary view is appropriate. These findings suggest a redefinition of balance in organizational adaptation, and explain how established firms can change through product innovation.

BACKGROUND AND HYPOTHESES

Product Innovation

In order to create innovative product portfolios, organizations acquire, create, and combine knowledge elements, “each providing a portion of knowledge necessary to achieve the transformation of materials and energy into the product” (Metcalfe & Gibbons, 1989: 170). However, which types of knowledge elements to assemble for successful product innovation is not clear. Whether new or older knowledge is preferred (Sørensen & Stuart, 2000), and, what areas of knowledge are required (Clark, 1985) has to be determined.

First, to create new products, organizations can either focus on search for new areas and knowledge, or search for more information of the already known ones (Levinthal & March, 1993; Thompson, 1967). This distinction between new and existing knowledge as separate sources of adaptation appears in several areas of organizational research. Evolutionary theory describes the twin processes of knowledge creation—variation and recombination (Holland, 1975)—that are based on new knowledge and combination of existing knowledge, respectively. From the perspective of organizational knowledge, Hargadon and Fanelli (2002) make a similar distinction between two types of knowledge: new knowledge that is acquired or learned, and existing knowledge that is continually transformed and redefined into new combinations. In strategic management, researchers make a similar distinction between two change processes: strategic change (based on new) and renewal (based on manipulation of current knowledge) (Huff, Huff, & Thomas, 1992).

The distinction between new and existing knowledge also appears in theorizing about innovative product portfolios. One approach is what I call in this study ecological. Authors in this view assume that managers should stack the efforts to acquire new knowledge and skills, and alternate these bursts with long periods of stability. Organizations that recognize and quickly adopt new technologies will have higher growth rates than others in the product class (Tushman & Anderson, 1986). Gersick (1989, 1994) found evidence of such ecological processes in a laboratory setting with teams developing a creative product, and in a startup with the goal to launch a new medical product. Technological S-curves and product development life-cycles (Abernathy & Utterback, 1978) provide other examples of this perspective. Overall, this perspective revolves around alternating periods of new knowledge and stability.

An alternative view is what I term evolutionary product strategy. According to this perspective, product development is an iterative learning process that builds on existing knowledge. In this view, organizations succeed at product development using a combination of recombination and trial and error processes. First, managers build on their prior experience by recombining knowledge that was acquired in prior efforts. Such recombination can also take more creative forms. For example Leonard-Barton (1995) described a strategy of creative abrasion that exploits the differences between the functional groups in an organization, and generates novel actions by eliciting interactions that enforce confrontation and creative resolution of otherwise different perspectives of the world. Second, evolutionary researchers argue that organizations also learn through trial and error experiments, from which managers can accumulate knowledge over time to predict what customers will want in the future (Sorenson, 2000). For example, products that fail, act as important probes into user space and can capture important information about what it would take to make a new effort successful (Maidique & Zirger, 1985). Overall, this perspective involves cumulative building on existing knowledge balanced with small amounts of experimentation.

Besides choosing between new and existing knowledge, managers also need to decide where to search. Historically, product innovation researchers have focused on two types of knowledge. One is technology. Researchers from the technology management perspective have studied how organizations manipulate and integrate technological knowledge to create innovative products (Nerkar, 2003). The other is markets. Researchers, especially from the marketing perspective, have emphasized how market uncertainty is reduced as organizations learn to know their customer bases better (von Hippel, 1988). Research has shown that both knowledge areas are extremely important to the development of new products: Clark (1985)

proposed that innovating organizations iterate between the needs of customers and the opportunities provided by technology, and Cyert and March (1963) that the degree to which firms learn about markets and technology is likely to increase their innovativeness. Following this prior work, and recent empirical research that has drawn increasing attention to these two dimensions (e.g., Adner & Levinthal, 2001; Sorenson, 2000), I chose to focus on technology and markets as central sources of knowledge for product development in this study.

A combination of technology and market knowledge is especially important for the creation of product portfolios that are the focus of this study. While technology-focused learning is essential for improving high-technology products such as biotechnology (e.g., Sørensen & Stuart, 2000), and market-focused learning essential for many user-driven areas such as late-stage computer industry (e.g., Sorenson, 2000), in the context of product development in industrial robotics where a high-technology product is created with the purpose that it will improve the productivity of another organization's production process, both technology and market knowledge are critical (Fleck, 1988). In robotics, and in many similar industries such as medical devices or production machinery, organizations need to manage these two areas of knowledge to create successful product portfolios. While a large majority of longitudinal innovation studies focus on technology (see Cohen, 1995 for a review), the role of market knowledge is often underexamined, yet critical. In fact, von Hippel and Tyre (1995) offered an example of a product introduction process where after the introduction, the users and developers identified 27 problems with a new product. 22 out of the 27 problems required market knowledge, and were identified only in the early field use of the product. Nevertheless, studies that simultaneously examine both technology and markets are rare. In the hypotheses that follow

I will examine both technology and market knowledge in the context of firms' adaptation through product innovations.

Hypotheses

The following hypotheses compare and contrast ecological and evolutionary theories on adaptation. Hypotheses 1a-6a are based on the ecological view, and Hypotheses 1b-6b on the evolutionary view. Each pair of hypotheses (e.g., H1a and H1b) examines a relationship between the same variables (such as new technological knowledge and innovativeness), but from two different theoretical perspectives, yielding opposite predictions. The predictions are then tested with a sample of robotics innovations to determine which view better predicts adaptation through product innovation.

Ecological view. The model of punctuated equilibrium originates in biology (Eldredge & Gould, 1972). The biological intuition was that while organisms were skilled at reproducing copies of themselves, the genetic code of a species worked to prevent, rather than encourage adaptation. In other words, small mutations (i.e., small changes to genes) faced infinitesimal chances of survival. However, punctuated equilibrium theorists suggested that change was more likely to be successful if a small part of the population that was mutated was isolated from its parent. In the isolated environment, mutations were protected from the norms of the parent population, and thus had a larger chance of survival. If the two populations were subsequently merged, when the smaller population was more fully developed, it had a chance to survive, and even displace its parent population (Levinthal, 1998).

Organizational ecology, and the organizational model of punctuated equilibrium is based on similar ideas. Researchers argue that organizational routines resist change (Hannan & Freeman, 1989; Tushman & Romanelli, 1985). Uncoordinated attempts to change that are

incompatible with the current organizational standards and norms are likely to fail. “A piecemeal approach” of change... ”gets bogged down in politics, individual resistance to change, and organizational inertia” (Tushman, Newman, & Romanelli, 1986: 38). According to the ecological view, change is also inherently uncertain. Effective organizations avoid prolonged periods of change that create instability, and, conversely, prefer rapid, compact change. Punctuated equilibrium researchers have also provided empirical support for their perspective. Miller and Friesen (1980) and Romanelli and Tushman (1994) showed that organizations that boldly altered their structures, decision-making routines, and information-processing devices (changing many attributes over a short period of time) performed better over their lives than organizations that changed gradually or incrementally. In contrast, “low-performing organizations...reorient all the time as they root around to find an effective alignment with environmental conditions” (Tushman et al., 1986: 39). Several factors such as changes that reinforce each other (as opposed to piecemeal change where one part is out of sync with the rest), little time for pockets of resistance to grow, and motivation and energy to change (windows of opportunity) explain the success of drastic change (Tushman et al., 1986; Tyre & Orlikowski, 1993). Several authors such as Sastry (1997) also argue that organizations need to allow for a pause after punctuation, to reflect, integrate and evaluate the effects of change. Taken together, the punctuated equilibrium view suggests that relatively long periods of stability are interrupted by compact, short periods of change. Multiple simultaneous changes enhance adaptation more than a single change, and, single changes are more likely to be harmful than beneficial.

Testing these ecological arguments in the context of product development, Hypotheses 1a, 2a and 3a focus on changes in two types of knowledge: how searching for new technological (H1a) and market (H2a) knowledge, and a combination of the two (H3a) affects the subsequent

innovativeness of the organization's product portfolio. Hypothesis 1a focuses on the increases in the number of new technological areas that the firm is searching. According to the ecological view, increasing the number of new technological knowledge areas is likely to decrease both the reliability of search, and organization's acceptance of it. New knowledge is rarely as good as the existing well-refined and well-tested knowledge, partly because knowledge that is away from the firm's immediate experience makes decision-making unreliable (Heiner, 1986: 84), and partly because such new knowledge is often seen as "illegitimate" and unwelcome in established firms (Dougherty & Heller, 1994).

Another source of important knowledge for the product development process is the market. Hypothesis 2a focuses on the increases in the number of new market areas that the firm is searching. Again, from the ecological perspective, the firm's ability to adapt starts to decrease as it explores a higher degree of new markets. Empirical studies have provided support for this argument. Several researchers (e.g., Leonard & Sensiper, 1998; von Hippel, 1994) have found that newcomers to a market often cannot carry out effective R&D, which "frequently depends on detailed understanding of product usage and relies on strong links to users" (Mitchell, 1991). Other studies have documented how organizational resistance to new markets also hampers adaptation (Burgelman, 1991; Christensen, 1997).

Hypothesis 1a. *Increased search of new technological areas has a negative relationship with innovativeness of the firm's product portfolio.*

Hypothesis 2a. *Increased search of new market areas has a negative relationship with innovativeness of the firm's product portfolio.*

In contrast, a third proposition based on the ecological view is the positive effect of compact, intense change. While technological and market change in isolation will hurt, as proposed above, bundling changes together through high levels of simultaneous technological and market change

is argued to be less disruptive for the organization, and to promote innovativeness. When changes in product development are coordinated and structured, important interdependencies between markets and technology can be taken into account (Hoopes & Postrel, 1999) and motivational barriers to change reduced (Katz & Allen, 1982). Based on these arguments, I propose:

Hypothesis 3a. *An interaction of new technology and new market search has a positive relationship with innovativeness of the firm's product portfolio.*

The second key assumption of the punctuated equilibrium view is that in-between change, organizations enjoy long periods of stability. During these periods, systems and structures become so interlinked that they only allow compatible changes (Gersick, 1989; Sastry, 1997). Inertia, motivational barriers, and social and structural relationships also grow to resist change (Tushman & Romanelli, 1985). Some punctuated equilibrium models also suggest that at extreme levels, inertia that exhausts the current resource pool will eventually serve as a trigger for change (Huff et al., 1992). Puzzles and boundary conditions related to the current way of doing things can initiate such drastic change (Gersick, 1991).

In contrast with Hypotheses 1a-3a that examined the effects of increasingly new knowledge, in Hypotheses 4a-6a the spotlight is on stability and the period when the firm is building on existing knowledge. Based on the ecological view, the prediction is that increasing experience with existing knowledge promotes inertia, and increases resistance to change. Hypothesis 4a focuses on how increasing knowledge of existing technology, and hypothesis 5a on how increasing knowledge of existing markets prevent organizational change. Hypothesis 6a examines their interaction.

Prior work on product development argues that when the same knowledge areas are used repeatedly, knowledge elements get incorporated in a steep associative hierarchy that makes it harder for managers to imagine them in any other combination (Hargadon & Sutton, 1997). Leonard-Barton (1992) showed how technologically experienced product development teams were the least likely to deviate from prior patterns, and, thus, the least likely to envision new uses for existing knowledge. Christensen (1997) proposed that increasing familiarity with a current customer base prevents change. In some instances routines and tradition even promote the use of certain combinations of knowledge, although the combination may be actually ineffective or harmful in the current situation. Bohn and Jaikumar (2000) cited an example where an employee at an anti-corrosion paint manufacturing plant had discovered that a compound added to the paint actually accelerated corrosion. Soon thereafter it was discovered that the compound was originally added as a temporary countermeasure to contamination in a raw material, and the combination became institutionalized only when the person who originally came up with the fix left the organization. Similarly, project leaders at the Jet Propulsion Laboratory point out that building on past knowledge requires “managers to swallow a different kind of risk—to trust stuff that others have produced” (Leonard, 2002: 11). Based on the ecological arguments, the proposition is that increasing experience with markets and technology is likely to sustain the same level of product innovativeness, or encourage the firm to go back to its previous designs (negative relationship), rather than improve innovativeness.

Hypothesis 4a. *Increasing expertise in familiar technological areas has a negative relationship with innovativeness of the firm’s product portfolio.*

Hypothesis 5a. *Increasing expertise in familiar market areas has a negative relationship with innovativeness of the firm’s product portfolio.*

Finally, the interaction effect of high levels of technological and market experience is proposed to promote innovativeness. As discussed above, the ecological argument is that resource shortages that result from reaching the limits of the current technology and market areas will eventually drive the firm to adapt (Gersick, 1991). This idea is also in line with the argument that decreases in performance, due to technology and market knowledge pools reaching their limits, increase the pressure for, and the likelihood of change (Cyert & March, 1963).

Hypothesis 6a. *An interaction of expertise in technology and market search has a positive relationship with innovativeness of the firm's product portfolio.*

Evolutionary view. The second view on organizational adaptation is evolutionary. Similar to the ecological view, the origins of the evolutionary view are in biology (Holland, 1975; Smith, 1989). According to evolutionary biologists, organisms adapt through search that uses two main mechanisms, recombination and mutation. Recombination is a structured way to produce new material that builds on existing material and thus makes use of the advances already made (Holland, 1975; Smith, 1989). In recombination, valuable parts of existing material are mixed and matched to even higher performing combinations (Smith, 1989). In contrast, mutations (that is, small variations) are “trial and error” events that are blind as to how well they fit the environment (Alchian, 1950). The role of mutations is to guarantee sufficient variety of new structures in the search process. Biological models emphasize that recombination and mutation are simultaneously at work to improve the results of the search (Holland, 1975).

Organizational evolution researchers similarly share the idea that organizations do not search perfectly: firms find it difficult to find the optimal way to search, but they can learn to search better with experience (recombinations) and through experimentation (trial and error) (Nelson & Winter, 1982). Organization theorists also emphasize path-dependency: search

behavior is both inertial (firms resist change) and exhibits momentum (once change is initiated, organizations keep changing in the same direction). Such tendencies tend to lead managers to both under and over search the optimal levels (March, 1991). Taken together, the evolutionary view outlines two ways to adapt to uncertain environments: efforts that support random variation, and, efforts that grow out of recombining learnings from previous search efforts. Researchers also stress the organizational tendency to migrate towards either extreme: to emphasize extensive variation, or to build solely on the past (March, 1991). Both extremes are argued to hurt, and a mix of both to promote innovativeness.

Similarly to Hypotheses 1a-3a, but from the evolutionary perspective, Hypotheses 1b, 2b and 3b focus on how searching for new technological (H1b) and market (H2b) knowledge, and a combination of the two (H3b) changes the subsequent innovativeness of the organization's product portfolio. Evolutionary theorists suggest that one mechanism through which new knowledge (that is, trial & error) increases innovativeness is the "selection effect of variation" (Levinthal & March, 1981; Nelson & Winter, 1982). According to this principle, the more alternatives there are to select from, the more innovative will be the contribution of the approach that is ultimately selected. In other words, trial and error experiments with new knowledge provide choice; local search leaves a firm with few options to choose from (March, 1991). This same selection effect was also evident in the robotics industry. For example, R&D managers of the industry leader explained how their firm had a policy not to try new technological ideas too hastily. This strategy had led the organization to avoid costly mistakes, but unfortunately also to miss on some exciting opportunities. In another interview with the same firm's customers, the customer characterized this particular firm as "reliable", but described its robots as "less advanced".

Research on product development also shows that organizations that experiment by searching new knowledge are more likely to produce innovative products (Ettlie et al., 1984). Both offline experimentation with new technologies (Pisano, 1994) and online experimentation with new market offerings (Sorenson, 2000) have been studied, and shown to improve innovativeness. Similarly, Kekre and Srinivasan (1990) argued that firms with broader product lines accumulated higher market shares, possibly because they had more trial and error opportunities to learn.

Hypothesis 1b. *Increased search of new technological areas has a positive relationship with innovativeness of the firm's product portfolio.*

Hypothesis 2b. *Increased search of new market areas has a positive relationship with innovativeness of the firm's product portfolio.*

An extreme case of variation is when both the organization's technology and market areas are changed simultaneously. According to the evolutionary view, organizations handle new knowledge well if some parts of their knowledge base remain unchanged (Nelson & Winter, 1982), but new knowledge starts to hurt if too much is changed simultaneously (March, 1991).

Hypothesis 3b. *An interaction of new technology and new market search has a negative relationship with innovativeness of the firm's product portfolio.*

In contrast with Hypotheses 1b-3b that examined the effects of new knowledge, in Hypotheses 4b, 5b and 6b the spotlight is again on existing knowledge. From the evolutionary perspective, repeated use of existing knowledge is likely to promote adaptation through three mechanisms. First, repeat use of knowledge can help the firm form a map of the "knowledge landscape", and thus help identify how knowledge can be combined most effectively to innovative products (Fleming & Sorenson, 2002; Nelson, 1982: 46). Frequent use of knowledge probably also indicates that it is valuable (c.f., Trajtenberg, 1990), indicating that the knowledge is a good

foundation for even more innovative combinations. Second, problems that become opportunities for innovation are often deviations from the existing rules, and “one needs to know the rules to recognize the problem” (Boas, 1959). For example, Duco lacquers which reduced the time to finish a car from days to hours were discovered by accident, as the powerhouse was shut down, and a barrel of nitrocellulose solution used in connection with photographic film research was left untouched for two days (Mueller, 1962). Recognizing the significance of the accident, however, required previous knowledge of the normal, expected behavior of the solution. Third, existing knowledge can be beneficial, because technological knowledge that the firm has used frequently in the past is more comprehensively understood, predictable, and legitimate (Dougherty & Hardy, 1996). Such reliability will increase efficiency, and help the firm avoid possible dead-ends in new product development (Cooper & Kleinschmidt, 1986).

Increased experience with the same market areas works through similar mechanisms. Repeat product introductions provide feedback from market’s reactions and thus guide future introductions (Sorenson, 2000). For example, software firms use controlled beta-releases to familiar market areas to avoid errors in subsequent product offerings. Market experience can also improve adaptation, since in many cases users rather than designers have generated ideas that have later been recombined to commercially significant new products (Leonard-Barton, 1995; von Hippel, 1988; Zirger & Maidique, 1990). At other times users have acted as co-inventors by using the products in innovative ways or by inventing around product’s weaknesses (Bresnahan & Greenstein, 1996). To provide effective ideas for new product development, designers often need to establish long-term relationships with users, and users need to understand the product technology at some level. Repeat introductions to the same market segment will increase the

likelihood of both, and ultimately promote innovativeness (Leonard-Barton, 1995; Nambisan, 2002).

Hypothesis 4b. *Increasing expertise in familiar technological areas has a positive relationship with innovativeness of the firm's product portfolio.*

Hypothesis 5b. *Increasing expertise in familiar market areas has a positive relationship with innovativeness of the firm's product portfolio.*

Evolutionary theorists propose that reuse of old knowledge has limits, however. Eventually, repeated search of the same areas will exhaust the new ideas that can be used to improve innovativeness (March, 1991). For example, as the users get more familiar with the designer's technology, they may, in turn, get trapped in a technological hierarchy that makes it more difficult to imagine new opportunities for improvement. Based on these mechanisms, a negative interaction that reflects extensive exploitation is proposed:

Hypothesis 6b. *An interaction of expertise in technology and market search has a negative relationship with innovativeness of the firm's product portfolio.*

METHODS

Industrial robotics

The empirical setting of this study is the industrial robotics industry. Companies in the industrial robotics industry develop products that can be programmed to move a gripper or tool through space to accomplish a useful industrial task (Hunt, 1983). This definition of robots is widely used in the robotics industry and in the industry publications. Consequently, industry boundaries, relevant actors, and products can be defined consistently.

Robotics, a complex combination of mechanics and electronics technologies, is a relatively new technology. The world's first robotics company, Unimation, was formed in 1956, and it installed the first robot for industrial use in 1961 (Mortimer & Rooks, 1987). During the

next several decades, robots have radically added value to the production processes in several industries. Robots lower production costs, improve quality and productivity, and make the processes faster. Mass customization and miniaturization further increase their value, and sometimes make robots indispensable (Vincent, 2000).

A list of industrial robotics companies for this study was obtained through an extensive search of robotics trade magazines and databases, and through discussions with industry experts. Companies that developed or planned to develop industrial robots were separated for the study. The final sample consisted of the industrial robot development efforts by European, U.S., and Japanese robotics companies during the 1984-1997 period. The study is restricted to these three geographical areas since they accounted for over 95% of the world's robot supply during this period (World industrial robots, 1996). There were 73 firms in the sample, and these firms had new product introductions in 327 firm-years. Eleven of the firms were European, eighteen from the U.S., and the rest were Japanese. All firms were public to secure reliable access to data.

Data

New products. I used two primary sources of data in analysis: product introduction announcements and patents. The product introduction data were compiled following the "literature-based innovation output indicator" method (Coombs, Narandren, & Richards, 1996). In this method, new product data are compiled from editorially-controlled new product announcement sections of technical and trade journals, from product databases, as well as from product catalogs. These data are highly reliable and comprehensive since multiple sources are used. Through this method, detailed information on product introduction dates, product specifications, such as speed, reliability, and payload of new robots, and user application areas is

gathered. The literature-based method has been used in previous studies on robotics technology (e.g., Schlesinger & Imany, 1986; Shim, 1994), and its use facilitates comparisons across studies.

New product introduction as a measure of innovation output has several strengths. New products are innovations that are in commercial use. Thus, they complement other popular measures of innovation, such as patents or scientific publications. Specifically, new products capture those innovations that were never legally protected nor presented in the scientific literature. Despite the benefits, there are also challenges. First, the propensity and pace to introduce new products is likely to differ across industries, and over time. In this paper I control for these effects by limiting the study to a single industry, and by controlling for the time period. The second problem with the new product measure is that most products are inherently heterogeneous (Alexander & Mitchell, 1985). To address this problem I present each product as a combination of its design characteristics, and use this measure to articulate the product's innovativeness, that is, its value to users.

Since it was critical to measure the product variables well, the data for the new product introductions were collected based on a comprehensive search of publications that list industrial robot product introductions, along their specifications. First, the "New products" –sections in *Industrial Robot*, *Robotics Today* and *Robotics World* trade magazines and publications such as *Robotics new product database (US)*, *Robotics product specifications in Japan* were searched. All product introduction data were then cross-checked and supplemented with the data collected from trade publications specializing in manufacturing and robotics (including *Assembly Automation*, *Automotive Industry*, *Automotive News*, *IEEE Robotics & Automation Magazine*, *Japan Robot News*, *Machine Design*, *Manufacturing Engineering*, *Mechanical Engineering*, *Newsletter on Japan Robotics*, *Production*, *Production Engineering* (also called *Automation*) and

Robot news), online databases such as *EI/Compendex Engineering Index* and *Dow Jones*, business sources such as *Wall Street Journal*, and directories such as *Predicasts*. In prior research Shim (1994) has used a subset of these same data sources to collect robotics product introduction data. Finally, I contacted each of the sample companies (by sending a product listing from my database), asking them to verify and complete their individual product records in the data. Any discrepancies in the data were solved, and in very few cases where a solution could not be found, the product was dropped from the sample. All of these steps were taken to ensure the reliability and comprehensiveness of the product data.

Patents. Comprehensive details of technology search processes for new products, especially over extended periods of time, are difficult to access and itemize. For example, when asked to describe the origin of one of the BMW's latest car prototypes, the head designer shrugged; he really could not describe it in words (Breem, 2002). In contrast, patent data provide an excellent source for measuring the technological knowledge used in product development, since they "provide one of the few direct quantitative glimpses into the innovation process available to us" (Griliches, 1984: 14). Consequently, several researchers have used patents to identify similarities in technological portfolios (Mowery, Oxley, & Silverman, 1998; Stuart & Podolny, 1996), to describe technology exploration (Rosenkopf & Nerkar, 2001), and to measure the age of technological knowledge used (Katila, 2002; Nerkar, 2003).

Patents as a measure of innovation activities naturally also has limitations. Previous studies propose that since the propensity to patent varies considerably across industries, patent data has less value in cross-industry comparisons (Cohen & Levin, 1989). However, patents usually provide a good, comparable measure of innovative efforts of firms when the analysis is restricted to one industry (Trajtenberg, 1990). Of course not all industries are equal. Several

reasons make industrial robotics as one of the industries where patents are good measures of development processes, however. First, patents are regarded as an important appropriability mechanism in the robotics industry (Grupp et al., 1990; Marklund, 1986), and in the industrial machinery industry in general (Cockburn & Griliches, 1987). In a 1993 survey of Europe's largest industrial firms, the leading four sectors in patent propensity rates were machinery (including robotics), precision instruments, pharmaceuticals and chemicals (Arundel & Kabla, 1998). Robotics patents also have a strong correspondence with scientific publications and other technometric indices in robotics (Grupp et al., 1990: 125). Finally, patents have frequently been used to describe technological developments in robotics (e.g. Brossia, 1983; Grupp et al., 1990; Kondo, 1990; Kumaresan & Miyazaki, 1999), and this study continues this tradition.

United States Patent and Trademark Office database was the source for patent data for the independent variables. *Who owns whom* directories were used to create the patent portfolios for each firm. Given the significant number of patents to be analyzed (for years 1979-1987, to construct the variables described below), the analysis would not have been feasible without custom-made computer programs written in C language to compile and analyze the data.

Measures

Dependent variable: Innovativeness of new products. In this study I evaluate the innovativeness of a new product from the user's perspective (see also Henderson, 1993). How the user defines an innovative product is inherently interesting and important, because it affects the commercial success of the firm's product innovation activities (von Hippel, 1988; Myers & Marquis, 1969). Technology-focused view of products that does not consider the priorities of users may result in a product that is at odds with the market's perception of it (Abernathy & Clark, 1985; Veryzer, 1998).

To operationalize *Innovativeness of new products*, I first had to define a new product. A robot is defined to be new if there is a change in one or more of its design characteristics in comparison with the firm's previous robots (e.g., Martin & Mitchell, 1998). Introducing an existing product design in a new geographical area, for example, does not qualify as a new product. Moreover, I excluded introductions of new automation systems and appliances, and robots in other than industrial application areas. I then used the core design characteristics of each new product, i.e., those characteristics that were important to users, to measure innovativeness. This design characteristics method is well-established in new product studies (Henderson, 1993; Keeney & Lilien, 1987; Sahal, 1985). For example, Dodson (1985) used a similar methodology to assess innovativeness of rocket motors (delivered impulse, thrust, motor weight), and Keeney (1999) to describe qualities of internet commerce (availability and security). In this study I used four characteristics of new industrial robots that prior research (Booth, Khouja, & Hu, 1992; McDermott & Alexander, 1984) has identified as especially important for the user's valuation of a new robot: repeatability, speed, load capacity, and degrees of freedom. Repeatability of the robot is defined as a closeness of agreement of repeated position movements under the same conditions to the same location. Speed of a robot is defined as the maximum speed at which the robot (i.e., its tool tip or end effector) can move, producing a satisfactory result. Load capacity is the maximum weight or mass of a material that the robot can handle without failure. Degrees of freedom (number of axis) determines the dexterity of the robot, that is the space where the robot is able to move. These characteristics are consistently reported in the robotics product catalogues (Booth et al., 1992). The measurement of these characteristics is also reliable. Robotics associations have instituted guidelines for the measurement procedures, and both American and international standards exist to force

compatibility (Dagalakis, 1998; Prange, 1986; RIA and ISO Robotics standards). I also verified that these characteristics were important in my sample using a Hedonic regression (please see Table 1). Since product price was not available for all products in the sample, the analysis was restricted to a smaller set, yet confirmed the importance of the four characteristics.

--- Insert Table 1 about here ---

Using these four characteristics, I defined innovativeness of the firm i 's product portfolio as a distance between the average characteristics of the firm's current year's robot introductions (s_i), and the characteristics of a baseline robot (in this case the first industrial robot; s_u) (Henderson, 1993; Saviotti, 1988). The higher the improvement in the characteristics relative to the baseline, the more innovative the firm's new products are defined to be. Since at times some of the characteristics of products are correlated or the variances of the characteristics differ, causing the traditional distance measures to overemphasize certain characteristics and underemphasize others (Stevens, 1992), I used a Mahalanobis distance measure that corrects for these effects through a variance-covariance matrix of the product characteristics (C). Addition of this matrix ensures that all characteristics are weighted equally. *Innovativeness of new products* for firm i at year t was then calculated as: $Innovativeness_{it} = \sqrt{(s_{it} - s_u)'C^{-1}(s_{it} - s_u)}$ where s is a service characteristic matrix as described above, and C a variance-covariance matrix.

Independent variables. Obtaining data on intrafirm innovation search (i.e., problem-solving) activities over a 10-year period is a major challenge. Patent data gave a detailed and consistent chronology of the technological dimension of these activities, since, by definition, patents include a description of a technical problem and a solution to that problem (Walker, 1995). Technology classes in which the patents are introduced further provide a natural way to describe the domains where this technological problem-solving takes place. Following a similar logic, I defined each product introduction as an effort to solve users' problems (Fleck & White,

1987; Sorenson, 2000). Consequently, user application areas where the firm's products were introduced in, provided a natural measure to describe the domains where the firm's market problem-solving takes place (Barnett & Freeman, 2001). Using these definitions, the following technology and market variables were created:

Technology variation. The patent office assigns patents to classes to characterize their technological foundations. These classes are widely used in patent studies: for example Jaffe (1989) used patent classes to describe technological positions of firms. In this study I use patent technology classes to describe the technology areas where the firm is searching, and define the technology variation variable as the proportion of new patent technology sub-classes (U.S. class/sub-class combination) the firm i enters in year $t-1$ (c.f. Rosenkopf & Nerkar, 2001). For example, if the firm patents in ten sub-classes in year $t-1$, and seven of them are new to the firm, the value of the variable is 0.7. Application date of a patent was used for determining the patent's year as is customary in the patent literature. More formally, I operationalize the variable as the proportion of those technology subclasses the firm's focal year patents are assigned to that cannot be found in the firm's past five years' patents. I use a five-year window since research has shown that organizational memory in high-technology companies is imperfect: knowledge depreciates sharply since last use, losing significant value within approximately five years (Argote, 1999). This variable ranges from 0 to 1, and the following formula is used:

$$\text{Technology variation}_{i,t-1} = (\text{Number of new patent tech classes}_{i,t-1}) / (\text{Total number of patent tech classes}_{i,t-1})$$

Technology experience. This variable describes how deeply the firm knows those technology areas it has used before. In keeping with the spirit of the learning theory findings (Baum et al., 2000), technology experience is measured as the number of times the firm has used a particular patent class before. This variable is created by calculating the number of times that,

on average, each patent class in the firm i 's current-year patents has been used by the firm during the past five years:

$$\text{Tech exp}_{it-1} = \left(\sum_{y=t-6}^{t-2} \text{Number of tech class uses by firm}_{iy} \right) / \left(\text{Total number of tech classes}_{it-1} \right)$$

Market variation. This variable describes the extent to which the firm is entering new market areas in its search. Based on the idea of product introductions as experiments (Sorenson, 2000), the variable is defined as the number of new robotics application areas—each providing knowledge of a unique set of user conditions (e.g. Dahlin, 1993; Fleck & White, 1987)—in which the firm i is introducing products in year $t-1$. For this measurement, I used robotics application area classification published and standardized by the International Federation of Robotics. When a new product is introduced, it is assigned into one or more of the 35 application areas using this classification. Schatz (1983) and Shim (1994) have previously used this classification to operationalize market diversity. In this study the market variation variable is defined as the proportion of application areas in the firm's current-year product introductions where the firm has not introduced products during the past five years:

$$\text{Market variation}_{it-1} = (\text{Number of new application areas}_{it-1}) / (\text{Total number of application areas}_{it-1})$$

Market experience. This variable describes how deeply the firm knows those market areas it has introduced products in before. Again, based on the learning literature, this variable is created by calculating the number of times that, on average, each application area in current-year products has been repeatedly used by the firm. The variable is measured as the average number of times the firm has introduced products in these user areas during the past five years:

$$\text{Market exp}_{it-1} = \left(\sum_{y=t-6}^{t-2} \text{Number of market area uses by firm}_{iy} \right) / \left(\text{Total number of market areas}_{it-1} \right)$$

Control variables

Several control variables were also included. There is significant variety in findings about R&D investments and innovativeness. Holding firm size fixed, Mansfield (1964) discovered a strong positive relationship between R&D and significant innovations, whereas Henderson (1993) and Chandy and Tellis (2000) suggested an opposite effect. I used the logarithmic value of the firm's yearly *R&D expenditure* (M\$) to control for the firm's total R&D inputs to the innovation process. I also added a control for the number of patents (*Patent frequency*) the firm applies each year to control for the effort spent in searching the technology. Since collaboration provides an alternative for internal R&D, I also included the yearly number of each sample firm's factory automation collaborations as a control (*Collaboration intensity*). For example, Tidd (1995) showed that collaborations potentially enhance introduction of novel products.

Many authors have also claimed that profitable firms have the slack to introduce more innovative products (Mansfield, 1964; Schumpeter, 1942). In contrast, prospect theorists predict the opposite: when performance is satisfactory, managers are less likely to make radical changes (Kahneman & Tversky, 1979). To examine these effects, I included a control for *firm performance* using a return on assets measure. Performance and R&D data were obtained from *Compustat*, *Worldscope* and *DIR Analyst's Guide*.

Since a diverse product portfolio potentially indicates decreasing managerial commitment to innovation (Hoskisson & Hitt, 1988), or, increasing competence at product introductions (Sorenson, 2000), I included a control for diversification as well. An entropy measure of product diversification is used (Jacquemin & Berry, 1979). The measure is defined for each firm yearly by: $Entropy = \sum_j p_j \log p_j$ where p_j is the fraction of the firm's yearly sales in the j th four-digit SIC code. The yearly four-digit SIC sales data for each company were collected from

annual reports, company databases, and directories such as *Worldscope* and *Japan Company Handbook*.

Finally, since the sample firms are from different geographical areas, I included a dummy variable to control for country-specific effects. Differences in culture and national technological infrastructures could explain differences in innovativeness (e.g., Shane, 1992). Region dummies (*European, U.S. firm*) were included to indicate the origin of the robotics firm. *Japanese* firms are the omitted category. And since over time innovativeness can vary for all firms, time effects were controlled through year dummies (1984-1996). Year 1997 was the omitted category.

Analysis

A panel regression approach is used for testing the hypotheses. The panel structure is unbalanced: the number of observation years varies across firms. Consequently, I estimate the models with the Generalized Estimating Equations method (Baron, Hannan, & Burton, 2001; Liang & Zeger, 1986). This method is appropriate for unbalanced panels, and accounts for autocorrelation—due to repeated yearly measurements of the same firms—by estimating the correlation structure of the error terms (Liang & Zeger, 1986). All independent and control variables were lagged by one year, based on qualitative evidence that there is an extremely short, approximately one year lag in introducing robotics products to market (Grupp et al., 1990).

RESULTS

Descriptive statistics and correlations for all variables are shown in table 2. Table 3 reports the results of the regression analysis. *Innovativeness of new products* is the dependent variable as described above. The first model reports the baseline with only the control variables. Here, the findings on R&D and collaboration intensity are the most consistent. As expected, firms that invest more effort into product development generally introduce more innovative

products. Model 2 tests arguments on knowledge variation. Model 3 focuses on experience. The full model (model 4 in table 3) includes all the variables and is used for describing the results.

--- Insert Tables 2, 3 and 4 about here ---

The results for technology and market variance support the ecological view (H1a, H2a, H3a). As expected by the punctuated equilibrium theory, robotics firms introduced more innovative product portfolios when high levels of technology and market change took place simultaneously, and firms avoided isolated change efforts. The evolutionary hypotheses on variation (H1b-H3b) were thus refuted. Conversely, the results on technology and market experience support the evolutionary view (H4b, H5b, and H6b). As predicted by the evolutionary researchers, innovativeness was increased by building on and recombining current technology and market expertise, and, as expected, at extreme levels such experience turned harmful leading to a competency trap and lower innovativeness. Ecological hypotheses on experience (H4a-H6a) were, in turn, refuted. Thus, the results present a hybrid view of adaptation through product innovation: ecological strategy significantly improved innovativeness when the firm was searching new knowledge, while the evolutionary strategy was significantly better when the firm built on its existing knowledge.

To corroborate these findings, and to account for possible bias due to the fact that not all sample companies introduced new products every year, I ran a generalization of the two-step Heckman sample selection correction method discussed by Lee (1983). I computed the selection correction by estimating the probability of the sample firms introducing a new product, and inserted this selection control lambda (λ) to the innovativeness regression reported in table 3. The following formula was used:

$$\lambda_{it} = \frac{\phi[\Phi^{-1}(F_i(t))]}{1 - F_i(t)}$$

where $F_i(t)$ is the cumulative hazard function for firm i at time t , ϕ is

the standard normal density function, and Φ^{-1} the inverse of the standard normal distribution function (Lee, 1983). Even after adding this sample selection correction (model 5, table 3), the results exhibited the same pattern as the original findings.

I also included other sensitivity tests. As an alternative operationalization for product portfolio innovativeness, I used each firm's yearly robotics sales as an alternative dependent variable. Robotics sales is an especially appropriate alternative, since product sales illustrates the economic significance of the development efforts (Comanor & Scherer, 1969), and several studies have used product sales data to measure how the market values a new product (Chandy & Tellis, 2000; Henderson, 1993), assuming that products with higher unit sales are likely to provide superior customer benefits and thus better adapt to the environment. Robotics sales data were obtained from yearly surveys by the *Japanese Robot Association*, *Prudential Bache Securities* and *High-Technology Database*, and from news articles and annual reports, and the variable was adjusted for inflation. Since the sales data were only available for part of the sample, the sample size was reduced to 199 firm-year observations. Nevertheless, the results presented in Table 4 confirm the original findings, with one exception. Technology experience has a weak negative, rather than a positive effect on innovativeness, possibly indicating that customers are less willing to pay for firms' technological capability building efforts (see also Henderson, 1993 for a similar finding).

I also used an alternative operationalization for *Innovativeness of new products* in unreported regressions. Instead of using the average product characteristics to illustrate the innovativeness of the firm's product portfolio each firm-year, I ran the results by including only

the most innovative product from each firm's portfolio as the value of the firm's innovativeness that year. This test again confirmed my original findings.

DISCUSSION

Why are some organizations more innovative than others? Both punctuated and evolutionary views offer intriguing alternatives for successful product innovation. Yet, the open question is how firms should choose between the two alternatives. Is the best strategy to follow a lumpy or a continuous pattern—to change in intensive episodes or to build gradually on existing knowledge?

In this study I compared the two views systematically in a longitudinal study of product innovation in the industrial robotics industry. To my knowledge, this was one of the first studies where punctuated equilibrium and evolutionary models have been compared empirically in a large-scale study of product innovativeness. I discovered that the discrepancy between the theoretical models may be partly due to difference in focus. While punctuated equilibrium studies have traditionally focused on, and paid most attention to the period when knowledge is new and uncertain, evolutionary studies have concentrated on the opposite period when knowledge is old and predictable. However, researchers from neither perspective have paid much attention to this difference. Yet, whether the knowledge is more uncertain (new) or more predictable (existing) seems to impact when each view is most predictive, at least in the context of product innovation activities. When organizations use new and uncertain knowledge to create new products, ecological view is relevant. When they use existing and predictable knowledge to create new products, evolutionary view is appropriate.

The results show that arguments from both ecological and evolutionary views partly explained how successful firms created innovative product portfolios. When the successful firms

changed, they coordinated their efforts and entered both new market and technological areas simultaneously, as predicted by the ecological view. However, successful firms also took full advantage of periods when no new knowledge was introduced, and used improvements in existing knowledge as a vehicle of continuous change, as predicted by the evolutionary view. These findings have implications for theories of organizational change and product innovation, as discussed below.

Organizational change

While organizational change studies have discussed the benefits of both ecological and evolutionary strategies for innovation, few, if any, have presented a systematic empirical comparison as is done in this study. This comparison is valuable for several reasons. First, the results of the study show that whether each strategy helps or hurts depends on the type of knowledge. Neither view is sufficient by itself; in fact, the results propose a redefined balance that combines the two views, and thus suggests a major clarification for how we define balance in organizational research. Second, the results are important for innovating firms: ecological and evolutionary strategies require widely different capabilities and coordination mechanisms, and organizations can benefit from knowing on which to focus and when.

The findings of the study also support the recent call for organizations to create ambidextrous structures (Tushman & O'Reilly, 1996). At the same time, the results suggest that ambidextrous structures, by focusing on the extremes of change and stability, pay little attention to the retransformations of existing knowledge, and may miss out the opportunity to use existing knowledge to create new. The results of the study provide an important additional, evolutionary mechanism for established organizations to adapt and change.

By drawing attention to the evolutionary process as a complement to the ecological view, the study also provides interesting new data on the role of existing knowledge in organizational adaptation. While organizational research has recently focused increasing attention on new knowledge (a.k.a. exploration) as a way to create new innovation (McGrath, 2001; Rosenkopf & Nerkar, 2001), this paper extends discussion on the potential of internal knowledge that the firm already owns, but often chooses to underexploit (see also Menon & Pfeffer, 2003). Recombination and experimentation that traditionally have been projected as major sources of innovation (Holland, 1975; Schumpeter, 1942) have received much less attention lately. This study draws attention back to both processes, and their benefits and drawbacks. The results show that new knowledge is not the sole source of innovative new products; existing knowledge plays a significant role as well.

I set two types of boundary conditions for the study. First, the periods of discontinuous change as defined by for example Anderson and Tushman (1990) and Christensen (1997)—that potentially introduce a whole new set of product attributes and have been relatively well-studied in the literature—are beyond the scope of this study. While such discontinuous changes are intriguing situations to study, improvements along the existing dimensions often play equally important roles in technical advance in many industries (Clark, 1985). In fact, most innovation activities in organizations take place between discontinuities (Eisenhardt & Martin, 2000). Second, the research methodology of the study is most applicable in industries where the products can be differentiated using multiattribute designs and product features, and less so in industries where the performance of the products is not directly comparable (MacCormack, Verganti, & Iansiti, 2001), or where user needs are homogeneous and products standardize quickly.

Product innovation

The study also has methodological contributions for product innovation research. The use of new products as a measure of innovation performance in this study builds on common invention measures such as scientific articles and patents (Ahuja, 2000), but provides a more direct operationalization of the commercial value of inventions. Using products as a dependent variable is also consistent with Sørensen and Stuart's (2000) and Rosenkopf and Nerkar's (2001) recommendations that we need more studies that examine commercialization of inventions.

My study also introduces a relatively novel way to measure innovativeness of new products. Foster (1986) argued that an appropriate product performance measure is valued by customers, and expressed in terms that make sense to scientists. The product's user characteristics fulfill these criteria, and provide a theoretically justified and empirically appealing measure of innovativeness (Saviotti, 1985). By using a user-based definition, I can also examine those aspects of innovativeness that prior industry, technology, or organization focused measures of innovativeness (e.g. Anderson & Tushman, 1990; Cardinal, 2001; Dewar & Dutton, 1986) have not been able to capture.

REFERENCES

- Abernathy, W., & Clark, K. 1985. Innovation: Mapping the winds of creative destruction. *Research Policy*, 14(1): 3-22.
- Abernathy, W., & Utterback, J. 1978. Patterns of industrial innovation. *Technology Review*, 50(7): 41-47.
- Adner, R., & Levinthal, D. 2001. Demand heterogeneity and technology evolution: Implications for product and process innovation. *Management Science*, 47(5): 611-628.
- Ahuja, G. 2000. Collaboration networks, structural holes, and innovation: A longitudinal study. *Administrative Science Quarterly*, 45: 425-455.
- Alchian, A. 1950. Uncertainty, evolution, and economic theory. *Journal of Political Economy*, 58: 211-221.
- Alexander, A., & Mitchell, B. 1985. Measuring technological change of heterogeneous products. *Technological forecasting and social change*, 27: 161-195.
- Allen, T. 1977. *Managing the flow of technology. Technology transfer and the dissemination of technological information within the R&D organization*. Cambridge, MA: MIT Press.
- Anderson, P., & Tushman, M. L. 1990. Technological discontinuities and dominant designs: A cyclical model of technological change. *Administrative Science Quarterly*, 35(4): 604-633.
- Argote, L. 1999. *Organizational learning: Creating, retaining and transferring knowledge*. Boston: Kluwer.
- Arundel, A., & Kabla, I. 1998. What percentage of innovations are patented? Empirical estimates for European firms. *Research Policy*, 27: 127-141.
- Banbury, C., & Mitchell, W. 1995. The effect of introducing important incremental innovations on market share and business survival. *Strategic Management Journal*, 16(Special Issue): 161-182.
- Barnett, W., & Freeman, J. 2001. Too much of a good thing: Product proliferation and organizational failure. *Organization Science*, 12: 539-558.
- Baron, J., Hannan, M., & Burton, D. 2001. Labor pains: Change in organizational models and employee turnover in young, high-tech firms. *American Journal of Sociology*, 106(4): 960-1012.
- Baum, J., Li, S., & Usher, J. 2000. Making the next move: How experiential and vicarious learning shape the locations of chains' acquisition. *Administrative Science Quarterly*, 45: 766-801.

- Boas, G. 1959. *The inquiring mind*. La Salle, Ill.: Open Court Pub. Co.
- Bohn, R. & Jaikumar, R. 2000. Firefighting by knowledge workers. Working paper. The Information Storage Industry Center, University of California.
- Booth, D., Khouja, M., & Hu, M. 1992. A robust multivariate statistical procedure for evaluation and selection of industrial robots. *International Journal of Operations & Production Management*, 12(2): 15-24.
- Breem, B. 2002. BMW: Driven by design. *Fast Company*, 62:123.
- Bresnahan, T., & Greenstein, S. 1996. Technical progress and co-invention in computing and in the uses of computers. *Brookings Papers on Economic Activity*, Special Issue: 1-77.
- Brossia, C. 1983. *Technology forecasting based on patent trend analysis using robotics technology as a case study*. Unpublished M. Sc. Thesis. Colorado School of Mines.
- Brown, S., & Eisenhardt, K. 1995. Product development: Past research, present findings, and future directions. *Academy of Management Review*, 20: 343-378.
- Burgelman, R. 1991. Intraorganizational ecology of strategy making and organizational adaptation: Theory and field research. *Organization Science*, 2(3): 239-262.
- Cardinal, L. 2001. Technological innovation in the pharmaceutical industry: The use of organizational control in managing research and development. *Organization Science*, 12(1): 19-36.
- Chandy, R., & Tellis, G. 2000. The incumbent's curse? Incumbency, size and radical product innovation. *Journal of Marketing*, 64(July): 1-17.
- Chaney, P., & Devinney, T. 1992. New product innovations and stock price performance. *Journal of Business Finance & Accounting*, 19(5): 677-695.
- Christensen C. 1997. *The innovator's dilemma: when new technologies cause great firms to fail*. Boston: Harvard Business School Press.
- Clark, K. 1985. The interaction of design hierarchies and market concepts in technological evolution. *Research Policy*, 14: 235-251.
- Clark, K., Chew, B., & Fujimoto, T. 1987. Product development in the world auto industry. *Brookings Papers on Economic Activity*, (3): 729-781.
- Cockburn, I., & Griliches, Z. 1987. Industry effects and appropriability measures in the stock market's valuation of R&D and patents. *NBER working paper* no 2465.

- Cohen, W. 1995. Empirical studies of innovative activity, In Stoneman, P. (Ed.), *Handbook of the economics of innovation and technological change*: 182-264, Oxford: Blackwell.
- Cohen, W. & Levin, R. 1989. Empirical studies of innovation and market structure. In Schmalensee, R., & Willig, R.D. (Eds.) *Handbook of industrial organization*. New York: North-Holland.
- Comanor, W., & Scherer, F. 1969. Patent statistics as a measure of technical change. *Journal of Political Economy*, 77(3): 392-398.
- Coombs, R., Narandren, P., & Richards, A. 1996. A literature-based innovation output indicator. *Research Policy*, 25: 403-413.
- Cooper, R., & Kleinschmidt, E. 1986. An investigation into the new product process: Steps, deficiencies, and impact. *Journal of Product Innovation Management*, 3(2): 71-85.
- Cyert, R., & March, J. 1963. *A behavioral theory of the firm*. Englewood Cliffs, N.J.: Prentice-Hall.
- Dagalakis, N. 1998. Industrial robotics standards. Chapter 27. In Nof, S. (Ed.) *Handbook of industrial robotics*. New York: Wiley.
- Dahlin, K. 1993. Diffusion and industrial dynamics in the robot industry. *International Journal of Technology Management*, 8(3-5): 259-281.
- Dewar, R., & Dutton, J. 1986. The adoption of radical and incremental innovations: An empirical analysis. *Management Science*, 32(11): 1422-1433.
- Dodson, E. 1985. Measurement of state of the art and technological advance. *Technological Forecasting and Social Change*, 27: 129-146.
- Dougherty, D., & Hardy, C. 1996. Sustained product innovation in large, mature organizations: Overcoming innovation-to-organization problems. *Academy of Management Journal*, 39(5): 1120-1153.
- Dougherty, D., & Heller, T. 1994. The illegitimacy of successful product innovation in established firms. *Organization Science*, 5: 200-219.
- Eisenhardt, K., & Martin, J. 2000. Dynamic capabilities: What are they? *Strategic Management Journal*, 21: 1105-1123.
- Eisenhardt, K., & Tabrizi, B.N. 1995. Accelerating adaptive processes: Product innovation in the global computer industry. *Administrative Science Quarterly*, 40: 84-110.

- Eldredge, N., & Gould, S. 1972. Punctuated equilibria: An alternative to phyletic gradualism. In T. J. M. Schopf (Ed.), *Models in paleobiology*: 82-115. San Francisco: Freeman, Cooper, & Co.
- Ettlie, J., Bridges, W., & O'Keefe, R. 1984. Organizational strategy and structural differences for radical vs. incremental innovation. *Management Science*, 6: 682-695.
- Fleck, J. 1988. *Innofusion or diffusation? The nature of technological development in robotics*. Working paper. University of Edinburgh, UK.
- Fleck, J., & White, R. 1987. National policies and patterns of robot diffusion: United Kingdom, Japan, Sweden and the United States. *Robotics*, 3: 7-22.
- Fleming, L., & Sorenson, O. 2002. *Science as a map in technological search*. Working paper.
- Fligstein, N., & Dauber, K. 1989. Structural change in corporate organization. In W. Richard Scott (Ed.), *Annual Review of Sociology*, 15: 73-96. Palo Alto, CA: Annual Reviews.
- Foster, R. 1986. *Innovation: the attacker's advantage*. New York: Summit Books.
- Garud, R., & Nayyar, P. 1994. Transformative capacity: Continual structuring by intertemporal technology transfer. *Strategic Management Journal*, 15(5): 365-385.
- Gersick, C. J. 1989. Marking time: Predictable transitions in task groups. *Academy of Management Journal*, 32: 274-309.
- Gersick, C. J. 1991. Revolutionary change theories: A multilevel exploration of the punctuated equilibrium paradigm. *Academy of Management Review*, 16: 10-36.
- Gersick, C. 1994. Pacing strategic change: The case of a new venture. *Academy of Management Journal*, 37: 9-45.
- Griliches, Z. 1984. Introduction. In Griliches, Z.(Ed.) *R&D, patents and productivity*: 1-20, Chicago, IL: University of Chicago Press.
- Grupp, H., Schwitalla, B., Schmoch, U., & Granberg, A. 1990. Developing industrial robot technology in Sweden, Ist Germany, Japan, and the USA. In J. Sigurdson (Ed.), *Measuring the dynamics of technological change*: 106-129. London: Pinter Publishers.
- Hannan, M. T., & Freeman, J. 1989. *Organizational ecology*. Cambridge, Mass.: Harvard University Press.
- Hargadon, A., & Fanelli, A. 2002. Action and possibility: Reconciling dual perspectives of knowledge in organizations. *Organization Science*, 13: 290-302.

- Hargadon, A., & Sutton, R. 1997. Technology brokering and innovation in a product development firm. *Administrative Science Quarterly*, 42(4): 716-749.
- Heiner, R. 1986. Uncertainty, signal-detection experiments. In Langlois, R. (ed.), *Economics as a process: Essays in the new institutional economics*. Cambridge University Press, Cambridge.
- Henderson, R. 1993. Underinvestment and incompetence as responses to radical innovation: Evidence from the photolithographic alignment equipment industry. *Rand Journal of Economics*, 24(2): 248-270.
- Henderson, R., & Cockburn, I. 1996. Scale, scope, and spillovers: The determinants of research productivity in drug discovery. *Rand Journal of Economics*, 27(1): 32-59.
- Holland, J. H. 1975. *Adaptation in natural and artificial systems*. The University of Michigan Press.
- Hoopes, D., & Postrel, S. 1999. Shared knowledge, glitches, and product development performance. *Strategic Management Journal*, 20: 837-867.
- Hoskisson, R., & Hitt, M. 1988. Strategic control systems and relative R&D investment in large multi-product firms. *Strategic Management Journal*, 9: 605-621.
- Huff, J., Huff, A., & Thomas, H. 1992. Strategic renewal and the interaction of cumulative stress and inertia. *Strategic Management Journal*, 13: 55-81.
- Hunt, D. 1983. *Industrial robotics handbook*. New York, N.Y.: Industrial Press.
- Jacquemin, A., & Berry, C. 1979. Entropy measure of diversification and corporate growth. *Journal of Industrial Economics*, 27: 359-369.
- Jaffe, A. 1989. Characterizing the “technological position” of firms, with application to quantifying technological opportunity and research spillovers. *Research Policy*, 18: 87-97.
- Kahneman, D., & Tversky, A. 1979. Prospect theory: An analysis of decision under risk. *Econometrica*, 47: 263-292.
- Kamien, M. & Schwartz, N. 1982. *Market structure and innovation*. New York: Cambridge University Press.
- Katila, R. 2002. New product search over time: Past ideas in their prime? *Academy of Management Journal*, 45: 995-1010.
- Katz, R., & Allen, T. 1982. Investigating the not invented here syndrome: A look at the performance, tenure, and communication patterns of 50 R&D project groups. *R&D Management*, 12: 7-19.

- Keeney, R. 1999. The value of internet commerce to the customer. *Management Science*, 45(4): 533-42.
- Keeney, R., & Lilien, G. 1987. New industrial product design and evaluation using multiattribute value analysis. *Journal of Product Innovation Management*, 4, 185-198.
- Kekre, S. & Srinivasan, K. 1990. Broader product line: A necessity to achieve success? *Management Science*. 36: 1216-1232.
- Kondo, M. 1990. Japanese R&D in robotics and genetic engineering. In Sigurdson, J. (Ed.) *Measuring the dynamics of technological change*: 130-145. London: Pinter Publishers.
- Kumaresan, N., & Miyazaki, K. 1999. An integrated network approach to systems of innovation - The case of robotics in Japan. *Research Policy*, 28(6): 563-585.
- Kusunoki, K. 1997. Incapability of technological capability: A case study on product innovation in the Japanese facsimile machine industry. *Journal of Product Innovation Management*, 14(5): 368-382.
- Lee, L.-F. 1983. Generalized econometric models with selectivity. *Econometrica*, 51: 507-512.
- Leonard, D. 2002. Managing knowledge and learning at NASA and Jet Propulsion Laboratory (JPL). Harvard Business School, 9-603-062.
- Leonard, D., & Sensiper, S. 1998. The role of tacit knowledge in group innovation. *California Management Review*, 40(3): 112-132.
- Leonard-Barton, D. 1992. Core capabilities and core rigidities: A paradox in managing new product development. *Strategic Management Journal*. 13(Summer): 111-125.
- Leonard-Barton, D. 1995. *The wellsprings of knowledge*. Boston: Harvard Business School Press.
- Levinthal, D. 1998. The slow pace of rapid technological change: Gradualism and punctuation in technological change. *Industrial and Corporate Change*, 7(2): 217-247.
- Levinthal, D., & March, J. 1981. A model of adaptive organizational search. *Journal of Economic Behavior and Organization*, 2: 307-333.
- Levinthal, D., & March, J. 1993. The myopia of learning. *Strategic Management Journal*, 14: 95-113.
- Liang, K.-Y., & Zeger, S.L. 1986. Longitudinal data analysis using Generalized Linear Models. *Biometrika*, 73: 13-22.

- MacCormack, A., Verganti, R., & Iansiti, M. 2001. Developing products on “Internet time”: The anatomy of a flexible development process. *Management Science*, 47(1): 133-150.
- Maidique, M., & Zirger, B. 1985. The new product learning cycle. *Research Policy*. 14: 299-313.
- Mansfield, E. 1964. Industrial research and development expenditures. Determinants, prospects, and relation of size of firm and inventive output. *Journal of Political Economy*, 72(4): 334-337.
- Mansfield, E. et al. (Eds.) 1972. *Research and innovation in the modern corporation*. New York: Norton.
- March, J. 1991. Exploration and exploitation in organizational learning. *Organization Science*, 2: 71-87.
- March, J., & Simon, H. 1958. *Organizations*. New York: Wiley.
- Marklund, P-O. 1986. Patents – a competitive factor. *The Industrial Robot*, October: 15-17.
- Martin, X., & Mitchell, W. 1998. The influence of local search and performance heuristics on new design introduction in a new product market. *Research Policy*, 26: 753-771.
- McDermott, K., & Alexander, M. 1984. Industrial robots/Form and function. *Industrial Engineering Conference Proceedings*, Fall: 66-72.
- McGrath, R. 2001. Exploratory learning, innovative capacity, and managerial oversight. *Academy of Management Journal*, 44: 118-132.
- Menon, T., & Pfeffer, J. 2003. Valuing internal vs. external knowledge: Explaining the preference for outsiders. *Management Science*, 49(4): 497-513.
- Metcalfe, S., & Gibbons, M. 1989. Technology, variety and organization. In Rosenbloom, R., & Burgelman, R. (Eds.), *Research on technological innovations, management and policy*: 153-193. JAI Press.
- Methe, D., Swaminathan, A., & Mitchell, W. 1996. The underemphasized role of established firms as the source of major innovations. *Industrial and Corporate Change*: 5(4): 1181-1203.
- Miller, D. & Friesen, P. 1980. Archetypes of organizational transition. *Administrative Science Quarterly*, 25: 268-299.
- Mitchell, W. 1991. Dual clocks: Entry order influences on incumbent and newcomer market share and survival when specialized assets retain their value. *Strategic Management Journal*, 12(2): 85-100.
- Moorman, C., & Miner, A. 1997. The impact of organizational memory on new product performance and creativity. *Journal of Marketing Research*, 34(1): 91-106.

- Mortimer, J., & Rooks, B. 1987. *The international robot industry report*. Bedford, UK: IFS Publications Ltd.
- Mowery, D., Oxley, J., & Silverman, B. 1998. Technological overlap and interfirm cooperation: implications for the resource-based view of the firm. *Research Policy*: 507-523.
- Mueller, W. 1962. The origins of the basic inventions underlying Du Pont's major product and process innovations, 1920 to 1950. In *The rate and direction of inventive activity*: 323-358, National Bureau of Economic Research, Princeton University Press.
- Myers, S., & Marquis, D. 1969. *Successful industrial innovations*. Washington DC: National Science Foundation.
- Nambisan, S. 2002. Designing virtual customer environments for new product development. *Academy of Management Review*, 27: 392-411.
- Nelson, R. 1982. The role of knowledge in R&D efficiency. *Quarterly Journal of Economics*: 453-470.
- Nelson, R., & Winter, S. 1982. *An evolutionary theory of economic change*. Cambridge, MA: Harvard University Press.
- Nerkar, A. 2003. Old id gold? The value of temporal exploration in the creation of new knowledge. *Management Science*, 49: 211-229.
- Pisano, G. 1994. Knowledge, integration, and the locus of learning. *Strategic Management Journal*, 15: 85-100.
- Prange, J. 1986. RIA sets standards for the industry. *Robotics World*, (4): 80-82.
- Roberts, P. 1999. Product innovation, product-market competition and persistent profitability in the U.S. pharmaceutical industry. *Strategic Management Journal*, 20: 655-670.
- Romanelli, E., & Tushman, M. 1994. Organizational transformation as punctuated equilibrium: An empirical test. *Academy of Management Journal*, 37: 1141-1166.
- Rosenkopf, L., & Nerkar, A. 2001. Beyond local search: Boundary-spanning, exploration, and impact in the optical disk industry. *Strategic Management Journal*, 22: 287-306.
- Rutenberg, D. 1986. Umbrella pricing. Working paper. Queens University.
- Sahal, D. 1985. Technological guideposts and innovation avenues. *Research Policy*, 14(2): 61-82.
- Sastry, M. A. 1997. Problems and paradoxes in a model of punctuated and organizational change. *Administrative Science Quarterly*, 42: 237-275.

- Saviotti, P. 1985. An approach to the measurement of technology based on the hedonic price method and related methods. *Technological Forecasting and Social Change*, 27: 309-334.
- Saviotti, P. 1988. The measurement of changes in technological output. In Van Raan, A. (Ed.), *Handbook of quantitative studies of science and technology*: 555-601. Elsevier.
- Schatz, D. 1983. *The strategic evolution of the robotics industry*. M Sc. Thesis. Sloan School of Management, Boston.
- Schlesinger, R., & Imany, M. 1986. Statistical investigation of robot performance specifications. *Human Systems Management*, 6: 157-165.
- Schumpeter, J. 1942. *Capitalism, socialism and democracy*. New York: Harper Press.
- Shane, S. 1992. Why do some societies invent more than others? *Journal of Business Venturing*, 7(1): 29-46.
- Shim, S. 1994. *Commercializing new technology: A comparison of the US and Japanese robotics industries*. Unpublished doctoral dissertation. Rensselaer Polytechnic Institute. Troy, New York.
- Smith, J. 1989. *Evolutionary genetics*. New York: Oxford University Press.
- Sørensen, J., & Stuart, T. 2000. Aging, obsolescence, and organizational innovation. *Administrative Science Quarterly*, 45: 81-112.
- Sorenson, O. 2000. Letting the market work for you: An evolutionary perspective on product strategy. *Strategic Management Journal*, 21: 277-292.
- Stevens, J. 1992. *Applied multivariate statistics for the social sciences*. Hillsdale, NJ: Lawrence Erlbaum.
- Stuart, T.E., & Podolny, J.M. 1996. Local search and the evolution of technological capabilities. *Strategic Management Journal*, 17(Summer): 21-38.
- Thompson, J. 1967. *Organizations in action*. New York: McGraw-Hill.
- Tidd, J. 1995. Development of novel products through intraorganizational and interorganizational networks: The case of home automation. *Journal of Product Innovation Management*, 12(4): 307-322.
- Trajtenberg, M. 1990. *Economic analysis of product innovation – The case of CT scanners*. Cambridge, MA: Harvard University Press.
- Tushman, M. L., & Anderson, P. 1986. Technological discontinuities and organizational environments. *Administrative Science Quarterly*, 31(3): 439-465.

- Tushman, M. L., Newman, W. H., & Romanelli, E. 1986. Convergence and upheaval: Managing the unsteady pace of organizational evolution. *California Management Review*, 29(1): 29-44.
- Tushman, M. L., & O'Reilly, C. A. III. 1996. Ambidextrous organizations: Managing evolutionary and revolutionary change. *California Management Review*, 38(4): 8-30.
- Tushman, M., & Romanelli, E. 1985. Organizational evolution: A metamorphosis model of convergence and reorientation. *Research in Organizational Behavior*, 7: 171-222.
- Tyre, M., & Orlikowski, W. 1993. Exploiting opportunities for technical improvement in organizations. *Sloan Management Review*, 35(1): 13-26.
- Veryzer, R. W. Jr. 1998. Key factors affecting customer evaluation of discontinuous new products. *Journal of Product Innovation Management*, 15(2): 136-150.
- Vincent, D. 2000. The robotics industry: Leading the charge to a productive 21st century. *Robotics Online*. <http://www.robotics.org>.
- von Hippel, E. 1988. *The sources of innovation*. New York: Oxford University Press.
- Von Hippel, E. 1994. "Sticky information" and the locus of problem solving: Implications for innovation. *Management Science*, 4: 429-439.
- Von Hippel, E. & Tyre, M. 1995. How learning by doing is done: problem identification in novel process equipment. *Research Policy*, 24: 1-12.
- Walker, R. 1995. *Patents as scientific and technical literature*. Metuchen, N.J.: The Scarecrow Press.
- World industrial robots*. 1996. Geneva, Switzerland: United Nations and International Federation of Robotics.
- Zirger, B., & Maidique, M. 1990. A model of new product development: An empirical test. *Management Science*, 36(7): 867-883.

TABLE 1

Hedonic Analysis of Robot Price. GLS Regression predicting $\text{Log}(\text{Product Price})^{a,b}$

Variable	Model
	1
Intercept	8.92 ***
	0.79
Repeatability ^c	-0.19 **
	0.06
Speed	0.10 **
	0.04
Load capacity (log)	0.33 ***
	0.04
Degrees of freedom	0.13 ***
	0.04
-2Log likelihood	578.90

† $p < 0.1$;

* $p < 0.05$;

** $p < 0.01$;

*** $p < 0.001$ (one-tailed tests)

^a The table gives parameter estimates; standard error is below each parameter estimate.

^b Price is collected when the product is introduced, and is inflection-corrected.

^c Lower values of repeatability indicate better performance.

Year dummies are included but not shown.

126 products.

TABLE 2

Descriptive statistics and correlations^a.

	Mean	s.d.	1	2	3	4	5	6	7	8	9	10	11
1 Innovativeness of new products _{it}	2.13	1.24											
2 Technology variation _{it-1}	0.65	0.24	-0.03										
			0.51										
3 Market variation _{it-1}	0.09	0.23	-0.10	-0.03									
			0.05	0.50									
4 Technology experience _{it-1}	0.87	0.84	0.11	-0.32	-0.02								
			0.02	<.0001	0.62								
5 Market experience _{it-1}	4.45	5.16	0.09	-0.028	-0.17	0.29							
			0.08	0.57	0.001	<.0001							
6 R&D expenditure _{it-1} (log)	4.16	2.30	0.12	-0.03	-0.04	0.51	0.12						
			0.03	0.61	0.42	<.0001	0.03						
7 Patent frequency _{it-1}	183.87	307.84	0.12	-0.22	-0.10	0.53	0.09	0.63					
			0.01	<.0001	0.04	<.0001	0.07	<.0001					
8 Performance _{it-1}	0.02	0.06	-0.03	0.03	0.09	-0.03	-0.03	0.05	-0.02				
			0.63	0.55	0.09	0.58	0.61	0.34	0.76				
9 Product diversification _{it-1}	1.11	0.44	-0.06	0.16	0.01	0.05	0.08	0.51	0.27	0.10			
			0.27	0.002	0.86	0.34	0.13	<.0001	<.0001	0.06			
10 Collaboration intensity _{it-1}	0.49	0.93	-0.03	0.07	-0.02	0.03	0.23	0.03	0.01	-0.03	0.01		
			0.50	0.17	0.72	0.49	<.0001	0.63	0.85	0.58	0.83		
11 European firm _i	0.15	0.36	-0.16	0.02	0.05	-0.19	-0.10	0.12	-0.13	0.12	0.38	-0.04	
			0.00	0.64	0.31	0.000	0.05	0.03	0.01	0.02	<.0001	0.43	
12 U.S. firm _i	0.12	0.33	-0.14	0.01	-0.10	-0.17	-0.16	-0.23	-0.08	-0.02	-0.35	0.16	-0.16
			0.01	0.91	0.05	0.001	0.001	<.0001	0.09	0.70	<.0001	0.002	0.001

^a N=327

TABLE 3

Generalized Estimating Equation predicting *Innovativeness of new products* it ^{a,b}

Variable	Model				
	1	2	3	4	5
Intercept	1.94 ***	1.97 ***	1.64 ***	1.69 ***	1.50 ***
	0.42	0.41	0.45	0.43	0.42
Technology variation _{it-1}		-0.45 *		-0.36 †	-0.36 †
		0.25		0.25	0.25
Market variation _{it-1}		-2.31 ***		-2.23 ***	-2.27 ***
		0.48		0.50	0.53
Technology variation _{it-1} x Market variation _{it-1}		2.29 ***		2.47 ***	2.50 ***
		0.74		0.75	0.79
Technology experience _{it-1}			0.19 *	0.18 **	0.22 **
			0.08	0.07	0.08
Market experience _{it-1}			0.04 **	0.03 *	0.03 *
			0.02	0.02	0.02
Technology experience _{it-1} x Market experience _{it-1}			-0.02 *	-0.02 *	-0.01 *
			0.01	0.01	0.01
<i>Innovation controls</i>					
R&D expenditure _{it-1} (log)	0.03	0.04	0.01	0.02	0.01
	0.04	0.04	0.04	0.04	0.04
Patent frequency _{it-1}	0.0002	0.00001	0.0002	-0.0001	-0.0002
	0.0003	0.0003	0.0003	0.0003	0.0003
<i>Operational controls</i>					
Performance _{it-1}	-0.70	-0.76	-0.26	-0.47	-0.54
	1.34	1.50	1.32	1.44	1.45
Product diversification _{it-1}	-0.21	-0.28	-0.33	-0.33	-0.32
	0.22	0.23	0.23	0.23	0.24
Collaboration intensity _{it-1}	0.01	0.02	0.01	0.04	0.003
	0.05	0.05	0.06	0.06	0.05
European firm _i	-0.37 †	-0.39 *	-0.26	-0.32	-0.27
	0.20	0.20	0.22	0.22	0.23
U.S. firm _i	-0.80 ***	-0.91 ***	-0.78 ***	-0.89 ***	-0.82 ***
	0.23	0.22	0.23	0.22	0.22
Lambda _{it-1}					0.19
					0.14
Deviance	425.3	406.7	418.3	401.2	401.1

† p < 0.1;

* p < 0.05;

** p < 0.01;

*** p < 0.001 (two-tailed tests for controls, one-tailed tests for hypothesized variables).

^a The table gives parameter estimates; standard error is below each parameter estimate.^b Year dummies included but not shown. All explanatory variables except nationality are measured using one-year lags. 327 firm-years.

TABLE 4
Generalized Estimating Equation predicting *Robot Sales*_{it}^{a,b}

Variable	Model				
	1	2	3	4	5
Intercept	1.27 †	1.48 *	1.67 **	1.75 **	1.63 *
	0.76	0.75	0.63	0.68	0.65
Technology variation _{it-1}		-0.67		-1.02 *	-0.98 *
		0.53		0.53	0.54
Market variation _{it-1}		-1.37 *		-1.30 *	-1.29 *
		0.70		0.72	0.70
Technology variation _{it-1} x Market variation _{it-1}		-1.37 *		1.44 *	1.37 †
		0.70		0.87	0.86
Technology experience _{it-1}			-0.17	-0.25 †	-0.27 †
			0.14	0.18	0.19
Market experience _{it-1}			0.06 ***	0.07 ***	0.07 ***
			0.02	0.02	0.02
Technology experience _{it-1} x Market experience _{it-1}			-0.04 **	-0.04 ***	-0.05 ***
			0.01	0.01	0.01
<i>Innovation controls</i>					
R&D expenditure _{it-1} (log)	0.14 *	0.15 *	0.14 **	0.16 **	0.15 **
	0.06	0.06	0.05	0.05	0.05
Patent frequency _{it-1}	0.0003	0.0001	0.0006 †	0.0005	0.0006 †
	0.0003	0.0004	0.0004	0.0004	0.0004
<i>Operational controls</i>					
Performance _{it-1}	-0.59	-0.55	0.39	0.49	0.57
	0.57	0.71	0.59	0.76	0.75
Product diversification _{it-1}	0.98 *	0.88 †	1.00 *	1.01 **	0.99 **
	0.50	0.46	0.41	0.38	0.38
Collaboration intensity _{it-1}	0.13 †	0.12	0.07	0.08	0.06
	0.08	0.08	0.06	0.07	0.06
European firm _i	0.38	0.38	0.12	0.02	0.03
	0.38	0.36	0.42	0.40	0.40
U.S. firm _i	0.69 †	0.53	0.73 †	0.65 †	0.67 †
	0.41	0.40	0.38	0.37	0.37
Lambda _{it-1}					0.18
					0.22
Deviance	158.0	153.9	147.7	139.9	138.6

† p < 0.1;

* p < 0.05;

** p < 0.01;

*** p < 0.001 (two-tailed tests for controls, one-tailed tests for hypothesized variables).

^a The table gives parameter estimates; standard error is below each parameter estimate.

^b Year dummies included but not shown. All explanatory variables except nationality are measured using one-year lags. 199 firm-years.