ASPIRATIONS, PERFORMANCE AND ORGANIZATIONAL CHANGE:
A MULTILEVEL ANALYSIS *

PINO G. AUDIA
London Business School
Regent’s Park
London NW1 4SA
United Kingdom
paudia@london.edu

OLAV SORENSON
Anderson School of Management
University of California, Los Angeles
110 Westwood Plaza, Suite B420
Los Angeles, CA 90095-1481
osorenso@anderson.ucla.edu

APRIL 2001

* We thank seminar participants at Insead, Stanford and UC Berkeley for useful suggestions. Special thanks go to Lee Fleming for generously providing us with the patent data and with comments on an earlier version of the paper. We acknowledge financial support from London Business School and the University of California.
ASPIRATIONS, PERFORMANCE AND ORGANIZATIONAL CHANGE:
A MULTILEVEL ANALYSIS

ABSTRACT

Both structural and psychological accounts can explain change in organizational behavior. We test critically for the relevance of psychological processes by examining the relationship between organizational performance and behavioral change across multiple levels inside the firm. While previous work often assumes that firm success leads to a generalized rigidity throughout the organization, we argue that constituencies within the firm differ in the content of their aspirations and these differences cause divergences in their responses to multiple performance dimensions. Top executives aspire to achieve organizational goals and are more prone to exhibit behavioral inertia in the face of firm success. In contrast, influential organizational members located lower in the hierarchy form aspirations linked to subunit activities and their behavioral rigidity is more likely to stem from subunit performance than from firm performance. We find support for these arguments in the computer workstations industry by focusing the analysis on changes in product portfolios and patent portfolios, two activities that come under the purview of two distinct groups within the organization, executives and technologists.
ASPIRATIONS, PERFORMANCE AND ORGANIZATIONAL CHANGE: A MULTILEVEL ANALYSIS

A well-established line of organizational theory argues that individual level psychological processes can generate inertia in successful organizations (Cyert and March, 1963; Levinthal and March, 1981; March and Simon, 1958). These accounts hold that the gap between aspirations and performance influences whether decision-makers decide to persist with the current strategy or to change it (Audia, Locke, and Smith, 2000; Greve, 1998; Lant, Milliken, and Batra, 1992; Miller and Chen, 1994; Singh, 1986). A positive gap, indicating success, engenders satisfaction with the status quo and a reduction in efforts toward strategic change. In contrast, the failure to meet expectations associated with a negative gap produces dissatisfaction and motivates the search for new, potentially more effective, strategies.

By highlighting individual level factors that can generate rigidity, these psychological perspectives complement structural accounts of organizational inertia (Hannan and Freeman, 1984). Nevertheless, they offer an oversimplified and, perhaps, unrealistic explanation of how inertial processes unfold inside organizations. Psychological accounts typically treat organizations as aggregates of individuals with homogeneous aspirations who respond as one to organizational performance. This assumption paints a picture of organizational rigidity as a uniform state that permeates the entire firm. In reality, organizational action more likely reflects the initiatives of multiple constituencies with varying ambitions and diverse foci of attention (Burgelman, 1983, 1994; Cyert and March, 1963; March, 1994). If psychological processes drive rigidity, these differences imply that influential groups within the organization may vary in which signals they interpret as indicative of success, suggesting that behavioral inertia may differ from one subunit to the next within an organization.
This study focuses on the role that aspirations play in the relationship between performance and change; however, unlike most previous empirical work, it treats organizations as collections of groups of individuals that influence organizational action. Specifically, it examines the response of different constituencies within the organization to firm performance, thereby developing a critical test of two contrasting perspectives on the relationship between organizational success and behavior. In the first scenario, firm success creates a generalized rigidity throughout the organization. Both executives and other influential groups of individuals lower in the hierarchy exhibit behavioral inertia. Several processes including the cementation of cause-and-effect beliefs (Prahalad and Bettis, 1986) and structural pressures (Hannan and Freeman, 1984) could account for this general ossification. Under the second scenario, consistent with the view that aspirations vary across constituencies within the firm and direct attention toward different performance dimensions, organizational performance differentially affects groups within the organization, thus mitigating the inertial effect of firm success.

To test these ideas, we analyze manufacturers of computer workstations, a high-technology industry characterized by small and continuous shifts in the competitive environment. This setting allows us to examine two strategic activities that critically influence the competitiveness of these organizations: changes in product portfolios and changes in technology – in this case patent portfolios. Product and patent portfolios arise largely from the actions of two distinct groups of individuals within the organization. Whereas executives play a dominant role in the decision to launch or withdraw a product (e.g., Dougherty and Hardy, 1996; Wheelwright and Clark, 1995), organizational members closer to the research and development process – scientists and engineers – wield more influence in the efforts that generate new patents (e.g., Roberts, 1988; Nelson, 1962). Do these constituencies react in unison or independently in
response to evidence of organizational success? To anticipate our conclusion, the findings presented here – consistent with the expectations of aspiration theory – suggest that organizational rigidity varies across constituencies within the firm. Strong sales growth relative to aspiration levels increases inertia in product related decisions but does not affect patenting activity. Meanwhile, engineers and scientists exhibit rigidity in their inventive activities when technological performance improves in relation to aspiration levels.

THEORY AND HYPOTHESES

The Role of Executives and Technologists in Strategic Activities

Managerial theorists often view executives at the top of the hierarchy as the primary source of a firm’s official strategy (e.g., Andrews, 1980). Based on their understanding of the organization’s current position and future opportunities, executives create policies that channel efforts and guide strategic decisions within the organization. Nevertheless, their activities alone do not determine strategic direction. Research into the strategy process reveals that strategic initiatives can originate from actions taken by actors below the apex of the organizational hierarchy (Burgelman, 1983, 1994). Organizational departments frequently receive license to act independently by virtue of their ability to deal with critical sources of uncertainty, such as new technological developments or changes in market conditions (Pfeffer and Salancik, 1977). Their autonomous actions generate opportunities that can point the organization in new strategic directions.

Which departments receive such strategic freedom depends on where the major sources of uncertainty in the organization lie, since uncertainty confers power to those organizational members who can control it (Lawrence and Lorsch, 1967). In high-technology organizations, the
focus of our empirical investigation, scientists and engineers – a group we will refer to as technologists – fall into this group of influential actors because they play a critical role in the innovation process. Technologists generate ideas and advance technical solutions that enable the introduction of novel products, the enhancement of existing products and the development of more efficient manufacturing processes. We now turn our attention to an examination of the effect of organizational performance on technologists and executives.

The effect of organizational performance on technologists and executives

Aspiration level theory, an important component of the behavioral theory of the firm (Cyert and March, 1963), holds that the level of performance one hopes to achieve, known as the aspiration level, regulates the behavior of the decision maker. Individuals classify the outcomes toward which they orient their behavior as successes or failures. The aspiration level denotes the point that divides outcomes into these two categories. This interpretation of environmental feedback leads to behavioral consequences. Successes generate satisfaction and consequently decrease the search for new solutions. Conversely, failures yield dissatisfaction and encourage individuals to seek out new ways of doing things.

Researchers use this psychological theory to propose relationships between firm performance and firm behavior, in particular organizational change (e.g., Bromiley, 1991; Greve, 1998; Levinthal and March, 1981; Miller and Chen, 1994). To move from individual level theory to organizational implications, most researchers assume employee homogeneity – that all organizational members hold the same aspiration level. Some studies apply this assumption implicitly to all of the individuals in the organization (Bromiley, 1991; Greve, 1998; Singh, 1986). Others apply it only to the top executives because they conceive organizational action as
originating primarily from the decisions of the upper echelon (Audia et al., 2000; Lant et al., 1992; Miller and Chen, 1994). The advantage of the homogeneity assumption lies in its parsimonious solution to how individual efforts aggregate to form organizational action, a recurring issue in micro-macro research (DiPrete and Forristal, 1994). Nevertheless, this assumption also creates a potentially unrealistic monolithic view of the organization, whereby firm performance above the aspiration level has pervasive and unvaried inertial effects throughout the firm. Whether this image of organizational rigidity as a uniform state matches reality or misleads depends on the validity of the homogeneity assumption. Do influential organizational members react in unison to firm performance, or do they differ in ways that cause divergences in their response to firm performance?

To address this question we return to aspiration level theory. Cyert and March’s original formulation offers two critical insights that yield important implications for how specific groups of individuals within the firm may react to organizational performance. First, although aspiration level theory focuses primarily on the level of aspirations, as its name suggests, it also considers aspiration content, what people see as important, as another critical dimension of organizational goals (Cyert and March, 1963: p. 162). Aspiration content acts as an attention filter, directing attention toward cues relevant to performance evaluation, and sets, together with the aspiration level, the evaluative standard that activates perceptions of success and failure (Locke and Latham, 1990). For example, if individuals frame their aspirations in terms of firm growth, they will attend more to information relevant to that performance dimension, will weight that information more heavily in evaluating their performance, and will react behaviorally and emotionally to their assessments. On the other hand, if firm growth does not constitute a chief concern, then it will play a limited role, with either a weak impact or no impact on their behavior.
Therefore, aspiration content critically affects organizational members’ responses to firm performance. A uniform response will only arise if all individuals have the same goals.

The second insight suggests that individuals within a firm will diverge in the content of their aspirations because the process of differentiation among sub-units critically shapes the foci of attention (Cyert and March, 1963; March, 1994). Organizations group activities to reduce the variety of the problems people face. This division of labor increases efficiency but also leads to unintended psychological consequences. Organizational subunits define natural social boundaries within which people form important connections with other individuals that share access to a codified body of knowledge, common interpretations of life and purpose, and mutual interests. In some cases, these groups transcend organizational boundaries and include peers that belong to the same professional community (Abbott, 1988). Since people often draw their identities from social group memberships (Turner, 1987), belonging to a subunit triggers a distinct social identity that directs attention back toward the group. This fits with research which consistently finds that group members gain satisfaction from the success of their group, favor the position of the group with which they identify, and generate arguments supporting their group much more easily than those opposing it (for a review, see Elsbach, 1999). The influence of social identity on individuals’ cognitive and motivational processes also explains Cyert and March’s argument (1963: 48-49) that in-group orientation shapes the aspiration content of subunit members. They note, for example, that production goals appear most central in the manufacturing side of the organization whereas sales goals seem most salient in decisions made by the sales department. The salience of sub-unit goals then determines what stimuli individuals pay the most attention to and what schemas they use to interpret this information.

Together these two insights suggest a weak link between firm performance and
organizational inertia. The process of differentiation leads to divergence in the aspirations of different constituencies in the firm. Thus, individuals inside organizational divisions create and monitor their own performance metrics and react differently to environmental feedback. Since the various dimensions of performance usually correlate only weakly (Meyer and Gupta, 1994), groups within the organization will typically vary in their satisfaction with organizational outcomes; some will perceive success and reduce exploration while others will perceive failure and activate search processes.

The forces creating such divergences may operate even more strongly on R&D groups than on members of other subunits because of the nature of inventive activities. Since uncertainty dominates these activities, anticipating future breakthroughs proves difficult, if not impossible (Nelson, 1962). Therefore, executives cannot easily subject technologists’ work to strategic planning; many view their involvement in the direction of inventive activities as counterproductive (e.g., Roberts, 1988). The effective management of technology development appears to require loose control – often to the extent of allowing technologists to pursue their own projects – because the autonomous initiative of the inventors themselves tends to drive technological innovation. These prescriptions create situations in which technologists focus narrowly on the development of technological competencies for the company, looking primarily at the generation of important new knowledge as an indicator of success and often becoming isolated from the rest of the organization. Detailed accounts of the social context in which technologists operate support this image and suggest that firm success does not usually constitute technologists’ primary concern (Hiltzik, 1999; Kidder, 1984). Because technologists’ aspirations differ in content from organizational goals, collectively their perceptions of success may not correlate strongly with the firm’s market performance, leading us to expect a weak inertial effect.
of market success on technologists’ innovative activities.

Although we anticipate a weak link between market success and inertia in the technology development process, we do not believe that technologists escape cognitive rigidity. Quite the contrary, they appear to exhibit an acute vulnerability to cognitive inertia (Dosi, 1982; Henderson and Clark, 1990; Kuhn, 1970). Aspiration level theory suggests that their rigidity, given their relative psychological distance from market goals and performance, more likely stems from their subunit’s performance. Scientists and engineers identify themselves with peers inside the organization and with their professional community. They have strong reference groups outside the organization and look to technologists in other organizations not only to learn of new developments but also to gauge their own performance. In fact, many technologists consider recognition of the importance of their inventive activities from members of their professional community a more valuable reward than salary increases or elevated status within their organization (Allen, 1977; Burns and Stalker, 1961; Gomes Mejia and Welbourne, 1990; Merton, 1957; Stern, 1999). Therefore, we anticipate that the assessment of their achievements in their professional communities will influence their perceptions of success and their correspondent behavioral inertia more than firm performance.

The research on technological paradigms illustrates how inertia in technological activities may develop (Dosi, 1982). Until technologists identify an effective solution to their technical problems, they experiment with critical variables, such as the material technology used or the physical properties exploited. Upon finding a successful solution, however, they form rigid mental models known as technological paradigms that “embody strong prescriptions on the directions of technical change to pursue and those to neglect” (Dosi, 1982: p. 152). More precisely, they show a tendency to move along the technological trajectory defined by current
solutions, which means that they cease to explore distant technological possibilities and instead
direct efforts toward the refinement of knowledge concerning elements of existing technological
solutions and the trade-offs among these elements (Henderson and Clark, 1990). Thus, inertia
does not manifest itself as decreased effort, as a lower volume of inventive activities would
reflect. Rather, it should appear as an increased tendency to refine the firm’s existing technology
(Sørensen and Stuart, 2000), a restrictive focus that could limit the firm’s ability to exploit new
opportunities as the technological frontier shifts (Dosi, 1982; Henderson and Clark, 1990). To
examine the differential effect of organizational and subunit success on technologists, we test the
following hypothesis:

\[
H1: \text{Technological performance in relation to the aspiration level lowers the rate of change to the patent portfolio more than firm performance in relation to the aspiration level}
\]

Executives occupy the only positions made more complex by the process of parsing work
into sub-units. Since the division of labor implies that no single sub-unit concentrates on
problems that concern the entire firm, they serve as a primary mechanism for integrating and
coordinating organizational action (Lawrence and Lorsch, 1967; Hambrick and Mason, 1984).
They also provide the primary interface with external actors that provide critical resources to the
organization, especially those that supply capital (Pfeffer and Salancik, 1978). They fulfill this
role by focusing their attention and efforts on the achievement of organization level goals that
external constituencies value, such as growth and profitability (Cyert and March, 1963; Perrow,
1970). Achieving those goals ensures the organization continued access to critical resources and
rewards top managers with power, money, and status. For these reasons executives’ aspirations
overlap both in content and level with organizational goals, implying that they direct their
attention toward signals relevant to overall firm performance and form perceptions of success or
failure depending on whether that performance exceeds or falls below their aspiration level.

The inertial effect of success on executives may become evident in their decisions concerning the array of products offered by the organization. In environments marked by incessant shifts, firms continuously modify their product portfolios to incorporate new technologies and meet new customer demands. Nevertheless, when organizations perform well, executives may perceive decisions to launch new products or to withdraw products that have been profitable in the past as unnecessary risks (Levinthal and March, 1993; March, 1991). Perceptions of success lead executives to develop strong convictions that the current product portfolio provides an ideal alignment between the organization and environmental demands. These deep-seated beliefs can reduce their sense of urgency in renewing the product portfolio and prevent them from making changes, leading to the following hypothesis:

\[ H2: \text{Firm performance in relation to the aspiration level lowers the rate of change to the product portfolio} \]

**Performance consequences of inertia in technology-based competition**

Inertia theory focuses on the process effects of change and predicts that change in the product portfolio decreases firm performance (Hannan and Freeman, 1984). It argues that changes to the organizational core - which includes an organization’s mission, authority structure, marketing strategy and technology - necessitate extensive modifications in structures and routines throughout the organization. The implementation of these changes creates coordination problems inside the organization and between the organization and external stakeholders, disrupting the normal functioning of the firm in ways that compromise the reliability of operations and the support of external stakeholders. In short, change undermines performance by eroding the value of accumulated experience.
While inertia theory focuses primarily on the process effects of change inside the organization, some research on high-technology firms looks at environmental demands and offers an opposing prediction: that change to the product portfolio benefits firms operating in environments subject to continuous modification, such as high-tech environments (e.g., Brown and Eisenhardt, 1997; Virany, Tushman and Romanelli, 1992). These environments experience incessant flows of small shifts that continuously alter the competitive context. If firms can process and react to the information about these shifts before the next environmental change occurs, they can benefit by changing their product portfolio and other organizational elements to match the environment.

One means of reconciling these predictions comes from acknowledging that change in the product portfolio entails multiple, potentially conflicting, effects on firms (Barnett and Carroll, 1995). The volume of change, evidenced by the number of products introduced and withdrawn, can create coordination problems that undermine firm performance (Barnett and Freeman, 2001). At the same time, however, to the extent that new products incorporate significant modifications that help the firm exploit new opportunities created by environmental modifications, change can have a beneficial effect on firm performance. This leads us to the following hypotheses:

\[ H3: \text{Product additions and product withdrawals decrease firm performance} \]

\[ H4: \text{Significant changes in product attributes increase firm performance} \]

Change in the patent portfolio should destabilize the activities of the firm less than change in the product portfolio. The intensification of inventive activities may require R&D units to purchase additional equipment and hire engineers and scientists. Nevertheless, these changes will rarely spill over into other parts of the organization. Thus, increases in the stock of patents should have little ‘process’ impact on firm performance compared to the disruption that product portfolio
change can cause.

The type of patents that firms obtain, however, could have important consequences. When firms increasingly patent inventions that cite their own previous patents, it may indicate that the firm has become increasingly out of touch with the changing demands of the environment (Sørensen and Stuart, 2000). Such technological obsolescence can lead to a degradation of firm performance. Moreover, a narrow focus on established technologies can degrade the ability of the firm to recognize and assimilate information in new domains (Cohen and Levinthal, 1990). When a firm lacks detailed knowledge of a particular technology, it cannot assess the commercial potential of new technological developments in that area. This failure to explore new areas due to knowledge gaps can give rise to self-reinforcing patterns that lock the firm out of new technological developments.

Small firms will more likely suffer from this technological obsolescence because they have limited access to the market of technologies (Arrow, 1962). Organizations can either develop new technology internally or purchase it, either licensing it from other firms or buying it through acquisitions. Large firms that discover that they lag behind competitors in the development of a new technology have the resources to catch-up by buying technology developed by other firms. Small firms operate with limited resources. Thus, these missed opportunities can threaten their survival. This leads to our final hypotheses:

\[ H5: \text{Increases in the proportion of self-citing patents reduce performance} \]

\[ H6: \text{Organizational size dampens the relationship between the proportion of self-citing patents and performance} \]
METHOD

Computer Workstation Industry

The industry began when Apollo Computer, a newly formed company founded by a high-profile group of computer industry insiders, announced the first workstation in October 1980. Apollo Computer established early market dominance, but other companies quickly introduced machines with similar characteristics to market. The workstation brought distributed computing power by incorporating several new technologies: a 32-bit microprocessor, a high speed Local Area Network (LAN), large shared virtual memory resources, and Winchester hard drives. It differed importantly from three other types of machines: terminals, servers and personal computers. While workstations included generalized processing capability, terminals could only process limited graphics locally and rely on processing from a central mainframe or server. Servers, on the other hand, typically sat in a back room providing shared resources to several users rather than providing computing power to one primary user. Finally, personal computers historically could not engage in distributed processing; the hardware and software for networked computing usually had to be added to the personal computer.

Two technological innovations dominate the evolution of the industry: the move to the Unix operating system and the development of RISC (Reduced Instruction Set Chip) processors. Apollo introduced their first machine with the proprietary Aegis operating system. This operating system provided some features unavailable in most other operating systems at the time, namely distributed processing and a shared virtual memory space. Distributed processing allows a user to harness the processing power of several machines. Shared virtual memory space makes efficient use of memory by allowing any machine in the network to make use of a memory space
on the network allocated for temporary usage. These features gave Apollo a clear advantage over competitors. Other companies that entered the market at this time often settled for somewhat reduced performance either by coupling a stand-alone operating system with some software to handle the network or by using scaled-down versions of operating systems developed for mainframes.

In 1984, Sun Microsystems released the NFS file extensions for UNIX. This code allows UNIX systems to share memory resources in a manner similar to Apollo’s Aegis operating system. Instead of keeping this software as a proprietary advantage specific to Sun machines, Sun freely licensed the software to any company that wished to use it on their own systems. At least eight competitors, including DEC, took advantage of this licensing agreement in the first year Sun offered it. Within two years, nearly every company using the UNIX operating system adopted NFS. Although UNIX already enjoyed a healthy market share prior to NFS, this development really made way for the demise of proprietary operating systems. This displacement occurred despite the fact that some of the proprietary operating systems were technically superior to and outperformed UNIX, even with the NFS extensions.

Sun Microsystems also pioneered RISC technology in the workstation industry. RISC technology, often associated with workstations, did not appear in the industry until 1988. Prior to that point, all manufacturers used CISC (Complex Instruction Set Chip) technology. Under RISC, the chip does not include the circuitry for performing certain complex instructions. Software emulates these complex instructions using sequences of less-complex instructions. RISC chips benefit from uniformity in processing. Each instruction in the reduced set requires exactly one cycle of the processor. They also allow easier development and cheaper manufacture because they involve fewer logic circuits. In 1988, Sun Microsystems began to push RISC
technology aggressively through their SPARC ‘standard’.

Our sample includes all U.S. manufacturers of computer workstations from 1980 to 1996. *Data Sources*, a publication that lists products in the computer industry, allowed us to identify workstation manufacturers for our observation period and provided organization and product level information on nearly all companies. Lexis-Nexis searches and *IEEE Graphical Computing and Applications* identified workstation manufacturers excluded from *Data Sources*. Corporate annual reports and Lexis-Nexis supplemented the organization level data and the *IDC Processor Survey* provided information on the annual sales of individual workstation models. A total of 677 company-years, representing the market histories of 175 companies in North America, comprise the data set. A significant number of firms enter and exit the industry as firm density reached its peak in 1992 with 76 firms and descended by 1996 to 45. The product level data include information on 1,276 products.

Information from the U.S. Patent and Trademark Office allowed us to link these companies to their patented technological innovations. A patent is a legal title that grants its holder the exclusive right of an invention for a limited area and time. It excludes others from using that invention, a right that the patent holder can enforce through the civil court system. We attributed patents to firms in the year in which they applied for those patents.

**Measures**

We computed two measures to detect changes in the patent portfolio. The first variable, **patents**, simply counts the number of patents received by the firm in a given year and thus captures the volume of inventive output. Our second measure, **the proportion of self-citing patents**, divides the number of patents that include a self-citation by the total number of patents the firm received
in a given year and thus captures the tendency for new inventions to build on technology owned by the firm. Since the extent to which technologists focus their efforts on refinements of technology owned by the firm interests us more than the sheer volume of inventive output, we rely primarily on evidence regarding the proportion of self-citing patents to test hypothesis 1, which suggests that technological performance has a stronger effect on the rate of change in the patent portfolio than firm performance.

The product data provided three measures of change. Firms renew their product portfolio by adding and removing products. Thus, both product additions, which counts the number of products introduced to the workstation market in a particular year, and product withdrawals, a tally of the number of products removed from the market in a given year, offer some insight into the degree of change in the product portfolio. Nevertheless, like the raw patent count, these measures provide only a crude measure of change because they focus on the volume of activity rather than its content; if the new products resemble the old models they replace, then the overall product line changes little. Therefore, we computed a third variable, attribute changes, which measures the extent to which new products differ from the existing product portfolio. This indicator variable takes a value of 1 if any of the organization’s new products include either a different processor or a different operating system from those used in the existing product line. Though most companies do not vary these critical components from year to year, the rapidly evolving nature of computer technology requires successful firms to adopt new technologies periodically.

Previous research suggests that profitability and growth provide two common measures of firm performance (Cyert and March, 1963; Perrow, 1970). In this study we use sales growth rather than profitability because in a newly formed industry, such as computer workstations, top
executives and the external actors who provide capital do not initially expect profits and instead focus their attention on increasing sales. Using sales information also allowed us to analyze more firms than profitability would because profits prove difficult to observe for the private companies that represent the majority of these data. Following research that finds that the number of times a patent receives citations from future patents offers a reasonable indicator of its importance (Carpenter, Narin and Wolff, 1981; Trajtenberg, 1987; Hall, Jaffe and Trajtenberg, 2000), our measure of technological success counts the number of citations received by the focal firm’s patents. We specifically exclude self-citations from this measure because a firm operating in a remote niche of technological space could cite its own patents many times even if competitors and the market in general consider this technology irrelevant (Sørensen and Stuart, 2000).

Although we present analyses with one-year performance lags, our preliminary analyses investigated using two- and three-year lags guided by the idea that changes in the product and patent portfolios often take more than a year to enact. Nevertheless, these longer lags failed to capture additional effects, probably because product development cycles last but a few months in this fast moving industry. Regardless, using one-year lags offers simplicity and allows us to include a larger set of the firms in the analysis.

Our hypotheses regarding the inertial effects of high performance depend crucially on aspiration levels. Aspiration levels allow individuals to categorize performance information as successes or failures, which determines the relationship between performance and change. Theory and evidence suggests that individuals use two primary sources of information to form their aspiration levels. Social comparison theory argues that individuals use information about socially similar others (Festinger, 1964). They observe the performance of these referents and adopt their average performance as an aspiration level. Individuals also use past experience,
looking back to their performance history and using that information to adjust their aspiration levels for the future (Cyert and March, 1963; Levinthal and March, 1981). Our analyses included performance in relation to both historical and social aspiration levels but found that only social aspiration levels predicted behavior well. Historical aspiration levels may play a lesser role in this study because the nascent workstation industry offers little historical information on which individuals can base their expectations. The models presented include only performance in relation to social comparisons.

We computed firm performance in relation to the aspiration level by logging the focal firm’s annual growth in the previous year divided by the average growth experienced by all firms in the workstations market that year. Negative values indicate performance below the industry average while positive values indicate above average performance. To calculate technological performance in relation to the aspiration level, we logged the ratio of the citations received by the focal firm’s patents in the previous year to the average number of citations received by all firms in the industry that year. Again, positive values indicate above average performance and negative values correspond to below average performance.

Previous research finds that the impact of a performance change on decision makers may vary depending on whether the performance is above or below the aspiration level (Greve, 1998; March and Shapira, 1992). When individuals find themselves above the target, a decrease in performance increases the probability of change. The impact of a decrease in performance when decision makers fall below the aspiration level is less clear. Prospect theory suggests that the probability of change may increase more rapidly as performance falls further and further below the aspiration level because individuals’ desire to avoid losses exacerbates risk seeking (Kahneman and Tversky, 1979). On the other hand, threat-rigidity theory offers a conflicting
prediction (Staw, Sandelands, and Dutton, 1981) if individuals perceive performance declines as a threat. Such threat perceptions can cause anxiety, which makes decision makers risk adverse and reduces their ability to expand search activities and identify new solutions.

To detect variations in the relationship between performance and change above and below the aspiration level we specify the effect of performance as a spline function (Greene, 1993). A spline specification allows the variable coefficient to change at a predetermined point, in this case the point where performance equals the aspiration level. Following Greve (1998), we specify a spline by entering separate variables for performance above and performance below the aspiration level. When the two coefficients match, performance has a constant effect on change. When the two coefficients differ, it indicates a change in slope.

Organizational size allows us to test whether the effect of proportion of self-citing patents of firm growth differs across small and large firms (hypothesis 6) but also acts as a control variable. Several factors point to the importance of controlling for organizational size. The bureaucratic structures that encumber larger organizations might stifle innovative activities (Hannan and Freeman, 1984). On the other hand, the economics literature suggests that large firms operate with stronger incentives to innovate because they can more readily appropriate the returns generated by their inventions (Arrow, 1962). Finally, large firms may also offer more extensive product lines. Workstation sales in US dollars, which we logged to account for decreasing returns to scale, provides our measure of size. To correct for inflation, we convert size to constant 1996 dollars using the Producer Price Index for Finished Goods published by the U.S. Department of Labor’s Bureau of Labor Statistics.

The models also include controls for organizational age, the lagged dependent variables, population density, changes made by other companies, and the calendar year. A variety of
processes affect the organization as it ages. On the one hand, organizations can stabilize internal relations and build up ties to other institutions and actors improving their life chances over time (Stinchcombe, 1965). On the other hand, organizations might become increasingly obsolete, thereby decreasing the viability of the organization as it matures (Barron, West and Hannan, 1994). Recent work has reconciled these diverging findings showing that aging has contradictory effects on innovation. Older organizations generate innovations more rapidly but their inventions tend to refine previous efforts incrementally rather than offering fundamental innovation (Sørensen and Stuart, 2000). In our models, one would expect to see these divergent effects of maturation across the two measures of technological change, with both patent rates and the propensity to self-cite increasing with age.

The models must also separate the effect of past performance from the effect of previous changes. Kelly and Amburgey (1991) argued that organizations more likely make changes when they made these changes in the past, irrespective of past performance. They maintained that the mechanism at work concerns not psychological processes but rather the development of routines, which, once in place, take on a life of their own and drive organizational action. By including lagged dependent variables in our models, we control for this possibility. In addition to this theoretical reason, methodological concerns also support the inclusion of lagged dependent variables (discussed in the ‘Analysis’ section).

Density, the count of firms in the industry, captures the intensity of competition and its potential effect on changes in the patent and product portfolio. Firms may also make more changes to the patent portfolio and to the product portfolio under the influence of what other firms do (Greve and Taylor, 2000). To control for this diffusion, our models include measures that capture the degree of industry change in the previous year. These measures sum changes
across companies; for example, the patent models include the total number of patents granted to workstation manufacturers in the previous year. Finally, the calendar year variable picks up other evolutionary processes that may occur during the observation period.

**Analyses**

Several of our dependent variables – the number of patents, product additions and product deletions – measure event occurrences bounded on the lower side by zero. Therefore, the use of linear regression could yield inefficient, inconsistent, and biased parameter estimates (Lindsey, 1995). Count models offer a better solution. Researchers often use Poisson regression to estimate count data, but the Poisson distribution constrains the mean and variance to be equal. Most count data, ours included, exhibit over-dispersion (i.e. the variance exceeds the mean). Therefore, we estimated negative binomial models, which alleviate these problems (Cameron and Trivedi, 1998).

The degree of change in product characteristics takes only values of zero or one. Probit regression, an appropriate method for this type of data, provides the estimation of these models (Maddala, 1986). Logistic regression yielded similar results, but the probit model fit the data better. We estimated the proportion of patents that self-cite using ordinary least squares (OLS).

In our data, the occurrence at time t of the dependent variables typically correlates strongly with its realization in previous time periods. To deal with this feature of the data, one can include as a control variable the lagged dependent variable (Cameron and Trivedi, 1998: 294). Doing so means that the models capture only the variation in the dependent variable over time. This procedure effectively controls for unobserved factors that systematically influence the dependent variable. Lagged dependent variables enter all of our models. Another commonly used
procedure for longitudinal data, fixed effects, generated a qualitatively similar pattern of results. Nevertheless, this procedure requires us to drop firms with constant zero outcomes, a frequent occurrence in the patent and product withdrawal models. Therefore, we report the models with lagged dependent variables.

Organizational growth rates capture the success of the organization in acquiring valuable resources. Using changes in the organizational sales (in 1996 dollars) from one period to the next allows us to model explicitly these expansion rates. The proportionate growth model provides a useful baseline for estimating growth rates. This model assumes that organizations follow ‘Gibrat’s Law’ – expanding and contracting at a random rate, drawn independent of organizational size (Barron, West, and Hannan, 1994; Ijiri and Simon, 1977). To control for unobserved heterogeneity across firms, we estimated these models using fixed effects. Therefore, changes in growth rates within the firm drive the parameter estimates.

RESULTS

Table 1 reports descriptive statistics and first-order correlations among all variables. Notably, firm performance and technological performance have little relation to one another, a finding with implications for the interpretation of our findings but one that should not surprise us since weak or no relationships among performance measures appears to be the norm (Meyer and Gupta, 1994).

--- Insert Tables 1 and 2 About Here ---

Table 2 presents models predicting the propensity to self-cite and the number of new patents. Model 1 includes only the control variables and suggests that large firms and firms with a history of building on their own prior research tend to self-cite. Model 2 shows that firm performance
does not affect the proportion of self-citing patents. In model 3, the two technological performance variables enter the analysis and cause a significant increase in variance explained. Since the coefficients are positive above and below the aspiration level, the proportion of self-citing patents increases monotonically as the performance relative to the social aspiration level increases. These findings provide strong support for hypothesis 1 according to which technological performance lowers the rate of change in the patent portfolio more than firm performance.

Figure 1 helps visualize the impact of these two performance dimensions. The figure uses the estimates of model 3 to graph the relative performance against the proportion of self-citing patents. On the horizontal axis a unit increment corresponds to an increase of one standard deviation in the performance measure. In addition to showing that the firm performance line has little effect, the graph shows that the proportion of self-citing patents clearly increases as the technological performance relative to the aspiration level increases, but it increases more rapidly above the aspiration level. Above the aspiration level, a two standard deviation increase in performance increases self-citation by 35% whereas below the aspiration level the same shift only increases self-citations by 5%. Below the aspiration level, firms exhibit less sensitivity to changes in performance, a finding that fits better with threat-rigidity than prospect theory and with the kinked curve hypothesized by Greve (1998).

The patent models provide additional evidence of the sensitivity of technological activities to technological performance as opposed to firm performance. Model 4 reveals that large firms and firms that patented in the previous period also patent more frequently in the next period, though the small magnitude of the lagged patents coefficient suggests that patenting
varies tremendously from one year to the next. Firms also patent less as the industry matures and patent more as firm density increases. Model 5 shows no effect of firm performance, but model 6 shows a significant improvement again to including the technological performance variables. Interestingly, the coefficients reveal a tent shaped functional form. Above the aspiration level, performance increases lead to decreases in the patenting rate, whereas below the aspiration level performance increases stimulate patenting. The slope below the aspiration level fits threat-rigidity theory, but a lock-out phenomenon could also explain it. Declines in technological performance below the aspiration level may not lead to increases in the number of patents because technologists at the low end of the performance continuum have accumulated insurmountable knowledge gaps that prevent them from catching up technologically (Cohen and Levinthal, 1990).

Table 3 reports the results of the product models. Again, model 1 shows several significant coefficients for the control variables. Large firms and firms that introduced new products in the previous year introduce more new products. Product introductions also increase as the industry matures and decrease as the number of products introduced in the industry in the previous year rises. In model 2, the two performance variables strongly affect product entry while model 3 demonstrates that technological performance has no significant impact on the rate of product additions. Surprisingly, the coefficients for firm performance have different signs. The expected negative effect of performance on product additions appears below the aspiration level. However, above the aspiration level performance increases appear to increase the probability of product additions.
Turning to the models for product withdrawals, model 4 finds that large and old firms eliminate products more rapidly from their offerings. Firm density and the number of products withdrawn in the industry in the previous year reduce the probability that the firm removes some of its own products from the market whereas the passage of time has the opposite effect. Model 5 reveals that firm performance below the aspiration level reduces the rate of product withdrawals, but it has no effect above the aspiration level. Model 6 indicates that technological performance once again does not have any effect. A similar pattern of results emerges in the models for product attribute changes. Model 7 shows that large and old firms and firms that have introduced products that incorporate significant attribute changes in the past are more likely to do so in the future. Model 8 and model 9 tell us that firm performance decreases the probability of change below the aspiration level but has no significant effect above the aspiration level. Neither coefficient for technological performance is significant. Overall, these findings provide support for hypothesis 2, that firm performance in relation to the aspiration level lowers the rate of change in the product portfolio. As a group, firms above the aspiration level show greater inertia than poorly performing firms. Moreover, firms with performance below the aspiration level show an increasing rate of change as their performance falls further. The heightened sensitivity to changes in performance below the aspiration level seems consistent with the expectations of prospect theory.

--- Insert Figure 2 About Here ---

Graphic analysis can show the relationships between firm performance and the product variables more clearly. Again, on the horizontal axis a unit increase represents an increase of one standard deviation in firm performance. The vertical axis denotes the multiplier of the probability of making the different changes in the product portfolio; thus, a .10 increment indicates a 10%
probability increase. Figure 2 shows that the product additions curve takes a V-shaped form, with a steeper slope below the aspiration level than above it. The product withdrawal curve bends above the aspiration level. It descends rapidly as performance increases below the aspiration level and then above the aspiration level appears to become stable and nearly insensitive to change in performance. The curve for product attribute change, not shown, has virtually the same shape as the curve for product withdrawals.

The results of the growth models appear in table 4. Model 1 includes only the control variables. The log size coefficient of less than one indicates that large firms grow at a slower pace than small firms (Barron, West, and Hannan, 1994). Age also depresses sales growth, but the total number of products increases it. Model 2 adds the product variables and shows that the adoption of a new CPU or operating system increases sales growth, though only marginally significant. In model 3 the addition of the patent variables shows no effect. When product and patent variables both enter model 4, product changes continue to affect firm growth. Product additions suppress firm growth as suggested in hypothesis 3, whereas changes in product attributes boost firm growth as suggested by hypothesis 4. The proportion of self-citing patents does not appear to influence firm growth, in opposition to hypothesis 5. However, after entering the interaction term with size (model 5), both the main effect of self-citation and the interaction term show significant coefficients in the expected directions supporting hypothesis 6. The negative effect of the proportion of self-citing patents on firm performance appears to depend on firm size, applying only to small firms.
Graphical depictions clarify the impact of these effects on firm growth. In Figure 3, the decreasing line shows the negative impact of introducing new products on firm growth. Introducing a new product causes disruption and reduces firm growth but this effect decreases as the firm adds more and more products. It ranges between a reduction of 7% in firm growth when the firm goes from one new product to two new products and a reduction of 2% in firm growth when the firm goes from fourteen to fifteen new products. Nonetheless, if any of these new products constitute a significant change of product attributes the firm experiences a substantial improvement in performance corresponding to a 215% increase of sales growth, offering strong evidence that change in the product portfolio has multiple and conflicting effects on firm performance and that the right changes might justify the negative process consequences of implementing them.

--- Insert Figure 4 About Here ---

Figure 4 depicts the interaction effect of the proportion of self-citing patents and firm size on firm growth. Clearly, the propensity to self-cite has a negative impact on small firms. Focusing on the effect of a 10 point increase in the proportion self-citing from .10 to .20, we see that the negative effect goes from a 24% reduction in firm growth for firms with sales close to zero to a 7% reduction in firm growth for firms with $17 million in sales. When firms exceed $42 million in sales the negative effect vanishes and the propensity to self-cite has a noticeable positive effect on firm growth only when firms exceed the $1 billion mark in sales. Since 50% of our observations report sales below $16 million, the negative performance consequences of building on technology owned by the firm dominates in this industry.

Taken together our findings suggest a consistent pattern. Firm performance affects product strategy but has no effect on innovative activity. Meanwhile, technological performance
influences the nature of innovation within the firm. Both product and technological choices affect firm growth.

DISCUSSION

Does firm performance generate uniform behavioral consequences across multiple constituencies within the firm? Drawing on aspiration level theory, we have argued that different constituencies, in this case executives and technologists, aspire to diverse outcomes and that these varied goals lead to divergences in their response to firm performance. Our findings support this argument. Executives identify their performance with that of the organization. As a result, when organizational sales grow, they reduce change in the product portfolio. Technologists give greater weight to indicators relevant to their subunit’s activities. Though not affected by organizational growth, they exhibit inertia in patenting activities in response to technological success, consistent with aspiration level theory. In sum, firm performance does not appear to have uniform consequences throughout the organization, as often assumed in previous work. Nonetheless, the relationship between performance in relation to the aspiration level and change holds within constituencies, as aspiration level theory predicts.

This study also importantly finds that inertia in the product portfolio has multiple and diverging effects on firm performance. Firms that launch new products suffer a reduction in sales growth, though at a decreasing rate as the number of product additions increases. Presumably this effect arises because product launches require organizational adjustments that disrupt the normal functioning of the firm. Nevertheless, if any of the new products incorporates a significant attribute change, either a new processor or a different operating system, firms experience a substantial increase in firm growth that exceeds the negative process consequences of change.
Inertia in the patent portfolio also has important performance consequences. Firms that isolate themselves in technological space, as evidenced by a high proportion of self-citing patents, suffer a dramatic reduction in the growth rate. However, only small firms suffer from this effect, presumably because they do not have sufficient resources to compensate for missing technological opportunities.

Our findings contribute to the study of the consequences of performance on organizational behavior. Drawing primarily on aspiration level theory, most previous work treats the firm as a unitary actor and examines the effect of firm performance on firm behavior. Undoubtedly, this approach has proven effective and will continue to allow researchers to address unresolved issues, such as the precise functional form of the relationship between change and performance in relation to the aspiration level. Relying exclusively on this approach has a downside, however. It precludes researchers from investigating what happens inside the firm. By placing individuals in the organizational context, elucidating the influence of fundamental organizational processes on their behavior, and distinguishing between the roles of subunits and of the upper echelon, this study shows one way to overcome this limitation.

The findings raise the intriguing possibility that top executives operate as the main impediment to organizational change in successful firms. The psychological consequences of enduring firm success seems to concentrate at the top and may spread slowly throughout the organization because people lower in the hierarchy focus more on their subunit’s activities. While top executives develop an attachment to the products that made the firm successful and resist change, initiatives by technologists and other influential actors distant from the upper echelon can create a reservoir of innovations available for launch when the firm needs renewal. Nevertheless, these efforts likely lead nowhere because the psychological forces that reduce top
executives’ ability to change will also degrade their ability to recognize the opportunities for change created internally (Greve, 2000). Our findings as well as an in-depth analysis of the strategy process at Intel (Burgelman, 1994) provide some initial evidence consistent with such an account. However, establishing precise links between activities at different levels inside the firm will require additional research.

This study also contributes to the larger literature on organizational change and inertia. Although most previous research has implicitly assumed that the rigidity induced by firm success permeates the entire firm, organizational theorists have long held the view that inertial forces vary inside the firm. Structural inertia theory (Hannan and Freeman, 1984), for example, holds that the organization comprises core and peripheral features. Core features include the stated goals, the form of authority, the technology, and the market strategy. Peripheral features include inter-organizational arrangements, organizational charts, and personnel. It then argues that inertial forces act more strongly on core features than on peripheral features because core features lie close to the identity of the organization and changes that threaten that identity cause greater resistance. This study adds another perspective. It suggests that performance increases in relation to the aspiration level generate rigidity. The behavioral consequences of performance, however, will vary throughout the firm because distinct groups inside the organizations attend to different performance dimensions that correlate weakly (Meyer and Gupta, 1994).

The findings add to our understanding of the performance consequences of change in two ways. First, they lend support to the distinction between the process and the content effects of change (Barnett and Carroll, 1995). If we had included in our models a simple count of new products, we would have incorrectly concluded that change in the product portfolio depresses sales growth. The inclusion of a product attribute change variable, instead, offers a different and
more realistic picture, suggesting that for firms that made the right modifications in the product portfolio, change had a positive overall effect. The size of the process effect and of the content effect offer some insight about the tradeoff firms faced as they balanced their product offerings over time. In this industry, firms could have afforded to wait for a hit for some time because its beneficial impact exceeded the process costs of introducing thirty new products that merely refined existing products.

Second, they contribute to our understanding of the environmental contingencies under which inertia appears to be detrimental. Previous research has shown that inertia hurts firms when they face a clear need to change previously effective strategies. Typically, these studies use discrete and radical environmental modifications, such as regulatory changes, to identify times when high performing firms must alter their strategies to experience continued success (Audia et al., 2000; Haveman, 1992; Smith and Grimm, 1987). The effect of inertia in contexts characterized by substantial uncertainty about the timing and consequences of change has been less clear. In these environments, choosing to persist with a successful approach might constitute a rational response. Persistence allows organizations to minimize the risk of adopting inappropriate technologies and also gives them more time to understand what technologies and products have real potential (Hedberg, 1981; Schilling, 1998). Nevertheless, our results suggest that this conservative strategy offers a less effective approach than changing the product and patent portfolios in response to a shifting environment. Organizational learning likely drives this finding. Product failures provide useful information about the technological and marketing adjustments needed to succeed in future product development efforts (Sorenson, 2000). Similarly, efforts at developing new technologies later abandoned can help increase the
knowledge base of the firm and consequently its ability to recognize where the best opportunities for future technology development lie.

This study suggests that firms might benefit from maintaining a loose coupling between the goals of executives and those of other critical subunits. If organizational members attend to multiple performance dimensions that correlate weakly, loose coupling in the goal system will limit the diffusion of the inertial tendencies caused by firm success – a special case of the more general idea that loosely coupled systems can adapt more readily (Simon, 1962; Weick, 1976). Interestingly, this prescription contradicts agency theory, which recommends a tight alignment for organizational effectiveness (Jensen and Meckling, 1976), and the recent trend toward the use of compensation linked to company goals (e.g. stock options) throughout the organization. Thus, it is possible that unknowingly managers amplify the inertial effect of firm success by creating goal and reward systems tightly aligned to firm performance measures.

Our results suggest several avenues for future research. Although organizations make extensive use of multiple performance dimensions, it has been an uneasy task to accommodate their role in organization theories (Meyer and Gupta, 1994). Drawing on aspiration level theory, this study provides some guidance about the meaning of different performance dimensions for those who study the behavioral consequences of performance. In essence, it suggests that multiple performance dimensions matter because they direct the attention of distinct groups inside the firm and have important effects on their behavior. Although this study examined the effect of sales growth and technological performance, two dimensions particularly relevant to a newly emerging high-technology industry, future research should explore the differential effects of performance dimensions that play more important roles in mature industries. For example, researchers could study the differential effects of return on sales and return on assets, two
dimensions often treated as substitutes in empirical studies but that likely speak to distinct groups inside the firm.

Like previous research (Greve, 1998), our study shows that social aspiration levels have predictive power and therefore that they are likely to be the focus of attention for many organizations much of the time. Nevertheless, some executives may aspire to do substantially better or even worse than the average. Consideration of individual differences and of the composition of the top management teams might help researchers predict variations in aspiration levels within the industry. Functional backgrounds may also play a role in determining executives’ aspirations. For example, companies led by executives with sales backgrounds might exhibit greater behavioral inertia in the face of strong sales growth, whereas executives whose origins lie in the finance function might respond more strongly to accounting measures of performance (e.g. ROE). These same effects might apply to other influential groups in the strategy-making process. For example, researchers might examine whether success affects the decisions made by boards of directors (Finkelstein and Hambrick, 1996; Pfeffer and Salancik, 1978). Board members experience outside the focal organization might influence their expectations for the firm and hence influence their perceptions of firm performance. Teasing out the role of such micro level processes and how they contribute to the emergence of organizational inertia offers an interesting path for future research.

The structure of the organization may also influence the degree of differentiation in aspirations across constituencies within the firm. For example, a firm can either structure its research facilities into a central laboratory or disperse them throughout the organization. Centralized laboratories might reinforce the importance of technological metrics of success for these researchers because their day-to-day interactions occur only with other researchers.
Meanwhile, decentralized R&D workers interact more intensively with co-workers attuned to the importance of market success. Such interaction might generate sensitivity to market performance in technologists. Clearly, future research could focus on a host of interesting issues surrounding the influence of aspirations on organizational behavior. Such work could advance our understanding of the intra-organizational dynamics that lead to the emergence of organizational change.
REFERENCES

Abbot, A.

Allen, T.

Andrews, K. R.

Arrow, K. J.

Audia, P. G., E. A. Locke, and K. G. Smith

Barnett, W. P., and G. R. Carroll

Barnett, W. P., and J. Freeman

Barron, D. N., E. West, E., and M. T. Hannan
1994 “A time to grow and a time to die: Growth and mortality of credit unions in New York: 1914-1990.” American Journal of Sociology, 100: 381-421

Bromiley, P.
1991 “Testing a causal model of corporate risk taking and performance.” Academy of
Brown, S. and K. M. Eisenhardt

Burgelman, R. A.
1983  “A process model of internal corporate venturing in the diversified major firm.” Administrative Science Quarterly, 28: 223-244

Burns, T., and G. M. Stalker

Cameron, C., and P. Trivedi

Carpenter, M. P., F. Narin, and P. Wolf
1981  “Citation rates to technologically important patents.” World Patent Information, 3: 160-163

Cohen, W. M., and D. A. Levinthal

Cyert, R. M., and J. G. March

DiPrete, T. A., and J. D. Forristal
1994  “Multi-level models: Methods and substance.” Annual Review of Sociology, 20: 331-357
**Dosi, G.**


**Dougherty D., and C. Hardy**


**Elsbach, K.**


**Festinger, L.**


**Finkelstein, S., and D. C. Hambrick**


**Gomes Mejia, L. R., and T. M. Melbourne**


**Greene, W. H.**


**Greve, H. R.**

2000  “Deciding to innovate: Performance, aspirations, and slack.” Unpublished manuscript, University of Tsukuba

Greve, H. R., and A. Taylor


Hall, B., A. Jaffe, and M. Trajtenberg


Hambrick, D. C., and P. A. Mason


Hannan, M. T., and J. Freeman


Haveman, H. A.

1992  “Between a rock and a hard place: Organizational change and performance under conditions of fundamental environmental transformation.” Administrative Science Quarterly, 37: 48-75

Hedberg, B. L. T.


Henderson, R. M., and K. B. Clark

Hiltzik, M.

Ijiri, Y., and H. A. Simon

Jensen, M. C., and W. H. Meckling

Kahneman, D. and A. Tversky

Kelly, D., and T. L. Amburgey

Kidder, T.

Kuhn, T.
1962   The Structure of Scientific Revolutions. Chicago, IL: Chicago University Press

Lant, T. K., F. J. Milliken, and B. Batra

Lawrence, P. R., and J. W. Lorsch
Levinthal, D. A., and J. G. March  

Locke, E. A., and G. P. Latham  

Maddala, G.  
1986  Limited-Dependent and Qualitative Variables in Econometrics. Cambridge: Cambridge University Press.

March, J. G.  

March, J.G., and Z. Shapira  

March, J. G., and H. A. Simon  

Merton, R. K.  

Meyer, M. W., and V. Gupta  
1994  “The performance paradox.” In B. M. Staw and L. L. Cummings (eds.), Research in

Miller, D., and M-J Chen


Nelson, R. R.


Perrow, C.


Pfeffer, J., and G. R. Salancik


Prahalad, C. K., and Bettis, R. A.


Roberts, E. B.


Schilling, M. A.

Simon, H. A.

Singh, J. V.

Smith, K. G., and C. M. Grimm

Sørensen, J. B., and T. E. Stuart

Sorenson, O.

Staw, B. M., L. E. Sandelands, and J. E. Dutton

Stern, S.
1999 “Do scientists pay to be scientists?” NBER working paper 7410.

Stinchcombe, A. L.
Trajtenberg, M.

Virany, B., M. L. Tushman, and E. Romanelli

Weelwright, S. C., and K. B. Clark

Weick, K. E.
Table 1: Descriptive Statistics and Correlations

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>S.D.</th>
<th>1.</th>
<th>2.</th>
<th>3.</th>
<th>4.</th>
<th>5.</th>
<th>6.</th>
<th>7.</th>
<th>8.</th>
<th>9.</th>
<th>10.</th>
<th>11.</th>
<th>12.</th>
<th>13.</th>
<th>14.</th>
<th>15.</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Firm performance – aspiration level (above) (t-1)</td>
<td>.24</td>
<td>.57</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2. Firm performance – aspiration level (below) (t-1)</td>
<td>-.23</td>
<td>.66</td>
<td>.15**</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>3. Technological performance – aspiration level (above) (t-1)</td>
<td>.060</td>
<td>.304</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>4. Technological performance – aspiration level (below) (t-1)</td>
<td>-3.83</td>
<td>1.55</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>5. Log size</td>
<td>16.53</td>
<td>2.39</td>
<td>.13**</td>
<td>.24**</td>
<td>.26**</td>
<td>.34**</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>6. Age</td>
<td>2.92</td>
<td>3.02</td>
<td>.09*</td>
<td>-.18**</td>
<td>.07*</td>
<td>.19**</td>
<td>.38**</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>7. Density</td>
<td>50.25</td>
<td>16.24</td>
<td></td>
<td></td>
<td>.04</td>
<td></td>
<td></td>
<td>.07*</td>
<td>.11**</td>
<td>-02</td>
<td></td>
<td>.22**</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>8. Patents in industry (t-1)</td>
<td>343.46</td>
<td>269.66</td>
<td>-.09*</td>
<td>.06</td>
<td>.08*</td>
<td>.13**</td>
<td>-02</td>
<td>.09*</td>
<td>.77**</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>9. Product additions in industry (t-1)</td>
<td>110.48</td>
<td>65.78</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>.01</td>
<td>.02</td>
<td>.01</td>
<td>.00</td>
<td>.22**</td>
<td>.55**</td>
<td>.03</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>10. Product withdrawals in industry (t-1)</td>
<td>60.40</td>
<td>45.09</td>
<td></td>
<td></td>
<td>-.02</td>
<td>.01</td>
<td>.02</td>
<td>.01</td>
<td>.00</td>
<td>.21**</td>
<td>.49**</td>
<td>-.02</td>
<td>.95**</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>11. Product attribute change in industry (t-1)</td>
<td>2.91</td>
<td>1.24</td>
<td></td>
<td></td>
<td>-.06</td>
<td>.05</td>
<td>.06</td>
<td>.07*</td>
<td>.00</td>
<td>.15**</td>
<td>.71**</td>
<td>.49**</td>
<td>.64**</td>
<td>.59**</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>12. Proportion of self-citing patents</td>
<td>.04</td>
<td>.13</td>
<td></td>
<td></td>
<td>.02</td>
<td>.03</td>
<td>.58**</td>
<td>.53**</td>
<td>.23**</td>
<td>.04</td>
<td>.06</td>
<td>.12**</td>
<td>-.03</td>
<td>-.05</td>
<td>.03</td>
<td></td>
<td></td>
</tr>
<tr>
<td>13. Patents</td>
<td>5.69</td>
<td>28.76</td>
<td></td>
<td></td>
<td></td>
<td>.00</td>
<td>.00</td>
<td>.85**</td>
<td>.45**</td>
<td>.21**</td>
<td>.03</td>
<td>.09*</td>
<td>.13**</td>
<td>-01</td>
<td>-.02</td>
<td>.06</td>
<td>.63**</td>
</tr>
<tr>
<td>14. Product additions</td>
<td>2.04</td>
<td>3.75</td>
<td></td>
<td></td>
<td>.09*</td>
<td>.02</td>
<td>.22**</td>
<td>.18**</td>
<td>.47**</td>
<td>.36**</td>
<td>.06</td>
<td>-.09*</td>
<td>.27**</td>
<td>.26**</td>
<td>.13**</td>
<td>.17**</td>
<td>.15**</td>
</tr>
<tr>
<td>15. Product withdrawals</td>
<td>1.08</td>
<td>3.21</td>
<td></td>
<td></td>
<td>-.10**</td>
<td>.19**</td>
<td>.20**</td>
<td>.42**</td>
<td>.48**</td>
<td>.06</td>
<td>-.06</td>
<td>.22**</td>
<td>.24**</td>
<td>.12**</td>
<td>.15**</td>
<td>.07</td>
<td>.64**</td>
</tr>
<tr>
<td>16. Product attribute change</td>
<td>.06</td>
<td>.13</td>
<td></td>
<td></td>
<td>.09*</td>
<td>-.02</td>
<td>.04</td>
<td>.14**</td>
<td>.23**</td>
<td>.19**</td>
<td>.00</td>
<td>-.01</td>
<td>.04</td>
<td>.04</td>
<td>.10**</td>
<td>.06</td>
<td>.05</td>
</tr>
</tbody>
</table>

N = 677; * p ≤ .05; ** p ≤ .01
Table 2: Models of Patenting Behavior

<table>
<thead>
<tr>
<th></th>
<th>Proportion Self-Citing (OLS)</th>
<th>Patents (negative binomial)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>1.</td>
<td>2.</td>
</tr>
<tr>
<td>Dependent (t-1)</td>
<td>.627***</td>
<td>.628***</td>
</tr>
<tr>
<td></td>
<td>(.036)</td>
<td>(.036)</td>
</tr>
<tr>
<td>Size</td>
<td>.005**</td>
<td>.005**</td>
</tr>
<tr>
<td></td>
<td>(.002)</td>
<td>(.002)</td>
</tr>
<tr>
<td>Age</td>
<td>-.002</td>
<td>-.002</td>
</tr>
<tr>
<td></td>
<td>(.002)</td>
<td>(.002)</td>
</tr>
<tr>
<td>Density</td>
<td>.000</td>
<td>.000</td>
</tr>
<tr>
<td></td>
<td>(.000)</td>
<td>(.000)</td>
</tr>
<tr>
<td>Patents in industry</td>
<td>.000</td>
<td>.000</td>
</tr>
<tr>
<td>(t-1)</td>
<td>(.000)</td>
<td>(.000)</td>
</tr>
<tr>
<td>Year</td>
<td>-.002</td>
<td>-.002</td>
</tr>
<tr>
<td></td>
<td>(.002)</td>
<td>(.002)</td>
</tr>
<tr>
<td>Firm performance –</td>
<td>.007</td>
<td>.006</td>
</tr>
<tr>
<td>aspiration level</td>
<td>(above)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(.008)</td>
<td>(.007)</td>
</tr>
<tr>
<td>Firm performance –</td>
<td>-.001</td>
<td>.005</td>
</tr>
<tr>
<td>aspiration level</td>
<td>(below)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(.007)</td>
<td>(.006)</td>
</tr>
<tr>
<td>Technological</td>
<td>.104***</td>
<td></td>
</tr>
<tr>
<td>perform –aspiration</td>
<td>(above)</td>
<td></td>
</tr>
<tr>
<td>level</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Technological</td>
<td>.017***</td>
<td></td>
</tr>
<tr>
<td>perform –aspiration</td>
<td>(below)</td>
<td></td>
</tr>
<tr>
<td>level</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Ln (alpha)</td>
<td>1.75***</td>
<td>1.75***</td>
</tr>
<tr>
<td></td>
<td>(.118)</td>
<td>(.118)</td>
</tr>
<tr>
<td>Log likelihood</td>
<td>-691.97</td>
<td>-691.95</td>
</tr>
<tr>
<td>Log Likelihood test</td>
<td>.04 (2)</td>
<td>129.9*** (2)</td>
</tr>
<tr>
<td>χ² (d. f.)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>R squared</td>
<td>.42</td>
<td>.42</td>
</tr>
<tr>
<td>N</td>
<td>487</td>
<td>487</td>
</tr>
</tbody>
</table>

Standard errors in parentheses
* p ≤ .10 ; ** p ≤ .05; *** p ≤ .01
Table 3: Models of Product Strategy

<table>
<thead>
<tr>
<th></th>
<th>Product additions (negative binomial)</th>
<th>Product withdrawals (negative binomial)</th>
<th>Product attribute change (probit)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dependent (t-1)</td>
<td>1. 0.10*** (.018)</td>
<td>2. 0.086*** (.018)</td>
<td>3. 0.086*** (.018)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>4. 0.034 (.026)</td>
<td>5. 0.018 (.025)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>6. 0.016 (.025)</td>
<td>7. 1.58*** (.433)</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>8. 1.59*** (.435)</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>9. 1.59*** (.437)</td>
</tr>
<tr>
<td>Size</td>
<td>0.304*** (.028)</td>
<td>0.353*** (.034)</td>
<td>0.359** (.035)</td>
</tr>
<tr>
<td></td>
<td>0.256*** (.036)</td>
<td>0.314*** (.041)</td>
<td>0.309*** (.044)</td>
</tr>
<tr>
<td></td>
<td>0.247*** (.030)</td>
<td>0.280*** (.033)</td>
<td>0.285*** (.035)</td>
</tr>
<tr>
<td>Age</td>
<td>0.003 (.024)</td>
<td>-0.018 (.025)</td>
<td>-0.016 (.026)</td>
</tr>
<tr>
<td></td>
<td>0.197*** (.032)</td>
<td>0.167*** (.033)</td>
<td>0.168*** (.034)</td>
</tr>
<tr>
<td></td>
<td>0.091*** (.025)</td>
<td>0.079*** (.026)</td>
<td>0.078*** (.026)</td>
</tr>
<tr>
<td>Density</td>
<td>-0.005 (.005)</td>
<td>-0.003 (.005)</td>
<td>-0.002 (.005)</td>
</tr>
<tr>
<td></td>
<td>-0.002 (.005)</td>
<td>0.000 (.005)</td>
<td>0.000 (.005)</td>
</tr>
<tr>
<td>Dependent in industry (t-1)</td>
<td>-0.004* (.002)</td>
<td>-0.005* (.002)</td>
<td>-0.005* (.002)</td>
</tr>
<tr>
<td></td>
<td>-0.008 (.004)</td>
<td>-0.007 (.004)</td>
<td>-0.009 (.004)</td>
</tr>
<tr>
<td></td>
<td>-0.009 (.004)</td>
<td>-0.010** (.004)</td>
<td>-0.009** (.004)</td>
</tr>
<tr>
<td></td>
<td>-0.008 (.007)</td>
<td>-0.009 (.007)</td>
<td>-0.009 (.007)</td>
</tr>
<tr>
<td>Year</td>
<td>0.127** (.049)</td>
<td>0.143*** (.048)</td>
<td>0.143*** (.048)</td>
</tr>
<tr>
<td></td>
<td>0.199*** (.074)</td>
<td>0.207*** (.075)</td>
<td>0.200*** (.075)</td>
</tr>
<tr>
<td></td>
<td>0.044 (.027)</td>
<td>0.042 (.028)</td>
<td>0.044 (.028)</td>
</tr>
<tr>
<td>Firm performance – aspiration level (above)</td>
<td>0.240** (.097)</td>
<td>0.236** (.097)</td>
<td>0.079 (.130)</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>0.079 (.130)</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>0.136 (.099)</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>0.129 (.099)</td>
</tr>
<tr>
<td>Firm performance – aspiration level (below)</td>
<td>-0.297*** (.094)</td>
<td>-0.306*** (.095)</td>
<td>-0.397** (.154)</td>
</tr>
<tr>
<td></td>
<td>-0.396** (.153)</td>
<td></td>
<td>-0.283*** (.099)</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>-0.289*** (.100)</td>
</tr>
<tr>
<td>Technological perform – aspiration level (above)</td>
<td>.025 (.171)</td>
<td>.124 (.267)</td>
<td>-1.61 (.228)</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>.006 (.048)</td>
</tr>
<tr>
<td>Technological perform – aspiration level (below)</td>
<td>-0.031 (.043)</td>
<td>-.005 (.057)</td>
<td>.006 (.048)</td>
</tr>
<tr>
<td>Alpha</td>
<td>.946*** (.133)</td>
<td>.861*** (.126)</td>
<td>.863** (.127)</td>
</tr>
<tr>
<td></td>
<td>.2.01** (.270)</td>
<td>1.92*** (.263)</td>
<td>1.93*** (.265)</td>
</tr>
<tr>
<td>Log likelihood</td>
<td>-790.81 (799.16)</td>
<td>-788.25 (790.81)</td>
<td>-675.09 (670.82)</td>
</tr>
<tr>
<td></td>
<td>-670.82 (670.82)</td>
<td>-668.65 (668.65)</td>
<td>-257.41 (253.04)</td>
</tr>
<tr>
<td></td>
<td>-251.87 (251.87)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Log likelihood</td>
<td>16.70*** (2)</td>
<td>5.12* (2)</td>
<td>8.36** (2)</td>
</tr>
<tr>
<td>Test χ² (d. f.)</td>
<td>(2)</td>
<td>(2)</td>
<td>(2)</td>
</tr>
<tr>
<td>N</td>
<td>518</td>
<td>518</td>
<td>518</td>
</tr>
</tbody>
</table>

Standard errors in parentheses

* p ≤ .10; ** p ≤ .05; *** p ≤ .01
Table 4: Models of Organizational Sales Growth

<table>
<thead>
<tr>
<th></th>
<th>1.</th>
<th>2.</th>
<th>3.</th>
<th>4.</th>
<th>5.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Log (size)</td>
<td>.456***</td>
<td>.448***</td>
<td>.454***</td>
<td>.441***</td>
<td>.414***</td>
</tr>
<tr>
<td></td>
<td>(.050)</td>
<td>(.049)</td>
<td>(.054)</td>
<td>(.055)</td>
<td>(.055)</td>
</tr>
<tr>
<td>Age</td>
<td>-.099***</td>
<td>-.110***</td>
<td>-.126***</td>
<td>-.142***</td>
<td>-.151***</td>
</tr>
<tr>
<td></td>
<td>(.031)</td>
<td>(.033)</td>
<td>(.037)</td>
<td>(.039)</td>
<td>(.038)</td>
</tr>
<tr>
<td>Density</td>
<td>.004</td>
<td>.004</td>
<td>.006</td>
<td>.005</td>
<td>.005</td>
</tr>
<tr>
<td></td>
<td>(.005)</td>
<td>(.005)</td>
<td>(.006)</td>
<td>(.006)</td>
<td>(.006)</td>
</tr>
<tr>
<td>Number of products</td>
<td>.040**</td>
<td>.057***</td>
<td>.050***</td>
<td>.088***</td>
<td>.090***</td>
</tr>
<tr>
<td></td>
<td>(.012)</td>
<td>(.016)</td>
<td>(.014)</td>
<td>(.020)</td>
<td>(.020)</td>
</tr>
<tr>
<td>Product additions</td>
<td>-.039</td>
<td>-.078**</td>
<td>-.083***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(.026)</td>
<td>(.032)</td>
<td>(.031)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Products withdrawals</td>
<td>.012</td>
<td>.014</td>
<td>.010</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(.018)</td>
<td>(.023)</td>
<td>(.022)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Attribute changes</td>
<td>.604*</td>
<td>.789**</td>
<td>.781**</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(.354)</td>
<td>(.395)</td>
<td>(.390)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Patents</td>
<td>.001</td>
<td>.002</td>
<td>.001</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(.003)</td>
<td>(.003)</td>
<td>(.003)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Self-citing</td>
<td>-.187</td>
<td>-.108</td>
<td>-11.22***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(.582)</td>
<td>(.579)</td>
<td>(3.62)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Log (size) X Self-citing</td>
<td></td>
<td></td>
<td></td>
<td>.634***</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>(.204)</td>
<td></td>
</tr>
<tr>
<td>R square (within)</td>
<td>.26</td>
<td>.27</td>
<td>.28</td>
<td>.30</td>
<td>.32</td>
</tr>
<tr>
<td>N</td>
<td>523</td>
<td>523</td>
<td>436</td>
<td>436</td>
<td>436</td>
</tr>
</tbody>
</table>

Standard errors in parentheses
* ≤ .10 ; ** p ≤ .05; *** p ≤ .01
Figure 1: Technological and firm performance and proportion of self-citing patents:

Change in the proportion of self-citing patents

Performance - Aspiration
Figure 2: Firm performance and product additions and withdrawals

- Firm performance - Aspiration
- Change in the multiplier rate of product additions and withdrawals

Legend:
- Pink triangles: Product withdrawals
- Blue triangles: Product additions
Figure 3: Product additions, product attribute change, and firm growth
Figure 4: Proportion of self-citing patents, firm size, and firm growth