Selection-based Learning: The Coevolution of Internal and External Selection in High-velocity Environments

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To understand the effects of selection on firm-level learning, this study synthesizes two contrasting views of evolution. Internal selection theorists view managers in multiproduct firms as the primary agents of evolutionary change because they decide whether individual products and technologies are retained or eliminated. In contrast, external selection theorists contend that the environment drives evolution because it determines whether entire firms live or die. Though these theories differ, they describe tightly interwoven processes. In assessing the coevolution of internal and external selection among personal computer manufacturers across a 20-year period, we found that (1) firms learned cumulatively and adaptively from internal and partial external selection, the latter occurring when the environment killed part but not all of a firm; (2) internal and partial external selection coevolved, as each affected the other's future rate and the odds of firm failure; (3) partial external selection had a greater effect on future outcomes than internal selection; and (4) the lessons gleaned from prior selection were reflected in a firm's ability to develop new products, making that an important mediator between past and future selection events.●

Theories of evolutionary change deal with variation, selection, and retention (Aldrich, 1999), yet scholars differ as to whether management or the environment is the primary driver of those processes. Research on technological change has detailed how scientific breakthroughs set off periods of ferment (variation), followed by eras when industries sift through technical alternatives and converge on a dominant design (selection) and then by long periods of incremental change, in which a few players come to dominate (retention) (Schumpeter, 1942; Tushman and Anderson, 1986; Dosi, 1988). Similarly, organizational ecologists argue that startups are the primary source of new organizational forms (variation). After their birth, various forms compete for resources as the environment culls out misfits (selection) until, finally, survivors' routines closely match the demands of their chosen niche (retention) (Hannan and Freeman, 1989; Carroll and Hannan, 2000). Because the ecology and technological change literatures emphasize how the environment picks the firms that survive and fail, they embody theories of external selection. Such theories view established firms as bundles of routines that evolve incrementally along smooth trajectories in which small organizational changes are possible, but major departures are rare and increase the odds of failure. According to this view, (a) novel technologies and organizational designs arise chiefly from new firms; (b) old technologies and organizational forms disappear because established firms fail; and (c) established firms may adapt to a single, large environmental jolt (Haveman, 1992, 1993), but long-term survival is doubtful in high-velocity settings that continually render existing skills obsolete (Tushman and Anderson, 1986; Amburgey, Kelly, and Barnett, 1993; Barron, West, and Hannan, 1994; Dobrev, Kim, and Hannan, 2001). External selectionists conclude, then, that the environment is the primary evolutionary agent, because managers in established firms mostly react to its moves, often maladaptively.

0001-8392/04/4901-0039/$3.00.

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We are indebted to Chris Ahmadjian, Mason Carpenter, Alison Davis-Blake, Don Hambrick, George Huber, Jeff Martin, Marc-David Seidel, Jim Wade, Jim Westphal, Editor Don Palmer, Managing Editor Linda Johanson, and three anonymous reviewers for their valuable comments on earlier drafts of this paper, and to Jungzheng Ding for his help in data coding. This research has benefited from the generous financial support of the Kelleher Center for Entrepreneurship, Growth, and Renewal.

In contrast, other research has described internal selection processes in established multiproduct firms, in which front-line managers and employees propose numerous initiatives (variation), which then compete for corporate resources and top management attention (selection) until a few surviving projects remain that receive substantial backing (retention) (Bower, 1970; Burgelman, 1983, 1991, 2002; Noda and Bower, 1996). Internal selection is distinct from wholesale changes in a firm's core activity or form, such as switches in the formats of radio stations (Greve, 1998) or movements along fitness landscapes (Levinthal, 1997), which affect all of a firm's outputs by altering the pipeline of processes that every product must traverse. Rather, internal selection theory allows that a firm may be internally diverse, with a portfolio of projects and technologies that arise through bottom-up initiatives. Managers are seen as the primary evolutionary agents because they frequently anticipate the environment's moves and adjust, often well before a firm's current approaches have stopped working. Even in old, well-established companies, front-line supervisors can proactively suggest a wide variety of new projects, and by shifting resources to new projects from less promising ones, executives can alter their firms either slightly or radically. Not all such moves are adaptive, since internal politics skew resource allocations, nor do they reflect rational planning, since internal variations include bootlegged projects that arise without top managers' approval (Burgelman, 1994). Nevertheless, bottom-up proposals enhance internal variety and allow experimentation, so they are seen as a powerful means of renewing established firms and mitigating threats posed by dramatic external change (Burgelman, 1983, 1991; Miner, 1990, 1991).

As this discussion suggests, the internal and external selection literatures are largely disjoint in their theory and proposed effects. That is troubling, since organizational learning links the internal and external realms, especially in high-velocity settings in which a firm can quickly develop new products and technological variations. Learning is a cumulative process in which elements of prior experience are retained that lead to systematic changes in future behavior (Levitt and March, 1988; Miner and Haunschild, 1995). That may occur, for instance, through a series of internal selection events, in which a firm tries out several products and then jettisons those whose technologies appear less promising, thus reducing the threat of environmental selection. Also, while external selection has been equated with an organization's death, a firm may survive even though the environment kills some of its products, as happened with the Ford Edsel, the IBM PC Jr., and Coca Cola's New Coke. Because environmental selection need not equate with organizational failure, it is important to ask if the death of some of a firm's products prods it to learn about its environment in ways that affect its future decisions about internal selection.

To date, research on internal selection has focused on large, diversified, and relatively successful firms, which begs the question of how they attained that status and whether smaller and less successful organizations behave differently. Aside from Miner's (1990, 1991) study of the internal selection rates of idiosyncratic jobs in a single large organization, internal selection research is based almost entirely on case studies, so the number of specific hypotheses formulated and systematically tested is quite small. Typically, those case studies have covered a narrow slice of time relative to the phenomena of interest. For example, Burgelman (1983) observed several projects across a 15-month period, yet he noted that project life cycles often exceed a decade. Thus we can conclude little about the long-term coevolution of firms and the projects within them. By considering bottom-up managerial initiatives and internal selection decisions along with the external selection environment over time, we stand to gain a better understanding of how firms evolve and why they differ in their abilities to cope with fast-paced external change.

While ecologists, learning theorists, and technology scholars have amassed an impressive body of research (Baum, 1996; Carroll and Hannan, 2000), none of those studies has considered how internal and external selection might coevolve and influence one another, particularly in high-velocity environments, which are defined by rapid and often discontinuous changes in demand, competitors, and technology (Eisenhardt and Bourgeois, 1988). In such settings, firms experience selection events frequently and repeatedly as innovation renders older technologies obsolete. Selection events are a potential engine of organizational learning because they trigger repeated trial-and-error searches, and the lessons derived from prior investigations can gradually accumulate and guide future actions. Our empirical setting, the personal computer (PC) industry from 1975 to 1994 is a prototypical high-velocity environment that has witnessed many abrupt changes in technologies and competitors, resulting in rapid shifts in demand for existing products (Eisenhardt, 1989).

To examine how internal and external selection may influence one another, we focus on three product-level events, which for our purposes, are mutually exclusive: (1) internal selection, in which a firm's managers proactively remove a product from the market before it becomes obsolete, an act that frees resources to develop new technologies; (2) partial external selection, in which the environment kills a product but leaves its host firm alive; and (3) full external selection, in which a product dies because the environment kills the entire organization in which it resides. We consider what a firm may learn about changes in technology and customer demands from the non-fatal product-level selection events in its past and develop hypotheses about how such learning drives future evolution.

COEVOLUTION OF INTERNAL AND EXTERNAL SELECTION

Qualitative case studies of resource allocation processes form the backbone of research on internal selection (Bower, 1970; Burgelman, 1983, 1991, 1994; Noda and Bower, 1996). That work details a bottom-up, emergent process of organizational change in which front-line, mid-level, and top managers play distinct but interlocking roles. Front-line managers, who are close to the market and understand key technologies, function as entrepreneurs who create strategic initiatives by proposing new products and ways to reach new customers. From these proposals, mid-level managers endorse chosen ones and broker deals with top executives and other mid-level managers to obtain the resources needed to pursue them. Since mid-level managers put their careers and reputations on the line with these proposals, they scrutinize them heavily before backing them. In comparison, top executives usually lack the knowledge to assess a project's economic and technical merits, so they focus on the credibility and track records of the sponsoring middle managers and seldom reject their recommendations.

To select among competing projects, middle managers must forecast future shifts in technology, competition, and customer demand. Since they are boundedly rational, managers' internal selection decisions are often flawed, yet those forecasts are typically a good deal better than random guesses, particularly in firms that can extrapolate from their experience and combine that information with real-time market feedback. While managers often misjudge the long-range potential of ideas that are still on the drawing board, technology evolves along quasi-predictable trajectories (Dosi, 1988), so firms can use their experience to interpret incoming market feedback and make moderately informed, forward-looking decisions about whether to kill or sustain existing offerings and whether to intensify the search for new technological variations.

Forecasting plays little role in external selection theory, but it is a daily fact of life in most organizations. Publicly traded firms must forecast their earnings to Wall Street. Marketing managers must forecast consumer preferences to decide which products to stock. And R&D managers must look ahead to decide what products to develop. Such forecasting may work poorly in the face of disruptive technologies or radical innovations, yet even in their midst, firms like IBM, Honda, and Hewlett-Packard have prospered due to bottom-up initiatives that have given them diverse technological portfolios from which to choose (Christensen, 1997), a process central to internal selection theory. While comparing the efficacy of forecasting and internal selection in eras of radical and non-radical change is beyond the scope of this study, their effects are important in both types of environments.

While internal selection theory describes how processes of variation, selection, and retention transform existing firms, external selectionists maintain that (a) the durable nature of a firm's founding imprint constrains its future changes; (b) stakeholders demand reliability, so external selection favors inertial organizations that reproduce their actions despite environmental change; and (c) while some major changes might offer long-run benefits, technical and sociopolitical forces make them difficult to implement because they decrease near-term reliability (Stinchcombe, 1965; Hannan and Freeman, 1984; Amburgey, Kelly, and Barnett, 1993). As a technology becomes established, incumbent firms develop deep structures and rigid paradigms that channel their routines and information processing (Tushman and Anderson, 1986; Henderson and Clark, 1990; Sørensen and Stuart, 2000). And while that process increases their competencies in existing technologies, it inhibits their ability to learn about and adapt to new ones. Established firms sometimes experiment and take risks (variation), but as they grow larger and older, such exploration is gradually driven out by exploitation (selection and retention), consisting of incremental refinements to the status quo (Cyert and March, 1963; March, 1991; Levinthal and March, 1993). This evolutionary bias toward exploitation gradually reduces the internal variety of established firms, which limits their ability to cope with environmental change and makes them less likely than startups to create new technologies. Like the technical change and ecology literatures, the organizational learning literature therefore concludes that young firms are the primary source of new ideas, and established firms with old ideas are the likely victims of environmental selection. As this discussion makes apparent, internal and external selectionists have contrasting ideas, the former viewing firms as loosely linked portfolios of multiple products and varied technologies, and the latter seeing firms as monolithic, indivisible wholes.

Internal selectionists think of firms as portfolios, and as Burgelman's (1994) case history of Intel's exit from the semiconductor memory business demonstrated, no product is indispensable to an organization, even those believed to embody most the firm's core technology and social identity. Survival following such a business exit is possible because links among products are rather weak, as evidenced by the latitude that front-line managers have to pursue the technologies, product features, production schedules, and markets they see fit (Bower, 1970; Burgelman, 1983, 1994, 2002). Front-line managers function, then, as independent entrepreneurs rather than cogs in an integrated corporate machine. Because their interactions are largely limited to drawing generic inputs from the same stockpile (e.g., cash, manufacturing capacity), they typically face pooled interdependencies, which require minimal coordination, not sequential or reciprocal ones that are harder to manage (Thompson, 1967). As a result, the death of one product has little operational effect on others, and each of a firm's offerings serves as an interchangeable backup that helps to insure the survival of the larger organization. In comparison, external selection theorists view a firm as a monolithic whole. While they distinguish between a firm's core and periphery (Singh, House, and Tucker, 1986), they assert that there is only one core per organization, and meddling with it tends to reset the liability-of-newness clock and increase the odds of failure (Amburgey, Kelly, and Barnett, 1993; Hannan and Freeman, 1984). While internal selectionists emphasize the autonomy and interchangeability of product-based technologies, external selectionists assert that a firm's core, and particularly its bundle of key technologies, forms an interlocking whole whose operation is rendered unreliable if any of its pieces are changed or replaced.

These two views lead to different predictions about the environments to which a firm can adapt. In external selection theory, rapid environmental change is antithetical to survival, since a firm must either preserve its core and risk obsolescence or change its core frequently and risk the reliability of its operations. External selectionists are pessimistic, then, about organizational adaptation in high-velocity settings that continually render existing skills obsolete (Barron, West, and Hannan, 1994; Ranger-Moore, 1997). In comparison, internal selectionists observe that multiproduct firms can run on-line experiments and retain those that seem likely to improve external fit. Multiproduct firms are believed to be able to survive and even flourish in a variety of environments, including fast-changing ones, because middle managers can support the internal variations that better match external demands at a given time (Burgelman, 1994). Although these views seem to conflict, key aspects of each can be reconciled by reconsidering the concept of a firm's core and its relationship to the environment.

According to internal selection theory, firms in high-velocity environments are usefully viewed as collections of products and development efforts, most of which are loosely linked. While each embodies variants of a firm's core technologies, any particular product can be selected out by either the environment or the firm's managers without killing the entire organization. The technological piece of an organization's core is better portrayed, then, as multipart and modular rather than monolithic. In contrast, external selection theory's view of firms as having a single, monolithic core coalesced from studies of newspapers and labor unions (e.g., Carroll, 1984, 1985; Hannan and Freeman, 1987), and because those organizations offered a single product, it was reasonable to view them as having an indivisible core. That, however, is less fitting in high-velocity settings in which opportunities for technical differentiation abound, industry mythology glorifies innovation and bottom-up entrepreneurship, and products are developed in fast cycles so that even a single team, as it repeatedly amends its earlier choices, can create multiple offerings with varied technologies (Kidder, 1981; Florida and Kenney, 1990; Eisenhardt and Tabrizi, 1995). An environment that encourages bottom-up innovation, technical variety, and loose coupling among products allows for selection events not accounted for in external selection theory.

Selection Events in High-velocity Environments

If firms are multipart and modular, then either a firm's managers or the environment might select out a product and its associated technologies, so living products are at risk of experiencing one of three mutually exclusive selection events. First, a firm's managers may decide to withdraw a product from the market, even though it is performing reasonably and remains viable in the current environment, an instance of internal selection. In that case, middle managers move proactively to free resources for other uses, such as developing new technologies, actions that internal selectionists have emphasized (Bower, 1970; Miner, 1990, 1991; Burgelman, 1991, 1994). For example, Hewlett-Packard introduced two personal computers in its Vectra line in early 1991, with Intel 386 processors running at 16 and 20 MHz. By 1992, their annual sales had increased 33 percent and 216 percent, respectively, yet each was internally selected to make way for five new Vectras based on Intel 486 processors, running at 25 to 66 MHz. By 1993, each of those newer models had at least doubled its sales, yet all five were internally selected to make room for the Pentium-based machines that HP had begun to deploy.

Although eliminating a viable, revenue-producing product seems counterintuitive, it is quite common in high-velocity settings, in which obsolescence occurs quickly and once a new technology is introduced, demand for older versions plummets. In the PC industry, prices of older products often drop by 50 percent in the months after new technology supersedes them, so firms caught with obsolete inventory incur losses as market prices drop below production costs (Magretta, 1998). To see how this affects selection decisions, we interviewed several middle managers working in high-velocity industries. The response of one who worked for a PC manufacturer was representative. His goal, he said, was to kill a product before its sales had fallen 10 percent from their historical peak, because (1) larger decreases created enough unused production capacity to increase unit costs; (2) a single obsolete product could poison the image of an entire product line; and (3) suppliers had little desire to continue making components based on older technologies, so they would raise prices on items with declining demand to encourage shifts to newer alternatives. Given the industry's narrow profit margins, any of those shifts, the manager reported, would generate losses if not preempted by internal selection. It usually took several months to clear a product's production and marketing pipelines, so internal selection required reasonably accurate forecasts of future demand. Those could easily be misjudged, but managers had clear incentives and intentions to make that sort of preemptive move.

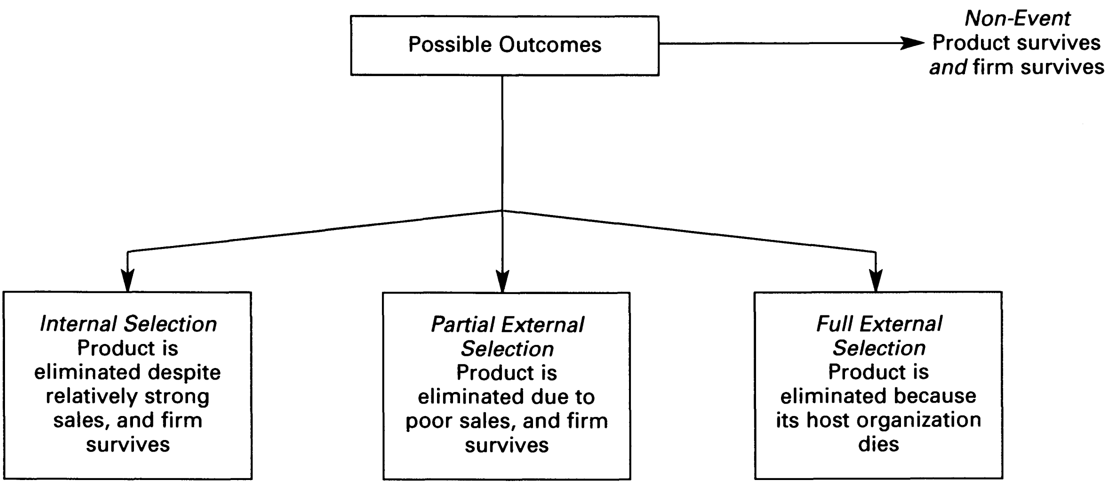
One might question whether internal selection includes events in which managers intentionally let products die slow deaths. That may be common in slow-moving industries, but it does not square with either Burgelman's (1994) account of the fast-paced semiconductor industry or comments by the middle managers from high-velocity industries that we interviewed, who stressed the costs of keeping outdated products alive. One manager remarked that if a product's sales began to soften, he would increase marketing efforts and upgrade its features to prevent losing ground to competitors. He said that if sales fell more than 30 percent from their peak before a product exited the market, then the environment had controlled its destiny, not him. In slower-paced industries, managers may intentionally let products linger, but in a high-velocity setting, when a product's sales drop sharply and it later dies, the environment is likely to have selected it out, not its managers.

A second type of selection event occurs when the environment removes a product by killing the firm it resides in, an instance of full external selection. That usually happens when most of a firm's products are struggling, yet it also includes cases in which a focal product is doing well but is eliminated when its host organization dies. Full external selection is therefore both a product-level and firm-level occurrence, so we consider both types of events. While studies of firm-level failures are the norm in ecology, product-level analyses, which give greater weight to the exits of firms with more products, offer additional insights because failures contribute unequally to population-level change. Different products embody different ideas, so in terms of the rate at which the environment selects out variants, the death of a 20-product firm may be a bigger event than the demise of a two-product rival. Accordingly, our analyses of full external selection consider both product-level and firm-level outcomes.

A third type of event, partial external selection, occurs when a firm survives, but the economic performance of the focal product is so poor that it is forced from the market. For example, consider Intel's exit from the dynamic random access memory (DRAM) market. According to Burgelman (1994), DRAMs accounted for over 90 percent of Intel's sales in the early 1970s, and the company had over 80 percent of world market share, but the emergence of Japanese competitors in the late 1970s led to a long slide so that by 1984, DRAMs accounted for only 5 percent of Intel's revenues, and its market share was only 1.3 percent. At that point, Intel exited the memory chip business, despite the long-held beliefs and stated intentions of its top executives, who continued to view the firm as a memory company throughout its long decline. Here, the external environment clearly prevailed over Intel's executives and selected the company out of the DRAM segment. While Intel survived and eventually prospered, those products did not. As this illustrates, organizational failure is not the only way that external selection occurs, and conversely, a firm's survival does not imply that the environment is not selecting out some of its internal variations (Miner, 1991). To capture that, one must look at the life cycles of specific projects within firms.

Figure 1 presents a typology of the three types of selection events and their outcomes. Managers and the environment may each play a role when a product dies in a firm that survives, suggesting a blurred boundary between internal and partial external selection. We treat those as distinct, mutually exclusive outcomes, however, because they are quite different theoretically. Internal selection is proactive and explorato-

Figure 1. Typology of selection event outcomes.



ry, since managers use forecasts of future environmental demands to remove products that remain viable today and reallocate resources to develop new products aimed at future conditions. Managers therefore emphasize predictions rather than historical outcomes in making internal selection decisions. That is seen, for instance, in Hewlett Packard's decision to kill its 1.3-inch Kittyhawk disk drive. After a slow start in 1992, its sales doubled in each of the next two years, yet it was internally selected because those revenues failed to meet HP's aggressive forecasts (Christensen, 1997). In comparison, partial external selection is reactive and focused on the present, since managers, as in the case of Intel, continue to exploit existing products until the environment provides clear evidence that they are obsolete. Given the sharp distinctions between exploration and exploitation (March, 1991), and between proactive moves based on forecasts and reactions to market outcomes (Miles and Snow, 1978; Zajac and Shortell, 1989), it is vital to distinguish between internal and partial external selection to discern their different effects on organizational learning.

Selection-based Learning

When firms respond to partial external selection or develop fresh ideas in anticipation of internal selection, they search for new solutions. Because firms must learn through trial and error to conduct effective searches, this creates a form of path-dependency that we call selection-based learning. Search comes in numerous forms, but we focus here on new product development, a vital mode of search in high-velocity settings, one that catalyzes organizational learning and creates relationships between past and future selection events.

Selection-based learning and future selection rates. The phrase variation-selection-retention may be misleading when applied to internal selection because it suggests that once a variant is selected out, its influence is gone. Firms, though, can learn from prior selection events and store that knowledge in their routines, so the ghosts of dead products live on, creating a subtle form of retention. For example, numerous internal selections in a firm's past indicate that its managers have taken an active role in pruning products before they become obsolete deadwood that would bog down internal routines (cf. Barron, West, and Hannan, 1994). Also, by using internal selection to weed out less-than-satisfactory experiments with new technologies while discovering and retaining more valuable ones, a firm can implement a form of trial-and-error learning that does not place heroic demands on its top executives to bet the future on a narrow set of technologies (Miner, 1990, 1991; Burgelman, 1994). The cumulative amount of internal selection speaks, then, to how broadly a firm has searched for viable technologies and whether it has maintained its nimbleness by developing routines to prune its portfolio proactively of older variations.

Internal selection offers benefits, yet it also creates challenges. If a product is doing well, the firm can lose revenue if it is eliminated. Also, customers need time to understand the benefits of new technologies (Rogers, 1995), so middle managers must consider whether a slow start by a novel offering constitutes a disappointing experiment that should be terminated or one with long-term potential that customers need more time to appreciate. Such choices are challenging in high-velocity settings because the simultaneous actions of numerous and shifting competitors make environmental feedback noisy and confusing (Eisenhardt, 1989; Levinthal and March, 1993). For example, demand for an existing product can fluctuate widely in the near term as rumors of new offerings temporarily freeze buyers.

Because of this, internal selection decisions and the resource transfers they entail are far from easy, particularly if middle managers have little precedent to guide them. But firms that experience several such events across time can engage in trial-and-error learning and gradually hone their skills in anticipating future demand shifts, moving personnel, and transferring production capacity to new uses, knowledge that becomes embedded in the routines a firm uses to review its product portfolio, to gather competitive intelligence, and to reassign teams to new projects (cf. Bower, 1970; Wheelwright and Clark, 1992). As firms accumulate experience with internal selection, they can better harness its benefits and overcome its challenges, reducing threats posed by the external environment. This suggests that the image of resilience and adaptability painted by internal selectionists is not an innate property of multiproduct firms but a condition that some evolve towards through experience.

Hypothesis 1a (H1a): There will be a negative relationship between the cumulative number of internal selection events in a firm's past and its future rates of partial external selection.

Hypothesis 1b (H1b): There will be a negative relationship between the cumulative number of internal selection events in a firm's past and its future rates of full external selection.

At first glance, partial external selection, in which the environment kills some of a firm's products, might seem to signal that failure is imminent because a company has overexploited its older technologies. We expect, though, that partial selection provides dramatic and sometimes surprising feedback that creates dissatisfaction with the status quo and prompts aggressive searches for new solutions. Given that managers in fast-paced industries have strong incentives to eliminate products before their sales decline too far, partial selection is often a negative surprise in which demand for a given technology disappears more quickly than managers had anticipated. Partial selection also includes cases in which firms invest in new technologies that the market subsequently rejects, another negative surprise. While outcomes that conform with expectations tend to reinforce the status quo, negative surprises catalyze search and learning because they are salient, contradict established beliefs, and bring more diverse information into organizations than ordinary, predictable outcomes (Buckley, 1967; March, Sproull, and Tamuz, 1991; Haunschild and Sullivan, 2002). In addition, negative surprises seldom meet a firm's aspirations, and the resulting gap between expected and actual outcomes drives organizational search and learning (Cyert and March, 1963;

Levinthal and March, 1993). Partial external selection therefore serves as a dramatic and informative wakeup call that triggers search. Coca-Cola, for example, experienced such a wakeup call with New Coke.

Following 20 years of market share losses to Pepsi, Coca-Cola announced in May 1985 that it was replacing its original formula with New Coke, a sweeter drink, similar to Pepsi. While New Coke's launch was based on $4 million in market research, 200,000 blind taste tests, and $10 million in advertising (Gilpin, 1985), it incited a storm of consumer complaints and such low sales that the firm was forced, just three months later, to remove New Coke and reintroduce its original formula. From this instance of partial external selection, Coca-Cola's executives learned about the symbolic meaning of their product, its role in customers' emotional ties to the past, and how value stemmed from Coke's brand, not its formula. Those new beliefs, which were formed after careful reviews of the blunder, guided Coca-Cola's decision to revamp its marketing campaign around a new slogan, "Red, White and You," that emphasized Coke's all-American spirit. Such efforts gradually reversed Coke's market share losses to Pepsi, raised its stock price, and helped it recapture the confidence of its bottlers and customers (Harris and Henderson, 1985; Pendergrast, 1993; Farrell and Comiteau, 1995). Coca-Cola learned a great deal from a single, spectacular instance of partial selection, yet partial selection events are often less dramatic, and a single small incident can be dismissed as random variation that falls within normal operating bounds (March, Sproull, and Tamuz, 1991). More typically, learning from partial external selection accumulates gradually, particularly in high-velocity settings, in which firms must adapt by searching for innovations rather than simply reintroducing an established product, as Coca-Cola did.

As Coca-Cola's recovery from the New Coke debacle suggests, firms that experience partial external selection will not abandon their existing routines completely, which would reset the liability-of-newness clock. Experienced firms cling to current arrangements, so partial selection will instead prompt them to retain existing activities and graft on new ones (cf. Huber, 1991) that they discover by searching areas that border their existing technologies and customers. That offers two benefits, particularly in fast-paced settings: (1) it breaks the self-reinforcing cycle that leads to over-exploitation of established routines (cf. March, 1991), and (2) new solutions are hybrids of new and old elements, and related diversification of that sort improves the odds of surviving external changes that render existing products obsolete (Haveman, 1992). In comparison, firms that seldom experience partial selection by the environment may be lulled into a false sense of security in which change becomes infrequent and extremely incremental, a combination that can lead to obsolescence. Overall, this form of selection-based learning is likely to improve a firm's ability to avoid external selection in the future.

Hypothesis 2a (H2a): There will be a negative relationship between the cumulative number of partial external selection events in a firm's past and its future rates of partial external selection.

Hypothesis 2b (H2b): There will be a negative relationship between the cumulative number of partial external selection events in a firm's past and its future rates of full external selection.

The cumulative number of selection events in a firm's past and its future rate of similar events are quite different, and hypotheses 2a and 2b reflect this. By definition, the cumulative number of partial selection events in a firm's past increases monotonically across time, and only after an event has occurred and then receded into the past does it add to that cumulative total. Increases in the knowledge embedded in a firm's cumulative partial selection experience should reduce the future odds of full external selection (H2b), resulting in a relatively durable benefit. In contrast, while cumulative selection experience increases monotonically, future selection rates may either rise or fall depending on the influences of various causal forces. Here, we predict that a firm's cumulative historical experience with partial external selection will decrease the future rate of similar events (H2a). That process of self-suppression is consistent with evidence in the learning curve literature that the payoffs to experience accumulate, but at an ever slower rate as opportunities for learning are gradually depleted (Argote and Epple, 1990).

Internal events driven by a firm's managers and partial selection driven by the environment are likely to contribute differently to selection-based learning. Specifically, partial external selection is apt to be the more beneficial of the two because it focuses attention on mismatches between organizational beliefs and market demands, while internal selection decisions are subject to the preferences of politically powerful managers. As evidenced by New Coke, partial selection prompts firms to question their understanding of links between a product's attributes and consumers' preferences. When an organization experiences a problem, it usually searches nearby for solutions (Cyert and March, 1963), so when the environment selects out part of a firm's portfolio, the firm will often respond by reassessing whether its existing activities satisfy external demands.

In comparison, internal selection decisions are colored more by organizational politics, since the projects that receive backing may not be those that best meet external demands but those whose internal champions are the most politically connected to top management (Bower, 1970; Miller, 1993). In firms with multiple product teams, the winners of prior internal contests get funding and executive backing that establishes their subgroup's influence. Once empowered, those subgroups make investments, choose managers, and define the criteria that guide future decisions in ways that reinforce their standing (Pfeffer and Salancik, 1978; Pfeffer, 1981), an example of the Matthew effect (Merton, 1968; Podolny, 1994). Similarly, in firms with a single development team, there is always the question, "After we finish this product, what do we do next?" Because the future is uncertain, reasonable people often reach different conclusions about which direction to take, resulting in political maneuvering among team members (Allison, 1969). While newer members may favor more radical departures, established leaders often prefer straightforward extensions of current products, since the underlying technologies require their expertise (Miller, 1993; Sørensen and Stuart, 2000). This narrowing of focus and power-begets-power process suggests that repeated instances of internal selection create dominant individuals and subgroups who then craft policies to limit changes that might threaten their control. As a result, internal selection may be less beneficial than partial external selection because the former creates dominant factions that are reluctant to eliminate the products and technologies that brought them to power, while the latter encourages firms to reassess their external fit, a vital task in fast-paced settings.

Hypothesis 3a (H3a): The cumulative number of partial external selection events in a firm's past will decrease its future full external selection rates more than the same number of prior internal selection events.

Hypothesis 3b (H3b): The cumulative number of partial external selection events in a firm's past will decrease its future partial external selection rates more than the same number of prior internal selection events.

To the extent that partial selection occurs in firms exposed to tough competition, it suggests "Red Queen" evolution, in which the survivors of strong rivalries adapt to become particularly hardy (Barnett, Greve, and Park, 1994; Barnett and McKendrick, 2001). Prior work has not identified and measured specific adaptive processes, however, as we do here, to ensure that organizational change and not survivor bias is driving empirical evidence of the Red Queen. One such adaptive process involves a firm's tendency kill its own products before they become obsolete, acts of internal selection.

We have argued that internal selection is cumulatively adaptive, yet we also expect that organizational politics eventually constrain the benefits of such experience. An internal selection decision not only terminates one project but also endows another with resources and a mandate to grow (Bower, 1970; Burgelman, 1983), so repeated instances either cement the power of existing subgroups or create powerful new ones and license them to build empires. Potent subgroups in growing empires try to fortify their influence, so they become less likely, as their power accumulates, to kill the products that gave rise to their control, resulting in less internal selection in the future and fewer opportunities to add to this form of knowledge. While internal selection is cumulatively adaptive, it is a self-braking process whose payoffs plateau, just as accumulating proprietary knowledge is self-braking, since firms with greater stocks of it search more narrowly and learn less from the environment (Sørensen and Stuart, 2000). Thus, we predict:

Hypothesis 4a (H4a): The cumulative number of internal selection events in a firm's past will decrease its future internal selection rates.

Some organizational changes become routinized, so experienced firms are the ones most likely to repeat them (Grusky, 1961; Amburgey, Kelly, and Barnett, 1993). If internal selection gathers a similar sort of positive momentum, that would contradict hypothesis 4a. But the pace of internal selection speaks to how many technological variations a firm is exploring, and experienced firms increasingly cling to existing variations rather than abandoning them (Hannan and Freeman, 1984; March, 1991). Consequently, internal selection may decelerate with repetition rather than become more frequent.

In sharp contrast to the self-braking tendency of internal selection, the surprise value of partial external selection and its challenge to established beliefs suggests that its capacity to fuel change will not decrease with repetition. As partial external selection recurs, a firm is less likely to view those events as so threatening that they induce rigidity and is more apt to treat them as small, manageable losses, outcomes that encourage firms to jettison old approaches and try new ones (Sitkin, 1992). Partial selection also reveals errors in managers' understanding of the external environment. When errors are rare, they seldom lead to meaningful change, since firms respond in simple-minded ways, such as blaming the person in charge. But as a firm experiences a wider variety of negative events, it is more likely to conduct deep analyses of the underlying causes, often leading to significant change (Miner et al., 1999; Haunschild and Sullivan, 2002). Because internal selection involves significant changes in resource allocations, we hypothesize:

Hypothesis 4b (H4b): The cumulative number of partial external selection events in a firm's past will increase its future internal selection rates.

Selection-based learning and future product introductions. Selection-based learning catalyzes new product development, a vital means of searching for new technological variations. Many searches yield little, but experienced firms gradually discern how to generate more variations in a more timely manner, some of which are likely to be viable (Eisenhardt and Tabrizi, 1995). When middle managers internally select otherwise viable offerings, replacements are needed to recoup lost revenues, so firms have strong incentives to launch new products to replace those that were selected out. Similarly, when partial external selection occurs, that negative feedback creates dissatisfaction with the status quo and triggers firms to search for new solutions. But while the desire to replace older products is pervasive, firms' ability to do so varies with their experience.

Many products, including personal computers, are highly complex and composed of numerous interacting subsystems (processor, operating system, video adapter, etc.), so they are developed through iterative cycles of design, test, redesign, and retest as errors are discovered and corrected (Kidder, 1981; Steffens, 1994). That trial-and-error discovery is time consuming, but with experience, development proceeds faster and more reliably because firms learn from their mistakes and develop routines to support better approaches. This includes procedures to test early prototypes more rigorously, so errors are caught sooner and corrected well before full production begins, a time when change becomes both slow and expensive (Wheelwright and Clark, 1992; Eisenhardt and Tabrizi, 1995). Similarly, experience teaches firms to anticipate their customers' future requirements, decreasing the need to change designs in mid-stream, which would delay new product launches.

The number of selection events in a firm's past is an important measure of such experience because many things cannot be learned until an product's entire life has been observed, including reactions by customers and competitors to its introduction and evidence of subtle design and production flaws that come to light only after extensive use. As a firm sees how more of its technical variations have fared externally, product developers can use those data to reduce the uncertainty they face. This is essential in high-velocity environments, where uncertainty often freezes decision makers and places them in vicious cycles in which they seek out data to confirm their initial choices, find that the environment has changed, and then restart their decision process (Eisenhardt, 1989; Eisenhardt and Tabrizi, 1995). In comparison, developers in firms that have experienced multiple product life cycles and selection events are likely to move more confidently, settle on a design, and introduce it quickly, rather than procrastinating for fear that a better choice is just over the horizon.

Hypothesis 5a (H5a): The cumulative number of internal selection events in a firm's past will increase its future rates of new product introduction.

Hypothesis 5b (H5b): The cumulative number of partial external selection events in a firm's past will increase its future rates of new product introduction.

While new product introduction entails certain risks (Dowell and Swaminathan, 2000; Barnett and Freeman, 2001), firms that produce more technological variations have better odds of discovering viable ones, a necessity for avoiding obsolescence and failure in fast-paced settings (Eisenhardt, 1989). If prior selection catalyzes product development, as hypotheses 5a and 5b suggest, then that type of search will partially mediate the relationship between earlier selection events and the future likelihood of organizational failure. Thus, more prior selection events should lead to more product development, which in turn should lower the future odds of full external selection. Firms with extensive selection experience can introduce more new products per year because they have accrued knowledge in their routines about customer needs, product testing, competitive reactions, moving resources from older to newer projects, and forecasting technological change. Firms familiar with internal and partial external selection are likely, then, to have strong abilities to introduce new products and the confidence to move quickly in the face of technological uncertainty. In turn, introducing more variants reduces the odds of failure because each new offering improves the chances of finding technologies that will fit emerging market demands.

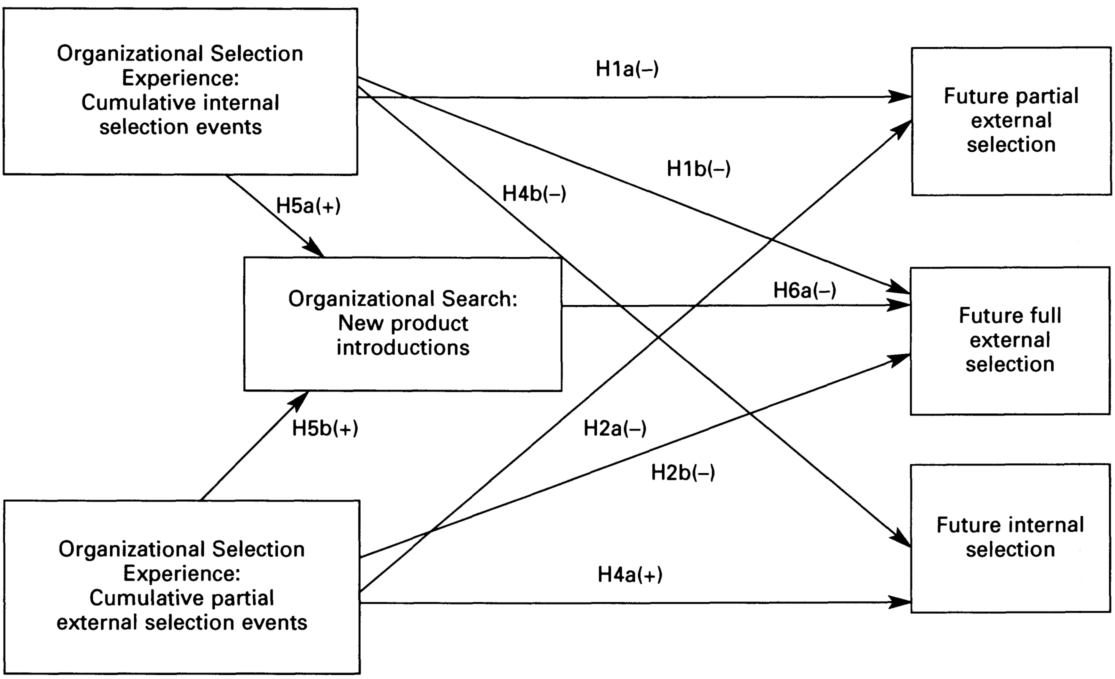
Hypothesis 6a (H6a): New product introductions will decrease future rates of full external selection.

Hypothesis 6b (H6b): New product introductions will partially mediate the effect of prior internal selection events on future rates of full external selection.

Hypothesis 6c (H6c): New product introductions will partially mediate the effect of prior partial external selection events on future rates of full external selection.

Figure 2 summarizes the hypothesized effects of selection events and shows that internal and external selection are interwoven phenomena. Managers use internal selection to prune deadwood and catalyze new product development, which affects the future odds of external selection. Conversely, partial external selection serves as a wakeup call that moves firms away from the status quo by increasing their rates of internal selection and searches for new technological variations.

Figure 2. Summary of hypothesized effects of selection events.



METHODOLOGY

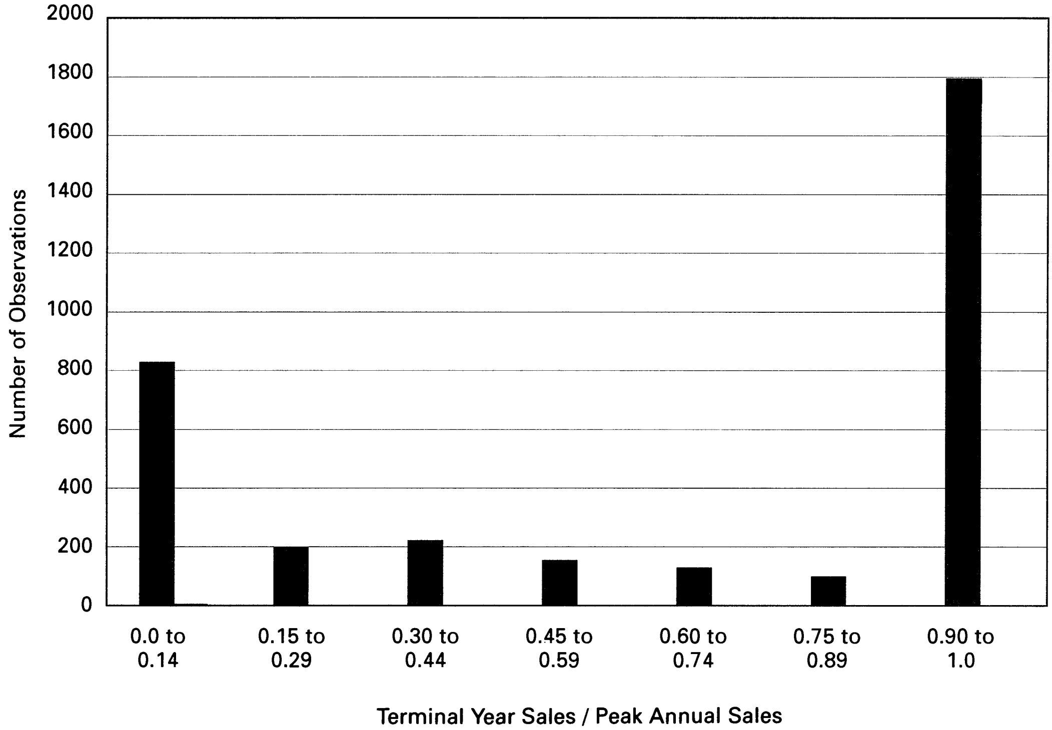
To test our ideas, we studied the population of firms in the U.S. personal computer industry from its founding in 1975 through 1994. This industry includes manufacturers of microcomputers (e.g., the Apple Macintosh) and desktop and deskside personal workstations (e.g., Sun Microsystems' SPARCstation). This industry is an appropriate one in which to test our theory because it is a prototypical high-velocity industry in which technologies, competitors, and product demand shift rapidly (Eisenhardt, 1989). Our data were drawn from a census listing, purchased from the International Data Corporation (IDC), of all domestic firms and foreign subsidiaries that built personal computers in the United States. IDC updated its listings annually and provided sales figures and some technical information on all models of personal computers introduced during that time. In all, there were 736 firms and 6,727 products. After lags in time-series data were accounted for, this yielded N = 11,707 product-years in the selection analyses and N = 2,709 firm-years in the product introduction and organizational failure rate models.

Dependent Variables

Selection events. Internal, partial external, and full external selection are mutually exclusive competing events, so three distinct variables tracked their rates. Whenever an event of one type took place (e.g., internal selection), the variables tracking the other two (e.g., partial and full external selection) were coded as right-censored (Allison, 1995). All three variables were coded as right-censored in year t if the product survived, as evidenced by positive sales in year t+1, or if the product had positive sales in 1994, the final year of observation. If, instead, a product had positive sales in year t and zero sales in all future ones, we coded a selection event and then identified its type. A full external selection event was coded when a focal product's host firm died, thus eliminating its entire portfolio. That happened in year t if each of a firm's products had zero sales in year t+1. Overall, there were 1,289 full external selection events. As detailed later, we also assessed full external selection by estimating organizational failure rates. In those analyses, there were 576 failure events.

Internal and partial external selection occurred only in surviving firms, the former when managers removed a viable product from the market, and the latter when a product's sales had dropped so much that the market forced that product's death. To make that distinction, we had to identify a sales drop threshold, which we did by examining product lifecycles. The lives of PC products were often short, with a mean product age of 2.31 years (s.d. = 1.50) and a maximum observed life of 12 years. This is typical of high-velocity settings in which obsolescence is a constant threat (Eisenhardt, 1989). Coupled with rapid industry growth (industry sales grew at a compound rate of 29.4 percent from 1975 to 1994), this caused most products to exhibit one of two sales trajectories across their lives. One was an inverted V, in which sales quickly ramped up as demand for a new iteration of technology surged then quickly ramped down as that technology became obsolete. Among such products, few ever reversed their downward slide after a substantial drop, say 50 percent, from their peak. Because the market drove such products' deaths, that indicates partial external selection. The other typical trajectory, which signals internal selection, was simply the first half of that cycle—an upward ramp that ended with the product's being withdrawn from the market at its historical sales peak. Products in surviving firms tended, then, to exit on positive upswings or sharp downward slides. The histogram in figure 3 echoes this. We constructed it by examining the terminal year of all product exits in surviving firms, which constitutes the full sample of internal and partial external selection events. For each exit, we divided the product's sales in its terminal year by the peak annual sales it had achieved during its life. If a product exited at its historical

Figure 3. A product's terminal-year sales divided by its peak annual sales: Counts of observed values in surviving firms.



peak, then that ratio equaled 1; that ratio approached 0 if sales had fallen dramatically from their historical high. As figure 3 shows, those ratios had a distinct bimodal distribution, so most products exited on a high note (internal selection) or were driven from the market due to low and sharply dropping sales (partial external selection). If we had modeled that ratio as a continuous outcome, it would have produced biased, inefficient, and inconsistent estimates due to non-normality, a truncated range between 0 and 1, and the fact that most observations were outliers, not centrally distributed outcomes (Greene, 1993). Instead, we treated the U-shaped distribution in figure 3 as two collections of separate events, internal and partial external selection.

We coded a partial external selection event in year t if the firm survived but the annual sales of the focal product were zero in year t+1, *and* that product's sales in year t had declined at least 50 percent from their rolling historical peak. For example, if a product lived for three years and had annual sales of $60, $100, and $10, then its sales peak was $100, and the threshold for a 50-percent drop was $50, which it fell below in its final year, indicating that it was selected out of the market by the external environment. In comparison, we designated an internal selection event in year t if a product's sales were zero in t+1, the firm survived, and the product's sales had not declined by at least 50 percent from their peak.[1] For example, in a surviving firm, a product that lived for three years with annual sales of $60, $100, and $120 would be coded as having an internal selection event,

1
To assess whether our results were sensitive to the choice of a 50-percent sales drop threshold, we reran our models using thresholds of 90 percent, 70 percent, and 30 percent. All results were unchanged, because few events changed type when we moved the dividing line, a result of the sharp bimodal distribution in figure 3. As an example, most internal events occurred at their product's historical sales peak, so they would have been designated as internal regardless of whether we used a 1-percent, 50-percent, or 99-percent threshold.

because it would likely have continued to sell, but its managers chose to redirect its resources. Like the latter time series, a large majority of internal selection events (72 percent) occurred at the product's historical sales peak, so managers frequently killed products that the market judged viable. Overall, there were 2,206 internal selection events and 1,004 instances of partial external selection.[2]

Product introductions. The number of new product introductions was the dependent variable in testing hypotheses 5a and 5b, so we obtained that count for each firm in each year using the product introduction dates in the IDC data. We also included the one-year lag of that count to help control for unobserved heterogeneity across firms (see below for other steps).

Independent Variables

The cumulative number of selection events across a firm's life taps its potential for selection-based learning. Events that are more distant in time often have less influence than more recent ones due to organizational forgetting and because environmental change renders older lessons obsolete, so we used a formula that discounts cumulative experience (Darr, Argote, and Epple, 1995; Ingram and Baum, 1997; Baum and Ingram, 1998). For internal selection:

$$\textit{Cumulative internal selection}_{i,t-1} = \log\left\{1 + \left(\sum_{j=1}^{T} \text{internal selections}_{i,j} * (\text{discount}^{T+1-j})\right)\right\},$$

where T is the age of the ith firm in year t-1, $\text{selections}_{i,j}$ is the number of products that were internally selected out of the ith firm's portfolio in the jth year of its life, and discount is a weight that depreciates the value of selection events across time. This measure was lagged by a year so that it was not confounded with selection events at time t. Some firms had no selection events for their first few years, so the quantity 1 was added to the event summation before logging it. We coded a similar measure for $\textit{cumulative partial external selection}_{i,t-1}$.

Following the authors cited above, we selected a discount weight by comparing models with values of 0.1, 0.3, 0.5, 0.7, 0.9, and 1.0, the latter indicating no discounting. In the selection models, goodness of fit was best using a value of 0.9, and those results are reported below. Results were unchanged using discounts of 0.7 and 1.0. The product introduction models are reported using a weight of 0.3, which provided the best fit. Those results were unchanged with weights of 0.1 and 0.5.

Hypotheses 5c and 5d predicted that prior product introductions would affect future external selection rates, so we included $\textit{product introductions}_{i,t-1}$ in the selection models.

Controls

Organizational controls. We controlled for several firm-level factors using measures lagged by one year. Numerous stud-

2
We could not observe a sales decline in products that survived only one year, so we calculated the average first-year sales of all new products introduced in the same year and then coded an internal event if a product survived one year and exceeded that average. If its sales were below average, we coded a partial external selection event. As noted earlier, internal and partial external selection occur only in surviving firms. Some studies have treated acquisitions as external selection events (i.e., failures), but takeovers were rare in this population, and when they occurred, firms' operations were not combined (Ingram, 1993). For example, when AT&T acquired NCR in 1991, their operations remained separate. Thus, we treated the eight cases in which acquisitions took place as the ongoing operation of distinct entities. Dropping the post-acquisition observations did not change the results.

ies have shown that organizational failure rates vary with age (Baum, 1996), so we controlled for *firm age* (and its square, if significant) by measuring the years that a firm had participated in the PC industry. Larger firms often have lower failure rates (Hannan and Freeman, 1989), so we controlled for *firm size* by calculating the natural logarithm of firm sales in year t-1, a measure that points to the scale of a firm's operations and the slack at its disposal (Henderson, 1999). Haveman (1993) found a curvilinear relationship between size and rates of change, so we included the square of size when it was significant.

Some personal computer firms altered their organizational cores by changing technology strategies (Henderson, 1999). That can affect failure rates (Amburgey, Kelly, and Barnett, 1993), and it may also coincide with increased rates of internal selection. In this industry, firms employed one of two technology strategies. Proprietary strategists developed their key technologies internally and emphasized performance and specialized features, while standards-based strategists used technologies that conformed with publicly available specifications and emphasized efficiency and time-to-market with new components developed by external suppliers (Henderson, 1999). Apple is an example of a proprietary strategist; Compaq and Gateway are standards-based.

To model strategy changes, which about 12 percent of the firms undertook, we followed Henderson's (1999) coding scheme, which draws on the fact that very few firms, other than strategy changers, offered a mix of proprietary and standards-based products. Products were deemed standards-based if they conformed with one of the industry's three publicly available specifications, which involved products with microprocessors that were Zilog Z80-compatible, Intel x86-compatible, or Sparc-compatible. All other personal computers were designated proprietary. Next, we determined if a firm derived over 50 percent of its annual sales from proprietary or standards-based products, and then *changed strategy* was coded 1 beginning in the year that a firm's sales switched to or from a proprietary majority. Once set at 1, it retained that value, and it was coded 0 otherwise. To assess the dynamics of change, *change clock* (Amburgey, Kelly, and Barnett, 1993) was initially set to 0, and in firms that switched strategies, it recorded the elapsed years since the change.[3]

Prospect theory suggests that firms whose performance is below their aspiration level are risk seeking, while those who exceed their aspirations are risk avoiding (Kahneman and Tversky, 1979). This may affect whether firms try to change through internal selection or fail altogether after gambling on long shots. This can be modeled using a spline function in which separate variables are coded for performance above and below a historical or socially based target (Greve, 1998). With historical aspirations, a firm compares its recent performance to its earlier ones. With social aspirations, a firm compares its recent performance to the average of other firms in the same industry. Here, social and historical aspiration measures were highly correlated (r > .84 for the below-aspiration spline; r > .98 for the above-aspiration spline) and yielded the

3
In analyses not reported here, the latter two variables were interacted with firm age, firm size, and a firm's founding technology strategy. None of those interactions was significant, and the other results were unchanged. Overall, this meets recent recommendations for modeling the process and content effects of organizational change (Barnett and Carroll, 1995; Baum, 1996).

same results. Social measures are reported below and equaled the fractional change in sales between t and t-1 for the focal firm minus the corresponding value for the entire industry excluding the focal firm. *Prior performance < aspirations* equaled the absolute value of that difference when it was negative and 0 otherwise. *Prior performance > aspirations* equaled that difference when it was positive and 0 otherwise.

We controlled for the *number of products* in a firm's portfolio, which can affect future viability by providing a firm with market data and feedback (Sorenson, 2000). Larger portfolios may also be associated with greater operating complexity since there are more potential interdependencies to consider (Thompson, 1967). If that slows a firm's responsiveness to external developments, external selection rates would rise. In the IDC data, each firm designated its own product distinctions. Some companies, such as Acer, often had small technological differences among products (e.g., an 8 MHz vs. 12 MHz processor), while others, such as IBM, typically had larger ones (e.g., different system architectures). Importantly, those differences were quite consistent within firms across time, so the fixed-effects models that we describe below controlled for such heterogeneity.

We also suspected that firms with very few products might be unlikely to internally select them because that would amount to exiting the business unless they introduced a replacement. Similarly, firms might hang on and resist external selection even in the face of extremely poor performance if it meant abandoning the business altogether. To control for this, we set the *models = 1 or 2* dummy to a value of 1 if a firm had only one or two products in its portfolio. That variable was coded 0 otherwise.

Product-level controls. The environment tends to select out products with older technologies (Greenstein and Wade, 1998), so we controlled for *product age*, measured in years. That count began at 1 in the year that a product was offered for sale, as listed in the IDC data. We also controlled for *product age^2* when it was significant. Managers may be hesitant to remove offerings that have previously accounted for substantial revenues, so we controlled for *product size*, measured by the natural logarithm of the focal product's sales in year t-1. That variable was set to zero in a product's first year.

Population and community-level controls. *Population density* may affect selection rates (Hannan and Carroll, 1992), so it was measured by counting the number of firms with non-zero personal computer sales in each year. Its square was not significant. To further control for density-driven competition and legitimation, we measured *product density/100* by counting the number of products in the industry with non-zero sales in each year, then dividing by 100. Its square was not significant. Tacit collusion among an industry's largest firms can also affect competition (Bain, 1951), so we calculated the four-firm concentration ratio, reported below as the *C4 ratio*, by adding the market shares of the four firms with the highest sales in each year.

Social contagion, imitation, and vicarious learning may prompt firms to introduce new products or select out old ones in response to similar moves by others (Davis, 1991; Levitt and March, 1988; Rogers, 1995). In the introduction analyses, we therefore controlled for *introduction mass*, which equaled the log of the count of new product introductions by all other firms in the prior year (cf. Barnett and Amburgey, 1990; Baum and Mezias, 1992). Similarly, we controlled for *selection mass/100* in the selection models, which equaled the sum divided by 100 of the internal, partial external, and full external selection events across the industry in the prior year, excluding those in the focal firm. We aggregated those three event types into a single count because they were highly correlated within years at the industry-level ($r > .88$). Results were unchanged using separate counts of prior event types. Selection mass and introduction mass were highly correlated ($r = .92$), so only the former appeared in the selection models, and only the latter appeared in the product introduction models.

Firms using similar technologies often form communities whose members compete with one another while also sharing infrastructure and legitimacy (Baum and Mezias, 1992; Wade, 1995). Following Wade (1996) and Henderson (1999), we classified community membership by the family of microprocessor used in a product because that substantially affects a personal computer's design and system architecture. Members of a microprocessor family have considerable compatibility in their hardware and assembly language software, so, for example, microprocessors in Motorola's 68000 line (the 6802, 6808, 6809, 68000, 68010, 68020, 68030, and 68040) formed one family, and personal computers that used any of those processors made up the 68000 community. Using the families listed in Wade (1996) and Henderson (1999), we identified 74 technical communities in this industry for the period 1975–1992, and then we identified 33 more that emerged during 1993 and 1994, years that extend beyond the time frame of those earlier studies (the list of 33 is available from the authors by request). We then coded several variables. A community's age may affect its legitimacy and the datedness of its technology (Stinchcombe, 1965), so we measured *community age* in years. The number of firms in a community may affect the level of competition and legitimation within it (Baum and Oliver, 1992), so we controlled for *community density*. To capture system-level economies of scale, we measured *community size* by logging the total annual sales of each community. Such economies might exist here because personal computers exhibit network externalities in which users benefit to the degree that other users adopt compatible technology (Katz and Shapiro, 1985).

Modeling and Estimation

Internal, partial external, and full external selection are mutually exclusive events that all products are at risk of, so we estimated their rates using event history analyses for competing events (Allison, 1995). Such models estimate a separate hazard rate for each event type, $h_{j,k}(t)$, the likelihood that the jth product will have a selection event of type k at time t.

Here, k equaled 1 for internal selection, 2 for partial external selection, and 3 for full external selection.

Though a product could experience one event at most, firms with several products could experience multiple events, and standard errors would be biased toward zero unless unobserved differences across firms (e.g., culture) were accounted for (Allison, 1995). Fixed-effects partial likelihood (FEPL) models do that by estimating hazard functions with the following form:

$$\log h_{i,j,k}(t) = \alpha_{i,k}(t) + \beta_k X_{i,j}(t) \tag{1}$$

Here, i indexes across firms; j indexes products; k indexes event types; α is vector of nuisance functions that account for unobserved heterogeneity across firms and allows them to vary by event type; β is a row vector of coefficient estimates that differs by event type; and X is a column vector of predictors that vary across products and time. Equation (1) yields event history models that account for both competing risks and repeated events (Allison, 1995). We implemented these models in SAS using PROC PHREG and its STRATA statement, which estimates partially parametric Cox models (Cox, 1972) with a fixed-effect for each organization in the α vector. While the α terms are latent, the hypotheses involve measured differences across firms and event types, which are captured in the β vectors. Since the data were recorded annually, there were numerous ties because one collection of events appeared to occur at exactly product age = 1, another at exactly product age = 2, and so on. We therefore used the EXACT option in PROC PHREG, which handles discrete data in which the year of each event is known but not its precise time.

Our predictions involve evolutionary changes *within* firms due to organizational learning, not stable differences across them. Fixed-effects models are highly appropriate, then, because they eliminate time-invariant differences across subjects and focus solely on within-firm change (Greene, 1993). For example, firms may differ in terms of durable practices that affect how great a technological advance their new products typically make. In a fast-paced world, products making bigger advances may survive longer before becoming obsolete, which could lower the rate of external selection. That, however, involves stable differences across firms, so the α terms in equation (1) fully absorb those effects. Similarly, firms may have stable but heterogeneous policies that affect how proactive their managers are in their internal selection decisions. Consistently proactive managers relying on forecasted demand might have high internal selection rates and pull products at the first hint of a downturn. Conversely, consistently reactive managers would leave products in the market until their sales had dropped, thus slowing internal selection. Again, the α terms in the FEPL Cox models fully account for such differences by allowing each firm to have its own base rate of each event type (Allison, 1995).

To buttress the product-level analyses of full external selection, we used Cox models to assess organizational failure rates. Because failures are not repeated events, those models did not contain fixed effects.

To model new product introductions, we shifted from product-year to firm-year analyses. Ecologists make similar shifts as they go from failure analyses using firm-level data to estimates of founding rates using population-level data (Hannan and Freeman, 1989). Before a product is born, one cannot specify all the actors in the risk set because that includes all entrepreneurs inside *and* outside an industry with the potential to create a product. One therefore assesses how organizational and industry conditions affect the number of introductions in each firm-year. Those non-negative counts can be modeled by a Poisson process if one corrects for time-series correlations due to unmeasured heterogeneity in stable firm-level characteristics and overdispersion in which the variances of event counts exceed their means (Hausman, Hall, and Griliches, 1984). Negative multinomial models do that by estimating overdispersion and using random effects to account for within-firm correlation (Guo, 1996). They assume, though, that the random effects are completely uncorrelated with the predictors, which is unlikely here, since the firms that frequently killed their own products probably had strong unmeasured abilities to introduce replacements. We therefore used negative binomial models to account for overdispersion, a first-order autoregressive process to account for temporal correlation, and robust variance estimates to further account for within-firm clustering (White, 1980; Carroll and Hannan, 2000). We implemented this in SAS using PROC GENMOD.

Factors affecting product introductions may also affect failure rates, resulting in sample selection bias, so we used a two-step procedure in the introduction models (Heckman, 1979; Lee, 1983). We first estimated an event history model with an exponential distribution and lagged predictors to obtain F(i,t), the cumulative probability density function for the failure of the ith firm at time t. Failures were coded as happening halfway through year t (Petersen, 1991), and non-failing observations were right-censored. Next, we used the estimates of F(i,t) and Lee's formula to obtain *sample selection* $\lambda_{i,t}$, the estimated likelihood that firm i would fail in year t, which was then controlled in the product introduction models.

RESULTS

Table 1 provides descriptive statistics using product-year data. Those statistics were essentially unchanged using firm-year data, so they are not reported. With few exceptions, correlations involving the independent variables are modest. The largest is between the existing number of products and new product introductions (r = 0.78). To ensure that collinearity did not affect the results, we took two steps. First, we used matrix decomposition to calculate condition indices (Belsley, 1991), which showed that the only problematic overlap was between community size and the C4 ratio. The former was not significant, so it was dropped from the models that

Table 1

Means, Standard Deviations, and Correlations of Key Variables (N = 11,707 product-years)

Variable	Mean	S.D.	1	2	3	4	5	6	7	8	9	10
1. Internal selection	0.19	0.39										
2. Partial external selection	0.08	0.27	–.14									
3. Full external selection	0.11	0.32	–.17	–.11								
4. Cum. internal selection	0.70	0.78	.26	.11	–.13							
5. Cum. external selection	0.50	0.68	.22	.10	–.14	.76						
6. Product introductions	6.94	11.36	.23	.10	–.17	.62	.61					
7. Firm age	5.70	4.03	.10	.12	–.13	.57	.71	.49				
8. Firm size	9.99	2.57	.12	.13	–.26	.56	.60	.46	.66			
9. Changed strategy	0.21	0.41	.00	.06	–.07	.22	.29	.25	.43	.25		
10. Change clock	1.07	2.61	.01	.07	–.07	.31	.45	.45	.56	.45	.80	
11. Prior perf. < aspirations	0.22	0.33	–.08	–.04	.10	–.19	–.12	–.18	–.15	–.18	.00	–.02
12. Prior perf. > aspirations	0.31	0.52	.00	–.02	–.02	–.11	–.20	–.04	–.24	–.04	–.08	–.13
13. No. of products	14.90	19.29	.22	.12	–.17	.65	.70	.78	.60	.55	.26	.51
14. Models = 1 or 2	0.13	0.34	–.14	–.09	–.09	–.28	–.25	–.24	–.26	–.24	–.10	–.12
15. Product age	2.31	1.50	–.11	.28	.11	–.21	–.16	–.21	.04	–.07	–.04	–.05
16. Product group size	8.12	2.15	.02	.25	–.01	.17	.23	.15	.36	.15	.17	.18
17. Population density	265.18	46.84	.01	.03	.03	.11	.10	.08	.12	.08	.04	.05
18. Product density	1524	662.3	.25	.11	.05	.53	.50	.46	.39	.46	.03	.18
19. C4 ratio	0.49	0.04	.00	–.02	–.01	–.08	–.08	–.07	–.08	–.07	.00	–.04
20. Selection mass	442.22	343.87	.30	.09	.06	.60	.57	.55	.40	.28	.01	.18
21. Introduction mass	6.01	0.79	.20	.09	.04	.45	.42	.40	.34	.26	.03	.14
22. Community age	9.86	2.50	.24	.10	.06	.50	.45	.43	.37	.43	.05	.17
23. Community density	212.22	87.13	.06	.03	.04	.15	–.10	.16	–.03	.16	.04	.09

Variable	11	12	13	14	15	16	17	18	19	20	21	22
12. Prior perf. > aspirations	–.39											
13. No. of products	–.19	–.11										
14. Models = 1 or 2	.26	–.04	–.27									
15. Product age	.03	–.06	–.20	.14								
16. Product group size	–.19	.07	.20	–.05	–.04							
17. Population density	–.25	.03	.08	–.38	–.03	–.05						
18. Product density	–.27	–.09	.47	–.41	–.11	–.06	.51					
19. C4 ratio	.25	–.03	–.08	.24	.02	.02	–.56	–.41				
20. Selection mass	–.19	–.09	.54	–.30	–.13	–.12	.20	.87	–.19			
21. Introduction mass	–.28	–.05	.41	–.45	–.09	–.11	.73	.92	–.43	.75		
22. Community age	–.19	–.11	.43	–.35	–.04	–.09	.39	.85	–.32	.77	.79	
23. Community density	–.21	.05	.14	–.33	–.11	–.19	.67	.51	–.53	.26	.60	.45

follow. Second, collinearity's greatest threat in terms of Type I errors is that small changes in the data may create large changes in the parameter estimates (Belsley, 1991), so we randomly excluded 10 percent of the observations and reran each model, then repeated that process multiple times. All results were robust, which further indicates that collinearity was not an issue.

Internal selection results. Table 2 reports results of the FEPL Cox models used to estimate internal selection rates. Model 1 contains the controls, and model 2 adds the independent variables. Hypothesis 4a predicted that the cumulative number of internal selection events in a firm's past would decrease its future internal selection rates. Model 2 supports that, suggesting that repeated instances of internal selection empower a dominant political coalition within a firm that then becomes reluctant to terminate the products and technologies upon which its influence is based. In comparison, cumulative partial selection increased future rates of internal selection, which supports hypothesis 4b. Managers therefore learned from the negative surprises of partial external selection and became more proactive, removing products

Table 2

Fixed-effects Partial Likelihood Cox Models of Internal Selection Rates*

Predictor variable	Model (1)	Model (2)
Cumulative internal selection		–1.105•••
		(0.074)
Cumulative partial external selection		0.358•••
		(0.089)
Product introductions	–0.033••	0.004
	(0.055)	(0.012)
Firm age	0.191	0.549•••
	(0.121)	(0.132)
Firm age^2	0.001	–0.010•••
	(0.002)	(0.002)
Firm size	0.526••	0.608••
	(0.169)	(0.188)
Firm size^2	–0.024••	–0.023•
	(0.009)	(0.010)
Changed strategy	0.219	0.618••
	(0.217)	(0.223)
Change clock	–0.093••	–0.154•••
	(0.034)	(0.038)
Prior performance < aspirations	0.230	0.087
	(0.120)	(0.128)
Prior performance > aspirations	0.030	–0.089
	(0.065)	(0.069)
Number of products	0.040•••	0.048•••
	(0.007)	(0.008)
Products = 1 or 2	–1.170•••	–0.843•••
	(0.171)	(0.176)
Product age	–0.134•••	–0.158•••
	(0.027)	(0.028)
Product group size	0.056•••	0.056•••
	(0.010)	(0.010)
Population density	–0.004	–0.006••
	(0.003)	(0.002)
Product density / 100	–0.009	–0.042
	(0.041)	(0.044)
C4 ratio	1.857	2.313•
	(1.123)	(1.148)
Selection mass / 100	0.027	0.090•••
	(0.025)	(0.027)
Community age	0.023	0.002
	(0.052)	(0.056)
Community density	–0.005•••	–0.005•••
	(0.001)	(0.002)
–2 * Log-likelihood	7828.337•••	7361.248•••
Δ Fit from prior model (χ^2)	n.a.	467.089•••

• $p < .05$; •• $p < .01$; ••• $p < .001$; two tailed tests.
* N = 11,707 product-years with 2,206 internal selection events.

from the market before the environment rendered them obsolete.

External selection results. Tables 3 and 4 report the FEPL Cox models used to estimate partial external selection (models 3 and 4) and full external selection (models 5–8). Models 3 and 5 contain the controls, and models 4 and 7 add the independent variables. Model 6, as explained below, helped to determine if product launches partially mediated the effects of prior selection. Model 8 replicates model 7 but analyzes firm-level failure.

Hypotheses 1a and 1b predicted that cumulative internal selection would decrease future rates of partial and full external selection. As models 4 and 7 show, hypothesis 1b is supported, but hypothesis 1a is not. Internal selection therefore

Table 3

Fixed-effects Partial Likelihood Cox Models of Partial External Selection Rates*

Predictor variable	Model (3)	Model (4)
β: Cumulative internal selection		0.106 (0.138)
γ: Cumulative partial external selection		–1.530*** (0.154)
Product introductions	–0.001 (0.019)	–0.067** (0.022)
Firm age	–0.375* (0.146)	–0.383* (0.152)
Firm size	0.136* (0.055)	0.066 (0.068)
Changed strategy	0.072 (0.298)	0.379 (0.329)
Change clock	–0.015 (0.048)	0.062 (0.057)
Prior performance < aspirations	0.158 (0.141)	0.475** (0.158)
Prior performance > aspirations	0.007 (0.090)	–0.057 (0.099)
Number of products	0.030** (0.011)	0.079*** (0.013)
Products = 1 or 2	–0.698*** (0.184)	–0.088 (0.199)
Product age	1.938*** (0.117)	1.922*** (0.122)
Product age^2	–0.148*** (0.013)	–0.152*** (0.014)
Product group size	0.074*** (0.019)	0.081*** (0.020)
Population density	0.006* (0.003)	0.007* (0.003)
Product density / 100	0.169*** (0.050)	0.298*** (0.056)
C4 ratio	–2.461 (1.444)	–2.314 (1.559)
Selection mass / 10	0.050 (0.039)	0.102* (0.042)
Community age	0.149* (0.066)	0.071 (0.072)
Community density	–0.004* (0.002)	–0.005*** (0.002)
–2 * Log-likelihood	4339.174***	3927.173***
Δ Fit from prior model (χ^2)	n.a.	412.001***

* $p < .05$; ** $p < .01$; *** $p < .001$; two tailed tests.
* N = 11,707 product-years with 1,004 partial external selection events. Hypothesis 3b predicted $|\gamma| > |\beta|$.

kept obsolete deadwood from forming, which enhanced organizational survival, yet it did not affect the viability of the individual building blocks in a firm's product portfolio. Hypotheses 2a and 2b stated that the cumulative number of partial external selection events would decrease a firm's future rates of partial and full external selection. Each of those predictions is supported, suggesting that partial selection shook managers out of their complacency and attuned them to environmental changes that would have otherwise threatened their products with obsolescence and their organizations with failure.

Hypotheses 3a and 3b compared the strengths of internal and partial external selection as engines of adaptive learning. As H3a predicted, a post-hoc analysis of model 7 showed

Table 4

Product-level and Firm-level Cox Models of Full External Selection*

Predictor variable	Product-level Models (5)	(6)	(7)	Firm-level Failure Model (8)
β: Cumulative internal selection			−1.089•••	−0.969•••
			(0.233)	(0.213)
γ: Cumulative partial external selection			−2.234•••	−3.711•••
			(0.206)	(0.300)
Product introductions		−0.141••	−0.059••	−0.246•••
		(0.047)	(0.022)	(0.055)
Firm age	1.042•••	1.006•••	1.396•••	1.005•••
	(0.198)	(0.201)	(0.214)	(0.275)
Firm age^2	−0.084•••	−0.080•••	−0.096•••	−0.051•••
	(0.009)	(0.009)	(0.010)	(0.007)
Firm size	0.678••	0.668••	1.074•••	0.183•
	(0.237)	(0.236)	(0.263)	(0.096)
Firm size^2	−0.029•	−0.029•	−0.051•••	
	(0.013)	(0.012)	(0.014)	
Changed strategy	0.216	0.208	0.498	0.715
	(0.304)	(0.304)	(0.328)	(0.445)
Change clock	−0.052	−0.052	0.014	−0.061
	(0.048)	(0.048)	(0.055)	(0.095)
Prior performance < aspirations	0.136	0.130	0.495••	0.466•
	(0.142)	(0.142)	(0.158)	(0.228)
Prior performance > aspirations	0.020	0.046	−0.066	−0.135
	(0.090)	(0.089)	(0.098)	(0.158)
Number of products	0.132•••	0.207•••	0.297•••	0.293•••
	(0.030)	(0.040)	(0.038)	(0.040)
Products = 1 or 2	−0.746•••	−0.744•••	−0.174	−0.384
	(0.187)	(0.187)	(0.198)	(0.277)
Product age (or portfolio age)	0.778•••	0.734 •••	0.700•••	0.306••
	(0.102)	(0.103)	(0.105)	(0.096)
Product age^2	−0.044•••	−0.040•••	−0.038•••	
	(0.011)	(0.011)	(0.011)	
Product group size	0.074•••	0.079•••	0.077•••	
	(0.019)	(0.019)	(0.020)	
Population density	0.020•••	0.019•••	0.017•••	0.010•
	(0.004)	(0.004)	(0.004)	(0.005)
Product density / 100	0.158•••	0.154••	0.246•••	0.277••
	(0.049)	(0.050)	(0.054)	(0.088)
C4 ratio	−2.662	−2.552	−2.755	−0.342
	(1.519)	(1.522)	(1.589)	(2.023)
Selection mass / 100	0.825•••	0.793•••	0.908•••	0.487•••
	(0.079)	(0.079)	(0.086)	(0.096)
Community age	0.141•	0.145•	0.070	0.151
	(0.067)	(0.067)	(0.071)	(0.099)
Community density	−0.005••	−0.004••	−0.006•••	−0.005•
	(0.002)	(0.002)	(0.002)	(0.002)
−2 * log likelihood	4306.763•••	4294.212•••	968.822•••	677.915•••
Δ fit from prior model (χ^2)	n.a.	12.551••	325.390•••	n.a.

• $p < .05$; •• $p < .01$; ••• $p < .001$; two tailed tests.

* Models 5–7 are fixed-effects partial likelihood analyses with N = 11,707 product-years and 1,289 full external selection events. Model 8 assesses organizational failure, and N = 2,709 firm-years with 576 failure events. Hypothesis 3a predicted $|\gamma| > |\beta|$.

that the magnitude of its coefficient for cumulative partial selection (γ) was significantly greater than the one for internal selection (β) (χ^2 = 15.97, 1 d.f., $p < .001$). A similar post-hoc analysis of model 4 supported hypothesis 3b, since the magnitude of its partial external selection coefficient (γ) was significantly greater than the one for internal selection (β) (χ^2 = 56.95, 1 d.f., $p < .001$). This indicates that partial selection, which highlights mismatches between managerial beliefs and market demands, was a more powerful engine of adaptive learning than internal selection, whose potential lessons are sometimes distorted by organizational politics.

Hypothesis 6a stated that new product introductions would decrease future rates of full external selection, and model 7 supports that. Hypothesis 6b predicted that new product introductions would partially mediate the relationship between prior selection and future rates of full external selection. If partial mediation exists, then (1) new product introductions should be significant in model 6, *and* (2) the cumulative counts of internal and partial external selection should be significant in model 7, *and* (3) the coefficient for new products that is significant in model 6 should be smaller or non-significant in model 7 (Baron and Kenny, 1986). Here, we find strong evidence of partial mediation. While the new product term remained significant, its *p*-value more than doubles between models 6 and 7 ($p < .0025$ to $p < .0059$), and more importantly, its magnitude decreases by over 58 percent (–0.141 to –0.059). That supports H6b's prediction of partial mediation by indicating that selection catalyzes new product development.

While the foregoing analyses consider product-level outcomes, model 8 reexamines full external selection but estimates organizational failure rates. Accordingly, it uses firm-year data, drops the measure of product size (firm size is still controlled), and drops product age, controlling instead for the average age of the products in a firm's portfolio. Because the squares of firm size and portfolio age were not significant, they are excluded from model 8. As table 4 shows, the cumulative numbers of internal and partial external selection events decrease the odds of organizational failure, as do greater numbers of new product introductions, supporting hypotheses 1b, 2b, and 6a. Managers therefore learned to trim their product portfolios and increasingly used partial external selection to understand mismatches between their existing technologies and market demands. In turn, those lessons guided their search for new products, whose introduction enhanced firm survival. Also, as H3a predicted, a post-hoc analysis showed that the magnitude of the partial selection coefficient (γ) was greater than the one for internal selection (β) ($\chi^2 = 66.525$, 1 d.f., $p < .001$), so partial selection was a more powerful engine of adaptive learning than internal selection. On the whole, model 8 reveals that results are the same regardless of whether full external selection is modeled as the death of an entire firm or the multiple deaths of each of its products.

Product introduction results. Models 9 and 10 in table 5 analyze new product launches. Model 10 shows that those introductions increased with the cumulative numbers of internal and partial external selection events in a firm's past, which supports hypotheses 5a and 5b. Firms therefore learned from non-fatal selection events and used that knowledge to generate greater numbers of technological variations, which as shown earlier, enhanced firm survival.

Table 5

Autocorrelative Negative Binomial Models of New Product Introduction Counts (N = 2,709 firm-years)

Predictor variable	Model (9)	Model (10)
Cumulative internal selection		0.635•••
		(0.111)
Cumulative partial external selection		0.517•••
		(0.140)
Product introductions (lagged)	0.005	–0.012
	(0.016)	(0.015)
Firm age	–0.020	–0.026
	(0.014)	(0.014)
Firm size	0.066•••	0.067•••
	(0.019)	(0.017)
Changed strategy	–0.237•	–0.389••
	(0.107)	(0.126)
Change clock	0.055••	0.079••
	(0.021)	(0.028)
Prior performance < aspirations	0.229••	0.216••
	(0.078)	(0.075)
Prior performance > aspirations	–0.005	–0.003
	(0.041)	(0.041)
Number of products	0.030••	0.002
	(0.010)	(0.008)
Products = 1 or 2	–1.492•••	–1.520•••
	(0.077)	(0.074)
Population density	–0.000	0.000
	(0.001)	(0.001)
Product density / 100	0.030•	0.010
	(0.010)	(0.010)
C4 ratio	–0.091	–0.679
	(0.642)	(0.642)
Introduction mass	0.060	0.090
	(0.112)	(0.128)
Community age	0.030	0.037•
	(0.019)	(0.019)
Community density	0.001•	0.001••
	(0.000)	(0.000)
Sample selection λ	–3.264•••	–3.528•••
	(0.334)	(0.297)
Dispersion parameter	0.366	0.344
	(0.034)	(0.033)
Deviance	2323.710•••	2287.170•••
Δ fit from prior model (χ^2)	n.a.	36.540•••

• $p < .05$; •• $p < .01$; ••• $p < .001$; two tailed tests.

DISCUSSION

Though earlier work has explored links between population-level change and wholesale alterations in an organization's core (e.g., Amburgey, Kelly, and Barnett, 1993; Levinthal, 1997; Greve, 1998), full external selection has been studied in isolation from internal selection, which involves managerially driven changes in the variety of a firm's products and technologies. In this study, we considered both internal and full external selection, introduced partial external selection as a third variety, and showed that the three arise from interdependent and coevolving processes. Coevolution occurred because internal selection events had a negative and cumulative effect on future rates of full external selection, which occurs when the environment kills an entire organization and each of the products in its portfolio. Conversely, partial external selection, which occurs when the environment kills some of a firm's products, had a positive and cumulative effect on future rates of internal selection. One process that linked the internal and external realms was new product development. Internal and partial external selection each catalyzed the creation of new products, and firms that introduced more technological variations decreased their future odds of full external selection and organizational failure.

When the environment selects out part of a firm, managers respond by eliminating additional pieces of their product portfolio and developing new variants to replace them, actions that affect the future odds of both product-level and firm-level survival. Partial external selection is therefore part of a coevolutionary loop, since it begets internal selection and technological variation, which shape the future chances that the environment will kill all or part of a firm. Another form of coevolution occurred because managers frequently killed products before they became obsolete. Those proactive moves prevented deadwood from forming and allowed managers to reshuffle resources, which enabled firms to adapt to changing external conditions. This is evidenced by (1) the positive and cumulative effect of internal selection events on new product development and (2) the negative effect of new product introductions on organizational failure and full external selection. While we doubt that managers can accurately forecast technological discontinuities, there is strong evidence that they often extrapolate from their experience to adapt in anticipation of fast-breaking future changes. Though managerial foresight does not figure in external selection theory, our findings square with the fact that forecasting, whether it involves designing new products, ordering next season's inventory, setting budgets, or giving financial guidance to investors, is a frequent occurrence in many firms, and as our findings indicate, one that is amenable to learning by doing.

On the whole, synthesizing theories of internal and external selection is vital. This study has taken a first step by proposing that firms in high-velocity settings can be viewed as loosely coupled collections of products, each embodying variants of a firm's core technologies. Since either the environment or a company's managers can select out a product without killing the entire organization, a firm's technological core is better viewed as multipart and modular rather than as the monolithic and indivisible whole discussed by external selectionists (e.g., Hannan and Freeman, 1984; Tushman and Anderson, 1986). By emphasizing the ways in which an organization functions as a single, integrated unit, external selection theory has limited its focus to the deaths of entire firms and equated external selection with the inability to adapt to changing circumstances (Schumpeter, 1942; Hannan and Freeman, 1984, 1989). In comparison, by studying multiproduct firms, we were able to see adaptations that occurred after the death of some of their subparts, instances of partial external selection that prompted companies to search for new solutions and redirect their resources in ways that increased the odds of both product-level and firm-level survival. In some multiproduct firms, a single team repeatedly develops new offerings, while in others, multiple teams operate in parallel and are organized into separate divisions. In the former type of firm, internal and partial external selection remove a product but leave its supporting team intact. That also happens in multi-team companies, yet they can also shed an entire organizational subunit and survive. An interesting topic for future research, which our data did not allow us to address, is to explore how product removal and subunit removal differ as engines of organizational adaptation.

Our analyses revealed that partial external selection was a more powerful driver of evolutionary adaptation than prior instances of internal selection in terms of (1) reducing, by a greater margin, the future hazards of environmental selection and (2) increasing, by a greater amount, the rate at which firms proactively pruned their portfolios. The reason, we asserted, is that partial selection drove firms to find and understand mismatches between their current products and external demands, while internal selection decisions were increasingly colored by politics as the winners of earlier resource battles gradually skewed selection criteria away from market-driven realities toward the preservation of their political power. While we could not measure political power directly, our results showed that internal selection was self-braking, since its rate declined with the cumulative number of such events. This contrasts with other research showing that many organizational actions build momentum and increase in frequency (Miller and Friesen, 1980; Amburgey, Kelly, and Barnett, 1993), especially actions proven to have value, because managers repeat what has worked in the past (Cyert and March, 1963). Here, internal selection was valuable in enhancing survival, so the forces that slowed its repetition are likely to have been potent. Future research is needed to determine if politics were, in fact, what most constrained internal selection, yet that seems likely, given that the quest to attain, exercise, and preserve power pervades both case descriptions in the internal selection stream (Bower, 1970) and general theories of external selection (Hannan and Freeman, 1984; Miller, 1993).

Hypothesis 1a, which predicted a negative and cumulative relationship between internal selection and future instances of partial external selection, was the only one not supported, possibly because internal selection gave rise to opposing forces. Our results strongly indicate that internal selection prevented deadwood from forming and allowed managers to reallocate resources to meet changing external demands. At the same time, the subgroups empowered by those reallocations may have also tried to entrench themselves by lobbying for incremental upgrades to existing products, rather than developing new ones, and suppressing novel ideas by internal competitors in favor of approaches based on existing technologies (Sørensen and Stuart, 2000). As a result, internal selection may have produced enough incremental change and portfolio pruning to forestall organizational failure, which is consistent with our support for H1b. Yet such changes were apparently not enough, as H1a predicted, to enhance the external viability of individual products. Internal selection therefore improved the viability of organizational wholes, but not the strength of their individual building blocks. To further assess this, future studies might examine how internal selection affects a firm's propensity to introduce incremental products rather than more daring ones based on major technological advances.

Along these lines, Sørensen and Stuart (2000) found that as firms age, they increasingly exploit their existing technologies, as a firm's dominant political coalition has strong incentives to pursue activities that require its members' expertise. Our analysis of internal selection compliments those authors' work by indicating that coalitions maintain dominance not only through choices about specific technologies but also by choosing to retain or kill system-level products. Systems are composed of bundles of component technologies that must function together coherently, and the distinction between systems and components is important because firms make decisions about each using different routines, management structures, and ways of handling information (Henderson and Clark, 1990). Given that, future research might probe the interplay between component selection and system-level product selection. For example, as firms age, grow, and gain selection experience, does their attention shift from creating new systems using existing components to using new components to prolong the lives of old systems? Employing cutting-edge components often requires investments in proprietary technologies (Henderson, 1999), so such choices are likely to create political battles for resources between system developers and component engineers that affect selection, innovation, and a firm's degree of vertical integration.

Like all studies, this one has limitations that suggest areas for future investigation. Aside from the small number of interviews we conducted, we did not have access to managers' decision making, so we had to assess each product's sales trajectory to distinguish between internal and partial external selection. Future research that tests our assumptions about when managers cancel products is therefore needed. Also, the fast pace and short product life cycles of the personal computer industry may have produced effects that do not generalize to slower settings. In more placid settings, such as branded foods or hotel lodging, in which products have long lives and technology changes little, selection-based learning is apt to play a less prominent role. Partial external selection may provoke threat rigidity rather than adaptive search in more placid settings in which managers expect products to live for decades rather than months, so research in other industries is needed.

While our data provided an excellent picture of the products that firms brought to market, they did not contain information about projects that companies initiated but abandoned before commercializing. In this industry, that posed little threat because development times were short, so most projects that were begun were probably completed. Yet in other settings, such as the pharmaceutical industry, in which product development times often exceed a decade and numerous variations are abandoned during clinical trials, greater attention to pre-commercial selection would be needed. In addition, decentralized firms in which products are backed by relatively autonomous teams are the norm in high-velocity industries, but functional structures and centralized decision making are common in more stable settings, so research in those contexts is required. Finally, product introductions were the only form of organizational search that we studied. Product development may often be incremental and adaptive, while more discontinuous changes, such as replacing a founder (Carroll, 1984), might not be. Research into other forms of post-selection search is therefore warranted.

In conclusion, our findings support our claim that internal and external selection are interwoven processes and not the disjoint phenomena that their separate theories, methods, and literatures would indicate. Future synthesis of those research streams is necessary and is likely to yield important advances. In thinking about how firms and the individual projects within them coevolve, we can begin to ask questions such as what sequences of internal and external selection events are most and least adaptive? How do the effects of selection-based learning vary with industry volatility and velocity? And what organizational structures and incentive schemes best enable selection-based learning? By addressing these questions, we stand to gain a richer understanding of how processes of variation, selection, and retention shape both organizational and industry evolution.

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