Too Much of a Good Thing? Product Proliferation and Organizational Failure

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Abstract

When organizations make important changes, such as introducing products based on new technologies, they may gain strategic advantages but they also experience disruptions. We argue that these disruptions are especially strong when organizations introduce multiple products simultaneously, leading to a temporary increase in the hazard of organizational failure. To test this hypothesis, we study the effects of new product introduction on the survival of U.S. semiconductor manufacturers. We find that having a large number of products—especially innovative products—lowers organizational mortality rates, but that mortality rates increase because of the simultaneous introduction of multiple products. This hazard is substantial, amounting to an increase in the market exit rate of over 40% for the "average" case of simultaneous product innovation. These results are robust in models that control for a wide variety of other factors. Our findings call into question the idea that organizations can overcome disruptions from structural inertia by introducing multiple products simultaneously.

(*Organizational Ecology*; *Organizational Change*; *Technological Change*; *Technological Innovation*; *Complexity*; *Organizational Inertia*; *Organizational Failure*; *Technological Competition*; *First-Mover Advantage*)

Two antagonistic facts make organizational adaptation difficult. The first is that new developments, such as technical innovations, rapidly change the basis on which organizations compete. These events typically are marked by the entry of new organizations pursuing novel strategies, employing new organizational processes, producing innovative products, and offering new services (Schumpeter 1934, Tushman and Anderson 1986). The second fact is that change by existing organizations is difficult and often slow or error-prone for various reasons (Stinchcombe 1965, Hannan and Freeman 1984). New social roles take time to develop and to be learned by organization members. Existing structures produce patterns of reward distribution whose disruption engenders resistance (Baron et al. 1991). Political processes slow and sometimes block change initiatives within organizations (Frost and Egri 1991). Change by organizations is slowed further by commitments to existing technologies (Henderson and Clark 1990), and in many cases, organizations employ outdated practices to deal with new circumstances (Levinthal and March 1993). As a result of these various forces, when dramatic organizational change does occur it tends to be disruptive, so that attempts by organizations to adapt to changing circumstances can be hazardous.

Since Hannan and Freeman (1977, 1984) elaborated this idea in their theory of structural inertia, a literature has developed looking at the causes and consequences of organizational change. Researchers now typically acknowledge the once controversial idea that organizational change is difficult and hazardous. Instead of debating whether organizations are inert, researchers look for the conditions under which organizations are more or less adaptive (see Barnett and Carroll 1995 for a review). This literature catalogues various factors that affect the strength of organizational inertia, including organizational characteristics (e.g., Haveman 1993a, Amburgey et al. 1993, Huber et al. 1993, Carroll and Teo 1996), the position of an organization in its environment (e.g., Miner et al. 1990, Singh et al. 1991), and the extent or type of change in question (e.g., Carroll 1984, Singh et al. 1986, Zajac and Shortell 1989, Anderson and Tushman 1990, Delacroix and Swaminathan 1991). Overall, research has progressed to the point where we are now beginning to understand the various conditions that affect the extent, benefits, and hazards of organizational change.

An interesting consequence of this progress is the recent renaissance in adaptationist thinking, in which researchers accept the reality of structural inertia but consider it to be a manageable variable. Researchers then look for cases of "best business practice," where organizations have been particularly capable of reacting to a changing environment (Burgelman 1994). So focused, attention goes to what makes some organizations change rapidly: what makes them decisive (Bourgeois and Eisenhardt 1988), quick to market products (Hansen 1996), or more

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generally to what gives organizations the capability to change (Teece and Pisano 1994).

One of the more widely accepted ideas in this body of work is that organizations may typically remain inert, but that they occasionally engage in multifaceted transformations when environmental demands are acute. The rationale behind this idea builds on the workings of structural inertia. Incremental changes are inhibited because organizations are systems made up of interdependent parts. When such systems do change, they are likely to do so in all-at-once jumps from one organizational configuration to another (Miller and Friesen 1984, Tushman and Romanelli 1985, Milgrom and Roberts 1990, Romanelli and Tushman 1994). Crucial to such transformations is the ability of an organization to simultaneously innovate, coordinating multiple innovations on different fronts at the same time (Iansiti and Khanna 1995, Tushman and O'Reilly 1997). In this way, large-scale innovation is thought to be a strategy for managers to overcome organizational inertia.

Clearly it is important to understand how organizations adapt through product innovation. We are concerned, however, that in their search for instances of adaptation, researchers may be overlooking the unintended consequences that may also result from such change (Merton 1936, March 1981). In particular, we think that when organizations add multiple products at once, they may benefit in some ways but also experience disruptions that increase their hazard of failure. These disruptions result, we argue, because product innovation typically requires adjustments in various parts of the organization. For the introduction of a single new product, these accompanying adjustments throughout the organization may be straightforward. When multiple innovations occur at once, however, adjustments made for one change may complicate adjustments made for the others. Consequently, we think it is hazardous for organizations to implement multiple, simultaneous product introductions.

To test our idea, we investigate how new product introductions have affected organizational survival chances in the U.S. semiconductor industry. To build an empirical model, we distinguish between two general consequences of change. On the one hand, change alters the *content* of organizational activity, bringing differences in the products and services offered by an organization. When researchers identify instances of adaptive, innovative organizations, they usually focus on such content effects of change. Controlling for these content effects, however, change also has *process* effects. These are the consequences that result from change per se: the often disruptive effects of altering organizational structures, procedures, capabilities, norms, roles, partnerships, and the like (Barnett and Carroll 1995). Our idea concerns the process effects of introducing multiple products simultaneously, which we think increases the chances of organizational failure, even when the resulting changes succeed in terms of content effects. Before conducting our empirical test, we first explain our thesis in more detail.

Organizational Inertia and Product Innovation

Hannan and Freeman (1984) argue that natural selection processes favor reliable, accountable organizational forms that maintain themselves in a relatively inert state. More recently, Kreps (1996) reasons that boundedly rational players sometimes prefer relatively inert behavior to coordinate with others. By either logic, theories of organizational inertia conclude that the organizations we see at any given time will tend to resist significant changes. In particular, inertia is thought to be strongest in an organization's "core" functions—its mission, authority structure, technology, or fundamental marketing strategy—when these would require new or different organizational structures, routines and procedures, roles among organizational members, and associations with other organizations (Hannan and Freeman 1984). Such deep-seated changes tend to be resisted, especially in established organizations that have learned well from their experiences (March 1988).

When organizational change does occur, new roles, procedures, and structures take time to build (Stinchcombe 1965, Hannan and Freeman 1984). It also takes time to form informal network relations within organizations, and to establish ties with other organizations. The effort and resources devoted to solving these managerial problems are not available for other purposes, some of which have direct effects on the probability of survival. For these reasons, structural inertia theory predicts that the process of organizational change initially causes higher rates of organizational failure, with a changed organization suffering from much the same liabilities as a brand-new organization (Hannan and Freeman 1984). As time passes after an organization changes, this hazard dissipates as the organization adjusts to its new form and circumstances (Amburgey et al. 1993).

These ideas apply well to new product introductions. New routines are put in place to design, produce, and distribute the new product. These routines often require different workforce and organizational capabilities (Tushman and Anderson 1986). The formal job responsibilities of some positions in the organization may be changed, including those of managers responsible for controlling the work activities of those using the new routines. With new and changing roles among the workforce come changes in the networks of relations and communications within the organization (Henderson and Clark 1990). Similarly, relationships with other organizations may need to be changed to accommodate the requirements of the new product, and new ties with other organizations may need to be formed (Rosenbloom and Christensen 1994). Following the logic of structural inertia theory, these various adjustments are unlikely to occur optimally at first, and so the organization is likely to experience disruption immediately following product innovation. Over time, these initial problems are then likely to dissipate as the organization learns how to support the new product.

This pattern of temporary resistance and disruption plagued some transistor producers, for example, when they initially attempted to produce integrated circuits (Brittain and Freeman 1980). At that time, transistors were sorted by their electrical properties after production. Consequently, there was no need to link specific customer needs to a producer's production, R&D, marketing, distribution, or sales organization. Instead, producers manufactured inventory that was sold "off the shelf." By contrast, integrated circuits typically were manufactured to order, with functionality specified by customer needs and designed prior to manufacture. This required considerably more attention to customer needs in virtually all stages of the research, development, production, distribution, and sales processes. It proved to be very difficult to adapt transistor production organizations to these very different requirements. Motorola, for instance, only succeeded in raising its semiconductor yields (the percentage of each batch that would pass inspection) when it pulled production out of its transistor manufacturing division and placed it in a new plant and organization dedicated to the new products. After a period of adjustment, the company's yields improved to competitive levels. In this way, product innovation can trigger the temporary disorganization predicted by structural inertia theory.

Inertia and Disruption in Multiple Product Innovation

We think that these difficulties during product innovation vary, depending on how many new products are added simultaneously. When only a single new product is introduced, an organization's systems need to adjust only to this product's requirements, and so the resulting disruption is likely to be relatively minor. When multiple products are introduced all at once, however, each will require an adjustment of organizational systems. These different, simultaneous organizational adjustments may each constrain, contradict, or interfere with one another in unexpected ways, increasing *coordination uncertainty* (Camerer and Weber 1998). This increase in uncertainty implies a greater chance that problems will occur during product introduction. For example, Iansiti (1997) reports that Intel suffered from problems coordinating concurrent innovations during the firm's development. According to Iansiti, these problems have been relieved since Intel has reduced its number of concurrent product development initiatives. More generally, we expect that problems of coordination uncertainty increase with the number of products that are introduced simultaneously by an organization.

We qualify our argument, however, because in many cases organizations avoid coordination uncertainty by "decoupling" weakly related innovations. In these cases, an organization is able to isolate innovations from one another, in separate groups or divisions, allowing independent adjustments to the requirements of each new product (Simon 1962, Hannan and Freeman 1984). This decoupling should decrease problems of coordination uncertainty among less-related innovations. By contrast, when innovations are closely related in either their technologies or their product markets, they are more likely to require adjustments in the same parts of the organization. Such mutual interdependency is known to increase the strength of organizational inertia, because adjustments for each of the interdependent products are then more likely to interfere with the others (Hannan and Freeman 1984, Henderson and Clark 1990, Carroll and Teo 1996, Sorenson 1997). For this reason, we think that problems of coordination uncertainty are greatest when the innovations being simultaneously adopted are more closely related.

To operationalize our prediction, we note that as the number of simultaneous innovations increases, the number of uncertainty-causing interactions among them increases at an increasing rate. (For a fully interdependent system, the number of interactions increases as a square of the number of new products.) For this reason, we expect the total amount of coordination uncertainty to increase nonlinearly with the number of related products introduced at once. Assuming that this uncertainty is hazardous to organizational life chances, we predict:

The simultaneous introduction of multiple, related products by an organization make it more likely to fail, an effect that increases at an increasing rate with the number of products introduced at once.

This increase in the failure rate is likely to abate over time, however, as coordination problems are resolved by trial-and-error learning. So we also predict:

This increase in the failure rate falls away as time passes after the change.

To test our ideas, we follow the approach used by

Miner et al. (1990) in their study of changes among newspaper publishing organizations. They distinguished between cases where a newspaper changed one aspect of its publication and cases where more than one aspect was changed simultaneously, finding that failure rates increased more when more than one aspect of the paper was changed at once. To investigate our idea, we need to adapt this approach to distinguish between cases according to the number of innovations that take place simultaneously—a variable that ranges along an interval scale. Specifically, in our model we will distinguish cases of single-product innovation from cases of multiple-product innovation, and then specify the latter term according to the number of related innovations that occur at once. To allow the effects of these innovations on the failure rate to change over time, we also include backward-recurrence clocks as used by Amburgey et al. (1993). These terms are then included together in the following model:

$$r_j(t) = r_j(t)^* \exp[\delta(\Delta P_j) + \gamma(\tau_{\Delta Pj}) + \delta_M(N_{\Delta Pj}) + \gamma_M(N_{\Delta Pj}\tau_{\Delta Pj})],$$

where $r_j(t)$ is the instantaneous failure rate of organization j, which is allowed to vary over the organization's time in the market t. The term $r_j(t)^*$ represents the baseline hazard rate for organization j, which we will specify as a function of variables thought to be important to organizational failure (as we discuss below). ΔP_j is an indicator variable equal to zero until organization j changes its product offerings and equal to one thereafter (starting with the year after the first change). $\tau_{\Delta Pj}$ is the time since the last change in organization j's product offerings (if any). Working together, ΔP_j and $\tau_{\Delta Pj}$ allow change to have an immediate effect on the failure rate (measured by coefficient δ) that then increases or decreases over time (as revealed by coefficient γ). These effects distinguish organizations that have changed their products from those that remain with their initial product offerings.

The variable $N_{\Delta Pj}$ is the number of related new products introduced all-at-once by organization j in its most recent product introduction (if more than 1 were introduced at once), and $N_{\Delta Pj}\tau_{\Delta Pj}$ is the interaction of this term and the time since these products were added. These two terms allow the effects of product introduction to differ according to the number of related new products added all-at-once. If our predictions are correct, then we will find that $\delta_M > 0$ and $\gamma_M < 0$, where adding multiple, related products temporarily increases the failure rate. Our theory predicts a disruptive effect that increases with $N_{\Delta Pj}$ at an increasing rate. In our model, this functional form arises by construction, because we use an exponential specification. Questioning this specification, we will also estimate the model with $N_{\Delta Pj}$ specified in the natural logarithm and as a quadratic—both functions that allow the effects of $N_{\Delta Pj}$ to increase at a decreasing rate.

Two Alternative Hypotheses

Punctuated Change. Contrary to our thinking, some analysts argue that multifaceted change is more adaptive because of organizational complexity.[1] Various scholars agree that integrated organizational systems find it more adaptive to change in multifaceted reorientations toward radically different configurations (Miller and Friesen 1984, Tushman and Romanelli 1985, Henderson and Clark 1990). If value-adding "complementarities" exist among parts of an organization, as in Milgrom and Robert's (1990) theoretical model, then it may be more adaptive to change many parts of the organization at once than it is to change just one part. The idea here is that changing just one part of such an organization incurs the cost of lost complementarities. Changing many parts, in contrast, allows the organization to "jump" to a new configuration with a different set of valuable complementarities. Furthermore, the existence of a small number of possible, discrete configurations should serve to simplify the decision at hand (Milgrom and Roberts 1995). As these authors conclude, ". . . changes need to be coordinated, multidimensional, and large . . . It also means that half-way measures—partial adjustments in the right general direction—are likely to yield worse results than staying at the original position." (Milgrom and Roberts 1995, p. 248). Applied to the question of new product introduction, this thinking motivates an alternative to our prediction: Simultaneous product introductions by an organization make it less likely to fail. If correct, this idea suggests that we will find $\delta_M < 0$, where adding a greater number of products all-at-once lowers the failure rate.

Interestingly, analysts taking this perspective have observed that organizations are unlikely to make this kind of reorientation perfectly. Instead, they speculate that after a major reorientation, an organization will probably benefit from continued local search and learning (Tushman and Romanelli 1985, Milgrom and Roberts 1995). This agrees with our prediction that organizational failure rates will fall as time passes after a major organizational change ($\gamma_M < 0$). Those who argue for the adaptiveness of punctuated change, then, disagree with our prediction about the immediate effects of such change while they agree with our prediction about improvement after the change.

In our view, all-at-once change may possibly shift an organization into a valuable new configuration, but such change nonetheless creates considerable coordination uncertainty. We doubt that the existence of discrete structural alternatives will serve to reduce this uncertainty to the point where such "bet-the-company" shifts are immediately adaptive. Rather, we think that the search for a new configuration probably begins with a low initial starting point. Furthermore, because this uncertainty compounds with the number of simultaneous changes, we expect that managers are likely to underestimate the difficulties involved. Over time, an improved configuration may be discovered through local search, but not before the organization has suffered a period of increased failure chances. In this way, we agree that all-at-once reorientations may be adaptive eventually, but only after a period of readjustment to the multifaceted change as we predict. With these arguments in mind, our approach is to resolve this disagreement empirically.

Technological Distance. Another alternative hypothesis is well established in the literature on technological change. We predict that coordination uncertainty is strong when multiple new products are related, but many scholars argue precisely the opposite, that organizational inertia is more of a problem when new products are technologically unrelated (Tushman and Anderson 1986, Anderson and Tushman 1990, Henderson and Clark 1990, Henderson 1993, Iansiti 1997). This disagreement results from a difference in underlying logic. Our argument focuses on disruption because of problems of coordination among multiple changes that constrain and interfere with one another. Such interdependencies are more likely the more that products are related to one another. By contrast, the alternative view focuses on the availability or appropriateness of organizational capabilities. When organizations add products that build on existing organizational and technological capabilities, these changes are predicted to be less disruptive and so less hazardous, while changes that require entirely different capabilities are thought to be more hazardous.

In testing our hypothesis, it is important that we separately control for the effect of moving into technologically distant product areas. We do this by including in the model the variable $N_{\Delta Dj}$, which counts the number of product groups being entered by organization j that are technologically distant from j's current products. If change is (temporarily) hazardous when it involves movement into technologically distant product areas, then we will find $\delta_D > 0$ and $\gamma_D < 0$, where δ_D is the effect of moving into technologically distant product groups, and γ_D allows for a time decay in that effect. Furthermore, if the adoption of technologically distant products is more hazardous than adopting related products, then we also will find $\delta_D > \delta_M$ (where δ_M is the effect of adding multiple, related products). By contrast, our hypothesis predicts that change is hazardous for simultaneous product additions especially when they are technologically related, so our hypothesis will be supported if $\delta_D < \delta_M$. In this way, separating out the effects of change according to technological distance allows a more precise test of our hypothesis. Also, this approach will prevent disruption because of technological distance from being mistakenly interpreted as support for our hypothesis.

Modeling the Consequences of Change

A problem pervading much of the research on organizational change is that different studies control for or condition on different variables, making it difficult to reconcile inconsistent results. This problem is made worse by the fact that models of the effects of organizational change are often sensitive to specification error (Barnett and Carroll 1995). With this in mind, our strategy is to lay out in advance a relatively comprehensive set of control variables and conditions that, according to prior research, should be explicitly incorporated in our model specification (over and above control variables that are particularly relevant to the semiconductor industry). Two general types of conditions appear in the literature: differences in the consequences of change having to do with the characteristics of organizations and differences that result from the competitive or institutional environment. We review each of these differences to build them into our empirical model, either as control variables determining the baseline hazard rate $r_j(t)^*$ or as additional specifications of the change variables.

Growth and Decline Trajectories. Contrary to our prediction, some studies that operationalize change in terms of new product introduction find that such changes decrease the hazard of organizational failure (Delacroix and Swaminathan 1991, Haveman 1992). However, organizations that add new products are likely to be experiencing good times generally, in which case they will also be less likely to fail. This coincidence may have spuriously affected the estimates of previous studies on the effects of product introduction, showing apparent support for the idea that change improves organizational life chances. If so, then these results are not causal but occur because other factors both make some organizations less likely to fail and allow them the opportunity to grow. This problem may also affect studies that operationalize change in terms of the market growth or alteration (Kelly and Amburgey 1991, Miller and Chen 1994). When this problem occurs, then the apparent "effects" of new product introduction simply reflect the fact that some organizations are on a growth trajectory, in which case it is unlikely that they would fail (Barnett and Carroll 1995).

To capture the effects of being on a growth (or decline) trajectory, we decompose the change indicator variable ΔP_j and clock $\tau_{\Delta Pj}$ to distinguish between product additions and product deletions. This approach allows us to separate the effect of adding products (δ_A) and the time decay in this effect (γ_A) from the effect of exiting from product categories (δ_E) and its time decay (γ_E). If product additions indicate that an organization is on a growth trajectory, then we would find $\delta_A < 0$ and $\gamma_A > 0$. These effects together predict lower failure rates for organizations experiencing more frequent product additions. Meanwhile, the opposite pattern of effects ($\delta_E < 0$ and $\gamma_E > 0$) is likely for the event of exiting from product categories, because frequent events of this sort suggest that an organization is on a decline trajectory. Our prediction of a temporary disruption because of multiple product introductions should hold after separately controlling for these effects of being on a growth or decline trajectory.

Organizational Age and Size. Many researchers argue or find that the causes and consequences of organizational change depend on an organization's age or size. Hannan and Freeman's (1984) theory argued that inertia increases with age, as organizational practices and relationships become institutionalized, suggesting that change is less likely and more hazardous as organizations age (see also Barron et al. 1994). Consistent with this idea, various studies find that older organizations are less likely to change (Delacroix and Swaminathan 1991, on California wineries; Baron et al. 1991, on California state agencies; Amburgey et al. 1993; on Finnish newspaper publishing organizations; Halliday et al. 1993, on state bar associations; Miller and Chen 1994, on airlines), although Baron et al. (1991) find that change again becomes more likely among very old California state agencies. Studies of the consequences of change show more mixed results. Amburgey et al. (1993) find that change is more hazardous for older newspaper publishing organizations, while Baum and Singh (1996) find the opposite effect among expanding child care centers.

There is some disagreement in the literature about whether larger organizations are more or less inert. Some have argued that the greater resources of larger organizations give them the wherewithal to change (Galbraith 1967, Kimberly 1976, Aldrich and Auster 1986). By contrast, Hannan and Freeman (1984) predicted that larger organizations are more complex, making them less likely to change and more likely to fail when they try. Empirically, Huber et al. (1993) find a positive relationship between organizational size and the likelihood of change in a retrospective study of surviving organizations. Several studies find a negative relationship between size and change (Delacroix and Swaminathan 1991, on the California wine industry; Halliday et al. 1991, on U.S. state bar associations; Baron et al. 1991, on California State agencies), while Haveman (1993a) finds that diversification is more likely among middle-sized savings and loans. On the consequences of change, two studies show that change is more hazardous for larger organizations: Carroll and Teo (1996) study technology change covering the entire history of the American automobile industry, and Baum and Singh (1996) study Toronto day care center expansion. Clearly, it is important to allow for size- and age-dependent effects of change on failure, and we do so in our analysis.

Innovation and Competition. Thus far, we have focused on the possibly disruptive *process* effects of change per se. We have not considered, however, the fact that product introduction is usually carried out with the intention of improving the *content* of an organization's strategy: making it more appealing to customers, better able to retain revenues as profits, and in general better able to compete with its rivals. We think that product introductions often result in these intended, adaptive consequences for organizations, and our model must control for these content effects of change for us to distinctly identify whether product innovation also carries the unintended, disruptive process effects that we predict (Barnett and Carroll 1995). For instance, Barnett's (1994) study of technological innovation among early telephone companies found evidence that such change increased failure rates, but this was revealed only in models that separately controlled for the strategic advantages conferred by newer technologies.

The content effects of innovation are well described in theories of industrial evolution, which identify two general ways that product innovation affects the fates of organizations (Schumpeter 1934). On the one hand, there are benefits to being the first organization to offer a particular type of product (Williamson 1975, Lieberman and Montgomery 1988). First-mover products establish a market position that later entrants may not be able to take away, as when innovative products cultivate a good reputation or gain a loyal customer base. Furthermore, first-to-market organizations benefit from learning advantages not had by those who follow. On the other hand, there are competitive advantages for waiting to come to market with the most advanced products, because these products typically outcompete earlier ones on the basis of price, qualitative characteristics, or both (Nelson and Winter 1982, Dosi 1984, Mitchell 1989, Khanna 1995, Carroll and Teo 1996).

Our objective is to control for each of these consequences of innovation: both the advantage of having an early market position and the counteradvantage of being more up-to-date. To control for the first effect, we note that during the period of our study, the semiconductor industry comprised 80 distinct product types. Organization j's presence in the market, then, can be described in terms of which of these products it offered in any given year. As a baseline, the survival implications of j's product offerings can be modeled in terms of an undifferentiated summary statistic $\lambda\Sigma_j P_j$, where P_j is a vector of 80 binary variables corresponding to the industry's possible set of products. Each variable is equal to one in a given year if organization j offers a given product, and zero otherwise. So defined, $\Sigma_j P_j$ is simply the size of organization j in a given year measured as its number of product offerings, and λ is the effect of size so measured on the failure rate.

To allow the timing of product arrivals to matter, we then decompose this sum and its effect into two terms, $\lambda_I \Sigma_j P_{Ij}$ and $\lambda_F \Sigma_j P_{Fj}$, corresponding to the number of innovative and follower products, respectively, offered in a given year by organization j. (We define a product to be innovative if it is the first ever of a given product category to appear in the industry, and all product offerings that come later within that category are considered followers.) The coefficient λ_I, then, is the effect of an organization having an innovative product, while λ_F is the effect of having a follower product. As specified in our model, the first-mover advantage is then equal to $\exp[\lambda_I - \lambda_F]$. Note that in our empirical tests, we are likely to exaggerate the size of this first-mover advantage. Often, innovative products fail to make it to market, a fact that makes experimentation a risky strategy (March 1991). Like most data taken from market guides, however, ours suffer from sample selection bias because they omit these most-onerous failures. For this reason, we probably overestimate the first-mover advantage (cf. Fleming 1998).

Separate from these effects, we also incorporate the competitive consequences of product introduction. Our approach here is based on the fact that as organizations change the content of their strategy, they encounter different—and potentially more formidable—competitors (Barnett 1990, Baum and Singh 1996, Greve 1996). In the case of these semiconductor firms, adding a product implies moving into competition with those organizations that already produce that product or who will produce it in the future. To measure this, we count the "product density" faced by each organization j: the number of products offered by other organizations in a given year in the same product categories where j offers products. In contrast to the density of organizations, which counts all organizations whether or not they are in the same or in different parts of the market, product density distinguishes between rival and nonrival products, similar to measures of "niche overlap" used in other studies (McPherson 1983, McPherson and Smith-Lovin 1988, Baum and Mezias 1992, Podolny et al. 1996).

We include in the model $\alpha\Sigma_{j\neq k} P_k$, as a baseline measure of product density, where $\Sigma_{j\neq k} P_k$ is the number of products offered by j's rivals k in the same product categories in which j offers products, and α is the competition coefficient representing the effect of these rival products on j's failure rate. The "average" strength of product competition is reflected in α, which we expect to be greater than zero. For comparison, we also include the number of products in categories where organization j has no products, which we call "nonrival product density." By comparing the effects of rival and nonrival product density, we measure the empirical importance of product overlap.

These measures of product density allow for niche overlap in product space, but they make no allowance for whether products are close or distant in *time*. Yet, as our discussion of Schumpeter's theory suggests, differences in time of arrival are likely to be very important to competition in technology-driven markets. Consequently, we also allow competitive intensity to vary according to whether j's rivals are more or less up-to-date. Our approach is to decompose the product density term into two parts, $\alpha_E \Sigma_{j\neq k} P_{Ek}$ and $\alpha_L \Sigma_{j\neq k} P_{Lk}$, corresponding to whether rival products arrived to market earlier or later in a given product category than j's product offering did. In our model, separating the effects α_E and α_L allows rivals to generate stronger competition by introducing a more recent product. Both terms represent the effects of other firms' products on organization j's failure rate, and so we expect them each to be positive. There would be no significant difference between these coefficients if all products generate competition of equal intensity. If more recently-introduced products and technologies generate stronger competition, as discovered in Carroll and Teo's (1996) study of innovation in the U.S. automobile industry, then we should find that $\alpha_L > \alpha_E$.

Taken together, these market timing and competition effects allow for a reasonably complete specification of the Schumpeterian tradeoff between being first-to-market and being up-to-date. Organizations with the greatest first-to-market advantage will face all of their competition (if any) in the form of more up-to-date rivals. Conversely, organizations that arrive to market consistently late miss out on the first-mover advantage, but instead reap the advantage of having less up-to-date rivals. Furthermore, by measuring these distinctions among the 80 different product categories in our data, we allow organizations to follow "mixed" strategies of being early in some parts of the market while they are more up-to-date in others.

Institutional Linkages. The consequences of organizational change also depend on the institutional position held by organizations, defined specifically in terms of relationships to other important organizations in its environment. In general, we know that such institutional affiliations matter to survival as a main effect (Carroll and Delacroix 1982, Baum and Oliver 1991). We also know that changes in an organization's institutional environment affect its likelihood of changing (Edelman 1990, 1992, Baron et al. 1991, Singh et al. 1991, Dobbin et al. 1993, Sutton et al. 1994). Our concern here is whether institutional affiliations may buffer organizations from the otherwise disruptive effects of organizational change, as Miner et al. (1990) found in their study of Finnish newspapers. In our data, the most obvious institutional distinction appears among semiconductor producers that are divisions of larger organizations. For these divisions, exit rates are known to be lower than is the case for standalone semiconductor firms (Hannan and Freeman 1989), and so we will control for this distinction in our models.

To summarize, Table 1 lists some of the predictions that we will test by estimating our model. The table starts with our central hypothesis: Simultaneous product innovation is hazardous to an organization's life chances. Then, we list the other change effects to be estimated, as well as the likely effects of innovation and competition.

Data and Method

Our analysis looks at the effects of product innovation on the exit rates of U.S. semiconductor firms from 1946–1984 (see Hannan and Freeman 1989). The data come primarily from a standard industry reference book, the *Electronics Buyer's Guide*. This annual publication lists standard electronic devices yearly, and all the companies in the U.S. that manufacture those devices and sell them on the open market. The data include firms and devices for the years 1946–1984. The study terminates in 1984 for two reasons: the *Electronics Buyer's Guide* ceased publication in the mid-1980s and Japanese manufacturers began making significant inroads in the U.S. market in the early 1980s (especially in DRAMs). After the Japanese entry, it made little sense to define the population as U.S. semiconductor manufacturers. The industry became truly global in short order. This data structure could be described as a three-dimensional array: firms by semiconductor devices by years. If a firm sold a particular device in a year, then it received a value of one; otherwise, the value was zero. Figure 1 shows the number of firms in the data over time.

Our dependent variable is *organizational failure*, operationalized as occurring when a semiconductor manufacturing organization ceased operating. If a semiconductor manufacturer continued to operate through 1984, the end of our study period, then its life is coded as "right censored" as of 1984, and for it no failure event is recorded. Semiconductor manufacturers which ceased operations during the study period were recorded as experiencing an organizational failure event as of their final year of operation. In some cases, a semiconductor manufacturing organization would be owned by a corporate parent and might be sold to another corporate parent or "spun off" to stand alone in the industry. In other cases, a semiconductor manufacturing organization might merge with another. Such ownership-change events, while possibly constituting a market exit for a parent corporation, were not coded as failures if the semiconductor organization continued business as usual after the ownership change. If, however, a semiconductor organization ceased operations as part of an ownership change, then we coded the event as an organizational failure, even if later in time the parts of the prior organization reappeared as parts of other organizations or were recombined to start over as another organization. Specifically, mergers and acquisitions were investigated to see whether name changes, changes in location, and significant changes in product offerings implied that an ownership change involved the ending of operations by the existing semiconductor organization. Only in those cases were ownership changes regarded as organizational failure events. So defined, the historical pattern of entries and exits in the industry are shown in Figure 2.

Products were coded according to a standard set of 80 *product categories*. For each firm, the data record the categories in which it offered products in its initial year and each subsequent year. For instance, one of these categories is "MOS Memory—Dynamic RAMs." These 80 product categories, in turn, are contained in nine *product groups* according to their technological relatedness. These product groups, and the historical proliferation of products, are shown in Table 2.

Our model specifies the effects of *product density*, measured as the number of products offerings (among the 80 possible categories) that exist in a given year, not including those offered by the focal organization. We also included the *product density faced by each organization upon market entry*, so-called density delay, which is typically associated with higher failure rates reflecting scarce

Table 1 Selected Exit Rate Model Coefficients and Their Interpretations

Independent Variables (Coefficients)	Coefficient Predictions	Interpretations
Change Effects:		
Number of technologically related products added (δ_M) . . . Also interacted with product addition clock (γ_M)	$\delta_M > 0$ $\gamma_M < 0$ $\delta_D < \delta_M$	Our hypothesis: Exit rates temporarily increase with the number of simultaneous product introductions, and this increase is greater when the new products are technologically related.
No. of technologically distant product groups entered (δ_D) . . . Also interacted with product addition clock (γ_D)	$\delta_D > 0$ $\gamma_D < 0$ $\delta_D > \delta_M$	An alternative hypothesis: Exit rates temporarily increase with the number of technologically distant product introductions, an effect that is stronger than that due to adopting related products.
Product addition indicator (δ_A) and product addition clock (γ_A)	$\delta_A < 0$ $\gamma_A > 0$	Recent addition of a product category may indicate that the organization is on a growth trajectory.
Product exit indicator (δ_E) and product exit clock (γ_E)	$\delta_E > 0$ $\gamma_E < 0$	Recent exit from a product category may indicate that the organization is on a decline trajectory.
Product addition × Org's industry tenure (δ_{Age}) . . . Also interacted with product addition clock (γ_{Age})	$\delta_{Age} > 0$ $\gamma_{Age} < 0$	Change by older organizations is especially, but temporarily, hazardous.
Product addition × Org's number of products (δ_{Size}) . . . Also interacted with product addition clock (γ_{Size})	$\delta_{Size} > 0$ $\gamma_{Size} < 0$	Change by larger organizations is especially, but temporarily, hazardous.
Innovation and Competition Effects:		
Organization's number of products, innovative products (λ_I) versus follower (λ_F) products	$\lambda_I < 0$ $\lambda_F < 0$ $\lambda_I < \lambda_F$	Size defined as the number of products lowers the failure rate, and the number of innovative products lowers the failure rate more than the number of follower products.
Rival product density, earlier arrivals (α_E) versus later arrivals (α_L)	$\alpha_E > 0$ $\alpha_L > 0$ $\alpha_L > \alpha_E$	More recently arriving products generate stronger competition due to technological recency.

Figure 1 Semiconductor Manufacturers in the U.S.

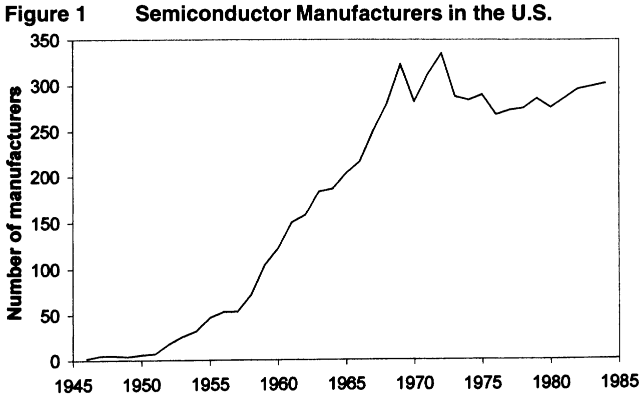
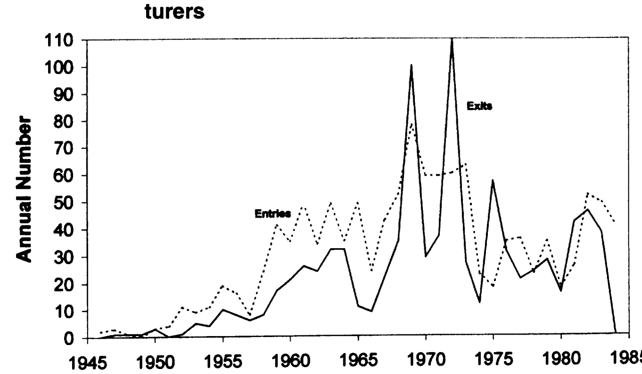


Figure 2 Entries and Exits of U.S. Semiconductor Manufacturers



founding conditions for organizations that enter a crowded market (Carroll and Hannan 1989).

We also include a number of variables as controls in our models. Some of these variables are described in detail in Hannan and Freeman (1989). They include the *number of exits the previous year*, the *bond interest rate* measured at year-end, *total sales of semiconductor products in North America*. We added a binary variable that has a value of 1 when a semiconductor firm is a *division of a larger corporation*. There were two *historical period*

Table 2 Product Proliferation in the U.S. Semiconductor Industry

	Number of Product Types Within Product Group/Total Number of Such Products on the Market								
Product Group	1946	1950	1955	1960	1965	1970	1975	1980	1984
Diodes and Rectifiers	1/2	1/6	2/51	7/235	9/497	9/551	10/371	9/365	9/392
Transistors and thyristors	0/0	0/0	2/32	6/167	10/392	10/438	12/347	12/321	11/364
Digital integ. circuits	0/0	0/0	0/0	0/0	6/84	17/258	18/378	18/296	13/203
Analog/linear integ. circuits	0/0	0/0	0/0	0/0	1/30	6/129	8/181	8/165	7/158
Signal convert. integ. circuits	0/0	0/0	0/0	0/0	0/0	0/0	2/16	2/45	2/45
Custom integ. circuits	0/0	0/0	0/0	0/0	0/0	3/19	4/127	3/107	3/125
Hybrid circuits	0/0	0/0	0/0	0/0	2/72	7/139	12/363	11/298	10/295
Light-emitting devices	0/0	0/0	0/0	0/0	1/5	1/14	1/49	1/56	1/65
Photo-sensitive devices	0/0	0/0	0/0	2/23	2/56	2/54	3/82	4/74	4/87
Total	1/2	1/6	4/83	13/425	31/1136	55/1602	70/1914	68/1727	60/1734

dummies: HP2 for 1960–1969 (the integrated circuit dates approximately from 1960); and HP3 for 1970–1985 (approximate introduction of the microprocessor to the end of the study). We include *fixed effects for the general product groups* listed in the first column of Table 2. As suggested by Barnett and Carroll (1995), this is the most comprehensive approach possible to controlling for "content" effects of changing strategies into and out of product groups. In this context, these fixed effects help to control the fact that each product group may have a different organizational carrying capacity.

Our models attempt to control for organizational size and age, but with two caveats. First, we do not have continuous measures of organizational size, such as sales, assets, or number of employees. Instead, we know the *number of products offered by each organization* in each year. While not an ideal measure, this variable does distinguish between organizations according to their sizes in a rough way. Second, *each organization's tenure in the industry* was defined as the time (in years) passed since it entered the industry. Tenure dependence was modeled using the piecewise exponential specification. This specification allows us to estimate the effects of duration without specifying a parametric distribution for duration dependence (Barron et al. 1994). Using interactions with these measures, we allow for both age- and size-dependent effects of product introductions on the exit rate: an age-dependent change effect (δ_{Age}), its time decay (γ_{Age}), a size-dependent change effect (δ_{Size}), and its decay (γ_{Size}). Descriptive statistics on all variables used in the analysis are shown in Table 3.

Our models include product-change variables and time clocks which allow the failure rate to vary after a change using the approach of Amburgey et. al. (1993). Each time-since-change clock is set at zero until a given type of change occurs, and then increments upward annually until another change of that type occurs. In the year following the next change, the clock is then reset to zero and again increments upwards each year until the next change. Meanwhile, separate variables measure whether, for a specific organization, a given type of product addition or deletion has occurred. These variables begin set at zero when an organization is born and then are set equal to one once an organization adds (or drops, for product deletion) a product. The multiple-product addition variable begins set at zero when the organization is born and then is set at the number of products added in the most recent multiple-product addition, if any. Combined, these product-change variables and their associated clocks allow for both the "main effect" of making a given type of change and for these effects to increase or decrease with the passage of time (see Barnett and Carroll 1995).

We measure each organization's simultaneous product additions by counting the number of new product categories entered by an organization (above one) in a given year. Following our discussion of technological distance, we distinguish between simultaneous product additions according to whether they occur in one of the product groups where an organization already has products. If a firm added products in a group where it did not previously offer a product, then this addition was counted in the variable *number of product groups added*. By contrast, if an organization added products in a group where it already produced, then this was counted in the variable *number of products added (current product groups)*. For comparison, we also include a variable that counts the *number of products added* without regard for whether they constituted a movement into a new product group.

Table 3 Description of Variables

Variable*	Minimum	Maximum	Mean	Std. Dev.
Bond interest rate	2.5300	14.17	8.0264	3.0691
Semiconductor sales in North America ($M)	108	13139	3741.1555	3236.7914
Lagged number of exits	0	110	34	24.7159
Lagged number of entries	0	78	41	16.9432
Product density delay	0	1140	140	163.8274
Non-rival product density	0	1975	1221	527.09
Rival product density	0	1787	246	275.6225
Rival product density, earlier arrivals	0	974	103	121.9227
Rival product density, later arrivals	0	1515	143	200.4743
Organization's number of product groups	1	9	2	1.6291
Number of product groups added in a given year	0	8	0.1244	0.4488
Organization's number of products	1	58	6	7.2206
Organization's number of innovative products	0	15	0.4981	1.3946
Organization's number of follower products	0	51	5	6.4624
Number of products added in a given year (>1)	0	33	0.7709	2.1236
Number of products added, current product groups	0	28	0.682	1.9432

*For each observation, measures of product densities exclude products of the focal organization.

All time-varying covariates were updated annually in the data. This was done by splitting each organization's spell into annual segments, with each organization's duration in the industry updated from segment to segment. We estimated the exit rate $r_j(t)$ using the statistical software TDA (Rohwer 1993, Blossfeld and Rohwer 1995). The algorithms in TDA allow for spell splitting, and take into account the information provided by the cumulative survival time of right-censored cases. This approach reduces the bias that otherwise results when right-censored cases are ignored (Tuma and Hannan 1984).

Results

Our strategy was to test our hypothesis in models that include the control variables as well as the various other effects of innovation, competition, and change summarized in Table 1. We gradually build these variables into the exit-rate models in Tables 4, 5, and 6. Table 4 shows the results of models that include the control variables and various specifications of organizational innovation and competition. The models in Table 5 also include the effects of change–both adding and dropping products–as well as age- and size-dependent effects of change. Table 6 tests our hypothesis in models that control for all these other effects. (Historical period effects, duration effects, and product-group fixed effects are estimated for each model, but are reported only for the final model below.) We first discuss our hypothesis test in Table 6, and then we review all three tables of results to discuss our other findings. Note that each of the coefficients reported in Tables 4–6 represent the effect of a one-unit change in the independent variable on the natural logarithm of the failure rate. A positive coefficient, then, means that the independent variable is associated with higher failure rates, while a negative coefficient means that the independent variable is associated with lower chances of failure.

Model 10 in Table 6 tests our idea that multiple, simultaneous product additions threaten survival. As predicted, failure rates increase with the number of new products simultaneously added, an effect that increases at an increasing rate by construction. (In models not shown, we estimated log and quadratic specifications of this effect, and found no evidence that the effect increases at a decreasing rate.) Also as predicted, Model 11 shows that the initial increase in the hazard because of multiple product innovation falls away as time passes. With this clock included, the hazardous effect of all-at-once product introductions becomes quite strong. Model 12 checks whether these effects come from technological distance, separating out the effects of entering new product groups from the effects of adding new products. In fact, we do not find evidence of a disruptive effect due to entering new product groups, but with this term controlled the hazardous effect of multiple-product introductions becomes even stronger. Overall, the results in Table 6 strongly support our hypothesis.

Figure 3 plots the predicted multiplier of the hazard

Table 4 Estimated Effects of Competition and Innovation on the Exit Rate

	Models†			
Independent Variables	(1)	(2)	(3)	(4)
Effects of Control Variables:				
Bond interest rate	0.2192**	0.2201**	0.2192**	0.2225**
	(0.0402)	(0.0403)	(0.0403)	(0.0403)
Semiconductor sales in North America	−0.0002**	−0.0002**	−0.0002**	−0.0002**
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Lagged number of exits	−0.0020	−0.0019	−0.0019	−0.0018
	(0.0019)	(0.0019)	(0.0019)	(0.0019)
Lagged number of entries	−0.0027	−0.0028	−0.0025	−0.0029
	(0.0029)	(0.0029)	(0.0029)	(0.0029)
Product density delay	0.0004	0.0005	0.0002	0.0003
	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Organization is a corporate division	−0.4014**	−0.4032**	−0.3885**	−0.3895**
	(0.0965)	(0.0967)	(0.0962)	(0.0964)
Organization's number of product groups	−0.2363**	−0.2225**	−0.2580**	−0.2194**
	(0.1047)	(0.1074)	(0.1047)	(0.1071)
Innovation and Competition Effects:				
Organization's number of products	−0.1561**	−0.1567**		
	(0.0306)	(0.0306)		
Organization's number of innovative products			−0.3307**	−0.3754**
			(0.0743)	(0.0785)
Organization's number of follower products			−0.1269**	−0.1214**
			(0.0320)	(0.0319)
Non-rival product density	−0.0001	0.0000	0.0000	0.0000
	(0.0002)	(0.0002)	(0.0002)	(0.0001)
Rival product density	0.0019**		0.0017**	
	(0.0006)		(0.0006)	
Rival product density, earlier arrivals		0.0017**		0.0008
		(0.0008)		(0.0008)
Rival product density, later arrivals		0.0022**		0.0025**
		(0.0007)		(0.0007)
Chi-squared•	147.80	148.14	155.74	159.00
Df	10	11	11	12

**$p < 0.05$. Standard errors are in parentheses.

†Models include two historical period effects, 16 duration-period effects, and eight products-group effects. Data cover 6856 organization-years, 1197 organizations and 895 exits.

•Compared to a model with only the historical period, duration, and product-group effects.

rate due to adding multiple products all at once.[2] The Figure plots the predicted multiplier for an organization that adds nine products all at once in Year 2. This move triggers an immediate increase in the failure rate to be over two and a half times higher than would have been the case for an organization that added these new products incrementally over time. Evaluated at the mean number of simultaneous product introductions observed in the data (equal to about three such products, conditional on such an event occurring), this increase in the failure rate is still high at 27%. And, for two simultaneous product additions, the failure rate increases by about 13%. Keep in mind, however, that these are strictly the effects of the all-at-once change per se. The "content" effects of adding the products, such as the increase in the organization's size, are specified separately in the model, and so are considered part of the baseline rate in this illustration. With these effects controlled, the disruptive effect of adding multiple products simultaneously is substantively very strong.

Table 5 Estimated Effects of Product Changes on the Exit Rate

	Models†				
Independent Variables	(5)	(6)	(7)	(8)	(9)
Effects of Control Variables:					
Bond interest rate	0.2181**	0.2186**	0.2164**	0.2188**	0.2164**
	(0.0404)	(0.0404)	(0.0405)	(0.0404)	(0.0405)
Semiconductor sales in North America	−0.0002**	−0.0002**	−0.0002**	−0.0002**	−0.0002**
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Lagged number of exits	−0.0016	−0.0019	−0.0019	−0.0019	−0.0019
	(0.0019)	(0.0019)	(0.0019)	(0.0019)	(0.0019)
Lagged number of entries	−0.0028	−0.0027	−0.0025	−0.0028	−0.0024
	(0.0029)	(0.0029)	(0.0029)	(0.0029)	(0.0029)
Product density delay	0.0005	−0.0001	0.0002	−0.0001	0.0002
	(0.0003)	(0.0004)	(0.0004)	(0.0004)	(0.0004)
Organization is a corporate division	−0.3712**	−0.3932**	−0.3886**	−0.3898**	−0.3919**
	(0.0969)	(0.0972)	(0.0973)	(0.0973)	(0.0973)
Organization's number of product groups	−0.2210**	−0.2089**	−0.2333**	−0.2095**	−0.2326**
	(0.1071)	(0.1067)	(0.1072)	(0.1068)	(0.1071)
Innovation and Competition Effects:					
Organization's number of innovative products	−0.3794**	−0.3723**	−0.4171**	−0.3729**	−0.4183**
	(0.0782)	(0.0784)	(0.0804)	(0.0784)	(0.0803)
Organization's number of follower products	−0.1198**	−0.1194**	−0.1835**	−0.1185**	−0.1862**
	(0.0318)	(0.0317)	(0.0395)	(0.0317)	(0.0395)
Non-rival product density	−0.0001	−0.0001	−0.0001	0.0000	−0.0001
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Rival product density, earlier arrivals	0.0007	0.0012	0.0017**	0.0012	0.0017**
	(0.0008)	(0.0008)	(0.0008)	(0.0008)	(0.0008)
Rival product density, later arrivals	0.0026**	0.0025**	0.0021**	0.0026**	0.0020**
	(0.0007)	(0.0007)	(0.0008)	(0.0007)	(0.0008)
Change Effects:					
Product change indicator	−0.2897**				
	(0.1037)				
Product change clock	−0.0322				
	(0.0313)				
Product exit indicator		0.3500**	0.3557**	0.3668**	0.3407**
		(0.1208)	(0.1214)	(0.1212)	(0.1208)
Product exit clock		−0.0480	−0.0512*	−0.0544*	−0.0460
		(0.0305)	(0.0309)	(0.0308)	(0.0306)
Product addition indicator		−0.5484**	−0.6612**	−0.4197**	−0.7828**
		(0.1244)	(0.1915)	(0.1671)	(0.1481)
Product addition clock		−0.0080	−0.0381	−0.0451	0.0000
		(0.0291)	(0.0691)	(0.0604)	(0.0367)
(Product addition indicator × Organizational tenure)			−0.0245	−0.0288	
			(0.0301)	(0.0300)	
(Product addition × tenure × Product addition clock			0.0030	0.0034	
			(0.0040)	(0.0039)	
(Product addition indicator Org's number of products)			0.0758**		0.0791**
			(0.0273)		(0.0272)
(Product addition × no. products × Product addition clock)			0.0034		0.0021
			(0.0079)		(0.0078)
Chi-squared•	170.64	186.72	199.42	188.20	196.32
Df	14	16	20	18	18

*$p < 0.10$, **$p < 0.05$. Standard errors are in parentheses.

†Models include two historical period effects, 16 duration-period effects, and eight product-group effects. Data cover 6856 organization-years, 1197 organizations and 895 exits.

•Compared to a model with only the historical period, duration, and product-group effects.

Table 6 Estimated Effects of Simultaneous Product Introductions on the Exit Rate

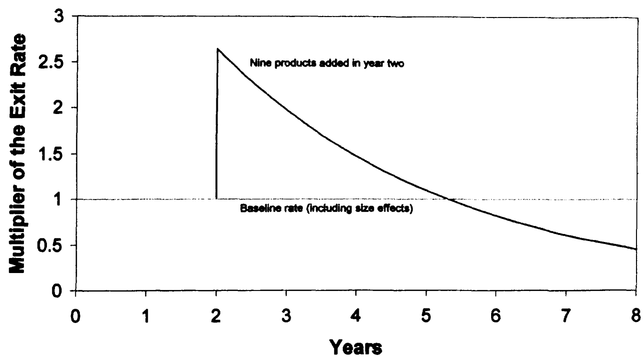
	Models†			
Independent Variables	(10)	(11)	(12)	(13)
Effects of Control Variables:				
Bond interest rate	0.2186**	0.2200**	0.2203**	0.2217**
	(0.0406)	(0.0406)	(0.0406)	(0.0406)
Semiconductor sales in North America	−0.0002**	−0.0002**	−0.0002**	−0.0002**
	(0.0001)	(0.0001)	(0.0001)	(0.0000)
Lagged number of exits	−0.0019	−0.0019	−0.0018	−0.0018
	(0.0019)	(0.0019)	(0.0019)	(0.0019)
Lagged number of entries	−0.0025	−0.0026	−0.0027	−0.0028
	(0.0029)	(0.0029)	(0.0029)	(0.0029)
Product density delay	0.0003	0.0004	0.0004	0.0004
	(0.0004)	(0.0004)	(0.0004)	(0.0004)
Organization is a corporate division	−0.3836**	−0.3828**	−0.3831**	−0.3843**
	(0.0972)	(0.0972)	(0.0972)	(0.0972)
Organization's number of product groups	−0.2201**	−0.2120**	−0.2021*	−0.1978*
	(0.1071)	(0.1072)	(0.1077)	(0.1075)
Innovation and Competition Effects:				
Organization's number of innovative products	−0.4078**	−0.4079**	−0.4080**	−0.4112**
	(0.0803)	(0.0805)	(0.0804)	(0.0801)
Organization's number of follower products	−0.1849**	−0.1827**	−0.1876**	−0.1881**
	(0.0394)	(0.0393)	(0.0397)	(0.0397)
Non-rival product density	0.0000	0.0000	−0.0001	0.0000
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Rival product density, earlier arrivals	0.0014*	0.0012	0.0013	0.0013
	(0.0008)	(0.0008)	(0.0008)	(0.0008)
Rival product density, later arrivals	0.0024**	0.0024**	0.0024**	0.0025**
	(0.0008)	(0.0008)	(0.0008)	(0.0008)
Change Effects:				
Product exit indicator	0.3136**	0.3150**	0.3141**	0.3116**
	(0.1218)	(0.1217)	(0.1216)	(0.1217)
Product exit clock	−0.0417	−0.0466	−0.0457	−0.0462
	(0.0306)	(0.0306)	(0.0306)	(0.0306
Product addition indicator	−0.7501**	−0.7389**	−0.7314**	−0.7467**
	(0.1491)	(0.1493)	(0.1498)	(0.1484)
Product addition clock	−0.0032	−0.0022	−0.0021	0.0163
	(0.0368)	(0.0370)	(0.0372)	(0.0313)
(Product addition indicator × Org's number of products)	0.0598**	0.0475	0.0479	0.0550*
	(0.0287)	(0.0297)	(0.0296)	(0.0285)
(Product addition × no. products × Product addition clock)	0.0001	0.0090	0.0090	
	(0.0079)	(0.0092)	(0.0093)	
Number of products added (above one)	0.0663**	0.1077**		
	(0.0281)	(0.0342)		
Number of products added (current product groups)			0.1295**	0.1216**
			(0.0370)	(0.0357)
Number of new product groups added			−0.0139	−0.0287
			(0.1235)	(0.1225)
(Number of products added × Product addition clock)		−0.0370*	−0.0456**	−0.0367*
		(0.0198)	(0.0214)	(0.0188)
Chi-squared•	201.26	205.16	207.20	206.30
Df	19	20	21	20

*$p < 0.10$, **$p < 0.05$. Standard errors are in parentheses.

†Models include two historical period effects, 16 duration-period effects, and eight product-group effects. Data cover 6856 organization-years, 1197 organizations and 895 exits.

•Compared to a model with only the historical period, duration, and product-group effects.

Figure 3 **Estimated Effects of Simultaneous Product Introductions**



Turning now to our other findings, Table 4 reports estimates of models that include the control variables as well as measures of product innovation and product-market competition. Model 1 includes, along with the control variables, a count of each firm's number of products, its number of product groups, and the number of rival and nonrival products faced by each firm in each year. These variables reveal a survival advantage to size as measured by the number of products as well as a survival advantage because of diversification across multiple-product groups. Not surprisingly, the model also shows evidence of competition only from "rival" products—product offerings that are in the same product categories in which a firm has a product offering.

Models 2, 3, and 4 make additional distinctions to Model 1, reflecting the survival consequences of firms' product strategies. Model 2 lifts a constraint on Model 1, allowing rival products to have different effects, depending on whether they arrived prior to or after a given firm's product offering in a given product market. Model 3, which is nested in Model 1, lifts a different constraint. It allows each firm's size in number of products to have differing effects, depending on whether they are innovations or follower products. Recall that the coefficients of these terms distinguish the survival implications of the first-mover versus the follower strategy. Model 4 then lifts both constraints, and improves statistically significantly over both Models 2 and 3 (although the improvement over Model 3 is only at the 0.10 level).

Model 4 shows a clear first-mover advantage, with an innovative product giving a firm about three times the survival advantage as a follower product. Meanwhile, the results also show interesting competition effects. Virtually all significant evidence of competition appears in α_L, the coefficient associated with rival products that arrive after a given firm's product. We do not find significant evidence of competition in the coefficient α_E, the one associated with products that arrived earlier than a given firm's product offering in any given product category. (A comparison to the constrained Model 3 suggests that the difference between these competitive effects is significant at the 0.10 level.) These results demonstrate the competitive downside to innovation: While being first in a market gives a first-mover advantage, this is offset by the fact that all rival products are more up-to-date followers. Note also that these findings were obscured in Model 2 and 3, which failed to distinguish both of these effects simultaneously. This is a familiar pattern, where the main effects of a strategy must be correctly specified to obtain unbiased estimates of the effects of competition and vice versa (Barnett 1990).

The effects of product changes are added to the model in Table 5. Model 5 introduces a product change indicator variable and a product change clock. Following our discussion of growth and decline trajectories, Model 6 separates this overall change effect into two distinct sets of terms: one set tracking product additions and the other tracking product exits. As expected, these two processes work in opposite directions. Firms adding products were less likely to fail and firms dropping products were more likely to fail, but the overall change effect in Model 5 confounded these two opposing effects. Like papers that modeled change in terms of product innovation, we found a survival-enhancing effect of product change. This turns out, however, to be entirely a product-growth effect, suggesting that the apparently beneficial consequences of change in such models are spurious, reflecting merely that times are good for organizations on growth trajectories and that times are bad for those that are exiting markets.

Model 7 then adds tenure- and size-change interactions to test for whether older or larger organizations reacted differently to product addition, and Models 8 and 9 sequentially include each of the interactions to demonstrate robustness. From these results, we do not find significant age-change interactions, neither in the immediate change effect nor in the clock that begins ticking as of a product addition. By contrast, Models 7 and 9 show an immediate increase in the failure rate among larger organizations. In Table 6, this size-change interaction is not robust, but it does remain marginally significant in Model 13 when we drop its associated clock (which is never significant in any specification).

The coefficients of the control variables also are noteworthy. As expected, general economic and market trends were important predictors of exit rates. Exits were more likely when interest rates were higher, but were less likely when semiconductor sales were strong. We found no significant effect for lagged exits and entries. Neither did we find significant effects for product density delay, although the direction of the effect was positive as predicted. Consistent with earlier analyses of these data, organizations that were divisions of larger corporations were less likely to exit the industry.

Finally, Table 7 reports the effects of market duration, history effects, and product-group dummy variables. These variables are included in all models, but are reported here only for the most complete specification, Model 13 in Table 6. Comparing the piecewise duration effects shows negative duration dependence, consistent with the results of earlier analyses of these data.

Discussion and Conclusion

Business lore tells of aggressive, fast-moving organizations that have introduced many new products at once, revolutionizing their industries and taking the upper hand in competition. But stories also tell of organizations that space product introductions in a gradual, incremental trajectory. Which of these strategies is more adaptive, all-at-once or incremental product introductions? Our results show that this difference in the timing of product introduction is an important predictor of organizational survival. Two organizations may have the same product strategy—the same mix of products and the same competitors—but according to our results they will have different life chances if they followed different paths of innovation. Organizations that introduce products incrementally will be more likely to survive, other things equal, than organizations that proliferate a large number of products simultaneously. Of course, other things may not be equal. For instance, the incrementalist may miss out on opportunities to be a first-mover in some markets. Nonetheless, after controlling for such differences in strategy content, we find evidence that incrementalists benefit from considerably less disruption than is the case for organizations that introduce products in all-at-once reorientations.

It is important to keep in mind that we find evidence of such a disruptive effect despite the fact that we are analyzing product additions that have been successful enough to be recognized by our data source. As we know from other studies (e.g., Zucker 1987, Haveman 1993b), organizations often increase their survival chances by following innovations that have proven to be successful. In the case of our data, we do not record attempts at innovation which failed to become a viable product; so like most studies, our findings are already inclined to demonstrate adaptive change among organizations. Nonetheless, we still find strong evidence of disruption because of multiple, simultaneous product innovation.

Our findings on growth and decline trajectories suggest a potentially troubling problem for some studies of the effects of change on failure—those that operationalize change in terms of growth or product addition. Performance differences among organizations are difficult to measure when studying entire organizational populations (a problem with our study, too). Consequently, most comprehensive population studies that look at how change affects failure are unable to separately control for whether organizations are moving along a growth or decline trajectory. Because of this unobserved heterogeneity, studies may report that change, in the form of adding new products, is negatively related to failure, but such results could be spuriously reflecting the fact that in good times organizations are both more likely to add products and less likely to fail. Our attempt to model this possibility revealed a pattern consistent with this scenario: Organizations that had recently added a product were less likely to fail, and organizations that recently dropped a product were more likely to fail. With these processes controlled in the model, we then separately detected the failure-enhancing effects of product proliferation. In this spirit, we suggest that researchers make some attempt to control for baseline growth and decline effects before looking for evidence of structural inertia.

One limitation of our study is that we look only at the ultimate consequences of product proliferation, but do not investigate in detail the organizational processes where we think coordination difficulties arise. We think it would be interesting for future research to look in more detail at what happens inside organizations when multiple products are added at once. Although such research would probably need to focus on a smaller number of organizations, it would serve as a much-needed complement to our research.

Our findings raise an intriguing strategic problem for complex, multiproduct organizations. To reap the advantages of complementarities among the parts of an organization, it may be necessary to change in all-at-once strategic jumps. However, such moves dramatically increase the uncertainty faced by an organization as it attempts to coordinate simultaneous action, and the resulting disruption causes a significant increase in the hazard of organizational failure. Strategic reorientations may be valuable, but the process of implementing them is costly enough to harm organizational survival chances.

Our results highlight one of the ironies running through the literature on organizational innovation and change: No one would be interested in how managers bring about adaptive, efficacious change if it were not difficult to do so. If all giants danced, then a title like *When Giants Learn to Dance* (Kanter 1989) would not be amusing. The literature on organizational change from Coch and French

Table 7 History, Duration, and Product-Group Effects on the Exit Rate† (Corresponding to Model 13 in Table 6)

Variables	Estimates	Variables	Estimates
Duration 0–1 year	−1.655**	1960–1969 period	−0.1559
	(0.2211)		(0.2174)
Duration 1–2 years	−2.027**	1970–1985 period	−0.1130
	(0.2369)		(0.1423)
Duration 2–3 years	−1.973**	Transistors and thyristors	0.2813**
	(0.2463)		(0.1169)
Duration 3–4 years	−2.035**	Digital integrated circuits	0.5253**
	(0.2570)		(0.1255)
Duration 4–5 years	−1.888**	Analog/linear integrated circuits	0.1449
	(0.2671)		(0.1654)
Duration 5–6 years	−2.138**	Signal converting integrated circuits	0.0904
	(0.2892)		(0.4570)
Duration 6–7 years	−2.088**	Custom integrated circuits	0.0002
	(0.2978)		(0.1967)
Duration 7–8	−1.982**	Hybrid circuits	0.2795**
	(0.3096)		(0.1115)
Duration 8–9 years	−1.996**	Light-emitting devices	−0.1172
	(0.3276)		(0.1718)
Duration 9–10 years	−2.500**	Photo-sensitive devices	0.3622**
	(0.3876)		(0.1527)
Duration 10–11 years	−2.511**		
	0.4008)		
Duration 11–12 years	−1.916**		
	(0.3656)		
Duration 12–13 years	−2.976**		
	(0.5326)		
Duration 13–14 years	−2.056**		
	(0.4238)		
Duration 14–15 years	−2.054**		
	(0.4498)		
Duration 15 years and up	−2.551**		
	(0.3887)		

** $p < 0.05$. Standard errors are in parentheses.
† For product-group effects, diodes and rectifiers is the left-out category.

(1948) on emphasizes how hard it is for manager to bring about wholesale change and how often they fail when they attempt it. Burns and Stalker (1961) is mainly about how managers fail when they attempt to reorganize from "mechanistic systems" to "organic systems" of production. Inertia is really just a name for all the things that make such reorganizations difficult. Another way of putting this is that if "best practice" can generate flexible organizations, and all organizations employed best practice, there would be nothing to write about. Sadly, most organizations do not employ best practice, which is why such treatments are interesting and useful.

This paper attempts to look in more detail at the complexities of competitive outcomes to organizations that innovate. The irony discussed above becomes even more salient when one realizes that in industries characterized by rapid, erratic change, failure to innovate is potentially life threatening (Jelinek and Schoonhoven 1990). It really is a tough world if the disruptive effects of innovation punish companies for introducing new products while condemning them to obsolescence and ultimate failure if they do not.

How do we get out of this theoretical box? This paper offers some suggestions. First, it is perhaps advantageous to think about the timing, as well as the extensiveness, of change. Few would argue that more fundamental change is more disruptive. So, if Proctor and Gamble decides to pull out of the cleaning product market, redeploying those resources to some very different field, such as machine tools, one would expect the disruption to be substantial. Our findings, however, shift attention to the timing of such changes. Managing several important changes simultaneously threatens to overwhelm a company. The greater the number of such changes occurring at once, the more we multiply the agony.

A second issue concerns the rivals to which a firm gains exposure when it innovates. The good news of such innovation is that it gives the organization access to resources that may not have been available before. The bad news is that those resources are likely to have other claimants who now react to the focal organization as a competitor. The obvious question is whether those new rivals are proficient or inept. When the product offerings of those competitors are more up to date, exposure to their competition is hazardous and may outweigh the advantages resulting from having an additional product to sell.

Another issue raised by this research is the motivation to innovate. Sometimes, companies innovate out of desperation. Their last dying gasp is to announce a new product they hope will save them as Hitler hoped his "secret weapons" would save Germany from the Allies. In other situations, companies launch new products one after another because the business they are currently in generates the resources to do so. Success breeds innovation. This may be because previous innovations have been successful, but this is not necessarily the case. Perhaps the market for existing products expands rapidly. Being in the right place at the right time can sometimes be confused with managerial acumen and the sort of overconfidence that the Midas touch stamps on a manager. So, studies of the strategic effects of innovation would be well advised to consider path dependence and possible spuriousness in the correlation between innovation and success.

To some degree, the ironies that have preoccupied us in this last section of the paper revolve around the scholar's intentions. Is research about rare examples of best practice, or is it about ordinary practice? If most organizations are ordinary—indeed, if this is what we mean by "ordinary"—then theories should explain their existence. This knowledge then supplies the baseline from which to understand the extraordinary.

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Endnotes

[1]Peli et al. (1994), in their formalization of Hannan and Freeman's (1984) structural inertia theory, point out the implicit assumption in the theory that complexity does not facilitate restructuring.

[2]The multiplier is found by computing $\exp[\delta_M(N_{\Delta Pj}) + \gamma_M(N_{\Delta Pj}\tau_{\Delta Pj})]$ based on the estimates of Model 13, where N is equal to the number of simultaneous product additions (above one).

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