The Red Queen, Success Bias, and Organizational Inertia*

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Abstract

Why do successful organizations often move in new directions and then fail? We propose that this pattern is especially likely among organizations that have survived a history of competition. Such experience adapts organizations to their environment, through so-called "Red Queen" evolution, but being well-adapted for one context makes moving into new contexts more hazardous. Meanwhile, managers in such organizations infer from their histories of competitive success a biased assessment of their organization's ability to change. Consequently, although surviving competition makes organizational change especially hazardous, managers in surviving organizations are especially inclined to such initiatives. We develop these ideas in an empirically testable model, and find supportive evidence in estimates of the model using data from the history of the U.S. computer industry.

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Many who study organizations note a puzzling regularity: Successful organizations often take on bold, new challenges, only to fail. Some in the field of strategic management argue that organizations can avoid this fate by developing the "dynamic capabilities" required to successfully change (Teece, Pisano, and Shuen, 1997; Helfat, 1997). In parallel, consulting firms specializing in change management abound, helping organizations to deal with this problem. And formal systems of management education routinely include courses on how to manage the difficult and hazardous process of organizational change. Presumably, as these initiatives progress, organizations will increasingly develop the ability to change, and so be less inclined to follow the all-too-familiar pattern of rise and decline. The challenge is well articulated in this quote from an authoritative book on the subject: "Too much capital, and, more important, too many social commitments are involved in industrial concerns for change to occur through the elementary birth and death cycle usual a hundred years ago. Firms...must keep alive, and in order to keep alive they must become adaptive; change must occur within the organization and not through its extinction and replacement, if it is to occur at all." (Burns and Stalker, 1961: 35)

Yet note the date of this quote by the influential management researchers Burns and Stalker. In the decades since these authors made this appeal for adaptation, a number of bestselling books have repeated their call (e.g. Ouchi, 1981; Peters and Waterman, 1982; Collins and Porras, 1994; Christensen, 1997). Over the same period, waves of foundings and failures have continued to transform industries, and many of the world's leading firms have faltered. Organizations that were once household names, such as PanAm and Bethlehem Steel, are gone, while others have fallen to obscurity, like Navistar International, or have been reduced to advertising slogans, such as AT&T. Meanwhile smaller organizations, though typically less well known, also continue to fail at high rates. Apparently, either the ability to change is uncommon, or we have yet to understand how this ability develops in organizations.

In this paper, we explain why bold failures by successful organizations are likely, and maintain that the socially-constructed belief in the ability to change makes these failures even more likely. We argue that the ability to change is shaped and limited through "Red Queen" competition – an ongoing process wherein competition triggers adaptive learning among organizations, making them more viable so that they compete more strongly, which in turn triggers adaptive learning in their rivals.[1] By adapting in the face of competition, organizations become especially well suited to the particular context in which they compete. Yet one consequence of being especially tailored to its context is greater disruption if and when an organization attempts to move into unfamiliar territory. Consequently, we argue, survivors of competition will find moving into new contexts to be especially hazardous. In this way, Red Queen competition contextualizes the ability to change, limiting its effective scope.

Meanwhile, the belief that an organization can change, as a social fact, grows when organizations evolve through Red Queen competition. Among people in organizations, surviving a history of competition constitutes a powerful datum that informs decision-making by an organization's managers. Inferring from a historical record of success in the face of competition, managers are likely to conclude that their organization is especially able to adapt. High-flying organizations find themselves held out as examples of "best practice" to be emulated, and their managers and organizational methods become the talk of business schools and the popular business press. Thus, for survivors of competition, a belief in the ability to change increasingly constitutes a social fact in the collective understanding shared within and around the organization. Decision makers, operating with such an assessment of their organization's adaptability, are especially likely to make bold forays in new directions. In short, we propose that surviving competition limits an organization's ability to change, making it less able to move successfully in new directions, but at the same time makes managers more convinced that such moves are a good idea.

Two Forms of Change

Most discussions of organizational change focus on the challenge of moving an organization in new directions, typically dubbed "exploration" in organization theory (March, 1991). Examples of exploratory change abound. Applied Materials, a leader in semiconductor manufacturing equipment, moved in the 1990s into the market for equipment that makes flat panel displays – a change that required new technologies, manufacturing in different countries, and relationships with new customers. The California-based specialty retailer Trader Joe's recently expanded into new geographic markets along the East Coast of the U.S, and faced the challenge in these new markets of replicating their unique culture and product selection system

[1] This type of self-accelerating coevolutionary processes was identified in biology by Van Valen (1973), with reference to the Red Queen in Lewis Carroll's *Through the Looking Glass*, who explains to the running Alice her relative stability in a context of others who are running: "Here, you see, it takes all the running you can do, to keep in the same place."

that had gradually evolved over decades. Research on such changes typically looks at what makes organizations more or less capable of executing such exploration (Teece, Pisano, and Shuen, 1997; Klepper and Simons, 2000).

However, not all adaptive change involves moving into new contexts. An organization can also engage in "exploitative" change, where it becomes increasingly adapted to its current context (March, 1991). For instance, the disk-storage company Seagate has become increasingly adept at releasing new disk drives to meet the time milestones of its customers. To gain this time-to-market advantage, Seagate reorganized in various ways so that its systems, technologies, and people were geared to meeting customer-driven time objectives. In this way Seagate has focused on exploiting the disk drive market rather than exploring other markets or products. In fact, Seagate's exploratory activity is carried out by a structurally differentiated R&D function, in order to allow the rest of the organization to maintain a focus on its present market and customers. In this example, an organization has become increasingly well adapted to its current competitive context.

The distinction between exploration and exploitation is important, because organizations face a trade off between them (March, 1991). Exploitative change makes organizations better adapted to their current context. Exploratory change moves organizations in new directions, but in so doing it risks disrupting an organization's current roles, routines, know-how, structures, and technologies. Mindful of this trade-off, many have argued that well-adapted organizations are especially disrupted by exploratory change. For instance, organizations are especially disrupted by changes to their "core" activities (Hannan and Freeman, 1984), changes that render an organization's capabilities inappropriate (Levitt and March, 1988; Tushman and Anderson, 1986; Christensen, 1997), and changes that require a different organizational design (Henderson and Clark, 1990). Similarly, some research looks at how change is more or less disruptive depending on differences in organizational characteristics thought to correspond to their capabilities, such as experience (Kraatz and Zajac, 2001), age (Hannan and Freeman, 1984; Amburgey et al., 1993), size (Haveman, 1993a; Carroll and Teo, 1996), or complexity (Levinthal, 1997; Hannan et al., 2003b). However operationalized, there is substantial support for the idea that exploratory changes are especially disruptive to organizations that are well adapted to their current context. Our view is that the trade off between exploitation and exploration emerges over time, and hinges on whether organizations have engaged in Red Queen competition.

The Red Queen and Exploitation

Our central argument is that exploitation develops through the process of surviving competition. When an organization is exposed to competition, the immediate consequence is greater scarcity and constraint on organizational action than would be the case if the organization faced no competition (Swaminathan, 1996). As a result, an organization facing competition is less likely to perform at a satisfactory level, other things equal, triggering so-called "problemistic search" as members of the organization attempt to restore satisfactory performance (March, 1988, 1994; Winter, 2000). Presumably such search remains incremental, unless no satisfactory solutions can be found without a broader search (Levinthal and March, 1981), and continues to the point where performance is restored to a satisfactory level (March and Simon, 1958).

Ordinarily, the search process is thought to end once performance is improved to a satisfactory level, or aspirations are lowered (Cyert and March, 1963). But when competition is operating, the process is likely to continue. Having improved performance in response to competition, an organization in turn is a stronger rival against other organizations. This increased competitive strength means that the organization's *rivals* now face a problem of lower performance due to strong competition, sending them into the process of problemistic search. Once these organizations restore performance to a satisfactory level, now they, too, will be stronger competitors – so that performance again falls among their rivals, sending these organizations yet again into the process of problemistic search. In an ecology of learning organizations, competition and organizational learning each trigger the other in an ongoing, self-exciting process: the Red Queen.

We expect that an organization involved in the Red Queen will become increasingly capable of exploiting its context over time – as long as the criteria for success remain constant. Meanwhile, its rivals also will become more capable of exploitation, since the process is co-evolutionary. To the extent that aspiration levels adjust upward by social reference (Herriott, Levinthal, and March, 1985; Lant, 1992), the co-evolutionary cycle is likely to accelerate. In fact, an organization that is particularly capable of exploitation will create especially big problems for its rivals, that in turn will require significant improvements among these rivals if they are to restore performance to satisfactory levels. These improvements, then, will further challenge the first organization to exploit even better. When organizations are engaged in Red Queen competition they may seem to be simply treading water when viewed relative to one another – even as their ability to exploit is advancing in absolute terms.

The Red Queen can also change the distribution of exploitative ability within an organizational population by acting through selection, and without organizational learning. In this view of the Red Queen, competition intensifies selection pressures on organizations and de-selects the weakest competitors. If we assume that organizations vary in competitiveness initially and that competitiveness does not change over time for any given organization, overall competitiveness across the population will increase over time as exposure to competition de-selects the least competitive members (Swaminathan, 1996; Sorenson, 2000). As competitiveness increases, the pressure to de-select less competitive organizations increases, leading to more increases in competitiveness, and so on. As time passes, newly founded organizations may continue to vary in their levels of competitiveness, but the threshold for survival for these organizations has been raised, and so only the most competitive organizations will survive. As Red Queen competition continues to increase the threshold for organizational survival through selection, the exploitative abilities of the population will be advanced. Of course, the specific outcome of this process will hinge on details of the context – namely the distribution of competitiveness among new entrants and the rates at which less-competitive organizations are de-selected. The important point is that selection, as well as organizational learning, may drive the Red Queen. In reality, we expect that the Red Queen will increase the exploitative abilities of organizations both through selection and organizational learning.

The Red Queen has important implications for history-dependence in competition. Surviving a history of competition increases an organization's exploitative capabilities, which in turn implies that the organization is more adapted to that particular context. Empirically, research has shown that organizations that have survived a history of competition in a given context are more viable in that context – in that they have lower failure rates and higher growth rates. Meanwhile, an organization's *rivals* in a given context generate stronger competition if they have survived a history of competition in that context (Barnett and Hansen, 1996; Ingram and Baum, 1997; Barnett and Sorenson, 2002; Barnett and McKendrick, 2004). This pattern is consistent with the idea that organizations develop – or are selected for having – greater exploitative ability as they survive a history of competition.

In this study, we investigate whether this same pattern of history-dependent competition developed in the computer industry. Appendix A describes how the predictions of Red Queen theory can be parameterized in an empirically testable model:

$$\mathbf{r_j(t) = r_j(t)^*exp[bT_j],}$$

where $\mathbf{r_j}$ is the failure rate of organization $\mathbf{j}$, which varies as a function of its market tenure $\mathbf{t}$. $\mathbf{r_j(t)^*}$ is the baseline failure rate for organization $\mathbf{j}$, estimated in terms of the control variables described in Appendix B. Among the other terms in the model, Red Queen theory predicts $\mathbf{b}<0$, where organizations are more viable the more that they have survived a history of competition in that context (measured by $\mathbf{T_j}$, the organization-years of competition to which **j** has been exposed historically).[2]

The Disruptive Consequences of the Red Queen

As organizations compete, they are rewarded for becoming increasingly aligned with the requirements of their context. Thus competition drives a process of contextualization, rewarding organizations for discovering and then adapting to the technological, institutional, and organizational requirements of a given context. Yet, as discussed, we know that alignment with one context limits adaptability into other contexts, making such exploratory moves hazardous. In this way, the notorious problem of disruption and inertia when moving into new markets is predicted to plague precisely those organizations that have learned from and survived competition. The Red Queen enhances the exploitative abilities of organizations, but in so doing it limits organizations' ability to explore.

To investigate this idea, the point of comparison needs to be carefully chosen. If we track the over-time change in a successful organization's viability as it moves into a new context, we may see an ensuing decline in viability because of regression to the mean (Greve, 1999). Alternatively, if we compare the viability of a changed organization to organizations in its initial context (that did not change), we conflate the effects of the content and the process of change (Barnett and Carroll, 1995). An other-things-equal comparison would be across all organizations in the *target* context. Those in the target context that have a history of having survived competition elsewhere should be less viable in the target context, compared to others in the target context who lack that historical legacy:

Hypothesis 1: Organizations that have survived a history of competition in one context will suffer higher failure rates if they move into a different context, compared to other organizations in that different context.

In Appendix A, we adapt the model of Red Queen competition to test this prediction:

$$\mathbf{r_j(t) = r_j(t)*exp[bT_j + dT_{Aj}],}$$

where organization **j**'s original market is denoted by **A,** while the failure rate $\mathbf{r_j}$ is in the market into which it has moved. $\mathbf{T_{Aj}}$ is defined as the organization-years of rivalry that **j** faced historically in market **A.** Hypothesis 1 predicts that having a history of competing in market **A** is harmful to **j**'s viability in its new market, which would be consistent with **d**>0.

[2] As explained in Appendix A, the model further distinguishes an organization's competitive history according to the recency of experience, with recent experience predicted to make an organization more viable, while distant-past experience may not due to changes in competitive conditions that render old lessons out of date.

An alternative explanation for this effect is the "jack of all trades" problem. Perhaps some organizations take a generalist strategy, operating in multiple markets but not doing especially well in any of them. In the strategic management literature, this idea appears in the work of Montgomery and Wernerfelt (1988), who note that generally applicable factors are less valuable in any given domain. Similarly, organizational ecologists have argued for a principle of allocation, wherein organizations can concentrate their fitness on a specific environment, or spread it thinly over various environments (Hannan and Freeman, 1977; Hsu, 2005). The jack-of-all-trades problem predicts lower viability in any particular market among organizations operating in multiple markets, regardless of the competitive experience of organizations. To control for this possibility, we will model the effect of being in multiple markets – an effect that is distinct from the competitive experience effects highlighted by our theory.

The Red Queen and Success Bias

A second process triggered by the Red Queen, we propose, is an increase in people's appraisals of an organization's ability to change. This increase can take place both at the level of individual people learning within organizations, and as a collective learning problem organization-wide. Even with full information, we know that individual decision makers are inclined to an "overconfidence bias" (Bazerman and Neale, 1986), which tends to be exacerbated by a "confirmation bias" in one's attention to and interpretation of data (Koriat, Lichtenstein, and Fischoff, 1980). Most important for organizations that survive competition, however, is the fact that the information available to decision makers in successful organizations is not complete. Participants in a successful organization face the problem of trying to generalize from a sample that systematically excludes evidence of possible negative outcomes (March et al., 1991). This bias is enhanced by the tendency for memory retrieval to recall information in a way that reinforces our expectations of what would have happened (Fischhoff, 1975), and to "explain away" exceptions (Einhorn and Hogarth, 1978).

In his theory of success bias, Denrell (2003) explains how this process can lead decision-makers to make incorrect inferences regarding the reasons for success. In particular, Denrell shows that especially risky policies will appear to correspond to success in situations where examples of failure are systematically underrepresented. Arguably, an organization that survives from a large pool of competition is such a situation. For instance, in one telecommunications company that has been particularly successful during a period when many of its competitors have fallen, we found that members of the organization consistently reported that the company was "especially capable" of doing precisely those things that "experts thought could not be done."

When pushed on the logic behind such a claim, participants tended to refer to the company's "proven record" as evidence of its "capability to innovate compared to its competition." In this way, while many organizations succumb to biases in their decision-making processes, we expect that an exaggerated belief in an organization's ability to explore is especially likely among organizations that have survived a history of competition.

Such an exaggerated belief in an organization's ability to explore is especially likely when considering major organizational endeavors. Such decisions are relatively rare and carry significant organizational implications; consequently the information available for such decisions is notoriously limited and ambiguous, and carries complex implications (March et al., 1991). In such contexts, we know that people tend to make social comparisons in order to help resolve uncertainty (Festinger, 1954), and so "vicarious learning" from other organizations is especially likely (Cyert and March, 1963; Miner and Haunschild, 1995). In the case of a survivor of competition, such comparisons lead to the conclusion that there must, in fact, be something special about the organization – and this conclusion is likely to be all the stronger the more competition it has survived.

Note also that the inferences drawn by participants in organizations will tend to be magnified by the tendency to attribute greater salience to data gathered by direct experience (Fischoff and Beyth, 1975). Data from experience arguably are more vivid and so more available to recall, making them likely to be invoked in decision-making heuristics (Tversky and Kahneman, 1973; Fiske and Taylor, 1991). The tendency for direct experience to speak loudly is further amplified by norms for deference typically shown in organizational settings to those who have "been there." We see this in discussions among managers, where relatively careful exchanges of thought are sometimes shut down by the announcement that one of the participants "was there," or has "done that." In this light, testimony by those who have seen the organization survive its history of competition will carry special weight when diagnosing an organization's ability to change.

The success bias may be magnified as members of an organization form a collective identity based on common experience. Within organizations, shared understandings of the organization, its identity, and its capabilities come to be social facts in themselves (Selznick, 1957). Once objectified, the notion that an organization is especially capable of change circulates, and can be reinforced in stories that pass among organizational participants. For instance, in a number of separate interviews we conducted in a successful medical equipment manufacturing organization, the same story highlighting the organization's technological prowess was repeated in virtually every interview – sometimes with substantial embellishment. Lessons about an organization's ability to change can thus be embodied in stories that "explain" its success, and transmit that social fact to new organizational members.

In many cases, these stories may diverge from reality, representing more of a retrospective rationalization than a true account (Weick, 1979). Oral historians (e.g. Portelli, 2003) reveal vivid cases where objectified accounts of "what happened" differ in important ways from what turns out to have been true. Once institutionalized, lessons about an organization's ability to change become social facts in and of themselves, sometimes without regard for whether they correspond to reality (Meyer and Rowan, 1977). Multiple stories and conflicting interpretations may come to be reduced by sharing stories (Martin, 1982; March et al., 1991). For this reason, the bias for exploration that we see among individuals making decisions in the context of a successful organization are likely to be reinforced collectively (March and Shapira, 1987; Strang and Macy, 2001).

Finally, the historical timing of survivorship is likely to be important in shaping the decision to enter a new market. It is known that more recently experienced events tend to carry greater weight in forming beliefs (Hogarth and Einhorn, 1992), and we expect that historical timing will be similarly important when members of organizations infer from having survived competition. Note that this recency effect need not be a recency "bias," as it is sometimes termed, because updating to more recent information would be appropriate the more that a context has undergone change. In any case, we expect that recent-past historical competition will be more important to deciding on new market entry than will historical competition from the more distant past.

In sum, we argue that participants in organizations that have survived a history of competition exhibit an exaggerated sense of the organization's ability to change, especially when this competitive experience is relatively recent. Such high estimates of the ability to change, in turn, increase the rate at which the organization enters into new markets. Consequently, we expect to see:

Hypothesis 2: Organizations that have survived a history of competition, especially in the recent past, have a higher rate of entry into new markets.

This prediction, expressed in the form of an estimable model in Appendix A, is especially interesting in light of our failure rate prediction. Precisely what makes organizations more likely to engage in a change also makes them more likely to fail due to such a change. Surviving a history of competition encourages participants within the organization to infer incorrectly that the organization possesses the abilities required for it to succeed broadly, while at the same time having survived this competition deepens and narrows the organization's domain.

It is interesting to contrast this hypothesis with the view that established organizations become increasingly myopic with experience (Christiansen, 1997). The myopia hypothesis focuses our attention on the situation where managers are blindsided due to their exposure to a limited range of alternatives. Note, however, that this bias operates at the point of recognizing alternatives – and many of the examples of myopia in the literature relate to the failure of organizations to recognize alternatives until too late. Our prediction, by contrast, comes into effect once an alternative is recognized. At that point, we argue, historically successful organizations will be especially prone to move into new directions.

An alternative hypothesis might account for our expected pattern of results. It is known that sometimes organizations move into new markets as a reaction to their poor performance in their home markets (Rumelt, 1974; Christensen and Montgomery, 1981; Montgomery, 1985). Such moves of desperation might be triggered by competition in one's home market, calling into question our interpretation of our hypotheses; perhaps a history of competition drives failing organizations into new markets, and results in a pattern consistent with our hypotheses but for the opposite reason. We will investigate this alternative hypothesis investigating whether surviving a history of competition harms or helps organizations to survive in their origin market. If a history of competition improves survival chances in the market of origin, as would be predicted by the Red Queen theory, then organizations that have a substantial competitive history are not failing, and we can rule out this alternative hypothesis.

Empirical Setting

We estimated our models using data on the life histories of every manufacturer of an electronic digital, general-purpose computer system in the United States from the beginning of the industry in 1951 through 1994. Most analyses of this industry draw on a single source, but we found that none of the various historical sources covering the industry were individually comprehensive. Consequently, we reviewed every known source that documented the computer industry, and then systematically combined and reconciled the data from the five most complete sources: *Computers and Automation* (Berkeley Enterprises, Inc., 1950-1973), *EDP/Industry Report* (International Data Corporation, 1968-1983), IDC (International Data Corporation, c.1997), *Computer Review* and *Minicomputer Review* (GML Corp, 1974-1987), and *Data Sources* (Ziff-Davis Pub. Co., 1982-1996). (See Barnett, Swanson, and Sorenson, 2003, for details.) This approach resulted in a dataset covering 2,602 organizations over a total of 10,655 organization-years.

Many specific markets have emerged within the broader computer industry. To model competition and change in this context, we needed to strike a balance in attending to such market distinctions. Sufficient specificity is required for us to correctly identify when organizations move into different markets. Meanwhile, we need to remain broad enough in our market distinctions so that competing organizations are grouped together within the same market definition. Often, researchers can strike this balance by employing common sense market distinctions that have become institutionalized in an industry. The history of this industry, however, is replete with shifting labels and changes in popular terminology, such that no clear common sense definitions are self-evident. Given these issues, we found three market categories to be temporally robust and useful in distinguishing among organizations. These were mainframe, or large computers, including supercomputers; midrange computers, including minicomputers, small business computers, servers, workstations and other medium-sized systems; and microcomputers. Although an organization could operate in any of these three markets in any given year, over the industry's history the great majority (about 88%) operated within a single market, about 11% operated in two markets at once, and only about 1% operated simultaneously in all three markets. The organizations are described in Appendix C, Tables C1-C4 and in Figures C1-C3. The operational variables created from these data, or appended from other sources, are described in Appendix B. Correlations among key variables are shown in Appendix D.

Before turning to the model estimates, we will briefly discuss the study context. In this discussion, our objective is to explain why we think our predicted pattern is plausible in the context of the computer industry, given what we know broadly about the industry's evolution. This overview then helps to make tangible the model estimates that follow.

From 1963 through to the end of our study period in 1994, the midrange computing market emerged through a competitive process, with 743 of its 831 organizations failing over that time. Through this competition, manufacturers discovered and then adapted to the specific technological, market, and organizational requirements of this context. The early minicomputer manufacturers of the 1960s appealed to technologically savvy users, offering smaller systems with powerful performance relative to price (Tushman and Anderson, 1986; Ceruzzi, 1998). These customers especially valued that they could interact directly with minicomputers – something that was not possible with mainframe systems. The early minicomputer manufacturers did not maintain elaborate service and support systems, but rather relied on competent users, who in turn formed user groups to defend the distinct identities of the midrange manufacturers in opposition to IBM (Rivkin and Harrar, 1988).

Continued competition drove midrange manufacturers to sell into various parts of the economy, as they created and sold “embedded” computers that operated within other systems (Bell and Newell, 1971). Supported by a proliferation of independent software development firms, competing midrange manufacturers by the 1970s created a market for small- to medium-sized businesses, which did not have the scale required to effectively deploy mainframe computing systems. Competition for these customers drove the continued adoption of technical advances, most notably integrated circuits in the early 1970s and ultimately microprocessors in the “super-minicomputers” of the late 1970s.

Competing to satisfy more sophisticated business computing needs in the 1980s, so-called “graphics computers” would evolve into workstations within distributed computing systems using a client-server architecture, made possible by advances in networking (Sorenson, 2000). So by the 1980s, midrange computing firms had become sophisticated technology firms with well-developed, business-oriented distribution, surrounded by supporting populations of software development firms, resellers, and user groups.

Meanwhile, the 1980s also saw the microcomputer move from the hobby shop to the mass consumer-electronics market. In particular, IBM’s entry into microcomputers in 1981 gave legitimacy to the microcomputer market – so much so that the already established Apple Computer company publicly welcomed IBM’s entry for this reason (Freiberger and Swaine, 1984). At that time, midrange manufacturers were widely seen as some of the most innovative organizations in the economy – lauded by the popular press and featured in books about adaptive organizations (e.g. Kanter, 1983). Established midrange computer manufacturers also moved into the microcomputer market in numbers, especially in the 1980s, as illustrated in Table C1 and Figure C3.

Yet the logic of competition emerging in the microcomputer market was turning out to be very different than that in midrange computing. According to a former engineer at a leading midrange firm of the time, many experienced leaders in midrange computing were sure that their technological abilities would serve them well in microcomputing. Yet microcomputing did not require the organizational capabilities valued in the midrange market. Specifically, prior to the microcomputer, the difficulty in computer design was building the “instruction set” – the logical command sequence followed during computer operations – into the architecture of the system in a way that resulted in efficient operation. In a microcomputer, however, the instruction set resided on the microprocessor. Thus the technical strengths of the midrange manufacturers were less relevant in the microcomputer market. Rather, by the 1980s microcomputer manufacturers typically assembled systems from standardized, modularized components made by suppliers

(Langlois, 1992). Competition instead came down to organizing assembly in such a way as to provide low-cost, easy-to-use computers to the mass market at a faster time-to-market (Anderson, 1995; Bothner, 2003; Henderson and Stern, 2004). In this setting, the organizational capabilities of the midrange manufacturers were out-of-place.

Consequently, midrange manufacturers that survived more competition, and so were best adapted to the context of midrange computing, would be least well adapted to the budding microcomputer market. By our theory, it is for this reason that such organizations would find moving into microcomputing to be especially hazardous. Yet, at the same time, managers in these organizations would be unaware of this problem. For instance, Data General, the legendary minicomputer pioneer described in Kidder's novel *Soul of a New Machine*, confidently introduced a microcomputer in 1983. Having out-competed some of the most technically advanced firms in the world prior to that point, Data General seemed well positioned to grow in the booming microcomputer market. But this organization would soon see its fortunes reversed, especially in microcomputing. According to a former Data General engineer who left the company at that time to start his own microcomputer firm, Data General's move into microcomputers was harmed by its history of success in minicomputers: "[Management]...were reading their own press clippings. Managers stopped listening because they thought they were smart."[3]

In these ways, we think our ideas are consistent with some of the illustrations we have found in studying the evolution of the computer industry. Of course, one can usually find examples to support an argument, and so we do not take these illustrations to be hypothesis tests. For that, we turn our attention to the model estimates.

Results

The model estimates are reported in Tables 1, 2, and 3. The estimates in Table 1 are specifications of the microcomputer market failure rate model. These models allow for a test of Hypothesis 1. Table 2 includes models of the entry rate of midrange manufacturers into the microcomputer market, in order to test Hypothesis 2. The models in Table 3 are of the failure rate in the midrange computer market. These models enable us to investigate the alternative hypothesis that organizations exposed to competition in the midrange market were failing, and so moved into the microcomputer market because of their poor performance in the midrange computer market.

[3] Interview with former Data General engineer, October 25 2005.

Hypothesis tests

Our first hypothesis is that competitive experience in one market increases failure rates when organizations move into another market. This prediction is tested in Model 3 of Table 1, which improves statistically on the baseline Model 1.[4] In Model 3, we see strong evidence that a history of competition in either the midrange or the mainframe market increased failure rates for organizations in the microcomputer market, consistent with our assertion that being well-adapted to one market makes moving to another market more hazardous. Meanwhile, tenure *per se* in the midrange and mainframe markets lowered failure rates in microcomputing (see also Klepper and Simons, 2000). This tenure effect possibly reflects heterogeneity in survivability, with organizations that are more likely to survive in one market also likely to survive in another for otherwise unobserved reasons. Note that, on average, this life-enhancing tenure effect was more than offset by the failure-increasing effect of exposure to midrange competition.[5]

Our second hypothesis, that surviving competition in one market increases rates of organizational expansion into other markets, is supported by the results in Table 2. Models 5 and 6 include different specifications of exposure to competition in the midrange market, and both improve statistically on the baseline Model 4.[6] (Note that we also estimated a pared-down version of Model 6, omitting many of the control variables that are non-significant, and found that our results were robust without these terms.) According to these models, midrange firms that survived competition were especially likely to move into the microcomputer market. Consistent with the theory, Model 6 shows that this effect was entirely because of recent competitive experience.

In light of the exit rate findings, this pattern is noteworthy. From the exit rate models, we know that a history of competition in the midrange market made moving to the microcomputer market hazardous. Specifically, a midrange firm moving into microcomputers was on average about 65% more likely to fail once it got there due to its historical competition in midrange. Yet that same exposure to competition made a midrange firm nearly 7 times more likely to make that

[4] A comparison of the likelihood ratios yields a X^2 equal to 60.78, which is significant at above the .01 level for 6 degrees of freedom.

[5] At the mean observed level of midrange competition (169 competitors), Model 3 predicts a multiplier of the failure rate of exp[.169x2.103], or exp[.35], due to enduring an average year of midrange competition. The life-enhancing tenure effect for one year is estimated to be exp[-.34]. At the maximum-observed level of competition in the midrange market (217 competitors), exposure to midrange competition increased an organization's microcomputer market failure rate by a multiplier of 1.126 (exp[.217x2.103-.34]) – meaning a 12% increase in the microcomputer failure rate due to midrange competitive experience, even when including the beneficial effects of midrange tenure *per se*.

[6] The likelihood-ratio X^2 for a comparison of Models 4 and 5 is 15.66, implying an improvement above the .01 level of significance for 1 degree of freedom. A comparison of Models 4 and 6 results in a X^2 of 24.08, again significant at above the .01 level with 2 degrees of freedom.

move.[7] Thus, survivorship in the midrange market dramatically increased the chances of failure for these organizations should they venture into the microcomputer market, but survivorship also made it especially likely that these organizations would decide to pursue this hazardous course of action.

Table 3 shows models testing the alternative hypothesis that exposure to historical competition harmed midrange firms, forcing them out of the midrange market and into the microcomputer market. The estimates of Model 8 show that historical competition in the midrange market lowered the failure rate of midrange firms in that market, consistent with the prediction of Red Queen theory. Model 8, which improves significantly over Model 7,[8] shows that midrange firms were on average 36% less likely to fail in the midrange market due to their exposure to historical competition in that market.[9] So the same experience that made it more hazardous for these organizations in the microcomputer market helped them in the midrange market, consistent with our theory.

Competition

Looking at the evidence of Red Queen competition in the microcomputer market, the models in Table 1 show that the survival-enhancing effect of historical exposure to competition (**T**) within the microcomputer market is driven entirely by recently experienced competition. Distant-past competition has the reverse effect, consistent with the idea that a competence trap develops over enough time in the industry. This distant-past competition effect is not robust when we change the specification of the model in various ways, however, so we are circumspect in our interpretation of this finding. The life-enhancing effect of recent-past competition is robust, and cumulates over time to more than offset the life-threatening effects of current-time competition for an organization facing the average number of competitors.

In microcomputer exit rate models not shown, industry-level density dependence is found to be monotonic and positive, indicating competition among computer manufacturers generally. Model 3 shows that density-dependence is market specific, and models not shown allow us to reject a non-monotonic density specification. Specifically, Model 3 shows evidence of density-

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[7] Setting historical competition in the midrange market equal to 236, the observed mean among midrange firms at risk of entry into microcomputers, model 3 implies an increase in the failure rate of exp[2.103×.236]=1.642, or about a 65% increase, and model 6 implies an increase in the microcomputer market entry rate of exp[8.68×.236]=7.756, more than a 7-fold increase.
[8] The likelihood-ratio X^2 for a comparison of Models 7 and 8 is 17.46 with 1 degree of freedom, a significant improvement at the .01 level.
[9] At the average observed historical competition level of 575, Model 8 predicts a multiplier due to this variable of exp[.575x-.7828], or .637 – a decrease in the failure rate of about 36% compared to what it would have been without the benefits of the Red Queen effect.

dependent competition among microcomputer organizations, and from midrange manufacturers affecting microcomputer manufacturers. The mainframe density effect is negative, indicating mutualism from mainframe manufacturers. Given the closer proximity of midrange organizations to microcomputer manufacturers in product space, this pattern is consistent with resource partitioning among these markets, or at least with the possibility that competition is localized to product niches.

A comparison of the microcomputer and midrange density effects in Model 3, however, shows considerably stronger competition (per rival) from midrange manufacturers than among microcomputer manufacturers. To see whether this stronger effect was, in fact, coming from microcomputer manufacturers that happened also to be in the midrange market, other models (not shown) break out midrange density into separate effects for midrange firms that were or were not also microcomputer manufacturers. These models revealed that very powerful competition came from midrange firms – but only those that were not microcomputer manufacturers. Similarly, in Table 3, the results indicate that microcomputer density increased exit rates among midrange manufacturers. Thus we find evidence that the midrange niche was overlapping the microcomputer niche over the study period.

Other effects in the failure models

Microcomputer market shipments were consistently positively associated with failure, evidence of so-called "mass dependence" (Barnett and Amburgey, 1990). Mass dependence is notoriously inconsistent across studies, and so this result raises the question of whether in fact there has been scale-based competition in the industry along the lines of Dobrev et al.'s (2003) model. Estimation of a fully scale-based competition model is beyond the scope of this study, although certainly this issue deserves further attention.

All models in Table 1 show consistent patterns of size and tenure dependence. Negative size dependence is found in all models, consistent with the literature (Carroll and Hannan, 2000). Meanwhile, tenure dependence hinges on size in a way consistent with Barron et al. (1994). Larger organizations exhibit negative tenure dependence, while smaller organizations show weak evidence of positive tenure dependence, indicating the possibility of increasing frailty among organizations that fail to grow. This said, the ultimate dynamic faced by these organizations depends in large part on whether they engage in Red Queen competition, since with age organizations typically accumulate competitive experience. In fact, for the average amount of competition faced by a microcomputer firm, the beneficial effects of the Red Queen rapidly overwhelm the positive tenure dependent effect, indicating that the liability of ageing in these data would be better thought of as a liability of isolation.

Lagged failures consistently predict higher failure rates, suggesting autocorrelation in the exit process. Meanwhile, no significant effects are found for lagged entries on the exit rate. Microcomputer density at entry is not significant, so we do not find support for the theory of density delay (Carroll and Hannan, 1989). One of the exogenous control variables, real gross domestic product, consistently predicts lower failure rates when the U.S. economy is up – a carrying capacity effect. Meanwhile, no robust results are found for interest rates. Finally, we note that de alio organizations have lower failure rates across all models, as found and studied in considerable detail by Swanson (2002).

Market entry models

The market entry models in Table 2 are estimated with considerably less statistical power, owing to the relatively small number (92) of events being analyzed. That said, some patterns do appear. The historical competition effect is strong, especially when specified to distinguish between recent and distant-past historical competition. With these effects explicitly modeled, tenure dependence then becomes clearly negative. (This is seen by looking across the values of the piecewise coefficients.) Thus, the baseline prediction of structural inertia theory – that of decreasing rates of change over time – are born out in these models (Hannan and Freeman, 1984; Amburgey et al., 1993). Yet this baseline finding is reversed entirely for organizations facing sufficient numbers of competitors. For such organizations, the hazard of change *increases* over time, consistent with the idea that surviving competition generates a success bias among decision makers.

In other results from these models, larger organizations and de alio organizations are each predicted to enter the microcomputer market at a greater rate. Older organizations initially look to be more likely to change in Model 4 – a surprising finding. In fact, this effect is dramatically reduced in Model 15, which controls for historical exposure to competition. Again, it appears that the estimates of the effects of duration hinge on whether one explicitly allows for the effects of a historical exposure to competition.

Discussion and Conclusions

Our findings show how Red Queen competition plays a key role, shaping both the likelihood and consequences of organizational change. Organizations with a history of competing in a market turned out to be more viable in that market, and yet were especially disrupted when they moved into another market. This result is consistent with the idea that competition increases an organization's ability to exploit its current context, while it makes exploration especially disruptive. Meanwhile, surviving competition constitutes a powerful datum, feeding the perception that an organization is able to adapt. Decision makers in this situation are especially likely to engage in exploratory change. Taken together, these processes lead to an ironic parallel: The Red Queen makes exploratory change especially disruptive, yet encourages managers to think such moves are a good idea. We think these processes may help to account for the notorious tendency of successful organizations to engage in ruinous initiatives.

We must temper our claim by noting that we do not directly measure the occurrence of a success bias among the decision makers in these organizations. But our goal has not been to demonstrate biased decision making among individuals. For direct investigation of decision biases, researchers typically take a very different approach – conducting controlled experiments in which the precise conditions for the particular bias under study can be established with internal validity. Rather, our goal has been to demonstrate the macro-level implications of our ideas, which required a research setting that would allow us to tease apart our predicted patterns of survivorship, change, and failure. Doing so required an investment in data covering thousands of organizations over the entire history of an industry – not a good setting for controlled micro-level experiments, but an ideal source of information on the behavior and consequent fates of organizations that survive a history of competition.

Our work here also has implications for macro-level research on structural inertia theory. For the most part, in such research decision-making processes are de-emphasized, or ignored entirely. Instead, virtually all research in this vein makes arguments about the likelihood of change and the consequences of change in parallel. For instance, where inertia is strongest, it is predicted that rates of change will be correspondingly lower, and when change does occur it is predicted to be especially hazardous. Where changes build on the status quo, rates of change are predicted to be higher and also to be less disruptive. Our findings show, however, that the likelihood and consequences of change may, in fact, cut in opposite directions. Surviving competition sets in motion micro-level processes that make change more likely, even as it reinforces the inertial forces that make such change disruptive. We think these results highlight an interesting future direction for research into other instances where the likelihood and implications of organizational change are opposed.

Our findings have implications for the growing literature connecting competition and organizational change. By and large, work in this vein predicts and finds that organizations tend to change in order to move away from especially competitive environments or move toward less competitive ones. Such a pattern appears, for instance, in Dobrev et al.'s (2003) study of change among automobile manufacturers. (See also Delacroix and Swaminathan, 1991; Greve, 1996; Baum and Korn, 1999; Haveman and Nonnemaker, 2000.) Our findings raise a question for such research, however. Perhaps the effects being attributed to current-time competition in these studies are reflecting the historical competition effects that we predict? That is, maybe these organizations are changing due to their history of surviving competition, rather than because of their desire to avoid current-time competition. Because these studies do not consider the historical effects of competition, this possibility has not been ruled out. Our findings suggest that it may be worthwhile to re-estimate models from the existing literature to see whether their results are being driven by current-time or historical competition.

To conclude, we note that it is worthwhile to conceive of Red Queen competition as more than a race among individuals. Very often, dynamic competition of this sort evokes the imagery of individuals engaged in an "arms race." This imagery has the disadvantage of rendering organizational decision makers as rational actors, and of anthropomorphizing organizations. Our exposition here has avoided both of these tendencies, we think. At the organization-level, Red Queen competition is a force that operates on organizational systems to build capabilities over time – for better or for worse when it comes to the organization's eventual movement into new markets where these capabilities may be less applicable or especially disrupted. Meanwhile, individual decision makers are depicted as searching through available and limited information in intendedly-rational ways, and so are subject to errors such as the success bias. So the processes set in motion by Red Queen competition operate distinctly at each level of analysis, even as they ultimately help to decide the fates of entire organizations and industries.

References

Anderson, Philip. 1995. "Microcomputer Manufacturers." In Glenn R. Carroll and Michael Hannan (eds) *Organizations in Industry: Strategy, Structure and Selection*: 37-58. New York: Oxford University Press.

Anderson, Philip and Michael L. Tushman. 1990. "Technological Discontinuities and Dominant Designs: A Cyclical Model of Technological Change. *Administrative Science Quarterly,* 35: 604-633.

Amburgey, Terry L., Dawn Kelly, and William P. Barnett. 1993. "Resetting the Clock: The Dynamics of Organizational Transformation and Failure." *Administrative Science Quarterly,* 38: 51-73.

Barnett, William P. 1993. "Strategic Deterrence Among Multipoint Competitors." *Industrial and Corporate Change*, 2: 249-278.

Barnett, William P. and Terry L. Amburgey. 1990. "Do Larger Organizations Generate Stronger competition?" In L.V. Singh (ed), *Organizational Evolution: New Directions*: 78-102. Newbury Park, CA: Sage.

Barnett, William P. and Glenn Carroll. 1995. "Modeling Internal Organizational Change." *Annual Review of Sociology*. 21: 217-236.

Barnett, William P. and Morten T. Hansen. 1996. "The Red Queen in Organizational Evolution." *Strategic Management Journal*, 17: 139-157.

Barnett, William P. and David McKendrick. 2004. "Why Are Some Organizations More Competitive Than Others? Evidence from a Changing Global Market." *Administrative Science Quarterly*, 49.

Barnett, William P. and Olav Sorenson. 2002. "The Red Queen in Organizational Creation and Development." *Industrial and Corporate Change,* 11: 289-325.

Barnett, William P., Aimee Noelle Swanson, and Olav Sorenson. 2003 "Asymmetric Selection Among Organizations." *Industrial and Corporate Change*, 12, 4: 673-695

Bazerman, Max and Margaret Neale. 1986. *Negotiating Rationally.* New York: Free Press.

Bell, C. Gordon and Allen Newell. 1971. *Computer Structures: Readings and Examples*. McGraw-Hill.

Bothner, Matthew S. 2003. "Competition and Social Influence: The Diffusion of the Sixth-Generation Processor in the Global Computer Industry." *American Journal of Sociology,* 108: 1175-1210.

Burns, Tom and George M. Stalker. 1961. *The Management of Innovation*. Oxford: Oxford University Press.

Carroll, Glenn R. and Michael T. Hannan. 1989. "Density Delay in the Evolution of Organizational Populations: A Model and Five Empirical Tests. *Administrative Science Quarterly,* 34: 411-430.

Carroll, Glenn R. and Michael T. Hannan. 2000. *The Demography of Corporations and Industries.* Princeton NJ: Princeton University Press.

Carroll, Glenn R. and Albert C. Teo. 1996. "Creative Self-destruction Among Organizations: An Empirical Study of Technical Innovation and Organizational Failure in the American Automobile Industry, 1885-1981." *Industrial and Corporate Change* 5: 619-644.

Ceruzzi, Paul. 1998. *A History of Modern Computing*. Cambridge: MIT Press.

Christensen, Clayton M. 1997. *The Innovator's Dilemma: When New Technologies Cause Great Firms to Fail.* Cambridge, MA: Harvard Business School Press.

Christensen, H. Kurt. and Cynthia Montgomery. 1981. "Corporate economic performance: diversification strategy versus market structure," *Strategic Management Journal*. 2: 327-343.

Collins, Jim and Jerry Porras. 1994. *Built to Last*. New York: HarperCollins.

Computers and Automation. Various years (1951-1973). Newtonville: Berkeley Enterprises.

Computer Review. Various years (1974-1982). Lexington: GML Corp.

Cyert, Richard M. and James G. March. 1963. *A Behavioral Theory of the Firm.* Engelwood Cliffs, NJ: Prentice-Hall.

Data Sources. Various years (1982-1996). New York: Ziff-Davis Pub Co.

Delacroix, Jacques and Anand Swaminathan. 1991. "Cosmetic, speculative and adaptive change in the wine industry: A longitudinal study." *Administrative Science Quarterly,* 36: 631-61.

Denrell, Jerker. 2003. "Vicarious Learning, Undersampling of Failure, and the Myths of Management." *Organization Science,* 14: 243.

Dobrev, Stanislav, Tai-Young Kim and Glenn R. Carroll. 2003. "Shifting Gears, Shifting Niches: Organizational Inertia and Change in the Evolution of the U.S. Automobile Industry, 1885-1981." *Organization Science,* 14: 264-282.

Einhorn, H. and R. Hogarth. 1978. "Confidence in Judgment: Persistence in the Illusion of Validity," *Psychological Review,* 85: 395-416.

EDP/Industry Report. Various years (1967-1983). Framingham: International Data Corp.

Electronic Buyers' Guide. Various years (1950-1986). New York: McGraw-Hill.

Federal Reserve Statistical Release: Annual bank prime loan. c.2002. www.federalreserve.gov/release/H15/data.htm.

Fischoff, B. and R. Beyth. 1975. "'I knew it would happen' – Remembered Probabilities of Once-future Things," *Organizational Behavior and Human Performance,* 13: 1-16.

Fiske, Susan T. and Shelley E. Taylor. 1991. *Social Cognition (2nd ed.)*. New York: McGraw Hill.

Freiberger, Paul and Michael Swaine. 1984. *Fire in the Valley: The Making of the Personal Computer*. Berkeley: Osborne/McGraw-Hill.

Greve, Henrich R. 1996. "Patterns of competition: The diffusion of a market position in radio broadcasting." *Administrative Science Quarterly*, 41: 29-61.

Greve, Henrich R. 1999. "The Effect of Change on Performance: Inertia and Regression Toward the Mean." *Administrative Science Quarterly,* 44: 590-614.

Hannan, Michael T. and Glenn R. Carroll. 1992. *Dynamics of Organizational Populations: Density, Legitimation, and Competition.* New York: Oxford University Press.

Hannan, Michael T. and John Freeman 1977. "The Population Ecology of Organizations." *American Journal of Sociology,* 82: 929-964.

Hannan, Michael T., and John H. Freeman. 1984. "Structural inertia and organizational change." *American Sociological Review*, 49: 149-164.

Hannan, Michael T. and John Freeman. 1989. *Organizational Ecology.* Harvard University Press: Cambridge, MA.

Hannan, Michael T., László Pólos, and Glenn R. Carroll. 2003. "Cascading Organizational Change." *Organization Science,* 14: 463-482.

Haveman, Heather. 1993a. "Organizational Size and Change: Diversification in the Savings and Loan Industry After Deregulation." *Administrative Science Quarterly,* 38: 20-50.

Haveman Heather. 1993b. "Follow the leader: Mimetic isomorphism and entry into new markets." *Administrative Science Quarterly,* 38: 593-627.

Haveman, Heather A. and Lynn Nonnemaker. 2000. "Competition in Multiple Geographic Markets: The Impact on Growth and Market Entry." *Administrative Science Quarterly*, 45: 232-267.

Helfat, Constance E. 1997. "Know-How and Asset Complementarity and Dynamic Capability Accumulation: The Case of R&D." *Strategic Management Journal*, 18: 339-360.

Henderson, Andrew and Ithai Stern. 2004. "Selection Based Learning: The co-evolution of internal and external selection in high-velocity environments." *Administrative Science Quarterly*, 49: 39-75.

Henderson Rebecca M. and Kim B. Clark. 1990. "Architectural innovation: The reconfiguration of existing product technologies and the failure of established firms." *Administrative Science Quarterly,* 35: 9-30.

Herriott, Scott R., Levinthal, Daniel and March, James G., 1985. "Learning From Experience in Organizations," *American Economic Review,* 75: 298-302.

Hogarth, R. M. & Einhorn, H. J. 1992. “Order effects in belief updating: The belief-adjustment model.” *Cognitive Psychology*, 24, 1-55.
Hsu, Greta. 2006. "Jacks of all trades and masters of none: Audiences' reactions to spanning genres in feature film production." *Administrative Science Quarterly* 51: 420-450.
Huber, George P., K.M. Sutcliffe, C.C. Miller, W.H. Glick. 1993. “Understanding and Predicting Organizational Change.” Pp. 215-263 in G.P. Huber and W.H. Glick (eds.) *Organizational Change and Redesign.* New York: Oxford.
International Data Corporation (IDC). c.1997. Electronic computer file. Framingham: International Data Corporation.
Ingram, Paul and Joel A.C. Baum. 1997. “Opportunity and Constraint: Organizations’ Learning from the Operating and Competitive Experience of Industries.” *Strategic Management Journal,* 18: 75-98.
Kanter, Rosabeth M. 1983. *The Change Masters: Innovation for Productivity in the American Corporation*. New York: Simon & Schuster.
Kelly Dawn and Terry L. Amburgey. 1991. “Organizational Inertia and Momentum: A Dynamic Model of Strategic Change.” *Academy of Management Journal,* 34: 591-612.
Kidder, Tracey. 1981 *Soul of a New Machine*. New York: Avon.
Kimberly, John. 1976. “Organizational Size and the Structuralist Perspective: A Review, Critique and Proposal. *Administrative Science Quarterly,* 21: 571-597.
Kimberly, John and R.H. Miles. 1980. *The Organizational Life Cycle.* San Francisco: Jossey-Bass.
Klepper, Steven, and Kenneth L. Simons. 2000. “Dominance by Birthright: Entry of Prior Radio Producers and Competitive Ramifications in the U.S. Television Receiver Industry.” *Strategic Management Journal*, Vol. 21: 997-1016.
Koriat, Asher, Sarah Lichtenstein, and Barauch Fischoff. 1980. “Reasons for Confidence.” *Journal of Experimental Psychology: Human Learning and Memory,* 6: 107-118.
Kraatz, Matthew S. and Edward J. Zajac. 2001. “How Organizational Resources Affect Strategic Change and Performance in Turbulent Environments: Theory and Evidence.” *Organization Science*, 12: 632-657.
Langlois, Richard. 1992. “External Economics and Economic Progress; the case of the Microcomputer Industry,” *Business History Review*, 66: 1-50.
Lant, Theresa K. 1992. “Aspiration Level Adaptation: An Empirical Exploration.” *Management Science,* 38: 623-644.
Levinthal, Daniel A. 1997. “Adaptation on Rugged Landscapes.” *Management Science,* 43: 934-950.
Levinthal, Daniel A., and James G. March 1981. “A model of adaptive organizational search.” *Journal of Economic Behavior and Organization*, 2: 307-333.
Levitt, Barbara and James G. March. 1988: “Organizational Learning.” *Annual Review of Sociology*, 14, 319-340.
Lexis-Nexis academic universe (online.) 1999-2001. Bethesda: LEXIS-NEXIS Academic Universe, Congressional Information Service.
March, James G. 1988. *Decisions and Organizations.* Cambridge, MA: Basil Blackwell.
March, James G. 1991. “Exploration and Exploitation in Organizational learning.” *Organization Science*, 2: 71-87.
March, James G. 1994. *A Primer on Decision Making: How Decisions Happen.* New York: Free Press.
March, James G. and Z. Shapira. 1987. “Managerial Perspectives on Risk and Risk Taking.” *Management Science,* 33: 1404-1418.
March, James G. and Herbert A. Simon. 1958. *Organizations.* New York: John Wiley.
March, James G., Lee S. Sproull, and Michal Tamuz. 1991. “Learning From Samples of One or Fewer.” *Organization Science,* 2: 1-13.

Martin, Joanne. 1982. “Stories and Scripts in Organizational Settings.” Pp. 255-305 in Hasdorf and Isen (eds.) *Cognitive Social Psychology.* New York: Elsevier-North Holland.
Meyer, John W. and Brian Rowan. 1977. “Institutionalized Organizations: Formal Structure as Myth and Ceremony.” *American Journal of Sociology,* 83: 340-363.
Miller Danny and M.J. Chen. 1994. “Sources and consequences of competitive inertia: A study of the US airline industry.: *Administrative Science Quarterly,* 39: 1-23.
Miner, Anne S., Terry L. Amburgey, and Tim M. Stearns. 1990. “Interorganizational linkages and population dynamics: buffering and transformational shields.” *Administrative Science Quarterly,* 35: 689-713.
Miner, Anne S. and Pamela R. Haunschild. 1995. “Population level learning.” In L.L. Cummings and B.M. Staw (eds.), *Research in organizational behavior*, 17: 115-66, Greenwich, CT: JAI Press.
Minicomputer Review. Various years (1974-1982). Lexington: GML Corp.
Montgomery, Cynthia A. 1985. “Product-Market Diversification and Market Power.” *Academy of Management Journal*. 28: 789-798.
Montgomery, Cynthia A. and Birger Wernerfelt. 1988. “Diversification, Ricardian Rents, and Tobin’s q.” *Rand Journal of Economics,* 19: 623-632.
Nelson, Richard R. and Sidney G. Winter. 1982. *An Evolutionary Theory of Economic Change.* Belknap Press.
Ouchi, William G. 1981. *Theory Z: How American Business can Meet the Japanese Challenge*. Reading, MA: Addison-Wesley.
Peters, Tom and Robert H. Waterman. 1982 *In Search of Excellence*. Warner Books, Inc.
Petersen, Trond. 1991. “Time-aggregation bias in continuous-time hazard-rate models,” Pp. in P. Marsden (ed.) *Sociological Methodology 1991*. Cambridge: Blackwell.
Podolny, Joel M. 1993. “A Status-Based Model of Market Competition.” *American Journal of Sociology,* 98: 829-72.
Porac, Joseph F., Howard Thomas, Fiona Wilson, Douglas Paton, and Alaina Kanfer. 1995. “Rivalry and the Industry Model of Scottish Knitwear Producers.” *Administrative Science Quarterly*, 40: 203-227.
Portelli, Alessandro. 2003. *The Order Has Been Carried Out.* New York: Palgrave Macmillan.
Rumelt, Richard. 1974. *Strategy, Structure, and Economic Performance*. Cambridge: Harvard University Press.
Scherer, Frank M. 1980. *Industrial Market Structure and Economic Performance.* Boston, MA: Houghton Mifflin.
Selznick, Philip. 1957. *Leadership in Administration.* New York: Harper and Row.
Singh Jitendra V., D.J. Tucker, A.G. Meinhard. 1991. “Institutional change and ecological dynamics.” In *The new institutionalism in organizational analysis*, eds. W.W. Powell and P.J. DiMaggio (eds.). Chicago: University of Chicago Press
Sorenson, Olav. 2000. “The Effect of Population Level Learning on Market Entry: The American Automobile Industry.” *Social Science Research,* 29: 307-326.
Stinchcombe, Arthur L. 1965: “Social Structure and Organizations.” In: March, JG (ed.), *Handbook of Organizations*. Chicago: Rand McNally & Company, 142-193.
Strang, David and Michael W. Macy. 2001. "In Search of Excellence: Fads, Success Stories, and Adaptive Emulation." *American Journal of Sociology* 107: 147-82.
Sutton, J.R., F. Dobbin, J.W. Meyer, W.R. Scott. 1994. “The legalization of the workplace.” *American Journal of Sociology,* 99: 944-971.
Swaminathan, Anand. 1996. "Environmental Conditions at Founding and Organizational Mortality: A Trial-by-Fire Model." *Academy of Management Journal*, 39: 1350-1377.
Swanson, Aimee-Noelle. 2002. *Form Coherence and the Fates of De Alio and De Novo Organizations in the U.S. Digital Computer Industry: 1951-1994.* Unpublished PhD Dissertation, Stanford University Department of Sociology.

Teece, David J., Gary Pisano, and Amy Shuen. 1997. "Dynamic Capabilities and Strategic Management." *Strategic Management Journal*, 18: 509-533.
Tuma, Nancy Brandon and Michael T. Hannan. 1984. *Social Dynamics: Models and Methods*. New York: Academic Press.
Tushman Michael L., Philip Anderson. 1986. "Technological discontinuities and organizational environments." *Administrative Science Quarterly,* 31: 439-465.
Tushman Michael L. and Elaine Romanelli. 1985. "Organizational evolution: A metamorphosis model of convergence and reorientation." In L.L. Cummings and B.M. Staw (eds.) *Research in Organizational Behavior,* 7: 171-222. Greenwich CT: JAI.
Tversky, Amos and Daniel Kahneman. 1973. "Availability: A Heuristic for Judging Frequency and Probability." *Cognitive Psychology*, 5: 207-232.
U.S. Department of Commerce. c.2001. "Real gross domestic product." Washington: U.S. Department of Commerce, Bureau of Economic Analysis.
U.S. Electronics Industry Directory. Various years (1990-1992). Twinsburg, OH: Harris Pub. Co.
Van Valen, L. 1973. "A New Evolutionary Law." *Evolutionary Theory,* 1: 1-30.
Weick, Karl. 1979. *The Social Psychology of Organizing*. Menlo Park, CA: Addison-Wesley.
Winter, Sidney G. 2000. "The Satisficing Principle in Capability Learning." *Strategic Management Journal*, Vol. 21: 981-996.
Who's Who in Electronics. Various years (1970-1987). Twinsburg, OH: Harris Pub. Co

Table 1
Estimates of the Organizational Exit Rate from the U.S. Microcomputer Market

	Model 1	Model 2	Model 3
Microcomputer market effects:			
Microcomputer market density/1000	3.154**	3.241**	3.649**
	(1.025)	(1.026)	(1.040)
Historical competition faced by org.		-0.2415**	
in the microcomputer market/1000		(0.0864)	
Recent historical competition faced			-1.006**
in the microcomputer market/1000			(0.2999)
Distant-past historical competition faced			0.6757*
in the microcomputer market/1000			(0.3714)
Effects of being also in the midrange market			
Organization also is in the	-0.2377**	-0.2471**	0.0387
midrange market	(0.0872)	(0.0874)	(0.1219)
Organization's tenure in the			-0.3415**
midrange market			(0.0681)
Midrange market density/1000	8.864**	8.533**	8.487**
	(3.698)	(3.717)	(3.752)
Historical competition faced by org.			2.103**
in the midrange market/1000			(0.4192)
Effects of being also in the mainframe market			
Organization also is in the	-0.4612	-0.4440	-2.454**
mainframe market	(0.3122)	(0.3122)	(0.7763)
Organization's tenure in the			-0.5374**
mainframe market			(0.1918)
Mainframe market density/1000	-22.77	-23.99*	-25.43*
	(14.00)	(14.03)	(14.11)
Historical competition faced by org.			37.28**
in the mainframe market/1000			(11.47)
Log Likelihood	-2400.30	-2396.41	-2369.91
(Degrees of freedom)	(30)	(31)	(36)

Note: The data include 1739 exits from a risk set of 1922 organizations over 6510 organization-years. Organizational size, market tenure, and other effects are included in each model, and are shown on the following pages. For coefficient estimates, standard errors are reported in parentheses.
*p<.10 **p<.05

Table 1 (continued)
Estimates of the Organizational Exit Rate from the U.S. Microcomputer Market

	Model 1	Model 2	Model 3
All Organizations:			
Market tenure 0-1 year	2.080	1.965	2.006
	(2.521)	(2.530)	(2.547)
Market tenure 1-3 years	2.444	2.433	2.754
	(2.517)	(2.526)	(2.542)
Market tenure 3-5 years	2.533	2.667	3.072
	(2.520)	(2.530)	(2.548)
Market tenure 5-10 years	2.419	2.729	3.027
	(2.526)	(2.537)	(2.554)
Market tenure 10-15 years	2.664	3.208	3.019
	(2.554)	(2.570)	(2.593)
Market tenure 15+ years	2.516	3.329	3.116
	(2.636)	(2.661)	(2.688)
Medium-Sized Organizations:			
Market tenure 0-1 year	-0.1458	-0.1754*	-0.2009**
	(0.0986)	(0.0991)	(0.1000)
Market tenure 1-3 years	-0.3085**	-0.3149**	-0.2925**
	(0.0802)	(0.0802)	(0.0804)
Market tenure 3-5 years	-0.6105**	-0.6017**	-0.5855**
	(0.1215)	(0.1216)	(0.1218)
Market tenure 5-10 years	-0.7897**	-0.7499**	-0.7532**
	(0.1389)	(0.1396)	(0.1403)
Market tenure 10-15 years	-0.8641**	-0.7915**	-0.5935
	(0.3765)	(0.3774)	(0.3921)
Market tenure 15+ years	-1.168	-1.210	-0.9714
	(1.225)	(1.225)	(1.226)
Large Organizations:			
Market tenure 0-1 year	-0.5432**	-0.6144**	-0.6384**
	(0.2170)	(0.2182)	(0.2181)
Market tenure 1-3 years	-0.9601**	-0.9761**	-0.9447**
	(0.1794)	(0.1796)	(0.1798)
Market tenure 3-5 years	-1.037**	-1.032**	-1.012**
	(0.2299)	(0.2299)	(0.2304)
Market tenure 5-10 years	-2.812**	-2.786**	-2.829**
	(0.4600)	(0.4600)	(0.4642)
Market tenure 10-15 years	-3.694**	-3.652**	-4.278
	(1.0459)	(1.046)	(1.182)
Market tenure 15+ years	-2.663**	-2.727**	-5.127**
	(1.227)	(1.227)	(1.587)

Note: Standard errors are in parentheses.
*p<.10 **p<.05

Table 1 (continued)
Estimates of the Organizational Exit Rate from the U.S. Microcomputer Market

	Model 1	Model 2	Model 3
Real U.S. gross domestic product	-0.0017**	-0.0017**	-0.0017**
	(0.0006)	(0.0006)	(0.0006)
U.S. Prime interest rate	0.0382	0.0347	0.0335
	(0.0307)	(0.0309)	(0.0313)
Dealio entrant	-0.1483**	-0.1523**	-0.1789**
	(0.0574)	(0.0574)	(0.0579)
Microcomputer market shipments/1000	0.0002**	0.0002**	0.0002**
	(0.0001)	(0.0001)	(0.0001)
Microcomputer manuf. entries/1000	-0.2196	-0.3557	-0.9802
	(1.202)	(1.204)	(1.230)
Microcomputer manuf. failures/1000	6.066**	6.210**	6.632**
	(1.253)	(1.258)	(1.276)
Microcomputer market density at entry/1000	-0.0952	-0.0610	0.2613**
	(0.5112)	(0.5094)	(0.5249)

Note: Standard errors are in parentheses.
*p<.10, **p<.05

Table 2
Estimates of the Entry Rate of Midrange Manufacturers into the Microcomputer Market

	Model 4	Model 5	Model 6
Organization's time in the industry before 1975	.0664**	.0258	0.0501*
	(.0239)	(.0285)	(0.0286)
Dealio entrant	.3566	.4028*	0.3618
	(.2322)	(.2280)	(0.2296)
Medium-sized organization	.7072**	.6583**	0.6266**
	(.2446)	(.2446)	(0.2441)
Large organization	.3925	.2999	0.2313
	(.4123)	(.4124)	(0.4124)
Real U.S. gross domestic product	.0020	.0005	0.0013
	(.0024)	(.0024)	(0.0023)
U.S. Prime interest rate	-.0039	.0689	0.1070
	(.0818)	(.0828)	(0.0842)
Microcomputer market shipments/1000	-.0004	-.0004	-0.0005
	(.0003)	(.0003)	(0.0003)
Microcomputer manufacturer entries (lagged)/1000	-8.987*	-7.431	-8.379
	(5.383)	(5.294)	(5.274)
Microcomputer manufacturer failures/1000	4.734	5.167	9.947
	(8.565)	(8.848)	(9.158)
Microcomputer market density/1000	2.539	1.997	1.050
	(3.975)	(4.078)	(4.180)
Midrange market shipments/1000	.0045	.0128	0.0146
	(.0103)	(.0105)	(0.0106)
Midrange manufacturer entries (lagged)/1000	28.56**	26.75**	48.23**
	(18.07)	(17.90)	(19.58)
Midrange manufacturer failures/1000	-3.319	-4.260	-12.75
	(18.37)	(18.19)	(18.45)
Midrange market density/1000	1.187	-1.527	-10.51
	(7.640)	(7.763)	(8.655)
Historical competition faced by organization		2.510**	
in the midrange market/1000		(.6395)	
Recent historical competition faced by organization			8.684**
in the midrange market/1000			(2.431)
Distant-past historical competition faced by organization			-2.140
in the midrange market/1000			(1.812)
Log Likelihood (Degrees of Freedom)	-232.49 (20)	-224.66 (21)	-220.45 (22)

Note: The data include 92 entries from a risk set of 637 organizations over 2723 organization-years. Piecewise market tenure effects are included in each model, and are shown on the following page. For coefficient estimates, standard errors are in parentheses. *p<.10 **p<.05

Table 2 (continued)
Estimates of the Entry Rate of Midrange Manufacturers into the Microcomputer Market

	Model 4	Model 5	Model 6
Midrange market tenure 0-2 year	-12.66*	-8.505	-11.55
	(7.836)	(7.801)	(7.68)
Midrange market tenure 2-3 years	-12.96*	-9.371	-13.15*
	(7.869)	(7.817)	(7.74)
Midrange market tenure 3-5 years	-12.24	-9.303	-13.43*
	(7.910)	(7.851)	(7.80)
Midrange market tenure 5-10 years	-12.22	-10.62	-14.59*
	(7.829)	(7.737)	(7.69)
Midrange market tenure 10-15 years	-12.17	-12.58*	-15.75**
	(7.884)	(7.775)	(7.69)
Midrange market tenure 15+ years	-11.11	-13.52*	-15.09**
	(7.917)	(7.811)	(7.68)

Note: Standard errors are in parentheses.
*p<.10, **p<.05

Table 3
Estimates of the Organizational Exit Rate from the U.S. Midrange Computer Market

	Model 7	Model 8
Midrange Market Effects:		
Midrange Market Density /1000	8.164**	7.240**
	(2.621)	(2.649)
Historical competition faced by organization in the midrange market/1000		-.7828**
		(.1880)
Effects of being also in the Microcomputer Market		
Organization also is in the microcomputer market	-.1707*	-.1531
	(.0971)	(.0972)
Microcomputer Market Density /1000	1.306*	1.429*
	(.7729)	(.7766)
Effects of being also in the Mainframe Market		
Organization also is in the mainframe computer market	-.4209**	-.4405**
	(.1827)	(.1827)
Mainframe Market Density /1000	-21.09	-17.21
	(14.88)	(14.94)
Other Effects:		
Real U.S. gross domestic product	.0003	.0002
	(.0004)	(.0004)
U.S. Prime interest rate	-.0511**	-.0502**
	(.0164)	(.0164)
Dealio entrant	-.0943	-.1078
	(.0814)	(.0813)
Midrange market shipments/1000	.0027	.0034
	(.0037)	(.0037)
Midrange manuf. entries/1000	-3.010	-2.992
	(5.941)	(5.945)
Midrange manuf. failures/1000	-1.613	-.8989
	(4.392)	(4.398)
Midrange market density at entry/1000	-4.142**	-2.560*
	(1.429)	(1.492)
Log Likelihood	-1063.47	-1054.74
(df)	(30)	(31)

Note: The data include 743 exits from a risk set of 831 organizations over 4466 organization-years. Organizational size and market tenure are included in each model, and are shown on the following page. For coefficient estimates, standard errors are in parentheses.
*p<.10 **p<.05

Table 3 (continued)
Estimates of the Organizational Exit Rate from the U.S. Midrange Computer Market

	Model 7	Model 8
All Organizations:		
Market tenure 0-1 year	-3.232**	-3.381**
	(1.514)	(1.516)
Market tenure 1-3 years	-2.704*	-2.666*
	(1.514)	(1.516)
Market tenure 3-5 years	-2.574*	-2.270
	(1.519)	(1.522)
Market tenure 5-10 years	-2.649*	-2.005
	(1.521)	(1.530)
Market tenure 10-15 years	-2.572*	-1.326
	(1.540)	(1.570)
Market tenure 15+ years	-3.359**	-1.345
	(1.568)	(1.639)
Medium-Sized Organizations:		
Market tenure 0-1 year	-.0080	-.0328
	(.2008)	(.2008)
Market tenure 1-3 years	-0.2488*	-.2623*
	(.1324)	(.1324)
Market tenure 3-5 years	-.4993**	-.5207**
	(.1664)	(.1665)
Market tenure 5-10 years	-.7322**	-.6726**
	(.1648)	(.1652)
Market tenure 10-15 years	-.9300**	-.9228**
	(.2761)	(.2760)
Market tenure 15+ years	-1.233**	-1.331**
	(.4658)	(.4673)
Large Organizations:		
Market tenure 0-1 year	-.0882	-.1206
	(.4701)	(.4702)
Market tenure 1-3 years	-1.531**	-1.551**
	(.4575)	(.4576)
Market tenure 3-5 years	-1.605**	-1.616**
	(.5123)	(.5124)
Market tenure 5-10 years	-1.365**	-1.321**
	(.3501)	(.3502)
Market tenure 10-15 years	-2.520**	-2.625**
	(.7350)	(.7348)
Market tenure 15+ years	-1.883**	-1.982**
	(.7923)	(.7931)

Note: Standard errors are in parentheses.
*p<.10, **p<.05

Appendix A: History-Dependent Models of Organizational Failure and Change

To test our ideas empirically, we specify models that allow for an organization's viability to depend on its history of exposure to competition as implied by Red Queen theory. We start with a model depicting history-dependent competition within a single market, which we will test within each of two markets in the computer industry: the market for midrange computers and the market for microcomputers. Then we expand the model to allow for our hypothesized cross-market effects, looking at how organizations with a history of competing in the midrange computer market fared if they moved into the microcomputer market.

History-Dependent Competition in a Single Market

Consider initially the dyadic case where a given organization **j** has been competing against a rival **k**. Allow $\mathbf{h_{jk}}$ to represent the effect on **j**'s viability of its history of competition with rival **k**. That is, the current-time competitive effect of **k** on **j** is specified in the model separately from the historical effect $\mathbf{h_{jk}}$, thus isolating the effect on **j**'s viability of having competed historically with **k**:

$$\mathbf{h_{jk} = b\tau_{jk},}$$

where $\boldsymbol{\tau_{jk}}$ records the time that **j** and **k** have competed historically, and **b** is the marginal effect of this historical competition on **j**'s current-time viability. This specification assumes that the competitive context of these two organizations has remained stationary over time, at least to the extent that lessons learned in the distant past remain relevant and that adaptations remain appropriate. (We relax this assumption momentarily.)

It is straightforward to allow for the possibility that **j** competes with an entire population of organizations. Assuming independence across its competitive relationships, and now allowing **k** to denote any rival from the population, the combined effect of **j**'s historical exposure to competition across the population can be represented by summing across all of **j**'s dyadic competitive relationships:

$$\mathbf{H_j = \Sigma_k h_{jk} = bT_j}$$

where $\mathbf{T_j = \Sigma_k \tau_{jk}}$, the number of organization-years of rivalry faced historically by **j** (or, put differently, the cumulative annual density faced historically by organization **j**).

Allowing $\mathbf{r_j}$ to represent the current-time failure rate of organization **j** in a specific market, we can operationalize history-dependent competition with the model:

$$\mathbf{r_j(t) = r_j(t)*exp[H_j],}$$

where **t** is organization **j**'s market tenure, $\mathbf{r_j(t)^*}$ is organization **j**'s baseline failure rate specified as a function of organization-specific factors and variables known to affect the carrying capacity for organizations such as **j**. $\mathbf{H_j}$ (and the other independent variables) are modeled in the exponential to prevent the estimation of (meaningless) negative rates, a standard approach in hazard modeling (Tuma and Hannan, 1984). Substituting, the model to be estimated is:

$$\mathbf{r_j(t) = r_j(t)^*exp[bT_j].}$$

According to Red Queen theory, we expect to find **b**<0, the improvement in current-time viability that comes with exposure to historical competition.

Now we can relax the stationarity assumption. Instead, assume that lessons learned more recently are more applicable to current-time conditions than are distant-past lessons. Under this assumption, one would discount competitive experience from any given year as an inverse function of its distance in the past. In particular, we discount by $\mathbf{1/\sqrt{\delta}}$, where $\boldsymbol{\delta}$ is the absolute value of a given historical year's distance from the current year, and we impose this discount on each organization-year of competitive experience prior to summing in order to create for each organization **j** at each point in time a recent historical experience term $\mathbf{T_{Rj}}$ (see Ingram and Baum, 1997; Darr, Argote, and Epple, 1995). Organization **j**'s distant-past competitive experience is then the difference between its total competitive experience and its recent competitive experience: $\mathbf{T_{Dj}=T_j-T_{Rj}}$. Substituting, the model can be expressed in a way that allows for more recent competitive experience to have a separate effect from distant-past experience:

$$\mathbf{r_j(t) = r_j(t)^*exp[b_DT_{Dj} + b_RT_{Rj}].}$$

If more recent experience contributes more to organization **j**'s current-time viability than its distant-past experience, then we expect to find $\mathbf{b_R}$<0 and $\mathbf{b_R}$<$\mathbf{b_D}$. And if a competency trap is operating within the market over time (Levinthal and March, 1981; Levitt and March, 1988), such that distant-past experience turns out to harm an organization's current-time prospects, then we would also find $\mathbf{b_D}$>0.

<u>History-Dependent Competition across Multiple Markets</u>

Building on the single-market failure model, it is straightforward to allow for the effects of historical competition across multiple markets described in hypothesis 1. Above and beyond the various market-specific effects in the model, our hypothesis points to historical effects for those organizations that have previously competed in some other market. In particular, surviving such competition in other markets is predicted to harm an organization's viability once it moves into the focal market. To include this historical term in our model, denote the other market by **A**, and the focal market as **B**. Allow $\mathbf{T_{Aj}}$ to represent the number of organization-years of rivalry faced historically by **j** in market **A**. We then can estimate:

$$\mathbf{r_j(t) = r_j(t)*exp[b_D T_{Dj} + b_R T_{Rj} + dT_{Aj}],}$$

where the failure rate $\mathbf{r_j}$ is with regards to failure in the focal market **B**, and where markets **A** and **B** differ in some fundamental way. According to hypothesis 1, we expect that a history of competing in market **A** harms an organization's viability in market **B**, such that **d**>0.

Of course, what constitutes "different" markets is likely to be important to whether this prediction finds support, and presumably, one would expect to see support for the theory the more substantial the differences between markets. The criteria for market differences, however, are not developed by our theory. There might be some potential merit in considering differences between markets as an extension of our theory, perhaps along the lines of "distance" between environmental states as theorized in Hannan and Freeman's (1977) niche theory. For now, however, we proceed in the more typical, *ad hoc* fashion, exploiting market differences as they appear in our particular study setting.

History-Dependent Competition in a Model of Organizational Change

We empirically investigate hypothesis 2, that a success bias operates among survivors of Red Queen competition, by analyzing entry rates into the microcomputer market among midrange computer manufacturers. Most organization-level research looking at changes of this sort refrains from exploring micro-level aspects of decision making, such as the operation of biases. Instead, organization-level research tends to focus on clearly organization-level aspects of change, while decision biases typically remain beyond our purview. In some cases, theories assume (implicitly) that intendedly-rational decision-makers will choose to change in directions that are viability enhancing, as in models that predict movement into less competitive contexts (e.g. Dobrev et al., 2003) or imitation of other organizations (Greve, 1996; Haveman, 1993b). In other cases, difficulties in the decision-making process are thought to be part of the larger set of organizational forces that inhibit rates of organizational change (Hannan et al., 2003a, 2003b).

Our hypothesis 2, by contrast, allows for the operation of a decision bias in a way that is predictable and visible, albeit indirectly, at the organization level. To test this hypothesis, consider the model:

$$\mathbf{r_{\Delta ABj}(t) = r_{\Delta ABj}(t)*exp[a_\Delta T_{DAj} + b_\Delta T_{RAj}],}$$

where $\mathbf{r_{\Delta ABj}}$ is that hazard of organization **j** in market **A** moving into market **B**, as a function of its tenure **t** in market **A.** $\mathbf{r_{\Delta ABj}(t)^*}$ is the baseline rate of change, estimated as a function of organizational and environmental factors discussed below. $\mathbf{T_{Aj}}$ is organization **j**'s competitive experience historically in market **A**, subscripted to denote recent and distant-past experience (calculated as in the failure analysis). So specified, our hypothesis 2 is supported if estimates reveal $\mathbf{b_\Delta}>0$ and $\mathbf{b_\Delta}>\mathbf{a_\Delta}$, meaning organizations that have survived a history of competition, especially in the recent past, have a higher rate of entry into the new market.

Aside from our hypothesized effects, we specify the baseline change rate $\mathbf{r_{\Delta ABj}(t)^*}$ as a function of various factors typically featured in such analyses, including both organizational characteristics that trigger or inhibit change, and environmental characteristics that affect rates of organizational change. We briefly and partially review the research on these forces in order to build aspects of each into our baseline model of new market entry.

Studies of organizational change and market entry have long emphasized organizational characteristics as either driving or inhibiting rates of change, with organizational size featured prominently. Life-cycle models envision organizations transforming to correspond to the structural requirements of increased size as organizations grow (Child and Kieser, 1981; Cafferata, 1982; Kimberly and Miles, 1980), while others propose that larger organizations engage in change at a greater rate due to their advantages in wielding resources (Kimberly, 1976; Aldrich and Auster, 1986). Contradicting these claims, Hannan and Freeman (1984) argued that larger organizations are less likely to change in fundamental ways, because their complex structures make the process of change more difficult and disruptive. Amid these differing claims, empirical evidence on the subject is mixed, with some showing large organizations to be more likely to change (Huber et al., 1993), others showing small organizations to be more inclined to change (Baron et al., 1991; Delacroix and Swaminathan, 1991; Halliday et al., 1993), and still others finding middle-sized organizations to be more likely to change or innovate (Scherer, 1980; Haveman, 1993a). In addition, high status organizations appear to be less susceptible to social influence (Bothner, 2003). Given that prestige often correlates with organizational size (Podolny, 1993), this finding bolsters the case for the size-inertia argument. In sum, it seems clear that our model of market entry should distinguish rates of change according to organizational size.

Building on Stinchcombe's (1965) arguments, Hannan and Freeman's (1984) theory of structural inertia predicts decreasing rates of change as organizations age, as their procedures, roles, and structures become institutionalized (see also Barron et al., 1994). In light of these arguments, considerable empirical support has been found for the hypothesis that organizations change at lower rates as they age (Delacroix and Swaminathan, 1991; Amburgey et al., 1993; Halliday et al., 1993; Kelly and Amburgey, 1991; Miller and Chen, 1994), and the findings in Baron et al. (1991) concur, although these authors also find some evidence that very old organizations appear to amenable to change as well. A related research stream advances the Schumpeterian tradition, arguing and demonstrating that established firms often are less able to move into new technological directions compared to entrepreneurial ventures (Tushman and Romanelli, 1985; Tushman and Anderson, 1986; Anderson and Tushman, 1990; Henderson and Clark, 1990). Consequently, we are careful to control for tenure-dependence in our change model

Considerable attention has been paid as well to environmental factors that constrain and trigger change in organizations. In some settings, institutional environmental factors have been shown empirically to be important in determining rates of change (Baron et al., 1991; Edelman, 1992; Halliday et al., 1993; Miner et al., 1990; Singh et al., 1991; Sutton et al., 1994). Perhaps more relevant to our analysis of the computer industry, various aspects of the market environment have been found to determine change rates, such as market volatility (Delacroix and Swaminathan, 1991), market growth and diversity (Miller and Chen, 1994), the speed of market change (Eisenhardt, 1989), and the examples set by other firms in the market (Greve, 1996; Haveman, 1993b). In light of these findings, our model will control for the general economic conditions, market size, entries, and exits for the markets involved in our analysis.

Especially important to our theory are several papers that show change to be affected by current-time competition among organizations. The basic idea and finding among these papers is that organizations move away from densely crowded market niches, and in the direction of less crowded niches, other things equal (Delacroix and Swaminathan, 1991; Greve, 1996; Dobrev et al., 2003). Others show organizations moving among markets in order to ease competitive pressure – that is, to share multiple markets with rivals (Baum and Korn, 1999; Haveman and Nonnemaker, 2000), a strategy known to lessen competitive pressure (Barnett, 1993). With these various results in mind, we control for current-time competition in each market involved in our change analysis.

<u>Model Specification and Estimation</u>

All modeled all transitions using a piecewise constant rate specification. This functional form is flexible across pieces, in that the rates are allowed to vary freely from period to period, and are assumed to remain constant with respect to duration only within each period (Blossfeld and Rohwer, 1996). In order to update the independent variables, we segmented each organization's history into one-year segments. The models were estimated using the stpiece STATA routine written by Jesper Sørensen.

Appendix B: Description of Variables

Market tenure (in years) recorded the time since an organization entered into a given market, up to the point when the organization either exited the market or the study period ended (so-called "right-censored" cases). The last observed year for each exiting organization was coded as the midpoint of the year, an approach that minimizes time-aggregation bias when estimating hazard models (Petersen, 1991).

Organization size was recorded annually for each organization. Three different size measures were available, each from different sources: an organization's number of employees (according to *Computers and Automation*), number of products shipped in a given year by an organization (according to *IDC*), and the number of product-types being sold on the market in a given year (according to *Data Sources*). We compared each organization's size on each of these measures relative to the other organizations in the given market in the given year. Because interval measures could not be translated across the different size variables, we coded for each organization a relative size category – small, medium, or large – for each year. We based these category assignments first based on numbers of employees. Where this variable was not available, we used annual shipments. When neither of these variables were available, we created an estimate of shipments based on the number of product types, using the results of a regression of shipments on the number of product types (in a given market) estimated on those observations that contained information on both of these variables. Also, we employed linear interpolation to fill gaps in the size data for a given variable over the life of a given organization, and extrapolated for up to 4 years forward or backward where necessary. Finally, for the 115 organizations that did not have any size measures, or for organizations that existed without any size measure for more than 4 years consecutively, we assigned a "small" designation after searching for information indicating otherwise.

De Novo organizations, those born as computer manufacturers, and *De Alio* organizations, those born in some other industry, were determined for each organization by Swanson (2002). This variable was coded primarily using a comparison of each organization's founding date with its date of first operation in the computer industry. Secondarily, organizations founded prior to first appearing in the computer industry were individually researched to see whether they were *de novo* computer manufacturers engaged in "pre-production," or whether they were *de alio* organizations. Long time lags before entering the computer industry, an examination of the organization's name over time, and an examination of internet searches, on-line sources, and archival documents (Lexis/Nexis, *Who's Who in*

Electronics, *U.S. Electronics Industry Directory* (Harris Publishing Co., various years), and *Electronic Buyer's Guide* (McGraw-Hill, various years) were used to determine this variable for questionable cases. Using this approach 1,906 of these organizations entered *de novo*, while 696 entered as *de alio* organizations.

Market exit was coded for organizations that ceased to operate in a given market. Since most organizations operated in only one market, most market exits (93%) were, in fact, exits from the entire computer industry. Organizations that were acquired by a considerably larger firm were designated as exits, but mere name changes were not treated as exits. Mergers among equals were not treated as exit events. We determined such events by checking every market exit against archival documents and Lexis/Nexis. This approach resulted in the identification of a few cases (N=11) of mergers among relatively equally-sized organizations, such as the merger of Burroughs and Sperry to create Unisys in 1987. For these events, we ended the life history of each of the merging organizations, coded the event as right-censored, and then started up the life history of a "new" organization with a new tenure clock. *Market entry* was coded for organizations in the first year that they are reported as offering (for sale or lease) a general-purpose, electronic digital computer in a given market (microcomputer, midrange, or mainframe).

Current-year organizational densities were computed as the numbers of organizations in the industry or respective market at the beginning of a given year. Because the exact timing of entry and exit was not known for most organizations, density at the beginning of the year was calculated as the density at the start of the prior year, plus entries and minus exits during the prior year. In this industry, an organization can be in more than one market in any given time, and if an organization is in multiple markets, it is counted in each of the appropriate market densities. In this way, the sum of the microcomputer, midrange, and mainframe densities do not necessarily sum to the industry density.

Historical competition was computed by summing the total number of competitors faced each year by an organization over its history, not including the current-year competitors in any given year. This measure, denoted by $\mathbf{T_j}$ in our model, is equal to the total number of competitor-years each firm has experienced, up to a given year (not including the number of competitors at the start of that year). *Recent versus distant-past historical competition* was calculated using a distributed lag weight prior to summing over the years of an organization's history. Specifically, recent historical competition was $\mathbf{T_j}$ calculated with each year's contribution to this sum weighted by $\mathbf{1/\sqrt{\delta}}$, where $\boldsymbol{\delta}$ is the number of years prior to the current year. Distant-past historical competition was then calculated as the organization's overall historical competition minus its recent historical competition.

Rivals' historical competition in the microcomputer market was computed for each organization. This term was calculated by summing the historical competition scores (**T**) over each organization's rivals. Similarly, the *sum of rivals' ages* was computed in the same way, but by summing the market tenure of each organization's rivals in a given year.

Exogenous environmental conditions likely to affect organizational survival were also measured in two ways. To reflect general economic conditions in the U.S., we included a measure of *real gross domestic product in the U.S.* (in 1987 U.S. dollars) (U.S. Department of Commerce, c.2001). We also included the *prime interest rate* lagged to the last day of the prior year to reflect the availability of capital (Federal Reserve, c.2002).

Appendix C: Descriptives

Figure C1. Number of General Purpose Digital Computer Manufacturers in the U.S.

Figure C2. Entries and Exits to and from the Microcomputer and Midrange markets in the U.S.

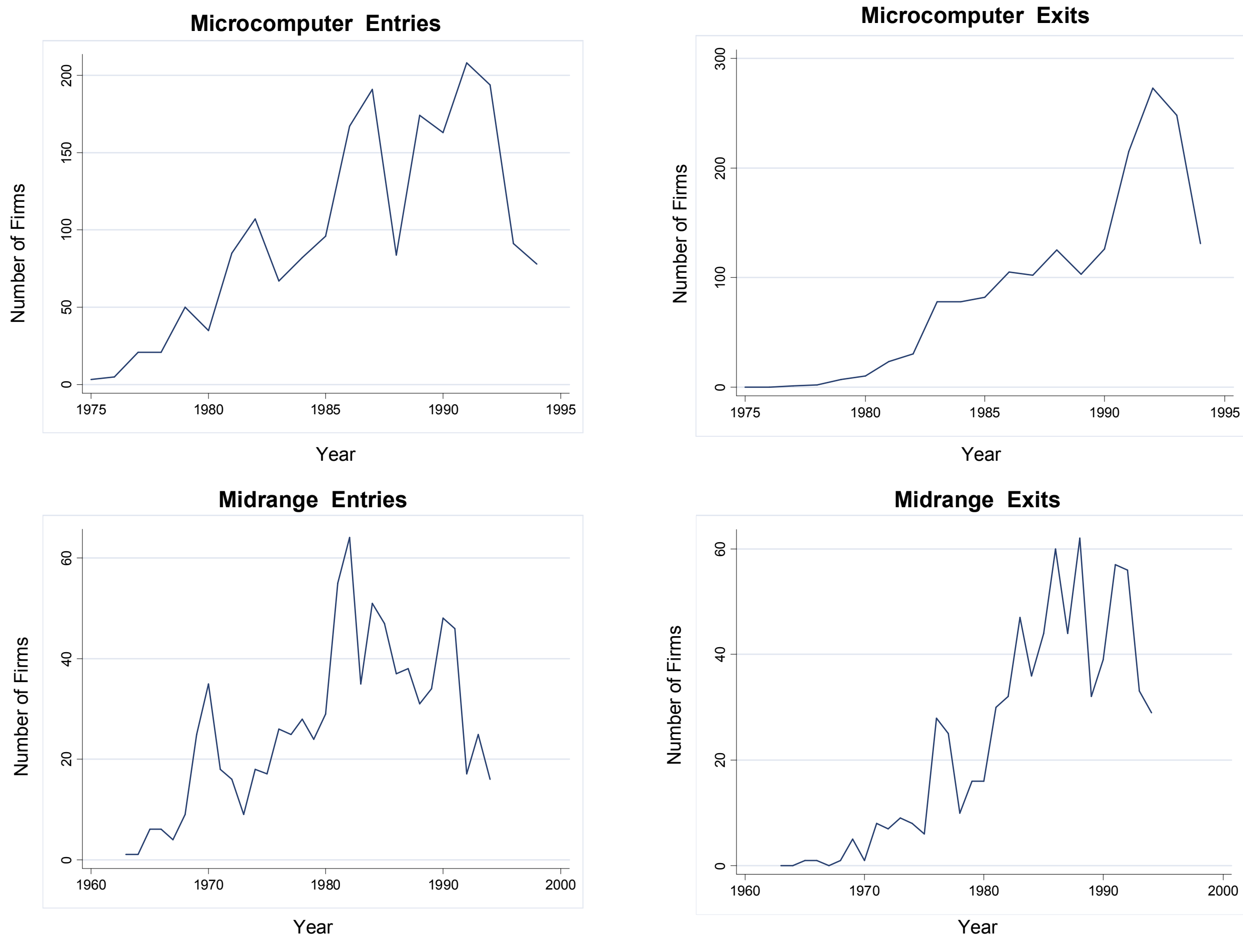

Figure C3. Movement into the Microcomputer Market by Midrange Computer Manufacturers

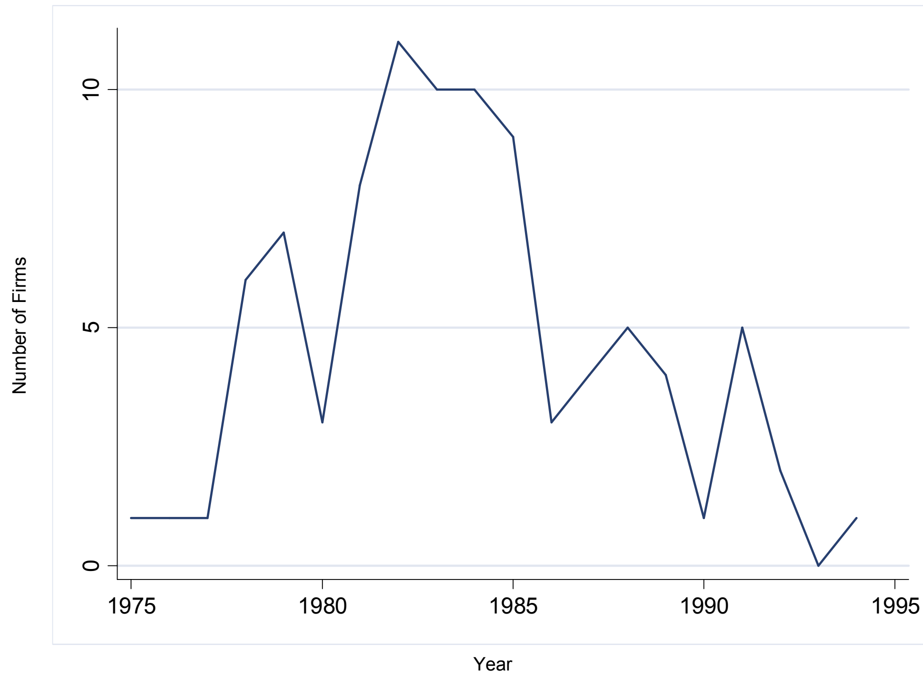

Table C1: Number of distinct general purpose digital computer manufacturers in the U.S. by market

	1955	1960	1965	1970	1975	1980	1985	1990	1994	Overall
Organizations in the microcomputer market only	0	0	0	0	2	100	253	535	278	1662
Organizations in the midrange market only	0	0	5	66	114	141	169	124	85	542
Organizations in the mainframe market only	22	25	27	6	5	10	23	8	7	97
Organizations in both (and only) the microcomputer and midrange markets	0	0	0	0	0	22	79	58	28	233
Organizations in both (and only) the microcomputer and mainframe markets	0	0	0	0	0	0	1	0	0	2
Organizations in both (and only) the midrange and mainframe markets	0	0	3	13	9	5	4	13	7	41
Organizations in all three markets	0	0	0	0	1	3	9	11	7	25
Organizations in any market	22	25	35	85	131	281	538	749	412	2602

Table C2
Descriptive statistics of the data used in the microcomputer exit rate analysis

	Mean	Standard Deviation	Minimum	Maximum
Dealio entrant	0.2803	0.4492	0	1
Real U.S. gross domestic product	4501	453	3212	5134
U.S. Prime interest rate	9.53	2.82	6	18.87
Small sized organization	0.3198	0.4664	0	1
Medium sized organization	0.5769	0.4941	0	1
Large sized organization	0.1032	0.3043	0	1
Microcomputer market shipments/1000	6896	3745	0	15691
Microcomputer manufacturer entries/1000	0.1335	0.0559	0	0.208
Microcomputer manufacturer failures/1000	0.1120	0.0750	0	0.273
Microcomputer market density at entry/1000	0.2738	0.1390	0	0.478
Microcomputer market density/1000	0.3357	001194	0	0.478
Midrange market density/1000	0.1698	0.0307	0.107	0.217
Mainframe market density/1000	0.0261	0.0051	0.01	0.034
Historical competition faced by org. in the microcomputer market/1000	0.6629	0.8123	0	4.337
Recent historical competition faced in the microcomputer market/1000	0.3755	0.3442	0	1.241
Distant-past historical competition faced in the microcomputer market/1000	0.2874	0.5057	0	3.111
Historical competition faced by org. in the midrange market/1000	0.1471	0.4728	0	3.484
Historical competition faced by org. in the mainframe market/1000	0.0071	0.0587	0	0.814

Table C3
Descriptive statistics of the data for the midrange-to-microcomputer market entry analysis

	Mean	Standard Deviation	Minimum	Maximum
Dealio entrant	0.2696	0.4438	0	1
Real U.S. gross domestic product	4153	558	3222	5344
U.S. Prime interest rate	10.37	.038	6	18.87
Small sized organization	0.5053	0.5000	0	1
Medium sized organization	0.4223	0.4940	0	1
Large sized organization	0.0723	0.2591	0	1
Midrange market shipments/1000	140.2	74.36	60.6	246.5
Microcomputer market shipments/1000	3184	3912	0	15691
Midrange manufacturer entries/1000	0.0363	0.0135	0.017	0.064
Lagged microcomputer manuf. failures/1000	0.0326	0.0162	0.006	0.062
Microcomputer manufacturer entries/1000	0.0851	0.0634	0	0.208
Lagged microcomputer manuf. failures/1000	0.0648	0.0701	0	0.273
Midrange market density/1000	0.1629	0.0366	0.107	0.217
Microcomputer market density/1000	0.2133	0.1529	0	0.478
Historical competition faced by org. in the midrange market/1000	0.4978	0.4935	0	3.429
Recent historical competition faced in the midrange market/1000	0.2367	0.1567	0	0.6189
Distant-past historical competition faced in the midrange market/1000	0.2611	0.3600	0	2.870

Table C4
Descriptive statistics of the data used in the midrange computer manufacturer exit rate analysis

Variables	Mean	Standard Deviation	Minimum	Maximum
Dealio entrant	.3345	.4719	0	1
Real U.S. gross domestic product	4003	663	2128	5135
U.S. Prime interest rate	9.873	3.248	4.500	18.87
Small sized organization	.4364	.4960	0	1
Medium sized organization	.4604	.4985	0	1
Large sized organization	.1032	.3043	0	1
Midrange computer market shipments/1000	.1353	.0848	0	.2465
Midrange computer manufacturer entries/1000	.0345	.0144	0	.0640
Midrange computer manuf. failures/1000	.0314	.0182	0	.0620
Midrange computer market density at entry/1000	.1276	.0630	0	.2170
Microcomputer market density/1000	.2116	.1636	0	.4780
Midrange market density/1000	.1531	.0480	0	.2170
Mainframe market density/1000	.0225	.0071	.0100	.0340
Historical competition faced by org. in the midrange computer market/1000	.5750	.6674	0	3.484
Midrange computer rivals' historical exposure to competition/1000	115.7	63.98	0	19 .4

Appendix D: Correlations Among Variables

		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
Microcomputer Market Density / 1000	**1**																		
Recent Historical Competition faced in microcomputer market (T) / 1000	**2**	0.363																	
Distant-Past Historical Competition faced in microcomputer market / 1000	**3**	0.213	0.894																
Organization's tenure in the midrange market	**4**	0.118	0.846	0.893															
Organization is also in the midrange market	**5**	-0.103	0.145	0.189	0.283														
Duration in the midrange market	**6**	-0.046	0.228	0.313	0.405	0.676													
Midrange Market Density / 1000	**7**	-0.114	-0.300	-0.287	-0.102	0.087	0.044												
Historical Competition faced by org in the midrange market	**8**	-0.004	0.271	0.358	0.437	0.643	0.973	0.039											
Organization is also in the mainframe market	**9**	-0.031	0.113	0.160	0.205	0.344	0.493	0.015	0.458										
Organization's tenure in the mainframe market	**10**	-0.053	0.082	0.128	0.203	0.282	0.509	0.019	0.438	0.767									
Mainframe Market Density / 1000	**11**	0.464	0.035	-0.046	0.025	-0.001	0.017	0.618	0.051	-0.003	-0.019								
Historical Competition faced by org in the mainframe market	**12**	-0.046	0.093	0.143	0.213	0.284	0.518	0.014	0.450	0.773	0.997	-0.017							
GDP	**13**	0.805	0.481	0.364	0.179	-0.122	-0.047	-0.516	-0.004	-0.033	-0.055	0.229	-0.045						
Prime Rate	**14**	-0.603	-0.374	-0.287	-0.135	0.084	0.027	0.205	-0.006	0.018	0.033	-0.238	0.026	-0.688					
Dealio entrant	**15**	-0.094	0.037	0.069	0.123	0.170	0.146	0.037	0.151	0.141	0.116	-0.034	0.113	-0.096	0.068				
Microcomputer Market Shipments / 1000	**16**	0.642	0.496	0.402	0.199	-0.109	-0.037	-0.559	0.002	-0.027	-0.046	0.103	-0.037	0.948	-0.746	-0.080			
Microcomuter manuf. entries / 1000	**17**	0.859	0.325	0.209	0.104	-0.096	-0.049	-0.130	-0.014	-0.030	-0.051	0.354	-0.044	0.686	-0.679	-0.080	0.576		
Microcomputer manuf. failures / 1000	**18**	0.572	0.479	0.388	0.186	-0.103	-0.038	-0.589	-0.005	-0.026	-0.042	-0.013	-0.034	0.838	-0.775	-0.075	0.911	0.606	
Microcomputer Market density at entry / 1000	**19**	0.708	-0.043	-0.200	-0.424	-0.266	-0.279	-0.290	-0.263	-0.144	-0.161	0.228	-0.159	0.741	-0.574	-0.153	0.683	0.617	0.638