# 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 micro- and macro-level processes combine to produce this pattern, and that both processes stem from the same source: surviving a history of competition. At the organization-level, surviving a history of competition adapts organizations to their environments, through so-called "Red Queen" competition, but being well-adapted for one market makes moving into new markets more hazardous. Meanwhile, managers in such organizations infer from their history of competitive success a biased assessment of their organization's capabilities. 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. Analysts attempting to explain this notorious pattern typically follow one of two general theoretical approaches. A more "micro" approach looks at the organizational decision-making processes that lead to such moves, focusing especially on how organizational learning can backfire when inferences are drawn from limited or success-biased experience (e.g. March et al., 1991; Denrell, 2003). From a more "macro" perspective, others frame the problem as one of organizational adaptation. Taking this approach, research focuses on the idea that different organizational environments require different, often incompatible organizational features (e.g. Tushman and Anderson, 1986; Carroll and Teo, 1996), and that attempts by organizations to change in such new directions are difficult and hazardous (Hannan and Freeman, 1984; Hannan et al., 2003a). Both of these general approaches have proved fruitful, and although they have remained relatively distinct, each helps to explain why successful organizations seem inclined to ruinous initiatives.

Although research on organizations often develops independently at different levels of analysis, we think that much can be gained by integrating across levels of analysis when studying organizational change. Our theory is that both the micro-level process of success-biased decisions to change, and the macro-level process of structural inertia, can stem from a common source: *competitive hysteresis*, wherein an organization's behavior at a given time depends on the historical path of competition faced by the organization prior to that point. Specifically, we think that by dealing with and surviving competition over its history, an organization experiences two distinct dynamics. At the organization level, the process of surviving competition increases an organization's fit with its environment through both learning and selection, so-called "Red Queen" evolution. Yet one consequence of being especially tailored to its environment 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 environments to be especially hazardous. Meanwhile, at the individual and group levels, the fact of 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 form exaggerated assessments of their organization's capabilities, such that bold forays in new directions are all the more likely. In short, we propose that surviving competition makes organizations less able to move successfully in new directions, yet at the same time it makes managers more convinced that such moves are a good idea.

In the next section, we explain our thinking in greater detail, beginning with an explanation of the importance of historical competition – both to organizational inertia and to success bias in the decision-making process. Our ideas motivate an empirically testable model that we estimate using data on the history of the computer industry.

## The Red Queen and Organizational Inertia

The process of significantly changing an organization is known to be difficult and hazardous, and organizations that engage in such change suffer higher failure rates (Hannan and Freeman, 1989). Notably, this increased hazard is found most consistently in studies that distinctly estimate the effects of the process of change *per se*, holding constant the effects of the organizational content that is being changed (Barnett and Carroll, 1995). Specifically, even if the change in content is a survival-enhancing improvement, organizational failure rates are likely to increase during the process of change to the extent that the change disrupts established organizational practices. So it is that significant change especially disrupts well-developed organizations, those that have established the roles, routines, know-how, structures, and technologies necessary to perform certain kinds of activity. The development of organizational capability thus is a two-edged sword, implying the ability to perform well in one area of activity, but implying also a constraint threatening the efficacy of attempts to move into other areas of activity (Hannan and Freeman, 1984; Levitt and March, 1988).

Mindful of this trade-off, much of the literature looks at when well-developed organizations are disrupted by significant change. For instance, organizations are especially disrupted by changes to their "core" activities (Hannan and Freeman, 1984), changes that render inappropriate an organization's capabilities (Levitt and March, 1988; Tushman and Anderson, 1986; Christensen, 1997), and changes that require a different organizational design (Henderson and Clark, 1990). Relatedly, some research looks for differences in organizational characteristics that correspond to how well-developed are an organization's capabilities, with development corresponding to an organization's 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 significant changes are especially disruptive to organizations with well-established capabilities. In this light, an important question is why some organizations are more capable than others in a given context.

We argue that many organizational capabilities result from competitive hysteresis. An organization is affected by surviving a history of competition (Swaminathan, 1996; Ingram and Baum, 1997). 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. 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). Such search, presumably, 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 stonger 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 can expect that an organization involved in the Red Queen will become increasingly capable over time – at least as long as the criteria for success remain constant (a condition we relax below). Meanwhile, its rivals also will become more capable, since the process is coevolutionary. And, to the extent that aspiration levels adjust upward by social reference (Herriott, Levinthal, and March, 1985; Lant, 1992), the coevolutionary cycle is likely to accelerate. In fact, a particularly capable organization will create especially big problems for its rivals, problems that in turn will require significant capability improvements among these rivals if they are to restore performance to satisfactory levels. Relative to one another, then, organizations in Red Queen competition may seem stable even as their capabilities are developing in absolute terms. Thus the allusion, coined by the biologist Van Valen (1973), 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."

Importantly, the Red Queen can alter the distribution of capabilities purely through selection, without recourse to organizational learning. This outcome requires that competition intensifies selection pressures on organizations, de-selecting especially the weakest competitors. Assuming that organizations vary in competitiveness initially, and that competitiveness does not change over time for any given organization, overall competitiveness across the population will still increase over time as exposure to competition de-selects the least competitive members of the population (Swaminathan, 1996; Sorenson, 2000). As competitiveness increases, 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 among these organizations is raised as the Red Queen continues, further increasing in the population's capabilities. Of course, this outcome hinges on specifics of the process – 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 arises 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 capabilities, which in turn implies that the organization is more adapted to that particular environment. 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 capabilities as they survive a history of competition. To begin our analysis in this study, we will first investigate whether this same pattern of competitive hysteresis developed in the computer industry.

If, through the Red Queen, competitive hysteresis determines which organizations are most capable, then so does it shape which are most disrupted by changing into new environments. Increasing organizations' adaptation to a given environment, the Red Queen thereby makes disruptive movement into other environments. 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.**

Thus the problem of disruption and inertia in organizations is predicted to plague precisely those organizations that have learned from and survived competition. This outcome implies a trade off: Organizations that have survived a history of competition may be the dominant players in their environment, but their capabilities are well-honed to that particular environment. As a result, one would be cautioned against moving such organizations into very different environments. That said, we think that precisely the opposite inference is drawn by managers when they experience such success.

## The Red Queen and Success Bias

A second dynamic triggered by the Red Queen, we propose, is a change in the way that people in organizations appraise possible future opportunities. This dynamic can take place both at the level of individual-level learning by people in 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 far from complete. Instead, participants in a successful organization face the problem of trying to generalize from a very limited sample, and one 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 a bias in favor of risky action is especially likely among organizations that have survived a history of competition.

These forces toward a bias for action are likely to be especially strong 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, we argue, by norms for deference typically shown in organizational settings to those who have "been there." We see this frequently in discussions among managers, where relatively careful exchanges of thought at times are shut down by the announcement that one of the participants "was there," or has "done that." In this light, an organization that has survived a history of competition is a context likely to produce exaggerated inferences that the organization is capable.

The success bias may be magnified, furthermore, 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" circulates and can be reinforced in stories that pass among organizational participants. For instance, in a number of separate interviews we conducted in a large semiconductor 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 capabilities 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 capabilities 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 action that we see among individuals making decisions in the context of a successful organization are likely to be reinforced by the collective definition of an organization's capabilities shared throughout the organization, and reinforced over time as it continues to survive despite competition (March and Shapira, 1987; Strang and Macy, 2001).

Finally, the historical timing of survivorship is likely to be important in shaping decision-making. 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 capabilities, especially when this competitive experience is relatively recent. Such high estimates of organizational capabilities, 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 is especially interesting in light of our failure rate prediction. Precisely those organizations that are most likely to fail due to such a change are the most likely to engage in the change – and for the same underlying reason. Surviving a history of competition deepens but narrows the organization's domain, while at the same time it encourages participants within the organization to incorrectly infer that the organization is likely to succeed broadly.

## Empirical Models

To test these ideas empirically, we first 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 hysteretic competition within a single market, 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.

### Hysteretic 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 hysteretic effect $\mathbf{h_{jk}}$, thus isolating the effect on **j**'s viability of having competed historically with **k**:

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

where $\boldsymbol{\tau_{jk}}$ records the time that **j** and **k** have competed historically, **b** is the marginal effect of this historical competition on **j**'s current-time viability, and the intercept **a** allows for a fixed cost to be associated with **j**'s adaptation to **k**'s rivalry. 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:

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

where $\mathbf{K_j}$ is the number of rivals faced historically by organization **j**, and $\mathbf{T_j = \Sigma_k \boldsymbol{\tau}_{jk}}$, the number of organization-years of rivalry faced historically by **j** (or, put differently, the cumulative annual density faced historically by organization **j**). The hysteretic effect $\mathbf{H_j}$ thus decomposes organization **j**'s historical exposure to competition in a way that distinguishes the breadth and depth of competitive experience. For a given level of $\mathbf{T_j}$, a low $\mathbf{K_j}$ implies fewer, longer competitive relationships, while a high $\mathbf{K_j}$ means that organization **j**'s experience has been spread more thinly over many historical rivals.

Allowing $\mathbf{r_j}$ to represent the current-time failure rate of organization **j** in a specific market, we can operationalize competitive hysteresis by estimating 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:

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

According to Red Queen theory, we expect to find $\mathbf{a}>0$, reflecting the costs associated with adapting to different rivals historically, and $\mathbf{b}<0$, the improvement in current-time viability that comes with exposure to historical competition net of the costs of adaptation.

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 $\mathbf{1/\delta}$, 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 $\mathbf{T_{Rj}}$. 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:

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

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 $\mathbf{b_D}>0$.

Red Queen theory also implies that the competition generated by each organization's rivals varies according to these *rivals'* histories of having competed. To model this variation, allow the competition generated by **k** against other organizations to be represented by $\alpha_k=w_k\mathbf{p}_k$, where $\mathbf{p}_k$ is the probability that **k** comes into competition with a given organization, and $w_k$ is the strength of competition generated by rival **k**, conditional on such competition occurring. Now if we allow the strength of competition generated by each rival **k** to depend linearly on its history of surviving competition, $\mathbf{T}_k$, such that $w_k=\varsigma+\gamma\mathbf{T}_k$, we can represent the competition generated by **k** against any given rival as $\alpha_k=\varsigma\mathbf{p}_k+\gamma\mathbf{p}_k\mathbf{T}_k$, in which $\varsigma$ is a fixed per-rival competitive effect and $\gamma$ is the effect of surviving a history of competition on the strength of rivalry (conditional on competition occurring). If the competitive strategies of **j**'s rivals are independent, then the total competition generated by these rivals against organization **j** can be represented by additive aggregation of the competition generated by each:

$$\alpha=\Sigma_k\alpha_k=\eta\mathbf{N}+\mathbf{c}\Sigma_k\mathbf{T}_k,$$

where **N** is population density, $\eta=\varsigma\mathbf{p}$ and $\mathbf{c}=\gamma\mathbf{p}$, and **p** is the average of the rival-specific probabilities $\mathbf{p}_k$. If, by design, we model $\alpha$ only among organizations that compete together in the same arena, then we can assume $\mathbf{p}=1$, and it becomes irrelevant to our estimates of the other parameters. If **p**<1, then it operates simply as a coefficient of proportionality as long as we can assume that it does not covary with the variables of interest. In either case, if competition intensifies through the Red Queen, then we will find evidence of this in the parameter **c**, and in the absence of Red Queen competition we would find **c**=0. In that case, competition is purely density dependent, and so is homogeneous across rivals (varying only according to the probability that **j** encounters a given rival).

To obtain empirical estimates of these competitive effects, we include this specification of $\alpha$ in the failure rate model to be estimated:

$$\mathbf{r_j(t) = r_j(t)^*exp[aK_j + b_D T_{Dj} + b_R T_{Rj} + \eta N + c\Sigma_k T_k].}$$

If surviving a history of competition makes organizations stronger competitors, then we expect to find **c**>0. If competition is not hysteretic, then this model reduces to a purely density-dependent specification, in which competition depends only on the number of competitors **N**. Note that we will also specify **N** as a quadratic, to allow for the combined effects of legitimation and competition; see Hannan and Carroll (1992).

## Hysteretic Competition across Multiple Markets

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 hysteresis 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:

$$\mathbf{r_j(t) = r_j(t)*exp[aK_j + b_DT_{Dj} + b_RT_{Rj} + \eta N + c\Sigma_k T_k + dT_{Aj}],}$$

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 competitive hysteresis from 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.

<u>Hysteretic Competition in a Model of Organizational Change</u>

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 sepecify 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 susceptable to social influence (Bothner, 2003). Given that prestige often correlates with organiztional 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). In light of these findings, 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.

## Data and Method

Our data include the life history 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 repleat 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 Tables 1-3 and in Figures 1-3.

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Insert Table 1-3 and Figures 1-3 about here

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Our operational variables were created from these data, or appended from other sources:

*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).  We also include in the model $\mathbf{K_j}$, the number of unique competitors each firm has faced historically up to a given 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 $\mathbf{1/\delta}$, 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).

Duration dependence was specified as a piecewise constant rate in both the hazard models and in the change models. 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 organizations history into one-year segments.  The models were estimated using the stpiece STATA routine written by Jesper Sørensen.

## Results

First we briefly summarize our overall pattern of results from the various models reported in Tables 4-7.  Table 4 develops specifications of current-time competition, showing evidence that competition in the industry was market-specific.  Building on those findings, Table 5 then lists several specifications of the effects of exposure to historical competition on organizations' survival chances.  The estimates from these models show evidence of the Red Queen among microcomputer manufacturers, in that organizations enjoyed lower exit rates with greater exposure to historical competition in that market.  Table 6 then builds on these results, finding additional support for Red Queen theory: the strength of rivalry among microcomputer firms hinged on rivals' exposure to competition.  Finally, Table 7 shows estimates of the rate of entry into the microcomputer market by midrange manufacturers.

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Insert Tables 4-7 about here

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*Hypothesis tests*

Hypothesis 1 states that competitive experience in one market increases failure rates when organizations move into another market.  This hypothesis is tested in Table 5.  In Model 10, 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. Comparing Models 9 and 10, note that these findings hinge on whether we also control for tenure dependence in other markets. Specifically, tenure in other markets appears to be survival enhancing, and only with this effect controlled do we see consistent evidence of the competency trap caused by exposure to competition in other markets.

Our second hypothesis, that surviving competition in one market increases rates of organizational expansion into other markets, is tested in Table 7. Looking across models 14-16, those midrange firms that survived competition were especially likely to move into the microcomputer market. Furthermore, Model 16 shows that this effect is due entirely to recent exposure to competition, consistent with the theory. 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 67% 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 18 times more likely to make that move.[1] 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.

[1] Setting historical competition in the midrange market equal to 236, the observed mean among midrange firms at risk of entry into microcomputers, model 10 implies an increase in the failure rate of exp[2.136×.236]=1.655, or about an 67% increase, and model 16 implies an increase in the microcomputer market entry rate of exp[12.28×.236]=18.139, nearly a 18-fold increase.

One interesting implication of our hypotheses appears in the various model estimates regarding diversification. The estimated effects of diversification – of a microcomputer manufacturer also being in either the midrange or mainframe markets – turns out to depend entirely on properly specifying history dependence. In particular, Models 1-9 predict lower failure rates for microcomputer firms that also are in the midrange market. Models 10-13 show that this effect turns out to be duration dependent, however – a benefit that accrues only with time spent in that market. Cutting against this benefit is the hazard-increasing effect of exposure to competition in the midrange market. In sum, time spent in the midrange market is survival enhancing for microcomputer firms, but only if we net out the hazardous implications of competitive experience in that market.

Similarly, being in the mainframe market turns out to be survival enhancing only in models that allow for a competency trap due to Red Queen competition in mainframes. Models 8-13 in Tables 5 and 6 show that experience in the mainframe market is survival enhancing for microcomputer firms, but again this effect is offset by an increase in microcomputer exit rates due to experiencing a history of competition in mainframes. A relatively small number of organizations are responsible for these very large effects, however, so although the results are significant we interpret them with caution.

*Red-Queen competition*

Looking more closely at the evidence of Red Queen competition in the microcomputer market, the models in Table 5 show that the survival-enhancing effect of historical exposure to competition (**T**) within the microcomputer market is driven entirely by recently experienced competition. Meanwhile, the number of distinct rivals faced historically (**K**) increases an organization's exit rate, consistent with the idea that there are fixed costs associated with adapting to each additional rival. Combining these two historical competition effects, we can then see whether their net effect is strong enough to offset the liability of current-time competition. Based on the estimates of model 10, figure 4 illustrates this comparison assuming that an organization faces the average observed number of competitors per year in the microcomputer market (335). Having this many current-time competitors implies nearly a four-fold increase in the chances of failure, so a new organization is seriously endangered by this much competition. Over time, however, the survival enhancing effects of historical competition cumulate, largely offsetting the effects of competition within 5 years in a population with no turnover. Within about 7 years, the benefits of historical competition completely offset current-time competition, so that the combined effects of competition are survival enhancing.

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Insert figure 4 about here

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Allowing for population turnover, however, attenuates the advantage of having faced historical competition, since adaptation costs increase with the number of distinct competitors to whom an organization must adapt – a number that increases as the population churns. Consequently, assuming that the population remains at 335 competitors but turns over at a rate of 10% per year, the benefits of historical competition are reduced and ultimately reverse as illustrated in figure 4. With enough new entries replacing existing firms, the costs of adaptation mount to the point where exposure to competition is no longer survival enhancing.  Thus, the effects of **T** and **K** imply a cost-benefit trade off in the process of Red Queen competition.

This trade off implies a threshold at which the survival enhancing benefits of **T** exactly offset the costs of adaptation due to **K**, as illustrated in figure 5.  The diagonal line illustrates this threshold, based on the estimates of model 13.  (We use model 13, because we note that the exact magnitudes of **K** and **T** are sensitive to fully specifying current-time competition.  A roughly similar threshold results from using the other model estimates.)  The illustrated points are observed pairings of **K** and **T** as they appeared in our data.  The higher a point at any given level of **T**, the more thinly is an organization's experience spread over relatively more historical rivals.  Similarly, the lower the point for a given **T**, the more that an organization has focused its adaptation to a relatively smaller number of historical rivals.  Given the greater costs implied by being above threshold, relatively few observations are found there.  This is a reflection of the failure rate findings, in that being above threshold implies an increase in the chances of exiting the data.  Note, as illustrated for two cases, that **T** typically tends upward over time more quickly than does **K**, implying a trend toward increased viability due to historical competition.  Only in years when a large number of organizations enter do we see relatively large increases in **K**.

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Insert figure 5 about here

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The models in Table 6 look at the other side of the Red Queen process, rivals' history of competition.  Model 11 builds on Model 10, additionally including for each organization the sum of its rivals' histories of competition (**T**) as of a given year. Model 12 also includes the sum of rivals' ages, in case increases in competitive intensity come with tenure rather than with exposure to competition (Barnett, 1997). Finally, Model 13 allows for competition to depend on organizational size, with the density terms broken out by size of rival. All three of these specifications are plagued by collinearity, as evidenced by the increases in the standard errors for the estimates of the microcomputer market density effects. (Models including both the sum of rivals' ages and size distinctions among rivals yielded inefficient results, and are not shown.) Nonetheless, once size distinctions are allowed in the density effects, historical exposure to competition is shown to increase the strength of rivals. Thus it appears that a history of competition not only made microcomputer firms more likely to survive, but also it made them more fearsome rivals as predicted by Red Queen theory.

*Current-time competition*

Comparing models 1 and 2 in table 4 shows that industry-level density dependence is found to be monotonic and positive, indicating competition among computer manufacturers generally. Models 3 and 4 break down density by market, Model 3 allowing for non-monotonic density dependence within the microcomputer market. A comparison of these models shows that density-dependence is market specific and purely competitive. Model 4 shows evidence of density-dependent competition among microcomputer organizations, and from midrange manufacturers affecting microcomputer manufacturers. No evidence is found of competition from mainframe manufacturers, and in Models 6-10 in Table 5 the mainframe density effect actually turns negative, indicating mutualism from mainframe manufacturers – although these effects are not robust when Red Queen and size-based competition are allowed in Table 6. 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 4, 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, Model 5 breaks out midrange density into separate effects for midrange firms that were or were not also microcomputer manufacturers. As this comparison shows, very powerful competition came from midrange firms – but we only find evidence of this competition from midrange firms that were not microcomputer manufacturers. Thus we find evidence that the midrange niche was encroaching on the microcomputer niche over the study period.

Market-specific competition in microcomputers appears to strengthen once you control for the benefits of historical competition (Models 6-10 in Table 5). This pattern suggests a suppression effect, where organizations facing competition often also enjoy a history of having competed. Once the historical effect is explicitly parameterized, the full strength of current-time competition is revealed. That said, current-time competition turns out to hinge on the degree of competition endured by these rivals, as predicted by Red Queen theory, and as suggested by the estimates in Model 13 of Table 6.

*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. Although the size-based density effects of Model 13 are not consistent with this idea, 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 Tables 4-6 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 typically is not significant, but is negative when significant, the opposite of what is predicted by the theory of density delay (Carroll and Hannan, 1989). If anything, this pattern is more consistent with Swaminathan's (1996) trial-by-fire model, although this effect's lack of robustness makes us reluctant to dwell on the finding.

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 7 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 14 – 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

As we observed at the outset, organizational change attracts attention from scholars at both the micro and macro levels of analysis – appropriately so, given the various processes involved when organizations change. Our theory illustrates, however, that there are gains to be made by considering the operation of both micro- and macro-level processes simultaneously when we study change. Surviving competition turns out to have implications at both levels – setting the stage for success bias at the micro level, making change more likely, while making the precisely such change more disruptive at the macro level. In this way, a consideration of both levels of analysis reveals parallel dynamics that become especially informative when seen in tandem, as they render organiztional change especially disruptive, while at the same time they make decision makers especially likely to engage in such change. This pattern helps to account for the notorious tendency of successful organizations to engage in ruinous initiatives.

We must of course 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 goad 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 self-defeating.

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 hysteretic 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 competition or competitive hysteresis.

These findings are relevant also to the growing literature on organizational identity. We know that institutionalized boundaries constrain organizations from engaging in activities not normatively associated with their identities (Meyer and Rowan, 1977; Zuckerman, 1999). In thoroughly institutionalized contexts, identity constraints likely prevent organizational decision makers from engaging in the full range of moves that the success bias might otherwise lead them to attempt – including moves that would be likely to fail. In this way, we expect that the success bias we document will be less likely to manifest where organizational identities are clearly institutionalized. Where identity definitions are not so distinct, however, much more fluid organizational mobility is likely (Ruef, 2000). In these less-defined organizational fields, the success bias can operate to trigger ventures into a greater range of possible organizational activities.

In this light, note that our analysis uses the computer industry, where form distinctions have been ill-defined historically. Even today, although we can retrospectively divide the industry for analytic purposes into three markets – mainframes, midrange computing, and microcomputers – blending mechanisms continue to blur these categorical distinctions. Consequently, organizations often have ventured across these markets, especially between the midrange and microcomputer markets. In this context both organizational inertia and the success bias appear to operate, hinging on competitive hysteresis: Organizations with more of a history of surviving competition in one market are especially likely to move into another market, and especially likely to fail having done so.

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.

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Figure 1.
Numbers of General Purpose Digital Computer Manufacturers in the U.S.

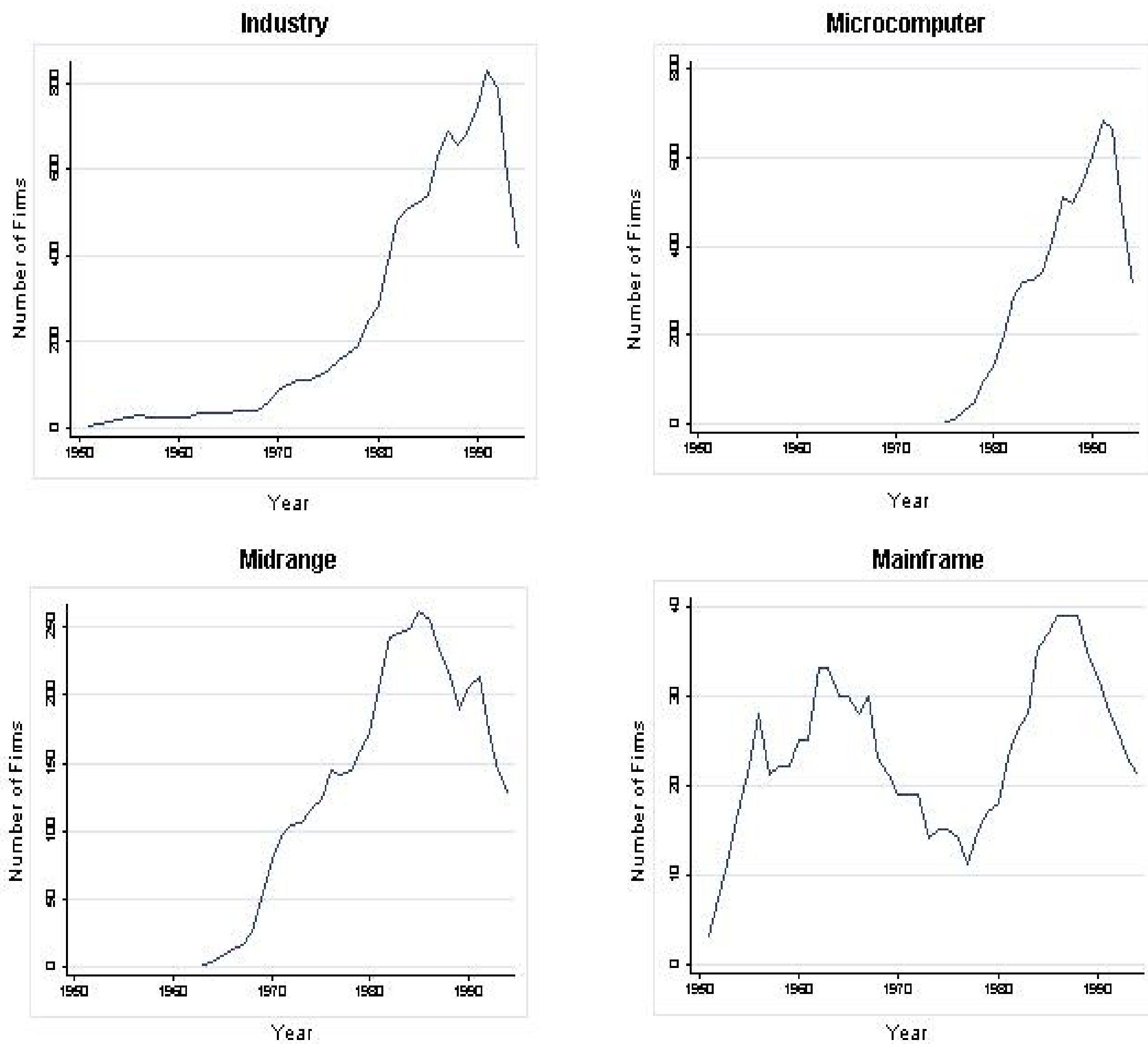


**Figure 2:**
**Entries and Exits to and from the Microcomputer market in the U.S.**

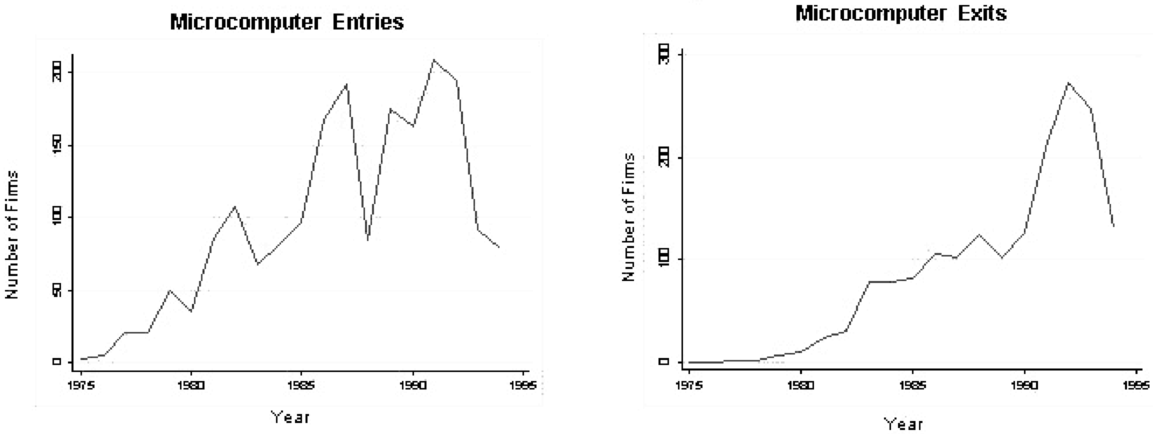
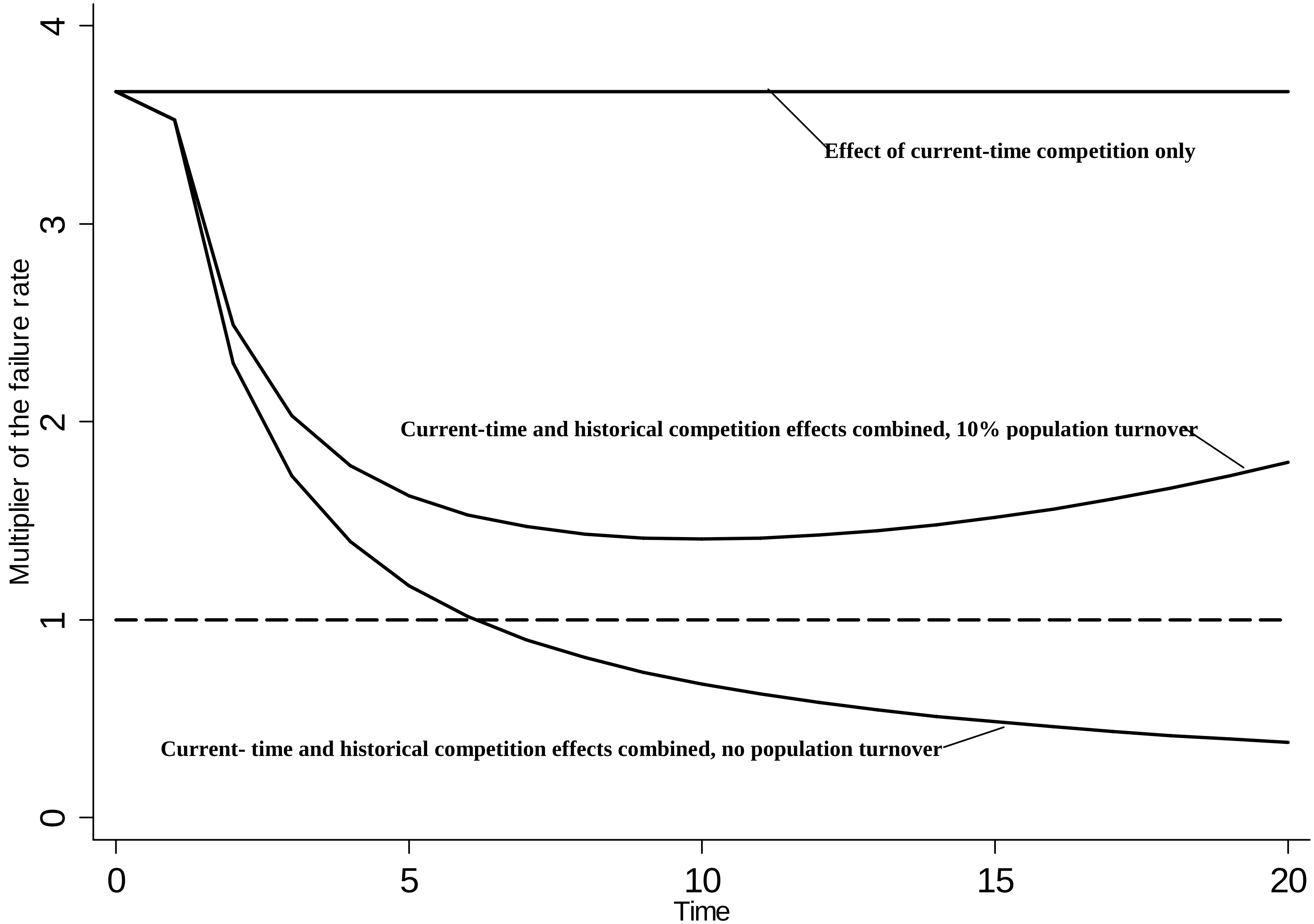


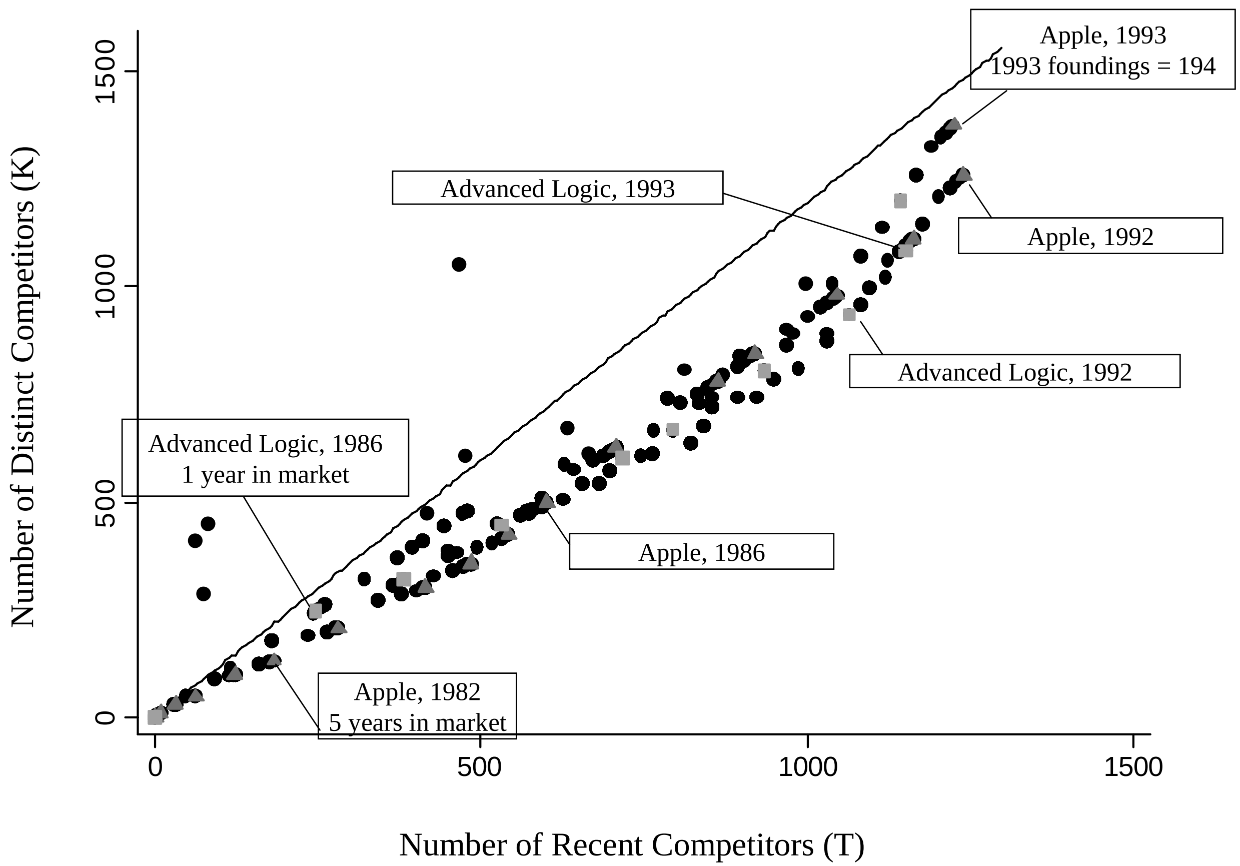

**Figure 3:**
**Movement into the Microcomputer Market by Midrange Computer Manufacturers**

**Figure 4:**
**Offsetting effects of current-time and historical competition in the U.S. microcomputer market***




*Based on the estimates of model 10, and assuming the average observed number of competitors per year (335).

**Figure 5**
**Observed distribution of K and T among U.S. microcomputer firms***




*The diagonal line represents the threshold of equality where the effects of K and T are exactly offsetting based on the estimates of model 13.

**Table 1: 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 2**
**Descriptive statistics of the data used in the 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 |
| Number of distinct rivals faced in the microcomputer market/1000 | 0.3313 | 0.3087 | 0 | 1.374 |
| 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 |
| Microcomputer rivals' historical exposure to competition/1000 | 347.5 | 226.0 | 0 | 664.8 |
| Sum of ages of microcomputer rivals/1000 | 9.000 | 5.996 | 0 | 20.25 |
| Number of small microcomputer rivals/1000 | 0.1036 | 0.0735 | 0 | 0.218 |
| Number of medium-sized microcomputer rivals/1000 | 0.1984 | 0.1656 | 0 | 0.468 |
| Number of large microcomputer rivals/1000 | 0.0304 | 0.0282 | 0 | 0.097 |

**Table 3**
**Descriptive statistics of the data used in the 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 4**
**Estimates of the Organizational Exit Rate from the U.S. Microcomputer Market: Models of Current-Time Competition**

| | Model 1 | Model 2 | Model 3 | Model 4 | Model 5 |
|---|---|---|---|---|---|
| Dealio entrant | -.1490** | -.1490** | -.1482** | -.1483** | -.1487** |
| | (.0574) | (.0574) | (.0574) | (.0574) | (.0574) |
| Real U.S. gross domestic product | -.0026** | -.0027** | -.0018** | -.0018** | -.0014** |
| | (.0004) | (.0004) | (.0006) | (.0006) | (.0006) |
| U.S. Prime interest rate | .0224 | .0223 | .0400 | .0382 | .0274 |
| | (.0244) | (.0245) | (.0312) | (.0307) | (.0311) |
| Microcomputer market shipments/1000 | .0003** | .00030** | .0002** | .0002 ** | .0002** |
| | (.00005) | (.00004) | (.00005) | (.00005) | (.00005) |
| Microcomputer manuf. entries/1000 | -.8189 | -.8057 | -.2158 | -.2196 | -.4090 |
| | (1.095) | (1.088) | (1.201) | (1.202) | (1.211) |
| Microcomputer manuf. failures/1000 | 5.098** | 5.074** | 6.176** | 6.066** | 8.255** |
| | (.9513) | (.9276) | (1.317) | (1.253) | (1.641) |
| Microcomputer market density at entry/1000 | -.5014 | -.0471 | -.0977 | -.0952 | -.0633 |
| | (.5073) | (.5059) | (.5113) | (.5112) | (.5119) |
| Organization also is in the midrange market | -.2375** | -.2376** | -.2379** | -.2377** | -.2391** |
| | (.0871) | (.0871) | (.0872) | (.0872) | (.0872) |
| Organization also is in the mainframe market | -.4671 | -.4673 | -.4606 | -.4612 | -.4615 |
| | (.3121) | (.3121) | (.3122) | (.3122) | (.3121) |
| Computer industry density/1000 | 4.365** | 4.574** | | | |
| | (2.018) | (.7646) | | | |
| (Computer industry density)$^2$/1000 | .0003 | | | | |
| | (.0022) | | | | |
| Microcomputer market density/1000 | | | 2.620 | 3.154** | 3.288** |
| | | | (2.318) | (.0250) | (1.029) |
| (Microcomputer market density)$^2$/1000 | | | .0083 | | |
| | | | (.0032) | | |
| Midrange market density/1000 | | | 8.896** | 8.864** | |
| | | | (3.673) | (3.698) | |
| Density of orgs. in both the midrange and microcomputer markets/1000 | | | | | -8.761 |
| | | | | | (9.130) |
| Density of orgs in the midrange market but not in the microcomputer market/1000 | | | | | 20.91** |
| | | | | | (6.805) |
| Mainframe market density/1000 | | | -20.90 | -22.77 | 3.842 |
| | | | (15.73) | (14.00) | (18.74) |
| Log Likelihood | -2401.14 | -2401.15 | -2400.26 | -2400.30 | -2398.07 |
| (Degrees of freedom) | (29) | (28) | (31) | (30) | (31) |

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

**Table 4 (continued)**
**Estimates of the Organizational Exit Rate from the U.S. Microcomputer Market:**

| | Model 1 | Model 2 | Model 3 | Model 4 | Model 5 |
|---|---|---|---|---|---|
| <u>All Organizations</u>: | | | | | |
| Market tenure 0-1 year | 5.832** | 5.761** | 2.202 | 2.080 | -.6776 |
| | (1.244) | (1.064) | (2.552) | (2.521) | (2.839) |
| Market tenure 1-3 years | 6.192** | 6.121** | 2.567 | 2.444 | -.3127 |
| | (1.240) | (1.061) | (2.548) | (2.517) | (2.835) |
| Market tenure 3-5 years | 6.285** | 6.214** | 2.656 | 2.533 | -.2183 |
| | (1.247) | (1.068) | (2.552) | (2.520) | (2.838) |
| Market tenure 5-10 years | 6.174** | 6.103** | 2.541 | 2.419 | -.3322 |
| | (1.251) | (1.077) | (2.556) | (2.526) | (2.842) |
| Market tenure 10-15 years | 6.430** | 6.360** | 2.785 | 2.664 | -.0790 |
| | (1.300) | (1.137) | (2.584) | (2.554) | (2.866) |
| Market tenure 15+ years | 6.282** | 6.212** | 2.639 | 2.516 | -.2298 |
| | (1.454) | (1.312) | (2.666) | (2.636) | (2.940) |
| <u>Medium-Sized Organizations</u>: | | | | | |
| Market tenure 0-1 year | -.1429 | -.1423 | -.1468 | -0.1458 | -.1416 |
| | (.0986) | (.0985) | (.0987) | (.0986) | (.0986) |
| Market tenure 1-3 years | -.3094** | -.3092** | -.3089** | -.3085** | -.3095** |
| | (.0802) | (.0802) | (.0802) | (.0802) | (.0802) |
| Market tenure 3-5 years | -.6133** | -.6129** | -.6111** | -.6105** | -.6109** |
| | (.1215) | (.1215) | (.1215) | (.1215) | (.1215) |
| Market tenure 5-10 years | -.7849** | -.7844** | -.7900** | -.7897** | -.7901** |
| | (.1388) | (.1388) | (.1389) | (.1389) | (.1389) |
| Market tenure 10-15 years | -.8629** | -.8628** | -.8636** | -.8641** | -.8653** |
| | (.3765) | (.3765) | (.3765) | (.3765) | (.3765) |
| Market tenure 15+ years | -1.167 | -1.167 | -1.169 | -1.168 | -1.170 |
| | (1.225) | (1.225) | (1.225) | (1.225) | (1.225) |
| <u>Large Organizations:</u> | | | | | |
| Market tenure 0-1 year | -.5341** | -.5321** | -.5457** | -.5432** | -.5343** |
| | (.2171) | (.2163) | (.2175) | (.2170) | (.2168) |
| Market tenure 1-3 years | -.9571** | -.9567** | -.9609** | -.9601** | -.9599** |
| | (.1795) | (.1794) | (.1795) | (.1794) | (.1794) |
| Market tenure 3-5 years | -1.036** | -1.036** | -1.038** | -1.037** | -1.041** |
| | (.2299) | (.2299) | (.2300) | (.2299) | (.2299) |
| Market tenure 5-10 years | -2.808** | -2.808** | -2.813** | -2.812** | -2.812** |
| | (.4600) | (.4599) | (.4600) | (.4600) | (.4600) |
| Market tenure 10-15 years | -3.696** | -3.697** | -3.693** | -3.694** | -3.694** |
| | (1.046) | (1.046) | (1.046) | (1.046) | (1.046) |
| Market tenure 15+ years | -2.650** | -2.649** | -2.666** | -2.663** | -2.652** |
| | (1.227) | (1.227) | (1.227) | (1.227) | (1.227) |

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

**Table 5**
**Estimates of the Organizational Exit Rate from the U.S. Microcomputer Market: The Effects of Exposure to Historical Competition**

| | Model 6 | Model 7 | Model 8 | Model 9 | Model 10 |
|---|---|---|---|---|---|
| <u>Microcomputer market effects:</u> | | | | | |
| Microcomputer market density/1000 | 3.241** | 3.707** | 3.776** | 3.771** | 3.871** |
| | (1.027) | (1.046) | (1.044) | (1.045) | (1.046) |
| Historical competition faced by org. | -.2415** | | | | |
| in the microcomputer market/1000 | (.0864) | | | | |
| Recent historical competition faced | | -1.098** | -2.148** | -2.234** | -2.552** |
| in the microcomputer market/1000 | | (.3499) | (.6230) | (.6368) | (.6852) |
| Distant-past historical competition faced | | .2044 | -.1324 | -.1374 | -.2252 |
| in the microcomputer market/1000 | | (.1948) | (.2593) | (.2596) | (.2628) |
| Number of distinct rivals faced | | | 1.861** | 1.982** | 2.433** |
| in the microcomputer market/1000 | | | (.9386) | (.9560) | (1.013) |
| <u>Effects of being also in the midrange market</u> | | | | | |
| Organization also is in the | -.2471** | -.2540** | -.2601** | -.2365** | .0621 |
| midrange market | (.0874) | (.0874) | (.0877) | (.1079) | (.1226) |
| Organization's tenure in the | | | | | -.3519 |
| midrange market | | | | | (.0685) |
| Midrange market density/1000 | 8.533** | 8.264** | 9.132** | 9.239** | 9.588** |
| | (3.717) | (3.752) | (3.778) | (3.777) | (3.787) |
| Historical competition faced by org. | | | | -.0407 | 2.136** |
| in the midrange market/1000 | | | | (.0920) | (.4207) |
| <u>Effects of being also in the mainframe market</u> | | | | | |
| Organization also is in the | -.4440 | -.4594 | -.4599 | -1.237 | -2.486** |
| mainframe market | (.3122) | (.3123) | (.3123) | (.5405) | (.7835) |
| Organization's tenure in the | | | | | -.5448** |
| mainframe market | | | | | (.1933) |
| Mainframe market density/1000 | -23.99* | -22.59* | -26.43* | -26.48* | -30.20** |
| | (14.03) | (14.08) | (14.19) | (14.19) | (14.25) |
| Historical competition faced by org. | | | | 3.142** | 37.89** |
| in the mainframe market/1000 | | | | (1.355) | (11.57) |
| Log Likelihood | -2396.41 | -2393.21 | -2391.33 | -2388.59 | -2367.40 |
| (Degrees of freedom) | (31) | (32) | (33) | (35) | (37) |

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 in parentheses.
*p<.10 **p<.05

**Table 5 (continued)**
**Estimates of the Organizational Exit Rate from the U.S. Microcomputer Market**

| | Model 6 | Model 7 | Model 8 | Model 9 | Model 10 |
|---|---|---|---|---|---|
| All Organizations: | | | | | |
| Market tenure 0-1 year | 1.965 | 1.769 | 1.601 | 1.496 | 1.750 |
| | (2.530) | (2.548) | (2.547) | (2.547) | (2.549) |
| Market tenure 1-3 years | 2.433 | 2.545 | 2.122 | 2.007 | 2.219 |
| | (2.526) | (2.543) | (2.550) | (2.550) | (2.554) |
| Market tenure 3-5 years | 2.667 | 2.825 | 2.470 | 2.358 | 2.603 |
| | (2.530) | (2.548) | (2.553) | (2.553) | (2.556) |
| Market tenure 5-10 years | 2.729 | 2.800 | 2.445 | 2.324 | 2.546 |
| | (2.537) | (2.555) | (2.560) | (2.560) | (2.563) |
| Market tenure 10-15 years | 3.208 | 3.049 | 2.568 | 2.458 | 2.479 |
| | (2.570) | (2.591) | (2.603) | (2.604) | (2.607) |
| Market tenure 15+ years | 3.329 | 2.942 | 2.461 | 2.313 | 2.559 |
| | (2.661) | (2.683) | (2.692) | (2.693) | (2.699) |
| Medium-Sized Organizations: | | | | | |
| Market tenure 0-1 year | -.1754* | -.2128** | -.1886** | -.1890** | -.1762** |
| | (.0991) | (.1001) | (.1009) | (.1009) | (.1011) |
| Market tenure 1-3 years | -.3149** | -.3015** | -.3081** | -.3117** | -.3005** |
| | (.0802) | (.0804) | (.0805) | (.0805) | (.0806) |
| Market tenure 3-5 years | -.6017** | -.5901** | -.5873** | -.5935** | -.5860** |
| | (.1216) | (.1217) | (.1217) | (.1218) | (.1218) |
| Market tenure 5-10 years | -.7499** | -.7658** | -.7695** | -.7662** | -.7584** |
| | (.1396) | (.1398) | (.1399) | (.1399) | (.1403) |
| Market tenure 10-15 years | -.7915** | -.8215** | -.7620** | -.7771** | -.5777 |
| | (.3774) | (.3778) | (.3808) | (.3941) | (.3924) |
| Market tenure 15+ years | -1.210 | -.2128 | -1.115 | -1.103 | -.9499 |
| | (1.225) | (.1001) | (1.226) | (1.226) | (1.226) |
| Large Organizations: | | | | | |
| Market tenure 0-1 year | -.6144** | -.6440** | -.6196** | -.6221** | -.6177** |
| | (.2182) | (.2178) | (.2185) | (.2186) | (.2190) |
| Market tenure 1-3 years | -.9761** | -.9533** | -.9602** | -.9634** | -.9515** |
| | (.1796) | (.1798) | (.1798) | (.1798) | (.1799) |
| Market tenure 3-5 years | -1.032** | -1.023** | -1.026** | -1.044** | -1.021** |
| | (.2299) | (.2299) | (.2300) | (.2303) | (.2305) |
| Market tenure 5-10 years | -2.786** | -2.803** | -2.812** | -2.859** | -2.847** |
| | (.4600) | (.4601) | (.4601) | (.4613) | (.4645) |
| Market tenure 10-15 years | -3.652** | -3.660** | -3.602** | -3.794** | -4.288** |
| | (1.046) | (1.046) | (1.047) | (1.058) | (1.188) |
| Market tenure 15+ years | -2.727** | -2.637** | -2.616** | -3.097** | -5.155** |
| | (1.227) | (1.228) | (1.228) | (1.278) | (1.594) |

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

**Table 5 (continued)**
**Estimates of the Organizational Exit Rate from the U.S. Microcomputer Market**

| | Model 6 | Model 7 | Model 8 | Model 9 | Model 10 |
|---|---|---|---|---|---|
| Dealio entrant | -.1523** | -.1525** | -.1497** | -.1514** | -.1772** |
| | (.0574) | (.0574) | (.0574) | (.0574) | (.0579) |
| Real U.S. gross domestic product | -.0017** | -.0017** | -.0016** | -.0016** | -.0016** |
| | (.0006) | (.0006) | (.0006) | (.0006) | (.0006) |
| U.S. Prime interest rate | 0.0347 | .0310 | .0310 | .0310 | .0335 |
| | (.0309) | (.0313) | (.0313) | (.0313) | (.0313) |
| Microcomputer market shipments/1000 | .0002** | .0002** | .0002** | .0002** | .0002** |
| | (.0001) | (.0001) | (.0001) | (.0001) | (.0001) |
| Microcomputer manufacturer entries/1000 | -0.3557 | -1.062 | -.9304 | -.9260 | -.9292 |
| | (1.204) | (1.239) | (1.238) | (1.238) | (1.237) |
| Microcomputer manufacturer failures/1000 | 6.210** | 6.699** | 6.695** | 6.723** | 6.761** |
| | (1.258) | (1.281) | (1.279) | (1.279) | (1.281) |
| Microcomputer market density at entry/1000 | -.0610 | .2082 | -.3147 | -.3578 | -.4621 |
| | (.5094) | (.5221) | (.5839) | (.5906) | (.6016) |

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

**Table 6**
**Estimates of the Organizational Exit Rate from the U.S. Microcomputer Market: The Effects of Rivals' Exposure to Historical Competition**

| | Model 11 | Model 12 | Model 13 |
|---|---|---|---|
| Effects of rivals' characteristics: | | | |
| Microcomputer rivals' historical exposure to competition/1000 | .0016* | .0017 | .0024** |
| | (.0010) | (.0012) | (.0008) |
| Sum of ages of microcomputer rivals/1000 | | -.0136 | |
| | | (.0913) | |
| Microcomputer market density/1000 | 1.860 | 1.846 | |
| | (1.606) | (1.609) | |
| Number of small microcomputer rivals/1000 | | | .9492 |
| | | | (1.153) |
| Number of medium-sized microcomputer rivals/1000 | | | .5270 |
| | | | (1.069) |
| Number of large microcomputer rivals/1000 | | | -2.162 |
| | | | (4.726) |
| Other model parameters: | | | |
| Recent historical competition faced | -2.671** | -2.681** | -2.576** |
| in the microcomputer market/1000 | (.6842) | (.6872) | (.6968) |
| Distant-past historical competition faced | -.2371 | -.2381 | -.0974 |
| in the microcomputer market/1000 | (.2609) | (.2610) | (.3712) |
| Number of distinct rivals faced | 2.584** | 2.598** | 2.156* |
| in the microcomputer market/1000 | (1.007) | (1.011) | (1.296) |
| Organization also is in the | .0619 | .0617 | .0449 |
| midrange market | .1228 | (.1228) | (.1242) |
| Organization's tenure in the | -.3555** | -.3555** | -.3520** |
| midrange market | (.0687) | (.0687) | (.0687) |
| Midrange market density/1000 | 8.844** | 8.923** | 9.519** |
| | (3.684) | (3.732) | (3.552) |
| Historical competition faced by org. | 2.1596** | 2.160** | 2.138** |
| in the midrange market/1000 | (.4219) | (.4219) | (.4226) |
| Organization also is in the | -2.490** | -2.489** | -2.478** |
| mainframe market | (.7869) | (.7870) | (.7858) |
| Organization's tenure in the | -.5453** | -.5453** | -.5451** |
| mainframe market | (.1936) | (.1936) | (.1933) |
| Mainframe market density/1000 | -7.578 | -10.02 | -3.127 |
| | (19.59) | (25.58) | (18.78) |
| Historical competition faced by org. | 37.94** | 37.94** | 37.92** |
| in the mainframe market/1000 | (11.60) | (11.60) | (11.57) |
| Log Likelihood | -2366.04 | -2366.03 | -2366.16 |
| (Degrees of freedom) | (38) | (39) | (40) |

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 in parentheses.
*p<.10 **p<.05

**Table 6 (continued)**
**Estimates of the Organizational Exit Rate from the U.S. Microcomputer Market**

| | Model 11 | Model 12 | Model 13 |
|---|---|---|---|
| All Organizations: | | | |
| Market tenure 0-1 year | 3.191 | 3.096 | 2.967 |
| | (2.632) | (2.714) | (2.599) |
| Market tenure 1-3 years | 3.656 | 3.560 | 3.371 |
| | (2.636) | (2.718) | (2.593) |
| Market tenure 3-5 years | 4.044 | 3.948 | 3.776 |
| | (2.639) | (2.722) | (2.599) |
| Market tenure 5-10 years | 3.982 | 3.885 | 3.730 |
| | (2.645) | (2.727) | (2.608) |
| Market tenure 10-15 years | 3.877 | 3.779 | 3.659 |
| | (2.679) | (2.763) | (2.651) |
| Market tenure 15+ years | 3.972 | 3.874 | 3.780 |
| | (2.772) | (2.854) | (2.753) |
| Medium-Sized Organizations: | | | |
| Market tenure 0-1 year | -.1782* | -.1775* | -.1765* |
| | (.1011) | (.1012) | (.1016) |
| Market tenure 1-3 years | -.3027** | -.3028** | -.3022** |
| | (.0806) | (.0806) | (.0806) |
| Market tenure 3-5 years | -.5870** | -.5867** | -.5884** |
| | (.1218) | (.1218) | (.1218) |
| Market tenure 5-10 years | -.7609** | -.7611** | -.7613** |
| | (.1403) | (.1404) | (.1404) |
| Market tenure 10-15 years | -.5578 | -.5577 | -.5718 |
| | (.3927) | (.3927) | (.3934) |
| Market tenure 15+ years | -.9555 | -.9560 | -.9470 |
| | (1.226) | (1.226) | (1.226) |
| Large Organizations: | | | |
| Market tenure 0-1 year | -.6184** | -.6161** | -.6212** |
| | (.2189) | (.2194) | (.2195) |
| Market tenure 1-3 years | -.9560** | -.9559** | -.9537** |
| | (.1799) | (.1799) | (.1801) |
| Market tenure 3-5 years | -1.021 | -1.019** | -1.027** |
| | (.2305) | (.2306) | (.2305) |
| Market tenure 5-10 years | -2.847** | -2.847** | -2.843** |
| | (.4645) | (.4645) | (.4645) |
| Market tenure 10-15 years | -4.267** | -4.268** | -4.263** |
| | (1.191) | (1.191) | (1.189) |
| Market tenure 15+ years | -5.164** | -5.164** | -5.165** |
| | (1.596) | (1.596) | (1.595) |

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

**Table 6 (continued)**
**Estimates of the Organizational Exit Rate from the U.S. Microcomputer Market**

| | Model 11 | Model 12 | Model 13 |
|---|---|---|---|
| Dealio entrant | -.1764** | -.1765** | -.1763** |
| | (.0579) | (.0579) | (.0579) |
| Real U.S. gross domestic product | -.0021** | -.0021** | -.0021** |
| | (.0007) | (.0007) | (.0007) |
| U.S. Prime interest rate | .0463 | .0471 | .0536* |
| | (.0309) | (.0315) | (.0293) |
| Microcomputer market shipments/1000 | .0002** | 0.0003** | .0002** |
| | (.0001) | (.0001) | (.0001) |
| Microcomputer manufacturer entries/1000 | -.0068 | .0932 | .6811 |
| | (1.364) | (1.522) | (1.120) |
| Microcomputer manufacturer failures/1000 | 5.278** | 5.452** | 5.193** |
| | (1.535) | (1.935) | (1.717) |
| Microcomputer market density at entry/1000 | -.5351 | -.5405 | -.1016 |
| | (.6029) | (.6042) | (0.7678) |

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

**Table 7**
**Estimates of the Entry Rate of Midrange Manufacturers into the Microcomputer Market**

| | Model 14 | Model 15 | Model 16 |
|---|---|---|---|
| Midrange market tenure 0-2 year | -12.66* | -8.505 | -12.67* |
| | (7.836) | (7.801) | (7.662) |
| Midrange market tenure 2-3 years | -12.96* | -9.371 | -14.43* |
| | (7.869) | (7.817) | (7.725) |
| Midrange market tenure 3-5 years | -12.24 | -9.303 | -14.69* |
| | (7.910) | (7.851) | (7.775) |
| Midrange market tenure 5-10 years | -12.22 | -10.62 | -15.72** |
| | (7.829) | (7.737) | (7.669) |
| Midrange market tenure 10-15 years | -12.17 | -12.58* | -16.82** |
| | (7.884) | (7.775) | (7.677) |
| Midrange market tenure 15+ years | -11.11 | -13.52* | -16.21** |
| | (7.917) | (7.811) | (7.676) |
| Organization's time in the industry before 1975 | .0664** | .0258 | .0517* |
| | (.0239) | (.0285) | (.0282) |
| Dealio entrant | .3566 | .4028* | .3629 |
| | (.2322) | (.2280) | (.2298) |
| Medium-sized organization | .7072** | .6583** | .6144** |
| | (.2446) | (.2446) | (.2439) |
| Large organization | .3925 | .2999 | .2207 |
| | (.4123) | (.4124) | (.4118) |
| Real U.S. gross domestic product | .0020 | .0005 | .0017 |
| | (.0024) | (.0024) | (.0023) |
| U.S. Prime interest rate | -.0039 | .0689 | .1040 |
| | (.0818) | (.0828) | (.0836) |
| Microcomputer market shipments/1000 | -.0004 | -.0004 | -.0006* |
| | (.0003) | (.0003) | (.0003) |
| Microcomputer manufacturer entries (lagged)/1000 | -8.987* | -7.431 | -8.395 |
| | (5.383) | (5.294) | (5.272) |
| Microcomputer manufacturer failures/1000 | 4.734 | 5.167 | 10.18 |
| | (8.565) | (8.848) | (9.170) |
| Microcomputer market density/1000 | 2.539 | 1.997 | .6783 |
| | (3.975) | (4.078) | (4.188) |
| Midrange market shipments/1000 | .0045 | .0128 | .0145 |
| | (.0103) | (.0105) | (.0106) |
| Midrange manufacturer entries (lagged)/1000 | 28.56 | 26.75 | 54.97** |
| | (18.07) | (17.90) | (19.96) |
| Midrange manufacturer failures/1000 | -3.319 | -4.260 | -17.15 |
| | (18.37) | (18.19) | (18.66) |
| Midrange market density/1000 | 1.187 | -1.527 | -15.19 |
| | (7.640) | (7.763) | (9.131) |
| Historical competition faced by organization | | 2.510** | |
| in the midrange market/1000 | | (.6395) | |
| Recent historical competition faced by organization | | | 12.28** |
| in the midrange market/1000 | | | (3.280) |
| Distant-past historical competition faced by organization | | | -.0552 |
| in the midrange market/1000 | | | (.9874) |
| Log Likelihood (Degrees of Freedom) | -232.49 (20) | -224.66 (21) | -217.88 (22) |

Note: The data include 92 entries from a risk set of 637 organizations over 2723 organization-years. For coefficient estimates, standard errors are in parentheses. *p<.10 **p<.05