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# On the Historical Efficiency of Competition between Organizational Populations<sup>1</sup>

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Much organizational theory and research uses an equilibrium assumption known as historical efficiency. This assumption implies that observed distributions of organizations at any point in time reflect the unique outcomes of underlying systematic processes, independent of historical details. In an attempt to assess the plausibility of this assumption in the context of organizational evolution, the authors use a well-established model to simulate trajectories of competing organizational populations. The findings show that path-dependent processes can often generate outcomes other than those implied by historical efficiency. Implications for theory and research are discussed.

Throughout its history, theory and research on organizations has often subscribed to an assumption of temporal equilibrium. That is, researchers have frequently assumed (often implicitly) that organizational arrangements observed at a particular point in time represent the unique outcome of some systematic process such as competition. March and Olsen (1989, pp. 5–6) refer to this as the assumption of “historical efficiency.” They explain: “Institutions and behavior are thought to evolve through some form of efficient historical process. An efficient historical process, in these terms, is one that moves rapidly to a unique solution,

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conditional on current environmental conditions, and is independent of the historical path. This equilibrium may involve a stochastically subtle distribution or a fixed point, but we require a solution that is achieved relatively rapidly and is independent of the details of historical events leading to it." Examples of studies using this assumption can be found in virtually all theoretical camps, but some perspectives seem more reliant on it (e.g., rational action theory; see Milgrom and Roberts 1992).

Recent developments in the study of technology, institutions, and related topics have sensitized social scientists to the potential problems of assuming historical efficiency. Theoretical analyses in these areas have shown that social processes with positive feedback (or self-reinforcement) can generate outcomes that arise from "chance" rather than a systematic force. Contexts where these outcomes occur are "path dependent" in the sense that prior decisions, choices, or actions affect the future behavior of the process.

Path dependence has received much attention from social scientists and historians (Arthur 1987; David 1985; Williamson 1993). Yet the concept remains mainly a fascinating idea. Much work continues to rely on the assumption of historical efficiency. Other work avoids this problem but still fails to develop fully the implication of path dependence for its conclusions. Such practice seems ill-advised for the study of organizations, because organizations frequently exhibit the types of positive feedback mechanisms that can give rise to path dependence—for example, learning-by-doing, economies of scale, and information-increasing returns.

Our efforts here represent an attempt to take the study of organizational path dependence one step further. We do so by tightening the focus on this phenomenon. We use an established general model of organizational evolution—organizational ecology's density model of legitimation and competition (Hannan and Carroll 1992)—to examine the likelihood of path-dependent outcomes. We build on empirical estimates of the model to simulate long-term trajectories of competing organizational populations defined by organizational form, a process that theorists often assume to be historically efficient. We arrange the simulations so that some populations are "structurally superior" to others, meaning that parameters lead one to expect that certain populations should outcompete others. Although in common parlance competitive victory may imply several dimensions of dominance, we use the simulation experiments to address three specific but central questions: First, how often does the structurally superior population dominate in numbers of organizations? Second, how long does it typically take for the "winning" population to dominate? Third, how much variability is there in the time required for the winning population to dominate?

The findings show clearly that path dependence can produce unexpected outcomes in this structured and realistic framework. Furthermore, the pattern of outcomes generated yields insights into the density model and related substantive issues of wide concern. By our assessment, the findings have important implications for theory and research on organizations.

#### EVOLUTION AMONG COMPETING ORGANIZATIONAL POPULATIONS

Virtually all theories of organization hold that some forms of organization have competitive advantages over other forms, although the particulars of the forms and the forces giving them advantage differ considerably by theory. In classical formulations (e.g., Weber 1968), formalized structures per se are held to be inherently more efficient than informal structures. Contemporary theories focus primarily on differences among formal organizations. In resource dependence theory (Pfeffer and Salancik 1978), organizations with structures capable of reducing environmental uncertainty are depicted as having operating advantages. In transaction cost theory (Williamson 1981, 1993), organizational structures that minimize costs are predicted to outperform others. In institutional theory (Meyer and Scott 1983), organizations that are structured in a manner consistent with prevailing norms are thought to be favored by authorities, customers, and employees. And in ecological theory (Hannan and Freeman 1989), organizational forms that are better matched to their environmental conditions are seen as capable of outcompeting other forms. For present purposes, it is important to recognize that each of these theories posits an underlying driving force that gives relative advantage to particular organizational forms and that leads to a substantive prediction of equilibrium whereby the advantaged forms should prevail (often referred to in the sociological literature as isomorphism; see Scott 1992).

Researchers often assume that the existence or relative abundance of particular organizational forms represents the outcome of some process yielding competitive advantage to those forms. This practice invokes the assumption of historical efficiency, wittingly or not, whether the underlying process is hypothesized to be market-driven efficiency, uncertainty reduction, cost minimization, normative consensus, or whatever.

Historical efficiency is a plausible assumption in this context, but it is not self-evident. The crucial questions concern the strength of the underlying forces yielding competitive advantage and the extent to which other factors, including random ones, impinge upon the organizations. Obviously, in settings where a strong driving force operates and there is little "noise," the system will adjust rapidly. Here the assumption of historical

efficiency is not only sustainable but practical. However, in settings where the underlying force is not as strong or where there is a significant amount of noise, assuming historical efficiency becomes potentially problematic. The system may not have had sufficient time to adjust or its outcomes may be obscured or even influenced by noise.

For organizations, there are also important substantive considerations in using the assumption of historical efficiency to infer competitive advantage. Organizational environments may be endogenous or nonstationary. Many organizational processes show signs of positive feedback or self-reinforcement (e.g., learning-by-doing and scale economies in production). Such processes create the conditions for path dependence among competing forms of organization. Path dependence deserves attention because it can lead to unexpected outcomes, such as the long-term survival of and dominance by an initially inferior competing form of organization. Analyses by Arthur (1989) and others have shown that systems with positive feedback can generate outcomes strongly affected by random events or noise even in the presence of strong systematic forces such as market selection.

How common are positive feedback mechanisms among organizational forms? We have hinted at their prevalence by referring to widely used concepts such as learning-by-doing and economies of scale. Organizational ecology's model of density-dependent legitimation and competition (Hannan and Carroll 1992) provides a compelling case for widespread prevalence of positive feedback in the evolution of organizational forms. As we illustrate below, the legitimation component of this model involves positive feedback. The model's empirical standing, which includes supporting evidence from a wide variety of organizational forms, suggests broad applicability. For this reason, we use this model as a framework for assessing the plausibility of the assumption of historical efficiency in organizational evolution. In particular, we build on empirical estimates of this established model to simulate long-term trajectories of organizational populations defined by form. For clarity of interpretation, we focus initially on cases of two competing organizational populations defined by form. We then extend our investigation to a multipopulation problem. We are especially interested in learning how frequently outcomes other than those implied by the systematic processes of legitimation and competition might result in evolutionary contexts. The strength of this approach lies in our ability to assess outcomes based on a widely applicable model using parameter values similar to those estimated for real-world populations. The primary limitation of the approach is that it allows us to look only at one class of competitive outcomes—numbers of organizations with particular forms and the trajectories of these populations over time.

## A MODEL OF LONG-TERM ORGANIZATIONAL EVOLUTION

How do organizational forms and populations defined by forms evolve over time? Although answers to this question are far from complete, recent research has established the validity of an ecological model of one aspect of the evolutionary process, that concerning change over time in the number of organizations using a particular form. The model is known in the literature as the density model (Hannan and Carroll 1992). It envisions organizational change as a selection process, meaning that changes in the number of organizations with a particular form occur through fluctuations in founding and failure rates rather than through transformations of existing organizations having other forms.

The density model holds that two general sociological forces drive long-term organizational evolution: legitimation (in the sense of social taken-for-grantedness) and competition. Legitimation of an organizational form increases with rises in the number of organizations using the form (density) at a decreasing rate. Competition also increases with rising density but at an increasing rate. So when density is low, legitimation dominates evolution; when it is high, competition does (see Hannan and Carroll [1992] for an in-depth exposition).

Three essential features define the density model empirically. First, organizational founding rates rise and then fall with increases in density. The pattern corresponds to the relative importance of legitimation and competition at different phases of evolution. Second, organizational mortality rates decline and then rise with increases in density, again in correspondence to the relative influences of legitimation and competition. Third, the greater the population density at the time of an organization's founding, the higher its lifetime mortality rate (across all ages). This last feature is purely a competition effect. Note that, in the first two empirical features, both the rise in founding rates and the decline in mortality rates yield positive feedback—the population grows as a function of its density, at least temporarily.

Although many functional forms could be used to depict the model mathematically, a simple and widely used specification casts stochastic rates of organizational founding and mortality as log-linear quadratic functions of density. For organizational founding, the rate,  $\lambda$ , is specified as

$$\lambda(t) = \exp[\beta_0 + \beta_1 N(t) + \beta_2 N^2(t)], \quad (1.1)$$

where  $N(t)$  is density at time  $t$  and the model predicts that

$$\beta_1 > 0; \beta_2 < 0. \quad (1.2)$$

For organizational mortality, the rate,  $\mu$ , is defined at the organizational level as

$$\mu(u) = \exp[\alpha_0 + \alpha_1 N(u) + \alpha_2 N^2(u) + \alpha_3 N_f] \exp[\gamma_0 \log(u)], \quad (2.1)$$

where  $\gamma_0$  is the coefficient associated with age dependence,  $N(u)$  is density at age  $u$ , and  $N_f$  is density at the time of an organization's founding. The model predictions are

$$\alpha_1 < 0; \alpha_2 > 0; \alpha_3 > 0. \quad (2.2)$$

The density model rests on strong empirical support.<sup>2</sup> The predicted relationships have been found in virtually all empirical studies conducted to date with appropriate observation periods. The published tests cover a wide range of organizational populations including beer brewing firms, labor unions, banks, life insurance companies, newspaper publishers, trade associations, medical diagnostic imaging manufacturers, and telephone companies (for a review, see Hannan and Carroll [1992]). Furthermore, simulations of estimated equations by Hannan and Carroll (1992) demonstrate that the model does a reasonably good job of reproducing observed time trajectories of the number of organizations in a population.<sup>3</sup>

The problem of historical efficiency concerns the evolution of not one organizational population but of two or more populations in competition with each other. The density framework incorporates such interdependence by allowing the vital rates of one population to depend not only on its own density but also on the densities of other populations.<sup>4</sup> In this way, the size of any particular population is affected by the presence and sizes of other populations.

<sup>2</sup> Debate about the density model has mainly concerned theoretical interpretation, especially that involving legitimation (see Petersen and Koput 1991). These issues need not concern us greatly here because we justify our use of the model on its empirical standing. To our knowledge, no one has questioned the empirical evidence of positive feedback effects, whatever their interpretation.

<sup>3</sup> Barnett (1993) has proposed a new model of organizational evolution based on aggregated competitive forces. His model complements rather than contradicts the density model. Although combining Barnett's model with the density model apparently improves predictive power, this fact does not undermine the density model's individual predictive ability.

<sup>4</sup> One reviewer has suggested that the superiority or inferiority of organizational forms should be reflected in their base rates of founding and mortality rather than their interdependence with other organizational forms. Although base vital rates may indicate a form's inherent viability or fitness, they do not indicate its competitive ability vis-à-vis another specific organizational form. Competitive ability is our focus here. In order to minimize the potentially confounding effects of inherent viability, we hold base rates constant in our simulations.

Imagine the case of two interdependent populations  $A$  and  $B$ . With simple monotonic interpopulation relationships (similar to the competition terms in the well-known Lotka-Volterra model), the vital rates can be specified by adding interpopulation competition terms to equations (1.1) and (2.1) to model the effect of the density of one population on the vital rates of the other. Adding these terms leads to the following specifications:

$$\lambda_A(t) = \exp[\beta_{A0} + \beta_{A1}N_A(t) + \beta_{A2}N_A^2(t) + \delta_A N_B(t)], \quad (3.1)$$

for founding of population  $A$ , and

$$\lambda_B(t) = \exp[\beta_{B0} + \beta_{B1}N_B(t) + \beta_{B2}N_B^2(t) + \delta_B N_A(t)], \quad (3.2)$$

for founding of  $B$ ;

$$\begin{aligned} \mu_A(u) = \exp[\alpha_{A0} + \alpha_{A1}N_A(u) + \alpha_{A2}N_A^2(u) \\ + \alpha_{A3}N_{Af} + \eta_A N_B(u)] \exp[\gamma_A \log(u)], \end{aligned} \quad (4.1)$$

for mortality of organizations of form  $A$ , and

$$\begin{aligned} \mu_B(u) = \exp[\alpha_{B0} + \alpha_{B1}N_B(u) + \alpha_{B2}N_B^2(u) \\ + \alpha_{B3}N_{Bf} + \eta_B N_A(u)] \exp[\gamma_B \log(u)], \end{aligned} \quad (4.2)$$

for mortality of organizations in population  $B$ . For foundings, a positive  $\delta$  parameter signifies mutualistic interdependence between the two populations; a negative  $\delta$  indicates competition. For mortality, the interpretations are reversed: a positive  $\eta$  parameter shows a competitive relationship, while a negative  $\eta$  denotes mutualism (see Hannan and Carroll 1992). The framework parallels models used in biology for multispecies interactions (see May 1974). What's more, it has proven useful in empirical studies of competing organizational subpopulations (see, e.g., Barnett and Carroll 1987; Hannan and Freeman 1989; Hannan and Carroll 1992).

In a historically efficient world, the direction and strength of competitive relationships determine the winner of the competition. What of the density model? Those familiar with Lotka-Volterra and related models of competition may recognize that models similar to that specified above have been induced to derive equilibrium solutions of population sizes (see May 1974). The solutions consist of various combinations of population parameters. However, this work has limited applicability to the model of density dependence for at least two reasons. First, the solutions derive from deterministic versions of the model, not the stochastic version specified above. The deterministic versions remove random variation by assumption. Second, the models used in these exercises are less complex than the ecological model of density dependence. The biggest difference

is that the ecological model contains nonmonotonic density dependence while the typical model dealt with analytically contains only monotonic density dependence.

In terms of analytical work, a more insightful analogy is between the ecological model of density dependence and nonlinear Polya processes (Cohen 1976).<sup>5</sup> Arthur, Ermoliev, and Kaniovski (1987, p. 294) define nonlinear Polya processes as those characterizing “systems where increments to proportions or concentrations occur with probabilities that are non-linear functions of present proportions or concentrations,” a general definition that applies to the model of density dependence. The interesting features of these processes can be readily seen in the simplest case, the standard Polya urn scheme (Eggenberger and Polya 1923; Cohen 1976; Arthur et al. 1987). Suppose we have an urn of unlimited capacity and it contains two balls, one blue and one gold. We draw randomly from the urn, look at the color of the ball drawn, and then return it. If a blue ball was drawn, we add a blue ball to the urn (so that the urn now contains two blue balls and one gold ball). If a gold ball was drawn, we add a gold ball to the urn. We continue this process indefinitely and observe the proportion of balls of each color, which also constitutes the probability that a ball of any given color will be chosen next. Some may expect that the proportions will endlessly shift back and forth; others may expect that the urn will eventually contain a preponderance of balls of one color. Neither of these expectations is correct. With a probability of one, the proportions of balls in the urn tend to a limit  $Z$  and that  $Z$  is a random variable uniformly distributed between 0 and 1. This means that, if we conduct the experiment numerous times, in each instance the proportions of balls will converge on a single set of proportions (say, .5213 blue and .4787 gold) but that across experiments the proportions will differ (say, .3825 blue and .6175 gold in the second experiment, .1253 blue and .8747 gold in the third experiment, etc.). Polya processes are path dependent because the probabilities of balls of either color being chosen depend on the sequence of previous draws; they are self-reinforcing because initially the more times a color is chosen, the more likely it will be chosen again; they are stable because an exact equilibrium point emerges; and they are indeterminate or nondegenerate because the equilibrium point varies randomly from trial to trial.

<sup>5</sup> Purely random processes can generate path-dependent trajectories for competitors; advantages obtained by chance can be surprisingly durable (Feller 1968). This effect helps us understand how the stochastic components of our model contribute to the path dependence we observe, but the probability that this behavior is the result of chance alone is vanishingly small for the extended time frame of our study. The regression analysis shows that population density is also a significant contributor to this effect.

Although the model of density dependence for competing populations has a structure that contains essential features of the nonlinear Polya process, it also has other aspects including negative feedback (driven by the second-order population coefficient), possible declines in population sizes, and possible simultaneity of population increments (or decrements). Accordingly, we are reluctant to rely on general analytical results from nonlinear Polya processes, and we have not been successful in deriving analytical solutions for the models of interest (indeed, we doubt that it is even possible to obtain such solutions). We also want to ensure that the model's behavior within the usual range of empirically estimated coefficients produces variations of magnitude sufficient to be substantively important. For all these reasons, we use a computer simulation to study and understand the model of density dependence for competing populations.

#### EXPERIMENTAL RESEARCH DESIGN

The assumption of historical efficiency implies that when two organizational populations stand in competition with each other, the "stronger" of the two will dominate in a fairly short period of time. For the assumption to be applicable to most real-world contexts, this outcome should occur regardless of when each population enters the competitive arena and regardless of the size of the other population at time of entry. By contrast, the path-dependent properties of models with positive feedback suggest that if populations follow trajectories implied by the density model, then other outcomes are possible. Our simulation experiments are designed to address this basic problem.

Initial simulation work on the density model by Hannan and Carroll (1992, chap. 8) studied the evolutionary paths of single populations. Using parameter estimates of data on real organizational populations, Hannan and Carroll made several general conclusions about the model's behavior for single organizational populations. First, they concluded that the model reproduced observed historical trajectories reasonably well once appropriate values of environmental and other covariates were used to make predictions. Second, they found that the model showed great variation in the timing of periods of rapid population growth or "take-off," even though the population almost always equilibrated at the expected level. The variation in timing was thought to be due to randomness or chance. Third, the strength of the density delay term ( $\alpha_{A3}$  and  $\alpha_{B3}$  in the models above) was found to affect directly population behavior near and after the peak number had been attained. Specifically,

the larger the density delay coefficient, the more likely is population decline (or sometimes cyclical behavior) after the peak.

The apparently strong role of chance in the timing of population take-offs prompted us in an earlier analysis to think that stochastic path dependence may affect multipopulation competition processes and outcomes (Carroll and Harrison 1993). We reasoned from the case of two populations *A* and *B* with a competitive relationship between each other such that the presence of organizations of one population inhibits the viability of the other. We let one of the populations, say *A*, emerge before the other and let them both be governed by identical processes of density dependence. We imagined two different scenarios of growth for *A* of the kind that seem possible simply because of chance—in the first, *A* grows rapidly and attains high density before *B* emerges, and, in the second, *A* grows slowly and is small in numbers when *B* emerges. Since the growth trajectory of population *B* depends on the path *A* has taken prior to its chance emergence, we conjectured that major differences in *B*'s evolution might result from chance variation in the size of *A* at the time when *B* starts. In other words, we believed that evolutionary processes among competing organizational forms following the model of legitimation and competition might be stochastically path dependent.

In an earlier article (Carroll and Harrison 1993), we reported the results of computer simulations used to investigate the problem more rigorously. We designed experiments of two competing organizational populations following the trajectories predicted by real-world estimates of the parameters of the density model. The simulations began with the growth of a single population; a second population appeared at a random time. The competitive relationships between the populations were set parametrically so that the second population was “structurally dominant”—it should always win the competition at equilibrium in a historically efficient world. We examined two cases, one with weak competitive relationships and one with strong competitive relationships. We assessed dominance by looking at the numbers of each population in the competition.

These earlier simulations showed that it is possible for a structurally inferior population to retain its early dominant position and to win outright the competition against a structurally superior competitor population. In fact, our study demonstrated that this unexpected outcome can occur commonly, even under conditions of strong competition. For instance, with the parameter settings examined, the structurally inferior population won the competition over 30% of the time. However, as with any simulation, the findings of this study were potentially very limited and the generality of the conclusions was an open issue.

Our efforts here extend this line of work. We report findings from

TABLE 1  
PARAMETERS OF THE BASELINE MODEL

|                              | $\beta_1$ | $\beta_2/1,000$ | $\alpha_1$ | $\alpha_2/1,000$ | $\alpha_3$ | $\gamma_0$ |
|------------------------------|-----------|-----------------|------------|------------------|------------|------------|
| Simulation experiments ..... | .005      | -.0063          | -.015      | .018             | .006       | -.021      |
| Argentinian newspapers.....  | .009      | -.097           | -.050      | .160             | .014       | -.194      |
| Irish newspapers .....       | .013      | -.033           | -.015      | .027             | .002       | -.027      |
| San Francisco newspapers...  | .005      | -.0063          | -.015      | .018             | .004       | -.021      |

many additional simulations as well as those from the previous study (for comparison).<sup>6</sup> The new simulations address a number of additional substantive questions and also allow for firmer conclusions. All simulations use the model of legitimation and competition as the baseline and all begin with a single organizational population and let a second population emerge at a random time.<sup>7</sup> As in the earlier study, we retain parameter settings for the baseline model that correspond closely to empirical estimates of newspaper organizational populations. Table 1 shows these settings (parameters correspond to those given in the equations above) and compares them to empirical estimates for three newspaper populations (as reported in Hannan and Carroll [1992]). Competition parameters vary by experiment and are given in relevant tables below; it should be noted that the values used are chosen to correspond to typical empirical estimates of interpopulation competition (see Hannan and Carroll 1992).

We report four sets of simulation experiments. One set of experiments resembles the previous study: the second population is set to be structurally superior or dominant. Another set of experiments uses the same framework but sets the two populations to be structurally equal. A third set also retains the framework but makes the initial or first population the structurally superior competitor. Finally, a fourth set extends the framework to multiple competing populations (as many as five), where populations are successively stronger in structural terms than earlier populations. Within each of the four general setups, the strength of the competitive relationships varies. We report findings for a total of 27 experiments (4 for the first setup, 5 for the second, 8 for the third, and 10 for the fourth), each run for at least 100 trials.

<sup>6</sup> The previously reported findings are shown in tables below as experiments B1 and B2.

<sup>7</sup> We make the assumption that a disappearing population cannot reemerge for simplicity. An obvious extension of the work reported here involves relaxing this assumption, which is captured in at least a qualitative sense by our simulations involving more than two populations.

Stated more technically, the experiments are designed as follows:

*Set 1: Structurally superior population B.*—Population *A* begins the simulation with size = 1 at time = 0. Population *B* emerges randomly at a later point in time stochastically set by a constant rate model. Both populations are governed by similar founding and mortality processes with identical baseline rates and identical forms of nonmonotonic density dependence. Population *B* is structurally superior to *A* in that its density exerts a negative effect on *A*'s founding rate and a positive effect on *A*'s mortality rate while *A* exerts analogous but much smaller effects on *B*. That is, in terms of the equations above,  $\delta_A < \delta_B < 0$  and  $\eta_A > \eta_B > 0$ . Once the density of either population reaches 0, it is considered defunct and cannot reemerge. The simulation is conducted for the equivalent of 500 years and then stopped. It is repeated in 100 or more independent trials, changing only the “seeds” used for the generation of random numbers. This set of trials constitutes one experiment. Experimental variation within this setup consists of varying the competitive intensity of the relationship between the two populations. That is, the absolute values of  $\delta$  and  $\eta$  are changed in different experiments.

*Set 2: Structurally equal strength populations.*—Identical to the set 1 experiments except that here the competitive relationship between populations are equal—neither *A* nor *B* is structurally superior. The parameters are set  $\delta_A = \delta_B < 0$  and  $\eta_A = \eta_B > 0$ . Again, different experiments within this setup also vary  $\delta$  and  $\eta$ .

*Set 3: Structurally superior population A.*—Set 3 is identical to experiments in the other two sets except that here the first population, *A*, is set to be the structurally superior competitor. The parameters are constrained such that  $\delta_B < \delta_A < 0$  and  $\eta_B > \eta_A > 0$ . Experiments within the setup vary competitive intensity between *A* and *B*.

*Set 4: Multiple populations with “progress.”*—The general structure of population evolution remains identical to the other sets of experiments. Here, however, as many as five populations are allowed to emerge.<sup>8</sup> Each successive population is set to be structurally superior to all previous populations. So the last, or fifth, population is the strongest overall. Experiments within the setup vary the relative and absolute competitive intensities among the five populations.

<sup>8</sup> Competitive relationships for multiple populations are modeled as pairwise population competition, and higher-order competitive effects are neglected. Hence the founding rate for the fifth population, *E*, is given by:

$$\begin{aligned}\lambda_E = \exp[ & \beta_{E0} + \beta_{E1}N_E(t) + \beta_{E2}N_E^2(t) \\ & + \delta_{EA}N_A(t) + \delta_{EB}N_B(t) \\ & + \delta_{EC}N_C(t) + \delta_{ED}N_D(t)].\end{aligned}$$

In a historically efficient system, the equilibrium outcomes of these experiments are obvious: the structurally superior population should eventually dominate the other population(s) numerically. However, as we have seen in the earlier study, path dependence arising from chance can sometimes undermine efficiency and lead to dominance in equilibrium by the structurally inferior population. Even when the structurally superior population wins the competition, the process sometimes takes a long time to reach equilibrium, and the inferior population(s) appear(s) to be dominant for much of the competitive history. Either situation implies that an analyst using the assumption of historical efficiency may be misled when viewing data. Accordingly, we use our experiments to seek to answer three questions: First, how often does the structurally superior population dominate in terms of numbers of organizations? Second, how long does it typically take for the winning population to dominate? Third, how much variability is there in the time required for the winning population to dominate? Although we have no exact rule by which to measure "acceptable" levels of unexpected outcomes, we believe that anything greater than a trivial level poses potential problems for those invoking historical efficiency as a working assumption.

Should path-dependent outcomes emerge, important questions arise as to their source. These are easiest to assess in the simple experiments with two competing populations, where two randomly induced variables seem potentially capable of playing major roles in generating path dependence: (1) the timing of the emergence of population *B*, and (2) the growth pattern of population *A* before the emergence of population *B*. Among other things, analysis of these variables might inform a recent debate in the strategic management literature on the relative importance of strategic maneuvers designed to exploit entry barriers (e.g., Porter 1980) versus those based on development of organizational capabilities and resources (e.g., Teece, Pisano, and Shuen 1990; Grant 1991). If timing of entry proves critical, then barriers that delay a competitor's entry may be more advantageous.

Our simulation methods build on the procedures developed by Hannan and Carroll (1992, chap. 8), who describe them in detail. Taking their program as a guide, we coded a more efficient and faster program in QuickBASIC. We expanded the program to include two or more populations and to allow them to interact in the ways specified above. We also refined the program by recalibrating the time periods to the equivalent of months rather than years; this change reduces instability due to the discrete time structure of the simulation.<sup>9</sup>

<sup>9</sup> We further examined stability by recalibrating the time periods to the equivalents of weeks, and then days. A number of test runs with the weekly and daily calibrations

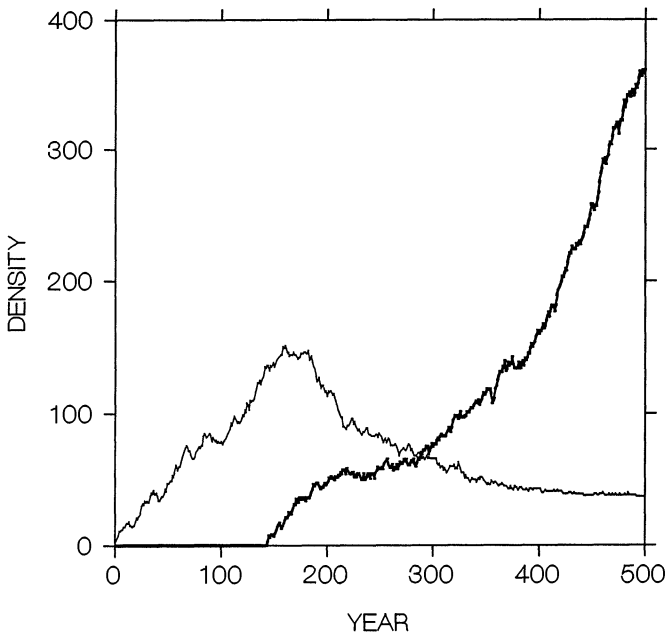


FIG. 1.—Realization of evolution of two organizational populations

## FINDINGS

Figures 1 and 2 illustrate the types of trajectories generated by the simulation. Both figures present plots of organizational density for the two competing populations *A* and *B* across the simulation period of 500 years. Both examples are from the set of runs where population *B* is structurally superior (set 1) and use identical parameter settings—differences in the two figures are the result of stochastic variation or chance.

In the realization shown in figure 1, population *A* initially grows steadily for 150 years or so, at which point it peaks at a density of roughly 150. It then declines gradually until the simulation's end. Population *B* emerges in this trial at about year 150 and grows rapidly at first, then slows, and finally grows very rapidly up to a final peak of about 350. Despite its eventual dominance of population *A*, the density of population *B* does not surpass that of *A* until almost 150 years after its emergence.

The realization for population *B* shown in figure 2 looks somewhat similar except that it begins earlier. (The peak of approximately 400 apparently represents the equilibrium density for the model with these

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showed no discernible substantive differences from the monthly calibrations. That is, system behavior remained similar under these fine-grained simulations.

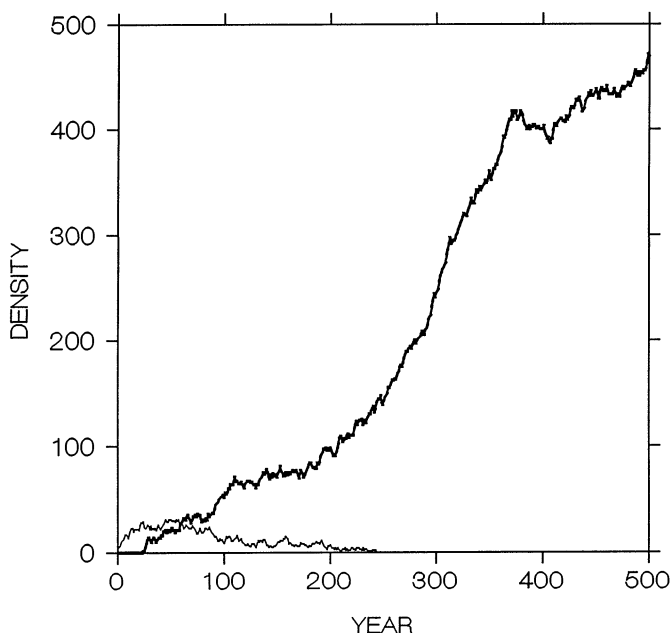


FIG. 2.—Another realization of evolution of two organizational populations

parameter settings.) Perhaps because of this earlier start of the dominant competitor, population *A* never develops much. After growing to a density of about 30 in year 50, *A* levels off, declines, and eventually disappears a bit after the 200-year point. Population *B* needs only about 30 years to dominate *A* numerically in this trial.

These two sample simulations illustrate the kind of stochastic variation in population growth processes that might generate path dependence in competitive struggles between populations. Because it is obviously silly to draw inferences from only two trials, we ran at least 100 trials of each experimental condition. The massive amount of data generated by these simulations limits us to reporting descriptive summary statistics for each experimental condition. Table 2 gives this information for the set of experiments with a structurally superior population *B* (set 1), table 3 does so for the set with structurally equal populations (set 2), and table 4 for those experiments when population *A* is set to be structurally superior (set 3).

Table 2 presents the outcomes of four experiments where the second population to emerge, population *B*, is structurally superior relative to the first population, *A* (set 1). The experiments differ in competitive intensity, showing progressively greater competitive interaction between

TABLE 2  
SIMULATION OUTCOMES FOR EXPERIMENTS WITH STRUCTURALLY SUPERIOR POPULATION *B* (SET 1)

| Experiment | <i>N</i> of Runs | $\delta_A$ | $\delta_B$ | $\eta_A$ | $\eta_B$ | % Trials<br><i>B</i> Dominates | Mean Time<br>until <i>B</i><br>Dominates* | % Trials<br><i>A</i> Disappears | % Trials<br><i>B</i> Disappears |
|------------|------------------|------------|------------|----------|----------|--------------------------------|-------------------------------------------|---------------------------------|---------------------------------|
| B1 .....   | 200              | -.010      | -.001      | .010     | .001     | 64                             | 621                                       | 33                              | 5                               |
| B2 .....   | 200              | -.030      | -.003      | .030     | .003     | 69                             | 416                                       | 62                              | 31                              |
| B3 .....   | 100              | -.060      | -.006      | .060     | .006     | 71                             | 257                                       | 70                              | 28                              |
| B4 .....   | 100              | -.100      | -.010      | .100     | .010     | 61                             | 179                                       | 61                              | 39                              |

\* Measured in simulated months.

TABLE 3  
SIMULATION OUTCOMES FOR EXPERIMENTS WITH STRUCTURALLY EQUAL POPULATIONS (SET 2)

| Experiment | N of Runs | $\delta_A$ | $\delta_B$ | $\eta_A$ | $\eta_B$ | % Trials<br>B Dominates | Mean Time<br>until B<br>Dominates* | % Trials<br>A Disappears | % Trials<br>B Disappears |
|------------|-----------|------------|------------|----------|----------|-------------------------|------------------------------------|--------------------------|--------------------------|
| AB1.....   | 100       | -.005      | -.005      | .005     | .005     | 27                      | 411                                | 3                        | 60                       |
| AB2.....   | 100       | -.010      | -.010      | .010     | .010     | 19                      | 521                                | 4                        | 85                       |
| AB3.....   | 100       | -.020      | -.020      | .020     | .020     | 12                      | 277                                | 6                        | 89                       |
| AB4.....   | 100       | -.030      | -.030      | .030     | .030     | 6                       | 51                                 | 6                        | 94                       |
| AB5.....   | 100       | -.060      | -.060      | .060     | .060     | 6                       | 21                                 | 6                        | 92                       |

\* Measured in simulated months.

TABLE 4  
SIMULATION OUTCOMES FOR EXPERIMENTS WITH STRUCTURALLY SUPERIOR POPULATION A (SET 3)

| Experiment | N of Runs | $\delta_A$ | $\delta_B$ | $\eta_A$ | $\eta_B$ | % Trials<br>B Dominates | Mean Time<br>until B<br>Dominates* | % Trials<br>A Disappears | % Trials<br>B Disappears |
|------------|-----------|------------|------------|----------|----------|-------------------------|------------------------------------|--------------------------|--------------------------|
| A1.....    | 100       | -.001      | -.005      | .001     | .005     | 9                       | 148                                | 4                        | 85                       |
| A2.....    | 100       | -.001      | -.010      | .001     | .010     | 5                       | 7                                  | 4                        | 94                       |
| A3.....    | 100       | -.003      | -.010      | .003     | .010     | 7                       | 64                                 | 4                        | 96                       |
| A4.....    | 100       | -.005      | -.010      | .005     | .010     | 17                      | 97                                 | 7                        | 89                       |
| A5.....    | 100       | -.007      | -.010      | .007     | .010     | 13                      | 338                                | 2                        | 91                       |
| A6.....    | 100       | -.005      | -.030      | .005     | .030     | 5                       | 1                                  | 5                        | 95                       |
| A7.....    | 100       | -.010      | -.030      | .010     | .030     | 1                       | 1                                  | 1                        | 96                       |
| A8.....    | 100       | -.020      | -.030      | .020     | .030     | 7                       | 27                                 | 3                        | 96                       |

\* Measured in simulated months.

populations in experiments B1 through B4. In a historically efficient world, one would expect that as competition intensifies, the more likely it is that the structurally superior population will dominate and the faster this outcome will obtain. Table 2 shows support for the second of these expectations (about speed of the process) but not the first (about dominance). As in our earlier simulations, the superior population dominates only 60%–75% of the trials, and this outcome is not a simple linear function of competitive intensity. In fact, the experiment with the most intense competition (B4) is the one where the inferior population *A* is most likely to dominate, showing up as the winner in over 38% of the trials.

For those trials where the structurally superior population *B* wins the competition, however, much of the system's behavior resembles a historically efficient process. This is seen clearly in the distributions of overtake times for *B* and the final joint distributions of density for *A* and *B*, which we have inspected.<sup>10</sup> Intensified competition leads to a faster overtake time for population *B*. It also increases the probability of elimination or competitive exclusion by either population.

Table 3 presents the simulation results for five experiments where the two organizational populations are structurally equal as competitors (set 2). Again, the experiments vary in the intensity of interpopulation competition. If efficiency alone were driving this process, one might predict that outcomes would be roughly equal among the populations. That is clearly not the case, however. In the vast majority of trials, the initial population, *A*, dominates the process. Population *B* manages to overcome *A*'s headstart an appreciable number of times only in the less intense competitive conditions—and even there *B* dominates with less frequency than did the inferior populations in the experiments of set 1 reported in table 2. So the timing of population entry and growth is apparently a strong force in determining these evolutionary outcomes.

Moreover, as with the set 1 experiments with *B* structurally superior, competitive intensity again exacerbates competitive exclusion of one or the other population. This reinforces and strengthens the conclusion about timing—not only does the first population dominate in these experiments, but it is also very likely to exclude its structurally equal competitor.

Table 4 shows the results of eight experiments where the first population to appear, population *A*, is structurally superior (set 3). If this system is historically efficient, population *A* will dominate, and given the above findings about timing of entry, it would not be unreasonable to expect *A* to win every competition—it is, after all, both first and structurally supe-

<sup>10</sup> Some of these distributions are shown in Carroll and Harrison (1993).

rior. Results show this not quite to be the case. Although population *A* does dominate in the vast majority of the trials in every experiment and it usually does manage to exclude population *B*, path dependence influences the outcome of the process 5%–15% of the time. Despite its disadvantaged entry order and its structural inferiority, population *B* still dominates the competition with nontrivial frequency.

How important are *B*'s entry time and *A*'s size at *B*'s entry in producing outcomes? Table 5 presents logistic regression estimates of simulation outcomes on variables measuring a population's competitive strength and these other two factors. The outcome measure is a binary variable signifying whether population *B* ever dominates the competition.<sup>11</sup> Because of their inherently different structures, a separate regression was run for each of the three different sets of experiments. Within a set, data for all the experiments were pooled. (So, e.g., set 1 contains 600 observations: 200 each for experiments B1 and B2 and 100 each for B3 and B4.) The first regression we estimated assessed only the effects of population competitive strength: It regressed the outcome variable on a set of dummy variables representing each experimental condition except an omitted one (represented by the intercept). A second regression included as independent variables the effects of *B*'s entry time and the effect of *A*'s size at *B*'s entry. For ease of comparison we do not present all the coefficients of the dummy variables. Rather, we present the summary measures of fit for both regressions and the coefficients associated with the timing and size variables in the second regression.

Comparing the measures of fit for the regression using only the strength-of-competition variables with those also using the timing and size variables demonstrates the importance of the latter in producing evolutionary outcomes. In all sets, adding the timing and size variables significantly improves the ability to predict the dominant population,<sup>12</sup> so the differences produced in the simulations by these randomly induced factors play a significant role in determining outcomes.

Between the two variables, *B*'s entry time and *A*'s size at *B*'s entry, the latter consistently shows the stronger effect on outcomes. Timing of *B*'s entry is nonsignificant, while *A*'s size when *B* enters always shows

<sup>11</sup> In a slightly different analysis we ran similar regressions on an outcome variable indicating *B*'s dominance at the end of the simulation. This analysis leads to similar conclusions. Another way to conduct this assessment would be to run regressions using the ratio of population *B*'s density to *A*'s (or to the total of *A* plus *B*) at the simulation's end. We believe that the approach reported in the table provides for a sharper focus on the question of primary theoretical interest.

<sup>12</sup> In the "*B* stronger" set of experiments (set 1), the variables measuring competitive strength do not even show a statistically significant relationship to the outcomes (see also Carroll and Harrison 1993).

TABLE 5  
LOGISTIC REGRESSION ESTIMATES OF SOURCES OF EVOLUTIONARY DOMINANCE

| SET OF EXPERIMENTS                   | SUMMARY MEASURE OF FIT                                          |                                                                | COEFFICIENT FOR <i>B</i> 's<br>ENTRY TIME <sup>b</sup> | COEFFICIENT FOR <i>A</i> 's SIZE<br>AT <i>B</i> 's ENTRY |
|--------------------------------------|-----------------------------------------------------------------|----------------------------------------------------------------|--------------------------------------------------------|----------------------------------------------------------|
|                                      | Model with Competitive<br>Strength Dummy Variables <sup>a</sup> | Model with Competitive Strength,<br>Timing, and Size Variables |                                                        |                                                          |
| Set 1— <i>B</i> superior .....       | 3.02 ( <i>df</i> = 3)                                           | 509.3 ( <i>df</i> = 5)                                         | .022                                                   | — .048*                                                  |
| Set 2— <i>A</i> and <i>B</i> equal.. | 27.5 ( <i>df</i> = 4)                                           | 271.0 ( <i>df</i> = 6)                                         | .069                                                   | — .178*                                                  |
| Set 3— <i>A</i> superior .....       | 24.9 ( <i>df</i> = 7)                                           | 335.6 ( <i>df</i> = 9)                                         | .113                                                   | — .217*                                                  |

NOTE.—The dependent variable for all trials is a dummy variable indicating whether *B* ever dominates *A*, as measured by population density.  
<sup>a</sup> Summary used is chi-square for  $-2$  log-likelihood ratio.  
<sup>b</sup> In order to facilitate comparison, the units for this variable have been divided by 100.  
\*  $P < .05$ .

a strong significant effect. Path dependence in this process, then, seems to depend most on the pattern of *A*'s growth.<sup>13</sup> That is, if *A*'s density has accelerated rapidly by the time of *B*'s entry, then *B* is less likely to dominate the competition, whatever its inherent competitive strength.

Table 6 presents ordinary least squares regressions of population *B*'s takeover or dominance time on the competitive strength, timing, and size variables for the cases in which *B* dominates. These estimates reinforce the above conclusions: The timing and size variables significantly increase explanatory power, especially the extent of population *A*'s growth, which appears to be the more important factor.

How general are these findings? Table 7 presents the results of a more general set of simulations with five competing populations (set 4). The simulation starts with a single population, *A*, which evolves according to the same density-dependent specifications used above. Subsequent populations *B*, *C*, *D*, and *E* emerge randomly and in order. Each successive population is governed by its own density-dependent processes of legitimation and competition but is also set to be structurally superior to all previous populations.<sup>14</sup> So population *E* is structurally the strongest of all and should dominate in a historically efficient world. The top panel of table 7 shows the exact structural relationships of the populations to each other—it depicts what is commonly referred to as the competition matrix.<sup>15</sup> (We give values for the competition matrix of founding rates; the mortality rate competition matrix is identical except that the signs of

<sup>13</sup> *B*'s entry time plays an indirect role in the sense that the later *B* enters, the more opportunity *A* has to reach its take-off point. The regressions show, however, that statistically it is *A*'s density when *B* enters that is the major factor.

<sup>14</sup> One reviewer raised questions about the substantive meaning of this setup, asking for a distinction between progressive new forms that improve on a basic technology and those that supplant an old technology with an entirely new way of doing things. As we interpret the model with the theory of legitimation and competition, the crucial distinction is between forms that require establishment of social taken-for-grantedness and those that do not (either because they are already taken for granted or because they are not perceived as being different from a previously established form). That is, the framework depicts a progressive sequence of organizational forms where each form cannot benefit from the legitimation of earlier populations and thus must undergo its own process of legitimation. It seems reasonable to think that populations using radically new technologies will be more likely to face this constraint than those using refinements of an existing technology, although social legitimation processes need not behave reasonably all the time.

<sup>15</sup> This is the  $\delta_{ij}$  matrix in the founding rate model:

$$\lambda_i = \exp[\beta_{i0} + \beta_{i1}N_i(t) + \beta_{i2}N_i^2(t) + \sum_{i \neq j} \delta_{ij}N_j(t)].$$

An analogous term,  $\sum \eta_{ij}N_j(\mu)$ , is used in the mortality rate model. For these experiments,  $\eta_{ij} = -\delta_{ij}$ .

TABLE 6  
ORDINARY LEAST SQUARES REGRESSION ESTIMATES OF SOURCES OF DOMINANCE TIME OF POPULATION *B*

| SET OF EXPERIMENTS                   | SUMMARY MEASURE OF FIT                                          |                                                                |        | COEFFICIENT FOR <i>B</i> 's<br>ENTRY TIME <sup>b</sup> | COEFFICIENT FOR <i>A</i> 's SIZE<br>AT <i>B</i> 's ENTRY |
|--------------------------------------|-----------------------------------------------------------------|----------------------------------------------------------------|--------|--------------------------------------------------------|----------------------------------------------------------|
|                                      | Model with Competitive Strength<br>Dummy Variables <sup>a</sup> | Model with Competitive Strength,<br>Timing, and Size Variables |        |                                                        |                                                          |
| Set 1— <i>B</i> superior .....       | .089                                                            | .593                                                           | .056   | .109*                                                  |                                                          |
| Set 2— <i>A</i> and <i>B</i> equal.. | .166                                                            | .628                                                           | — .009 | .226*                                                  |                                                          |
| Set 3— <i>A</i> superior .....       | .230                                                            | .454                                                           | .001   | .162*                                                  |                                                          |

NOTE.—The dependent variable for all trials is the time in months from the start until *B* achieves numerical dominance.

<sup>a</sup> Summary measure used is  $R^2$ .

<sup>b</sup> In order to facilitate comparison, the units for this variable have been divided by 100.

\*  $P < .05$ .

TABLE 7  
SIMULATION OUTCOMES FOR EXPERIMENTS WITH MULTIPLE POPULATIONS (SET 4)

| A. EFFECT OF POPULATION DENSITY ON FOUNDING RATES |       |       |       |       |       |
|---------------------------------------------------|-------|-------|-------|-------|-------|
| DEPENDENT POPULATION                              | A     | B     | C     | D     | E     |
| A .....                                           | 0     | -.008 | -.012 | -.016 | -.020 |
| B .....                                           | -.004 | 0     | -.008 | -.012 | -.016 |
| C .....                                           | -.003 | -.004 | 0     | -.008 | -.012 |
| D .....                                           | -.002 | -.003 | -.004 | 0     | -.008 |
| E .....                                           | -.001 | -.002 | -.003 | -.004 | 0     |

| B. NUMBER OF TRIALS WON              |                 |                 |                 |                 |                 |
|--------------------------------------|-----------------|-----------------|-----------------|-----------------|-----------------|
| MULTIPLIERS OF<br>COMPETITION MATRIX | Population<br>A | Population<br>B | Population<br>C | Population<br>D | Population<br>E |
| 1 .....                              | 67              | 25              | 24              | 28              | 106             |
| 2 .....                              | 77              | 18              | 17              | 36              | 102             |
| 3 .....                              | 90              | 26              | 23              | 32              | 79              |
| 4 .....                              | 106             | 36              | 28              | 25              | 55              |
| 5 .....                              | 128             | 25              | 26              | 16              | 55              |

NOTE.—Panel A shows the coefficients of the population density variables on the founding rates. The set of coefficients is commonly referred to as a competition matrix (see nn. 8 and 15). Each row of panel B shows the distribution of outcomes for 250 trials at the specified level of competitive intensity (given by the multiplier of the competition matrix).

the coefficients are reversed.) The lower panel of the table gives the distribution of dominance outcomes by population at simulation end. Each row shows the number of trials won (meaning numerical dominance at the end of the simulation) by the various populations out of a total of 250 trials. Successive rows report separate simulation trials where competitive intensity was increased by multiplying the competition matrix by integer factors. For instance, the last row shows simulation outcomes for experiments with the greatest competitive intensity, where the values of the competition matrix are five times the values shown in the top panel of the table.

The bottom panel of Table 7 shows that many of the conclusions from the two-population simulations (sets 1–3) hold for this more general case as well. In the first group of experiments listed, those with a competition matrix multiplier of unity, the structurally superior competitor, population *E*, wins the most trials. However, the percentage of trials *E* wins is less than half, 106 out of 250. Moreover, in those trials where *E* does not win, the most likely winner is population *A*, the structurally inferior competitor. Even more striking is the shift in the distribution of winners as competition intensifies. As the competition matrix multiplier increases, the percentage of trials where *E* wins drops almost by half (55 out of 250

TABLE 8  
SIMULATION OUTCOMES FOR EXPERIMENTS WITH MULTIPLE POPULATIONS (SET 4)

| A. EFFECT OF POPULATION DENSITY ON FOUNDING RATES |        |       |       |       |       |
|---------------------------------------------------|--------|-------|-------|-------|-------|
| DEPENDENT POPULATION                              | A      | B     | C     | D     | E     |
| A .....                                           | 0      | -.008 | -.016 | -.032 | -.064 |
| B .....                                           | -.004  | 0     | -.008 | -.016 | -.032 |
| C .....                                           | -.002  | -.004 | 0     | -.008 | -.016 |
| D .....                                           | -.001  | -.002 | -.004 | 0     | -.008 |
| E .....                                           | -.0005 | -.001 | -.002 | -.004 | 0     |

| B. NUMBER OF TRIALS WON              |                 |                 |                 |                 |                 |
|--------------------------------------|-----------------|-----------------|-----------------|-----------------|-----------------|
| MULTIPLIERS OF<br>COMPETITION MATRIX | Population<br>A | Population<br>B | Population<br>C | Population<br>D | Population<br>E |
| 1 .....                              | 47              | 13              | 18              | 37              | 135             |
| 2 .....                              | 59              | 12              | 27              | 38              | 114             |
| 3 .....                              | 44              | 23              | 20              | 42              | 121             |
| 4 .....                              | 60              | 18              | 23              | 40              | 109             |
| 5 .....                              | 77              | 33              | 29              | 42              | 74              |

NOTE.—Panel A shows the coefficients of the population density variables on the founding rates. The set of coefficients is commonly referred to as a competition matrix (see nn. 8 and 15). Each row of panel B shows the distribution of outcomes for 250 trials at the specified level of competitive intensity (given by the multiplier of the competition matrix).

trials) and the corresponding percentage for *A* almost doubles (to 128 out of 250). In the experiment with the most intense competitive relations between populations, those with a matrix multiplier of five, the weakest competitor, population *A*, wins over half of the trials.

Table 8 presents similar findings for the same type of simulation but with different parameter settings in the competition matrix. Relative to table 7, these settings reflect greater structural superiority of each successive population. That is, the increase in the structural competitive advantage for each new population is greater than in the previous simulations. Here the outcomes for *E* show a system slightly more efficient. However, the same general patterns in outcomes found above are replicated. Most notably, as competition intensifies, the likelihood of the structurally inferior competitor (population *A*) prevailing increases as well. These findings increase our confidence in the generality of the earlier simulations.<sup>16</sup>

<sup>16</sup> Our confidence in the findings is further enhanced by the results of a sensitivity analysis of the simulation models. In this analysis, experiments were rerun with a change of 25%–33% in a major parameter (quadratic density terms were dealt with in pairs). The experiments were rerun for another 100 trials. Experiments representing the endpoints of the range for each set were rerun: B1 and B4, AB1 and AB4, and

## DISCUSSION

Our goal here was to make a structured assessment of the consequence of assuming historical efficiency in organizational evolution. We used as our basic framework the empirically supported ecological model of density-dependent legitimation and competition. We focused on a version of this model with two or more competing populations where the timing of all but the first population's appearance is random. We designed experiments that varied the structural superiority of the populations—and thus the expected equilibrium outcomes—and the intensity of competition between them. Using computer simulations based on empirical estimates of model parameters, we addressed three basic questions concerning (1) the frequency with which the structurally superior population actually dominates, (2) the time it takes for a population to achieve a position of dominance, and (3) the variability in the time to achieve dominance.

At a general level, the findings show clearly that assuming historical efficiency in organizational evolution can be problematic. Outcomes that appear irrational from the point of view of a population's structural superiority or inferiority were observed in a variety of experimental conditions. These outcomes can be explained in the simulations as path-dependent consequences of random variations in population growth before the emergence of competing populations.

In more specific terms, we found that both previous growth of early populations and entry time of later populations strongly affected outcomes. Early populations that grew fast showed remarkable resilience in warding off later but structurally superior competitors. Relatedly, subsequent competitors that entered the competitive arena quickly were better able to exert their structural superiority and to dominate. Although other interpretations may also apply, the theoretical mechanism in the model hypothesized to be responsible for these effects is the legitimation or social taken-for-grantedness of the earlier organizational form. That is, the social acceptance of a particular organizational form may embed the population defined by it so strongly in the social fabric of its environment as the “right way” to accomplish a particular task or goal that it renders

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A4. Parameter variations were made systematically in both up and down directions and each major model parameter was varied. In general, substantive conclusions do not change within these additional experiments. Population *B* still dominated in a substantial proportion of the trials in each experiment. For example, with  $\alpha_3$  set to .004 (so that the experiments had parameter settings identical to those found in the San Francisco newspaper study), population *B* dominated in 56% of the trials in experiment B1 and in 41% of the trials in experiment B4 (cf. table 2); in the multiple population experiments in set 4 (table 7), population *A* dominated more often and population *E* less often with  $\alpha_3 = .004$ , and the proportion of *A*'s dominance still increased with increases in the competition matrix multiplier.

technically superior alternatives unthinkable and thus unviable.<sup>17</sup> Because of such legitimation, a population of, say, 1,000 established organizations may outlast a technically superior population of, say, 20 organizations. The eventual dominance of automobile manufacturers using gasoline-powered internal combustion engines over those using steam- and electric-powered engines in the early part of the automobile industry is by some accounts the result of such a socially constructed process.

In our simulations, entry time of all but the initial population (and, by inference, population density of the initial population at the time of a competitor's entry) was simulated as a random factor. In the real world, of course, a firm's entry time is frequently a calculated decision. We do not think that this fact undermines our results—in fact, it strengthens them because organizational strategists can likely do better in making such calculations than random action allows. More generally, this finding implies that theories of strategic management that focus on entry processes (e.g., Porter 1980) should not be neglected by those theories (e.g., Teece et al. 1990; Grant 1991) that attend to organizational capabilities or resources.

We also found that in multipopulation competitions more intense structurally induced competition gave advantages to both the strongest and weakest populations, with the advantage shifting more to the first (and weakest) population as intensity rose. This pattern likely emerged because these contexts created greater instability in the system as a whole by accelerating the interaction dynamics—many populations got competitively excluded at early states. The finding complements May's (1974) classic discovery that complexity begets instability in models of this kind.

The findings strike some with whom we have discussed them as surprising. Given analytical work on related nonlinear Polya processes, however, we believe they are credible.<sup>18</sup> The findings are also generally consistent with empirical studies of technological evolution, which show long lag times between the emergence of a new superior technology and its eventual dominance (see Cooper and Schendel 1979).

Williamson (1993), in considering the findings of our simulations as well as other apparently path-dependent phenomena, has suggested that outcomes of the kind we observed here may not be important because they are "irremediable." For him, remediable inefficiencies are "those conditions for which a feasible alternative can be described which, if introduced, would yield net gains" (p. 140). Although his comments might be interpreted in various ways as it pertains to our modeling framework, it seems to us that for an organizational form to be "structurally

<sup>17</sup> Alternatively, such embedding may create network externalities that tilt the economics of the situation in favor of the earlier form.

<sup>18</sup> The broadly similar work by Kauffman (1993, pp. 270–76) also reinforces our confidence in the findings.

superior” as we have defined it, the form *must* yield net gains in terms of the underlying evolutionary process if the process is to be considered efficient. That is, structural superiority, as we have defined it, in fact implies remediability. Yet path-dependent outcomes are apparent.

So that our findings are not overinterpreted, we think it is important to emphasize that the systematic component of the model we used in our simulations did account for a large percentage of observed outcomes. However, these were not so common as to justify the unthinking use of the assumption of historical efficiency. In fact, our findings suggest that matter-of-fact use of this assumption might lead to incorrect inferences about competition as much as one-third of the time in real-world settings when complete competitive histories are used. The error rate is likely higher for censored data.

We stress the possibility of this problematic condition, not its inevitability. We have no doubt that it is possible to rerun these simulations with different parameter settings and different population relationships so as to produce results that are “better” for historical efficiency. Such demonstrations would be beside the point in our opinion, especially if they used unrealistic parameter settings. As long as true parameters are unknown in the real world, the dangers of historical efficiency lurk potentially behind every analysis assuming it.

We also note that our study has considered only one of a variety of outcome variables relevant to competition between organizational forms. We chose number of organizations because of its importance to many sociological questions and because a well-established model for its long-term evolution was available. It remains an open question as to whether historical efficiency is a plausible assumption for other important competitive outcomes such as market share, average size of organizations, and the like.

Looking past the problems of historical efficiency, the simulation findings raise thorny issues for empirical research on organizational evolution at least as it pertains to numbers of organizations. If “inferior” populations can sometimes dominate “superior” ones, then how can researchers assess the causes of dominance in any particular historical instance? One strategy would be to assess analytically the specific characteristics of each organizational form independent of historical experience.<sup>19</sup> In many

<sup>19</sup> Studies of colonization in bioecology (e.g., MacArthur and Wilson 1967) suggest that a broad definition of performance should be considered in making such assessments. In particular, organizational characteristics associated with the fast proliferation of a form may be more important in explaining early dominance than those characteristics associated with narrow conceptions of efficiency. That is, organizational forms that can be easily copied may be able to achieve numbers sufficient to overcome the efficiency advantages of competing forms that are not easily duplicated. In ecology, this is the classic distinction between so-called r-strategists and K-strategists (Hannan and Freeman 1989).

cases, it would be difficult to find data appropriate to making such an argument, especially for organizational forms appearing well back in history. We also question how objective such an analysis could be, since knowing the outcome of the historical struggle is likely to color a researcher's view of the data.

To discern contexts where path dependence may have affected organizational population evolution, one clue would be the presence of organizational forms with positive feedback mechanisms. The most prevalent of these are likely density-dependent legitimation, learning-by-doing, economies of scale, and network externalities. Many of these can be identified and have their strength assessed with established methods and available data. In general, the more such mechanisms are present and the greater their strengths, the more likely organizational evolution is path dependent.

What looks to be the best strategy to avoid mistaken inferences, however, would be to examine outcomes across a number of similar contexts. As Cohen (1976, p. 393) aptly comments in recognizing similar problems of inference in bioecology, "The variation in an ensemble of replications must become an object of study when the limit random variable of an individual replication is nondegenerate." The value of this approach is readily demonstrated by reexamining the simulations and thinking of the multiple runs across specific parameter settings as ensembles (referred to as sets throughout the paper). In all but a very few of these ensembles, the structurally superior population dominates the greatest proportion of trials (note also that the exceptions involve the sets of experiments with strongest competitive intensity). Therefore, a researcher examining outcomes across a number of contexts and looking for central tendencies would be much less likely to make an incorrect inference.

Calling for comparative research, as the suggestion to examine sets of similar context does, is an old saw for sociology. What is different here is the suggestion that comparisons should be made across populations and environments, not single organizations. Successful comparison of this kind requires the use of comparable models and measures, a nontrivial demand on empirical research. Work in organizational ecology shows, however, that such research is possible.

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