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A Systems Methodology for Measuring Operational Organization Effectiveness: A Study of the Original Equipment Computer Manufacturing Industry, 1948 to 2001

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A SYSTEMS METHODOLOGY

FOR MEASURING OPERATIONAL ORGANIZATION EFFECTIVENESS:

A STUDY OF THE ORIGINAL EQUIPMENT COMPUTER

MANUFACTURING INDUSTRY 1948 TO 2001

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ABSTRACT

A SYSTEMS METHODOLOGY FOR
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Optimizing operational organizational effectiveness is the central, although often unstated, goal of engineering management and systems engineering research and applications. Two fundamental problems remain to be addressed in pursuit of this goal. First, despite over fifty years of research in various disciplines, there is still no universally accepted definition of organizational effectiveness. Second, no methodology exists to identify the domains, dimensions, and determinants of operational organizational effectiveness and dynamically model operational organizational effectiveness within a given population.

This research synthesizes a systems engineering methodology for identifying the domains, dimensions, and determinants of and dynamically modeling operational organizational effectiveness for an identified population. First, the methodology takes the concept of the niche from ecological theory as its definition of effectiveness. Specifically, an organization that is able to sustain a real nonnegative growth rate in its niche dimension under a set of competitive conditions is defined as being effective. Next, the methodology integrates organizational ecology and open systems theories, principles, and models into a unified systemic model of environmental and organizational domains and dimensions that provide the structure for research into the determinants of organizational effectiveness. Based on this model, the methodology gathers observable data on hypothesized determinants of effectiveness and applies event history survival and effectiveness analyses to identify the statistically significant determinants. The methodology's final two steps are to construct and validate a dynamic simulation model of organizational effectiveness based on the identified determinants and to perform sensitivity analyses. Model construction provides information on sources of underlying

organizational effectiveness dynamics not identified in the significant covariates effectiveness model. Sensitivity analyses provide information on potential internal actions an engineering manager may take to maintain or increase his respective organization's effectiveness and the potential reactionary changes in dynamic patterns of population behavior resulting from those actions.

Modeling of one organizational population, the original equipment computer manufacturing industry, indicated that the systemic model and methodology are sufficient for identifying significant covariate determinants of organizational effectiveness and modeling structural and instantaneous rate effectiveness trajectories.

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CHAPTER I

INTRODUCTION

1.1 Background

The construct of organizational effectiveness is deeply embedded in all aspects of engineering management and systems engineering research and applications. Indeed, it is the, often unstated, goal, in some form or other, to maximize or optimize some aspect of or overall organizational effectiveness. Organizational theorists Goodman and Pennings argued that "organizational effectiveness is not only a central theme in the practical sphere; it is a central theme in organizational theory as well. In fact, it is difficult to conceive of a theory of organizations that does not include the construct of effectiveness . . ." (2). In their respective works, French, Bell, and Zawacki and Kilmann, Pondy, and Slevin claimed that improved organizational effectiveness is the goal of organizational development and design. Soft systems theorist Checkland measured the success of organizational transformation functions against three criteria: 1) Efficacy—the transformation means accomplish the desired outcome; 2) Efficiency—the transformation means utilize the minimum of input resources per unit of output; and 3) Effectiveness—the transformation means are the right combination of activities to accomplish long-term goals (*Soft Systems Methodology in Action* 39). Viable systems theorist, Beer set forth a criterion of effectiveness as organizational ability to adapt to environmental variety while simultaneously maintaining internal coherence (*The Heart of Enterprise* 101, 393). In a content analysis of Engineering Management literature for the period 1993 through 2000, Kern found that four of five major categories which dominated research were related to organizational effectiveness: management skills 38%, leadership skills 24%, technical skills 16%, and people skills 9%. The remaining category of industry specific related articles accounted for only 13% of all research.

Through direct inquires and factor analytic methods, organizational theorists and researchers have attempted to develop taxonomies and models of organizational

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The MLA Handbook was used as the model for reference format and placement of figure and table titles.

effectiveness. No single method or analysis, however, has been successful in identifying the domains, dimensions, and determinants of effectiveness. Some research uncovered effectiveness determinants ignored by others, other research was conducted on differing levels of analysis, and other research traded off different dimensions based on the selected perspective. Jointly, all research produced conflicting results. Attempts to unify research results have produced statistically insignificant results for predictor variables found to be significant in prior studies. Most limiting to application, however, derived effectiveness models were constructs of concepts (i.e. flexibility, control, stability, employee moral, etc.) from the theorists and researchers perspectives that did not translate readily into domains, dimensions, and determinants that could be applied by managers and stakeholders to assess operational effectiveness of differing organizational structures in differing competitive environments.

Initially, open systems theorists and researchers developed deterministic and stochastic systemic organizational models. Subsequently, they derived organizational models based on biological and cybernetic analogies of organizational processes. This class of models has been termed "hard systems methodologies." In the last quarter of the twentieth century, other open systems theorists developed organizational models based on social analogies, which have been termed "soft systems methodologies." Other branches of open systems theorists and researchers have sought to integrate or unify systems methodologies and models. Socio-technical systems researchers sought to optimize organization technical and social subsystems jointly to achieve some future "ideal" organization given environmental constraints. Systems dynamics theorists and researchers integrated aspects of all systems models into computer simulations with the goal of assisting decision makers in predicting the effectiveness of differing organizational structures and actions within differing competitive environments. Critical systems theorists have attempted to develop a universal or meta-systems methodology that unifies open systems theory. Open systems theory has been criticized, however, for 1) ignoring the ecological effects among systems of systems, 2) not relating theory to the observable variation in organizational structures, 3) not fully accounting for the multi-cephalous nature of organizations, 4) ignoring findings from organizational theory that are not accounted for in open systems theory, and 5) being too narrowly focused at the systems level four of Boulding's hierarchy of complexity when organizations exist across all eight levels (Pondy and Mitroff). More important for the purpose of this research, open systems theories and models have not addressed the issue of mapping the operational domains, dimensions, and determinants of organizational effectiveness.

Organizational ecology theorists and researchers have focused on the demographic dynamics of organizational population densities in order to understand the birth, transformation, and demise of organizational forms. Whereas organizational and open systems theorists and researchers consider only organizational adaptation to changing environmental conditions, organizational ecologists consider the effects of environmental selection and random transformation processes. Organizational populations are analyzed at three levels of complexity: 1) the "demography of organizations" or the vital rates of founding, merger, absorption, and demise of organizations within a population; 2) the "population ecology of organizations" or the links of vital rates among populations; and 3) the "community ecology of organizations" or how the interactions among populations affect the viability of the community as a whole (Hannan and Freeman *Organizational Ecology* 13-14). Given their ecological framework, organizational ecologists consider organizations themselves as "black boxes" and, accordingly, have not considered the operational domains, dimensions, and determinants of effectiveness of individual organizations.

Even with all of the research into organizational effectiveness in the various disciplines, there is still no universally accepted definition of effectiveness and no agreement as to the operational domains, dimensions, and determinants of organizational effectiveness. Engineering managers, systems engineers, and organizational stakeholders are still unable to assess the operational determinants of organizational structures and processes that predict with confidence organizational actions which will improve the probability of continued viability let alone improved effectiveness under dynamic competitive environmental selection and random transformation processes. Despite the difficulties encountered, Cameron and Whetten note that there are "theoretical, empirical, and practical reasons" to pursue research in organizational effectiveness. From the theoretical perspective, "the construct of organizational effectiveness lies at the very center of all organizational models. . . . the nature of organizations have embedded in them notions of the nature of effective organizations." From the empirical perspective, "organizational effectiveness is the ultimate dependent variable in organizational research. The need to demonstrate that one structure . . . is better in some way than another makes the notion of effectiveness a central empirical issue." From the practical perspective, "individuals are continually faced with the need to make judgments about the effectiveness of organizations" in order to decide which organizational forms should be supported and propagated as most capable of benefiting them personally and society as a whole (1-2).

From a system's perspective, the integration of open systems and organizational ecology principles and models provides a holistic framework for extending research into the operational domains, dimensions, and determinants of organizational effectiveness. Organizational ecology theorists recognize that structural causal factors of organizational effectiveness are not readily observable. Internal organizational structures and processes are often concealed, and dynamic causal environmental forces are not easily measured. Thus, organizational ecologists rely on a strategy of building dynamic models of vital rates and niche widths of populations of organizational forms from observable features (founding, merger, absorption, and demise) that are comparable over time and from observable changes in qualitative environmental contexts. This approach has allowed organizational ecologists to build dynamic models of organizational survival in response to environmental competitive and selection forces not previously considered by organization or open systems theorists and researchers. Conversely, through Beer's Viable System Model (VSM) and socio-technical systems methodology, the open systems framework provides a recursive, cybernetic structure that allows the linkage of environmental competitive and selection forces to observable features of organizational knowledge (policy), decision (intelligence and control), and social and technical structures (coordination and production). The VSM's recursive system theorem implies that organizational populations and communities of populations themselves must be viable systems and that hypothesized organizational determinants can be added to ecological competition models as covariates to create integrated models of observable domains, dimensions, and determinants of operational organization effectiveness.

1.2 Purpose of the Research

The general strategy of this research was to integrate organizational ecology and open systems theories, principles, and models into a unified framework with the goal of extending those theories and models into the research of the domains, dimensions, and determinants of operational organization effectiveness. Applying this strategy, the purpose of this research was to investigate the relationships among environmentally determined, observable dynamic vital rates due to selection forces on an organizational population, the original equipment computer manufacturing industry, and observable organizational structural features of knowledge creation of the policy function, joint adaptation and control of the intelligence and control functions, and the efficiency of the socio-technical subsystem structures as determinants of organizational effectiveness.

1.3 Research Question, Premises, and General Hypotheses

The central qualitative question of this research was whether or not organizational ecology and open systems theories and models could be unified to provide a systemic model of and methodology for measuring operational organization effectiveness. The question is derived directly from the observation that integration of organizational ecology's theory of environmental selection as an optimization process (Hannan and Freeman *Organizational Ecology* 19), the Viable Systems Model's Recursive System Theorem (Beer *The Heart of the Enterprise* 118) as the cybernetic linking process, and socio-technical systems methodology of joint internal optimization (Taylor and Felten 4-5) as the adaptive processes yields a systemic model of environmental and organizational domains and dimensions of effectiveness. Likewise, the integration of organizational ecology's approach of building dynamic models of vital rates and niche widths of organizational populations with systems dynamics approach to structural modeling yields a systemic methodology for measuring dynamic operational organization effectiveness.

The fundamental premises of these three research perspectives were combined in this research into a definition of organizational effectiveness. From organizational ecology, Hannan and Freeman (*Organizational Ecology* 19-20) argue:

> Natural selection, as actually used in evolutionary population biology, serves mainly as an *optimization process*. Evolutionary population biologists wish to provide a theoretical explanation of observed cross-sectional patterns in terms of some underlying mechanism. They invoke natural selection as the optimizing principle that selects one, perhaps a few, outcomes from the broad range of outcomes that might be consistent with the genetic transmission mechanism. Thus, a . . . possible definition of evolutionary theory is a theory of change that depends on the maximization of fitness . . . .
>
> With regard to the first meaning of the term—evolution is a factual statement about chains of descent—we do describe organizational change as evolutionary. In particular, we reject the view that the diversity of organizational structures at any time reflects only recent adaptations of these organizations in favor of the view that diversity reflects a long history of foundings and disbandings of organizations with fairly unchanging structures.
>
> Our views on the . . . aspect of evolutionary argument, that natural selection is an optimization process and that cross-sectional patterns can be explained as the outcomes of such a process . . . . In fact we do think that selection in organizational populations is systematic, that various kinds of organizations differ in their survival chances, and that selection capitalizes on such differences. To argue otherwise implies that there is no disciplined way to relate environmental events to changes in organizational populations.

This research accepted as a fundamental premise Hannan and Freeman's argument that the effects of environmental selection and random transformation processes are jointly an optimization process that result in maximization of competitive fitness.

This research also accepted as a second fundamental premise the open systems view that organizations operating under environmental selection and random transformation processes adapt to and seek to minimize the impact of environmental variety on their survival chances. Beer's Recursive System Theorem maps the cybernetic linking process through which the counterbalancing forces of environmental selection and organizational adaptation dynamically interact. The Recursive System Theorem is stated formally as follows:

> In a recursive organizational structure, any viable system contains, and is contained in, a viable system (*The Heart of Enterprise* 118).

The Recursive System Theorem implies that competitive environments are themselves meta-organizational forms and that, correspondingly, ecological theories and models of organizational population dynamic processes can be extended and applied to the measurement of subsystem populations within organizations.

The third fundamental premise of this research is that organizations are proactive, not just reactive, agents in their adaptation to environmental selection forces. The socio-technical systems methodology of joint optimization (Taylor and Felten 4-5) implies that organizations not only seek to minimize the impact of environmental variety on their survival chances, but also they seek to maximize their survival chances by influencing environmental selection processes. They seek maximization of survival chances through the establishment of and work toward achievement of some future "ideal" organizational structure and outcome within given environmental selection forces.

From these three premises, this research defines organizational effectiveness as an organization's ability to adapt its core knowledge, intelligence and control, and socio-technical subsystems to environmental selection variety while simultaneously maintaining and improving internal coherence toward a defined future state (the "ideal" future structure) as it takes collective action toward the establishment, maintenance, and expansion of its competitive niche width (the "ideal" future outcome).

Since the ecological dynamics of the organizational form investigated herein have not been established previously, this research first establishes the population's environmental dynamics of entry and demise (disbanding, merger, or acquisition) against four density dependence theorems proposed by Hannan and Carroll (44-47). Theorems 1 and 2 establish the response of founding rates to population density.

T1: Density dependence in founding rates is nonmonotonic. At low density the marginal effect of density increases the founding rate at a *decreasing* rate, but at high density the marginal effect of density decreases the founding rate.

T2: Density dependence in founding rates is nonmonotonic. At low density the marginal effect of density increases the founding rate at an *increasing* rate, but at high density the marginal effect of density decreases the founding rate.

Theorems 1 and 2 are alternate theories, because prior research indicates that different populations in different environments exhibit differing founding rate trajectories. Determination of the applicable theorem for a given organizational population is made on the basis of the characteristics of the distribution that best fits the population's founding rate trajectory. Both Theorems, however, state that the overall relationship between the founding rate and density graphically takes the shape of an inverted U. Theorems 3 and 4 establish the response of mortality rates to population density:

T3: Contemporaneous density dependence in the mortality rate is nonmonotonic. At low density, the mortality rate declines with increases in density, but at high density the mortality rate increases with increases in density.

T4: The mortality rate of organizations at time t is proportional to the density at time f of their founding.

Theorem 3 states that the overall relationship between the contemporaneous mortality rate and contemporaneous density graphically takes a U shape. Theorem 4 assumes a frailty period of only the first year with proportionality of the mortality rate to density at time of founding thereafter. In the original equipment computer manufacturing industry, the frailty period appeared to last up to approximately ten to fifteen years. This implies that the effect on the mortality rate of density at time of founding is an inverse rather than proportional relationship. Thus, this research statistically tested for an inverse relationship between the mortality rate and density at time of founding.

The above theorems provide the basis for following population and subpopulation level survival and effectiveness hypotheses posed by this research. Hypotheses H1-a, H1-b, and H1-c are direct tests of Theorem 3 at the population, cohort, and region levels.

H1-a: Organizational survival times are nonmonotonically related to population density.

H1-b: Organizational survival times are nonmonotonically related to the density within its respective cohort.

H1-c: Organizational survival times are nonmonotonically related to the density within its respective region of entry.

At the time of this research, no theories existed concerning the behavior of effectiveness times, either monotonic or nonmonotonic, in relation to contemporaneous density. Thus, in this research the contemporaneous density dependence of effectiveness times was estimated as a monotonic function.

H1-d: Organizational effectiveness times are inversely related to contemporaneous population density.

H1-e: Organizational effectiveness times are inversely related to contemporaneous cohort density within its respective cohort.

H1-f: Organizational effectiveness times are inversely related to contemporaneous region density within its respective region of entry.

Hypotheses 2-a, 2-b, and 2-c are direct tests of Theorem 4 at the population, cohort, and region levels.

H2-a: Organizational survival and effectiveness times at time t are inversely related to population density at respective times e of entry.

H2-b: Organizational survival and effectiveness times at time t are inversely related to its cohort's density at respective times e of entry.

H2-c: Organizational survival and effectiveness times at time t are inversely related to its region's density at respective times e of entry.

This research also considered the relationships between observable, organizational structural attributes and organizational survival and effectiveness times. Four organizational structural hypotheses were tested.

H3: Organizational survival and effectiveness times are statistically different for different organizational types.

H4: Organizational survival and effectiveness times are statistically different for different organizational structures.

H5: Organizational survival and effectiveness times are statistically different for different organizational cohort groups.

H6: Organizational survival and effectiveness times are statistically different for different geographic regions of entry.

The seventh hypothesis considers the effects of total market size (the population niche width) on organizational effectiveness time.

H7: Organizational effectiveness times increase with increases in the population's market size niche.

The central hypotheses of the relationships between observable, systemic organizational variables and organizational effectiveness times are as stated below.

H8: Organizational effectiveness times increase with increases in contemporaneous organizational market share (niche dimension).

H9-a: Organizational effectiveness times increase with increases in the contemporaneous level of information technology knowledge creation (policy).

H9-b: Organizational effectiveness times decrease with increases in the contemporaneous level of "other" knowledge creation (policy).

H10: Organizational effectiveness times increase with increases in the contemporaneous number of new products released annually (joint adaptation and control).

H11: Organizational effectiveness times increase with increases in contemporaneous annual dollar volume earnings per employee (socio-technical efficiency).

This research also considered the relationships between observable, environmental selection variables and organizational effectiveness times. Two environmental selection hypotheses were tested.

H12: Organizational effectiveness times increase with increases in contemporaneous home market Gross National Product.

H13: Organizational effectiveness times increase with increases in the total contemporaneous Gross National Product of the world regional markets in which respective organizations competed.

1.4 Delimitations of the Research

The first delimitation of this research is that it was conducted from an integrated organizational ecology and open systems perspective. Following the standard event history analysis methodology, the base data set was constructed from readily available, public sources of observable data and contained information only on organizational vital rates, patents granted annually, the number of new products released annually, and the inflation adjusted, annual dollar volume earnings per employee as covariates. These variables were selected on the basis of a mapping to the policy, intelligence and control, and socio-technical components of Beer's Viable System Model. Data from relevant economic indicators, the home market Gross National Product and the total Gross National Product of the regional markets in which each organization competed, were used to model the environmental selection and random transformation forces on the population under study.

The second delimitation is that data available from historical case studies, surveys, and other financial indicators representing the internal characteristics of specific organizations were not included in this research. Historically, effectiveness studies have been conducted from the perspective of the "organization in focus" using case studies, surveys, and financial reports to test hypotheses and validate findings. Case study and survey data cannot be included in a comprehensive event history analysis unless the data were uniformly gathered from all organizations in the population under study. Any non-uniformity in the data presents the potential for introduction of biases in the final analyses. This systems research methodology can be extended to include case study, survey, or financial data on the internal organizational characteristics through covariate analysis. The inclusion of case study, survey, or financial data, however, needs to be considered a priori from a research design perspective to minimize or account for induced biases in the final analyses. Being conducted from a posterior perspective, this research was unable to incorporate such design considerations.

Data from other financial indicators were not included in this research, because the latitude in Generally Accepted Accounting Procedures within the United States and differences in accounting procedures between countries permit a wide variety in the reporting of financial metrics. In many cases, performance indicators of organizations in the same population cannot be compared directly from standard financial reports.

The third delimitation of this research approach is its exclusive dependence on survival and effectiveness covariate analyses. As noted above, the internal characteristics of the organizations within the populations under study were not included. Thus, only inferences can be made concerning the internal determinants of effectiveness that cause observed dynamics in the included variables. Specific correlations often reported in widely used regression methods will not be available to point to any potential, underlying causal factors of knowledge creation, joint adaptation and control, or socio-technical efficiency. Only the sign and magnitude of statistically significant, variable coefficients will indicate covariate effects. This, however, is not a severe limitation. True internal causal factors of effectiveness are not easily observed or captured in survey data. Correspondingly, case studies that do capture determinants of effectiveness in qualitative terms are often limited in prescriptive terms and are not easily translated to quantitative working models. Finally, exclusive focus on internal determinants of organizational effectiveness are cross-sectional and static in nature and miss the dynamic interaction between organizational adaptation and environmental selection processes that create emergent organizational effectiveness. That is, organizational effectiveness is an emergent property of dynamic recursive systemic processes and is observable only in respect to the population level dynamics. Thus, the integrated organizational ecology and open systems methodology established herein presents a more holistic systems approach to modeling organizational effectiveness than historically applied organizational theory methodologies.

The fourth delimitation of this research is that only one organizational population was studied. This population was selected primarily because it has been dominated by one organization, International Business Machines, throughout its life span. This population provided the opportunity to examine the relationship between dominance and effectiveness. Thus, the findings of this study may not be fully generalized to other organizational populations. This may not, however, be a severe limitation, since all organizational populations have a life history that, to some extent, is unique to the time and dynamics of their respective existence.

1.5 Significance of this Research

This research contributes to the Engineering Management body of knowledge through the integration of organizational ecology theory, the Viable Systems Model, and socio-technical systems methodology in a holistic framework and methodology to extend research into the domains, dimensions, and determinants of operational organization effectiveness. Organizational ecology provides the means for modeling the environmental selection and random transformation processes domain. The Viable Systems Model provides the operational domains and dimensions of recursive organizational effectiveness, and the socio-technical systems methodology of joint optimization implies proactive organizational actions to influence environmental selection processes and maximize effectiveness and the chance of survival. The systems methodology applied herein unifies ecological selection and the systemic operational domains of organizational effectiveness through survival and effectiveness covariate analyses and dynamic simulation modeling. The static, factor analytic models of organizational effectiveness applied previously have produced statistically insignificant results and negative correlations among predictor variables, have not fully accounted for environmental dynamics, and have not yielded operational domains, dimensions, and determinants of organizational effectiveness. This research was designed to contribute to the closure of this gap. Future researchers may apply and extend the methodology and models developed by this work and the results of this research to extend knowledge of organizational systems operational effectiveness.

1.6 Research Approach Overview

The general strategy of measuring operational organizational effectiveness in this research differs from prior empirical research in organizational theory. Prior approaches attempted to explain organizational effectiveness by factor analytic methods in terms of difficult to observe, internal characteristics of selected organizations. This research approach concentrates on observable environmental and organizational covariates.

The methodology was conducted in six phases. In the first phase, this approach defined the population's physical and time boundaries and tested for density dependence. This definition provided the specification of the organizational population under study and validated that the specification was such that theoretical environmental and population level selection forces held. The original equipment computer manufacturing industry was selected as the organizational population for study, because: 1) its birth is well defined occurring in 1948 with the invention of the transistor which provided performance-price economies of scale needed for the commercialization of computers; 2) its history is well documented; and 3) its dominance by one company, International Business Machines (IBM), presented the opportunity to evaluate the relationship between dominance and effectiveness.

In the second phase, this approach developed a systemic model, based on the Viable System Model, of the domains and dimensions of organizational effectiveness of the population and its organizational entities and hypothesized observable covariate determinants for environmental and organizational dimensions. In phase three, a historical database of observed values for each covariate was constructed. For this study, the observable environmental selection and random transformation determinants of interest were dynamic organizational density as determined by entry, equal-status merger, absorption, and disbanding events, dynamic total market size represented by the total inflation adjusted United States dollar volume of computer product sales, and relevant economic indicators of the home market Gross National Product and the total Gross National Product of the regional markets in which each organization competed. The observable, organizational attributes of interest were the number of United States patents granted annually per organization to indicate knowledge creation, the number of new products released annually to indicate joint adaptation and control, and the inflation adjusted dollar volume earnings per employee to indicate socio-technical efficiency. Patents were categorized as "information technology" or "other" related. The "information technology" patents included those issued for hardware, networking, software, artificial intelligence, and computer or software production and maintenance processes. The "other" patents generally resulted from other business activities of conglomerates that also participated in the original equipment computer manufacturing industry. New products were classified as 1) mainframe, 2) minicomputer, 3) personal computer, or 4) workstation. The mainframe category included both commercial mainframes and supercomputers, because the distinction between the two subcategories blurred as the study period progressed. The minicomputer category included commercial minicomputers, special purpose minicomputers, and servers and routers. The response variables of interest were years surviving until organizational demise for the period 1949 to 2001 and years effective for the period 1976 to 2001. For the later period, effectiveness was defined as an organization's ability to sustain annual nonnegative growth in its inflation adjusted, organizational dollar volume sales market share niche.

In phase four, the effectiveness indicator data were standardized into unit niche space. Standardization involved translating annual international monetary sales data to United States dollars and multiplying the sales data by the Consumer Price Index to obtain constant dollars. An initial time period, $t_0 = 1976$, was selected and the population's cumulative deflated sales data were standardized to 1.00 for that initial time period (i.e. all population cumulative deflated sales data and individual organizational sales data in all subsequent time periods t_i were divided by the population cumulative deflated sales data in period t_0). This two-step standardization yielded unbiased estimates of changes in real population and organizational sales niche widths over the population's time boundary.

In phase five, event history analysis (Allison and Niemi; Blossfeld and Rohwer; Mayer and Tuma; Tuma and Hannan) was performed to determine population and subpopulation best-fit survival and effectiveness models and the statistically significant covariates for each model. In this study, survival or effectiveness for a given organization was identified by "0" and "1" indicator variables for each year of operation, "0" indicating survival or effective and right censored and "1" indicating failure or loss of sales market share. The best-fit distribution models established the relationships between observable, structural organizational predictors and years surviving or years effective. The covariate model building process followed standard backward, stepwise survival analysis procedures. The full model with all hypothesized predictor covariates was constructed. Statistically insignificant covariates were removed in subsequent partial models until the final model was indicated by all remaining covariates being statistically significant. The final population and subpopulation survival and effectiveness covariate models indicate the dynamic links between environmental selection and random transformation processes and internal organizational knowledge, intelligence and control, and socio-technical subsystems adaptations.

Model validation was established and sensitivity analyses were performed in the sixth phase. A system dynamics simulation model was constructed based on the identified population model covariate parameters, the model was refined to account for nonlinearities and discontinuities not captured in the covariate effectiveness model, and simulation results were validated for structural fit of simulated trajectories of sales market share niche data to the actual observed historical trajectories of sales market share niche data. Sensitivity analyses were performed to determine changes in organizational effectiveness trajectories resulting from changes in decision variables controllable by engineering management within the population's organizations. Sensitivity analyses provided information on potential internal actions an engineering manger may take to maintain or increase his respective organization's effectiveness (niche width) and the potential reactionary changes in dynamic patterns of population behavior resulting from those actions.

CHAPTER II

LITERATURE REVIEW

2.1 Organization Theory Research into Organizational Effectiveness

During the last forty years of the twentieth century, organization theorists made multiple attempts at defining, developing models of, and measuring organizational effectiveness. This literature review will present only a selected chronology of representative research into organizational effectiveness to illustrate the variety of perspectives and the difficulty encountered in modeling and measuring the construct of effectiveness by static, cross-sectional and factor analytic methods. The first two studies exemplify organization theorists' assumptions, methodologies, and variability in findings.

In their 1957 article, Georgopoulos and Tannenbaum assumed that all organizations attempt to achieve their objectives, "develop group products" through productive facilities and to maintain themselves. They reasoned from these assumptions that effectiveness criteria must consider both organizational means and ends. From this conception, they defined organizational effectiveness "as the extent to which an organization as a social system, given certain resources and means, fulfills its objectives without incapacitating its means and resources and without placing undue strain upon its members" (535). Based on this definition, they set forth organizational effectiveness criteria as: 1) productivity, 2) internal flexibility and adaptation to external change, and 3) absence of intra organizational strain. They studied "structurally homogenous and organizationally parallel" workstations in an industrial organization using a rating questionnaire completed by operators, supervisory personnel, and a group of independent experts. Analyses showed statistically significant rank-order correlations for station productivity, inter group strain, and flexibility and for interrelationships among the criteria. From this study, they concluded that studies of organizational effectiveness must be based on the dimension of organizational means and ends.

In their 1968 article, Friedlander and Pickle hypothesized that "effectiveness criteria must take into account the profitability criteria of the organization, the degree to which it satisfies its members, and the degree to which it is of value to the larger society of which it is a part" (293). Effectiveness was defined as the degree to which the needs of the different constituencies (external stakeholders, employees, and owners) were fulfilled. They studied ninety-seven small businesses that each had only one level of management and from four to forty employees. The study consisted of submitting Likert-type survey questionnaires to community members concerning management participation; obtaining publicly available records on business compliance to community, state, and federal regulations; submitting Likert-type survey questionnaires to customers, suppliers, and creditors concerning business relations; completing SRA Employee Inventories to measure employee satisfaction; and measuring the degree of owner satisfaction with financial results. They performed rank correlation analysis to explore the relationships among internal and external constituencies. Statistically significant correlations were relatively weak, with community relations by working conditions at 0.33, customer relations by employee development at 0.32, community relations by confidence in management at 0.28, and owner financial profit by employee development at 0.23, all significant at $p < 0.01$. Six other relationship correlations ranged from 0.20 to 0.23, all significant at $p < 0.05$. Twenty-three relationship correlations ranged from –0.21 to 0.12 and were not statistically significant. From these results, Friedlander and Pickle concluded that organizations are capable of fulfilling only a limited number of competing external and internal fulfillment needs. Accordingly, organizations seek only to satisfy several needs simultaneously.

In 1968, Price wrote the first book that directly addressed the subject of organizational effectiveness. The purpose of his work was "to present the core of what the behavioral sciences now know about the effectiveness of organizations: what we really know, what we nearly know, and what we think we know" (1). In his work, Price developed an inventory of effectiveness propositions from an intensive analysis of fifty prior organizational studies. He applied four criteria in accepting a study as being relevant to organizational effectiveness: 1) information pertinent to effectiveness, 2) analyses performed in great detail and length, 3) research based on primary sources, and 4) research into administrative organizations only. From his research, Price developed four propositions concerning the organization's economic system, four concerning its internal political system, ten concerning it external political system, ten concerning its control system, and three relating the organization to its ecology. Price concluded that an effective organization "is characterized by: high degrees of division of labor, specialized departmentalization, . . . mechanization, and by continuous systems assembling of output" (203). Unfortunately, as pointed out by Cameron and Whetten in their 1983 edited work, Price's conclusions were premature, because "many of the propositions that he claimed were known about effectiveness were not known then, and are still not known in the behavioral sciences. The causal associations between certain predictor variables and effectiveness that were claimed to exist simply never have been empirically demonstrated" (3).

In their 1972 book, Taylor and Bowers reported the application of a diagnostic instrument, Survey of Organizations (SOO), which was designed to measure leadership, peer behavior, group processes, and employee satisfaction as indicators of organizational effectiveness. The SOO was constructed on the premise that effective organizations were those in which management concentrated on developing participative work groups and maximized productivity through these groups. In application, the SOO was a self-evaluation instrument that used a Likert-type instrument and sought to measure the adaptive processes and outcomes of small groups within organizations.

In his 1975 article, Steers reviewed "17 multivariate models of organizational effectiveness in terms of their primary evaluation criteria, their normative or descriptive nature, their generalizability, and their derivation" (546), developed a Pareto listing of fourteen criteria used in two or more of the models, and discussed eight problems that limited the evaluation of effectiveness in the studies. Table 1 summarizes the studies and their respective evaluation criteria. Out of the seventeen studies, fourteen evaluation criteria were used in two or more studies. Table 2 lists these criteria in Pareto order of frequency. Adaptation-flexibility with a frequency of 10, productivity with a frequency of 6, and employee satisfaction with a frequency of 5 were the most often used criteria. Steers concluded, "little consistency was found in the evaluation criteria . . ." (546). He suggested that the lack of consistency was due to the following eight problems.

Construct validity	Effectiveness is an abstract construct that is difficult to define and measure.
Criterion stability	Evaluative criteria are unstable over time and conditions.

Time perspective	Criteria for short-run effectiveness differ from that of long-run effectiveness and may counter each other.
Multiple criteria	Although advantageous in modeling more structural variation, multivariate methods have the potential to produce models with conflicting criteria.
Measurement Precision	Precise quantification of effectiveness criteria has not been achieved consistently and may not be achievable.
Generalizability	Given that competitive environmental selection tends to favor functional specialization, effectiveness models developed for one organizational form may not be applicable to other forms.
Theoretical Relevance	Theoretical relevance questions of model purpose. Most important, does a given model increase our understanding of operational effectiveness and assist managers and stakeholders in selecting organizational actions that improve future effectiveness.
Analysis Level	There appears to be little integration between micro- and macro-level models. Organizational effectiveness can be modeled only from a systems perspective to capture the interaction among internal and environmental forces that determine resultant effectiveness.

Steers recommended that the development of effectiveness models could be facilitated by: 1) viewing effectiveness in terms of goal attainment, 2) accounting for dynamic, differential weights of various criteria, and 3) allowing for irreducible constraints that limit maximization of effectiveness.

Table 1.

Organizational effectiveness studies evaluated by Steers.

Study	Criteria	Type of Measure	Generalizability
Georgoupoulos and Tannenbaum (1957)	Productivity, Flexibility, Absence of Organizational Strain	Normative	All
Bennis (1962)	Adaptability, Identity, Capacity to test reality	Normative	All
Blake and Mouton (1964)	Simultaneous achievement of high production and people-centered	Normative	Business
Caplow (1964)	Stability, Integration, Voluntarism, Achievement	Normative	All
Katz and Kahn (1966)	Growth, Storage, Survival, Control over environment	Normative	All
Lawrance and Lorsch (1967)	Optimal balance of integration and differentiation	Descriptive	Business
Yuchtman and Seashore (1967)	Resource acquisition, Control over environment	Normative	All
Friedlander and Pickle (1968)	Profitability, Employee satisfaction, Societal value	Normative	Business
Price (1968)	Productivity, Conformity, Morale, Adaptiveness, Institutionalization	Descriptive	All
Mahoney and Weitzel (1969)	Business—productivity, planning, reliability, initiative R&D—Reliability, cooperation, development	Descriptive	Business, Research & Development
Schien (1970)	Open communication, flexibility, creativity, psychological commitment	Normative	All
Mott (1972)	Productivity, flexibility, adapability	Normative	All
Duncan (1973)	Goal attainment, integration, adaptation	Normative	All
Gibson, et. al. (1973)	Short-run—production, efficiency, satisfaction Intermediate—adaptiveness, development Long-run—Survaval	Normative	All
Negandhi and Reimann (1973)	Behavioral index Manpower acquisition, retention, and utilization. Interpersonal and interdepartmental relations. Employee satisfaction. Economic index Sales growth, net profit	Normative	Business
Child (1974, 1975)	Profitability, growth	Normative	Business
Webb (1974)	Cohesion, efficiency, growth, support	Descriptive	Religous

Source: Steers, Richard M. "Problems in the Measurement of Organizational Effectiveness." *Administrative Science Quarterly* 20 (1975): 548.

Table 2.

Steers' summary frequency of evaluation criteria occurrence.

Evaluation Criteria	**Times Used in a Study (N = 17)**
Adaptation—Flexiblity	10
Productivity	6
Satisfaction	5
Profitability	3
Resource acquisition	3
Absence of strain	2
Control over environment	2
Development	2
Efficiency	2
Employee retention	2
Growth	2
Integration	2
Open communications	2
Survival	2
All other criteria	1

Source: Steers, Richard M. "Problems in the Measurement of Organizational Effectiveness." *Administrative Science Quarterly* 20 (1975): 549.

Campbell, Brownas, Peterson, and Dunnette in 1974 and Campbell in 1977 surveyed the existing literature on organizational effectiveness with a focus on identifying organizational characteristics "significantly associated with organizational effectiveness" and how effectiveness criteria should be applied to evaluate development efforts and to compare organizations (Campbell 13). Campbell set forth six decision purposes that effectiveness criteria would support.

1. Evaluate organizational variables in its state space to determine which are in "good" or "bad" states.
2. Diagnose an organization to determine why it is in its current state.
3. Plan actions to change organizational state space.
4. Compare organizations along effectiveness criteria for public support.
5. Evaluate the effects of organizational development efforts.
6. Rank order organizations on the basis of effectiveness criteria. (Campbell 17)

Two major themes were seen as organizing effectiveness criteria into "a two-tiered hierarchical structure:" the goal-centered view and the natural systems view (Campbell

19). The goal-centered view assumed that effectiveness criteria were concrete and finite so as to be manageable and that the organization was managed by rational decision makers who possessed complete knowledge of and capacity to apply the criteria to guide the organization to improved effectiveness. Conversely, the natural systems view assumed that organizational state space was so complex that it was not possible to define organizational effectiveness criteria; rather, the goal was to maintain organizational viability. Table 3 summarizes 30 different criteria of effectiveness that Campbell compiled from social psychology empirical research literature.

Table 3.

Campbell's list of effectiveness criteria.

Overall effectiveness	Goal internalization
Productivity	Role and norm congruence
Efficiency	Managerial interpersonal skills
Profit	Managerial task skills
Quality	Information management and communication
Accidents	Readiness
Growth	Utilization of environment
Absenteeism	Evaluation by external entities
Turnover	Stability
Job Satisfaction	Value of human resources
Motivation	Participation and shared influence
Morale	Training and development emphasis
Control	Achievement emphasis
Conflict/cohesion	
Flexibility/adaptation	
Planning & goal setting	
Goal consensus	

Source: Campbell, John P. "On the Nature of Organizational Effectiveness." In Goodman, Paul S. and Johannes M. Pennings, ed., *New Perspectives on Organizational Effectiveness.* San Francisco: Jossey-Bass, 1977, 36-39.

Campbell concluded by noting that "it is probably counterproductive to follow a multivariate approach in the development of effectiveness measures . . . . it is simply not physically or economically possible . . ." (45). He proposed that effectiveness assessment should be pursued through the development of organization-specific models and goals by which measurement of attainment would be operative.

In their 1977 work, Pennings and Goodman sought to construct "a new conceptual framework of organizational effectiveness" (146) from the cumulative knowledge of past research by integrating "the open systems notion of complex organizations with the assumption that organizations represent a political arena where different groups try to promote their interests" (148). They viewed the internal determinants of effectiveness from the open systems model of "inputs, transformations, maintenance, and output subsystems" (149). They hypothesized that organizational effectiveness emerged from the effectiveness of subsystems and interactions among subsystems and among subsystems and their respective environments. They viewed subsystems as arenas in which internal constituencies pursued their own interests. They viewed effective organizations as those in which a dominant coalition, comprised of "direct or indirect 'representation' or cross-section of horizontal constituencies" (152) developed a consensus on the criteria of organizational effectiveness and external constituencies "set constraints and define appropriate referents of organizational effectiveness which become incorporated in the overall assessment of organizational effectiveness" (154). Three aspects of external constituencies strategic contingencies—substitutability, centrality, and institutionalization—influenced the focal organization's functioning to yield emergent effectiveness. Substitutability was defined as how easily suppliers or customers may be replaced. Centrality was the "importance or degree of connectivity" (155) of suppliers and customers. Institutionalization was the level of collective structure through which suppliers and customers interact with the focal organization. Pennings and Goodman proposed that organizational effectiveness is worked out through "dyadic relationships with other organizations in its environment" (157). Figure 1 illustrates the conceptual framework of Pennings and Goodman's description of organizational dyadic relationships.

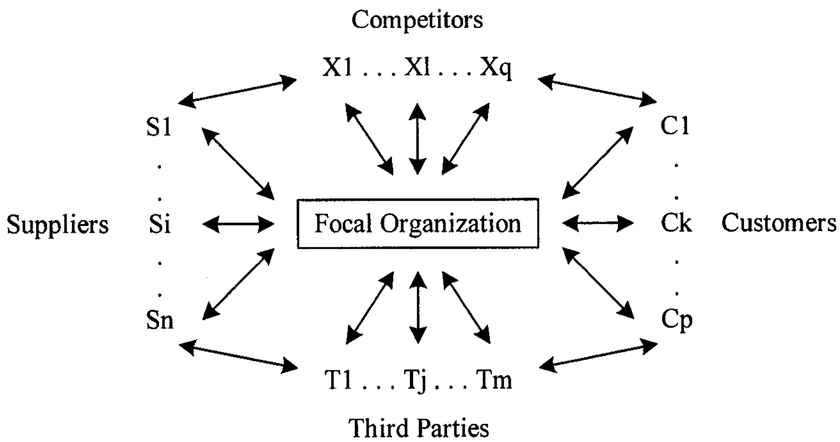


Figure 1. Pennings and Goodman's description of environmental dyadic relationships.

For Pennings and Goodman, "organizations are effective if relevant constraints can be satisfied and if organizational results approximate or exceed a set of referents for multiple goals" (160).

In his 1980 book, Miles categorized organizational effectiveness from five frameworks: scientific management, human relations, socio-technical systems, organizational development, and economics. He categorized these frameworks into two general effectiveness classifications: goal attainment and systems models. He identified problems with the approach of each classification. Difficulties with goal attainment include identification, evaluation perspective, stakeholder priorities, and differentiation between goals and strategies. He considered systems approaches as being too focused on viability and insufficiently focused on identifying the means toward viability. Miles proposed the integration of the goals and systems models into an ecology model in which he defined organizational effectiveness as "the ability of the organization to minimally satisfy the expectations of its strategic constituencies" (375). Miles proposed a contingency approach in which modeling, measuring, and monitoring effectiveness is a continuous process.

In a significant departure from other organizational theorists, Zammuto in 1982 proposed an evolutionary model of organizational effectiveness. Zammuto's model considers the ecological dynamics that determines every organization's effectiveness: "1) the role of constituent preferences in defining the preferred direction of social evolution; 2) how constraints create niches within which organizations exist; and 3) the effect of time on organizational performance" (59). Zammuto argued, "biological and social evolution function in much the same manner. Both are processes by which biological and social organisms fill empty niches within an ecosystem. The evolutionary pattern consists of three processes: variation, selection, and retention" (60-61). Zammuto defined variation as an organization's generation of adaptive mutational variety in reaction or response to environmental variety. The generation of organizational variety was based on Ashby's Law of Requisite Variety (206), which states that a control device must have as much variety, both in amount and pattern, as that in the system being controlled. Through legitimating selection processes, environmental constituents select organizational mutations, most useful to their purposes, which are to fill ecosystem niches and be retained as structural features of the organizational population. The adaptation-selection, legitimation process is dynamic, evolving over time in accordance with the variety in state changes of constituent preferences. For Zammuto, "the fundamental difference between social and biological evolution is that societies do not have an encodable genetic structure" (61). Rather societies encode environmental-organizational structure selection in cumulative human knowledge. In the evolutionary model framework, Zammuto defined organizational effectiveness as an organization's ability to create "variations in its behavior for selection into the social system's repertoire" (154). Zammuto discussed the application of the evolutionary model of organizational effectiveness in case studies of the effectiveness of physician extender training programs and the Big Three United States automakers in the 1970s. In the case study of the physician extender training programs, Zammuto illustrated how internal, goal-based systems "place blinders on evaluators and administrators" eventually leading to ineffective performance relative to constituent preferences" (147). In the Big Three automaker case study, Zammuto illustrated "how low variety evaluative and control mechanisms can prevent organizations from detecting and acting on critical changes in constituent preferences and environmental constraints" (148).

Quinn and Rohrbaugh submitted Campbell's 1977 list of effectiveness criteria to a panel of organizational effectiveness experts with the requirement that the panel "reduce and organize the criteria so that they were all on the same level of analysis, non-overlapping, and specifically related to organizational performance" (Quinn and Cameron 41). The organized criteria were submitted to multidimensional scaling to identify its bases dimensions. The analytical results indicated that the experts evaluated organizational effectiveness along three dimensions: 1) an *internal focus* on personnel satisfaction versus *external focus* on goal accomplishment, 2) organization structural *flexibility* versus *control*, and 3) *ends* related to metrics of efficient operations versus *means* related to goal setting, planning, and application of resources. From these three dimensions, they organized the model as illustrated in Figure 2 and labeled it as the competing values approach. They observed that the bases clustered the criteria into the eight possible combinations of the three dimensions, and they also observed that the bases of effectiveness criteria were consistent with the four major models of organizational effectiveness in use up to that time: the open systems model, the rational goal model, the human relations model, and the internal process model.

Quinn and Cameron extended the competing values approach to model organizational effectiveness over life cycle stages. They hypothesized that the pattern of effectiveness criteria changes over organizational life cycle stages. They reviewed the following nine organizational life cycle models that were dominant at the time to identify the common life cycle stages supported by all of the models.

- Downs (1967); Motivation for Growth.
- Lippit and Schmidt (1967); Critical Managerial Concerns.
- Scott (1971); Strategy and Structure.
- Greiner (1972); Problems Leading to Evolution and Revolution.
- Tobert (1974); Mentality of Members.
- Lyden (1975); Functional Problems.
- Katz and Kahn (1978); Organizational Structure.
- Adizes (1979); Major Organizational Activities.

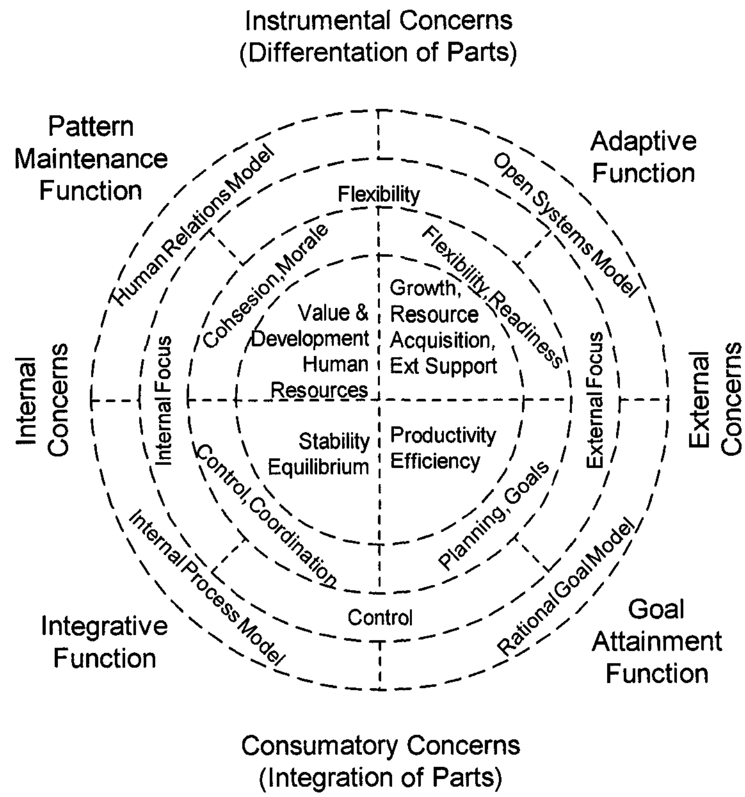


Figure 2. Quinn and Rohrbaugh's competing values model of organizational effectiveness. Quinn, Robert E. and John Rohrbaugh. "A Spatial Model of Effectiveness Criteria: Towards a Competing Values Approach to Organizational Analysis." *Management Science* 29.3 (March 1983): 372.

From this analysis, they identified four summary life cycle stages: 1) entrepreneurial, characterized by innovation, niche formation, and creativity, 2) collectivity, characterized by high cohesion and commitment, 3) formalization and control, characterized by institutionalization and stability, and 4) structure elaboration and adaptation, characterized by domain expansion through renewal or decentralization. Quinn and Cameron recast the competing values approach into the effectiveness model illustrated in Figure 3 to demonstrate the appropriateness of the four major organizational models in relation to effectiveness over four summary life cycle stages.

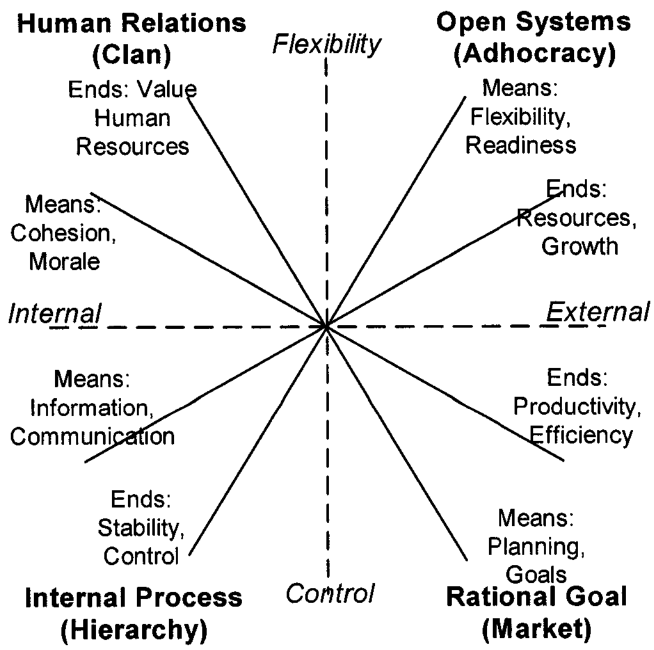


Figure 3. Quinn and Cameron's competing values model of organizational effectiveness. Quinn, Robert E. and Kim Cameron. "Organizational Life Cycles and Shifting Criteria of Effectiveness: Some Preliminary Evidence." *Management Science* 29.1 (1983): 42.

Figure 4 illustrates their hypothesized pattern of effectiveness during the entrepreneurial stage. The entrepreneurial stage is typified by innovation and the acquisition of resources to realize the translation of the idea into the product. Quinn and Cameron hypothesize that an organization will strongly emphasize the open systems effectiveness criteria of resource acquisition, flexibility, growth, and development of external support. In their 1999 book, Cameron and Quinn subsequently labeled the open systems orientation in the upper right quadrant as the "adhocracy" cultural type.

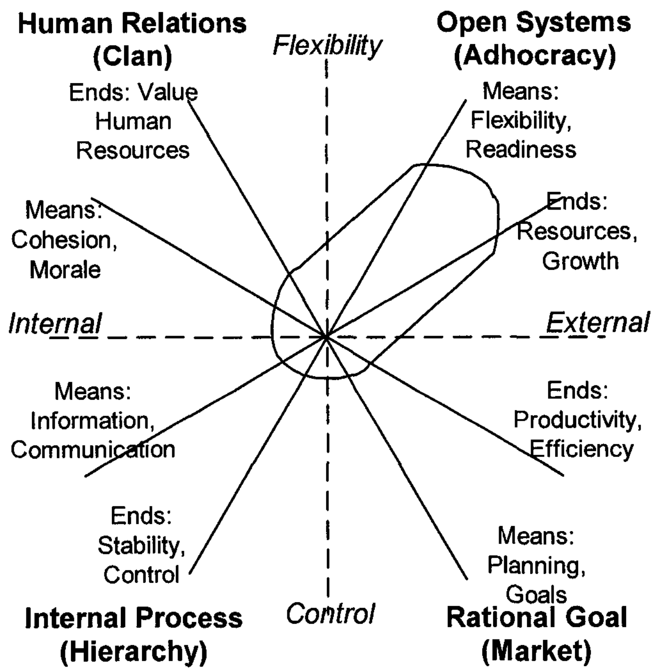


Figure 4. Competing values model effectiveness pattern in the entrepreneurial stage. Quinn and Cameron 43.

Figure 5 illustrates the hypothesized pattern of effectiveness during the collectivity stage. Informal communications and structure, a sense of cooperation and high commitment, and a highly personal leader characterize the collectivity stage. In this stage, Quinn and Cameron hypothesize that organizational effectiveness will expand to include the human relations model emphasizing criteria such as personnel development and satisfaction, morale, and cohesion while maintaining continued focus on open systems criteria. Cameron and Quinn subsequently labeled the human relations orientation of the upper left quadrant as the “clan” cultural type.

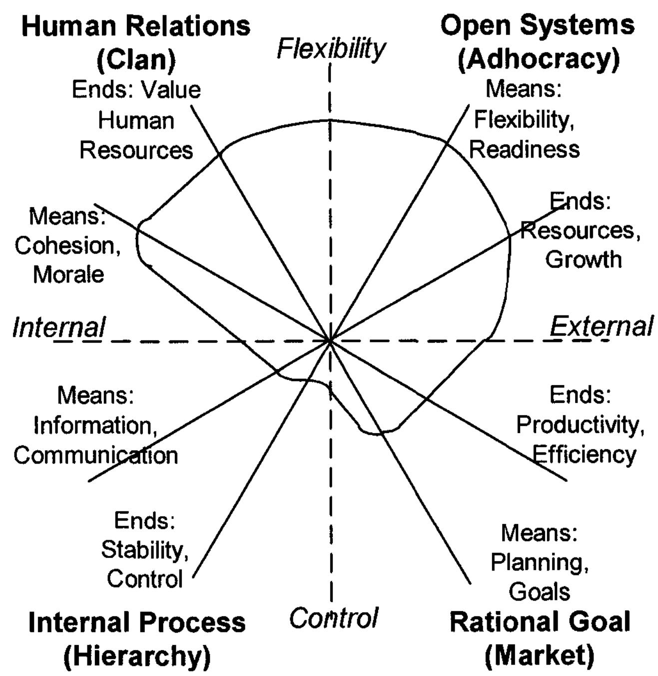


Figure 5. Competing values model effectiveness pattern in the collectivity stage. Quinn and Cameron 43.

Figure 6 illustrates the hypothesized pattern of effectiveness during the formalization and control stage. In the formalization stage, organizations are characterized by stability and efficiency of production, formalization of the decision-making and control structure, and standardization of procedures. The criteria for organizational effectiveness shifts more toward the rational process and internal process models. Cameron and Quinn subsequently labeled the internal process control orientation of the lower left quadrant as the "hierarchy" cultural type and the rational goal orientation of the lower right quadrant as the "market" cultural type.

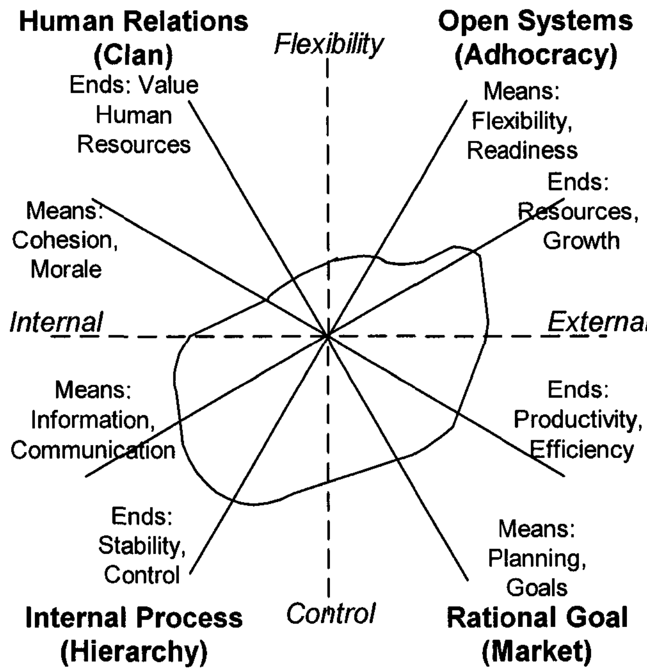


Figure 6. Competing values model effectiveness pattern in the formalization and control stage. Quinn and Cameron 43.

Figure 7 illustrates the hypothesized pattern of effectiveness during the structure elaboration and adaptation stage. In this stage, organizations return focus to the external environment to expand their domains and ensure renewal through decentralization. Decentralization is necessary to balance differentiated structures with integrated decision-making. Moderate focus remains on internal process, human relations, and rational goal model criteria, because these issues have been addressed in previous stages. In order to expand organizational boundaries, focus shifts back mainly to the open systems criteria of resource acquisition, flexibility, and growth.

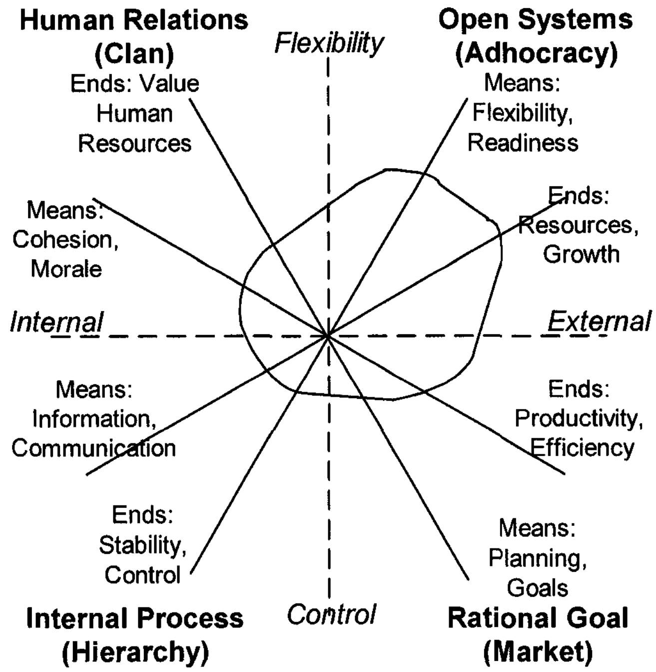


Figure 7. Competing values model effectiveness pattern in the structure elaboration and adaptation stage. Quinn and Cameron 43.

In their 1986 article, Lewin and Minton noted, "effectiveness is determined in relative terms and often requires some subjective means of combining multiple measures or a judgment to use a single aggregate measure" (528). Traditional approaches to the measurement of organizational effectiveness rely on multiple performance metrics, ratio analyses, and least squares estimation methods. Multiple metrics are limited to the perspective of the evaluator. Ratio analyses are limited in the measurement of effectiveness, because they often yield conflicting results; that is, some organizations are better on some ratios and worse on others. The question then becomes how to weight the ratios in terms of predictive capability. Least squares estimation methods assume independence among determinants and normality of residuals. Least squares estimators are useful for identifying central tendencies, but are less useful in identifying outliers in the form of maximally effective organizations. Lewin and Minton stated that a "theory-based mathematic" exhibiting the following properties would be useful in the measurement of organizational effectiveness:

- Capable of analytically identifying relatively most effective organizations in comparison to relatively least effective organizations.
- Capable of deriving a single summary measure of relative effectiveness of organizations in terms of utilization of resources and their environmental factors to produce desired outcomes.
- Able to handle noncommensurate, conflicting outcome measures, multiple resource factors, and multiple environmental factors . . .; and not be dependent on a set of a priori weights or prices for the resources utilized, environmental factors or outcome measures.
- Able to handle qualitative factors . . . .
- Able to provide insights as to factors that contribute to relative effectiveness ratings.
- Able to maintain equity in the evaluation (529).

They proposed that Data Envelopment Analysis (DEA) would provide a "theory-based mathematic for calculating the relative effectiveness of an organization (over time or in comparison to other referent organizations)" (529). DEA, which is based on the economics concept of Pareto optimality, provides a means for separating organizations "which define the performance frontier from those which are underperforming" and to relate outcomes to resources utilized adjusted for environmental factors (530). To support their proposal, Lewin and Minton demonstrated how DEA could be applied to a generalized organization process model.

Dennison, 1990, presented a theory of organizational effectiveness based on corporate culture from the following four hypotheses:

- Involvement hypothesis: Effectiveness is a function of the values and beliefs held by the members of an organization. Dennison specifically hypothesizes that "transaction costs can be minimized when each member of an organization acts from an intuitive value consensus" (8) to produce coordinated action within the organization.

- Consistency hypothesis: Effectiveness is a function of translating the core values and beliefs into policies and practices in a consistent manner. Dennison specifically hypothesizes that "a strong culture, with well-socialized members, improves effectiveness because it facilitates the exchange of information and coordination of behavior" (9).
- Adaptability hypothesis: Effectiveness is a function of the policies and practices used by an organization. The leader's vision can be operationalized efficiently and effectively only through a strong culture. Dennison notes that three aspects of adaptability impact effectiveness: 1) "the ability to perceive and respond to the external environment," 2) "the ability to respond to internal customers," and 3) "the capacity to restructure and reinstitutionalize a set of behaviors and processes that allow the organization to adapt" (12).
- Mission hypothesis: Effectiveness is a function of the interrelation of core values and beliefs, organizational policies and practices, and the business environment of the organization. An organization's mission states how it will achieve its goals in its competitive environment. Dennison notes "a sense of mission provides two major influences on an organization's functioning. First, a mission provides purpose and meaning (as to) why the organization's work is important. Second, a sense of mission provides clear direction and goals that serve to define the appropriate course of action for the organization and its members" (13).

Dennison claims that through these four hypotheses "most of the implicit or explicit ideas about culture and effectiveness that have appeared in the literature have been represented" (14), and he claims that the integration of these four hypotheses into the following integrated framework provides a means of measuring organizational effectiveness.

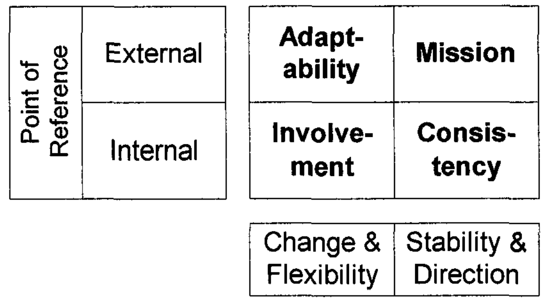


Figure 8. Dennison's culture and effectiveness model. Dennison, Daniel R. *Corporate Culture and Organizational Effectiveness*. New York: Wiley, 1990, 15.

Dennison presented the results of research designed to investigate the hypothesized relationships. The research was divided into two parts. The first part was "a comparative study of culture, climate, and effectiveness that uses a standard set of measures applied in a comparable fashion to a sample of 34 organizations" (39). The standard set of measures was the Survey of Organizations (SOO) questionnaire (Taylor and Bowers, 1972) and the Organization Survey Profile (OSP) (Rensis Likert Associates). The surveys were conducted between the years 1966 and 1980. Outcome financial data were obtained from Standard and Poor's statistical service, COMPUSTAT. Behavioral indicators were measured at year 0, B_0, and the performance of a selected subset of 17 financial indicators was correlated back to the behavior indicators from years 0 to +5, P_0 to P_5. From the study, Dennison concluded, "the results provide compelling evidence that it is quite possible to use cultural and behavioral measures to predict the performance and effectiveness of an organization over time" (83). He also noted that some of the behavioral indicators appear to be better predictors of short-term performance while others are better predictors of long-term performance. The second part of the research was a qualitative study of five selected organizations (Detroit Edison, Medtronic, People Express, Proctor & Gamble, and Texas Commerce Bancshares), which sought answers to four questions:

- How was the development of the culture related to the development of the business itself? Was it purposefully planned and created, or did it develop spontaneously?
- What is the current culture of the organization and how is it changing?
- What is the relationship between the meaning system and the overt management practices and behaviors that structure the organization?
- What is the process by which the organization's culture contributes to effectiveness? (91)

For the purposes of this research, only the conclusions related to the last question will be reported.

> Involvement: The case studies identified two types of involvement: formalized and planned versus spontaneous and informal. Both appear to have a positive impact on effectiveness (179).
>
> Consistency: Four forms of consistency were identified: consistency between 1) stated ideology and actual practices, 2) internalized controls and shared values and norms, 3) the organization's bureaucratic, control processes and environmental market functioning, and 4) conformity to values and norms in the achievement of consistency in 1) to 3). The results on the consistency hypothesis were mixed. When all forms of consistency held, consistency appeared to be a precondition to motivation and motivation to effectiveness. On the other hand, "when structure, feedback, and control become ends in their own right . . . the resulting conformity can become a barrier of bureaucratization" (182).
>
> Adaptability: Two types of adaptability were identified: 1) the internal capacity to transform, reorganize, and redirect and 2) the capacity to respond to external forces. It was observed that effective organizations are "usually obsessed with customers and vigilant analysis of competition" throughout the organization. In cases where parts of the organization are insulated from external forces, traditional ways of operating and bureaucratization quickly become obstacles to adaptability (182-183).

Mission: The case studies found an important link between a strong sense of mission and organizational effectiveness. The major crises observed in each case study were linked to the organization's fundamental mission coming into question. Dennison concluded "meaning, direction, and the structures linking the two must be continually recreated in reaction to a fluid and turbulent environment" (183-185).

In conclusion, the purpose of this literature review was to present a selected chronology of representative research into organizational effectiveness to illustrate the variety of perspectives and the difficulty encountered in modeling and measuring the construct of effectiveness. The difficulties in measuring organizational effectiveness may be summarized in the following points:

- The formal study of organizational effectiveness is a relatively new area of inquiry and research having arisen to prominence in the 1970s.
- A single, universal paradigm with a unified definition of organizational effectiveness does not exist.
- The construct space of domains, dimensions, and determinants of organizational effectiveness remain unknown.
- The dynamics of time frames remain unmapped. The first issue concerns environmental dynamics. Specifically, what changes in environmental forces necessitate a re-weighting of effectiveness domains, dimensions, and criteria? The second and third issues relate to the organization itself. The second issue is the time frame from the organization's and its stakeholders' viewpoints. Effectiveness domains, dimensions, and criteria may be weighted differently in short versus long time frames, and the domains, dimensions, and criteria of short versus long term effectiveness may be opposing. Third, effectiveness domains, dimensions, and criteria may be weighted differently at different stages of organizational maturity.
- The organizational level at which effectiveness is to be assessed has not been clearly defined. Effectiveness has been assessed empirically at the individual participant or stakeholder level, the group level, the

department level, the functional level, cross-functional structural levels, the organizational level, the extra-organizational (organization of organizations), or systemic level (organizational and environmental forces). Meaningful diagnosis of effectiveness is dependent on choosing the appropriate level of analysis-synthesis.

- The choice of constituencies has not been clearly defined. To date, no purely objective criteria of organizational effectiveness has been defined. Rather, effectiveness must be assessed from someone's viewpoint: internal constituencies, managers, the dominant coalition, external stakeholders or constituencies, a researcher, or society at large. Each constituency determines the weights placed on domains, dimensions, and criteria of effectiveness, and ". . . the criteria used by different constituencies to define effectiveness often differ markedly. . . . organizations never satisfy all their constituencies, and what appears to be high effectiveness from one point of view may be interpreted as being moderate or low effectiveness from another point of view" (Cameron and Whetten 270).
- The framework for assessing and diagnosing effectiveness must delineate internal and external determinants of effectiveness. The problem is made difficult, because internal and external determinants are found at individual, group, departmental, functional and cross-functional structural, organizational, extra-organizational, and systemic levels. Often, determinants of organizational effectiveness are not readily observable. Internal organizational structures and processes are often concealed, and causal environmental forces are not easily measured. Additionally, organizational effectiveness is influenced not only by external stakeholders and constituencies but also by external chaotic and random external forces. Natural and man-made disasters and swings in economic conditions affect the effectiveness of even relatively closed or highly buffered organizations.

- The referents against which to judge organizational effectiveness have not been clearly specified. Four approaches have been applied to the selection of referents. In the first approach, ideal or standard effectiveness referents and levels are set. Likert's 1967 "System 4" characteristics set is an example of referent standards. Assessment seeks to determine how effective an organization is relative to the theoretical ideal. The second approach is to compare the effectiveness of different organizations against the same set of referent indicators. In this case, assessment seeks to determine, rate, and rank the effectiveness of organizations relative to each other. The third approach is to compare effectiveness relative to stated and identified organizational goals. The degree to which goals are attained is interpreted as the degree of organizational effectiveness. The final approach is to compare effectiveness against a consistent set of indicators over time. Under this approach, assessment seeks to determine whether or not the organization is improving over time.
- The final difficulty lies in the joint issues of purpose and assessment strategies. The purpose of the assessment determines the weighting of domains, dimensions, and criteria and the selection of levels, constituencies, and stakeholders. The purpose can change depending on who sets it: the assessor, a manager, constituents, or stakeholders. An assessor may seek only to compare the effectiveness of various organizational structures and processes from a research perspective, a manager will generally seek to increase the effectiveness of his or her organization, and constituencies and stakeholders will seek to influence the effectiveness of an organization or a group of organizations relative to their specific goals. The assessment purpose determines the data to be collected, the sources to considered, and, correspondingly, the assessment strategy itself. Ultimately, the purpose constrains the selection of assessment strategies and the ultimate judgment of effectiveness.

Despite these difficulties, Cameron and Whetten state that there are "theoretical, empirical, and practical reasons" (1-2) to pursue continuing research into organizational effectiveness. In a manner similar to mathematical or physical theory, a foundation of theoretically validated models of organizational effectiveness are needed to provide the basis for research into and engineering of optimal organizational forms. Empirically, organizational research is centered on demonstrating that one structural form, or set of structural forms, is better in some way than another, or others. Practically, individuals need to and do make intuitive judgments about the effectiveness of organizations in order to decide which organizational forms should be supported and propagated as most capable of benefiting them personally and society as a whole.

2.2 Open Systems: The Viable Systems Model and Socio-technical Systems

The Viable System Model (VSM) evolved out of thirty years of research in which Stafford Beer sought to explain "*how systems are viable*—that is, capable of independent existence" (Beer *The Viable System Model* 11). Beer developed the principles and mechanisms underlying the VSM from Ashby's Law of Requisite Variety (Ashby 206-213), which may be summarized as:

> A control device must have requisite variety. That is, a control device possesses the capacity to maintain the outcomes of a controlled process within the limits of its set of viable states if, and only if, it has the capacity to detect and respond to all patterns and amounts of environmental disturbances that are capable of causing the controlled process to move beyond the limits of its set of viable states.

Beer codified the VSM's principles, theorems, and laws in a three-volume trilogy, *Brain of the Firm*, 1972, which translated the original set-theoretic model into a neurophysiological model, *The Heart of Enterprise*, 1979, which established the structural model of communications and control within a viable system, and *Diagnosing the Systems for Organizations*, 1985, which was intended to be a manager's guide. Two features of the VSM are most applicable to the development of an integrated model of organizational effectiveness: the cybernetic organizational structure and the recursive system theorem.

Without going into theoretical development from basic principles of the Law of Requisite Variety, the VSM can be represented in the simplified block diagram format of Figure 9. According to the VSM's cybernetic model, five interacting subsystems are necessary and sufficient for systemic viability. The first subsystems, indicated as *1* in Figure 9, are those that produce the system. In organizations, subsystems *1*, the circles, are the productive systems that transform inputs into outputs and create the system's purpose for existing. Subsystem *2*, the triangle, is an anti-oscillatory function that coordinates vertical interactions among operational subsystems *1* and the subsystem *3* control function. Its purpose is to ensure that the correct pattern and amount of variety is communicated to the control function and, at the same time, reduce the variety demand on the control function. The control function's goal is to achieve operational cohesion among the subsystems *1*. By cohesion, it is meant that the control function must find a systemic balance between control for efficient subsystems *1* functioning and autonomous flexibility to assure the correct pattern and amount of environmental variety is distributed among the subsystems *1* to attain proper adaptation. The control function assures that the flexible, operating autonomy allocated to the subsystems *1* units remains consistent with systems functioning through an independent monitoring channel. Monitoring is accomplished through an extra communications channel directly connected to subsystems *1* operations. The internal, operational focus of the control function *3* is counterbalanced by the external, environmental focus of intelligence function *4*. The intelligence function scans the competitive environment for threats to system viability and opportunities to expand the system's environmental niche. The control and intelligence functions counterbalance in that they seek to achieve the same goal but from internal versus external perspectives: the definition, implementation, and adjustment of the system's identity and viability in its niche. Counterbalance is achieved by the policy function *5*. The policy function chooses systemic courses of action based on environmental information filtered through the intelligence function and internal operational information filtered through the control function. The policy function orchestrates and monitors the debate between the intelligence and control functions with a goal of choosing those courses of action that maximize systemic viability. The policy function also serves as the knowledge repository of the system, storing knowledge on the outcomes of past actions and applying that knowledge to the debate on present and future courses of action.

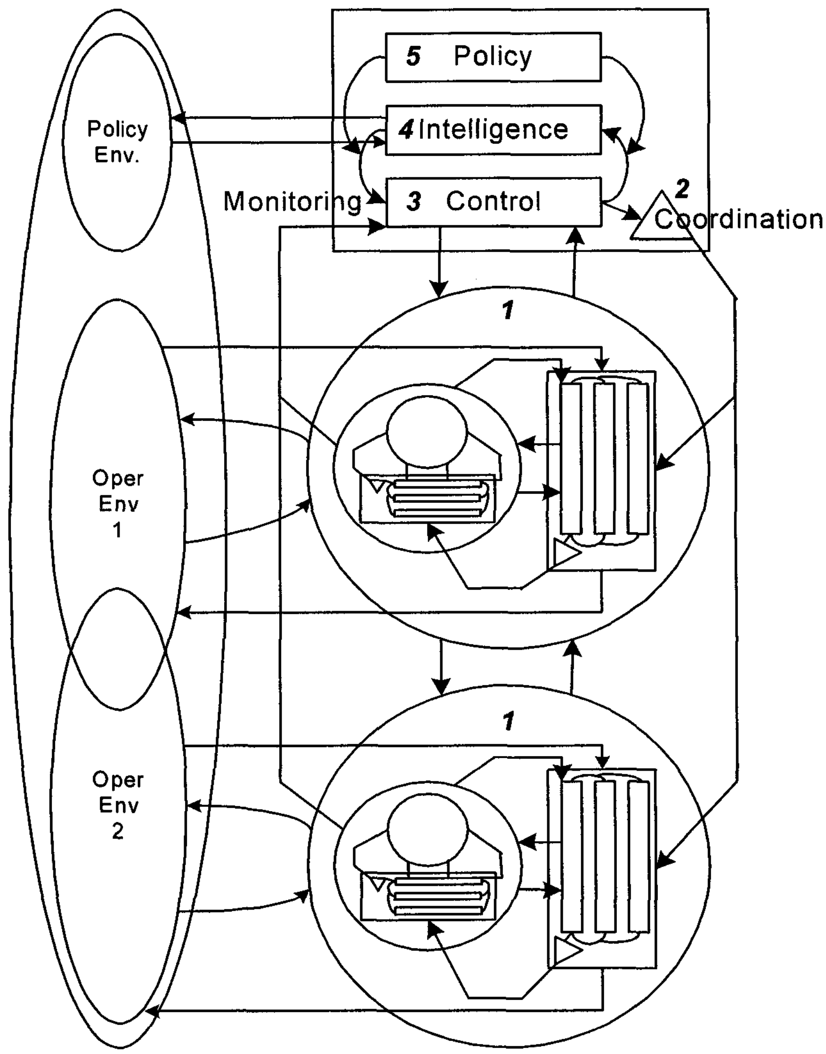


Figure 9. VSM's structural model of organization communications and control subsystems.

Figure 9 also illustrates the most important feature of the VSM: its recursive structure. Subsystems *1*, those that produce the system, must themselves be viable systems and contain subsystems that, in turn, produce them. Thus, VSM's neurophysiological model directly implies the Recursive System Theorem.

> In a recursive organizational structure, any viable system contains, and is contained in, a viable system (Beer *The Heart of Enterprise* 118).

Recursion within the VSM is the cybernetic, structural linking process between environmental selection dynamics and internal adaptive processes. The Recursive System Theory implies that competitive environments are themselves meta-organizational forms taking on the same VSM neurophysiological structure. Under the Recursive System Theorem, organizations are subsystems *1* in populations of organizations, and, in turn, populations of organizations are subsystems *1* in communities of organizations. At each level, policy, intelligence, and control functions are formalized in agreements, contracts, and legislation or are worked out through higher-level self-organization. The competitive environment itself is not a black box as represented by many organization theories; rather, the environment is a viable system in which selection processes are worked out through interactions among organizations and populations of organizations, the later which contains constituencies of organizations in a given population. Apparent environmental chaos arises because the interactions induce nonlinearities and randomness into selection processes.

Where Beer's VSM defines the neurophysiological structure of competitive environments and provides cybernetic links between environments and viable, systemic organizational forms, the socio-technical systems methodology integrates human aspects into organizational design to achieve adaptive, internal processes. Socio-technical systems theorists (Trist and Bamforth, Trist et al, Rice, Taylor and Felton) hypothesize that joint optimization of internal social and technical subsystems maximize organizational performance toward the accomplishment of its central purpose and goals. From the socio-technical systems perspective, all organizations are comprised of "a technical subsystem to produce the core output" and a social subsystem to provide flexibility in the adaptation and coordination of activities (Taylor and Felton 1). The socio-technical systems methodology is built on four principles:

- Organizations can be "purposive" with unstated but observable mission or "purposeful" with a clearly articulated mission and objectives.
- An effective organization focuses on its "product" or output.
- Historical "mechanistic" organizational models are inadequate in the achievement of organizational effectiveness.
- Organizational design intents cannot be achieved without the participation and empowerment of all organizational personnel (Taylor and Felton 2-3).

The socio-technical systems methodology consists of the seven major steps and four phases illustrated in Figure 10. The "discovery" phase seeks a shift to the socio-technical systems paradigm. The shift is achieved through acceptance of a customer/product/ purpose focus within a holistic systems framework. In the second phase, a holistic systems understanding of the organization is achieved through a joint "open system scan" to establish the reference competitive environment, a "technical analysis" to establish technical system capability, and a "social analysis" to establish the supporting social network. In the third phase, a system design or redesign is accomplished through "joint optimization" and "provisional design." The design process is guided by eleven principles:

Compatibility: All organizational members contribute to the design.

Minimum Critical Specification: Specify only *what* has to be accomplished by the new design. The *how* of task accomplishment should be left to the discretion of individual teams to keep options open for creative problem solving.

Variance Control: Technical variances not eliminated during design must be controlled at the point of origin or at the closest possible point after origin.

Boundary Location: Operational boundaries should not be artificially set. Boundaries should be set to maximize the transfer of information, knowledge, and skills.

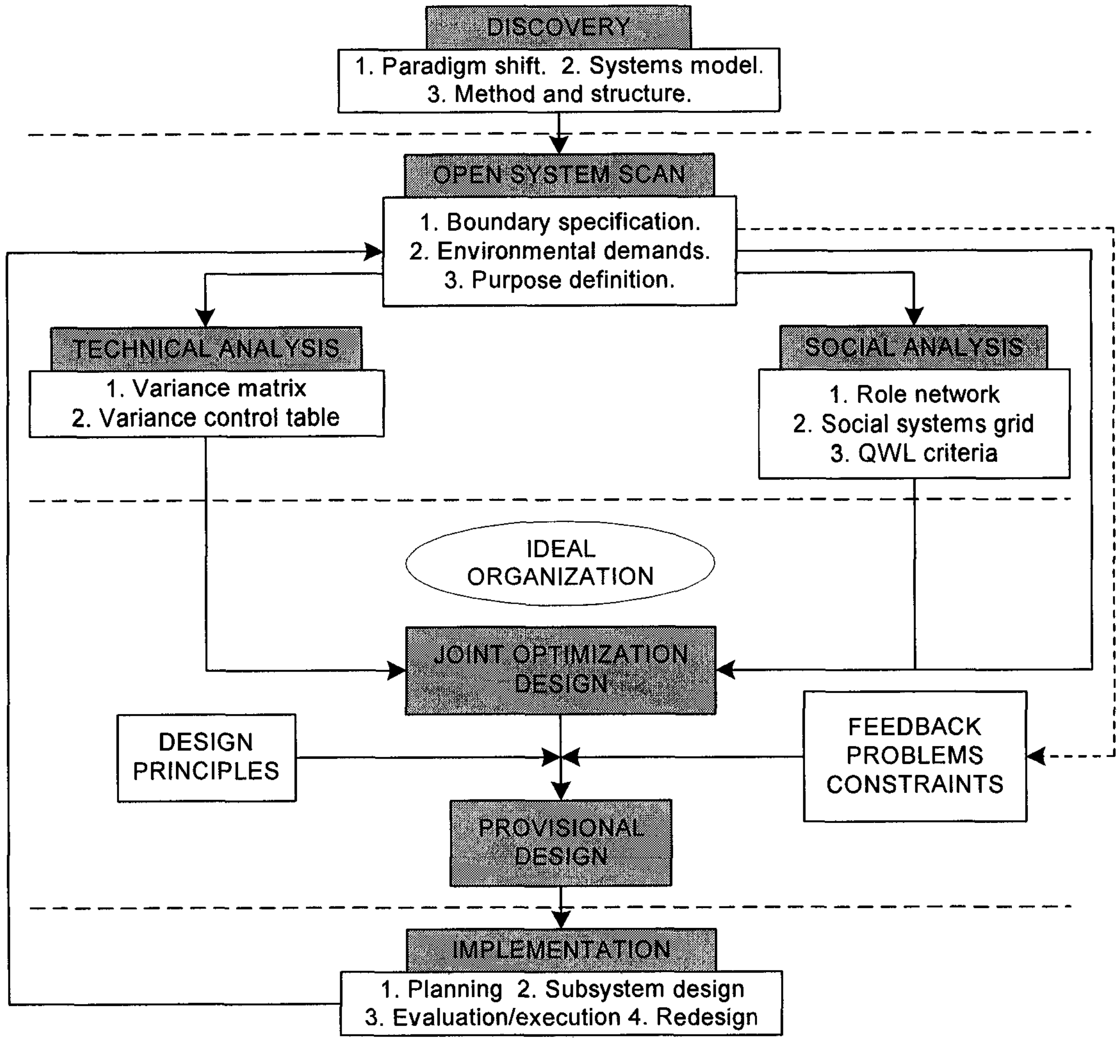


Figure 10. The socio-technical systems process. Taylor, James C. and David F. Felton. *Performance by Design: Sociotechnical Systems in North America.* Englewood Cliffs, NJ: Prentice Hall, 1993, 5.

Information Flow: Information should flow directly to the points of process transformation.

Power and Authority: Power and decision-making authority should be distributed to the points of process transformation.

Multifunctional/Multi-skills: Invest in training to make operational personnel multi-skilled and flexible.

Support Congruence: Develop social support systems (teams, conflict resolution skills, performance assessment, etc.) to reinforce the behaviors needed to transition to the new design.

Design and Human Values: Provide a high quality of work life.

Bridging the Transition: Minimize stress through participation and communications during the transition to the new organizational design.

Incompletion—Building Continuous Improvement: Organizational design is an iterative process. Adaptation to environmental changes requires that organizational members continuously review and revise system design. (Taylor and Felton 154-159)

In the fourth phase, the design is implemented and evaluated for effectiveness, and organizational members return to the "open system scan" step to begin the redesign process.

Open systems studies of organizational effectiveness have tended to focus on the system of interest (Flood and Carson 73-74) and ignore wider interacting environmental selection forces that play out over time. Environmental factors have been incorporated in models only from the perspective of their effects on the system of interest and have been observed from static cross-sectional perspective. From the hard systems perspective in *The Heart of Enterprise* and a subsequent work, Beer describes the application of the Viable System Model to a large mutual insurance company over the period 1973 to 1983. Espejo illustrated the application of the Viable System Model to a small British manufacturing company observed in 1978. Britton and McCallion reported the use of the Viable Systems Model as the basis for the development of New Zealand government's policy on vocational training. The policy was developed from publicly available documents and approximately 40 interviews over the period 1981 to 1984. Leonard analyzed the commercial television broadcasting industry, as it existed in the mid 1980s, in terms of the Recursive System Theorem. Likewise, Holmberg described the application of the Viable System Model to a Swedish paper and packing company in the mid 1980s. Similarly, soft systems theorist, Checkland reports multiple applications of the Soft Systems Methodology to various organizations over a forty-year period. Some applications evolved over as much as twenty years. Again, however, the soft systems methodology focuses on the "system of interest" with consideration of environmental factors as they directly affect the problem under consideration. From a "systems thinking" perspective, Gharajedaghi reports the application of the contingency approach of organizational design to the government of an Indian nation, a health system, a hotel chain, an energy corporation, and a manufacturing firm. The "systems thinking" paradigm does consider the historical background of the "system of interest" and the current, evolving environmental dynamics from a qualitative, descriptive perspective.

2.3 Organizational Ecology

In their original 1977 proposal of organizational ecology, Hannan and Freeman sought to answer why diversity exists among organizational forms. In addressing this question, Hannan and Freeman noted that we must understand the "(1) sources of increasing diversity, such as the creation of new forms, and (2) sources of decreasing diversity, such as competitive exclusion of forms" (Hannan and Freeman *Organizational Ecology* 7). Specifically, organizational ecology seeks to understand how environmental social dynamics affect the rates of formation and legitimation of new organizational forms, evolution of existing organizational forms, and demise through competition of forms no longer viable.

Under the population ecology model, organizations are viewed as "vehicles for action" (Hannan and Freeman *Organizational Ecology* 3). The diversity of organizational structures is theorized to arise from longitudinal, cumulative Darwinian processes of environmental selection and systemic-organizational adaptation that are punctuated by random periods of rapid change. Differing organizational structures are hypothesized to be more effective in varying types of environments. Organizational structures are seen to exist at three levels: 1) demography of organizations, which considers the birth, life cycle, and death rates of organizational forms; 2) populations of organizations, which considers birth, life cycle, and death rates and the interactions within isomorphic populations of organizations; and 3) communities of organizational populations, which investigates the evolutions of and dynamics among populations of organizations.

Based on biological ecology, organizational ecology focuses its analyses on numerical aspects of interactions of organizations within a population and organizational forms among populations. The theoretical strategy is based on three assumptions about organizations. "The first assumption is that populations can be defined in such a way that they have a unitary character . . ." (Hannan and Freeman 1989, 45). Unitary character means that organizations within a population are similarly affected by environmental dynamics. The most often observed unitary character is a common dependence on the economic, physical, and social environments for niche creation and maintenance. The second assumption is that information on common organizational characteristics within a population or the location of social boundaries permits the population to be identified a priori (Hannan and Freeman 1989, 45). Assumption two is necessary and sufficient to allow the formulation of falsifiable hypotheses about the effects of competitive interactions of organizations within the identified population and interactions between the identified population and other populations on the dynamic density trajectory of the population under study. Unlike biological populations in which unitary character is encoded in genetics, social organizations can, and do, make radical changes in strategy and structure. Partitioning of organizations into a population requires the establishment of common dimensions through time such that common changes define the unitary character of the population under study. Organizations that change strategy or structure so radically so as to depart from the unitary character of the population must be accounted for in mortality rates. The third assumption "is that the characteristics locating individual organizations in a population rarely change rapidly relative to the processes of interest" (Hannan and Freeman 1989, 66). That is, a given organization is characterized by relative inertia that defines its membership within the population. Inertia constrains individual organizational changes such that it maintains its identity within its population, although it may be subject to environmental shocks and expanding or contracting niche width.

Niche width analysis models the effects of environmental variations and legitimation and competition dynamics on population vital rates. Specifying a population's or an organization's niche width requires construction of the population's natural history through event history analysis to map the economic, physical, political, and social dynamics necessary to create and sustain the population. The fundamental niche is defined as the set of n-dimensional environmental states in which a population's growth rate is nonnegative. The fundamental niche characterizes the vital rates of isolated populations. The realized niche admits interactions from competition among populations and organizations within a population. When populations or organizations within a population interact through competition, the presence of one population or organization changes the niche width and, in turn, the vital rates of the others. Changes in vital rates and niche widths are indicators of organizational effectiveness in competitive environments.

Organizational ecology theorists recognize that structural causal factors of organizational survival are not readily observable. Internal organizational structures and processes are often concealed, and dynamic causal environmental forces are not easily measured. Thus, organizational ecologists rely on a strategy of building dynamic models of vital rates and niche widths of populations of organizational forms from observable features (founding, merger, absorption, and demise) that are comparable over time and observable changes in qualitative environmental contexts. This approach has allowed organizational ecologists to build dynamic models of organizational survival in response to environmental competitive and selection forces not previously considered by organization or open systems theorists and researchers.

The organizational ecology methodology extends from the mid 1970s. Hannan and Freeman proposed organizational ecology "as an alternative to the dominant adaptation perspective" (*American Journal of Sociology* 82, 929) of organizational theory in their 1977 paper entitled "The Population Ecology of Organizations." During the last quarter of the twentieth century, organizational ecology studies have been conducted for populations of electronics components industry (Brittain and Freeman, 1980; Wilson, Ashton, and Egan, 1980; and Wholey and Brittain, 1986) newspaper publishers (Carroll and Delacroix, 1982; Carroll and Huo, 1986; Carroll and Hannan, 1989; Hannan and Freeman, 1989), restaurants (Freeman and Hannan, 1987), national labor unions (Hannan and Freeman, 1987, 1988, 1989), semiconductor manufactures (Hannan and Freeman, 1989), brewers in America (Carroll and Wade, 1991; Carroll and Swaminathan, 1992), life insurance companies (Hannan and Carroll, 1992), and banks (Hannan and Carroll, 1992). Taking an approach similar to that proposed in this work, Blough (2000), in his dissertation, applied organizational ecology to establish the ecological dynamics in a study of evolutionary technical change in the American brewing industry.

2.4 Product Diversification, System Dynamics Modeling

Malerba, Nelson, Orsenigo, and Winter propose a product diversification, system dynamics approach to modeling, which they term as "history friendly" modeling. The purpose of their proposed modeling approach is to develop an evolutionary economic model that explains the mechanisms the empirical patterns of technological advance observed by researchers in a given population of organizations. This methodology begins with the observable history and empirical findings from qualitative research of the population under study. Next, formal models are proposed of relationships among: 1) the number of organizations in the population; 2) the respective inputs, technologies, and decision rules applied; and 3) the respective outputs produced, market share attained, and profitability as a function of population conditions of product demand, factor supply, and prices. These formal relationships are codified in a system dynamics model, and the model is run under a "wide range of settings" to generate various simulated organizational and population histories. "Some, but not all, of the parameter settings will lead to patterns of industry evolution than, in effect, 'replicate' the industry history being modeled" (*Dynamics of Organizations* 368). The models that most closely replicate the population history are retained and examined for their parametric values. New theoretical relationships are proposed, and new models constructed and simulated until a best-fit model is obtained. The formal model is then applied to explain in finer detail the causal relationships underlying the mechanisms observed in empirical research and observable history.

Malerba, Nelson, Orsenigo, and Winter applied this methodology to study the evolution of technology in the computer industry. They developed formal relationships for innovation, market, and transition dynamics. Technological capabilities were measured as a two-dimensional tradeoff between "cheapness" versus "performance" per unit, with the technological frontier designated as L_i in any given period. For innovation dynamics, they assumed at time t_0, 1948 with the invention of the transistor, that a number of organizations had randomly determined initial research and development budgets but equal design capabilities. The initial research and development budgets were spent in respectively equal amounts for a pre-specified number of simulation periods. The period-to-period change in technical capability that each organization was able to achieve was modeled as:

$$\Delta X_i = a_0 (R_i)^{a1} (T_j)^{a2} (L_i - X_i)^{a3} e$$

where: a_0 is an intercept term; R_i is a given organization's research and development expenditure targeted at achieving i = 1 performance improvements or i = 2 cheapness improvements; T_j is the number of periods that an organization has worked on a particular technology; $L_i - X_i$ is the distance of the achieved design to the technological frontier; and e is a residual random element to account for variation in technological achievement. Variables a1, a2, and a3 were shape parameters that were adjusted to achieve the best fit of observed historical change. Gross profits were calculated in each period as:

$$\pi_t = M (p - k)$$

where: M is the number of computers sold; p is the price per unit; and k is the production cost per unit. Price was obtained by adding a constant mark-up, equal for all organizations, to production costs.

$$p = k (1 + \mu)$$

Research and development expenditures were calculated as a constant fraction, ϕ, of gross profits minus budgeted expenses σ.

$$R_t = \phi \pi_t (1 - \sigma)$$

Similarly, advertising expenditures were calculated as a constant fraction, δ, of gross profits minus budgeted expenses σ.

$$A_t = \delta \pi_t (1 - \sigma)$$

Market dynamics were modeled as a function of the "merit" of each given machine.

$$M = b_0 (X_1 - X_1 \min)^{b1} (X_2 - X_2 \min)^{b1}$$

where: M is the number of machines that customers in a given sub-market may purchase with M = 0 if threshold requirements are not met; X_1 and X_2 are performance and cheapness variables; and b1 and b2 are shape parameters. For each sub-market, the probability that an individual customer will purchase a particular computer is defined as,

$$P_i = c_0\,(M_i)^{c1}\,(m_i + d_1)^{c\,2}\,(A_i + d_2)^{c\,3}$$

where: c_0 is specified so that the sum of the probabilities was one; m_i is the fractional market share for the given computer; d_1 is set so that new entrant computers captured some sales; and d_2 is set so that new entrant computers not yet allocated advertising expenditures also captured some sales; and c1, c2 and c3 are parameters.

Transition dynamics were designed to measure an organization's perception of and transition to a new technology as opposed to locking in on a current technology in which it had established a high competence. The adoption of a new technology was modeled in two steps. First, an organization must perceive the advantages of the new technology. That perception was modeled as a stochastic process dependent upon the organization's current technological position relative to the technological frontier and the progress realized by the new technology.

$$Pr_{\,perc} = ((z_i^{\,g} + z_{mp}^{\,h}) / 2)^{\lambda}$$

where: z_i is the fraction of the existing technological frontier covered by firm i; z_{mp} is the fraction of the new technology frontier covered by the best practice organization; and λ measures the general difficulty of perceiving the new technology. Once an organization perceives the potential of the new technology, it has to invest in order to acquire the new technology. This investment was measured as,

$$C_{ad} = F_{ad} + q\,B_t$$

where: F_{ad} is the fixed cost, equal for all organizations, of acquiring the new technology; q is the fraction of given organization's accumulated budget B_t.

Malerba, Nelson, Orsenigo, and Winter reported that the final model tended simulate the historical transitions from transistor to integrated circuits to microprocessors reasonably well. Noting that International Business Machines established an independent operation to bring its personal computer line to market, the researchers also tested a "diversification" strategy versus a "competence-driven" strategy. They found that in the short term, the diversification strategy yielded a higher rate of growth in market share, but in the long term the competence-driven strategy yielded a higher market share.

2.5 Original Equipment Computer Manufacturing Industry

A brief review of the history of the original equipment computer manufacturing industry will be presented with an emphasis on 1) how each new cohort of manufacturers used technological advances to fill niches not addressed by established organizations using prior technologies and 2) how organizations within a given cohort established their respective niches. This review was drawn from historical accounts provided by Harman 1971, Flamm 1988, Chandler 1997, Bresnahan and Malerba 1999, *Hoover's Handbook of American Business*, *Hoover's Handbook of World Business*, and multiple editions of *Moody's Industrial Manual* 1950-1999.

The history of the computer manufacturing industry can be categorized into a period of pre-commercialization development and three periods of technological revolution: mainframes, minicomputers, and personal computers and workstations. The pre-commercial period was initiated during World War II when collaboration between the British and the United States governments and universities in their respective countries resulted in the invention of high-speed calculators, code-breaking devices, servo-mechanical gun fire control on Navy ships, and Harvard's electromechanical Mark I aircraft simulator (industrial development support provided by International Business Machines) for Navy fighter pilots. The Whirlwind Computer Project was initiated at MIT's Servomechanism Laboratories in 1944. The prototype Whirlwind computer, which also included the development of magnetic core memories, was designed to be the first real-time digital computer with the capability of transmitting and receiving data over telephone lines. The ENIAC, the first digital electromechanical computer, was developed at the Moore School of the University of Pennsylvania in 1946 to calculate ballistic tables for the U.S. Army. The commercial computer industry was established in 1946 when J. W. Presper Eckert and John W. Mauchly, along with Jon von Neumann the inventors of the ENIAC, established the Eckert-Mauchly Corporation to develop computers for scientific and financial accounting. That same year, Harold Engstrom and William Norris, formerly senior analysts in the Navy's Cryptoanalysis Unit, formed Engineering Research Associates (ERA) to build a general-purpose, stored program computer, which became the Atlas I in 1950. In the Britain, Manchester University developed the Mark I, the first digital computer to use a magnetic drum memory, in 1948 and the Digital Machine in 1949. Cambridge University developed the EDSAC in 1949. Eckert-Mauchly delivered the BINIAC to the U.S. National Bureau of Standards in 1949. Remington Rand Corporation acquired the Eckert-Mauchly Corporation in 1950 and a year later delivered the UNIVAC I to the U.S. Census Bureau. MIT's Whirlwind computer was delivered to the U.S. Air Force in 1951. The invention of the transistor in 1948 marked the birth of the original equipment computer manufacturing industry and the initiation of its first period of mainframe manufacturing. The transistor provided the revolutionary performance-price economies of scale over existing vacuum tube technology needed for the commercialization of computers.

With the delivery of the UNIVAC I, Remington Rand became the new industry's market leader. In addition to the development capability with the purchase of Eckert-Mauchly, Remington Rand had previously established Remington Rand Laboratories in Norwalk, Connecticut, in 1949, and acquired ERA in 1953. Thus, Remington Rand held the bulk of computer knowledge in its three research organizations and had a three-year lead in the shipment of computers. Remington Rand, however, never successfully combined the three research organizations and never commercialized computers through its sales force. Rather, the company, even after its merger with Sperry Corporation in 1955, continued to be organized along functional lines with computers being sold as one of many office products. "The sales force failed to develop close relationships with either the production or the development department. It had little understanding of computer technology and how such technology might be used by customers. Few computer-oriented capabilities were created" (Chandler 48). Rather, Remington Rand continued to rely on designing and building computers for the U.S. Air Force and the Atomic Energy Commission. It failed to research or understand the computer's potential for business applications and spin off commercial computer products from government contracts.

After the Soviet Union successfully tested its first nuclear weapon in 1952, the U.S. Air Force moved to implement a digital computer-based air defense system. The system, SAGE (Semi-Automatic Ground Environment), was designed to provide early warning and tracking of Soviet airplanes as they traveled toward and across the United States and to dispatch fighter aircraft to intercept any such invasion. The Air Force authorized MIT's Laboratories to upgrade the Whirlwind prototype computer to a reliable practical design, which could be commercially manufactured, installed, and maintained. MIT recognized that it needed the support of an industrial organization with computer knowledge in order to achieve the reliability and manufacturability requirements. MIT conducted discussions with RCA, Raytheon, Remington-Rand, Sylvania, and IBM, and, in October 1952, selected IBM. At the time of the discussions, IBM had released and was producing the model 607 digital computer and was in the design stage for models 701 and 702. In April 1953, the Air Force awarded IBM the prime contract to develop detailed specifications for the SAGE system, and, in September 1953, the Air Force asked IBM to fabricate, deliver, and support two prototype SAGE computers. In February 1954, IBM purchased 200 acres of land near Kingston, New York, and began construction of the production facility for the SAGE computers. It transferred many of its engineers who were working on the 701 and 702 computers to the SAGE contract and provided them with a six-month field engineering training course on SAGE computers installation and maintenance. These engineers, in turn, trained new employees for the production facility, facilitated start up and production, and trained customer engineers transferred from other IBM assignments. At the project's peak, IBM employed between 7,000 and 8,000 employees. The SAGE contract yielded "substantial technical, manufacturing, and educational benefits to IBM by allowing it to place into actual production many of the most advanced concepts, designs, and technologies known at the time" (Chandler 28). The SAGE and other governmental research contracts provided the financial basis on which IBM built its commercial computer operations. IBM built and delivered 56 computers at $30 million each under the SAGE contract. Out of SAGE, IBM commercialized its design as the Model 701 in 1953. The Model 701 was the first computer to be produced in volume. In 1954, IBM added Models 650 business machines and 704 scientific machines to its computer line. The Model 704 computer was the fastest and largest computer of its day. In 1955, with its aggressively priced and marketed Model 705 large business machine computer, IBM captured the lead in the computer industry from Remington Rand. In 1957, IBM had its first year of revenues above $1 billion. In 1958, IBM introduced its second generation of computers, the Model 7080 for the scientific market and the Model 7090 for the commercial market. In 1960, it introduced the 1401 series of small business systems. With rentals of 20,000 units, the series 1401 machines became the most successful computer to that time. Up until 1960, a total of only 6,000 general-purpose computers had been installed in the United States. In 1960, on the strength of its second generation of computers, IBM rentals climbed to $1.8 billion with a net profit of $217 million for a 12 percent profit margin.

IBM established its organizational model for competitive effectiveness under the SAGE contract and applied its model iteratively to achieve early dominance. IBM's organizational model for competitive effectiveness was characterized by: (1) direct contact with its customer base through customer engineers who were trained to resolve technical and business problems, (2) joint investment in technology, marketing, and management to leverage its socio-technical structure; (3) consolidation of its dominant position through technological innovation, and (4) and maintenance of its dominance by iteratively introducing leading edge new products that progressively opened new markets.

The remaining major U.S. mainframe manufacturers of the 1950s, Control Data Corporation (CDC), National Cash Register (NCR), Burroughs, and Honeywell pursued niche strategies. CDC, founded in 1957, focused on the strategies of: 1) developing computers for U.S. government agencies at the high end of the price-performance range and spinning off commercial products; 2) pursuing technology acquisition through vertical integration; 3) building a technically knowledgeable sales force; and 4) establishing data services and time-sharing facilities to expand the use of its computers. From these strategies and the acquisition of small manufacturers of peripheral equipment, CDC became IBM's most successful challenger by the end of the 1960s. NCR entered computer manufacturing in 1952 with the purchase of Computer Research Company, which produced small computers for military applications. NCR targeted its computers toward banking organizations but sold its systems through its cash register sales force.

During the 1950s, NCR failed to transform its electromechanical cash registers into digital electronic systems, and, by 1962, it derived only two percent of its sales from computers and peripheral equipment. Burroughs, the fourth largest manufacturer of electromechanical business machines, entered the computer industry in 1956 with its purchase of Electrodata. Burroughs released its first computer in 1957, the Datatron, which used vacuum tubes as its logic devices. The Datatron was an immediate market failure, but Burroughs quickly redesigned it to a transistor-based logic. Burroughs was moderately successful in marketing the Datatron to its bank accounting customers. Like NCR, Burroughs did not convert its base of electromechanical business machines to electronic systems. By 1963, Burroughs' total data processing revenue was just under $39 million. Honeywell entered into computer manufacturing in 1955 through a joint venture with Raytheon to build a commercial computer. The computer performed so poorly that Raytheon exited the venture. Its next transistor-based computers, the 800 and 200 series, achieved limited market success. In 1962, Honeywell entered into an agreement with Nippon Electric Company to sell its computers in Japan. Like NCR and Burroughs, Honeywell did not convert its industrial electromechanical products to electronic systems, and by 1963 it had only $27 million in computer product sales.

During the 1950s, IBM successfully translated the technical capabilities of its first- and second-generation computers through superior marketing and field service support into dominance of the European and Japanese markets. IBM developed its "World Trade" marketing strategy, "making itself as local a company as possible. This meant involving nationals in almost all roles, including senior management. The point of localization was to ensure that relationship selling efforts worked" (Bresnahan and Malerba 93). Conversely, European and Japanese entrants into the computer industry remained small and fragmented, and they focused solely on strategies of filling regional and technical niches with incompatible systems. Britain spawned nine small computer-manufacturing organizations and France four. Nixdorf's predecessor, Labor fur Impulstechnik, built the first vacuum tube based, electronic calculator and gained computer expertise by building computers for other European computer companies. In Italy, Olivetti released an electronic calculator in 1959 but remained committed to its electromechanical office products and subsequently sold it Electronic Division to General

Electric in 1964. With significant protection and support from the Japanese government, Fujitsu, Hitachi, Mitsubishi, Nippon Electric Company (NEC), Oki Electric Company, and Tokyo Shibaura Electric (later changing its name to Toshiba) initiated semiconductor and computer manufacturing operations during the late 1950s.

The invention and patenting of the first integrated circuit in 1959 ushered in the second period of minicomputer manufacturing. Minicomputers revolutionized the computing industry, as opposed to the incremental, evolutionary approach of the mainframe period. The cohort of minicomputer manufactures consisted primarily of entrepreneurs who focused on engineering and academic computing niches. The pioneering competitors—Digital Equipment Corporation (DEC), Scientific Data Systems, Data General, and Prime Computer—invested heavily in development of "technically advanced production facilities, . . . national and then international marketing and service organizations, and recruited large labor forces and technically trained teams . . ." (Chandler 68). The rise of the minicomputer cohort of organizations, however, was a co-evolution of new firms operating in a new niche market parallel to the existing mainframe manufacturers.

The cohort one, mainframe manufacturers continued to focus on their respective technology. On April 4, 1964, after three years of development, delays, and cost overruns, IBM introduced the System 360 computer, the first mainframe computer based on integrated chip technology. IBM started shipping the first System 360 computers a year later in 1965, but manufacturing and software development issues continued to delay full production until 1967. In 1967, IBM resolved all of the production and performance issues and flooded the market with System 360 computers. Based on the strength of the System 360 line, IBM controlled 70 percent of the world's market for general-purpose computers in 1970 with rental revenues of $7.5 billion and $1 billion in net profit for a 13.6 percent profit margin. In 1970, it introduced the System 370, which was an evolutionary extension of the 360 with a monolithic integrated processor and high-speed cache memory that yielded a four times increase in performance. Despite the strength of its competitive position in 1970, IBM struggled through the 1970s. IBM's worldwide market share slipped from 70 percent to 40 percent. While the computer industry as a whole reduced manufacturing costs by more that 20 percent per year, IBM could managed only 15 percent per year cost improvements. CDC created and developed the market for low cost, IBM-compatible memory upgrades and peripherals. In 1975, Amdahl Corporation, founded by Gene Amdahl one of the chief engineers who designed the IBM 360 and 370 series of mainframes, released its first IBM-compatible mainframe with a higher performance-price ratio than IBM's 370 mainframe. In a joint venture, Fujitsu and Hitachi released the M Series, IBM-compatible mainframe and related peripherals.

DEC, the largest minicomputer manufacturer with about one-third of total minicomputer sales from 1960 to about 1985, traced its founder's, Ken Olsen, roots back to MIT's Whirlwind and IBM's SAGE computers. The MIT research team completed and tested the Whirlwind computer during Olsen's undergraduate years. In 1951, Professor Jay Forrester, who managed the development of the Whirlwind computer, recruited Olsen to work on the SAGE project. DEC minicomputers revolutionized the way people use computers. Before DEC, all computing was done in batch mode on large mainframe computers housed in specially constructed computer rooms. Olsen recognized that engineers did not need room-sized, multi-million dollar mainframe computers like Remington Rand's Univac or IBM's Model 705 for simple computing tasks such as monitoring experiments, performing engineering computations, and maintaining inventory lists. He observed that the computing needs of the engineering community were not being met and reasoned correctly that if DEC supplied small, rugged, and inexpensive computers, engineers in all disciplines would find multiple uses for them. DEC released the PDP-1 (Programmable Data Processor) computer in 1960. In rapid succession, PDP-5 and 6, a large time-sharing computer designed to serve multiple users, followed between 1960 and 1963. The engineering community responded immediately and welcomed DEC's first minicomputers as a revolutionary development. DEC was the first to sell computers outright rather than rent them. DEC minicomputers sold initially for $120,000 and used the same floor space as a large filing cabinet. DEC introduced its first mass produced minicomputer, the PDP-8, in 1965 priced under $20,000. The PDP-8 was followed in rapid succession with the PDP-9, 10, and 11 lines. The PDP-11 was the most popular minicomputer ever made. Its total sales exceeded 250,000 units. The PDP-11 line was so popular that despite DEC's attempt to replace it with the VAX (Virtual Address Extension) line in the late 1970s, customers still demanded it into the mid 1980s. DEC sales soared from $25 million in 1966 to $1 billion in 1977. Revenues grew at an annualized rate of 86 percent. DEC minicomputers were not revolutionary simply as a result of their small size and price. They were relatively easy to use, ran interactively, allowed simultaneous access by multiple users, and gave engineers and academics the capability to explore information processing in new ways. DEC minicomputers gave birth to the concept of linking individual computers in a network to take care of an organization's computing needs without relying on a central computer room. DEC spawned the first wholesale computer market by selling its minicomputers to systems houses and OEMs who, in turn, equipped them with additional hardware and specialized software to meet the needs of niche markets.

Belatedly, IBM offered its first minicomputer in 1975, and it quickly built a minicomputer business among its commercial users. None of the competitors, however, including IBM was able to dislodge DEC's hold on the scientific and engineering market. To counter, DEC unveiled its 32-bit VAX-11 line in 1977 to compete with the IBM 3031 and 3032. Digital used its customer base effectively and aggressively promoted and sold its new VAX line. The new VAX generation represented a significant leap forward in integration technology. The new line was configurable in any manner needed to address a given customer's computing needs. The line ranged from small, desktop machines to clusters of computers all running the same software and sharing data over a network with a central VAX superminicomputer. Within a year Digital controlled 40 percent of the superminicomputer market, and by 1982, Digital had sold about 5,000 VAX-11 units.

Founded in 1961 by two former Packard-Bell engineers, Scientific Data Systems quickly became DEC's primary rival through its production of low-cost, scientific minicomputers. Released in 1966, the SDS 940 effectively competed with the PDP-6. Scientific Data Systems, however, relied heavily on U.S. government contracts. To broaden its market niche, Scientific Data Systems moved into the low-end mainframe market in the late 1960s. Xerox acquired SDS in 1970 in an effort to enter computer manufacturing, but Xerox was unable to hold its share of the minicomputer market and ceased computer manufacturing in 1975.

Edwin Castro and a number of the primary design engineers on the PDP-8 left DEC in 1968 and founded Data General Corporation. Data General quickly developed and released the NOVA minicomputer with the first 16-bit processor and improved memory capability. The NOVA was priced at just under $8,000. In 1974, Data General moved into the low-end mainframe market releasing its Eclipse series of computers. Eclipse computers could be linked in a network and had interfaces to IBM 360 and 370 systems.

Founded in 1971, Prime Computer grew quickly on the strength of its series of Prime 100 to Prime 500 minicomputers with supporting peripherals and software. In the late 1970s, Prime went into decline after its original core of founding managers and engineers left to found Apollo Computer.

As a result of the growing use of minicomputers to control scientific instrumentation, instrument firms such as Hewlett-Packard, Perkin-Elmer, and Gould entered into minicomputer manufacturing in the late 1960s and early 1970s. Hewlett-Packard was the most successful, releasing in 1972 its HP 3000 minicomputer. The HP 3000's success was based on its capability to perform a broader range of general-purpose computations than existing minicomputers. In 1976, Hewlett-Packard expanded the HP 3000's capabilities to accommodate time-sharing, multiprocessing, batch, or online processing.

In Europe, the 1960s and 1970s was a period of consolidation in and national protection of European computer manufacturers. Governmental policies in European countries were designed to establish and protect nationalized mainframe computer manufacturers. In Britain, International Computers Limited was formed in 1968 "from the merger of International Computers and Tabulators (ICT) (already incorporating the computer operations of BTM, Ferranti, General Electric Powers, and EMI) and English Electric Computers (EEC) (already incorporating the computer operations of Elliott Automation, English Electric, Leo Computers, and Marconi). In the same period in France, CSF/CGE and SEA of the Schneider Group merged to form CII" (Bresnahan and Malerba 101). European governments provided support by directing the majority of their orders for computers and peripheral equipment to their respective nationalized computer manufacturers. Siemens, Compagnie Internationale pour l'Informatique (CII), and

Philips formed a pan-European joint venture, UNIDATA, in an effort to compete directly with IBM. Managerial control issues were never resolved and the venture failed in 1975. In spite of niche strategies and governmental nationalization and protection, European computer manufacturers were never effective competitors. "For example, in France in 1972 IBM controlled 58 percent of the installed base while CII, Siemens, and Philips claimed 12 percent and Honeywell and Bull 18 percent. In 1980 IBM still had 52 percent of the installed base . . . while CII-Honeywell-Bull controlled 31 percent. In the United Kingdom International Computer Limited's (ICL) market share declined from 41 percent in 1968 to 31 percent in 1985" (Bresnahan and Malerba 102).

Japanese computer manufacturers, with protection from the Japanese government, sought to counteract IBM's dominance through the formation of consortia. FONTAC, one of the first of many consortia that involved both private and government participation, lasted from 1962 to 1964 and was designed to develop a computer that would directly compete with the IBM 1401. The venture ended in 1964 with IBM's release of its System 360 computer. With the release of the System 360, however, Japanese governmental and computer manufacturing leaders recognized the importance of standardization, compatibility, and scale. Japan's Ministry of International Trade and Industry (MITI) coordinated the "Super High-Performance Computer Project" initiative with the largest Japanese computer manufacturers to build Japanese technical and manufacturing capabilities. Fujitsu, Hitachi, Mitsubishi, Nippon Electric Company, Oki Electric Company, and Tokyo Shibaura Electric participated in the initiative, all building base technical competence and reduced time to market. By the time IBM released its System 370 in 1970, Japanese computer manufacturers had captured a large share of the Japanese computer market, but still lagged in exports. During the 1970s, the Japanese government gradually reduced its protection of the Japanese computer manufacturing industry, and the industry responded by forming supplier-manufacturer "keiretsus" of joint cooperation. In the late 1970s, MITI and Nippon Telephone and Telegraph each sponsored consortia of Japanese computer supplier-manufacturer "keiretsus" to create very large-scale integrated (VSLI) chip engineering and manufacturing capabilities. These initiatives developed Japanese computer manufacturing competence and laid the foundation of subsequent Japanese competitiveness. By 1979, Fujitsu held 22 percent, Nippon Electric Company 17 percent, and Hitachi 15 percent of the installed Japanese computer base as compared to IBM's 20 percent. In the early 1980s, Japan became a net exporter of IBM-compatible mainframe computers.

Microprocessors, introduced in 1971 for use in desktop calculators, provided the processing power that drove the transition to the third period of microcomputer manufacturing. "By 1975, amateur 'hobbyists' were assembling cheap, readily available components into small, inexpensive computers. Then kits—the MITS Altair and IMSAI 8080—were sold to buyers who could construct their own computers" (Chandler 80). In 1977, the first of the cohort of microcomputer manufacturers, Apple Computer, Tandy Corporation, and Commodore, released their first personal computers.

Apple's history is well documented. Steven Jobs and Steve Wozniak designed the Apple I computer in Job's garage, and by 1980, through Job's entrepreneurial creativity and Wozniak's computer genius, Apple Computer was the leading manufacturer of microcomputers in the United States. Apple's early dominance of the microcomputer market was a result of standardization and marketing. Wozniak standardized Apple technology on the MOS 6502 microprocessor and developed an open, nonproprietary BASIC operating system. With the exception of its disks and disk drives, all of Apple's components were outsourced. "Software developers could rely on the Apple . . . environment to provide a stable platform for applications or utilities development" (Bresnahan and Malerba 109). The first highly successful software application, the VISICALC spreadsheet, provided access to the low-end business market and established Apple as the first business personal computer. On the marketing side, Jobs set up Apple to operate as a business and established the first customer support facilities in the new industry. Apple's competitors of the late 1970s operated in an entrepreneurial manner and provided little organized customer support.

Don French, a buyer at Tandy Corporation's headquarters in Fort Worth, Texas, initiated Tandy's move into the microcomputer market. He acquired the needed technological knowledge by hiring an engineer from National Semiconductor. Tandy's TRS model was based on the Z-80 microprocessor, ran on its own proprietary operating system, and used proprietary application software developed within Tandy. Tandy sold the TRS microcomputer exclusively through its Radio Shack retailers for personal use or entertainment.

Commodore's PET microcomputer was based on the MOS 6502 microprocessor and ran on its own proprietary operating system and application software. The PET microcomputer was targeted on the low end, home computer market. Interestingly, although Commodore was an American firm based in Pennsylvania, it never captured a significant share of the American market but the dominated the European home computer market through the mid 1980s.

In 1978, the above three early entrants held an estimated 72 percent of world microcomputer market—Tandy with 50 percent, Commodore with 12 percent, and Apple with 10 percent. Tandy and Apple dominated the market in the United States while, as noted above, Commodore dominated in Europe. By 1980, Apple held 27 percent of the world market, Tandy held 21 percent, and Commodore 20 percent.

In 1980, the whole computer market was fragmenting, and mainframe sales had slowed to a single digit growth rate. IBM management recognized the potential of the microcomputer market and determined that it would not miss the next revolution in the computer industry as it had with minicomputers in the 1970s. Minicomputer sales and data services were almost one-fourth of the total industry sales, and IBM had never been the major player in the market losing out to the minicomputer leader Digital Equipment Corporation. To this end, IBM assessed the microcomputer market and estimated that expenditures for personal computers would rise to about 30 percent of the data processing market by the end of the 1980s. Its management, however, questioned whether IBM could compete with entrepreneurial run, specialized companies such as Apple, Tandy, and Commodore whose cost per unit was significantly lower than what IBM could accomplish with its overhead. To address this opportunity, IBM set up its personal computer operation as an independent business unit (IBU) to focus exclusively on bringing its product to market. This represented a totally new approach for IBM. Previously, IBM had been fully vertically integrated designing and building all of its own components, peripherals, and software. Breaking with IBM's past, the personal computer IBU purchased its components, peripherals, and software from outside suppliers in order to shorten its time to market and to benefit from externally created economies. The first

IBM personal computer was based on Intel's older 8-bit microprocessor rather than Motorola's state-of-the-art chips or even Intel's more powerful 16-bit 8086. This choice allowed IBM to aggressively price its entrant personal computers in order to capture market share. IBM turned to Microsoft, who had pioneered a version of BASIC, for its operating system. Microsoft accepted the IBM contract with its nondisclosure agreement, purchased Computer Products' SCP-DOS operating system it had written for the 8088 microprocessor, and converted the code to MS-DOS. Once MS-DOS was fully developed, IBM agreed to allow Microsoft to license it to other computer manufacturers in the belief that it would assure the availability of MS-DOS by making it the industry's standard. IBM marketed its PCs through its own sales and service force, but later expanded to a worldwide network of franchises and mass retailers. Under this strategy, IBM's personal computer leaped from a new entrant in the summer of 1981 to the sales leader in 1983. IBM shipped over 700,000 personal computers in 1983 and over 3 million units worth $3 billion in sales in 1984. Even with the entrance of multiple IBM personal computer clone competitors in the 1980s, IBM still retained its leadership position in 1989 with 22.3 percent of the worldwide market.

Of the IBM-compatible clone manufacturers to enter the personal computer market in the early 1980s, Compaq was the most successful in transforming individual capabilities into organizational capabilities. Rod Canion and two other engineering managers from Texas Instruments founded Compaq in 1982. Compaq's strategy was to simply build an IBM-compatible personal computer clone that had more features and capabilities than the IBM's personal computer and sell it at a slightly higher price. Compaq's first computer, a portable unit, exploited a niche that IBM had not yet entered. Compaq distributed its personal computer through a national retail network of authorized dealers supported by a strong marketing and distribution organizations. During 1985, Compaq enlisted Intel and Microsoft's assistance in the development of its new desktop computer, the Deskpro 386. At Intel's request, Compaq included in its development efforts the testing of Intel's next-generation 32-bit, 80386 microprocessor to assure compatibility with software already running on Intel's existing 80286 chip. During development, Canion had Intel adjust the chip's design to meet Compaq requirements, and the 80386 was selected as the Deskpro's microprocessor. At the same time, Canion worked with Microsoft to increase the amount of computer memory available to programs to be run on the Deskpro 386. This operating system subsequently became Microsoft Windows 386. With these enhancements, the Deskpro 386 represented a significant increase in PC capability, and with its introduction in 1986 it provided sales and revenues that propelled Compaq to the third largest personal computer manufacturer in the world. By 1988, IBM, Apple, and Compaq were the world's three largest microcomputer manufacturers with IBM's market share at 25.5 percent, Apple's at 10.5 percent, and Compaq's at 7.4 percent. American competitors included Hewlett-Packard, Unisys, AT&T, and Zenith. Japanese competitors included Toshiba, Fujitsu, NEC, Matsushita, and European competitors included Olivetti and Amstrand.

By the early 1990s, personal computers had become commodities, and marketing had replaced technology as the key to growth. In its meticulous, engineering manner, Hewlett-Packard (HP) quietly grew the sales of its personal computers, workstations, and printers throughout the 1980s. In 1990, HP's total revenues were $13.2 billion with $9.24 billion coming from personal computers and peripherals sales. In the late 1980s, Dell Computer of Austin, Texas, pioneered the direct marketing of personal computers. Dell machines were ordered over the telephone and were customized to meet each customer's needs. Dell established a 24-hour telephone customer support and service operation and guaranteed repairs within 24 hours. These strategies eliminated retailer's markups and allowed Dell to sell its personal computers at lower prices. By 1992, Dell was among the top fifteen personal computer manufacturers in sales. But the barriers of entry into the personal computer market were low, and other manufacturers quickly developed alternate low price strategies. Gateway 2000 copied Dell's direct marketing strategy. Packard Bell sold its computers through Wal Mart and other mass retailers and discount stores. AST marketed through multiple channels from personal computer dealers to chains such as Sears. In 1992, IBM, Apple, and Compaq retained the top three positions in worldwide market share. Dell Computer was at seventh with 4.1 percent, AST at ninth with 2.6 percent, Gateway at tenth with 2.5 percent, and Packard Bell at fourteenth with 2.0 percent.

Where personal computers met the needs of the mass market of individual users, it failed to meet the "the needs for high-powered, complex data processing required by scientific, engineering, industrial, medical, financial, and some commercial institutions . . ." (Chandler 89). This was the market that minicomputers served, but the performance-price capabilities of the microprocessor meant that significant performance gains could be attained at the same price of existing minicomputers. Workstation technology networked departmental or enterprise-wide high-end microcomputer workstation clients to a high-end minicomputer or mainframe server to generate, transmit, store, and share computation-intensive data. Recognizing the potential of the workstation market, the first entrants were the leading producers of minicomputers—DEC, Hewlett-Packard, IBM, and Apollo Computer, the later started by Prime Computers' former senior management who left to form Apollo specifically to enter the workstation market. Sun Microsystems was the one successful new entrant to the workstation market. The joint capabilities of the minicomputer manufacturers and the calculation-intensive needs of workstation users acted as a barrier to "the de facto standards set for personal computers by Intel and Microsoft. These inherited capabilities permitted these firms to defeat a powerful attempt by the newcomers to become the de facto standard in their sector" (Chandler 90). Initially, each workstation manufacturer remained vertically integrated, developing and manufacturing its own microprocessors and writing its own operating system software. In the late 1980s, however, they gravitated to reduced-instruction-set-computing (RISC) microprocessors and the nonproprietary UNIX operating software as open standards.

DEC entered workstation competition in 1983 with the release of its VAXstation line. Initially, the VAXstation line was an extension of DEC's minicomputer line with more powerful, upgraded desktop units using DEC microchips and running on the VAX operating system. As the demand for RISC-based systems running on the UNIX operating system grew, DEC partially joined the move toward the open standard. It purchased a 20 percent ownership of the microprocessor design company MIPS, and jointly developed a RISC microprocessor for its next generation VAXstation 2000. Unlike its competitors, however, DEC did not completely abandon its proprietary VAX line. In parallel with the development of the VAXstation 2000, DEC developed and released the VAXstation 3100 operating on its newly developed, more powerful 64-bit Alpha processor. Alpha, manufactured at DEC's new chip manufacturing facility in

Hudson, Massachusetts, was the fastest microprocessor in the world. It was capable of performing 2.4 billion instructions per second, 50 percent more than Intel's fastest Pentium Pro chip. More important than its speed, however, was its chameleon-like behavior that gave it the ability to run any operating system (Windows, NT, VMS, UNIX, etc) with no loss in performance. When it originally introduced Alpha, DEC experienced manufacturing problems and was unable to make shipments. This resulted a sharp decline in sales of its VAX minicomputers and workstations as customers put purchase plans on hold awaiting the new technology. It was not until mid 1993 that DEC resolved its production problems and started shipping Alpha-based computers ranging from $15,000 workstations to $316,000 mainframes. To counteract it loss in sales, DEC announced that any recently purchased VAX machines could be upgraded to operate as Alpha machines. Reassured that they would not be purchasing equipment that would soon be obsolete, customers began buying VAX machines as Alpha output ramped up. DEC's sales rose to $3.4 billion in the quarter that Alpha began to ship. As a result of strong sales of Alpha-based machines, DEC finished fiscal year 1993 with revenues of $14.4 billion and a net loss of $251.3 million, down sharply from the previous year's net loss of $810.0 million.

Founded in 1980 by Prime Computers' former senior management who left to enter the workstation market, Apollo Computer was the largest manufacturer of networked workstations until 1987. Apollo manufactured its own processors and developed its own proprietary operating system, Aegis, which had a Posix-compliant front-end to the nonproprietary, open UNIX standard. Apollo's network software was the first to allow a high degree of network transparency and the first to provide demand-paging. As a result of its commitment to its proprietary system, however, Apollo lost market share from 1987 to 1989. It tried to counteract this loss by producing its own RISC processor and releasing its Parallel RISC-based Multiprocessing (PRISM) operating system with improved networking capabilities. These new products, however, could not overcome the transition to the open UNIX operating standard, and Apollo was acquired by Hewlett-Packard in 1989.

By the early 1980s, Hewlett-Packard had only one successful computer product, its HP 3000 minicomputer. It had tried but failed to market a personal computer. During this period, Hewlett-Packard invested $250 million to develop its own RISC processors and proprietary Spectrum UNIX system, and, in November 1982, it released the HP 9000 workstation. To promote demand for its proprietary Spectrum UNIX system outside the United States, it licensed Hitachi and Samsung to manufacture its RISC processor. Under this niche strategy, Hewlett-Packard was able to capture 12 percent of the world market for workstations by 1987. After a difficult period in 1989 through 1991 of absorbing Apollo into its organizational structure, Hewlett-Packard introduced an improved RISC microprocessor and "New Wave" software in 1991. Based on this new technology, Hewlett-Packard's workstation market share grew to 22 percent with revenues of $1.52 billion in 1992.

Following its successful strategy for developing and introducing its personal computer, IBM formed an independent business unit (IBU) in 1987 to design its own RISC microprocessor and produce a workstation computer. Although using a new RISC processor, the workstation was designed to run on IBM's version of UNIX or its OS/2 operating system. IBM established a performance goal for its RISC microprocessor to be twice as powerful as it next nearest competitor. IBM placed its RS 6000 workstation on the market in February 1990, and, by the end of 1992, IBM had captured 13.7 percent of the world workstation market.

Founded in 1982, Sun Microsystems set out to become the world leader in the workstation market by jointly developing a low-cost, high-speed microprocessor and an open UNIX operating system. Sun adopted AT&T Corporation's open UNIX operating system standard, because it provided the most transparent networking environment. Sun kept its manufacturing costs low by using standard technologies and purchasing peripherals from outside suppliers. Like DEC in its introduction of minicomputers, Sun leveraged its early marketing effort by selling its workstations to value-added resellers who added their own specialized peripherals and application software. In 1985, Sun initiated work on its SPARC RISC microprocessor and formed an alliance with AT&T Corporation to fully integrate UNIX into the design. After two years of development, Sun released its SPARC microprocessor and immediately licensed its production to Fujitsu in Japan, NV Philips in the Netherlands, and Cypress Semiconductor, Bipolar Integrated Technology, LSI Logic, and Texas Instruments in the United States to stimulate mass production, reduce per unit cost, and to promote production of third-party software. More important, licensing production of the SPARC microprocessor allowed Sun to focus its limited resources on building an international marketing infrastructure to expand the SPARC-based workstation and software market share as rapidly as possible. On this strategy, by the end of the 1980s over 2,800 third-party software applications had been written for SPARC workstations, and Sun became the workstation computer market leader with a 29 percent world market share. In 1989, Sun, Hewlett-Packard, DEC, and IBM were the four leading workstation manufacturers with a total of 70 percent of the world market share.

European computer manufacturers did not enter the microcomputer market until the mid 1980s and then unsuccessfully. In the early 1980s, American microcomputer manufacturers established production facilities and marketing infrastructures in Europe and rapidly dominated the European microcomputer market. Correspondingly, the proliferation of American microcomputers in Europe eliminated European minicomputer manufacturing in all but the government-supported, nationalized computer manufacturers. With the release of its M24 personal computer in 1982, Olivetti was the only European manufacturer to successfully enter the European market. Olivetti tried to strengthen its position in the personal computer market through international alliances, cooperative agreements, and acquisitions. In 1985 it acquired 80 percent ownership of Acorn Computers, and in 1986 it purchased Triumph-Adler from Volkswagen. The strategy was insufficient, and by 1991 Olivetti posted financial losses. In 1997, Olivetti sold its personal computer operations to a group of venture capitalists. In Germany, Siemens initiated personal computer production in 1985 and tried to strengthen its position in the European market by acquiring failing Nixdorf in 1990. In Britain, ICL entered the personal computer market in 1987. In 1989, Fujitsu acquired 80 percent ownership of ICL, and ICL-Fujitsu acquired Nokia's Data System Division as Nokia exited the personal computer market. A few new entrants, Acorn Computers, Amstrad, Apricot, Cambridge Computers, and Psion, captured niche markets in Britain in the late 1980s. Throughout Europe, however, governmental protectionist policies were ineffective in mitigating open market competitive forces, and European entrants into the personal computer market never captured any significant or sustaining market share.

The Japanese personal computer market remained isolated and fragmented during the globalization of microcomputers by American manufacturers. As in Europe, Japanese computer manufacturers did not enter the microcomputer market until the mid 1980s. NEC dominated the Japanese domestic market with its line of personal computers and proprietary, standardized operating system. NEC's dominance was built on operating system compatibility across its products, development of advanced software applications, and use of multiple marketing channels within Japan. By the early 1990s, NEC held just over 50 percent of the Japanese domestic personal computer market share. NEC, however, never successfully exported its personal computers, because its proprietary hardware and operating system software did not conform to the IBM-Intel-Microsoft de facto standard. In an effort to overcome this barrier of entry to the worldwide personal computer market, NEC purchased a 20 percent ownership in Packard Bell, a United States personal computer manufacturer, in 1995 and merged its personal computer manufacturing into Packard Bell. NEC acquired control of Packard Bell in 1998 increasing its ownership to 53 percent but the next year was forced to close its Packard Bell NEC division due to continuing losses. Other Japanese computer manufacturers, most successfully Toshiba, have entered the world personal computer market by manufacturing IBM-Intel-Microsoft compatible clones. The net outcome of Japanese personal computer manufacturing was a fragmented domestic market with no penetration into the world market, and the IBM-Intel-Microsoft de facto personal computer standard attained dominance of the Japanese market by the end of the 1990s.

Some researchers define the 1990s as a fourth period of transition to client/server network integration of open standards computer systems. As documented herein, however, linking computers in networks was initiated in the 1960s with the introduction of Digital Equipment Corporation's PDP series of minicomputers, IBM pioneered the move to open standards with the introduction of its personal computer in 1981, and the initiation of workstation computer technology in the mid 1980s established "client/server" computing. Thus, this research found insufficient evidence supporting or countering a client/server, network integration fourth period. An indicator variable was included in analyses to test for its presence.

CHAPTER III

RESEARCH METHODOLOGY

3.1 Open Systems Model of Effectiveness

The empirical work of this research rests on the hypothesis that environmental ecological competition models of population and organizational niche widths extended through the Viable System Model's recursive cybernetic structure and socio-technical systems' concept of joint optimization represent a general model of systemic organizational effectiveness. This systemic model of organizational effectiveness must be based on a general definition of the organization and a fundamental set of axioms that establish its form and functioning.

Toward establishing a general definition of the organization, this research accepts Hannan and Freeman's definition that organizations are "vehicles for action" (*Organizational Ecology* 3). This definition, however, is too broad in that it does not define form and only vaguely defines functioning. To establish form and functioning more clearly, this research turns to definitions from the three main perspectives in organizational research: rational, natural, and open systems. "From the rational system perspective, organizations are instruments designed to attain specific goals" (Scott 33). The rational system perspective adds to the "vehicles for action" definition by specifying that the functional purpose of organizational action is to achieve specific goals or outputs. This definition also implies that organizations, being designed instruments, must have internal structural forms that jointly apply a stated set of technologies to transform a set of inputs into defined outputs. The requirement for a stated set of technologies recognizes that at any given time there are knowledge and physical technological frontiers and that an organization may be economically, socially, or knowledge constrained from applying the frontier technologies.

Conversely, the natural system perspective notes that organizations are more than just vehicles for accomplishing goals. "First, there is frequently a disparity between the stated and 'real' goals . . . . Second, . . . even when stated goals are actually being pursued, they are never the only goals governing participants' behavior. . . . all organizations must pursue *support* (or 'maintenance') goals in addition to output goals"

(Scott 57). From these observations, the natural system perspective defines organizations as "... social groups attempting to adapt and survive in their particular circumstances" (Scott 57). The natural system perspective defines the fundamental organizational form as being a social group. This definition further implies that not only is the organization itself a social group, but also each organization is made up of individual people who aggregate into formal and informal social groups within the larger organizational social group. The natural system perspective adds to the goals functionality the requirement that organizations must adapt, survive, and be self-maintaining. The adaptation requirement implies that organizations are cybernetic entities with internal structures that function optimally in respective states of equilibrium, which in the aggregate result in an optimal state of organizational equilibrium relative to its respective population. In order to maintain states of equilibrium, internal structures must interact within the organization and the organization with its population to detect changes in organizational and population states that may affect respective states of equilibrium. Each internal structure and the organization itself must possess knowledge or self-awareness as to its respective optimal equilibrium, how deviations in organizational or population states cause changes from its respective equilibrium point, what counteractions must be taken to restore equilibrium, and how to control and monitor counteractions so that they return the internal structure and organization to equilibrium. The desired outputs of cybernetic actions are survival, counteracting maximum organizational and population state deviations to achieve minimal functionality, and maintenance, equilibrium functionality to produce desired organizational outputs in some optimal manner.

The open systems perspective adds to the natural systems perspective of organizations as social, cybernetic entities the observations that organizations are made up of loosely coupled, hierarchical structures (Scott 85). The cybernetic requirement of internal equilibrium in internal structures aggregating to an optimal organizational equilibrium implies that organizations themselves are hierarchical structures of internally controlled organizations within the organizational entity and that organizational entities are hierarchical structures subject to environmental selection control through competition within the larger population of organizations. The "loosely coupled" observation results from recognizing that taut coupling between systemic elements means that failure in one element instantly affects all other elements to which it is coupled and can, depending on the criticality of the element, cause instantaneous system failure. Thus, some degree of looseness in coupling among organizational systemic elements and between the organization and its population are required to allow time for cybernetic detection and reaction to effect counteractions that restore equilibrium. The "loosely coupled" observation also results from recognition that organizations are made up of social groups, and that social groups tend toward independent autonomous actions that are weakly linked to the autonomous actions of other social groups and organizations themselves.

From the above perspectives, this research defines an organization as a loosely coupled, hierarchical, cybernetic structure of self-aware social groups that act to attain and maintain aggregate organizational equilibrium and to apply a stated set of technologies to transform defined inputs into desired outputs that achieve aggregate organizational goals.

Next, this research defines a fundamental set of axioms that establish form and functioning of observable organizational adaptation behaviors. The first and second organizational axioms are derived directly from Pennings and Goodman's description of organizational dyadic relationships.

A1: The fundamental relationship among individuals, individuals and groups, or groups and groups is the dyadic interaction. All other relationships, no matter how complex, can be decomposed to a set of fundamental dyadic interactions.

A2: Actual or perceived organizational effectiveness are respectively functions of aggregated dyadic interactions between an organization and other individuals, organizations, or populations in its referent environment.

Axioms one and two establish the basic relationships represented in ecological competition models through environmental, population, and organizational covariate predictors of niche width effectiveness.

Derived directly from Beer's Viable Systems Model (VSM), axioms three and four establish the cybernetic mechanisms through which actual and perceived organizational effectiveness are worked out through dyadic interactions.

A3: The Viable System Model represents the necessary and sufficient cybernetic structure of a viable system.

Axiom three implies that viability, survival, is the minimum effectiveness requirement and that minimum effectiveness requires the minimum cybernetic structure of the VSM. Axiom four extends the minimum viability implication of Axiom three to populations and environments through the Recursive System Theorem.

A4: The Recursive System Theorem is the invariant linking process through which the cybernetic structures and processes of individual, group, organizational, population, and environmental viable systems are realized through fundamental dyadic interactions. That is, the Recursive System Theorem holds universally.

Axiom four implies that competitive environments are themselves meta-systemic organizational forms that must exhibit the structures and processes of the Viable System Model, and it further implies that these cybernetic structures and processes must be designed or worked out through self-organizing dyadic interactions.

Axiom five recognizes the invariant principle that all VSM level one, productive subsystems require interacting social and technical subsystems to transform inputs into outputs and create the system's purpose for existing.

A5: Social and technical sub-systemic structures and processes are necessary and sufficient for the transformations of inputs into outputs at the Viable Systems Model's subsystem one level of recursion.

Next, this research adopts a set of axioms directly from organizational ecology theory (Hannan and Carroll 30-49) that establish the fundamental mechanisms of environmental and population level selection forces. Axioms six through eight consider the effects of competition on vital rates. All three axioms are based on empirical observations that increases in competitive intensity depresses founding rates and increases mortality rates (Appendix A provides definitions of symbols used in this research).

A6: The founding rate of an organizational population at time t, $\lambda(t)$, is inversely proportional to the intensity of competition within the population at that time, C_t. That is, $\lambda(t) \propto C_t^{-1}$.

A7: The mortality rate of organizations in a population at time t, $\mu(t)$, is directly proportional to the intensity of competition within the population at the time (contemporaneous competition). That is, $\mu(t) \propto C_t$.

A8: The mortality rate at time t of organizations founded at time f, $\mu(t, f)$, is directly proportional (at any age) to the intensity of competition at the time of founding, C_f. That is, $\mu(t, f) \propto C_f$.

Axioms nine and ten consider the effects of legitimation on vital rates. The basis of both axioms is that as more organizations adopt an organizational form the form takes on a taken-for-granted social status. New organizational forms have dubious social standing in their early stages of development. As the population grows or as the new form is adopted by other organizations, the new form takes on a taken-for-granted status as an appropriate structure for attaining collective goals. "The capacity to mobilize potential members and resources increases greatly when those who control resources take the organizational form for granted. Reducing the need for such justification lowers the cost of organizing" (Hannan and Carroll 36).

A9: The founding rate in an organizational population at time t is directly proportional to the legitimation of its organizational form at that time, L_t. That is, $\lambda(t) \propto L_t$.

A10: The mortality rate in an organizational population at time t is inversely proportional to the legitimation of its organizational form at that time. That is, $\mu(t) \propto L_t^{-1}$.

Axioms eleven and twelve consider the relationship between competition and density. Elementary observation suggests that an increase in population density relative to available resources (members, raw materials, capital, customers, etc.) intensifies competition at an increasing rate. When the population is small relative to available resources, the addition of single organization has little effect on other organizations in the population. When the population is at or near the carrying capacity of environmental resources, the additional of a single organization highly impacts other organizations in the population. "From the viewpoint of the actions of a single organization, the difficulty of fashioning a strategy that works against all, or most, competitors becomes extraordinarily difficult when very many pairwise interactions must be considered simultaneously" (Hannan and Carroll 40).

A11: The intensity of contemporaneous competition, C_t, increases with density, N_t, at an increasing rate. That is, $C_t = \varphi(N_t)$; and $\varphi' > 0$ and $\varphi'' > 0$.

A12: The intensity of competition at the time of founding, C_f, increases at an increasing rate with density at the time of founding, N_f. That is, $C_f = \nu(N_f)$; and $\nu' > 0$ and $\nu'' > 0$.

Axioms thirteen through fifteen consider the relationship between legitimation and density. Again, elementary observation suggests that the more rare an organizational form the greater its problems in establishing legitimacy. Organizations achieve a taken-for-granted status through two processes. In the first process, legitimation is realized through "action by members of the population to define, explain, and codify its organizational form and to defend itself from claims and attacks by rival populations." The second process is "collective learning by which effective routines and social structures become collectively fine-tuned, codified, and promulgated" (Hannan and Carroll 41). Once an organizational form works through the definitional and learning processes and achieves legitimacy, however, increases in the number of organizations adopting the form will have little effect on its taken-for-granted, legitimate standing. At the point of taken-for-granted legitimacy, approximately all of the relevant constituents assume the legitimacy of the organizational form as a normative structure. New organizations that adopt the form assume its legitimate status.

A13: Legitimation increases with density at a decreasing rate. That is, $L_t = \gamma(N_t)$; and $\gamma' > 0$ and $\gamma'' < 0$.

A14: The relationship between density and legitimation is positive with a point of inflection (N_λ) such that legitimation increases at an increasing rate with density to some point (the inflection point) beyond which legitimation grows with density at a decreasing rate. That is, $L_t = \upsilon(N_t)$; and $\upsilon' > 0$, and $\upsilon'' > 0$ if $N_t < N_\lambda$, and $\upsilon'' < 0$ if $N_t > N_\lambda$.

A15: Legitimation is stronger than competition at very low densities. In particular, $\gamma(N_t) > \varphi(N_t)$, and $\upsilon(N_t) > \varphi(N_t)$ when $N_t < 2$.

From this research's definition of the organization, its five axioms of organizational adaptation set forth in the necessary and sufficient cybernetic structure of Beer's Viable System Model, and the ten axioms establishing the fundamental mechanisms of environmental selection forces from organizational ecology, the general systemic model of the domains and dimensions of organizational effectiveness for this research is illustrated in Figure 11.

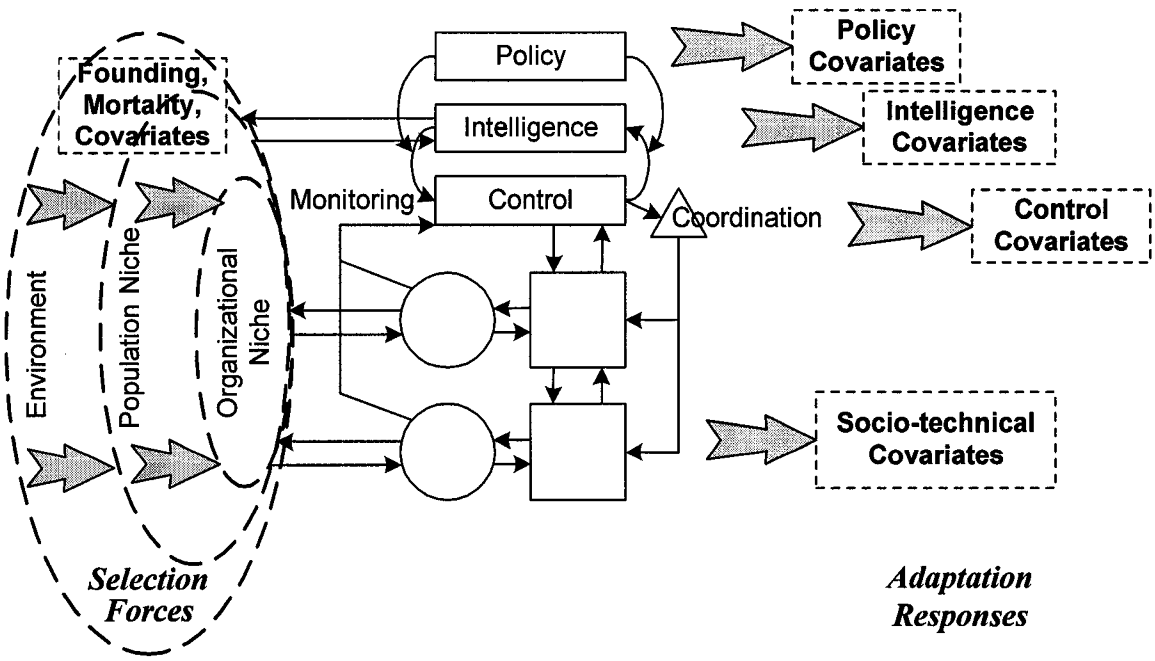


Figure 11. Systemic model of the domains and dimensions of organizational effectiveness.

The general systemic model of organizational effectiveness consists of two domains. The environmental domain is comprised of communities of organizational populations self-organized into population niches, populations of organizations self-organized into organizational niches, and each organization within its respective niche. The model illustrates that selection forces do not arise from organizations interacting with their respective environments; rather, each organization within its respective niche interacts with other organizations within their respective niches within the population niche. The interactions among organizational niches within the carrying capacity of the population niche create self-organizing population level competitive selection forces. From the Recursive System Theorem, self-organizing environmental level competitive selection forces likewise arise from populations interacting with other populations within their respective niches. These environmental and population level competitive selection forces are, by the Recursive System Theorem, respectively self-organized into the five interacting subsystems (production, coordination, control, intelligence, and policy) of the Viable System Model. These self-organizing forces arise from the constraint of the environmental carrying capacity on the population niche width, and, as such, represent random density determinants of effectiveness. The nonrandom determinants of effectiveness are modeled by observable environmental and population covariates.

The organizational domain is Beer's cybernetic Viable System Model of the five interacting subsystems, which are necessary and sufficient for systemic viability. The organizational domain is made up of the four nonrandom effectiveness dimensions of observable policy, intelligence, control and coordination, and socio-technical covariates plus random technical and social covariates. Some researchers might argue that the social and technical components of the level one production system should be modeled separately. This research, however, accepts socio-technical systems methodology's fundamental axiom that it is the interaction of the social and technical components of the VSM level one production subsystem that produces organizational outputs and the organization itself. Thus, this research models the level one production subsystem as a joint socio-technical subsystem.

3.2 Methodology for Effectiveness Analysis and Modeling

Two criteria guided the development of this systems methodology for measuring operational organization effectiveness. The first criterion is that it must be an applied methodology based on systems theory. The test for the applied part of this criterion is that any engineering manager in any organization be able to follow the steps of the methodology and develop his or her own assessment of effectiveness for an identified organizational population. The theoretical foundation for the methodology is set forth in axioms one through fifteen above. The second criterion is that effectiveness assessment be performed through event history analysis of observable features of the identified organizational population across a bounded time period. Blossfeld and Rohwer define event history analysis as the study "transitions across a set of discrete states, including the length of time intervals between entry to and exit from specific states" (38). Hannan and Carroll justify the application of event history analysis as a strategy for research into organizational dynamics as follows:

> The general strategy of theory building and empirical research . . . differs from that of much contemporary work in the sociology and economics of organizations. Most other theories and research attempt to explain processes of the organizational world in terms of difficult-to-observe features of organizations. Prominent examples include organizational culture and transaction costs. Because of the cost and difficulty in obtaining comparable measurements on large numbers of organizations (especially over time), theories that emphasize the causal primacy of such subtle features are rarely tested comparatively.
>
> Our strategy puts complexity into the theories and models rather than into heroic requirements for observations. We concentrate on features of organizational populations that can be easily observed. And we relate covariation among variables to theories and models that represent general sociological processes (17).

For this systems methodology of measuring operational organization effectiveness, Beer's Viable System Model establishes the cybernetic adaptation response process, and axioms six through fifteen establish the theoretical processes of environmental and population selection forces. Event history analysis provides the means for assessing operational organization effectiveness in standardized units of time over a bounded time interval by relating covariation between an observable organizational metric that indicates effectiveness or ineffectiveness states to observable organizational adaptation covariates and population and environmental selection covariates. For this research, the effectiveness state was defined as an organization's ability to sustain annual nonnegative growth in its inflation adjusted, organizational dollar volume sales market share niche.

As illustrated by Figure 12, this system methodology for measuring operational organizational effectiveness is conducted in the following six general phases:

Phase 1 Define population's physical and time boundaries, and test for density dependence.

Phase 2 Develop a VSM model of the population and its organizations, and hypothesize observable covariates for the environmental and organizational dimensions.

Phase 3 Identify reliable sources of data and build a historical database of observed values for each covariate in each unit of time within the population's time boundary. If records are incomplete, statistically estimate missing data to minimize induced bias in the final effectiveness model.

Phase 4 Standardize the effectiveness indicator data to "unit" niche space. The data are taken from the metric that best provides an unbiased estimate of the total population niche width and respective organizational niche widths within the population. Standardization is performed in two steps. If a monetary metric, as was the case in this study, is used as the niche data, the data are normalized to a given national monetary unit in each time period and then deflated using that national monetary unit's inflation index. In the second step, an initial time period, t_0, is selected and the population's cumulative deflated niche data are standardized to 1 for that initial time period (i.e. all population cumulative deflated niche data and individual organizational niche data in all time periods t_i are divided by the population cumulative deflated niche data in period t_0). This two-step standardization yields unbiased estimates of changes in real population and organizational niche widths over the population's time boundary.

Phase 5 Perform event history analyses to determine population and subpopulation best-fit survival and effectiveness models and the statistically significant covariates.

Phase 6 From the population best-fit covariate model, develop a dynamic simulation model. Validate the simulation model, and perform dynamic sensitivity analyses to determine the dynamic effects of changes in controllable covariate parametric values.

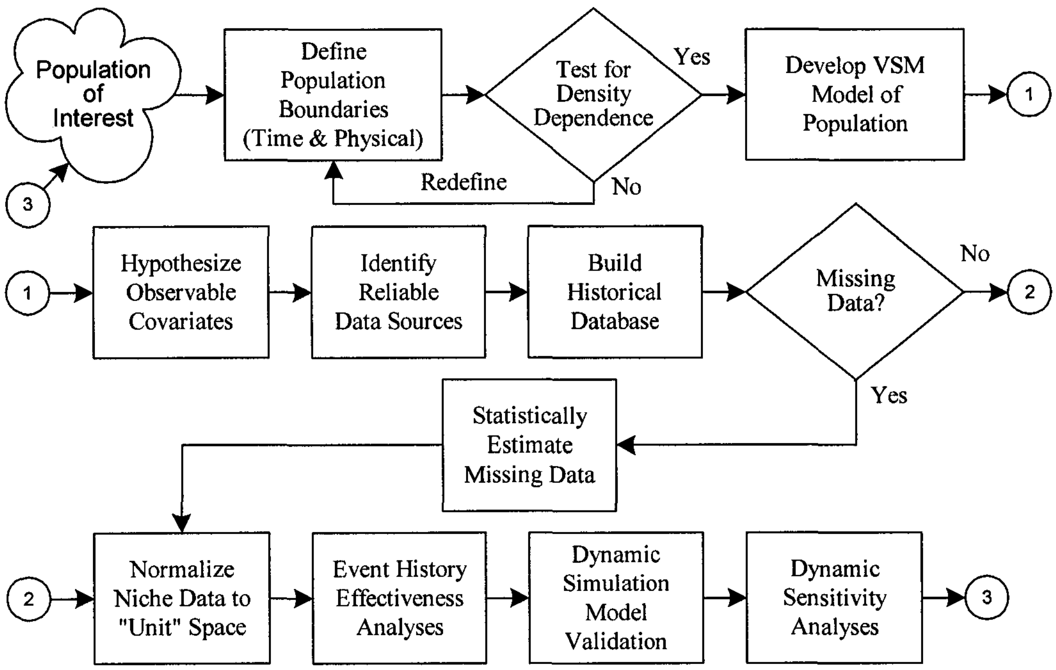


Figure 12. System methodology for measuring operational organizational effectiveness.

For this research, the population's physical boundary was inclusion in the group of dominant, original equipment computer manufacturers. Dominance was defined as:

1. An original equipment computer manufacturer that was reported in historical accounts as being among the dominant few in worldwide market share revenues within each cohort for the years 1949 to 1975.

2. An original equipment computer manufacturer that was included in the annual *Datamation* "Top 50" or "Top 100" list of companies in the data processing industry for any given year for the period 1976 to 1997.

These periods were selected, because one organizational covariate, number of United States patents granted annually, did not have annual data available from the United States Patent Office prior to 1976. This definition of dominance allowed this research to focus on the computer manufacturers that determined the industry's competitive dynamics. As consistently reported in the annual *Datamation* articles, on average IBM held 40 to 50 percent of the world market and the top nine or ten companies (including IBM) accounted for 80 to 90 percent of the world market. An original equipment computer manufacturer was defined as a company that designs, manufactures, sells, and services its own brand of mainframe, minicomputer, personal computer, or workstation system as its primary product. This definition excluded data processing companies that:

- Manufactured peripherals or other computer related equipment as their primary products.
- Provided subcontract, manufacturing services to original equipment computer manufacturers.
- Produced only software products.
- Provided computer or network design and support services.
- Provided network equipment or services as their primary product.
- Provided data services.
- Provided data communications equipment or services as their primary product.
- Manufactured reproduction or copier products.
- Manufactured other electronic equipment as their primary products.
- Provided or produced any combination of the above as their primary products.

The time boundaries of 1949 to 2001 for the research period was selected, because:

- The invention of the transistor in 1948, year zero, marked the birth of the commercial original equipment computer manufacturing industry and the initiation of its first period of mainframe manufacturing. Prior to 1948, computers were vacuum tube based, experimental units with performance-price ratios that were too low to justify commercialization. Transistor technology increased the performance-price ratio to the point where it became commercially feasible to manufacture and market mainframe computers as business machines.
- At the time this research was initiated in early 2003, annual organizational, financial, and patent data was complete only through 2001.

The time frame was subdivide into three cohort periods: 1) 1949 to 1959 in which mainframe computer manufacturers rose to dominance, 2) 1960 to 1976 in which minicomputer manufacturers established their niche on the improved performance-price ratio of the integrated circuit, and 3) 1977 to 2001 in which personal computer and workstation manufacturers established their niche on the power of the microprocessor. Data were gathered and recorded in the standardized time unit of one calendar year, because all members of this population operated and provided financial reports on an annual basis.

Tests of density dependence for conformance to the first four ecological theorems stated under section "3.3 Effectiveness Hypotheses" indicated that hypothesized environmental selection forces held for this population. The results of these tests are provided in section "4.1 Exploratory Analyses."

The VSM model of the original equipment computer manufacturing population and its organizations is illustrated in Figure 13. Survival and effectiveness response variables and their definitions are set forth in Table 4. Hypothesized, observable environmental and organizational domain covariates and their definitions are set forth respectively in Tables 5 and 6.

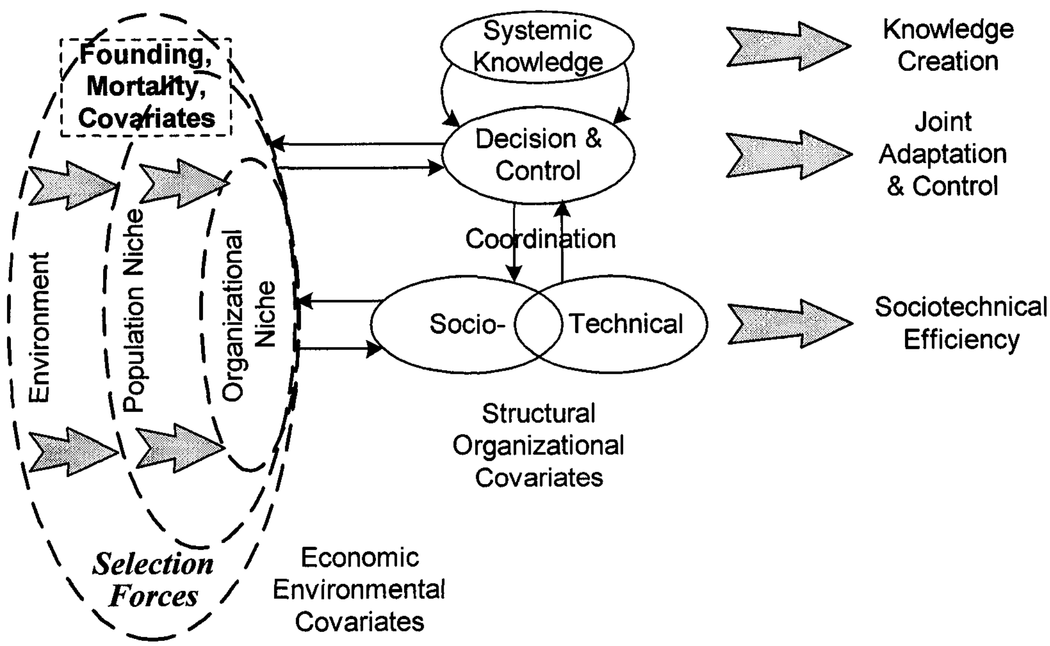


Figure 13. Computer manufacturing industry VSM model.

Table 4.

Survival and effectiveness response variables.

Type	Variable	Definition	Code	Type / Values
Survival	Years Competing	Number of years competing from entry to demise.	YrsComp	Numeric. Year of entry = 1. Incremented by +1 for each year until year of demise.
	Demise Indicator	0-1 survival-demise indicator variable for each year of the study period.	DemiseInd	Indicator. 0 = survive and right censored. 1 = exact event of demise.
Effectiveness	Years Effective	Number of years of nonnegative growth in normalized market share.	YrsEffect	Numeric. 1 for first year of nonnegative growth and incremented by +1 for each subsequent year of nonnegative growth. First year of negative growth in sequence incremented by +1. Each subsequent sequential year of negative growth assigned the value 0.5.
	Effectiveness Indicator	0-1 effective-ineffective indicator variable for each year of the study period.	EffectInd	Indicator. 0 = nonnegative growth and right censored. 1 = exact event of negative growth.

Table 5.

Computer manufacturing industry VSM environmental covariates.

Type	Variable	Definition	Code	Type / Values
Environmental Survival and Effectiveness	Year Identifier	Sequential year number	YrID	Numeric. 0 = 1948. Incremented +1 for each year of study period.
	Density	Number of dominant organizations in population each year of study.	Density	Integer. Count 1, 2, 3, ...
	Entry Density	Number of dominant organizations in population in an organization's year of entry.	EntryDensity	Integer. Count 1, 2, 3, ...
	Cohort Density	Number of dominant organizations in a cohort of manufacturers each year of study.	CohtDensity	Integer. Count 1, 2, 3, ...
	Entry Cohort Density	Number of dominant cohort organizations in an organization's year of entry.	EntryCohtDen	Integer. Count 1, 2, 3, ...
	Region Density	Number of dominant organizations in a region of manufacturers each year of study.	RegionDensity	Integer. Count 1, 2, 3, ...
	Entry Region Density	Number of dominant regional organizations in an organization's year of entry.	EntryRgnDen	Integer. Count 1, 2, 3, ...
Environmental Effectiveness	Standardized Home Market GNP	Standardized annual GNP of a given organization's national home market.	SGNPHMkt	Numeric. National GNP, converted to U.S. dollars in each year, deflated using 1982 CPI = 1, and divided by deflated 1976 total IT earnings.
	Standardized World Markets GNP	Standardized annual GNP of the regional markets in which a given organization competed in each year.	SGNPWMkt	Numeric. Sum of national GNPs, converted to U.S. dollars in each year, deflated using 1982 CPI = 1, and divided by deflated 1976 total IT earnings.
	Piecewise Period Indicator	Indicator of pre-PC, PC, and networking periods in the 1976-2001 study period.	PwPrd	-1 = 1976 to 1980 pre-PC 0 = 1981 to 1990 rise of PC +1 = 1991 to 2001 networking period

Table 6.

Computer manufacturing industry VSM organizational covariates.

Type	Variable	Definition	Code	Type / Values
Effectiveness	Information Technology U.S. Patents	Number of information technology U.S. patents granted per year for hardware, networking, software, artificial intelligence, and computer or software production and maintenance processes.	ITPat	Integer. Count 0, 1, 2, ...
	Other U.S. Patents	Non information technology U.S. patents granted per year.	OtherPat	Integer. Count 0, 1, 2, ...
	New Mainframe Products	Number of new mainframe products released per year.	NPMF	Integer. Count 0, 1, 2, ...
	New Mini-computer Products	Number of new mini-computer products released per year.	NPMini	Integer. Count 0, 1, 2, ...
	New Personal Computer Products	Number of new personal computer products released per year.	NPPC	Integer. Count 0, 1, 2, ...
	New Work-station Products	Number of new work-station products released per year.	NPWS	Integer. Count 0, 1, 2, ...
	Normalized Socio-technical Efficiency	Normalized socio-technical efficiency per year.	NSTechEff	Numeric. Total IT earnings in U.S. dollars divided by number of employees for each year deflated using 1982 CPI = 1.
	Standardized Parent Market Size	Parent corporation's total annual market size.	SmktPar	Numeric. Total parent earnings in U.S. dollars in each year, deflated using 1982 CPI = 1, and divided by deflated 1976 total IT earnings.
	Standardized IT Market Share	Computer operations market share per year.	SMktShrIT	Numeric. Computer operations earnings in U.S. dollars for each year, deflated using 1982 CPI = 1, and divided by deflated 1976 total IT earnings.
	Standardized Total IT Market Size	The population total IT market size in U.S. dollar sales normalized to 1.0 for 1976.	TMktIT	Numeric. Total computer operations earnings in U.S. dollars in each year, deflated using 1982 CPI = 1, and divided by deflated 1976 total IT earnings.

Table 6 (continued).

Computer manufacturing industry VSM organizational covariates.

Type	**Variable**	**Definition**	**Code**	**Type / Values**
Structural	Year Entry	Year entry into computer market.	YrEntry	Integer. 0 = 1948. Incremented +1 for each year of study period.
	Organization Code	Organization code assigned by years surviving order 1949 to 2001. Used in survival analyses.	OrgCode	Orthogonal coefficient –40 to +40.
	Standardized Organization Code	Organization codes assigned by Pareto order of average market share 1976 to 2001. Used in effectiveness analyses.	SOrgCode	Orthogonal coefficient –75 to +75.
	Organization Type	Existing organization expanding into computer manufacturing or newly founded organization.	OrgType	Numeric. 0 = Existing 1 = New
	Organization Structure	Legal structure.	OrgStruct	Numeric. 1 = Entrepreneur 2 = Private 3 = Company 4 = Corporation, single 5 = Corporation with divisions 6 = Conglomerate.
	Cohort Group	Cohort group by entry period.	CohortGrp	Numeric. 1 = mainframe, 1949-1959 2 = minicomputer, 1960-1976 3 = microcomputer, 1977-2001
	Region	World regions in which dominant OEM computer manufactures were founded.	Region	Numeric. 1 = United States, Canada 2 = Britain, Europe 3 = Japan, Taiwan

The number of information technology United States patents granted per year for hardware, networking, software, artificial intelligence, and computer or software production and maintenance processes represented knowledge creation in the VSM Policy function. The category number of "other" patents was included to represent the knowledge resources diverted to non-computer manufacturing. The number of new mainframe, minicomputer, personal computer, and workstation products released annually represented joint adaptation and control by the VSM Intelligence and Control functions. This representation is based on the hypothesis that the Intelligence and Control functions must jointly adapt to changes in the environment by detecting shifting product preferences and responding with new products to address those shifts. The covariate normalized socio-technical efficiency indicated the ability of each organization's production operations to adapt to changes in the environment and deliver new products to cost-effectively compete with other organizations. The piecewise period indicator was included to test for a hypothesized fourth period of transition to network integration.

Organizational, subsidiary operations, sales, financial, products, and employment data for each organization included in the database were obtained from multiple editions of *Moody's Industrial Manual* 1950-1999, *Datamation* 1976-1997, and *Hoover's Online* 2004. Supplemental data were obtained from *Hoover's Handbook of American Business 1995*, *Hoover's Handbook of American Business 2001*, and *Hoover's Handbook of World Business 2000*. Detailed computer product data were obtained during 2004 from *The Computer Archives* at Internet site http://www.computer-archiv.de. Patent data were obtained from the United States Patent Office Internet site http://www.uspto.gov during 2003 and 2004 using the advanced search utility to obtain data by organization name and year. Patent data were classified into the categories hardware, networking, software, artificial intelligence, and computer or software production and maintenance processes. All remaining patents not falling in these categories were classified as "other." Gross National Product data for countries within defined world market regions were obtained from the *Statistical Abstract of the United States* published by the United States Census Bureau for years 1953 to 2003 and from the 2003 *International Financial Statistics Handbook* published by the International Monetary Fund. World market regions were taken from Huntington's 1996 classification of world civilizations for post-1999 and modified as shown in Table 7 to account for evolving political and economic barriers during the study period. The average annual Consumer Price Index normalized to 1982

United States dollars for the years 1950 to 2002 was obtained from the 2003 *Statistical Abstract of the United States* published by the United States Census Bureau.

Table 7.

World market regions as defined in this study.

Region	**Code**
United States, Canada	1
Britain, Europe	2
Japan, Taiwan	3
Middle East (Northern Africa through Pakistan)	4
Africa	5
India	6
Southern Pacific (Australia, New Zealand, Philippines, Indonesia, Hong Kong, Southeast Asia)	7
Mexico, Central America, South America	8
Soviet Block (Russia and Eastern Europe)	9
China	0

For the effectiveness study period of 1976 to 2001, 348 of 1221 records had missing data for at least one value of the parent corporation's annual dollar volume sales, annual information technology dollar volume sales, number of employees reported annually, or number of new computer products released annually. The missing data were estimated using the conditional Gaussian data augmentation model in the missing library module of S-Plus 6.1, version 3. Schafer notes that many statisticians and analysts deal with missing data by "... *case deletion* or *imputation* … by the observed mean for that variable, or, in a slightly less naïve approach, by some sort of predicted value from a regression model … to force the incomplete dataset into a rectangular complete-data format" (1). He notes the following problems with these approaches:

> …. In multivariate settings where missing values occur on more than one variable, the incomplete cases are often a substantial portion of the entire dataset. If so, deleting them may be inefficient, causing large amount of information to be discarded. Moreover, omitting them from the analysis will tend to introduce bias, to the extent that the incompletely observed cases differ systematically from the completely observed ones.

Ad hoc methods of imputation are no less problematic. Imputing averages on a variable-by-variable basis preserves the observed sample means, but it distorts the covariance structure, biasing estimated variances and covariances toward zero. Imputing predicted values from regression models, on the other hand, tends to inflate observed correlations, biasing them away from zero. Standard errors, p-values and other measures of uncertainty calculated by complete-data methods could be misleading, because they fail to reflect any uncertainty due to missing data (1-2).

Reported values for the parent corporation's annual dollar volume sales, annual information technology dollar volume sales, and number of employees reported annually were converted to logarithm-base-ten values in order to avoid negative estimates of missing values and to minimize the potential for memory overflow on the personal computer used in this research. Reported values for the number of new computer products released annually for each product category were retained in their original count units, and their missing values estimated in separate code. The S codes for the estimates of each set of missing values are presented in Appendix B. The S code for missing values of dollar volume sales and number of employees is labeled L10MD7601USD, and the S code for missing values of new products is labeled MD7601NP. Missing values were estimated in the following five steps:

1. Specify a restricted loglinear model for the covariates organization code, organization type, cohort group, and region (Schafer 367-368).
2. Estimate the model parameters using the Expectation Maximization algorithm (Dempster, Larid, and Rubin; McLachlan and Krishnan).
3. Plot the autocorrelation function of the worst linear function to assess convergence. Figure 14 shows the plot of the autocorrelation function for parameter estimates of missing values of dollar volume sales and number of employees. The autocorrelation plot indicates convergence by iteration two. Figure 15 shows the plot of the autocorrelation function for parameter estimates of missing values of new products. The autocorrelation plot indicates convergence by iteration eight.

4. Estimate the missing values from the Expectation Maximization model parameters using the data augmentation algorithm for 750 iterations, discarding the first 49 iterations, and saving every 50th estimate. The decision to discard the first 49 iterations is based on the assessment of convergence in step 3.
5. Convert the logarithm-base-ten estimates back to their respective whole dollar values and whole number-of-employees values. Enter the resulting 15 estimates for each missing value into a Microsoft Excel worksheet and calculate the mean of the 15 estimates.

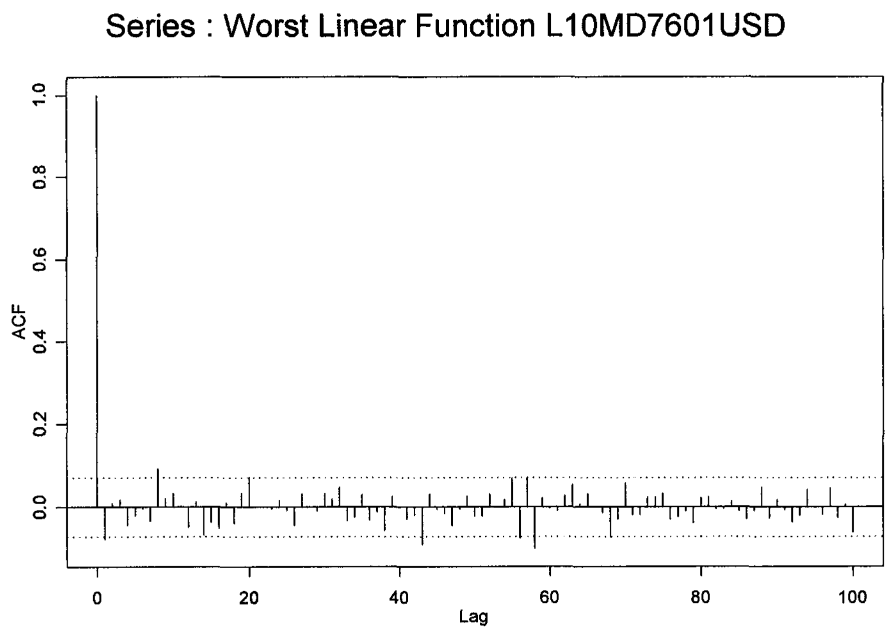


Figure 14. Plot of the autocorrelation function for parameter estimates of missing values of dollar volume sales and number of employees.

Out of 348 records with missing values, 271 values were estimated using the above 5-step method and 77 were inestimable and removed from the database. The 77 inestimable and removed records represented a partial loss of information on 9 of the 76 organizations included in the 1976 to 2001 study period. Schafer notes that "for many datasets, particularly if the number of cells D in the contingency table is large, we may find that portions of μ or Σ (the mean and covariance matrices) are poorly estimated or inestimable ....". Schafer recommends that attempts "... to stabilize the inference

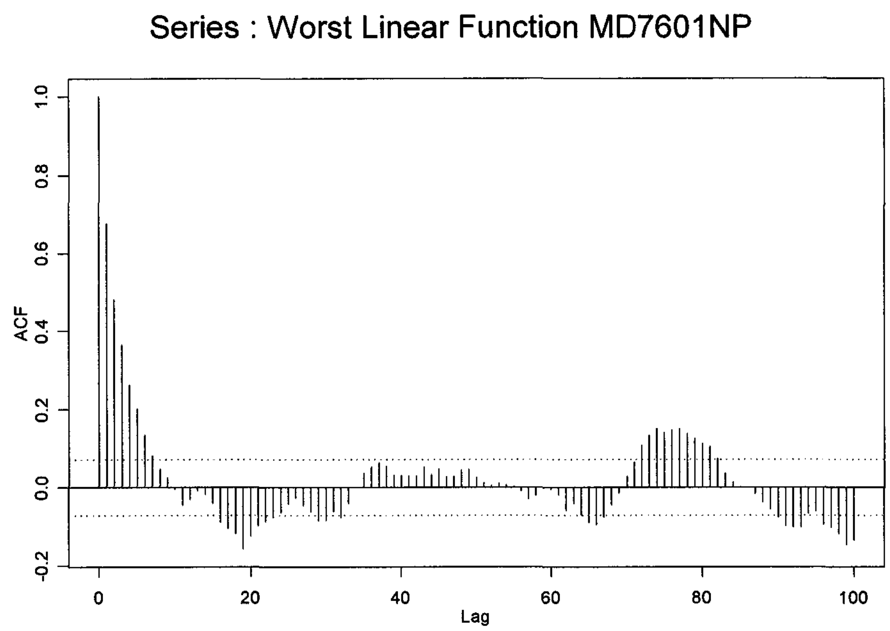


Figure 15. Plot of the autocorrelation function for parameter estimates of missing values of new products.

through informative priors for μ or Σ..." not be made. Rather, he recommends specifying "...a more parsimonious regression model ...reducing the number of free parameters and enforcing simpler relationships...." (341). Since in this case, the simplest loglinear model with only main effects for organization type, organization structure, cohort group, and region was specified (see the S code in Appendix B), the 77 inestimable values were removed from the dataset. This research recognizes that removal of these missing values may have introduced some bias in subsequent survival and effectiveness analyses. The focus of obtaining estimates for the missing values, however, was only on minimizing introduced bias in subsequent survival and effectiveness analyses by estimating as many missing values as possible given the structure of the missing values. In this sense, the missing value analysis served it purpose.

The mean of each missing value obtained in step 5 represents the unbiased estimate of the single true value of each missing value. Obtaining the missing values by the above 5-step method, as opposed to simple regression models, uses all of the observed data to estimate each missing value and captures observed-data variation in the mean estimates, which mitigates the problem of inflating observed correlations in subsequent survival and effectiveness models.

In phase four, each organization's annual computer operations earnings in U.S. dollars were used as the measurement of the organization's niche width. Data sources *Moody's Industrial Manual*, *Datamation*, and *Hoover's* all converted reported annual computer operations earnings into U.S. dollars using the average exchange rate for each respective reporting year. Each organization's annual computer operations earnings were deflated using 1982 CPI = 1. The deflated earnings were then divided by deflated, 1976 total IT earnings to standardize the data into "unit" niche space.

In phase five, event history analyses were performed to determine the best-fit survival and effectiveness models and the statistically significant covariates using S-Plus 6.1, version 3, Survival Life Testing S code. Standard backward, stepwise survival analysis was performed to determine the statistically significant covariates. Organizational survival and effectiveness modeling require covariate information at all intermediate recurrent censoring times as well as event times and end of study censoring times, because organizations, unlike mechanical or electrical components, possess the ability to expand their niche widths and renew themselves. Lawless shows that for any multiple event process specified by intensities, covariate information, and event histories the probability of any set of entities surviving to any time is the product-integral of their survivor functions given event histories in the prior time interval (512 – 518). Extending this logic, it may be shown that the probability of any set of entities with covariate information and event histories surviving over multiple intermediate censoring time intervals to any time is the product-integral of their survivor functions over the given set of intermediate censoring time intervals. This product-integral is equivalent to a sequence of Bernoulli trials over the intermediate censoring time intervals with a geometric mean hazard rate and a mean intensity time equal to the cumulative average censoring times of the set of surviving entities (see Appendix C). This research adopted this approach and modeled the cumulative average censoring time for each intermediate censoring time interval between founding and demise events for survival analysis and between loss-of-effectiveness events for effectiveness analysis. Modeling cumulative average censoring times linked intermediate censoring times and times to event, demise or loss of niche width, to changes in the geometric hazard rate and geometric survivor function and permitted estimation of organizational survival or effectiveness trajectories in each calendar year unit time step. Concomitant covariate information in intermediate censoring times linked through intermediate cumulative average censoring times to the geometric hazard rate and survivor function. Recurrent loss-of-effectiveness events were assigned average values of 0.5 year, which yielded a cumulative average of 0.5 year for each time step in recurrent loss-of-effectiveness episodes. The S codes for the survival analysis for the period 1949 to 2001 are presented in Appendix D and effectiveness analyses for the period 1976 to 2001 are presented in Appendices E through H. Event history survival and hazard functions for the time to failure and the time to loss of effectiveness data were obtained from MINITAB, release 13. Outputs from survival and effectiveness analyses are presented in sections "4.2 Event History Survival Analysis" and "4.3 Event History Effectiveness Analysis."

A dynamic simulation model was developed in Vensim PLE Plus 32, Version 5.0c1, from the best-fit covariate statistical effectiveness model. The simulation model was refined to account for nonlinearities and discontinuities not captured in the covariate effectiveness model. Structural model validity was established from the fit of simulated organizational market share niche trajectories to observed historical trajectories. Dynamic sensitivity analyses were then performed to determine the dynamic effects of changes in controllable covariate values. The schematic diagram of the organizational effectiveness simulation model and discussion of its construction and validation are presented section "4.4 Dynamic Simulation Model Construction, Validation, and Sensitivity Analyses." Results of dynamic sensitivity analyses are discussed in section "5.3 Dynamic Simulation Sensitivity Analyses."

3.3 Effectiveness Hypotheses

Since the ecological dynamics of the organizational form investigated herein have not been established previously, this research first establishes the population's environmental dynamics of entry and demise (disbanding, merger, or acquisition) against four density dependence theorems proposed by Hannan and Carroll (44-47). Theorems 1 and 2 establish the response of founding rates to population density. Theorem 1 is derived jointly from axioms 6, 10, 11, 13, and 15.

T1: Density dependence in founding rates is nonmonotonic; $\lambda(t) \propto (L_t / C_t) = (\varphi(N_t) / \gamma(N_t))$, and $\lambda(t)' > 0$ if $N_t < N_\lambda^*$, and $\lambda(t)' < 0$ if $N_t > N_\lambda^*$; where N_λ^* denotes the turning point in the relationship.

Theorem 2 is a parallel to theorem one and is derived by replacing axiom 13 with axiom 14.

T2: Density dependence in founding rates is nonmonotonic; $\lambda(t) \propto (L_t / C_t) = (\upsilon(N_t) / \gamma(N_t))$, and $\lambda(t)' > 0$ if $N_t < N_\lambda^*$, and $\lambda(t)' < 0$ if $N_t > N_\lambda^*$; where N_λ^* denotes the turning point in the relationship.

"The main difference from Theorem 1 concerns the behavior of the relationship at low density. Theorem 1 states that the relationship increases at a decreasing rate at very low density (axiom 13), and Theorem 2 postulates that the relationship increases at an increasing rate in this range (axiom 14)" (Hannan and Carroll 45). Both Theorems, however, state that the overall relationship between the founding rate and density graphically takes the shape of an inverted U. Hannan and Carroll delineate between founding and entry. They note, "processes of entry into an industry likely differ from founding processes because entry includes foundings and adaptive changes of firms that operated in other industries" (77). They cite studies of entry rates in which the observed density dependence in entry rate was both nonmonotonic and monotonic. For this research, however, the process of entry was of interest for two reasons. First, fifty-one of the eighty-one companies included in the study were entrants from other industries. Many such as Burroughs, IBM, and Sperry Rand were founded decades before entering into computer manufacturing. Second, of the thirty companies founded for computer manufacturing, many operated in a design and development mode or under protectionist policies for a number of years before releasing their first computer products into the world competitive marketplace. Amdahl, for example, was founded in 1970 but did not release its first computer product until 1975. Cray Research was founded in 1972 but did not release its first computer product until 1976. Similarly, the major Japanese computer manufacturers were founded in the 1950s and 1960s but did not come out from under the protectionist policies of the Japanese government to begin competing in the world computer market until the 1970s. For this research, therefore, Theorems 1 and 2 are of interest only to test for conformance of this population's entry rate for density dependence. The primary focus of this research is on the effects of environmental and population level selection forces on the survival and effectiveness of existing organizations. Entrance into the competitive marketplace was of interest only to the extent that it contributed to environmental and population level selection forces. Accordingly, Theorems 1 and 2 are only tested graphically with results provided in section "4.1 Exploratory Analyses." Formal survival and effectiveness analyses consider the year of entry as the release of an organization's first computer product into the competitive marketplace.

Axioms 7, 10, 11, 13 and 15 imply a parallel theorem concerning the effect of contemporaneous density on mortality rates. Theorem 3 provides the basis for testing Hypotheses 1-a, 1-b, and 1-c.

T3: Contemporaneous density dependence in mortality rates is nonmonotonic; $\mu(t) \propto (C_t / L_t) = (\gamma(N_t) / \varphi(N_t))$, and $\mu(t)' < 0$ if $N_t < N_\mu^*$, and $\mu(t)' > 0$ if $N_t > N_\mu^*$; where N_μ^* denotes the turning point in the relationship.

Theorem 3 states that the overall relationship between the contemporaneous mortality rate and contemporaneous density graphically takes a U shape. Hannan and Carroll (124-127) consider four forms of mortality: disbanding, equal-status merger, acquisition, and suspension of operations. They note that the organizational ecology theory of density-dependent legitimation and competition was developed to explain mortality in the form of disbanding. Further, they argue that the different types of organizational mortality might have different causal mechanisms. Their research indicates that mortality due to disbanding or acquisition displays the hypothesized nonmonotonic, U-shape relationship. Mortality due to merger or suspension shows no statistically significant relation to density dependence. For this research, survival analyses were conducted solely to establish population density dependence in entry and mortality rates. Three forms of mortality were observed: disbanding, equal-status merger, and acquisition. All were considered equally as mortality in survival analysis. Density dependence in the population entry and mortality rates establishes the presence of the domains of self-organizing environmental and population level selection forces and organizational adaptation as hypothesized by the general systemic model of organizational effectiveness. Theorem 3 is tested both graphically for density dependence with results given in section "4.1 Exploratory Analyses" and formally with results given in section "4.2 Event History Survival Analysis."

Derived from axioms 8, 10, and 12, Theorem 4, which provides the basis for testing Hypotheses 2-a, 2-b, and 2-c, postulates a delay in density effects at the time of founding.

T4: Density at founding permanently increases mortality rates. That is, the mortality rate at time t of organizations founded at time f is proportional to the density at that time; $\mu(t, f) \propto C_f = \nu(N_f)$, and $\mu(t, f)' > 0$, and $\mu(t, f)'' > 0$.

As noted in the discussion of founding versus entry under Theorems 1 and 2, this research considers only the year of entry through the release of an organization's first computer product into the competitive marketplace. Likewise, Theorem 4 is restated in terms of entry. For this research, Theorem 4 implies that organizations entering into the competitive marketplace at a time of higher density, N_e, in a population's life cycle will, throughout their lifetimes, have a proportionally higher mortality rate than organizations entering at a time of lower density in the population's life cycle. Theorem 4 assumes a frailty period of only the first year with proportionality of the mortality rate to density at time of founding thereafter. In the original equipment computer manufacturing industry, the frailty period appeared to last approximately ten to fifteen years. This implies that the effect on the mortality rate of density at time of founding is an inverse rather than proportional relationship. Thus, this research statistically tested for an inverse relationship between the mortality rate and density at time of founding. Theorem 4 is graphically tested for long term proportional density dependence in section "4.1 Exploratory Analyses" and statistically tested for inverse density dependence in sections "4.2 Event History Survival Analysis" and "4.3 Event History Effectiveness Analysis."

The above theorems provide the basis for the following population and subpopulation level survival and effectiveness hypotheses posed by this research. Hypotheses 1-a, 1-b, and 1-c are tests of Theorem 3 at the population, cohort, and region levels.

H1-a: Organizational survival times are nonmonotonically related to population density. That is, the covariate coefficient, β_i, for population density will be statistically different from 0 with β_1 for population density negative in sign and β_2 for population density squared positive in sign.

H1-b: Organizational survival times are nonmonotonically related to the density within its respective cohort. That is, the covariate coefficient, β_i, for cohort density will be statistically different from 0 with β_1 for cohort density negative in sign and β_2 for cohort density squared positive in sign.

H1-c: Organizational survival times are nonmonotonically related to the density within its respective region of entry. That is, the covariate coefficient, β_i, for region density will be statistically different from 0 with β_1 for region density negative in sign and β_2 for region density squared positive in sign.

At the time of this research, no theories existed concerning the behavior of effectiveness times, either monotonic or nonmonotonic, in relation to contemporaneous density. Thus, the contemporaneous density dependence of effectiveness times was estimated as a monotonic function in this research.

H1-d: Organizational effectiveness times are inversely related to contemporaneous population density. That is, the covariate coefficient, β_i, for population density will be statistically different from 0 and negative in sign.

H1-e: Organizational effectiveness times are inversely related to the contemporaneous density within respective cohorts. That is, the covariate coefficient, β_i, for cohort density will be statistically different from 0 and negative in sign.

H1-f: Organizational effectiveness times are inversely related to the contemporaneous density within respective regions of entry. That is, the covariate coefficient, β_i, for region density will be statistically different from 0 and negative in sign.

Hypotheses 2-a, 2-b, and 2-c are direct tests of Theorem 4 at the population, cohort, and region levels.

H2-a: Organizational survival and effectiveness times at time *t* are inversely related to population density at respective times *e* of entry. That is, the covariate coefficient, β_i, for population density at time *e* of entry will be statistically different from 0 and negative in sign.

H2-b: Organizational survival and effectiveness times at time *t* are inversely related to its cohort's density at respective times *e* of entry. That is, the covariate coefficient, β_i, for cohort density at time *e* of entry will be statistically different from 0 and negative in sign.

H2-c: Organizational survival and effectiveness times at time *t* are inversely related to its region's density at respective times *e* of entry. That is, the covariate coefficient, β_i, for region density at time *e* of entry will be statistically different from 0 and negative in sign.

This research also considered the relationships between observable, organizational structural attributes and organizational survival and effectiveness times. Four organizational structural hypotheses were tested.

H3: Organizational survival and effectiveness times are statistically different for different organizational types. That is, the covariate coefficient, τ_i, for the attribute of organization type will be statistically different from 0.

H4: Organizational survival and effectiveness times are statistically different for different organizational structures. That is, the covariate coefficient, τ_i, for the attribute of organization structure will be statistically different from 0.

H5: Organizational survival and effectiveness times are statistically different for different organizational cohort groups. That is, the covariate coefficient, τ_i, for the attribute of organization cohort group will be statistically different from 0.

H6: Organizational survival and effectiveness times are statistically different for different geographic regions of entry. That is, the covariate coefficient, τ_i, for the attribute of geographic region of entry will be statistically different from 0.

The seventh hypothesis considers the effects of total market size (the population niche width) on organizational effectiveness time.

H7: Organizational effectiveness times increase with increases in the population's market size niche. That is, the covariate coefficient, β_i, for the population's total market size niche will be statistically different from 0 and positive in sign.

The central hypotheses of the relationships between observable, systemic organizational variables and organizational effectiveness times are as stated below.

H8: Organizational effectiveness times increase with increases in contemporaneous organizational market share niche width. That is, the covariate coefficient, β_i, for the organizational market share niche will be statistically different from 0 and positive in sign.

H9-a: Organizational effectiveness times increase with increases in the contemporaneous level of information technology knowledge creation (policy). That is, the covariate coefficient, β_i, for the organizational number of information technology related patents granted annually will be statistically different from 0 and positive in sign.

H9-b: Organizational effectiveness times decrease with increases in the contemporaneous level of "other" knowledge creation (policy). That is, the covariate coefficient, β_i, for the organizational number of "other" category patents granted annually will be statistically different from 0 and negative in sign.

H10: Organizational effectiveness times increase with increases in the contemporaneous number of new products released annually (joint adaptation and control). That is, the covariate coefficient, β_i, for the organizational number of new computer products released annually will be statistically different from 0 and positive in sign.

H11: Organizational effectiveness times increase with increases in contemporaneous annual dollar volume earnings per employee (socio-technical efficiency). That is, the covariate coefficient, β_i, for organizational dollar volume earnings per employee annually will be statistically different from 0 and positive in sign.

This research also considered the relationships between observable, environmental selection variables and organizational effectiveness times. Two environmental selection hypotheses were tested.

H12: Organizational effectiveness times increase with increases in contemporaneous home market Gross National Product. That is, the covariate coefficient, β_i, for home market Gross National Product will be statistically different from 0 and positive in sign.

H13: Organizational effectiveness times increase with increases in contemporaneous cumulative Gross National Product of the geographical regional markets in which respective organizations competed. That is, the covariate coefficient, β_i, for cumulative geographical regional markets Gross National Product will be statistically different from 0 and positive in sign.

CHAPTER IV

ANALYSES

4.1 Exploratory Analyses

Exploratory analyses were performed in two steps to establish that hypothesized environmental selection forces and organizational adaptation responses held for this population. The first step involved plotting annual U.S. dollar volume and the standardized information technology market shares for the Pareto set of the eleven organizations that controlled 70 to 83 percent of the total market from 1976 to 2001. The second step involved testing for population density dependence as hypothesized by Theorems 1 to 4 in section "3.3 Effectiveness Hypotheses." Tests of these hypotheses involved plotting the population's entry rate and mortality rate versus density and plotting each organization's mortality rate versus density at entry from 1949 to 2001.

Figure 16 plots the annual U.S. dollar volume information technology market shares for the Pareto set of the eleven organizations that controlled the computer market during the study period of 1976 to 2001. Figure 17 plots the annual standardized information technology market shares for the study period. Of these eleven organizations, nine were in operation in 1976 at the start of the study period and controlled 70 percent of the total market. During the study period, one company of the original nine was acquired and two entered into the market leaving ten companies at the end of the study period controlling 83 percent of the total market. The remaining sixty-five organizations controlled 1.5 percent or less of the total market respectively. Figures 16 and 17 jointly illustrate environmental selection forces at work in the original equipment computer manufacturing population with rankings for positions two through eleven shifting among organizations. The standardized market shares in Figure 17 also show environmental selection forces acting on the market leader IBM with its standardized market share topping out at 1.02 in 1990, declining to 0.86 in 1994, and rebounding to 1.05 in 1999.

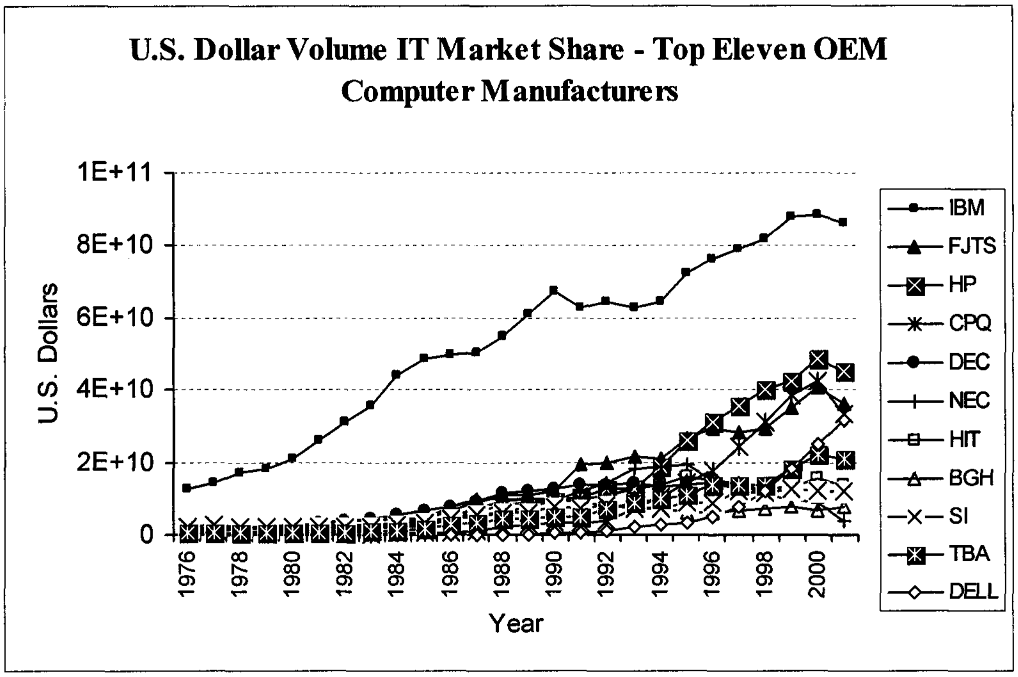


Figure 16. Annual U.S. dollar volume information technology market shares.

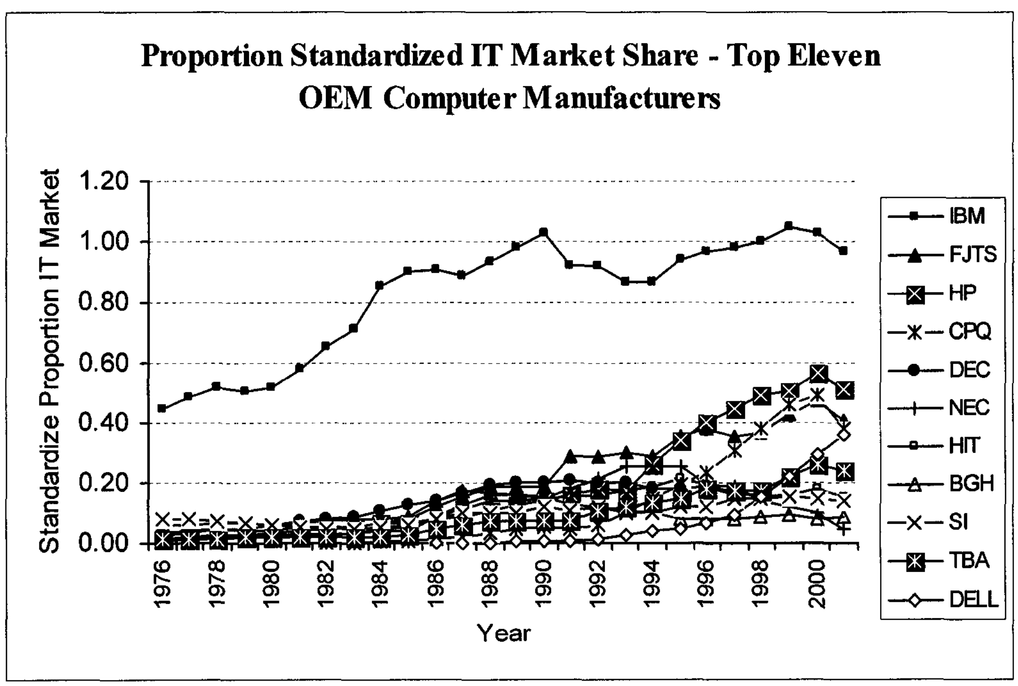


Figure 17. Annual standardized information technology market shares.

The plots of the historical evolution of the original equipment computer manufacturing industry population density in Figure 18, its population density by cohort group in Figure 19, and its population density by region in Figure 20 support density dependence on environmental selection forces. All plots display the inverted U shape indicating the presence of the fundamental mechanisms of environmental and population level selection forces arising from competition and legitimation processes.

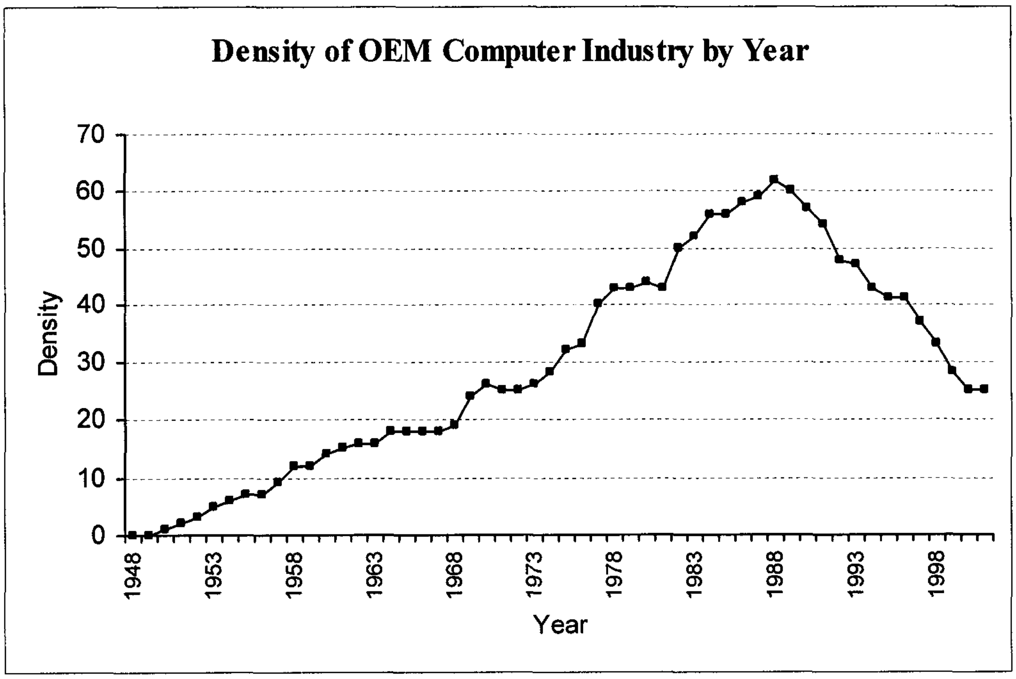


Figure 18. Historical evolution of the OEM computer industry population density.

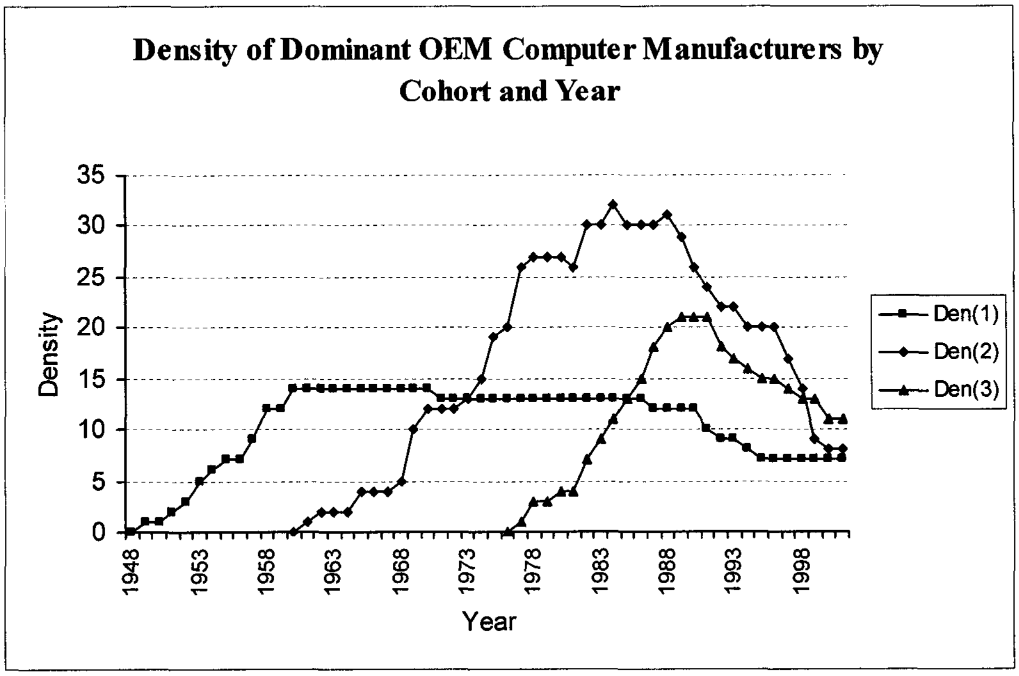


Figure 19. Historical evolution of the OEM computer industry population density by cohort group.

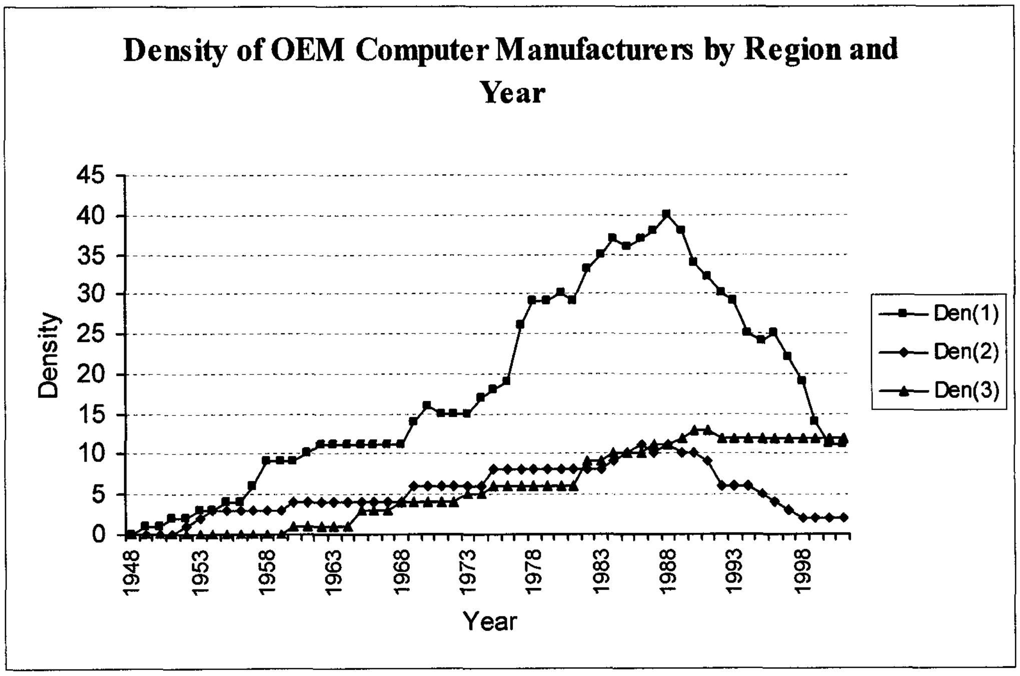


Figure 20. Historical evolution of the OEM computer industry population density by region.

Next, this research tested for population density dependence as hypothesized by Theorems 1 to 4 in section "3.3 Effectiveness Hypotheses" above. Axioms 6, 10, 11, 13, 14, and 15 and Theorems 1 and 2 imply that entry rates are not constant. Rather, entry rates depend on contemporaneous density and possibly on a vector of time-varying covariates. In the exploratory phase, however, such best-fit model information was not available. Further, effectiveness assessment is interested primarily in failure rates due to mortality or loss of effectiveness (niche width). All that is needed in the exploratory analysis phase of effectiveness assessment is a simple model of the population's entry arrival process to verify density dependence. The one-parameter exponential distribution provides a useful baseline process by assuming the entry rate to be constant, $\lambda(t) = \lambda > 0$ (Hannan and Carroll 237). An unbiased estimate of the entry rate in any time interval t_i is simply,

$$\lambda(t_i) = e_i / n_i$$

where e_i = number of entries in interval t_i and n_i = number of organizations surviving at the beginning of interval t_i. In order to find the expected entry rate in any interval, t_i from time t_0, the mean time to entry in any interval t_i is,

$$I\,(\Sigma_i\ \lambda(t_{0,\,i}))^{-1} = \theta(t_{0,\,i}) = (\Sigma_i\ \Sigma_j\ t_{ij}) / I$$

Where $(\Sigma_i\ \lambda(t_{0,\,i})$ is the cumulative entry rate through interval i from time t_0, $\theta(t_{0,\,i})$ is the mean time to entry through interval i from time t_0, t_{ij} is the time to entry in intervals for the j organizations entering in interval t_i, and I is the number of time intervals from time t_0. Thus, the expected entry rate through any interval t_i from time t_0 can be estimated as,

$$E[\,\lambda(t_i)\,] = \theta(t_{0,\,i})^{-1} = \Sigma_i\ \lambda(t_{0,\,i}) / I = (\Sigma_i\, e_i / n_i\ ) / I$$

The resulting plot in Figure 21 for the expected entry rate in the original equipment computer manufacturing industry population sorted by density displays the inverted U shape hypothesized by Theorems 1 and 2. Density dependence in entry rate for the original equipment computer manufacturing industry population appears to be supported.

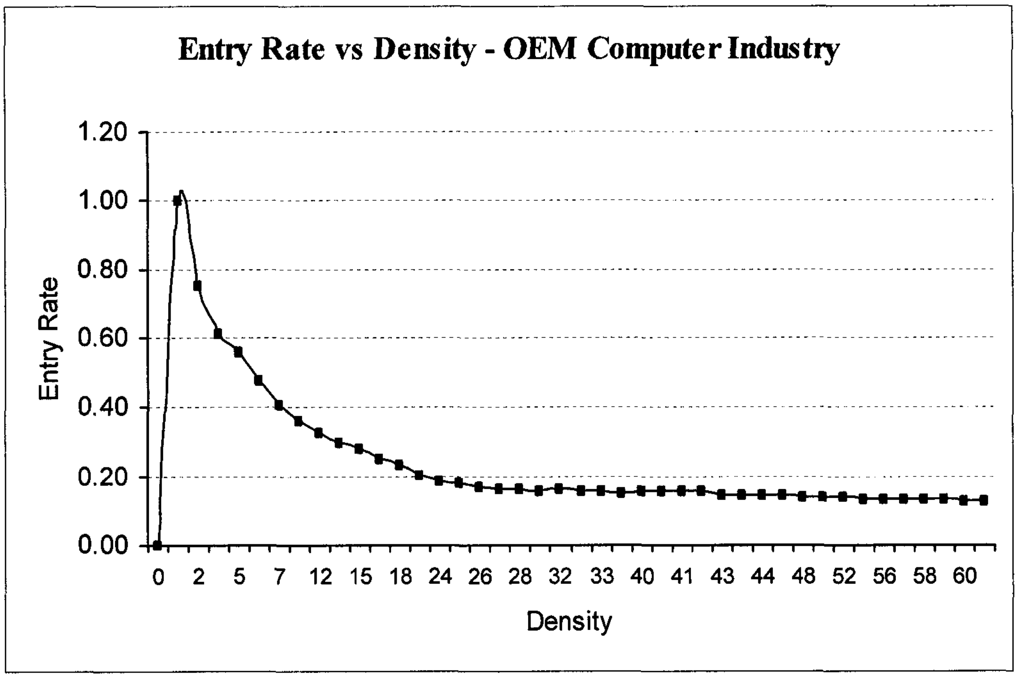


Figure 21. Entry rate versus density in the original equipment computer manufacturing industry.

Applied in a similar manner, the Nelson-Aalen estimator of the cumulative hazard function divided by the number of time intervals I from time t_0 provides an unbiased estimate of the expected hazard or mortality rate in interval $t_{0,\,i}$.

$$E[\ \mu(t_i)\ ] = \Lambda(t_{0,\,i}) / I = (\Sigma_i\, d_i / n_i) / I$$

where $\Lambda(t_{0,\,i})$ = the cumulative hazard or mortality function and d_i = the number of number of organizations failing in interval t_i. The resulting plot in Figure 22 for the expected mortality rate in the original equipment computer manufacturing industry population sorted by density displays the U shape hypothesized by Theorem 3. Density dependence in mortality rate for the original equipment computer manufacturing industry population appears to be supported.

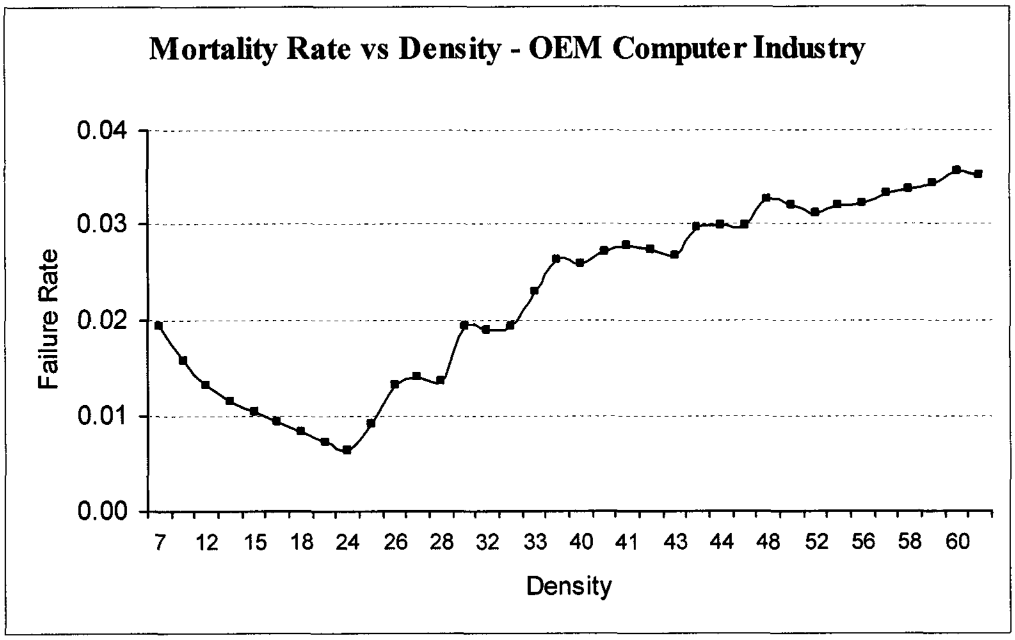


Figure 22. Mortality rate versus density in the original equipment computer manufacturing industry.

To test Theorem 4 that the long-term mortality rate was proportionally related to density at entry, the failure rate for each of the fifty-six organizations that failed during the study period was estimated as the reciprocal of its years surviving and the data were sorted by density at time of entry. The resulting plot in Figure 23 appears to support the hypothesized proportionally between the long-term mortality rate and density at the time of entry.

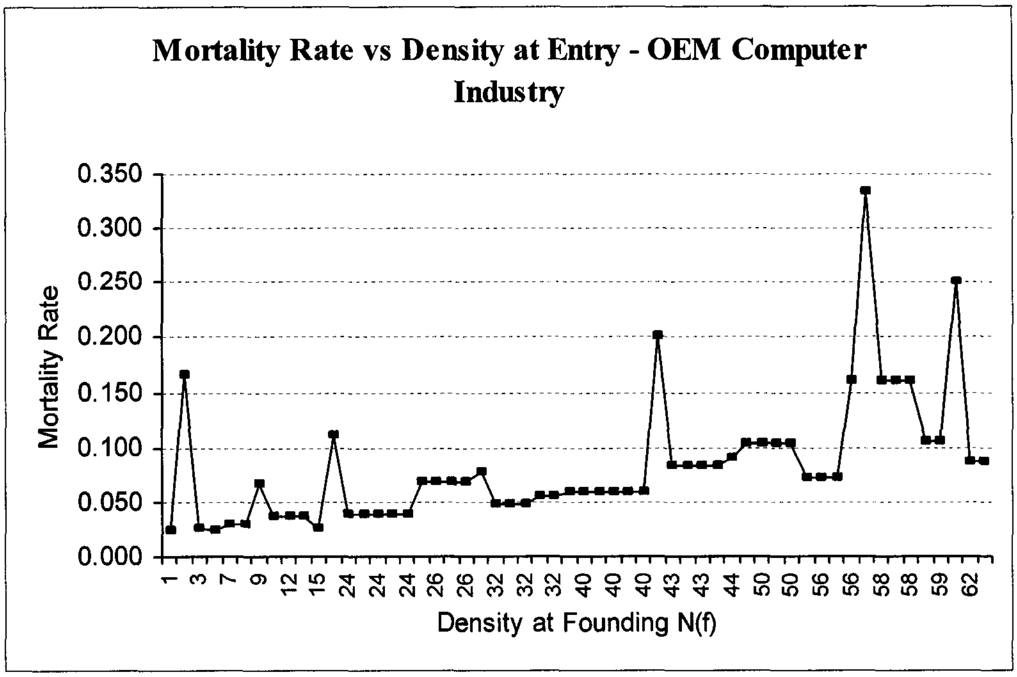


Figure 23. Mortality rate versus density at entry for the original equipment computer manufacturing industry.

4.2 Event History Survival Analysis

Through event history survival analysis, this research tested for dependence of organizational survival times on density and on a limited set of categorical organizational variables for the period 1949 to 2001. The main questions to be answered by survival analysis were posed by hypotheses H1-a through H1-c and hypotheses H2-a through H2-c. Hypotheses H1-a through H1-c stated that organizational survival times are nonmonotonically related to contemporaneous population density (Density), cohort density (CohtDensity), or region density (RegionDensity). Hypotheses H2-a through H2-c stated that organizational survival times are inversely related to the population density (EntryDensity), cohort density (EntryCohtDen), or region density (EntryRgnDen) at respective times of entry into the competitive marketplace for each organization.

To account for the nonmonotonic behavior in survival times as hypothesized for the mortality rate by Theorem 3, the mortality rate given the vector of covariates was specified as a log-quadratic function of contemporaneous density and covariates (Hannan and Carroll 116 – 119; Kalbfleisch and Prentice 40 – 46; Tableman and Kim 95 – 106):

$$\mu(u) = \exp(\beta_1 N_u + \beta_2 N_u^2 + \beta_3 N_{ei}) \exp(\beta_{ui} x_{ui}'),$$

$$= \exp(\beta_1 N_u + \beta_2 N_u^2 + \beta_3 N_{ei} + \beta_{ui} x_{ui}'), \quad \beta_1 < 0, \beta_2 > 0, \beta_3 < 0$$

where $\mu(u)$ is the contemporaneous mortality rate, N_u is the contemporaneous density or number surviving in the population or cohort or region at the start of time u = t; N_{ei} is the density at the time e that organization i entered into the competitive computer marketplace; and x_{ui} is a vector of hypothesized environmental and organizational covariates for organization i in each time period u = t. The specification of $\beta_1 < 0$ and $\beta_2 > 0$ predicts the hypothesized nonmonotonic U-shape relationship between the mortality rate and contemporaneous density. This specification yields a survivor function of

$$S(t|u,x) = \exp(-\int_0^t \mu(u)\,du),$$

with a mean survival time of

$$E(t|u,x) = \int_0^\infty \exp(-\int_0^t \mu(u)\,du)\,dt,$$

and a survival time model of

$$Y = \ln(t|u,x) = \beta_0 + \beta_1 N_u + \beta_2 N_u^2 + \beta_3 N_{ei} + \Sigma \beta_i X_i + \sigma Z$$

where σ is the scale parameter and Z is a standard extreme value, standard logistic, or standard normal random variable.

The categorical organizational variables tested were organizational code (OrgCode), type, structure, cohort group, and region. Hypothesis H3 stated that organizational survival times are statistically different for different organizational types (OrgType). Hypothesis H4 stated that organizational survival times are statistically different for different organizational structures (OrgStruct). Hypothesis H5 stated that organizational survival times are statistically different for different cohort groups (CohortGrp). Hypothesis H6 stated that organizational survival times are statistically different for different geographic regions of entry (Region). For each variable, the hypothesis tested was

$$\text{Ho:} \quad \beta_i = 0$$

$$\text{Ha:} \quad \beta_i \neq 0$$

$$\alpha = 0.05$$

where β_i = best fit slope coefficients.

The response variables years competing (YrsComp) and demise indicator (DemiseInd) were modeled versus the organization code variable to select the baseline best fit, time to failure distribution. The parametric distributions available in S-Plus 6.1, version 3, for time to failure modeling included: 1) exponential and logexponential, 2) logistic and loglogistic, 3) normal and lognormal, 4) Rayleigh and logRayleigh, and 5) Weibull and extreme. Table 8 indicates that the Weibull distribution provided the best fit of the event history survival data. Table 9 presents the estimates of the coefficient parameters, and Table 10 provides the distributional characteristics of the best fit, baseline Weibull distribution. Figure 24 displays the event history baseline survival function plot, and Figure 25 displays the event history baseline hazard function plot.

Table 8.

Survival analysis, best fit distribution selection.

Model	Terms	No. Parameters	LogLik	-2*LogLik	AIC
Rayleigh	OrgCode	3	-1019.584	2039.168	2043.168
Exponential	OrgCode	3	-327.099	654.197	658.197
Logexponential	OrgCode	3	-313.519	627.037	631.037
LogRayleigh	OrgCode	3	-237.827	475.654	479.654
Extreme	OrgCode	3	-185.703	371.406	377.406
Normal	OrgCode	3	-172.599	345.198	351.198
Logistic	OrgCode	3	-169.619	339.238	345.238
Loglogistic	OrgCode	3	-153.520	307.040	313.040
Lognormal	OrgCode	3	-152.035	304.070	310.070
Weibull	OrgCode	3	-150.813	301.626	307.626

Table 9.

Estimates of the best fit, baseline Weibull survival distribution parameters.

Parameter	Estimate	Std Error	95% Lower CI	95% Upper CI
Shape	2.7021	0.1983	2.3401	3.1201
Scale	41.777	3.037	36.228	48.175

Table 10.

Characteristics of the best fit, baseline Weibull distribution model.

Characteristic	Estimate	Std Error	95% Lower CI	95% Upper CI
Mean(MTTF)	37.152	2.6335	32.3331	42.6896
Standard Deviation	14.8290	1.8766	11.5716	19.0034
Median	36.4775	2.3987	32.0665	41.4954
First Quartile (Q1)	26.3443	1.4001	23.7383	29.2363
Third Quartile (Q3)	47.1446	3.7451	40.3472	55.0871
IQR	20.8003	2.6879	16.2378	26.6448

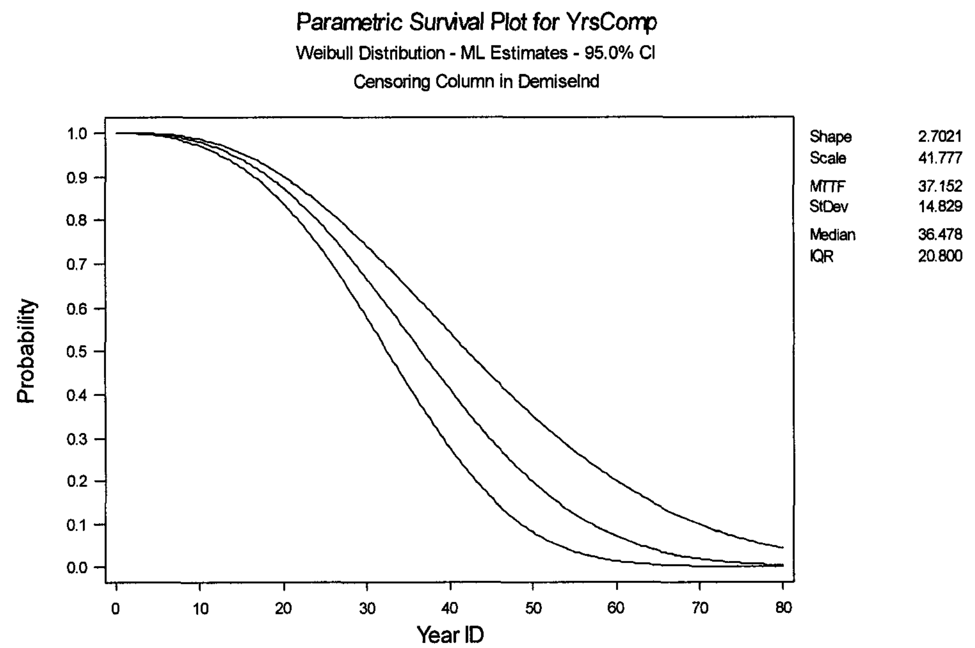


Figure 24. Survivor function plot for best fit, baseline Weibull distribution.

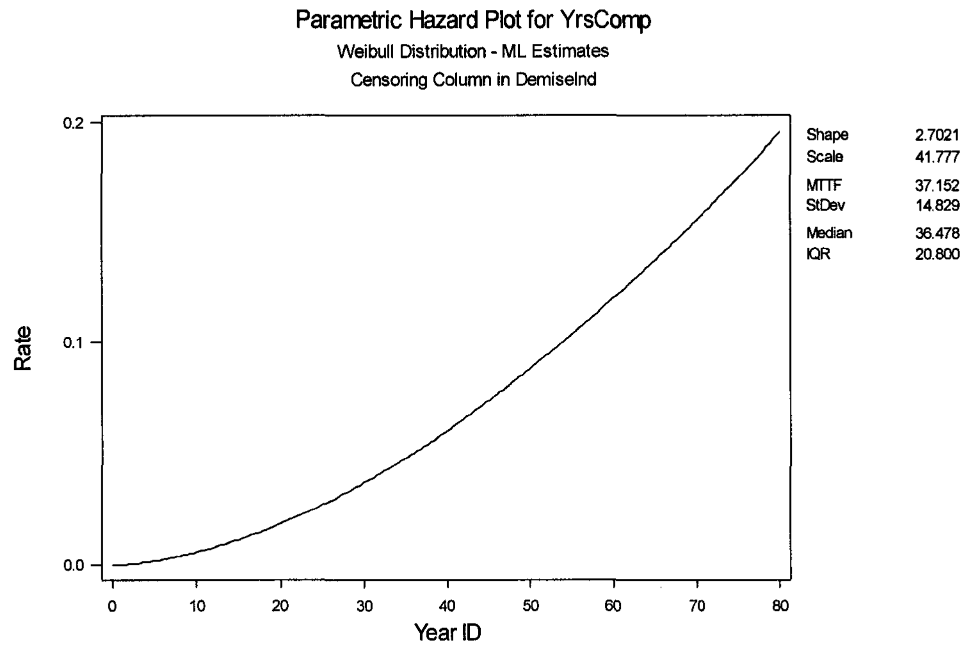


Figure 25. Hazard function plot for best fit, baseline Weibull distribution.

As a check for model bias, the Kaplan-Meier product limit estimate survivor function (Kalbfleisch and Prentice 14 -19) was computed for the observed population failures and plotted against the best-fit Weibull distribution parametric survival plot presented in Figure 24. Comparison of the Kaplan-Meier survivor function versus the best-fit Weibull distribution survivor function in Figure 26 indicates an acceptable fit with some underestimation of the survival rate between years 29 to 42 but no statistical difference from years 43 to 53. Thus, the best-fit Weibull survival model was accepted as the baseline survivor function model of the historical population survival rate.

The full Weibull model with all hypothesized predictor covariates was constructed. Standard, backward, stepwise regression was conducted to sequentially remove covariates whose coefficient p-values were larger than the allowable $\alpha = 0.05$. Statistically insignificant covariates were removed in subsequent partial models until the final model was indicated by all remaining covariates being statistically significant with p-values less than 0.05. Table 11 shows the full survival model, and Table 12 shows the final survival model with all remaining statistically significant covariate coefficients.

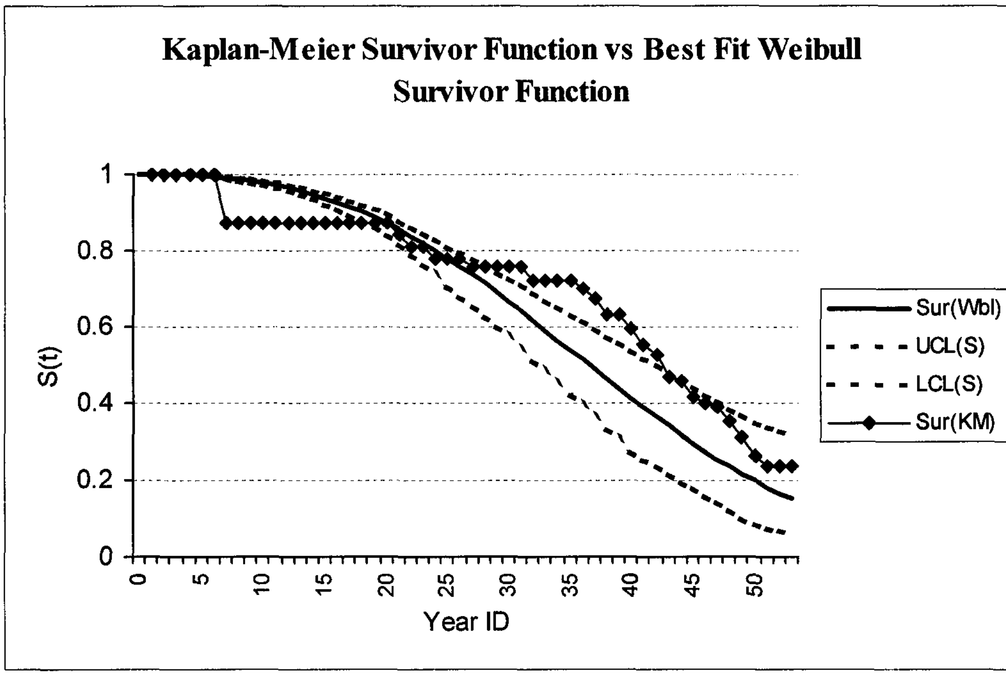


Figure 26. Kaplan-Meier survivor function versus best fit Weibull survivor function.

Table 11.

Full Weibull distribution, covariate survival model.

Term	Coef. Est.	Std. Err.	95% LCL	95% UCL	z-value	p-value
Intercept	3.4592134	0.400077	2.675076	4.243351	8.646	5.32e-018
OrgCode	0.0256208	0.004150	0.017488	0.033754	6.174	6.64e-010
YrID	0.0198685	0.009700	0.000856	0.038881	2.048	4.05e-002
OrgType	-0.1007664	0.039669	-0.178515	-0.023017	-2.540	1.11e-002
OrgStruct	-0.0333122	0.022425	-0.077265	0.010640	-1.485	1.37e-001
CohortGrp	-0.6827757	0.148636	-0.974097	-0.391454	-4.594	4.36e-006
Region	0.1377238	0.086912	-0.032621	0.308068	1.585	1.13e-001
Density	-0.0267998	0.018141	-0.062355	0.008755	-1.477	1.40e-001
EntryDensity	0.0205739	0.008222	0.004458	0.036690	2.502	1.23e-002
CohtDensity	0.0730027	0.025386	0.023248	0.122758	2.876	4.03e-003
EntryCohtDen	-0.0374484	0.007753	-0.052645	-0.022252	-4.830	1.37e-006
RegionDensity	-0.0213560	0.011406	-0.043711	0.000999	-1.872	6.12e-002
EntryRgnDen	0.0069881	0.004679	-0.002182	0.016158	1.494	1.35e-001
Den2	0.0000306	0.000202	-0.000364	0.000426	0.152	8.79e-001
CohtDen2	-0.0010065	0.000589	-0.002161	0.000148	-1.708	8.76e-002
RgnDen2	0.0007350	0.000268	0.000209	0.001261	2.738	6.17e-003

Table 12.

Final Weibull distribution, significant covariates survival model.

Term	Coef. Est.	Std. Err.	95% LCL	95% UCL	z-value	p-value
Intercept	3.51557	0.187853	3.147382	3.88375	18.71	3.77e-078
OrgCode	0.02717	0.001542	0.024149	0.03019	17.62	1.71e-069
CohortGrp	-0.26926	0.130575	-0.525186	-0.01334	-2.06	3.92e-002
EntryDensity	0.01472	0.006310	0.002351	0.02708	2.33	1.97e-002
CohtDensity	-0.03708	0.017505	-0.071389	-0.00277	-2.12	3.42e-002
EntryCohtDen	-0.01580	0.006980	-0.029483	-0.00212	-2.26	2.36e-002
CohtDen2	0.00103	0.000434	0.000177	0.00188	2.37	1.78e-002

A Weibull probability plot of the residuals of the significant covariates survival model, Figure 27, shows an acceptable fit of the data. The S code and output coefficients and correlation tables for the significant covariates survival model are presented in Appendix D.

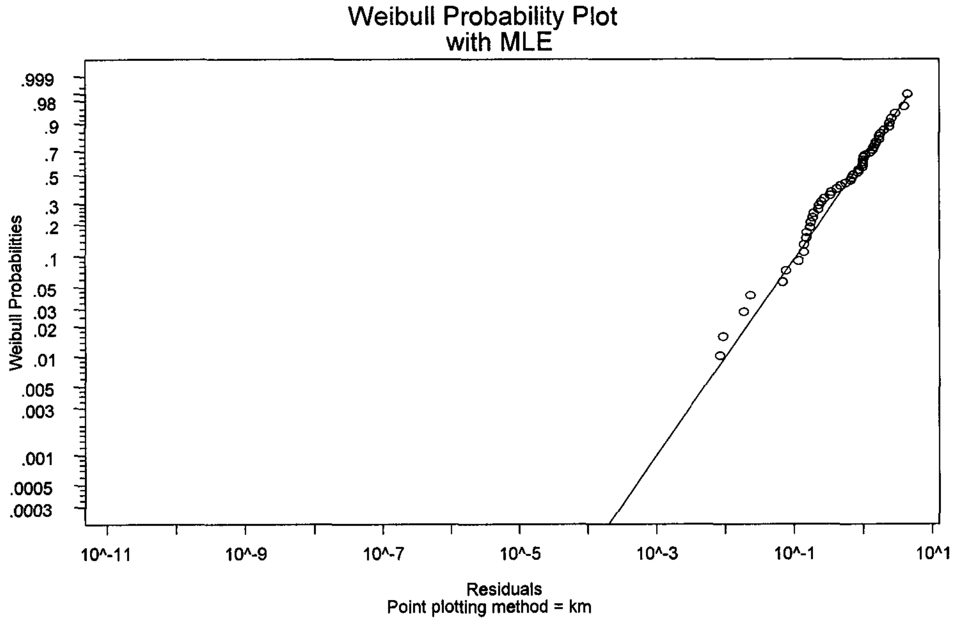


Figure 27. Weibull probability plot of the residuals of the significant covariates survival model.

4.2 Event History Effectiveness Analysis

Through event history effectiveness analysis, this research tested for the dependence of organizational effectiveness times on density and on a hypothesized set of organizational and environmental variables for the period 1976 to 2001. The dataset with 271 missing values estimated using the conditional Gaussian data augmentation model was used for effectiveness analysis. The questions to be answered were posed by hypotheses H1-d through H13. Hypotheses H1-d through H1-f stated that organizational effectiveness times are inversely related to contemporaneous population density (Density), cohort density (CohtDensity), or region density (RegionDensity). At the time of this research, no theories existed concerning the behavior of effectiveness times, either monotonic or nonmonotonic, in relation to contemporaneous density. Thus, the contemporaneous density dependence of effectiveness times was estimated as a monotonic, log-linear function. Hypotheses H2-a through H2-c stated that organizational effectiveness times are inversely related to the population density (EntryDensity), cohort density (EntryCohtDen), or region density (EntryRgnDen) at respective times of entry.

Again, the categorical organizational variables tested were standardized organizational code (SOrgCode), type, structure, cohort group, and region. Hypothesis H3 stated that organizational effectiveness times are statistically different for different organizational types (OrgType). Hypothesis H4 stated that organizational effectiveness times are statistically different for different organizational structures (OrgStruct). Hypothesis H5 stated that organizational effectiveness times are statistically different for different cohort groups (CohortGrp). Hypothesis H6 stated that organizational effectiveness times are statistically different for different geographic regions of entry (Region).

Hypothesis H7 considered the effects of the total population market size niche on organizational effectiveness times. Hypothesis H7 stated that organizational effectiveness times are proportionally related to the population's total market size niche (TMktIT).

The primary questions to be answered by this research concerning the relationships between observable, systemic organizational variables and organizational effectiveness times were posed by hypotheses H8 through H11. Hypothesis H8 stated that each organization's effectiveness time is proportionally related to its contemporaneous organizational information technology market share (SMktIT). Hypothesis H9-a tested the knowledge creation (policy) function stating that an organization's effectiveness time is proportionally related to the number of information technology patents granted to it annually (ITPat). Hypothesis H9-b tested for diversion of the knowledge creation (policy) function stating that an organization's effectiveness time is inversely related to the number of other patents granted to it annually (OtherPat). Hypothesis 10 tested for joint adaptation and control stating that an organization's effectiveness time is proportionally related to the number of new products it released annually. Since some organizations specialized in a given category or only two or three categories of product types, Hypothesis 10 was tested separately for the number of new mainframe (NPMF), minicomputer (NPMini), personal computer (NPPC), and workstation (NPWS) products released annually. Hypothesis 11 tested the socio-technical function's efficiency stating that an organization's effectiveness times are proportional to contemporaneous annual dollar volume earnings per employee (NSTEffcy).

Two environmental selection variables were tested for their respective relationships to organizational effectiveness time. Hypothesis H12 stated that organizational effectiveness times are proportional to the standardized annual GNP of each organization's national home market (SGNPHMkt). Hypothesis H13 stated that organizational effectiveness times are proportional to the standardized annual GNP of the regional markets in which each organization competed in each year (SGNPWMkt). To test for the fourth period of transition to client/server network integration of open standards as hypothesized by some researchers, the piecewise period indicator (PwPrd) of pre-personal computer (1976 to 1980, -1), personal computer (1981 to 1990, 0), and networking period (1991 to 2001, +1) was tested for statistical significance.
Again, the hypothesis tested for each variable was

$$\text{Ho:} \quad \beta_i = 0$$

$$\text{Ha:} \quad \beta_i \neq 0$$

$$\alpha = 0.05$$

where β_i = best fit slope coefficients.

Following the above procedure, the response variables years effective (YrsEff) and effectiveness indicator (EffInd) were modeled versus the standardized organizational code (SOrgCode) to select the baseline best fit, time to loss of market share distribution. Table 13 indicates that the lognormal distribution provided the best fit of the data. Table 14 presents the estimates of the baseline distribution parameters, and Table 15 provides the distributional characteristics of the best fit, baseline lognormal distribution. Figure 28 displays the baseline effectiveness survivor function plot with 95 percent confidence interval, and Figure 29 displays the baseline effectiveness hazard function plot.

Table 13.

Effectiveness analysis, best fit distribution selection.

Model	Terms	No. Parameters	LogLik	-2*LogLik	AIC
Rayleigh	SOrgCode	3	-6807.072	13614.144	13618.144
Exponential	SOrgCode	3	-5208.501	10417.002	10421.002
LogRayleigh	SOrgCode	3	-1610.274	3220.548	3224.548
Extreme	SOrgCode	3	-1605.884	3211.769	3217.769
Logistic	SOrgCode	3	-1516.232	3032.465	3038.465
Normal	SOrgCode	3	-1497.429	2994.858	3000.858
Logexponential	SOrgCode	3	-1255.759	2511.518	2515.518
Loglogistic	SOrgCode	3	-1248.121	2496.241	2502.241
Weibull	SOrgCode	3	-1246.107	2492.214	2498.214
Lognormal	SOrgCode	3	-1234.035	2468.070	2474.070

Table 14.

Estimates of the best fit, baseline lognormal distribution parameters.

Parameter	Estimate	Std Error	95% Lower CI	95% Upper CI
Shape	2.26984	0.08768	2.09799	2.44170
Scale	1.81780	0.07194	1.68214	1.96441

Table 15.

Characteristics of the best fit, baseline lognormal distribution model.

Characteristic	Estimate	Std Error	95% Lower CI	95% Upper CI
Mean(MTTF)	50.5037	10.0168	34.2372	74.4987
Standard Deviation	258.6676	85.1514	135.6825	493.1284
Median	9.6779	0.8486	8.1497	11.4926
First Quartile (Q1)	2.8399	0.1935	2.4848	3.2457
Third Quartile (Q3)	32.9810	4.0983	25.8519	42.0762
IQR	30.1412	3.9792	23.2694	39.0423

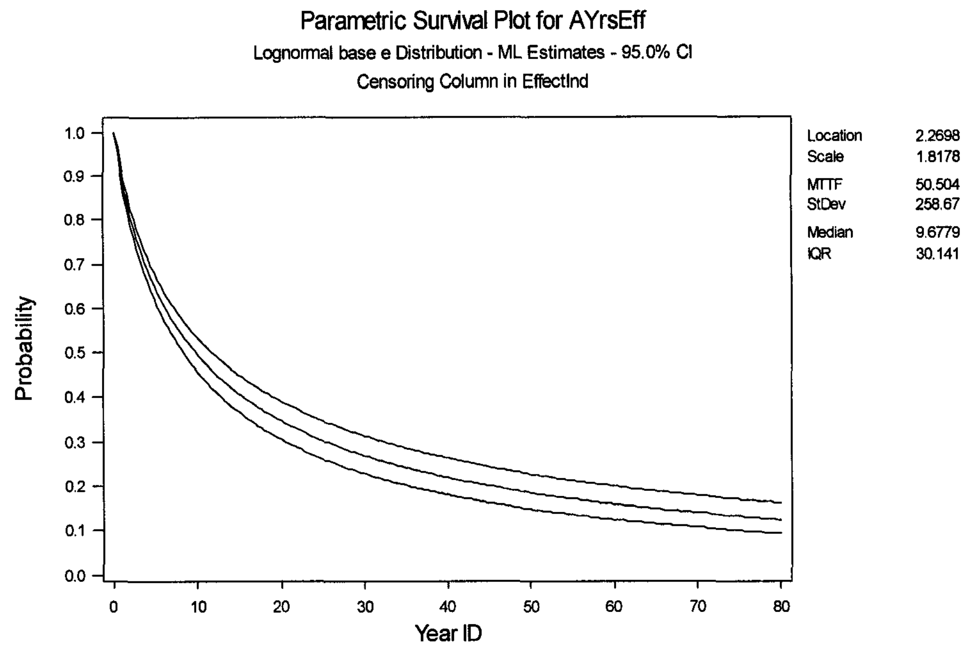


Figure 28. Effectiveness survivor function plot with 95 percent confidence interval for best fit lognormal distribution.

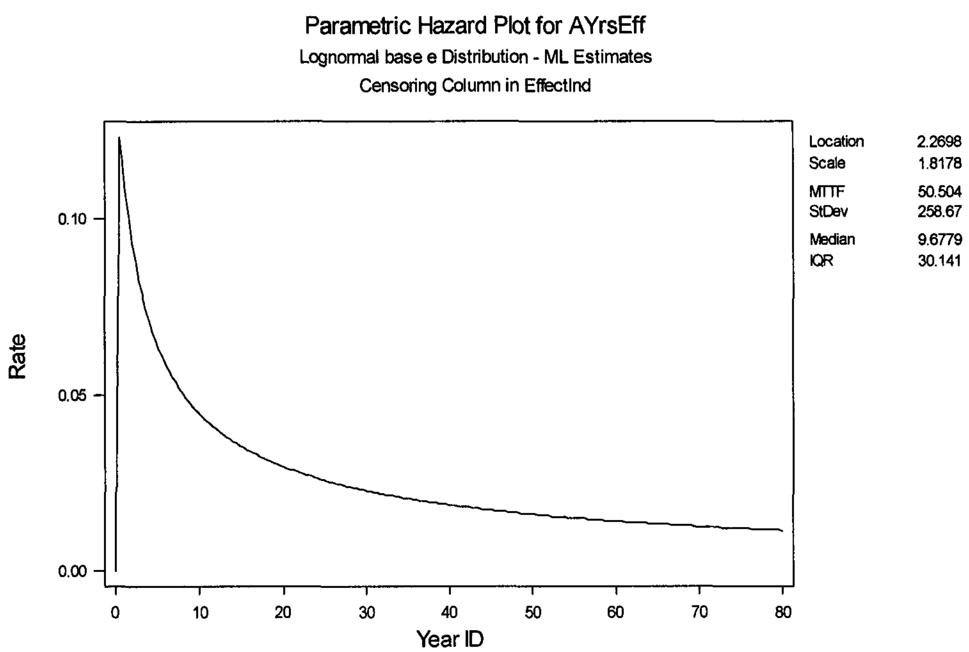


Figure 29. Effectiveness hazard function plot for best fit lognormal distribution.

The full lognormal model with all hypothesized predictor covariates was constructed. Standard, backward, stepwise regression was conducted to sequentially remove covariates whose coefficient p-values were larger than the allowable $\alpha = 0.05$. Statistically insignificant covariates were removed in subsequent partial models until the final model was indicated by all remaining covariates being statistically significant with p-values less than 0.05. Table 16 shows the full effectiveness model, and Table 17 shows the final effectiveness model with all remaining statistically significant covariate coefficients.

Table 16.

Full lognormal distribution, covariate effectiveness model.

Term	Coef. Est.	Std. Err.	95% LCL	95% UCL	z-value	p-value
Intercept	6.9297374	2.18e+000	2.66e+000	1.12e+001	3.1804	1.47e-003
SOrgCode	0.0102960	1.89e-003	6.60e-003	1.40e-002	5.4536	4.94e-008
YrID	-0.1986868	6.21e-002	-3.20e-001	-7.70e-002	-3.1999	1.37e-003
OrgType	0.5888147	1.67e-001	2.61e-001	9.16e-001	3.5252	4.23e-004
OrgStruct	-0.2023900	1.03e-001	-4.04e-001	-7.55e-004	-1.9673	4.91e-002
CohortGrp	0.0029330	1.75e-001	-3.41e-001	3.47e-001	0.0167	9.87e-001
Region	1.1293621	1.73e-001	7.90e-001	1.47e+000	6.5136	7.34e-011
ITPat	-0.0007203	4.20e-004	-1.54e-004	1.03e-004	-1.7151	8.63e-002
OtherPat	0.0009870	6.16e-004	-2.20e-004	2.19e-003	1.6027	1.09e-001
NPMF	-0.0682502	6.13e-002	-1.88e-001	5.20e-002	-1.1125	2.66e-001
NPMini	0.0514714	3.36e-002	-1.44e-002	1.17e-001	1.5307	1.26e-001
NPPC	-0.0040336	2.23e-002	-4.78e-002	3.97e-002	-0.1808	8.57e-001
NPWS	0.0417344	7.29e-002	-1.01e-001	1.85e-001	0.5724	5.67e-001
NSTEffcy	0.0000015	8.57e-007	-1.79e-007	3.18e-006	1.7510	7.99e-002
SmktPar	-0.9794282	6.37e-001	-2.23e+000	2.69e-001	-1.5378	1.24e-001
SMktIT	3.7281088	1.12e+000	1.52e+000	5.93e+001	3.3164	9.12e-004
TMktIT	0.4963571	3.12e-001	-1.15e-001	1.11e+000	1.5906	1.12e-001
SGNPHMkt	-0.0002927	6.28e-004	-1.52e-003	9.37e-004	-0.4664	6.41e-001
SGNPWMkt	-0.0003604	5.19e-004	-1.38e-003	6.57e-004	-0.6944	4.87e-001
PwPrd	-0.4201073	2.11e-001	-8.35e-001	-5.67e-003	-1.9868	4.69e-002
Density	-0.0166003	1.21e-002	-4.04e-002	7.20e-003	-1.3672	1.72e-001
EntryDensity	-0.0136725	9.14e-003	-3.16e-002	4.24e-003	-1.4957	1.35e-001
CohtDensity	0.0259247	1.97e-002	-1.26e-002	6.45e-002	1.3187	1.87e-001
EntryCohtDen	-0.0260000	1.18e-002	-4.91e-002	-2.92e-003	-2.2100	2.73e-002
RegionDensity	0.0164000	9.50e-003	-2.27e-002	3.50e-002	1.7200	8.52e-002
EntryRgnDen	0.0759000	1.38e-002	4.88e-002	1.03e-001	5.4900	3.97e-008

Table 17.

Final lognormal distribution, significant covariates effectiveness model.

Term	Coef. Est.	Std. Err.	95% LCL	95% UCL	z-value	p-value
Intercept	6.5819	0.41329	5.77188	7.3919	15.93	4.20e-057
SOrgCode	0.0100	0.00166	0.00679	0.0133	6.06	1.36e-009
YrID	-0.1731	0.01112	-0.19487	-0.1513	-15.56	1.27e-054
OrgType	0.8775	0.13488	0.61314	1.1419	6.51	7.74e-011
Region	0.7992	0.10528	0.59289	1.0056	7.59	3.16e-014
SMktIT	2.2726	0.53858	1.21697	3.3282	4.22	2.45e-005
EntryCohtDen	-0.0334	0.00895	-0.05091	-0.0158	-3.73	1.93e-004
EntryRgnDen	0.0713	0.00819	0.05527	0.0874	8.71	3.15e-018

A lognormal probability plot of the residuals of the significant covariates effectiveness model, Figure 30, shows an acceptable fit with some truncation in the upper tail. The S code and output coefficients and correlation tables for the significant covariates effectiveness model are presented in Appendix E.

As a test for bias induced by missing data, effectiveness analysis was performed on the 873 records with complete data. Table 18 indicates that the lognormal distribution provided the best fit of the complete data. Table 19 shows the final effectiveness model with all remaining statistically significant covariate coefficients for the complete data records. A comparison of Table 19 with Table 17 shows that organizational structure (OrgStruct), cohort density (CohtDensity), and region density (RegionDensity) were included in the complete data model and entry cohort density (EntryCohtDen) was rejected. Thus, there is evidence of the introduction of bias due to missing data in the complete data model of Table 19 versus Table 17 in which missing values were estimated using the conditional Gaussian data augmentation model. Accordingly, this research accepted Schafer's observation that missing values "tend to introduce bias, to the extent that the incompletely observed cases differ systematically from the completely observed ones" (1-2), and the final lognormal distribution, significant covariates effectiveness model of Table 17 was accepted as the minimum bias model. The S code and output coefficients and correlation tables for the complete data, effectiveness analyses are presented in Appendix F.

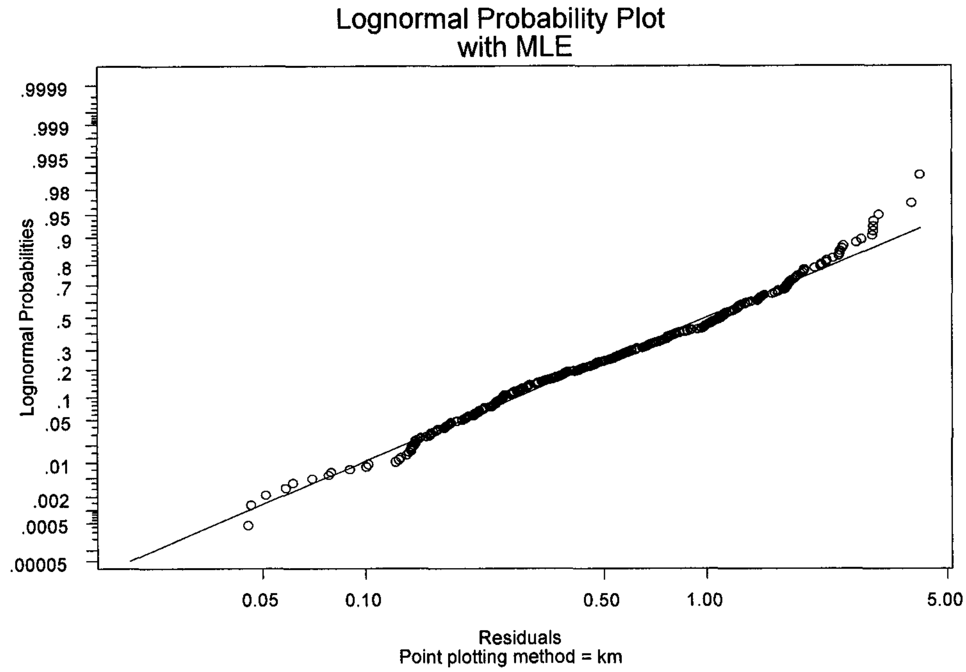


Figure 30. Lognormal probability plot of the residuals of the significant covariates effectiveness model.

Table 18.

Event history effectiveness analysis, best fit distribution selection for complete data.

Model	Terms	No. Parameters	LogLik	-2*LogLik	AIC
Rayleigh	SOrgCode	3	-4581.471	9162.942	9166.942
Exponential	SOrgCode	3	-3471.615	6943.230	6947.230
Extreme	SOrgCode	3	-1094.679	2189.358	2195.358
LogRayleigh	SOrgCode	3	-1095.003	2190.006	2194.006
Logistic	SOrgCode	3	-1047.705	2095.410	2101.410
Normal	SOrgCode	3	-1031.620	2063.240	2069.040
LogLogistic	SOrgCode	3	-880.030	1760.060	1766.060
LogLogistic	SOrgCode	3	-880.425	1760.850	1764.850
Weibull	SOrgCode	3	-876.160	1752.320	1758.320
LogNormal	SOrgCode	3	-872.462	1744.924	1750.924

Table 19.

Final Lognormal distribution, significant covariates effectiveness model for complete data.

Term	Coef. Est.	Std. Err.	95% LCL	95% UCL	z-value	p-value
Intercept	10.0466	1.02159	8.04428	12.0488	9.83	8.02e-023
SOrgCode	0.0147	0.00210	0.01060	0.0188	7.00	2.47e-012
YrID	-0.1997	0.01783	-0.23462	-0.1647	-11.20	4.07e-029
OrgType	0.6345	0.20987	0.22315	1.0458	3.02	2.50e-003
OrgStruct	-0.3338	0.12516	-0.57912	-0.0885	-2.67	7.65e-003
Region	0.2693	0.05994	0.15180	0.3868	4.49	7.04e-006
SMktIT	1.9787	0.54302	0.91437	3.0430	3.64	2.69e-004
CohtDensity	0.0344	0.01314	0.00864	0.0601	2.62	8.86e-003
RegionDensity	-0.0314	0.00953	-0.05012	-0.0128	-3.30	9.65e-004
EntryRgnDen	0.0550	0.00840	0.03850	0.0714	6.54	5.98e-011

In order to gain initial insight into organizational effectiveness in the original equipment computer manufacturing industry, a conditional expected years effective trajectories chart, Figure 31, was created from the final lognormal distribution, significant covariates effectiveness model in Table 17 for the Pareto set of the eleven organizations that controlled from 70 percent of the total market in 1976 to 83 percent of the total market in 2001. The Pareto set of the top eleven organizations was chosen, because they collectively determined the dynamics of effectiveness in the original equipment computer manufacturing industry during the study period. IBM dominated the original equipment computer market holding a 45 percent share at the start of the study period in 1976, but its competitors gradually eroded its share to 23 percent by the year 2000. Five organizations increased their respective market shares during the study period. Hewlett-Packard started with a 1.5 percent share in 1976 and increased its share to 12.9 percent by 2000. For the same years, Fujitsu increased its share from 3.5 percent to 10.8 percent, and Toshiba from 1.5 percent to 5.7 percent. Compaq entered in 1982 acquiring a 0.1 percent share but gained to an 11.2 percent share by 2000. Similarly, Dell Computer entered in 1986 acquiring a 0.02 percent share but gained to a 6.7 percent share by 2000. Three organizations initially gained but then lost market share during the study period. NEC gained to a 6.9 percent share in 1994 but held only a 1.1 percent share in 2001. Similarly, Hitachi gained to a 5.2 percent share in 1995 but saw its share reduced to 3.9 percent in 2001. Univac (Burroughs) held a 5.9 percent share in 1987, the year after it acquired Sperry Corporation, but saw its share drop to 2.1 percent in 2001. Conversely, Siemens entered the study period with an 8.3 percent market share in 1976, saw its share drop to 2.4 percent in 1983, and regained share to 4.0 percent by 2001. Digital Equipment Corporation steadily gained from a 2.6 percent market share in 1976 to 5.9 percent in 1989, but its market share declined to 4.0 percent in 1997 its last full year of operations before being acquired by Compaq.

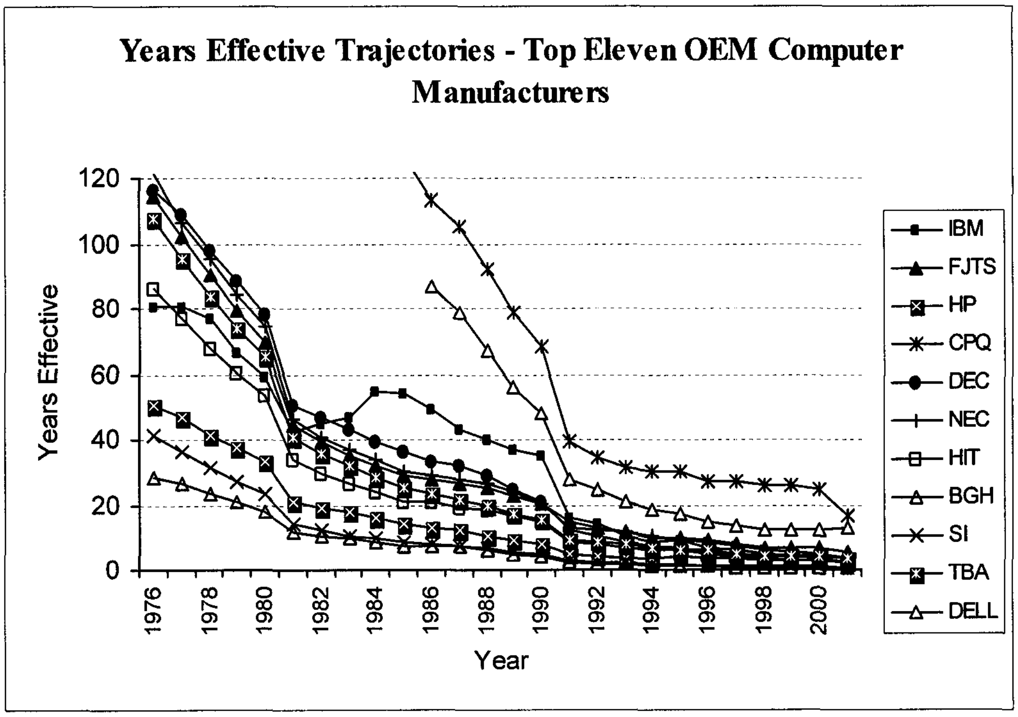


Figure 31. Years effective trajectories of the top eleven OEM computer manufacturers.

Figure 31 indicates that two manufacturers, Compaq and Dell Computer, ranked one and two respectively in conditional expected years effective. IBM's effectiveness trajectory sharply increased from 1981 to 1984 with the success of its personal computer. IBM was able to sustain this increase in effectiveness from 1985 to 1990 after which its effectiveness trajectory dropped to just above the upper limit of the normal effectiveness zone of the next seven organizations. Fujitsu's effectiveness trajectory rose above IBM's in 1993 and maintained a marginal separation from the zone of effectiveness of the next seven organizations. Figure 30 illustrates two forms of effectiveness. The first form is structural effectiveness. Compaq and Dell Computer were able to attain and sustain structural adaptation flexibility as new entrants. The second form of effectiveness is a change in trajectory at a discontinuity point as exhibited by the sharp increase in IBM's effectiveness trajectory initiated in 1981 with the success its independent personal computer business unit in establishing and maintaining market share leadership.

4.4 Dynamic Simulation Model Construction, Validation, and Sensitivity Analyses

In order to perform sensitivity analyses to determine the dynamic effects of changes in controllable covariate values on respective market shares and effectiveness times, a dynamic simulation model of the Pareto set of the top eleven organizations was constructed in Vensim PLE Plus 32, Version 5.0c1, from the best-fit, lognormal distribution, significant covariates effectiveness model of Table 17. Five criteria were followed in the construction of the simulation model.

1. The final simulation model must be constructed such that each organization freely completes for its respective market share niche.
2. The final simulation model must be the simplest model that produces simulated organizational market share niche trajectories structurally consistent with historical organizational market share niche trajectories observed in the study period.
3. The final model must have inputs of only the sequential year identification, the annual standardized total IT market size, the values of the statistically significant covariate parameters from the significant covariates effectiveness model, and the corresponding organizational covariate values.
4. In keeping with criteria one and two, the only refinements allowed to the base simulation model are those necessary to account for nonlinearities and discontinuities not captured in the linear covariate effectiveness model.
5. Structural model validity is achieved when simulated organizational market share niche trajectories fit observed historical organizational market share niche trajectories.

The identification and structural modeling of nonlinearities and discontinuities in criterion four provided additional information on the sources of the underlying dynamics of organizational market share and effectiveness time trajectories in the original equipment computer manufacturing industry during the study period which were not identified in the significant covariates effectiveness model.

An overview schematic diagram of the base dynamic simulation model is presented in Figure 32. The base simulation model is comprised of three basic modules. The population module imported the historical values of the total standardized market of the Pareto set of the top eleven organizations and created the market gap which was available to these organizations at each simulation step. The equations of the population module were as follows.

Time bounds: INITIAL TIME = 28, FINAL TIME = 53, TIME STEP = 0.25

Units for time = Year (Year 28 = 1976 and Year 53 = 2001)

change in market = GET XLS DATA('TMKIT7601.xls', 'Sheet1', '3', 'C5')

Units = Std Total Market/Year

NOTE: Annual incremental changes in the standardized total market were imported by the GET XLS DATA function.

Total IT Market = INTEG(change in market, 0.704389)

Units = Std Total Market

NOTE: Initial total standardized market share for the top eleven manufacturers was 0.704389.

market gap = Total IT Market – Sum of IT Market

Units = Std Total Market

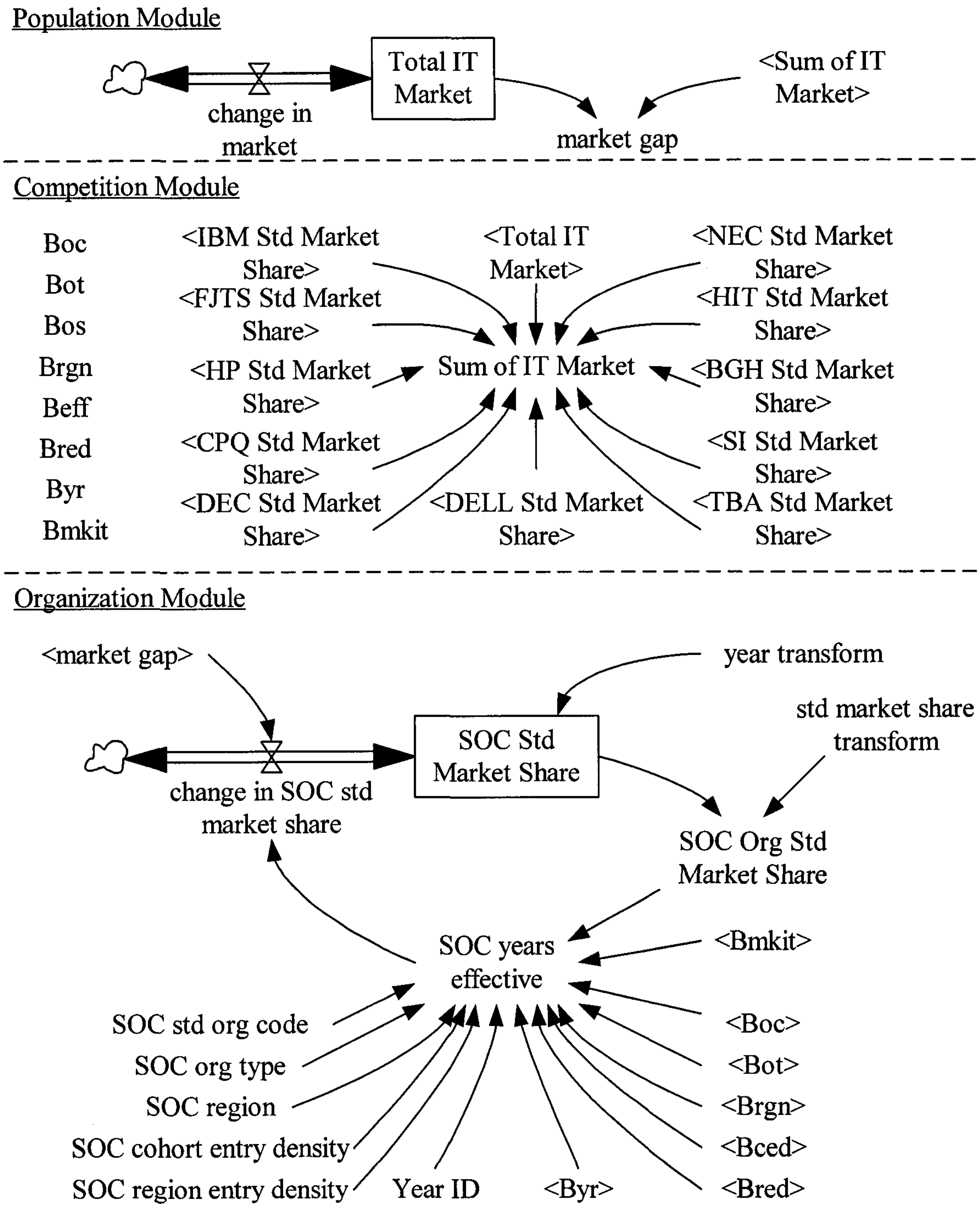


Figure 32. Overview of the base dynamic simulation model of the Pareto set of top eleven, original equipment computer manufacturers.

The competition module provided a single input area for the values of the parameters from the statistically significant covariates effectiveness model of Table 17, and it captured the sum of the organizational standardize market shares from competition within the model. The definitions and equations of the competition module were as follows.

Boc = 0.01 {coefficient for standardized organization codes}
Units = Dimensionless

Bot = 0.8775 {coefficient for organization type, varied in sensitivity analysis}
Units = Dimensionless

Brgn = 0.7992 {coefficient for world region of founding}
Units = Dimensionless

Bced = -0.0334 {coefficient for cohort entry density}
Units = Dimensionless

Bred = 0.0713 {coefficient for region entry density}
Units = Dimensionless

Byr = -0.1731 {coefficient for sequential year identification; 28 for 1976 to 53 for 2001 of the effectiveness study period}
Units = Dimensionless

Sum of IT Market = MIN(Total IT Market, IBM Std Market Share + FJTS Std Market Share + HP Std Market Share + CPQ Std Market Share + DEC Std Market Share + NEC Std Market Share + HIT Std Market Share + BGH Std Market Share + SI Std Market Share + TBA Std Market Share + DELL Std Market Share)
Units = Std Total Market

The use of the minimum function in calculating the "Sum of IT Market" variable prevented the creation of an artificial exponential negative feedback loop through the "market gap" variable and the standardized organization code market share (SOC Std Market Share) levels. Use of the minimum function allowed a positive market gap to be created during periods of positive growth in the "Total IT Market" variable. During periods of zero or negative growth in the "Total IT Market" variable, it allowed the market gap to go to zero and forced a joint reduction in the respective standardized organization code market shares.

There were eleven organization modules, one for each of the eleven Pareto set organizations. Each module was constructed as illustrated in Figure 32. The only differences between organizations were the input values for each respective organization's covariate variables and the structure of the integral equation within each organization's standardized organization code market share (SOC Std Market Share) level to account for differing market share trajectories. The common equations across the organization modules were as follows:

SOC std org code = Orthogonal coefficients {75 = IBM, 73 = FJTS (Fujitsu), 71 = HP (Hewlett-Packard), 69 = CPQ (Compaq Computer), 67 = DEC (Digital Equipment Corporation), 65 = NEC, 63 = HIT (Hitachi), 61 = BGH (Univac / Burroughs), 59 = SI (Siemens), 57 = TBA (Toshiba), and 55 = DELL (Dell Computer)}

Units = Dimensionless

SOC org type = 0 for existing organization; 1 for new entrant

Units = Dimensionless

SOC region = 1 for United States and Canada, 2 for Britain and Europe, and 3 for Japan and Taiwan

Units = Dimensionless

SOC cohort entry density = Cohort entry density value for each respective organization {IBM = 3, FJTS = 5, HP = 17, CPQ = 35, DEC = 10, NEC = 4, HIT = 6, BGH = 6, SI = 4, TBA = 3, and DELL = 38}

Units = Dimensionless

SOC region entry density = Regional entry density value for each respective organization {IBM = 5, FJTS = 6, HP = 17, CPQ = 35, DEC = 10, NEC = 4, HIT = 6, BGH = 6, SI = 4, TBA = 3, and DELL = 38}

Units = Dimensionless

Year ID = GET XLS DATA('YrID7601.xls', 'Sheet1', '3', 'C6')

NOTE: Year 28 = 1976 to Year 53 = 2001

Units = Dimensionless

change in SOC std market share = IF THEN ELSE(SOC years effective <1 :AND: market gap > 0, - market gap, IF THEN ELSE(market gap = 0, 0, market gap))

Units = Std Total Market

year transform = 1

NOTE: Used to achieve dimensional consistency.

Units = 1/Year

SOC Org Std Market Share = SOC Std Market Share * std market share transform

NOTE: Used to achieve dimensional consistency.

Units = Year

std market share transform = 1

NOTE: Used to achieve dimensional consistency.

Units = Year / Std Total Market

SOC years effective = MAX(0, cf * EXP(6.5819 + Boc * SOC std org code + Bot * SOC org type + Byr * YearID + Brgn * SOC region + Bced * SOC cohort entry density + Bmkit * SOC Org Std Market Share + Bred * SOC region entry density)

NOTE: The "cf" term is a correction factor applied to organizations CPQ, DEC, DELL, FJTS, HIT, and SI to achieve on average fit of respective historical years effective trajectories.

Units = Year

For the base simulation model, standardized organization code market share (SOC Std Market Share) levels for organizations with monotonically increasing or decreasing market shares were estimated as follows:

IBM Std Market Share = INTEG(change in IBM std market share * year transform, 0.446597)

Units = Std Total Market

FJTS Std Market Share = INTEG(change in FJTS std market share * year transform, 0.035858)

Units = Std Total Market

HP Std Market Share = INTEG(change in HP std market share * year transform, 0.015701)

Units = Std Total Market

CPQ Std Market Share = INTEG(STEP(change in CPQ std market share * year transform, 34), 0.001502)

NOTE: The STEP function accounts for Compaq's entry in simulation year 34.

Units = Std Total Market

SI Std Market Share = INTEG(change in SI std market share * year transform, 0.08309)

Units = Std Total Market

TBA Std Market Share = INTEG(change in TBA std market share * year transform, 0.014871)

Units = Std Total Market

DELL Std Market Share = INTEG(STEP(change in DELL std market share * year transform, 38), 0.00062)

NOTE: The STEP function accounts for Dell Computer's entry in simulation year 38.

Units = Std Total Market

For those organizations that initially gained and then lost market share, standardized organization code market share (SOC Std Market Share) levels were estimated as follows in the base model:

DEC Std Market Share = INTEG(IF THEN ELSE(STEP(1, 47) = 0, (change in DEC std market share * year transform), -1/(14.0362 * EXP(0.071244 * ((Year ID * year transform * dmnl transform) – 47))) * PULSE(47,4)), 0.025857)

Units = Std Total Market

NEC Std Market Share = INTEG(IF THEN ELSE(STEP(1, 46) = 0, (change in NEC std market share * year transform), -1/(43.0209 * EXP(0.023245 * ((Year ID * year transform * dmnl transform) – 46))) * PULSE(46,7)), 0.013619)

Units = Std Total Market

HIT Std Market Share = INTEG(IF THEN ELSE(STEP(1, 47) = 0, (change in HIT std market share * year transform), -1/(106.622 * EXP(0.009379 * ((Year ID * year transform* dmnl transform) – 47))) * PULSE(47,6)), 0.009353)

Units = Std Total Market

BGH Std Market Share = INTEG(IF THEN ELSE(STEP(1, 39) = 0, (change in BGH std market share * year transform), -1/(173.963 * EXP(0.005748 * ((Year ID * year transform * dmnl transform) – 39))) * PULSE(39,14)), 0.059443)

Units = Std Total Market

In each IF THEN ELSE function, the true condition allowed free competition with monotonically increasing market share. The false condition fit an exponentially decreasing function to the historical decrease in market share.

A simulation run of the base model showed that it missed upward turning discontinuities in IBM, Fujitsu, Hewlett-Packard, and Compaq Computer's respective historical market shares. These missed discontinuities caused the model to underestimate the respective market shares for IBM, Fujitsu, Hewlett-Packard, and Compaq Computer and to overestimate the market shares for the remaining organizations. The most severe underestimation was made in IBM's simulated market share. The upward discontinuity in IBM's historical market share started in simulation year 33 (1981) and continued to simulation year 42 (1990) and was the result of the success of IBM's personal computer. A second smaller but downward discontinuity occurred in IBM's historical market share in simulation year 42 and continued to simulation year 46 (1994) at which time an upward correction discontinuity occurred. The upward discontinuities in Fujitsu, Hewlett-Packard, and Compaq Computer's market shares occurred respectively in simulation years 43, 46, and 45. These underestimates were due to the linear formulation of the "SOC years effective" variable from the best-fit lognormal effectiveness covariate model. To correct for these estimation errors, a second simulation model was constructed in which IBM's market share level variable was modified to account for the discontinuities at simulation years 33 and 46, and correction factor multipliers were introduced in the market share level variables of the remaining organizations. The correction factor multipliers were simultaneously adjusted through subsequent simulation trials until they converged to an on average fit of historical market share trajectories. For this correction factor simulation model, final standardized organization code market share (SOC Std Market Share) levels were estimated as follows:

IBM Std Market Share = INTEG(change in IBM std market share * year transform * (1+PULSE(30, 8) * 10) * (1+PULSE (40, 13) * (-0.99)), 0.446597)

FJTS Std Market Share = INTEG(change in FJTS std market share * year transform * 0.4732 * (1+PULSE(41, 5) * 5) * (1+PULSE(46, 7) * (-0.5)), 0.035858)

HP Std Market Share = INTEG(change in HP std market share * year transform * 0.601339, 0.015701)

CPQ Std Market Share = INTEG(STEP(change in CPQ std market share * year transform, 34) * 0.443589, 0.001502)

DEC Std Market Share = INTEG((IF THEN ELSE(STEP(1 , 47) = 0, (change in DEC std market share * year transform) , -1/(11.6267 * EXP(0.086009 * ((Year ID * year transform * dmnl transform)-47))) * PULSE(47, 4))) * 0.828178, 0.025857)

NEC Std Market Share = INTEG(IF THEN ELSE(STEP(1 , 46) = 0, (change in NEC std market share * year transform) * 1.27256, -1/(31.5507 * EXP(0.031695 * ((Year ID * year transform * dmnl transform) -46))) * PULSE(46, 7)), 0.013619)

HIT Std Market Share = INTEG((IF THEN ELSE(STEP(1 , 47) = 0, (change in HIT std market share * year transform) * 1.24204 , -1/(49.0287 * EXP(0.020396 * ((Year ID * year transform * dmnl transform) -47))) * PULSE(47, 6))) * 0.750969, 0.009353)

BGH Std Market Share = INTEG((IF THEN ELSE(STEP(1 , 39) = 0, (change in BGH std market share * year transform) * 1.48207 , -1/(123.251 * EXP(0.008114 * ((Year ID * year transform * dmnl transform) -39))) * PULSE(39, 14))) * 0.886161, 0.059443)

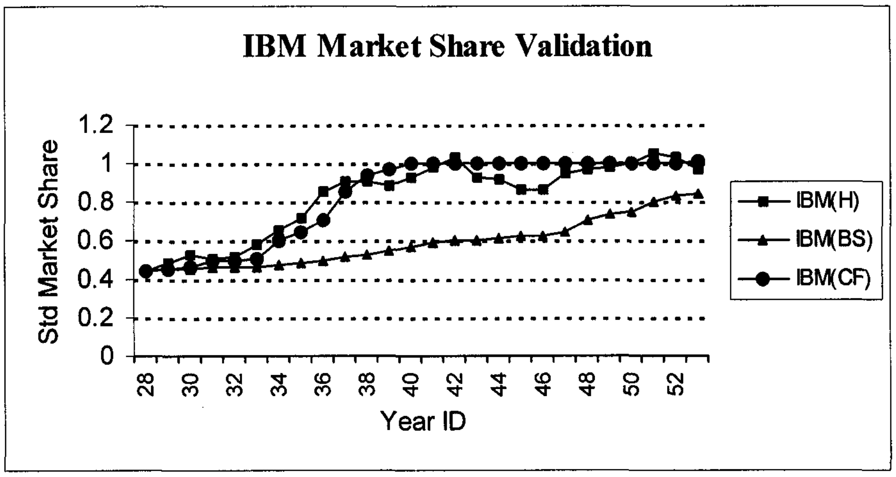
SI Std Market Share = INTEG(change in SI std market share * year transform * 0.06487, 0.08309)

TBA Std Market Share = INTEG(change in TBA std market share * year transform * 0.239907, 0.014871)

DELL Std Market Share = INTEG(STEP(change in DELL std market share * year transform, 38) * 0.295969, 0.00062)

Units = Std Total Market {all organizations}

The dynamic behavior of the correction factor simulation model was validated in two steps. The first validation step was for behavior reproduction. Validation for behavior reproduction answers the question, "Does the model reproduce the behavior of interest in the system?" (Sterman 860). Validation for behavior reproduction was conducted by examining the correction factor simulation model's organizational market share trajectories for on average fit to historical market share trajectories. This examination is presented in the organizational market share validation graphs of Figure 33. In each graph, trajectories are coded as SOC(H) = historical market share, SOC(BS) = base simulation model market share, and SOC(CF) = correction factor simulation model market share. Evaluation of the correction factor simulation model trajectories versus historical market share trajectories reveals that a significant amount of inertia remains in the simulation model due to the linear formulation of the "SOC years effective" variable. Although the model's trajectories achieve an on average fit of the historical market share trajectories, its trajectories still miss historical short-term upward or downward turning point discontinuities in individual organizational market share trajectories and lag historical turning point discontinuity trajectories. These observations indicate that improvements in the fits of individual historical organization market share trajectories are still possible through the inclusion of additional STEP, PULSE, and possibly SIN functions in the standardized organization code market share (SOC Std Market Share) level integral equations. For this research, however, the question arose as to how much model refinement could be made before modeling criteria one and two were violated and free competition was restricted. Since the purpose of this simulation model was to perform sensitivity analyses to determine the dynamic effects of changes in controllable covariate values, this first correction factor model was accepted as providing sufficient fit to historical market share trajectories but still allowing free competition needed for sensitivity analyses.



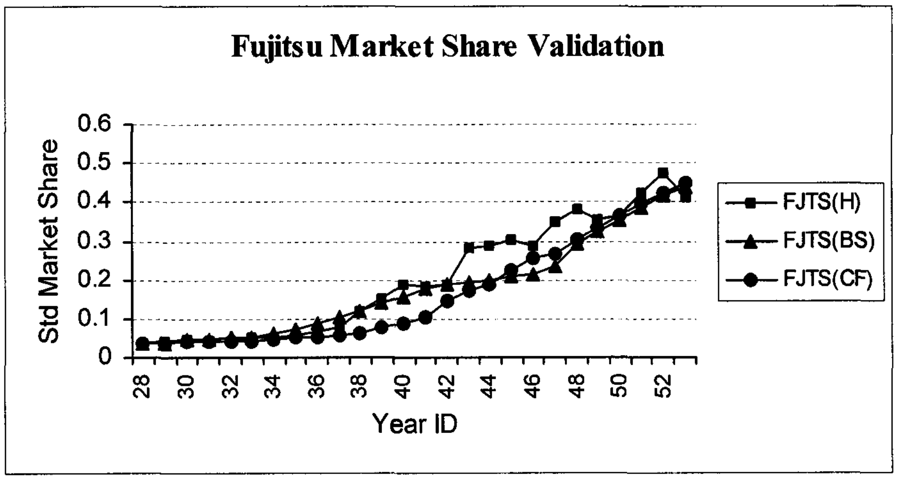
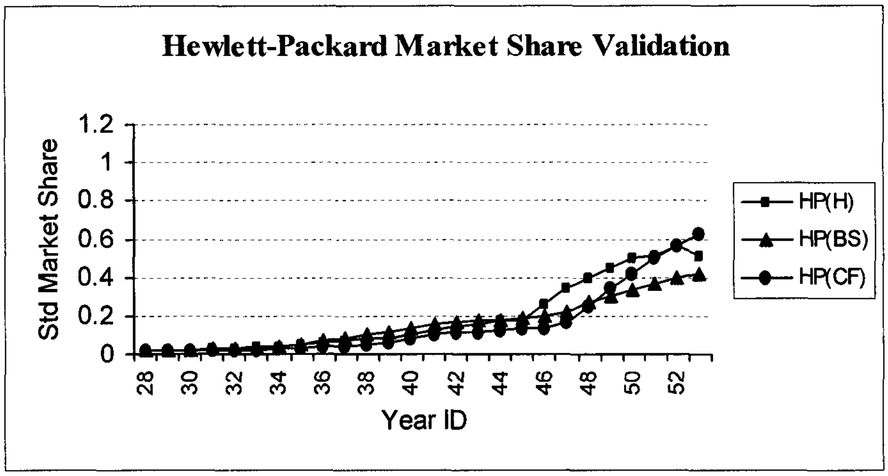
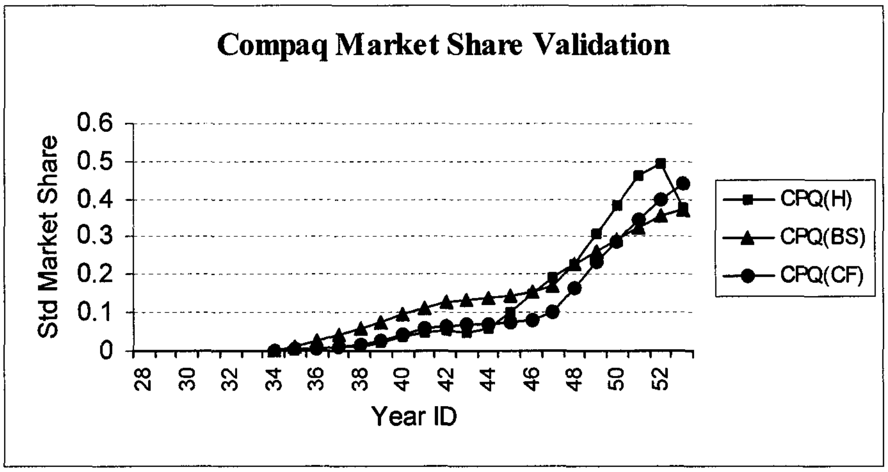


Figure 33. Correction factor simulation model market share validation graphs.





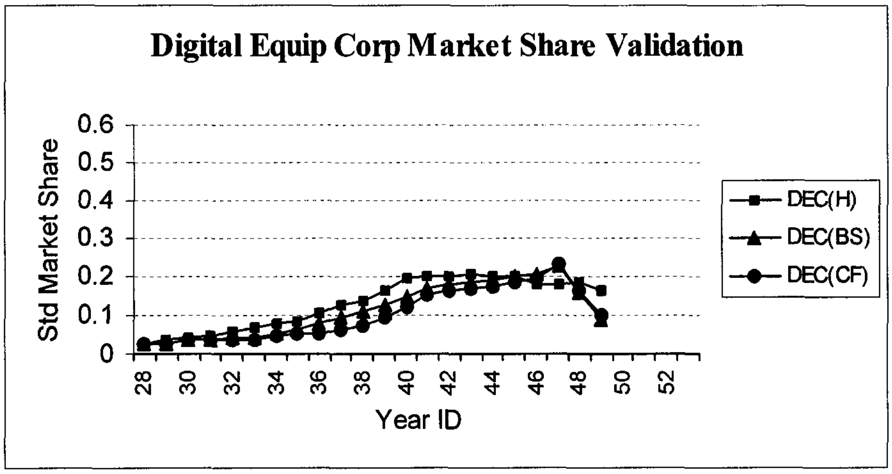
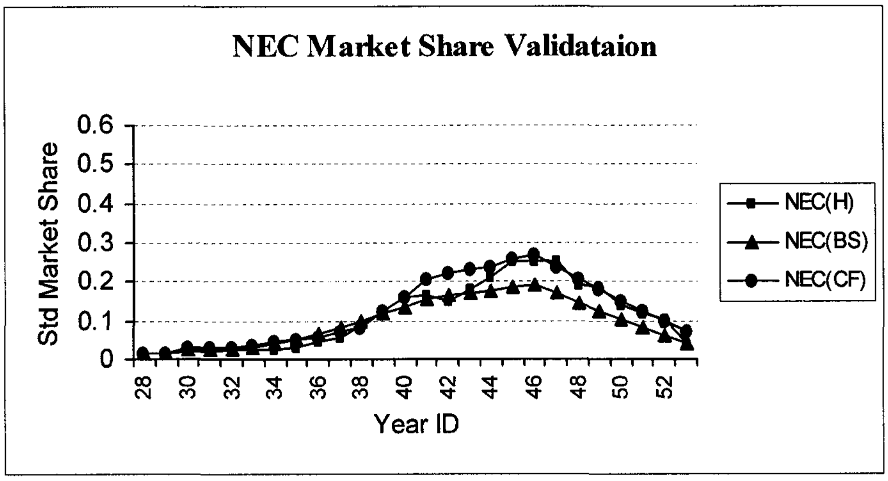
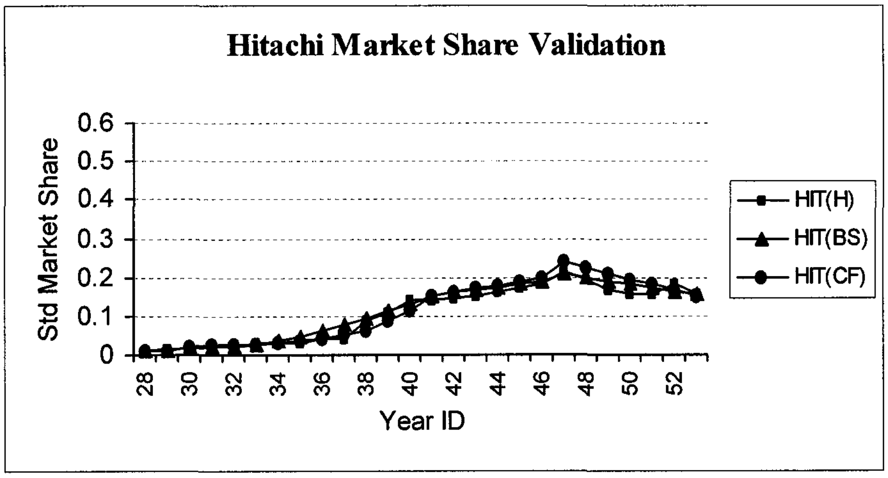


Figure 33 (continued). Correction factor simulation model market share validation graphs.





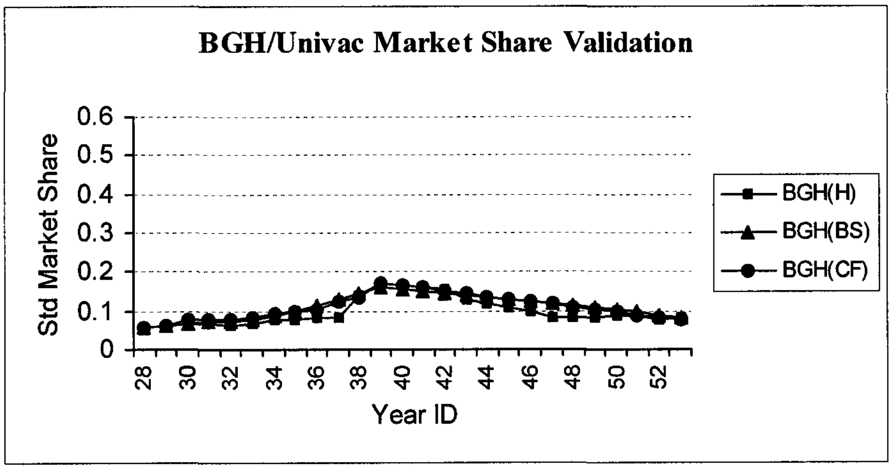
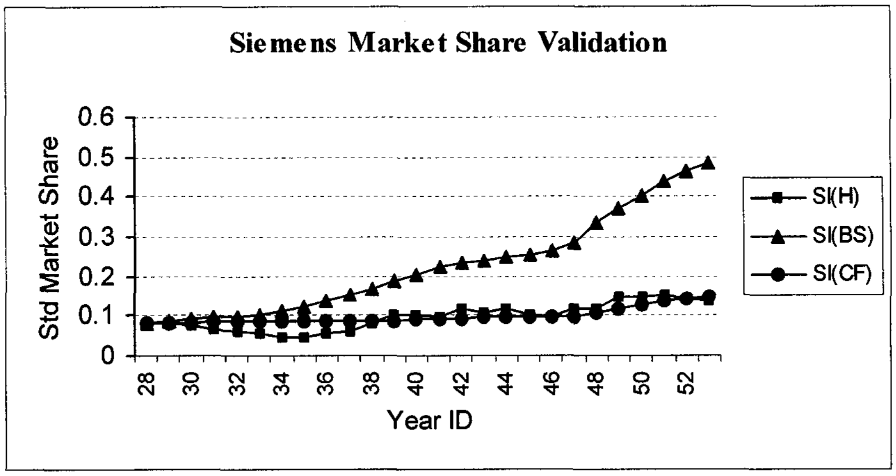
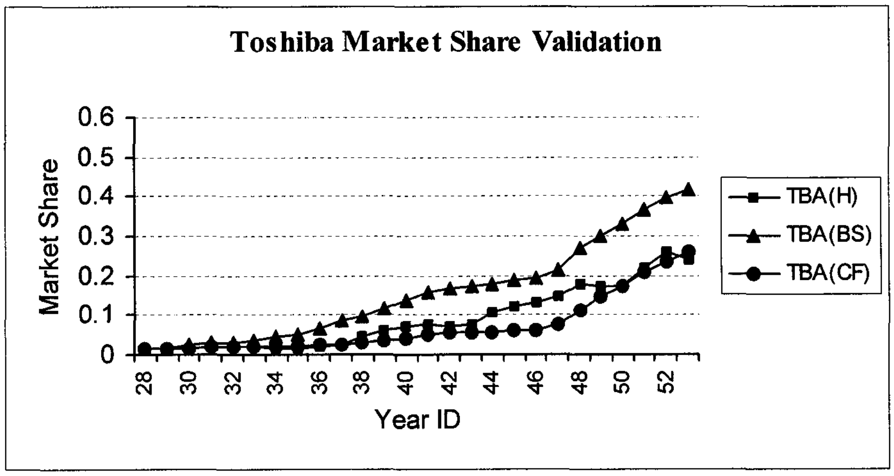


Figure 33 (continued). Correction factor simulation model market share validation graphs.





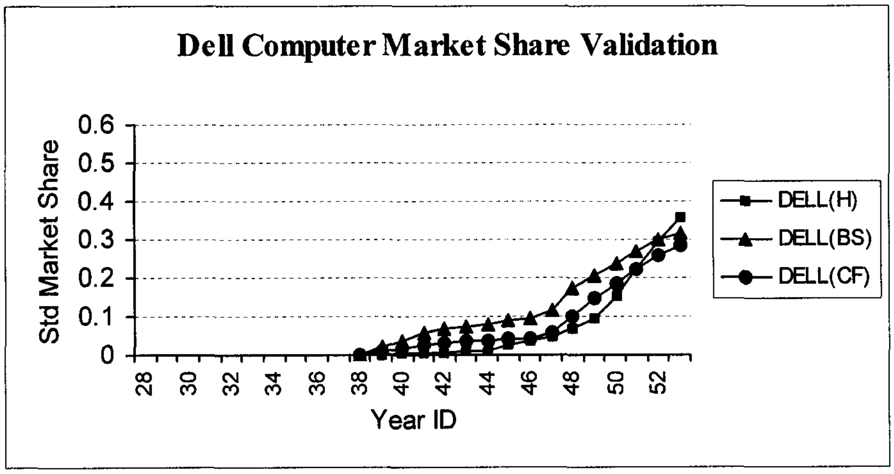


Figure 33 (continued). Correction factor simulation model market share validation graphs.

The correction factor simulation model market share trajectories for the Pareto set of dominant computer manufacturers are presented in Figure 34. Comparison of the model market share trajectories in Figure 33 and comparison of the model market share trajectories for the Pareto set of dominant computer manufacturers in Figure 34 to the historical trajectories in Figure 17 indicates that the model achieves behavior reproduction validation and captures the fundamental structure of the environmental selection forces at work in the original equipment computer manufacturing population during the study period.

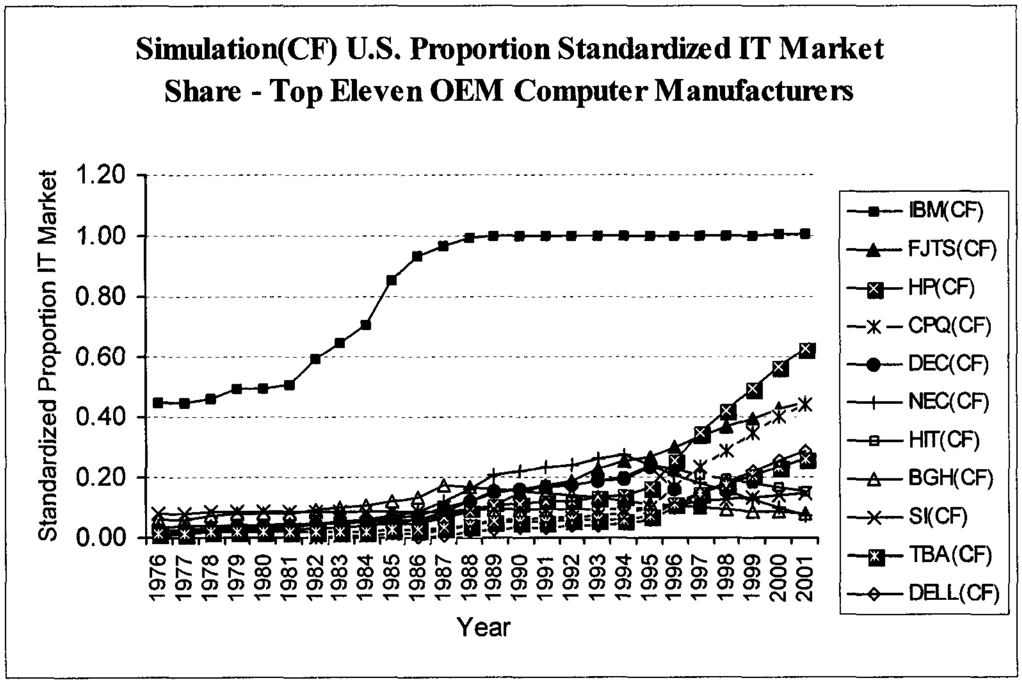


Figure 34. Correction factor simulation model market share trajectories.

The second validation step was for robustness to generalization. For this simulation model, validation for robustness to generalization seeks to answer the question, "Can the model generate the behavior observed in other instances of the same system?" (Sterman 860). Validation for robustness to generalization of the correction factor simulation model was conducted by adding the next four dominant original equipment computer manufacturers during study period and examining the market share trajectories of the original Pareto set of the top eleven computer manufacturers. For this model, the criteria for acceptance of robustness to generalization was that after achieving an on average fit of model market share trajectories to historical trajectories for the next four dominant computer manufacturers the market share trajectories of the Pareto set of top eleven computer manufacturers exhibited no significant changes in trajectories. That is the correction factor simulation model is sufficiently robust to generalization to the population of original equipment computer manufacturers, and the effectiveness dynamics observed in the correction factor model are unbiased for the population.

The next four dominant original equipment computer manufacturers during study period, AT&T, NCR Corporation, Sun Microsystems, and Sperry Corporation, collectively controlled 5 percent to 9 percent of the total market from 1976 to 2001. Combined, the top eleven plus this group of four collectively controlled from 79 percent of the total market in 1976 to 88 percent of the total market in 2001. A validation simulation model was created, and these four organizations were added to the model. Their respective annual changes in market shares were added to the "change in market" rate variable, their respective covariate values were entered into the common equations, and their standardized organization code market share (SOC Std Market Share) levels were estimated as follows.

ATT Std Market Share= INTEG (IF THEN ELSE(STEP(1 , 49) = 0, (change in ATT std market share * year transform) * PULSE(35, 14) * 0.583547 + STEP(-0.326293, 48), 0), 0.01618)

Units = Std Total Market

NCR Std Market Share= INTEG (IF THEN ELSE(STEP(1,44)=0,(change in NCR std market share * year transform) * PULSE(28, 16) * 0.333296 + STEP(-0.103304, 43),0)), 0.039797)

Units = Std Total Market

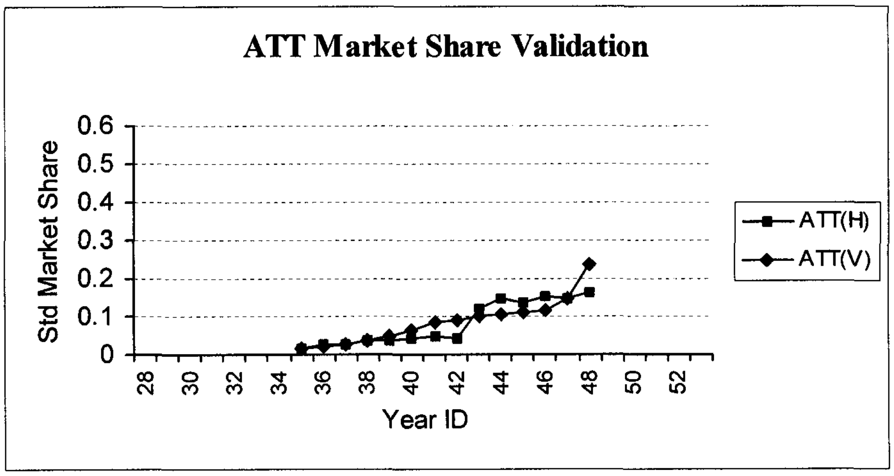
SUNW Std Market Share= INTEG ((STEP(change in SUNW std market share * year transform,36)) * 0.21202, 0.000749)

Units = Std Total Market

SRND Std Market Share= INTEG (IF THEN ELSE(STEP(1,39)=0,(change in SRND std market share * year transform) * PULSE(28, 11) * 0.180974 + STEP(-0.068342, 38),0), 0.050219)

Units = Std Total Market

The STEP and PULSE functions in the integral equations model historical entry into and exit from the computer market, and the correction factors provide an on average fit to historical market share trajectories. Validation for on average fit to historical market share trajectories for these organizations is presented in the market share validation graphs of Figure 35.



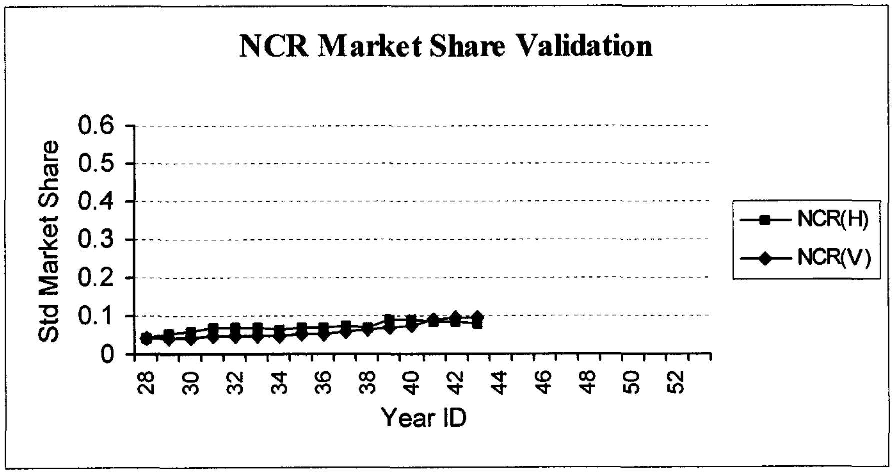
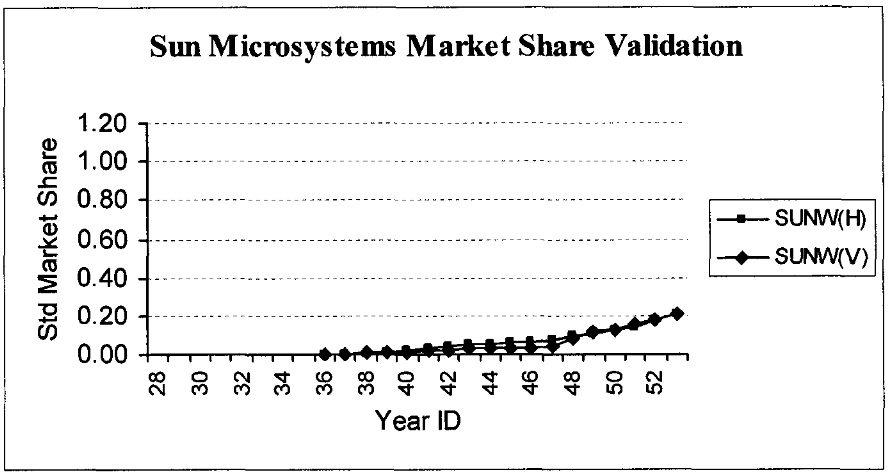


Figure 35. Correction factor simulation model market share validation graphs of the next four dominant original equipment computer manufacturers.



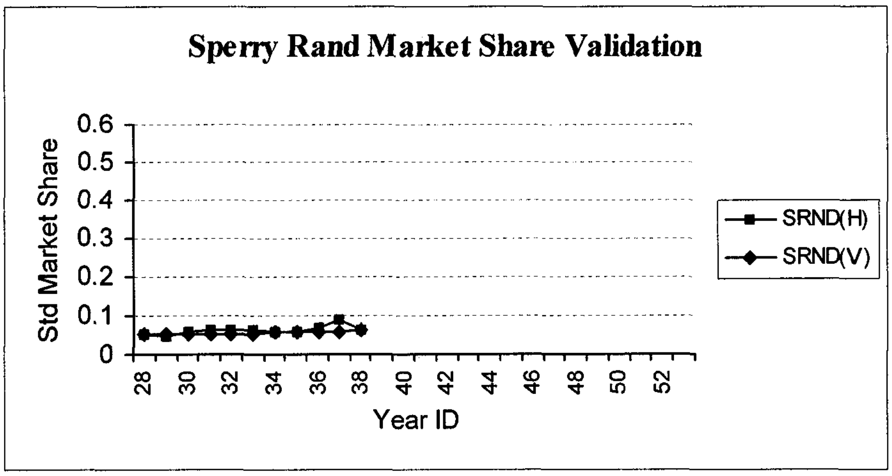
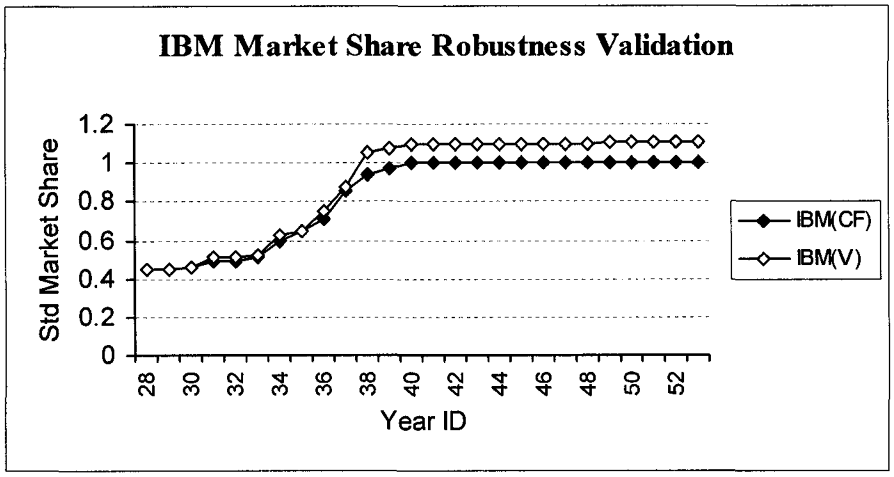
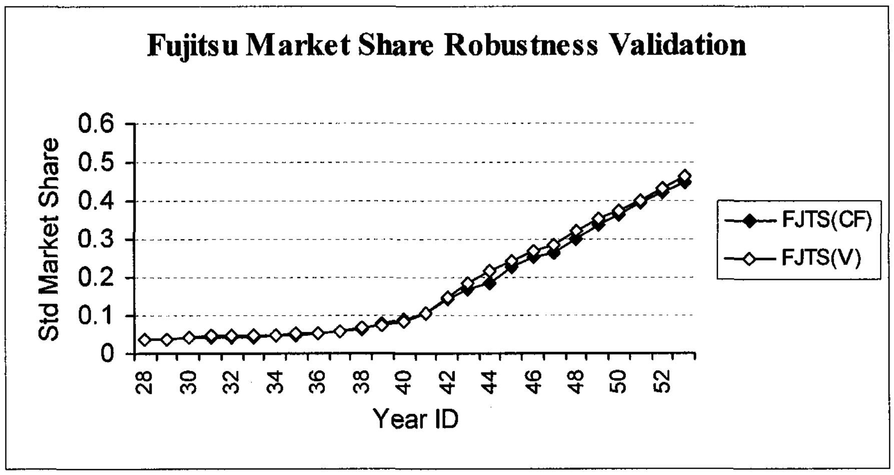


Figure 35 (continued). Correction factor simulation model market share validation graphs of the next four dominant original equipment computer manufacturers.

Given acceptable on average model market share trajectories for the next four dominant original equipment computer manufacturers, the question of correction factor model robustness to generalization was answered by examining the market share trajectories of the original Pareto set top eleven computer manufacturers in Figure 36.





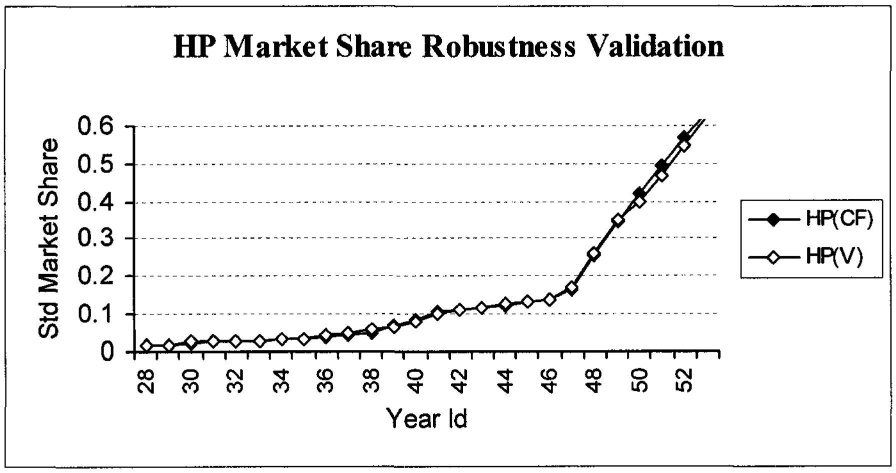
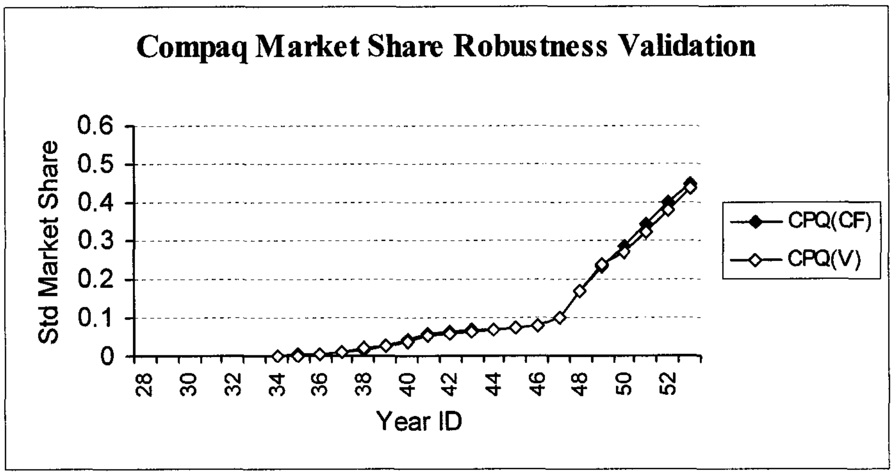
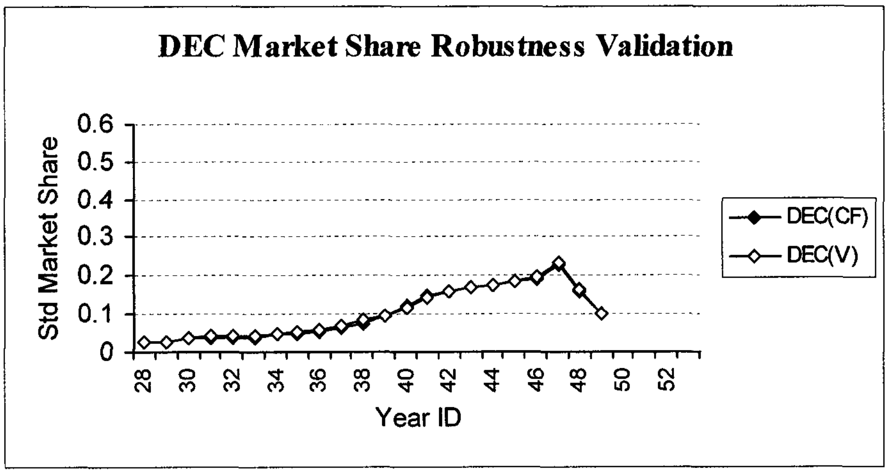


Figure 36. Correction factor simulation model market share robustness validation graphs.





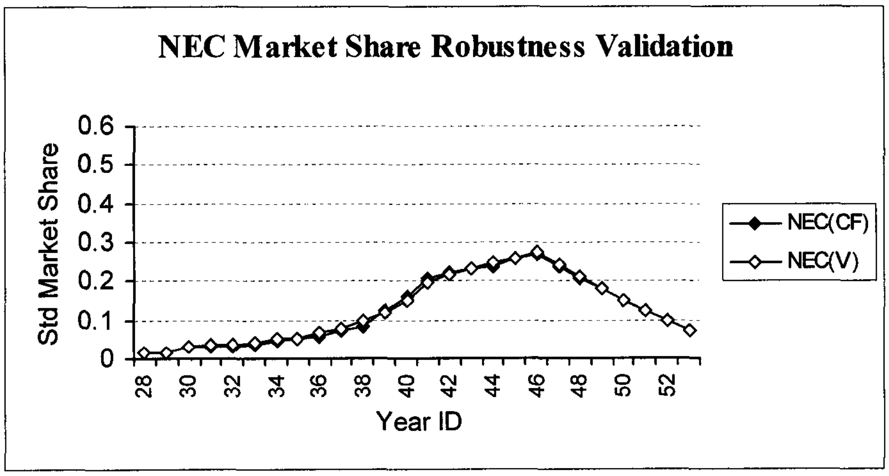
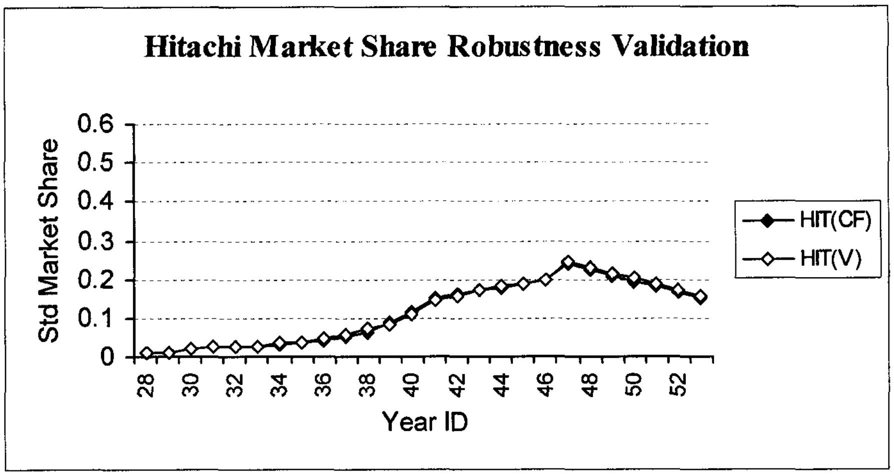
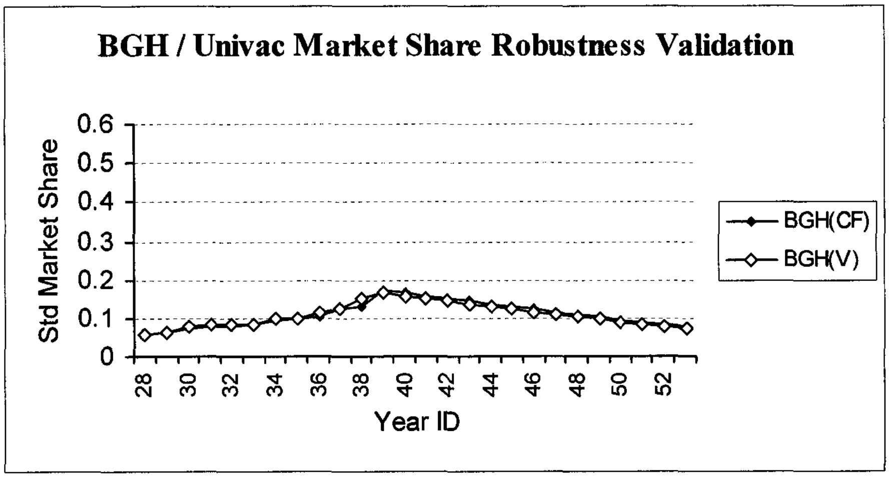


Figure 36 (continued). Correction factor simulation model market share robustness validation graphs.





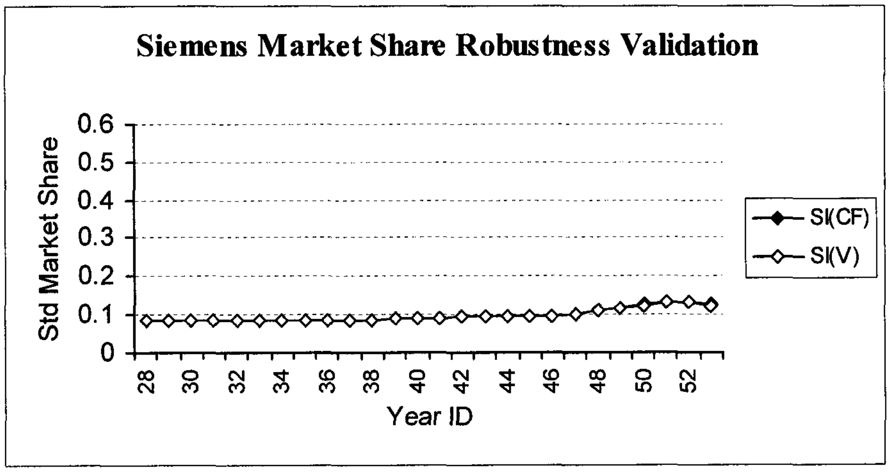
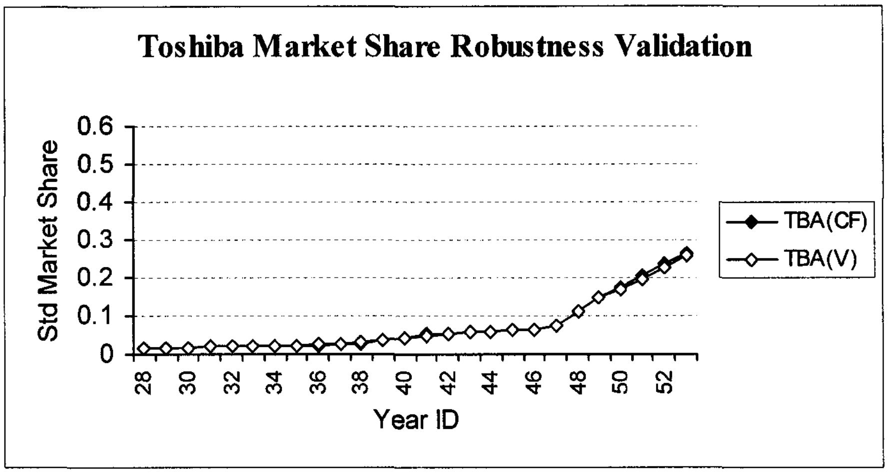


Figure 36 (continued). Correction factor simulation model market share robustness validation graphs.



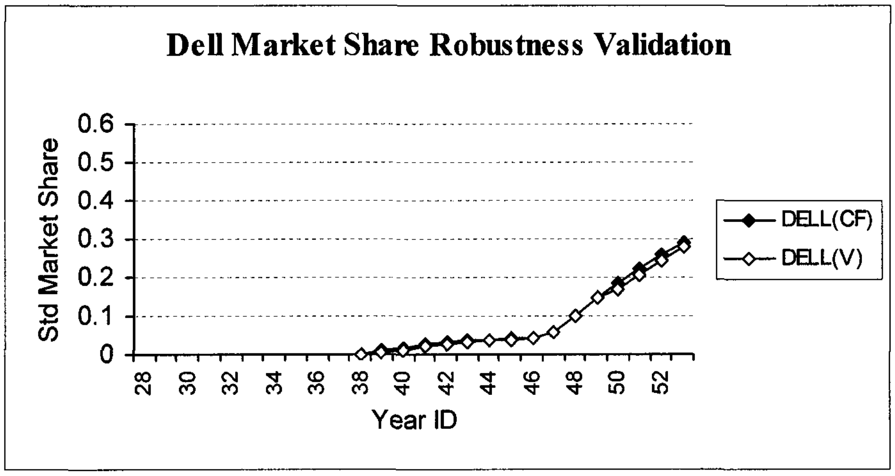
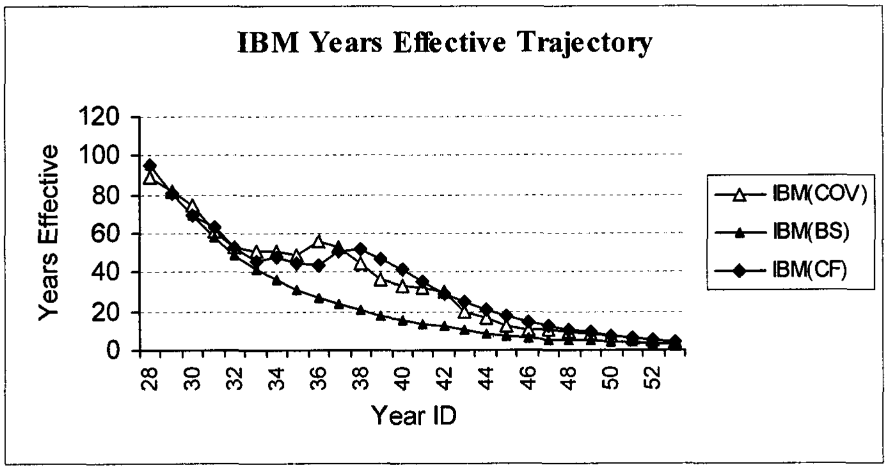


Figure 36 (continued). Correction factor simulation model market share robustness validation graphs.

The market share trajectories of the original Pareto set top eleven computer manufacturers in Figure 36 exhibited no significant structural changes in trajectories. The respective market shares for IBM and Fujitsu increased slightly over the range of the study period, and the respective market shares for Hewlett-Packard, Toshiba, and Dell Computer decreased correspondingly. These changes can be corrected with appropriate changes in respective correction factors. The other organizations exhibited no change in levels. Given these results the correction factor simulation model was accepted as achieving both behavior reproduction validation and robustness to generalization validation.

Having established correction factor simulation model validation, the years effective trajectories for each of the Pareto set of the dominant original equipment computer manufacturers were examined for prediction differences between the covariates effectiveness model, the base simulation model, and the correction factor simulation model. These trajectories are presented in Figure 37 with trajectories coded as SOC(COV) = covariates effectiveness model, SOC(BS) = base simulation model, and SOC(CF) = correction factor simulation model.



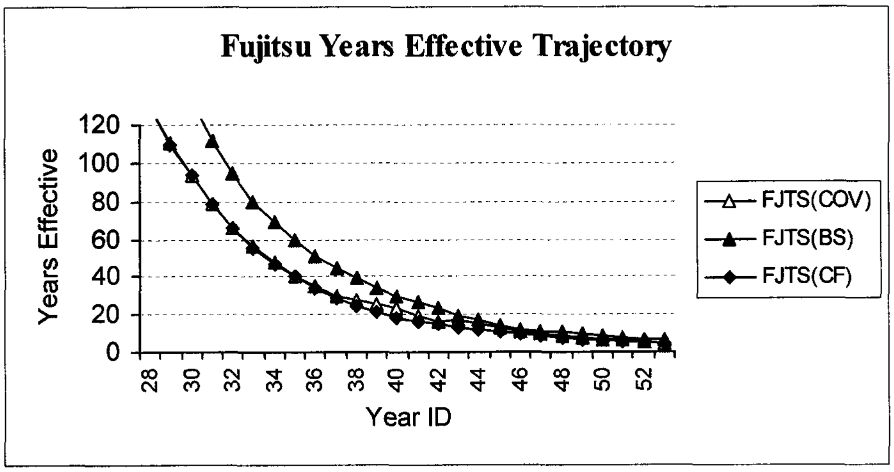
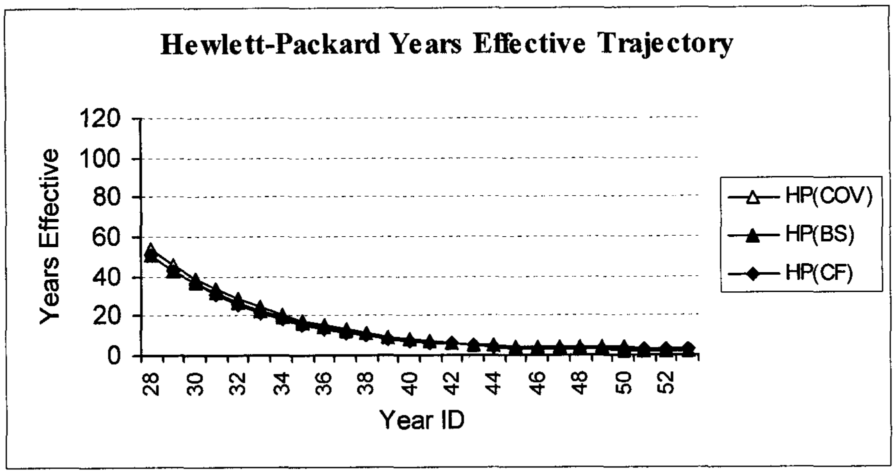
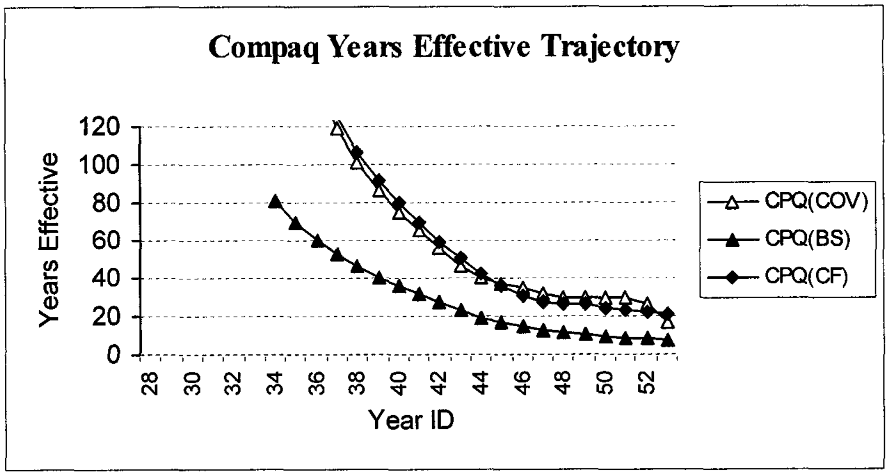


Figure 37. Prediction differences in years effective trajectories for the different models.





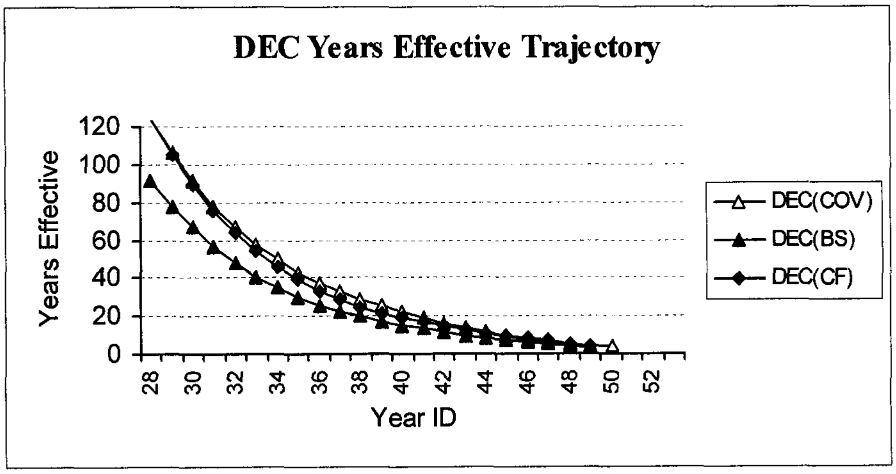
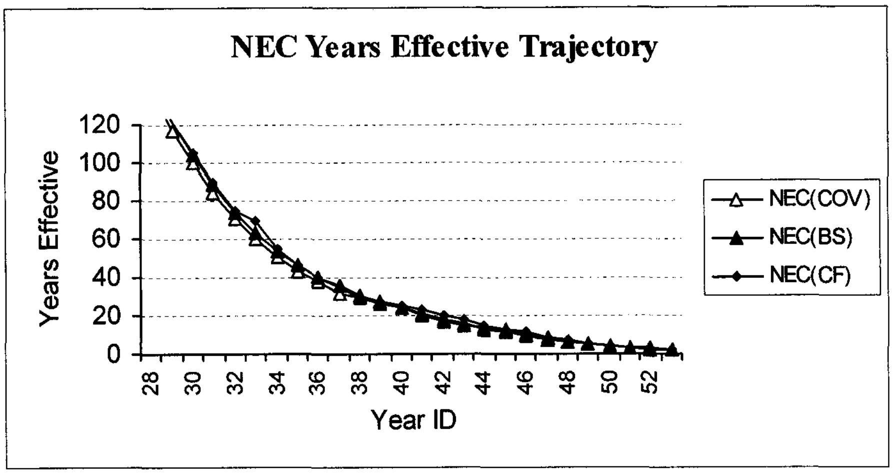
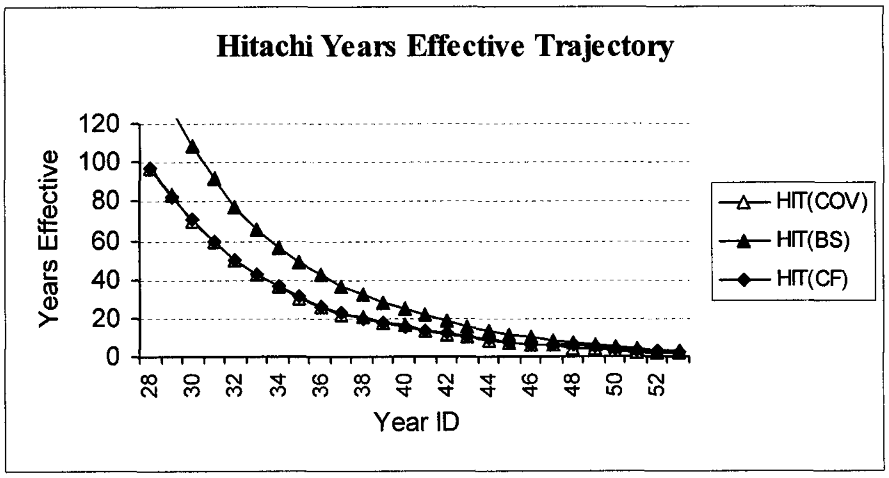


Figure 37 (continued). Prediction differences in years effective trajectories for the different models.





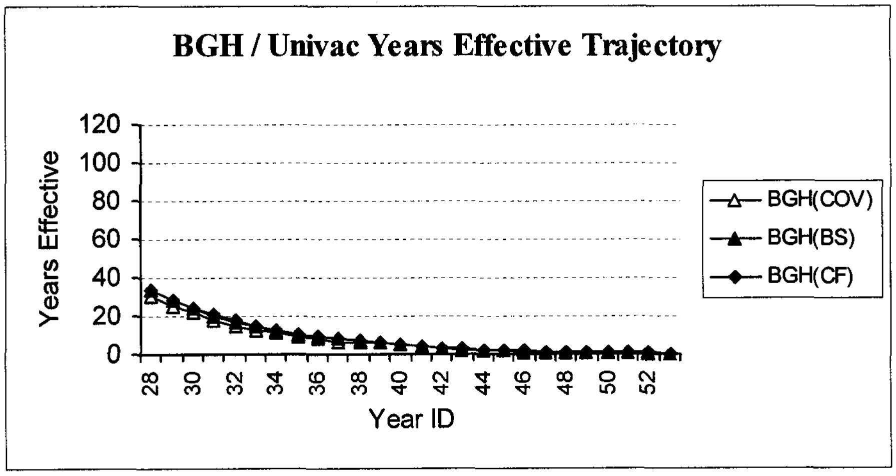
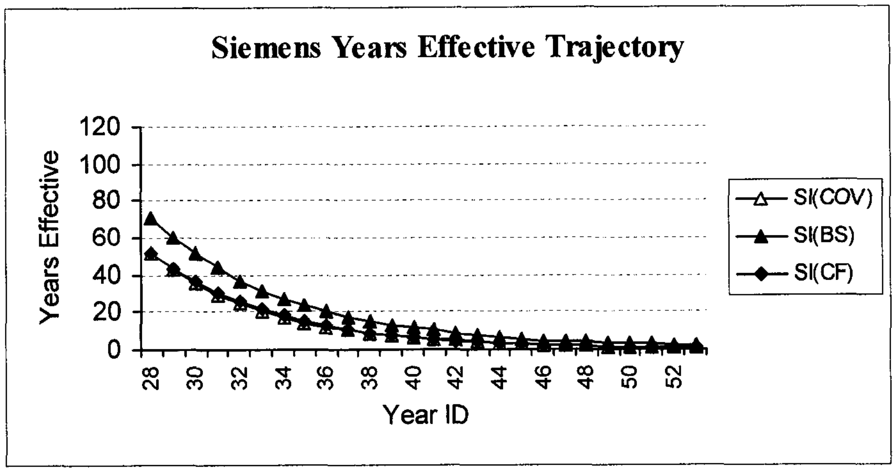
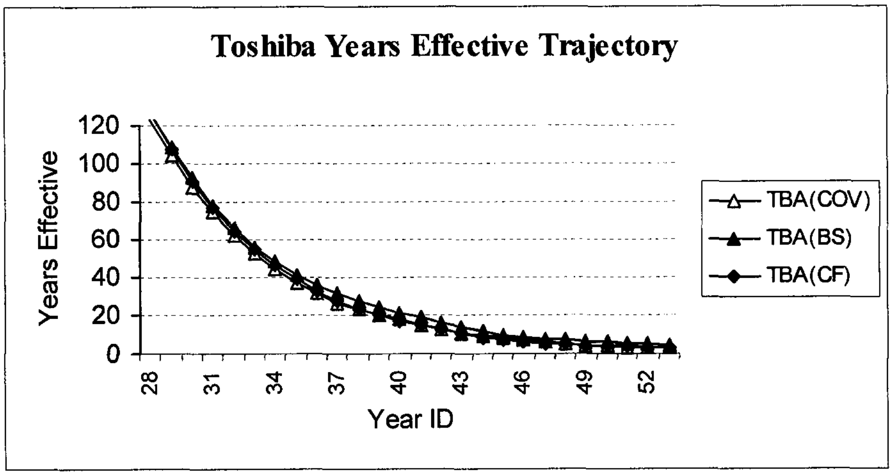


Figure 37 (continued). Prediction differences in years effective trajectories for the different models.





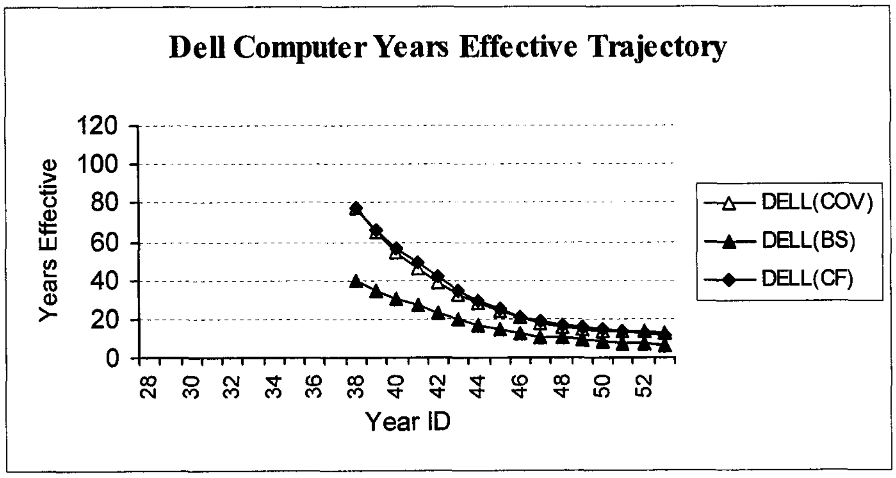


Figure 37 (continued). Prediction differences in years effective trajectories for the different models.

The correction factor simulation model agreed with the covariate effectiveness model. The base simulation model under and overestimated conditional expected years of non-negative growth in market share niche effectiveness. The plot of the correction factor simulation model conditional expected years effective trajectories is presented in Figure 38. Comparison of the model trajectories in Figure 38 to the covariate model trajectories in Figure 31 indicates that the correction factor model reproduces the fundamental conditional expected years effective trajectories.

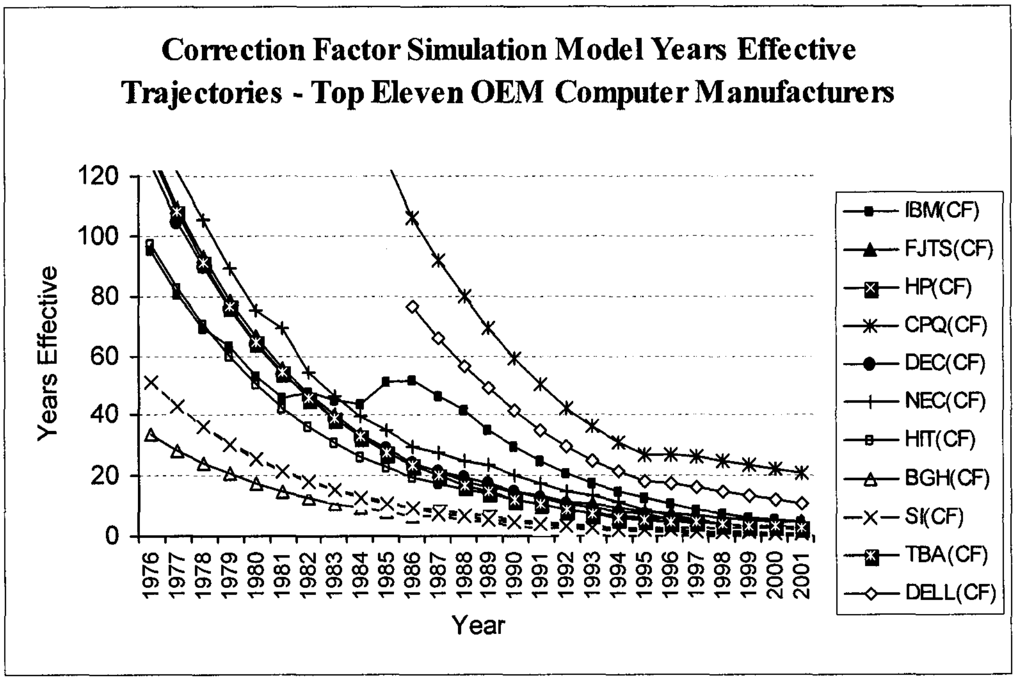


Figure 38. Correction factor model conditional expected years effective trajectories for the Pareto set of dominant computer manufacturers.

Having established correction factor simulation model validation, sensitivity analyses were conducted for the internally controllable variable of organization type to assess the effect of changing its value from 0, existing organization, to 1, new entrant, on standardized organizational market shares and conditional expected years effective for those manufacturers that entered into computer manufacturing. The remaining organizational variables identified as statistically significant in the covariate effectiveness model in Table 17 were not internally controllable by engineering managers within respective organizations. Sensitivity testing of organization type was conducted on a one-factor-at-a-time approach. For each organization, the code for organization type was changed for one organization while holding the organization type value for all other organizations at the original correction factor simulation model level.

Figure 39 presents the results of sensitivity testing in changes in respective organization market shares for changes in organization type code, SOC(OT). Increases in market shares relative to the respective market shares predicted by the correction factor simulation model, SOC(CF) were observed but only at a 0.0001 level relative to the standardized market share value of one.

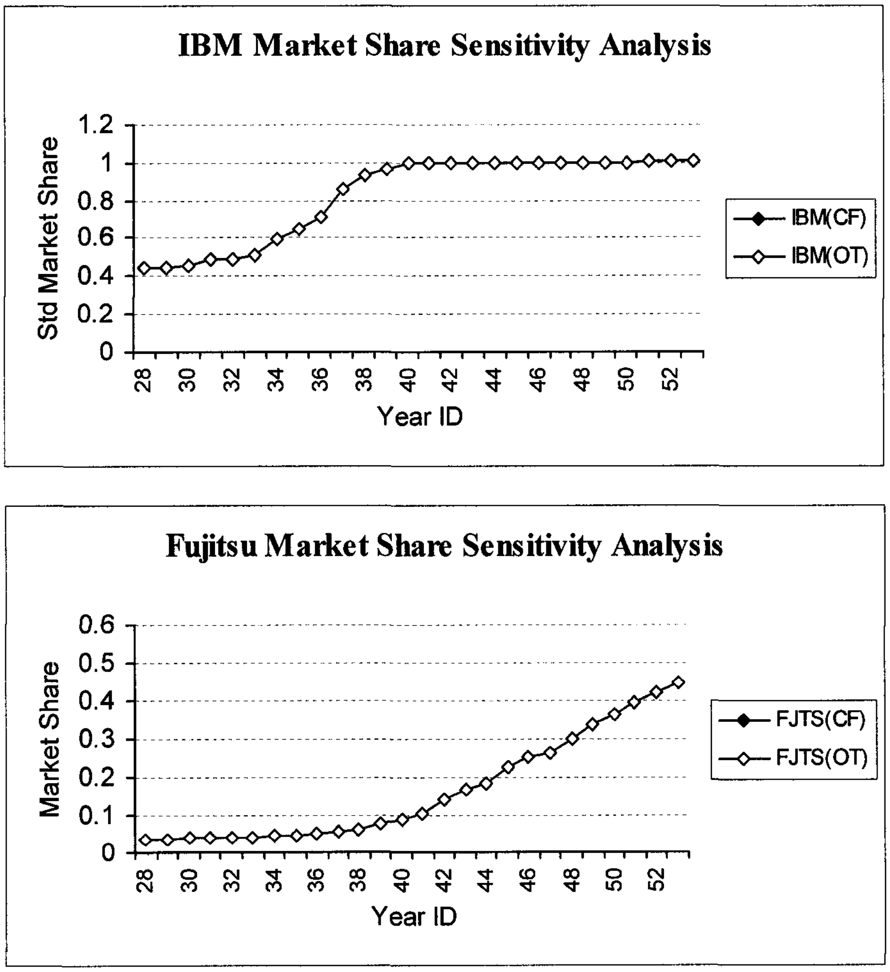
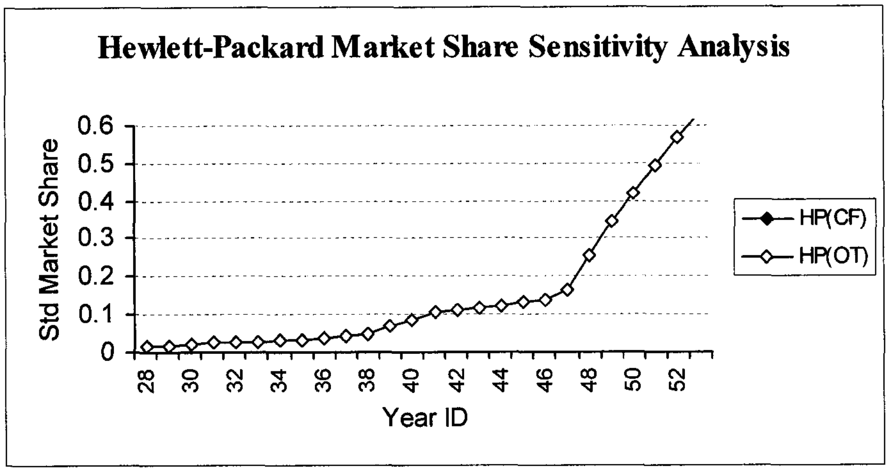
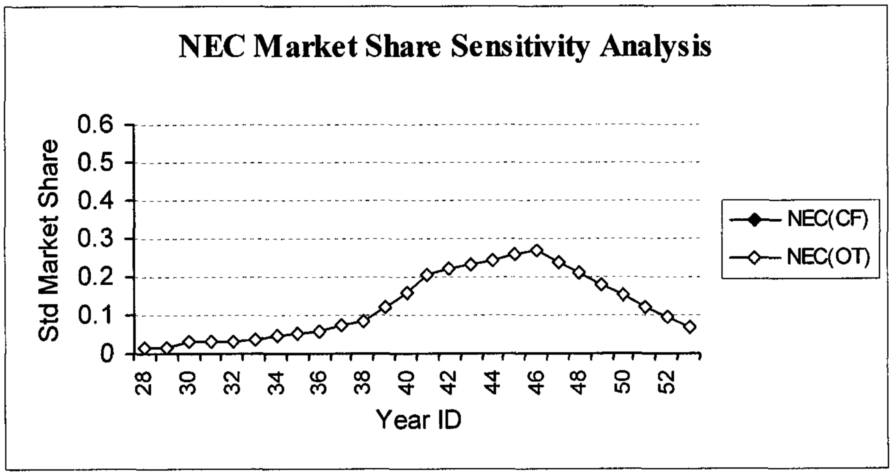


Figure 39. Market share sensitivity analyses.





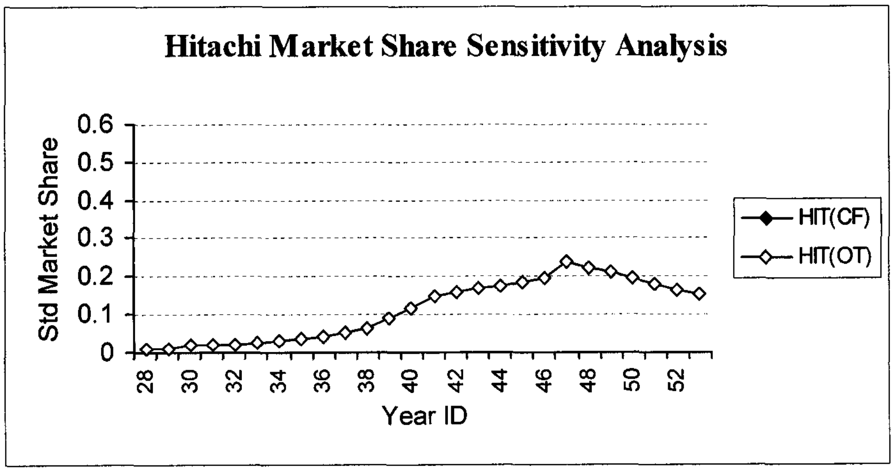
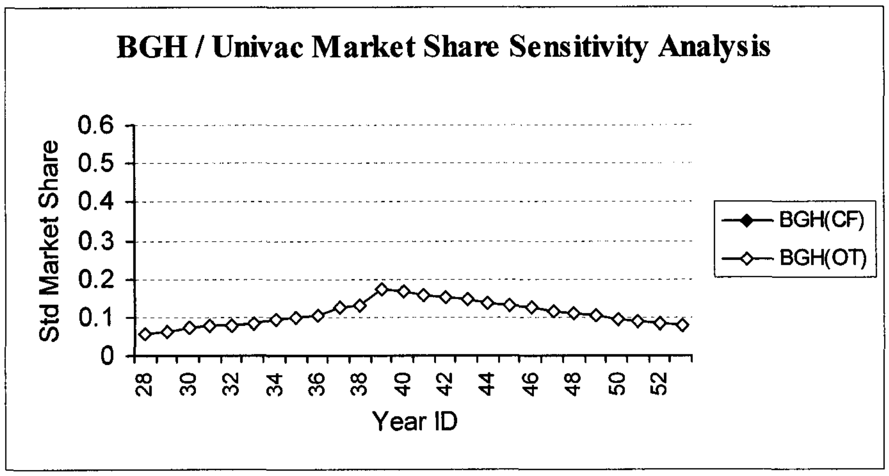
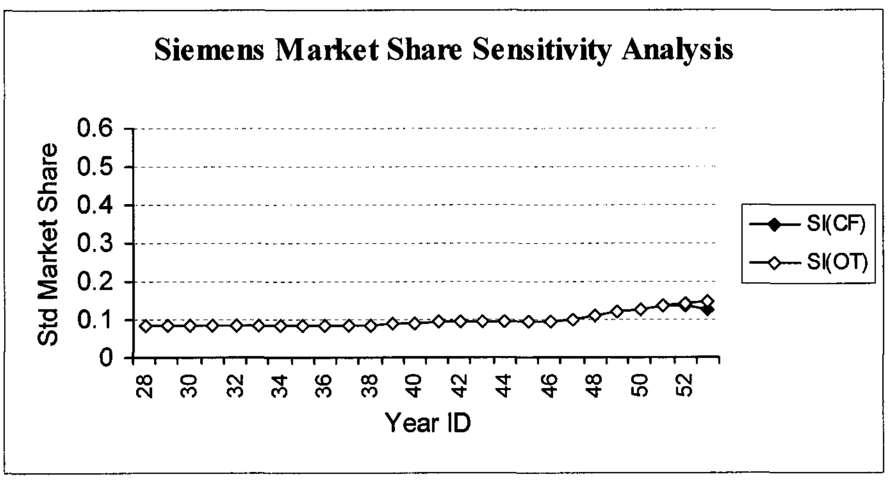


Figure 39 (continued). Market share sensitivity analyses.





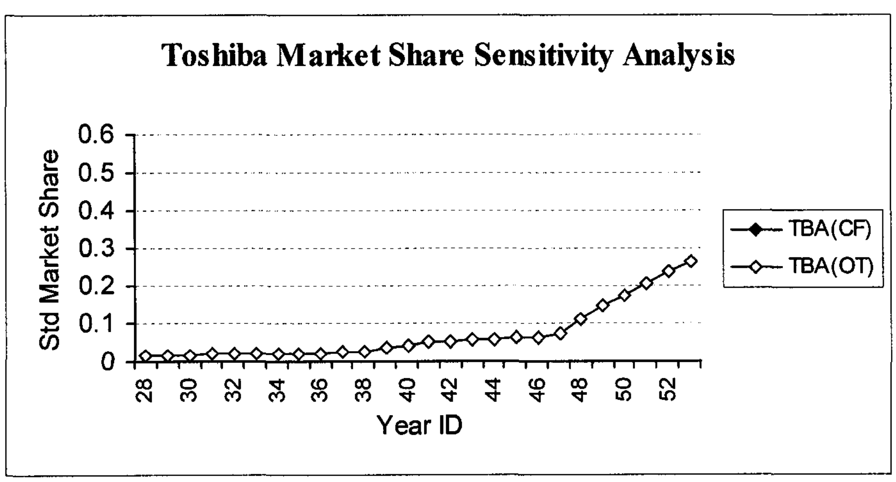
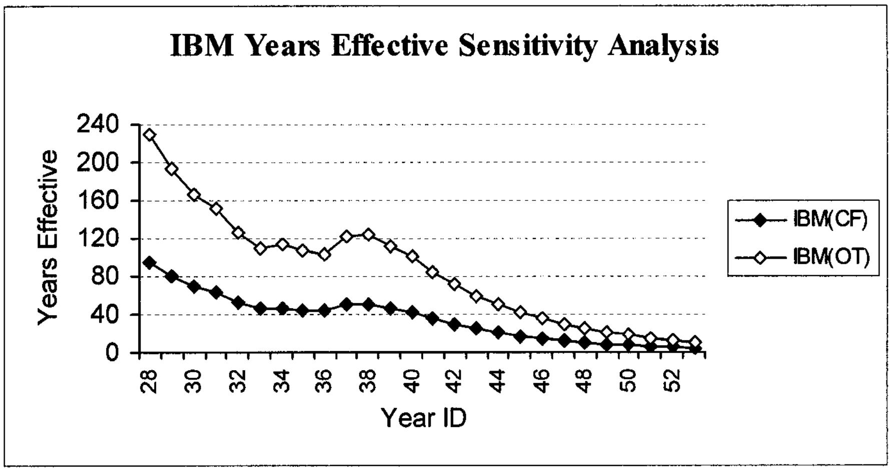


Figure 39 (continued). Market share sensitivity analyses.

Figure 40 presents the results of sensitivity testing for changes in respective organization years effective given changes in organization type code, SOC(OT). All organizations exhibited an increase in conditional expected years effective over the study period, with IBM, Fujitsu, Hewlett-Packard, and Toshiba each exhibiting a marginal positive increase through the end of the study period.



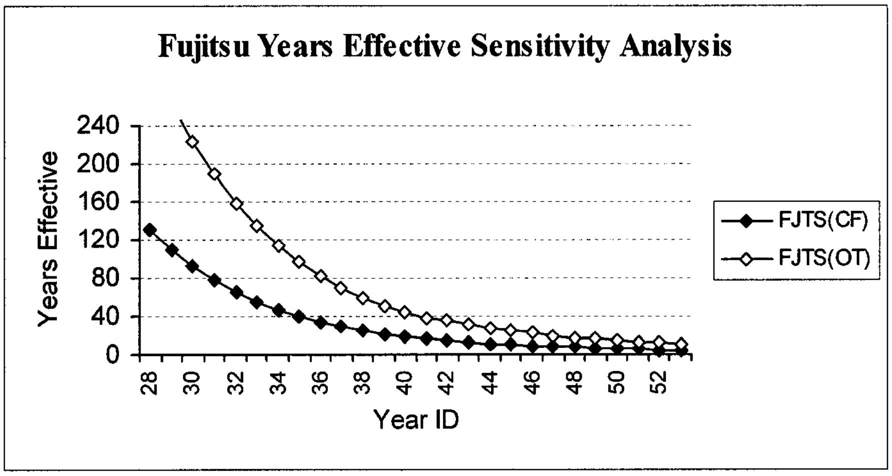
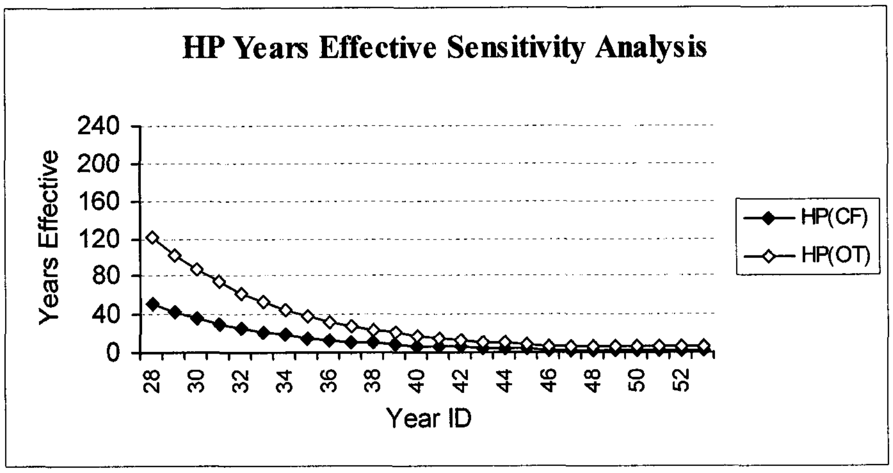
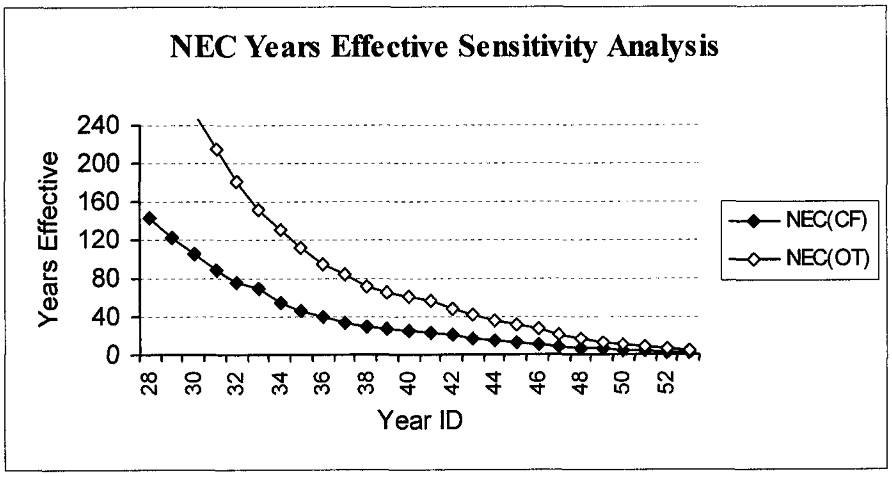


Figure 40. Conditional expected years effective sensitivity analyses.





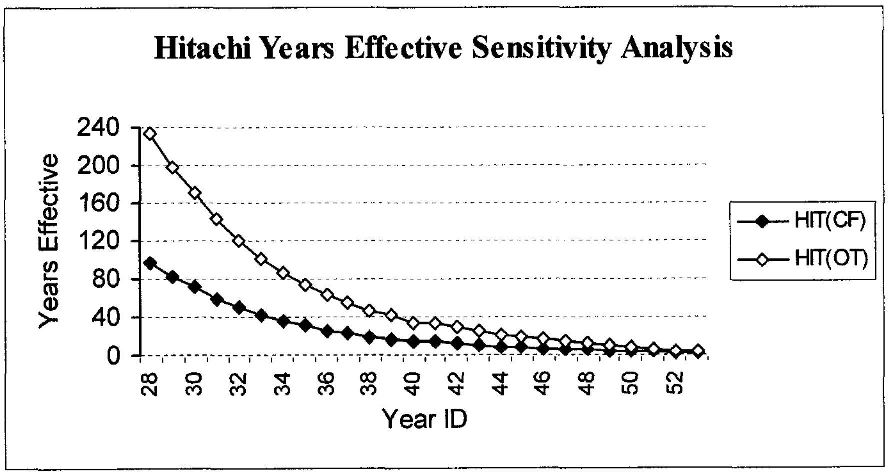
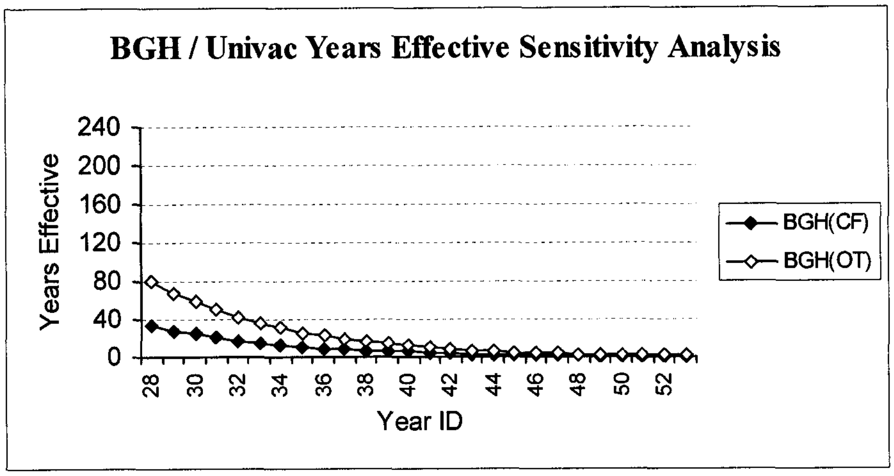
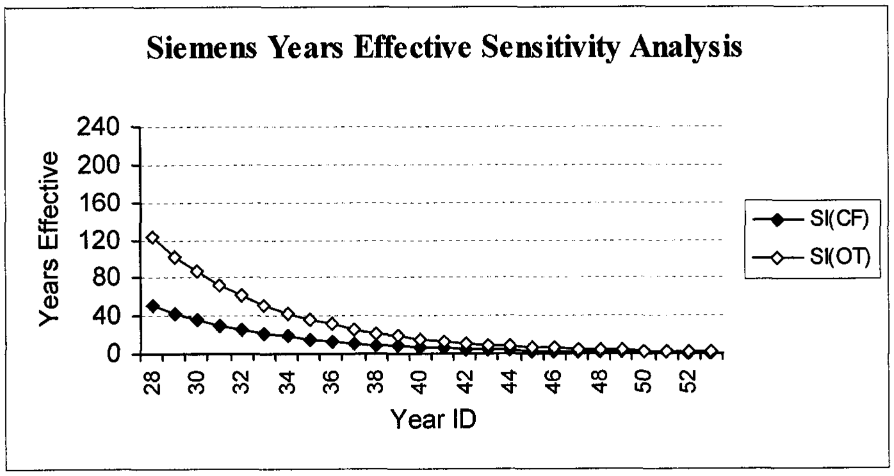


Figure 40 (continued). Conditional expected years effective sensitivity analyses.





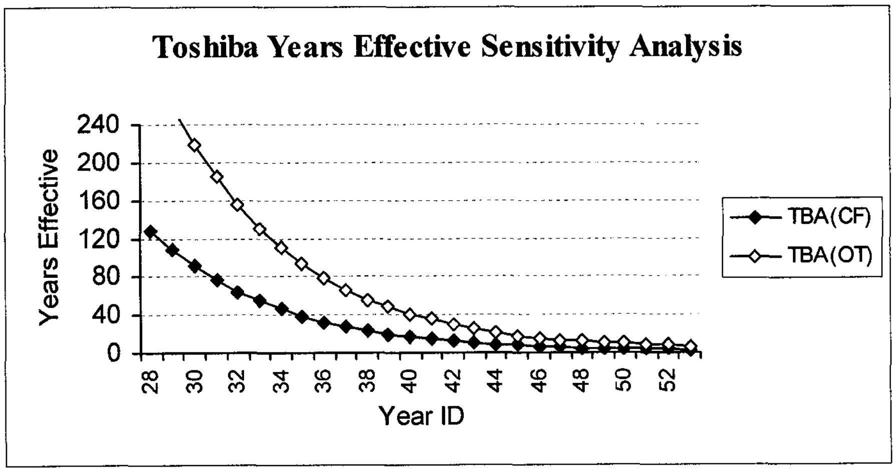


Figure 40 (continued). Conditional expected years effective sensitivity analyses.

CHAPTER V

RESULTS AND DISCUSSION

5.1 Event History Survival Analysis

This chapter summarizes and discusses the findings of event history survival and effectiveness analyses and dynamic simulation model and sensitivity analyses presented in chapter IV. Recall from chapters I and III that the purpose of this research was to investigate the relationships among environmentally determined, observable dynamic vital rates due to selection forces and observable organizational structural features of the Viable System Model's recursive cybernetic structures of knowledge creation, joint adaptation of the intelligence and control functions, and the efficiency of the social and technical subsystem structures as determinants of organizational adaptation effectiveness in the original equipment computer manufacturing industry. Likewise, recall from section "3.3 Research Hypotheses," that for this research survival analyses were conducted to establish population density dependence in entry and mortality rates. Three forms of mortality were observed: disbanding, equal-status merger, and acquisition. All were considered equally as mortality in survival analysis. Establishment of density dependence in entry and mortality rates in survival analysis indicates a priori the presence of the domains of self-organizing environmental and population level selection forces and organizational adaptation as hypothesized by the general systemic model of organizational effectiveness.

Exploratory graphical analyses presented in Figures 21 through 23 appear to support density dependence in entry and mortality processes of the original equipment computer manufacturing industry. The plot of entry rate versus density in Figure 21 displays the inverted U shape hypothesized by Theorems 1 and 2. The entry process, however, appears to exhibit more of a standard Weibull process with a scale parameter equal 1 and a shape parameter between 0.5 and 1.0 than the simple, constant rate exponential process used to model the entry process. The plot of the expected mortality rate versus density in Figure 22 displays the U shape hypothesized by Theorem 3; however, there appears to be a very strong linear increase in the mortality rate beyond year 24. The plot of long-term mortality rate versus density at the time of entry in Figure

23 generally displays proportionally between mortality rate and density at the time of entry as hypothesized by Theorem 4.

The shape parameter of 2.7021, with 95 percent confidence interval of 2.3401 to 3.1201, of the best fit, Weibull survival distribution in Table 9 and the survival plot in Figure 24 indicate that wear-out mechanisms operated throughout the life span of the original equipment computer manufacturing industry causing a sharp decrease in the survival function below the median of 36.48 years, an inflection point somewhere around the median, and a continued decrease in survival but at a decreasing rate above the median. The convex hazard function plot in Figure 25 with its mortality rate increasing at an increasing rate supports the observation of the presence of wear-out mechanisms in the population of original equipment computer manufacturers. The scale parameter in Table 9 indicates an expectation of 63.2 percent of the original equipment computer manufacturers failing by 41.78 years. The distributional characteristics in Table 10 indicate the median time-to-failure of 36.48 years with 25 percent of the organizations expected to fail by 26.34 years and 75 percent by 47.14 years. Table 10 estimates the mean time to failure of original equipment computer manufacturers at 37.15 years.

Tables 11 and 12 present the primary results of covariate survival analysis for the original equipment computer manufacturing industry. Hypotheses H1-a through H1-c stated that organizational survival times are nonmonotonically related to contemporaneous population density (Density), cohort density (CohtDensity), or region density (RegionDensity). With p-values of 1.40e-001 for population density and 8.79e-001 for population density squared (Den2) from Table 11, hypotheses H1-a and Theorem 3 are not supported for population density. With p-values of 9.21e-002 for region density and 4.75e-001 for region density squared (RgnDen2) from intermediate coefficients tables in Appendix D, hypotheses H1-c and Theorem 3 are not supported for region density. With final p-values of 3.42e-004 for cohort density and 1.78e-002 for cohort density squared (CohtDen2) from Table 12, cohort density is found to be a statistically significant predictor of survival time. The coefficient estimates of –0.03708 for cohort density and +0.00103 for cohort density squared supports the hypothesized nonmonotonic U shape between survival time and cohort density as set forth in hypothesis H1-b.

Hypotheses H2-a through H2-c stated that organizational survival times are inversely related to the population density (EntryDensity), cohort density (EntryCohtDen), or region density (EntryRgnDen) at respective times of entry into the competitive marketplace for each organization. With a p-value of 1.35e-001 for region entry density from Table 11, hypothesis H2-c is not supported. With final p-values from Table 12 of 1.97e-002 and 2.36e-002 respectively, population entry density and cohort entry density are found to be statistically significant predictors of survival time. The estimated coefficient of +0.01472 for population entry density does not support hypothesis H2-a's inverse relationship prediction. Conversely, the estimated coefficient of -0.03708 for cohort entry density does support hypothesis H2-b's inverse relationship prediction. The results for hypotheses H2-a through H2-c are mixed for entry density dependence. The findings of statistical significance for hypotheses H2-a and H2-b and the negative coefficient for cohort entry density indicate the presence of expected environmental and population selection forces within cohorts, but the positive coefficient for population entry density is opposite to that hypothesized by hypothesis H2-a.

Hypothesis H3 stated that organizational survival times are statistically different for different organizational types (OrgType). With a p-value of 7.60e-002 from an intermediate coefficients table in Appendix D, hypothesis H3 is not supported, and organizational type is not found to be a statistically significant predictor of survival times. Hypothesis H4 stated that organizational survival times are statistically different for different organizational structures (OrgStruct). With a p-value from Table 11 of 1.37e-001, hypothesis H4 is not supported for survival times. Hypothesis H5 stated that organizational survival times are statistically different for different cohort groups (CohortGrp). With a final p-value from Table 12 of 3.92e-002, hypothesis H5 is supported, and cohort group is found to be a statistically significant predictor of survival times. Its estimated coefficient of –0.26926 indicates that survival times decrease for each successive new cohort group. Hypothesis H6 stated that organizational survival times are statistically different for different geographic regions of entry (Region). With a p-value from Table 11 of 1.13e-001, hypothesis H6 is not supported, and region is not found to be a statistically significant predictor of survival times.

Although no hypothesis was developed concerning the passage of time, the sequential year number (YrID) was not found to be statistically significant with a p-value of 5.06e-001 from an intermediate coefficients table in Appendix D. There appears to be no additional time dependent predictors of survival times in the original equipment computer manufacturing population.

From combined analyses of cohort density and cohort entry density, this research concludes that theorized environmental and population selection forces were operational through density dependence within cohorts in the original equipment computer manufacturing industry during the study period. These findings support the presence of the domains of within cohorts, self-organizing environmental selection forces and organizational adaptation as hypothesized by the general systemic model of organizational effectiveness.

5.2 Event History Effectiveness Analysis

Analysis now turns to the central focus of this research, the assessment of organizational effectiveness in the original equipment computer manufacturing industry. Table 13 indicates that the lognormal distribution provided the best fit of the time to loss of market share data. The scale parameter of 1.8178, with 95 percent confidence interval of 1.68214 to 1.96441, of the best fit, lognormal distribution in Table 14, the effectiveness survival plot in Figure 27, and the hazard function plot in Figure 28 indicates early loss of effectiveness due to of wear-out mechanisms. From Table 15, the median effectiveness time of 9.68 years indicates that on average 50 percent of original equipment computer manufacturing organizations fail to maintain market share for ten years in a row. The hazard function plot in Figure 28 indicates that these organizations experienced a hazard rate between 0.04 and 0.12.

Tables 16 and 17 present the primary results of covariate effectiveness analysis for the original equipment computer manufacturing industry. Hypotheses H1-d through H1-f stated that organizational effectiveness times are inversely related to contemporaneous population density (Density), cohort density (CohtDensity), or region density (RegionDensity). With p-values from Table 16 of 1.72e-001 for population density, 1.87e-001 for cohort density, and 8.52e-002 for region density, hypotheses H1-d through H1-f are not supported. Density dependence in effectiveness time is not observed in the original equipment computer manufacturing industry.

Hypotheses H2-a through H2-c stated that organizational effectiveness time is inversely related to the population density (EntryDensity), cohort density (EntryCohtDen), or region density (EntryRgnDen) at respective times of entry into the competitive marketplace for each organization. With a p-value from Table 16 of 1.35e-001, population entry density is not found to be a statistically significant predictor of effectiveness time, and hypothesis H2-a is not supported. With a final p-values from Table 17 of 1.93e-004 and 3.15e-018 respectively, cohort entry density and region entry density are found to be statistically significant predictors of effectiveness time. The estimated coefficient of –0.0334 for cohort entry density supports hypothesis H2-b's inverse relationship prediction, but the estimated coefficient of +0.0713 for region entry density does not support hypothesis H2-c's inverse relationship prediction in effectiveness time. External factors in environmental and population selection forces within regions proportionally increased organizational effectiveness time relative to density at entry in the computer manufacturing industry. The regional density plot in Figure 20 suggests regional or cultural impacts on legitimation and competition forces. In region one, North America, the mix of government supported research and private enterprise allowed legitimation to dominate from 1949 to 1987 when the regional population peaked at 40 organizations, but it also allowed competitive forces to operate freely from 1988 to 2001 when the regional population fell to 11 organizations. In region two, Europe, protectionist policies and governmental support of nationalized computer manufacturers potentially prolonged the legitimation period from 1951 to 1987 when its regional population peaked at 11 organizations. When competitive forces took over, however, the European population declined sharply to 2 organizations in 2001. In region three, the Japanese government's early protectionist policies, promotion of private joint ventures among regional computer manufacturers to develop competitive competencies, and then gradual reduction in protectionist policies to promote competition tended to support legitimation forces over competition forces. Legitimation tended to dominate from 1959 to 1990 when the regional population peaked at 13 organizations. In 1991, one organization withdrew from computer manufacturing, and the regional population stabilized at 12 organizations through the end of the study period in 2001. Hypotheses concerning regional factor effects on the relationship between effectiveness time and within region entry density could not be tested, because the matrices for regional subpopulations were not positive definite.

Hypothesis H3 stated that organizational effectiveness times are statistically different for organization types (OrgType). With a final p-value from Table 17 of 7.74e-011, hypothesis H3 is supported, and organizational type is found to be a statistically significant predictor of effectiveness time. The estimated coefficient of +0.8775 indicates that organization type by code is proportionally related to organizational effectiveness time. New entrants (coded +1) brought with them stronger adaptation capabilities and on average have longer effectiveness times than existing organizations (coded 0) that expanded into computer manufacturing. Hypothesis H4 stated that organizational effectiveness times are statistically different for different organizational structures (OrgStruct). With a p-value from an intermediate coefficients table in Appendix E of 1.12e-001, hypothesis H4 is not supported for effectiveness times, and organization structure by code not a statistically significant predictor of organizational effectiveness time.

Hypothesis H5 stated that organizational effectiveness times are statistically different for different cohort groups (CohortGrp). With a p-value from Table 16 of 9.87e-001, hypothesis H5 is not supported, and cohort group is not found to be a statistically significant predictor of effectiveness times.

Hypothesis H6 stated that organizational effectiveness times are statistically different for different geographical regions (Region) of entry. With a final p-value from Table 17 of 3.16e-014, hypothesis H6 is supported, and geographical region of entry is found to be a statistically significant predictor of effectiveness times. Its estimated coefficient of +0.7992 indicates that respective effectiveness times increased as organizational region of entry changed from North America (coded 1) to Europe (coded 2) to Japan-Taiwan (coded 3) respectively. Recall from effectiveness analysis above that region entry density had a positive coefficient indicating that density within regions at the time of entry proportionally increased organizational effectiveness times. Also, recall from the literature review that governmental support increased by region code. Thus, the findings for hypotheses H2-c and H6 must be tempered. Findings of increased effectiveness times with higher regional entry density and region code may be confounded with increased governmental support by region code or an interaction between regional entry density and increased governmental support by region code. This yields an important implication for engineering managers in the remaining dominant computer manufacturing organizations. It suggests that there might be an optimal mix of private enterprise and governmental support. Engineering managers in regions with lower or incorrectly designed and applied governmental support or lower average regional entry density may be at a permanent disadvantage to engineering managers in regions with higher and correctly designed and applied governmental support or higher regional densities. Assuming that all organizations in the industry maintain a continual stream of countering improvement projects, engineering managers' improvement projects in regions of low or incorrectly designed and applied governmental support or below average regional entry densities will always have to produce results that nullify the negative impact of governmental support or above average regional entry density before realizing any increase in organizational effectiveness times in the marketplace.

Hypothesis H7 stated that organizational effectiveness times increase with increases in population market size niche (TMktIT). With a p-value from Table 16 of 1.12e-001, hypothesis H7 is not supported, and the size of the population market niche is not found to be a statistically significant predictor of organizational effectiveness time.

Hypotheses H8 through H11 are the central hypotheses concerning relationships between observable, systemic organizational variables and organizational effectiveness niche widths. Hypothesis H8 stated that organizational effectiveness time increases with increases in contemporaneous organization market share niche (SMktIT). With a final p-value from Table 17 of 2.45e-005, contemporaneous organization market share niche size is found to be a statistically significant predictor of effectiveness times. The estimated coefficient of +2.273 supports the hypothesized proportional relationship between organizational effectiveness time and market share niche size.

Hypothesis H9-a stated that organizational effectiveness times increase with increases in the contemporaneous level of information technology knowledge creation (policy) as measured by the number of information technology related patents granted annually. With a p-value of 8.63e-002 from Table 16, hypothesis H9-a is not supported and the contemporaneous level of information technology knowledge creation (policy) as measured by the number of information technology related patents granted annually is not found to be a statistically significant predictor of organizational effectiveness. This finding does not, however, rule out patent valuation as a potential predictor of organizational effectiveness. It may have been that a few high value patents provided effectiveness leverage to some computer manufacturers. At the time of this research, there was no unified theory of patent valuation to allow testing of patent value as a predictor of organizational effectiveness. Rather, there were only differing patent valuation models with variable prediction capabilities. Similarly, hypothesis H9-b, which stated that organizational effectiveness times decrease with increases in the contemporaneous level of "other" knowledge creation (policy) as measured by the number of "other" category patents granted annually, was also found not to be statistically significant with a p-value of 1.09e-001 from Table 16.

Hypothesis H10 stated that organizational effectiveness times increase with increases in the contemporaneous number of new products released annually (joint adaptation and control). Since some organizations specialized in a given category or only two or three categories of product types, hypothesis H10 was tested separately for the number of new mainframe (NPMF), minicomputer (NPMini), personal computer (NPPC), and workstation (NPWS) products released annually. With p-values of 2.66e-001, 1.26e-001, 8.57e-001, and 5.67e-001 respectively for each category of product type from Table 16, hypothesis H10 is not supported. The number of new products released annually is not found to be a statistically significant predictor of organizational effectiveness. This does not, however, rule out that a few key products such as the Model 700 series, Models 360 and 370, and the personal computer for IBM, or the PDP-11 for Digital Equipment Corporation, or the Deskpro 386 for Compaq, provided leverage in effectiveness times for some computer manufacturers. At the time of this research, detailed company records of individual product sales necessary to test this hypothesis were not available.

Hypothesis H11 tested the socio-technical function's efficiency stating that an organization's effectiveness times are proportional to contemporaneous annual dollar volume earnings per employee (NSTEffcy). With a p-value of 7.99e-002 from Table 16, hypothesis H11 is not supported, and socio-technical efficiency is not found to be a statistically significant predictor of efficiency times.

Hypotheses H12 and H13 tested for relationships between organizational effectiveness times and observable environmental variables. Hypothesis H12 stated that organizational effectiveness times increase with increases in contemporaneous home market Gross National Product, and hypothesis H13 stated that organizational effectiveness times increase with increases in contemporaneous cumulative Gross National Product of the geographic regional markets in which respective organizations competed. With respective p-values from Table 16 of 6.41e-001 and 4.87e-001 respectively, hypotheses H12 and H13 are not supported, and contemporaneous home market Gross National Product and organizational cumulative regional markets Gross National Product are not statistically significant predictors of organizational effectiveness time.

Although no hypothesis was developed concerning a relationship between organizational effectiveness and the passage of time, the sequential year number (YrID) was found to be statistically significant with a final p-value of 1.27e-054 from Table 17. Its estimated coefficient of -0.1731 indicates that on average organizational effectiveness times for the population of original equipment computer manufacturers declined with the passage of time. This finding supports representations of environmental carrying capacity in ecological mathematical models. That is as a population's density increases relative to it environment's carrying capacity, organizational effectiveness time trajectories as measured by the conditional expected years of non-negative growth in market share niche would be expected to decline asymptotically toward one as competition increases. At the environment's carrying capacity, equilibrium in competition should occur with on average one year of market share niche for all organizations in the population.

The final covariate model of Table 17 is a population best fit, covariate model of organizational effectiveness. The observation from Figure 31 that effectiveness can occur in two forms, structural or as changes in trajectories at discontinuity points, prompted the question as to whether or not the same covariates were significant for different subpopulations that exhibited different structural effectiveness. The discussion of structural and discontinuity effectiveness suggested that the Pareto set of the top eleven organizations in the original equipment computer manufacturing industry could be partitioned into two subpopulations. The top four subpopulation comprising Compaq, Dell Computer, IBM, and Fujitsu exhibited structural and discontinuity effectiveness. The subpopulation of the next seven organizations exhibited no structural or discontinuity effectiveness that moved any of them outside their normal zone of effectiveness.

Data sets were constructed for each of the above subpopulations, and event history effectiveness analyses were performed for each subpopulation. The S code and output coefficients and correlation tables for the top four subpopulation are presented in Appendix G and for the next seven subpopulation in Appendix H. The Weibull distribution was selected as the best-fit distribution of effectiveness times for both subpopulations. Table 20 presents the final effectiveness model with all remaining statistically significant covariate coefficients for the top four subpopulation, and Table 21 presents the final effectiveness model with all remaining statistically significant covariate coefficients for the next seven subpopulation. Table 22 qualitatively contrasts the

Table 20.

Final Weibull distribution, significant covariates effectiveness model for the top four subpopulation.

Term	Coef. Est.	Std. Err.	95% LCL	95% UCL	z-value	p-value
Intercept	21.23285	2.505700	16.32177	26.143932	8.47	2.37e-017
YrID	-0.71878	0.082925	-0.88131	-0.556253	-8.67	4.40e-018
OrgType	6.91109	0.797846	5.34734	8.474840	8.66	4.63e-018
OtherPat	0.00722	0.001226	0.00481	0.009618	5.88	4.00e-009
SmktPar	14.72452	2.407567	10.00578	19.443267	6.12	9.60e-010
SMktIT	-8.35974	2.461081	-13.18337	-3.536110	-3.40	6.82e-004
TtlMktIT	3.22075	0.346755	2.54112	3.900381	9.29	1.57e-020
NPMF	0.27027	0.063513	0.14579	0.394757	4.26	2.09e-005
NPMini	-0.11005	0.026119	-0.16125	-0.058862	-4.21	2.51e-005
SGNPWMkt	-0.00158	0.000672	-0.00290	-0.000266	-2.36	1.85e-002
RegionDensity	-0.19375	0.024836	-0.24243	-0.145072	-7.80	6.14e-015

Table 21.

Final Weibull distribution, significant covariates effectiveness model for the next seven subpopulation.

Term	Coef. Est.	Std. Err.	95% LCL	95% UCL	z-value	p-value
Intercept	-1.97888	1.837536	-5.58038	1.6226255	-1.08	2.82e-001
SOrgCode	0.08165	0.027590	0.02757	0.1357268	2.96	3.08e-003
ITPat	-0.00129	0.000463	-0.00255	-0.0000262	-2.00	4.54e-002
SMktPar	1.59293	0.659059	0.30119	2.8846576	2.42	1.57e-002
PwPrd	-1.59926	0.364110	-2.31291	-0.8856218	-4.39	1.12e-005
Density	-0.05479	0.018375	-0.09081	-0.0187780	-2.98	2.86e-003
CohtDensity	0.13130	0.025585	0.08116	0.1814450	5.13	2.87e-007

Table 22.

Contrast of significant covariates for the population and subpopulation models.

Population	Top Four	Next Seven
SOrgCode		SOrgCode
YrID	YrID	
OrgType	OrgType	
Region		
	OtherPat	ITPat
	SMktPar	SMktPar
SMktIT	SMktIT	
	TtlMktIT	
	NPMF	
	NPMini	
	SGNPWMkt	
		PwPrd
		Density
EntryCohtDen		CohtDensity
EntryRgnDen	RegionDensity	

statistically significant coefficients of the subpopulation models with those of the population model. It must be noted that the subpopulation models cannot be quantitatively contrasted for coefficient values and signs, because the partitioning created independent subpopulation data sets with information matrices that differed from each other and the population information matrix. Further, in the partition for the top four subpopulation the covariates organization structure, cohort group, and region were collinear and removed from the modeling process. Similarly, in the next seven subpopulation information matrix organization structure, cohort group, region, and all entry density covariates were collinear and removed from the modeling process.

Table 22 suggests that different covariates are significant for different original equipment computer manufacturing subpopulations. The most effective organizations appear to include internal adaptation covariates of information technology knowledge creation (policy) in terms of the number of patent grants obtained annually and joint adaptation and control in terms of the number of new products released annually. Similarly, the most effective organizations appear to exhibit stronger relationships between organizational effectiveness times and organizational effectiveness niche width covariates of parent market size, information technology market share, and the population's total information technology market size niche. The most effective organizations also appear to exhibit stronger relationships between organizational effectiveness times and observable environmental covariates such as the cumulative Gross National Product of the world regions in which they competed. Finally, organizational effectiveness times appear to exhibit contemporaneous density dependence at the population and subpopulation levels with the structure of the covariate dependence differing for each level and between subpopulations.

5.3 Dynamic Simulation

The construction of the simulation model of organizational effectiveness and subsequent sensitivity analyses provided information on the sources of the underlying dynamics of organizational market shares and years effective trajectories in the original equipment computer manufacturing industry during the study period which were not identified in the significant covariates effectiveness model.

The first source of additional dynamics is the feedback from the "SOC years effective" variable to the "change in SOC std market share" variable. In the significant covariates effectiveness model, years effective was the independent response variable estimated as,

$$\text{Ln(years)} = \beta_0 + \beta_{oc} * \text{SOC std org code} + \beta_{ot} * \text{SOC org type} + \beta_{yr} * \text{YearID} + \beta_{rgn} * \text{SOC region} + \beta_{ced} * \text{SOC cohort entry density} + \beta_{mkit} * \text{SOC Org Std Market Share} + \beta_{red} * \text{SOC region entry density} + \sigma * Z$$

In the simulation model, the "change in SOC std market share" variable, not explicitly included in the covariates effectiveness model, was necessary to implement competition among organizations for the changes in the "Total IT Market" variable over time. The feedback from the "SOC years effective" variable accounted for three potential, mutually exclusive outcomes in competition due to combinations of market gap and individual organizational effectiveness values.

Outcome	SOC years effective	market gap	change in SOC market share
1	< 1	> 0	- market gap (< 0)
2	>= 0	= 0	0
3	>= 1	> 0	market gap (> 0)

The feedback from the "SOC years effective" variable to the "change in SOC std market share" variable indicates that organizational effectiveness as measured by years effective is not an independent, units-of-time-to-event response variable as modeled by covariate effectiveness model. Rather, it is part of a systemic, instantaneous feedback loop through the "change in SOC std market share" variable and the "SOC Std Market Share" level variable to itself. Use of the term "instantaneous feedback loop" recognizes that as changes in unit time steps are allowed to approach zero, organizational effectiveness as measured by conditional expected years to loss of market share (niche width) approaches its true instantaneous rate and must be measured in terms of its instantaneous time position, velocity, and acceleration.

The observation that organizational effectiveness must be measured as an instantaneous rate leads to an understanding of why early research into organizational effectiveness produced mixed results. Early researchers sought to develop models of organizational effectiveness through direct inquiries and static, factor analytic methods. Both analytical approaches are designed to uncover only multivariate structural differences. Additionally, factor analytic methods assume that the stochastic processes being studied are covariance stationary. Neither method can measure or model changes in instantaneous rate variables such as organizational effectiveness. In both methods, effects of changes in the instantaneous effectiveness rate variable are allocated to the residuals error matrix.

The second source of additional dynamics is observable in the organizational years effective trajectories in Figures 38 and 31. Both plots indicate that organizational effectiveness takes two forms. The first form is acceleration or deceleration at discontinuities. IBM's effectiveness trajectory reversed from its decline beginning in simulation year 33 (1981), exhibited a near zero slope until simulation year 36 (1984), increased in simulation years 37 (1985) and 38 (1986), and maintained it marginal improvement until about simulation year 43 (1991) as a result of the success of its personal computer independent business unit in capturing and maintaining market share leadership. Similarly, Compaq and Dell Computer's effectiveness trajectories decelerated in decline in simulation year 44 (1992) and exhibited near zero slopes until simulation year 52 (2000). These observations suggest that new products or services must provide significant competitive advantages in order to create a discontinuity turning point and increase organizational effectiveness. The second form of effectiveness is structural. Figures 38 and 31 show that Compaq and Dell Computer were the most effective computer manufactures during the study period, IBM was the third most effective, and Fujitsu achieved effectiveness equal to IBM's by the end of the study period. From these observations of structural differences, this research concludes that there is a weak link between dominance and effectiveness. In the 1950s and 1960s, IBM was effective in achieving a dominant market share position, but in the 1980s and 1990s new entrants were able to erode IBM's dominance through more effective operational adaptations to changing market environments.

The third, and final, source of additional dynamics observable in organizational years effective trajectories is jointly exhibited in the market share sensitivity analyses graphs of Figure 39 and the years effective sensitivity analyses graphs of Figure 40. In Figure 39, there were no observable changes in respective market shares relative to the respective market shares predicted by the correction factor simulation model, SOC(CF) for improvements in the internally controllable variable of organization type adaptation flexibility. Measurable increases in respective market shares did occur but only at 0.0001 values relative to the standardized value of one. This suggests that an organization in a mature population operating at its environment's carrying capacity may not realize an observable change in market share niche width from significant internal adaptation improvements. Conversely, in Figure 40, there were significant observable increases in effectiveness for the change from existing organization type to new entrant type for all organizations with IBM, Fujitsu, Hewlett-Packard, and Toshiba each exhibiting a marginal positive increase in effectiveness through the end of the study period. Jointly, these observations suggest that organizations which expect traditional of changes of one to ten percent in market share as a metric of effectiveness may miss opportunities for real improvements in effectiveness or may abandon internal actions that yield true improvements in effectiveness. One caveat to these observations is necessary. Sensitivity analyses in Chapter IV were conducted using the one-factor-at-a-time approach. In actual competitive situations, it would be expected that organizations in a given population would produce a continual set of counteracting improvements, which would nullify improvements by other organizations in the population. Thus, measuring and monitoring dynamic organizational effectiveness is much more difficult in actual practice.

5.4 Effectiveness in the Original Equipment Computer Manufacturing Industry

In summary, organizational effectiveness in the original equipment computer manufacturing industry population appears to be a function of both environmental selection force variables and organizational adaptation variables. The finding of statistical significance and a positive covariate coefficient for contemporaneous organization market share supports its use as a sufficiently sensitive measure of organizational niche width in the original equipment computer manufacturing industry. The finding of statistical significance for cohort entry density and region entry density suggests that environmental and population selection forces in the form of density dependence affect organizational effectiveness of computer manufacturers. The positive coefficient for region entry density, however, indicates that the affect of region entry density, and potentially other population density predictor variables, on organizational effectiveness may be modified by other environmental variables. The finding of statistical significance and a positive covariate coefficient for geographical region of entry indicates that environmental variables such as increased governmental support by region may alter the direction of density dependent, environmental forces on organizational effectiveness as opposed to those hypothesized. The findings of statistical significance of and a positive covariate coefficient for the organizational type (existing organization versus new entrant) suggests that more flexibly structured, new entrants bring with them stronger adaptation capabilities than those possessed by existing organizations that expand into computer manufacturing.

In contrast, the subpopulation effectiveness analyses in Tables 20 to 22 identified knowledge creation (patents obtained annually), joint adaptation and control (new products released annually), and environmental covariates (parent market size, total information technology market size, and cumulative world region Gross National Product) as predictors of effectiveness. This suggests that different environmental and organizational variables are important to different subpopulations or even individual computer manufacturers in securing, maintaining, and expanding their respective competitive niches. The structure of the covariates in Table 22 also suggests that the most effective computer manufacturers systemically link internal knowledge, control, and adaptation to environmental selection forces as hypothesized by the systemic model of organizational effectiveness in Figure 11.

Finally, the structure of the dynamic simulation model indicates that organizational effectiveness is an instantaneous rate variable that must be continuously measured and monitored in terms of its time position, velocity, and acceleration as determined by the interaction between environmental selection forces and internal adaptation actions. Sensitivity analysis further suggests that traditional expectations of changes of one to ten percent in market share as a result of internal adaptation improvements may not be rational, particularly in a mature population, such as the computer manufacturing industry, operating at its environment's carrying capacity. More sensitive metrics of effectiveness with better resolution are required to measure and monitor effectiveness trajectories.

CHAPTER VI

CONCLUSIONS AND RECOMMENDATIONS

6.1 Conclusions on the Systems Methodology for Measuring Operational Organization Effectiveness

This research into operational organization effectiveness has answered its qualitative research question in the affirmative. Organizational ecology and open systems theories and models can be unified to provide a systemic model of and a methodology for measuring dynamic operational organization effectiveness.

The systemic model of organizational effectiveness in Figure 11 defines the environmental domain and dimensions of selection forces and the organizational domain and dimensions adaptation responses. Taken jointly from organizational ecology and the Recursive System Theorem, the environmental domain is the comprised of communities of organizational populations self-organized into population niches, populations of organizations self-organized into organizational niches, and each organization within its respective niche. Interactions among niches within each level create the self-organizing, random density determinants of selection forces that feedback into and constrain organizational effectiveness. The nonrandom determinants of effectiveness are modeled by observable environmental and population covariates. The organizational domain is Beer's cybernetic Viable System Model of the five interacting subsystems, which are necessary and sufficient for systemic viability. The organizational domain is made up of the four nonrandom effectiveness dimensions of observable policy, intelligence, control and coordination, and socio-technical dimensions plus random technical and social covariates.

The six phase methodology of Figure 12 provides the means for identifying statistically significant covariate determinants of effectiveness and constructing a dynamic simulation model of organizational effectiveness. The dynamic simulation model and subsequent sensitivity analyses provide information on sources of underlying dynamics of organizational effectiveness trajectories not identified in the significant covariates effectiveness model. The dynamic simulation model yields trajectories of years effective that permit the identification of structural differences in organizational effectiveness and acceleration or deceleration in years effective trajectories at discontinuity points. Sensitivity analysis of internally controllable covariate determinants of effectiveness provides information on actions that engineering managers may take to improve the effectiveness of their respective organizations.

Jointly, the systemic model and the six phase methodology address many of the difficulties encountered by early researchers of organizational effectiveness.

- The systemic model in Figure 11 provides a single, universal paradigm of organizational effectiveness that structures the environmental and organizational domains and dimensions into recursive, hierarchical self-organizing selection force and adaptation response determinants of organizational effectiveness.
- The methodology develops a unified definition of organizational effectiveness that encompasses the fundamental premises of ecological, rational, natural, and open systems perspectives of organizations.
- The systemic model in Figure 11 structures the construct space of organizational effectiveness into environmental and organizational domains and dimensions in which the determinants of effectiveness for an identified population of organizations may be identified through event history survival and effectiveness covariate analyses and dynamically modeled through dynamic simulation models.
- Through the Viable System Model's Recursive System Theorem, the systemic model and six phase methodology allow organizational effectiveness models to systemically encompass all organizational and environmental levels.
- The systemic model of organizational effectiveness in Figure 11 and the six phase methodology may be applied by any organizational constituency to model organizational effectiveness independently for any identified organizational population. Provided data are available,

any given constituency may model organizational effectiveness from any perspective it chooses.

- The systemic model in Figure 11 provides a single, universal framework of organizational effectiveness that may be used to assess and diagnose external environmental and internal organizational domains, dimensions, and determinants of effectiveness.
- The systemic model of organizational effectiveness in Figure 11 and the six phase methodology may apply any desired referents (standards, indicators, goals) for which data are available in addition to its standard referent of niche dimension.
- The systemic model of organizational effectiveness in Figure 11 and the six phase methodology can accommodate any purpose or assessment strategy for which data are available. The statistically significant coefficients of the final covariate effectiveness model determine the weighting of domains, dimensions, and determinants of effectiveness. If desired, any given constituency may apply additional weighting criteria to suit its respective assessment purpose.

6.2 Limitations of the Systems Methodology

The primary limitation of this systems methodology for modeling operational organization effectiveness is the lack of effectiveness theory similar to the density dependence theory proposed in organizational ecology. Without a fundamental set of testable theorems as a foundation, the assessment and measurement of dynamic organizational effectiveness will remain an empirical modeling approach.

The second limitation of this systems methodology for modeling operational organization effectiveness is the assumption of an independent time-to-event response variable in the survival and effectiveness analysis phase. As illustrated by the dynamic simulation model, the effectiveness time response variable may not be independent, but may feedback as an input into the niche dimension variable.

A third modeling limitation arises as confounding introduced by holding categorical covariates constant over the covariate and dynamic simulation modeling time frame. In this research, this may have unknowingly contributed to under and overestimation of true organizational effectiveness for certain organizations. For example, when IBM established its personal computer operation as an independent business unit its organizational type became a mixed 0 for existing organization and 1 for new entrant. The success of IBM's personal computer line was attributable qualitatively to the new entrant flexibility granted to its personal computer operation. Similarly, organizational structure constants may not have reflected true organizational structures over time. All organizations tend to move up the structure scale toward more formal structures. During the study period, Digital Equipment Corporation's organizational structure code was held constant at 4 for a single entity corporation; however, the company evolved to a more formal category 5 corporation with divisions during the late 1970s and early 1980s to support the introduction if its VAX line of computers. Similarly, Univac temporarily assumed a category 6 conglomerate structure in the late 1980s after it acquired conglomerate Sperry Corporation. By about 1990, Univac had divested all former Sperry non-computer divisions and returned to it original category 5 corporation with divisions structure. Conversely, with the establishment of its personal computer operation as an independent business unit, IBM took on a dual structure of code 3 for an independent company (the personal computer operation) and code 5 for its main operations until it folded the personal computer business unit back into its corporate structure. In the environmental domain, the gradual lessening of government support in Europe and Japan over the study period meant that their respective region codes could have been considered to have evolved from 2 and 3 respectively toward code 1 for private free enterprise.

A fourth modeling limitation arises from inherent nonlinearities from different entrance and exit times and different market share trajectories. With their independent time-to-failure response variables, survival and effectiveness covariate modeling methods produce hyper surface models that miss inherent nonlinearities and discontinuities in market share trajectories. Dynamic simulation models can be modified to yield improved fits to nonlinearities and discontinuities through the inclusion of additional STEP, PULSE, and possibly SIN functions and correction factor multipliers. However, even with the inclusion of functions and multipliers, dynamic simulation models still exhibit inertia and produce only on average fits to historical data.

As a result of the above limitations, unknown errors were induced in effectiveness estimates in the final correction factor dynamic simulation model due to residual over and underestimation of market share trajectories.

The fifth limitation is that current event history modeling techniques focus at the population level in order to identify systemic relationships. As illustrated by the subpopulation analyses in Tables 20 to 22, significant covariate structures may be different for subpopulations and individual organizations in securing, maintaining, and expanding respective niche dimensions. Conditional, hierarchical, piecewise covariate survival and effectiveness analysis methodologies are needed to more accurately identify organizational and subpopulation significant covariate structures and more accurately model organizational effectiveness trajectories.

The final modeling limitation of this methodology is that it does not include data from prior research by organizational theorists. This research demonstrated the impact of cultural differences on organizational effectiveness through the identification of region and associated varying governmental support and protection as a statistically significant predictor. There is potential knowledge to be gained through the integration of Quinn and Cameron's competing values model of effectiveness to account for different criteria in different organizational life cycle stages, Zammuto's evolutionary model of ecological dynamics, or Dennison's corporate cultural and behavioral model with the systemic model and methodology developed in this research.

6.3 Recommendations for Future Research and Application

Recommendations for future research follow directly from the above identified limitations.

First, the systemic model and methodology must be applied across differing organizational populations to determine commonalities and differences in effectiveness structures and trajectories. A fundamental set of testable theorems should evolve from this modeling work as a foundation for the assessment and measurement of dynamic organizational effectiveness. Integration of cybernetic theory and Malerba, Nelson, Orsenigo, and Winter's product diversification, system dynamics modeling approach into this systemic modeling approach could potentially contribute to the development of organizational effectiveness theory.

Second, the development of conditional, hierarchical, piecewise covariate survival and effectiveness analysis methodologies would mitigate the effects of assumed independent time-to-event response variable, fixed covariate categorical variables, differing entrance and exit times, differing subpopulation covariate structures, and differing niche dimension trajectories in resulting hyper surface models. Covariate survival and effectiveness models could be developed for each organization with respect to its organizational covariate determinants in order to achieve the best fit of niche dimension and effectiveness trajectories at the organizational level. Next, covariate survival and effectiveness models could be developed for subpopulations of organizations from the best-fit organization level models to achieve the best fit of niche dimension and effectiveness trajectories at the subpopulation level. Population model covariate survival and effectiveness models could then be fit with respect to environmental and population covariate determinants from the subpopulation models. The dynamic simulation model could then be constructed in the same hierarchical, piecewise manner and sensitivity analyses conducted. A hierarchical, piecewise modeling approach may permit more precise modeling of inherent nonlinearities and discontinuities in niche dimension trajectories in both covariate and dynamic simulation models. Likewise, a hierarchical, piecewise modeling approach may reveal statistical significance of some covariates at the organizational or subpopulation level, which are not found statistically significant at the aggregated population level. As examples, in this study the number of patents granted annually, policy knowledge creation, and the number of new products released annually, joint adaptation and control, were found to be not statistically significant at the population level. As was the case in this study for density dependence within region one, the number of new patents granted annually and new products released annually may be found to be statistically significant at the organizational or subpopulation level for some organizations that used these covariates for competitive leverage.

Finally, research is needed to integrate prior research by organizational theorists. This research represents a vast body of knowledge, which could be integrated as additional environmental and organizational covariate determinates to further explain structural and instantaneous rate differences in organizational effectiveness and potentially contribute to the development of organizational effectiveness theory. Conversely, for future organizational effectiveness research, case study, survey, and financial data could a priori designed into longitudinal organizational effectiveness research.

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APPENDIX A

Definitions of Symbols

Definitions of Symbols

Organizational ecology symbols

$\lambda(t)$	Founding rate of an organizational population at time t
$\mu(t)$	Mortality rate of organizations in a population at time t
C_t	Intensity of competition within an population at time t
L_t	Intensity of legitimation processes of an organizational form at time t
N_t , N_u	Density of an organizational population at time t
$\varphi(N_t)$	Competition density function of an organizational population at time t
φ' , φ''	First and second derivatives of the competition density function
$\nu(N_f)$	Competition density at time of founding function at time f
ν' , ν''	First and second derivatives of the density at time of founding function
$\gamma(N_t)$	Legitimation density function of an organizational population at time t
γ' , γ''	First and second derivatives of the legitimation density function
$\upsilon(N_t)$	Legitimation density dependence function
υ' , υ''	First and second derivatives of the legitimation density dependence function

Definitions of Symbols

Survival and effectiveness covariate model symbols

β_0	Intercept term for survival or effectiveness covariate models
β_i	Slope coefficient for survival or effectiveness covariate models
$\lambda(t)$	One parameter exponential entry rate at time *t*
e_i	Number of entries in interval t_i
n_i	Number of organizations surviving at the beginning of interval t_i
$\theta(t_{0,i})$	Mean time to entry through interval i
t_{ij}	Time to entry in intervals for the j organizations entering in interval t_i
I	Number of time intervals from time t_0
$\Lambda(t_{0,i})$	Cumulative hazard or mortality function
d_i	Number of number of organizations failing in interval t_i
x_{ui}	Vector of hypothesized environmental and organizational covariates
$S(t\|u,x)$	Survivor function
σ	Scale parameter
Z	Standard extreme value, logistic, or normal random variable
Ho	Null hypothesis
Ha	Alternate hypothesis
α	Significance level

APPENDIX B

S Codes for the Estimates of Missing Values

S Codes for the Estimates of Missing Values

L10MD7601USD: Missing values for dollar volume sales and number of employees.

```
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S : Copyright Lucent Technologies, Inc.
Professional Edition Version 6.1.3 Release 3 for Micros
oft Windows : 2002
Working data will be in C:\Program Files\Insightful\spl
us61\users\Cotter
> library(missing)
> L10MD7601USD.miss <- miss(L10MD7601USD)
> summary(L10MD7601USD.miss)
Summary of missing values
  9 variables, 1221 observations, 8 patterns of missing values
   3   variables (33%) have at least one missing value
  256 observations (21%) have at least one missing value

Breakdown by variable
 V O   name Missing % missing
 1 9 LNoEmp    151       12
 2 7 LUSDPar    175       14
 3 8 LUSDIT    229       19
V = Variable number used below,  O = Original number (before sorting)
No missing values for variables:
YearID OrgCode OrgType OrgStruct CohortGrp Region

Patterns of missing values (variables in columns, patterns in rows)
Pattern Variables
      123
   1 ...
   2 ..m
   3 .m.
   4 m..
   5 .mm
   6 m.m
   7 mm.
   8 mmm

Pattern #Missing #Obs Observations
   1       0  965 1:2 4:11 14:15 17:20 23:24 30 32:34 36 38 40:42 44
                  46:52 55:56 58:61 64:65 71:72 74:76 78 80:81 83:85 87
                  89:95 98:99 101:104 106:109 114:115 117:119 121:124
                  126:128 130:138 141:142 144:147 149:152 157:158
                  160:162 164:167 169:171 173 175:183 186:187 189:191
```

```
                194:197 202 205:207 209:212 214:215 217 219 221:230
                233:235 237:239 242:246 251 253:255 258 260:262
                264:265 267 269 271:281 284:286 288:290 293:297 302
                304:306 309 312:314 316:317 319:343 345:351 353:360
                362:363 365 368:373 375:376 378:416 420:421 423
                425:431 433:434 436:443 445:465 467:474 476:481 483
                485:491 493:504 506:521 523:528 530:538 540:544
                547:568 570:600 602:607 609:632 634:639 641 643:644
                646:664 666:671 673:684 686:693 695:717 719:725
                727:732 734:740 743:752 755:760 762:767 769:771
                773:778 780:783 785:787 789:798 800:801 803:809
                812:823 825:826 828:830 832:833 836:837 841 843:852
                854:855 857:863 866:871 873:877 879:887 889 891:900
                902:903 905:911 915:921 923:924 926:934 936:943
                945:946 949:950 952:956 958 960:971 973:976 978:990
                992:993 995:1000 1002:1018 1020:1034 1036:1037
                1039:1041 1043 1045:1059 1061:1073 1075:1076 1078:1093
                1095:1096 1100 1104 1106:1107 1110 1113:1118 1120
                1122:1129 1132 1135 1139 1142:1143 1145:1149 1151:1158
                1161 1168 1170:1171 1173:1185 1187 1193 1195:1196
1     0  965 1198:1210 1212 1218 1220:1221
2     1   54 25 39 66 82 125 168 213 257 263 308 315 364 422 482 545
                608 672 733 1074 1094 1098 1101:1103 1105 1109 1111
2     1   54 1130 1134 1136:1138 1140 1144 1160 1163 1165:1167 1169
                1172 1186 1189:1192 1194 1197 1211 1214:1217 1219
3     1    1 418
4     1   22 256 307 742 753:754 768 799 810:811 824 853 864:865 878
                901 912:913 925 948 959 991 1001
5     2   50 192 203 377 417 419 435 466 475 522 529 539 546 633 640
                642 645 685 694 718 741 761 772 779 827 831 834:835
                839:840 872 914 922 944 947 957 972 1035 1038 1044
                1077 1099 1108 1112 1119 1121 1131 1141 1150 1159 1164
6     2    5 35 77 120 163 208
7     2    4 361 788 842 890
8     3  120 3 12:13 16 21:22 26:29 31 37 43 45 53:54 57 62:63 67:70
                73 79 86 88 96:97 100 105 110:113 116 129 139:140 143
8     3  120 148 153:156 159 172 174 184:185 188 193 198:201 204 216
                218 220 231:232 236 240:241 247:250 252 259 266 268
                270 282:283 287 291:292 298:301 303 310:311 318 344
                352 366:367 374 424 432 444 484 492 505 569 601 665
                726 784 802 838 856 888 904 935 951 977 994 1019 1042
                1060 1097 1133 1162 1188 1213
```

```
> L10MD7601USD.s <- preCgm(L10MD7601USD)
> margins.form <- ~ OrgType + OrgStruct + CohortGrp + Region
> options(contrasts = c("contr.treatment", "contr.poly"))
```

```
> design.form <- ~ OrgType + OrgStruct + CohortGrp + Region
> L10MD7601USD.EM <- emCgm(L10MD7601USD.s, margins = margins.form,
+       design = design.form, prior = 1.05)
Steps of ECM:
1...2...3...4...5...6...7...8...9...10...11...12...13...14...15...16...
> L10MD7601USD.EM$algorithm
final log-likelihood =  -9409.519

difference in the log-likelihood (or log posterior density) =  6.614937e-008

maximum absolute relative change in parameter estimate on last iteration =
0.0008588625
> dataDepend <- dataDepPrior(L10MD7601USD.s, nPriorObs = 50,
+       algorithm = "da")
> L10MD7601USD.DA <- daCgm(L10MD7601USD.EM, prior = dataDepend,
+       control = list(niter=800, save=51:800))
> worst.est <- worstFraction(L10MD7601USD.EM, method = "power")
> worst.est$fraction
[1] 0.9999997
> wlf <- worstLinFun(L10MD7601USD.DA, worst.est)
> wlf.acf <- acf(wlf, lag.max = 100, plot = F)
> wlf.acf$series <- "Worst Linear Function L10MD7601USD"
> acf.plot(wlf.acf)
> L10MD7601USD.imp <- impCgm(L10MD7601USD.DA, nimpute = 15,
+       control = list(niter = 50))
> miSubscript(L10MD7601USD.imp, 1)
```

S Codes for the Estimates of Missing Values

MD7601NP: Missing values of new products.

```
S-PLUS : Copyright (c) 1988, 2002 Insightful Corp.
S : Copyright Lucent Technologies, Inc.
Professional Edition Version 6.1.3 Release 3 for Micros
oft Windows : 2002
Working data will be in C:\Program Files\Insightful\spl
us61\users\Cotter
> library(missing)
> MD7601NP.miss <- miss(MD7601NP)
> summary(MD7601NP.miss)
Summary of missing values
   10 variables, 1144 observations, 2 patterns of missing values
    4   variables (40%) have at least one missing value
   127 observations (11%) have at least one missing value

Breakdown by variable
 V  O name Missing % missing
 1  7  MF     127       11
 2  8 Mini    127       11
 3  9  PC     127       11
 4 10  WS     127       11
V = Variable number used below,  O = Original number (before sorting)
No missing values for variables:
YearID OrgCode OrgType OrgStruct CohortGrp Region

Patterns of missing values (variables in columns, patterns in rows)
Pattern Variables
     1234
    1 ....
    2 mmmm

Pattern #Missing #Obs Observations
    1       0 1017 1:9 11:14 16:18 20:28 30:44 46:49 51:53 55:64 66:81
                   83:86 88:90 92:101 103:119 121:124 126:128 130:139
                   141:158 160:163 165:167 169:178 180:199 201:205
                   207:209 211:220 222:242 244:248 250:263 265:288
                   290:295 297:308 310:315 318:342 344:349 351:362
                   364:369 372:400 402:408 410:422 424:428 430:460
                   462:469 471:483 485:488 491:523 525:528 530:545
                   547:549 552:583 585:587 589:602 604:606 608:610
                   613:643 645:646 648:661 663:665 667:669 672:700
                   702:703 705:717 719:721 723:725 728:758 760:771
                   773:774 776:778 781:811 813:822 825 828:868 871
```

```
              874:882 884:902 904:912 914 918:943 945:949 951:953
              955 959:983 985:989 991:993 995 999:1019 1021:1025
              1027:1029 1031 1035:1053 1055:1059 1061:1063 1068:1081
              1083:1087 1089:1090 1095:1106 1108:1114 1118:1129
              1131:1137 1141:1144
   2    4 127 10 15 19 29 45 50 54 65 82 87 91 102 120 125 129 140
              159 164 168 179 200 206 210 221 243 249 264 289 296
              309 316:317 343 350 363 370:371 401 409 423 429 461
              470 484 489:490 524 529 546 550:551 584 588 603 607
              611:612 644 647 662 666 670:671 701 704 718 722
              726:727 759 772 775 779:780 812 823:824 826:827
              869:870 872:873 883 903 913 915:917 944 950 954
              956:958 984 990 994 996:998 1020 1026 1030 1032:1034
              1054 1060 1064:1067 1082 1088 1091:1094 1107 1115:1117
              1130 1138:1140
> MD7601NP.s <- preCgm(MD7601NP)
> margins.form <- ~ OrgType + OrgStruct + CohortGrp + Region
> options(contrasts = c("contr.treatment", "contr.poly"))
> design.form <- ~ OrgType + OrgStruct + CohortGrp + Region
> MD7601NP.EM <- emCgm(MD7601NP.s, margins = margins.form, design =
design.form, prior = 1.05)
Steps of ECM:
1...2...3...4...5...6...7...8...9...10...11...12...13...14...15...16...17...18...19...20...21...22..
.23...24...25...26...27...
> MD7601NP.EM$algorithm
final log-likelihood =  -14963.77

difference in the log-likelihood (or log posterior density) =  1.159424e-008

maximum absolute relative change in parameter estimate on last iteration =
0.0009877807
> dataDepend <- dataDepPrior(MD7601NP.s, nPriorObs = 50, algorithm = "da")
> MD7601NP.DA <- daCgm(MD7601NP.EM, prior = dataDepend, control = list(niter =
800, save = 51:800))
> worst.est <- worstFraction(MD7601NP.EM, method = "power")
> worst.est$fraction
[1] 0.678894
> wlf <- worstLinFun(MD7601NP.DA, worst.est)
> wlf.acf <- acf(wlf, lag.max = 100, plot = F)
> wlf.acf$series <- "Worst Linear Function MD7601NP"
> acf.plot(wlf.acf)
> MD7601NP.imp <- impCgm(MD7601NP.DA, nimpute = 15, control = list(niter = 50))
> miSubscript(MD7601NP.imp, 1)
```

APPENDIX C

Cumulative Average Censoring Times Link to Geometric Hazard Rate and Geomteric Survivor Function

Cumulative Average Censoring Times Link to Geometric Hazard Rate and Geometric Survivor Function

Let $t_{s+\Delta 1}, t_{s+\Delta 2}, \ldots, t_{s+\Delta j}$ be observed failure times in time interval $t_t > t_{s+\Delta} > t_s$ from a risk set of n_i entities with covariate information X_{ni} surviving at t_s where $t_{s+\Delta}$ is one in a sequence of time intervals $t_s > t_{r+\Delta} > t_r > t_{q+\Delta} > t_q > \ldots > t_{1+\Delta} > t_1 > t_{0+\Delta} > t_0$. Let the n_i entities be from a homogenous population with (unknown) survivor function S(t) and hazard rate μ (t). Let d_i be the number of entities failing in $t_{s+\Delta}$ and $c_i = n_i - d_i$ be the number of entities censored in $t_{s+\Delta}$. Lawless (512 – 518) shows that the probability of the c_i entities being censored in $t_{s+\Delta}$ is

$$\Pi_s^{\Delta} (1 - \Sigma_i \mu_i (t \mid X_{ni}))$$

Correspondingly, the probability of the n_j entities surviving to t_s is

$$P(T = t_s) = S(t_s) = \Pi_{0+\Delta}^{r+\Delta} (1 - \Sigma_i \mu_i (t \mid X_{ni}))$$

This probability may also be expressed as the product of a sequence of independent Bernoulli trials at each $t_i \leq t_s$ with

$$p = \breve{u}_s (t \mid X_{ni}) \qquad \text{and} \qquad \check{S}(t_s) = \Pi_1^{s} (1 - \breve{u}_s (t \mid X_{ni}))$$

where $\breve{u}_s$ is the geometric mean hazard rate and $\check{S}(t_s)$ is the geometric mean survivor function. Under this formulation, the mean intensity time of the intermediate censored Bernoulli trials for $\check{S}(t_s)$ at any time t_s is

$$M[t_s] = (t_{r+\Delta})\, \check{S}(t_s) + (t_{q+\Delta})\, \check{S}(t_s) + \ldots + (t_{0+\Delta})\, \check{S}(t_s)$$

$$= [(t_{r+\Delta}) + (t_{q+\Delta}) + \ldots + (t_{0+\Delta})] / r$$

or the cumulative average censoring times of the n_i entities surviving at t_s.

Using the geometric mean survivor function, the probability of failure in any $t_{s+\Delta}$ is

$$P(t_{sj} \leq T \leq t_{si+\Delta i}) = \check{S}(t_{si}) - S(t_{si+\Delta i}).$$

The contribution to the likelihood of a censored survival time at any t_t is

$$P(T > t_t) = S(t_{ti})$$

which is appropriate provided that censoring is independent. The probability of the data is then of the form

$$L = \Pi_0{}^k [(\check{S}(t_{si}) - S(t_{si + \Delta i}))^{di} \; \Pi_1{}^{ci} S(t_{ti})]$$

which given the data is the likelihood function on the space of all geometric mean survivor functions. The maximum likelihood estimate (MLE) is the geometric mean survivor function that maximizes L, and standard survival analyses apply.

APPENDIX D

S Codes for Survival Analysis for the Period 1949 to 2001

S Codes for Survival Analysis for the Period 1949 to 2001

```
S-PLUS : Copyright (c) 1988, 2002 Insightful Corp.
S : Copyright Lucent Technologies, Inc.
Professional Edition Version 6.1.3 Release 3 for Micros
oft Windows : 2002
Working data will be in C:\Program Files\Insightful\spl
us61\users\Cotter

> censorReg(formula=censor(YrsComp,DemiseInd)~OrgCode,
+       data=DissSurAnal4801SDFr1, na.action = na.exclude,
+       distribution = "exponential", threshold = 0, control = list(e.scale = 0.0001))
Call:
censorReg(formula = censor(YrsComp, DemiseInd) ~ OrgCode, data =
        DissSurAnal4801SDFr1, na.action = na.exclude, distribution = "exponential",
        threshold = 0, control = list(e.scale = 0.0001))

Distribution: Exponential

Coefficients:
 (Intercept)   OrgCode
    23.5903 0.5451246

Dispersion (scale) fixed at 1
Log-likelihood: -327.0986

Observations: 1659 Total; 1603 Censored
Parameters Estimated: 2
Threshold Parameter: 0

> censorReg(formula=censor(YrsComp,DemiseInd)~OrgCode,
+       data=DissSurAnal4801SDFr1, na.action = na.exclude,
+       distribution = "logexponential", threshold = 0, control = list(e.scale = 0.0001))
Call:
censorReg(formula = censor(YrsComp, DemiseInd) ~ OrgCode, data =
        DissSurAnal4801SDFr1, na.action = na.exclude, distribution =
        "logexponential", threshold = 0, control = list(e.scale = 0.0001))

Distribution: Logexponential

Coefficients:
 (Intercept)    OrgCode
   4.996027 0.06148837
```

```
Dispersion (scale) fixed at 1
Log-likelihood: -313.5187

Observations: 1659 Total; 1603 Censored
Parameters Estimated: 2
Threshold Parameter: 0

> censorReg(formula=censor(YrsComp,DemiseInd)~OrgCode,
+       data=DissSurAnal4801SDFr1, na.action = na.exclude,
+       distribution = "logistic", threshold = 0, control = list(e.scale = 0.0001))
Call:
censorReg(formula = censor(YrsComp, DemiseInd) ~ OrgCode, data =
        DissSurAnal4801SDFr1, na.action = na.exclude, distribution =
        "logistic", threshold = 0, control = list(e.scale = 0.0001))

Distribution: Logistic

Coefficients:
 (Intercept)   OrgCode
   21.81628 0.4820016

Dispersion (scale) est = 1.573465
Log-likelihood: -169.6192

Observations: 1659 Total; 1603 Censored
Parameters Estimated: 3
Threshold Parameter: 0

> censorReg(formula=censor(YrsComp,DemiseInd)~OrgCode,
+       data=DissSurAnal4801SDFr1, na.action = na.exclude,
+       distribution = "loglogistic", threshold = 0, control = list(e.scale = 0.0001))
Call:
censorReg(formula = censor(YrsComp, DemiseInd) ~ OrgCode, data =
        DissSurAnal4801SDFr1, na.action = na.exclude, distribution =
        "loglogistic", threshold = 0, control = list(e.scale = 0.0001))

Distribution: Loglogistic

Coefficients:
 (Intercept)    OrgCode
   2.889025 0.02866191

Dispersion (scale) est = 0.1134543
Log-likelihood: -153.5195

Observations: 1659 Total; 1603 Censored
```

Parameters Estimated: 3
Threshold Parameter: 0

```
> censorReg(formula=censor(YrsComp,DemiseInd)~OrgCode,
+       data=DissSurAnal4801SDFr1, na.action = na.exclude,
+       distribution = "normal", threshold = 0, control = list(e.scale = 0.0001))
Call:
censorReg(formula = censor(YrsComp, DemiseInd) ~ OrgCode, data =
        DissSurAnal4801SDFr1, na.action = na.exclude, distribution = "normal",
        threshold = 0, control = list(e.scale = 0.0001))

Distribution: Normal

Coefficients:
 (Intercept)   OrgCode
   22.18046 0.4836104

Dispersion (scale) = 3.123409
Log-likelihood: -172.5992

Observations: 1659 Total; 1603 Censored
Parameters Estimated: 3
Threshold Parameter: 0

> censorReg(formula=censor(YrsComp,DemiseInd)~OrgCode,
data=DissSurAnal4801SDFr1,
+       na.action = na.exclude, distribution = "lognormal", threshold = 0,
+       control = list(e.scale = 0.0001))
Call:
censorReg(formula = censor(YrsComp, DemiseInd) ~ OrgCode, data =
        DissSurAnal4801SDFr1, na.action = na.exclude, distribution =
        "lognormal", threshold = 0, control = list(e.scale = 0.0001))

Distribution: Lognormal

Coefficients:
 (Intercept)   OrgCode
   2.886216 0.03010897

Dispersion (scale) = 0.202935
Log-likelihood: -152.0353

Observations: 1659 Total; 1603 Censored
Parameters Estimated: 3
Threshold Parameter: 0
```

```
> censorReg(formula=censor(YrsComp,DemiseInd)~OrgCode,
+       data=DissSurAnal4801SDFr1, na.action = na.exclude,
+       distribution = "rayleigh", threshold = 0, control = list(e.scale = 0.0001))Call:
Call:
censorReg(formula = censor(YrsComp, DemiseInd) ~ OrgCode, data =
        DissSurAnal4801SDFr1, na.action = na.exclude, distribution =
        "rayleigh", threshold = 0, control = list(e.scale = 0.0001))

Distribution: Rayleigh

Coefficients:
 (Intercept)  OrgCode
   -4359515 124142.3

Dispersion (scale) fixed at 0.5
Log-likelihood: -1019.584

Observations: 1659 Total; 1603 Censored
Parameters Estimated: 2
Threshold Parameter: 0

> censorReg(formula=censor(YrsComp,DemiseInd)~OrgCode,
data=DissSurAnal4801SDFr1,
+       na.action = na.exclude, distribution = "lograyleigh", threshold = 0,
+       control = list(e.scale = 0.0001))
Call:
censorReg(formula = censor(YrsComp, DemiseInd) ~ OrgCode, data =
        DissSurAnal4801SDFr1, na.action = na.exclude, distribution =
        "lograyleigh", threshold = 0, control = list(e.scale = 0.0001))

Distribution: Lograyleigh

Coefficients:
 (Intercept)   OrgCode
   3.554198 0.04117319

Dispersion (scale) fixed at 0.5
Log-likelihood: -237.8268

Observations: 1659 Total; 1603 Censored
Parameters Estimated: 2
Threshold Parameter: 0

> censorReg(formula=censor(YrsComp,DemiseInd)~OrgCode,
+       data=DissSurAnal4801SDFr1, na.action = na.exclude,
```

```
+       distribution = "weibull", threshold = 0, control = list(e.scale = 0.0001))
Call:
censorReg(formula = censor(YrsComp, DemiseInd) ~ OrgCode, data =
        DissSurAnal4801SDFr1, na.action = na.exclude, distribution = "weibull",
        threshold = 0, control = list(e.scale = 0.0001))

Distribution: Weibull

Coefficients:
 (Intercept)    OrgCode
    2.95397 0.02703917

Dispersion (scale) = 0.137182
Log-likelihood: -150.8128

Observations: 1659 Total; 1603 Censored
Parameters Estimated: 3
Threshold Parameter: 0

> censorReg(formula=censor(YrsComp,DemiseInd)~OrgCode,
data=DissSurAnal4801SDFr1,
+       na.action = na.exclude, distribution = "extreme", threshold = 0,
+       control = list(e.scale = 0.0001))
Call:
censorReg(formula = censor(YrsComp, DemiseInd) ~ OrgCode, data =
        DissSurAnal4801SDFr1, na.action = na.exclude, distribution = "extreme",
        threshold = 0, control = list(e.scale = 0.0001))

Distribution: Extreme

Coefficients:
 (Intercept)    OrgCode
   24.27598 0.5443555

Dispersion (scale) = 2.390863
Log-likelihood: -185.7033

Observations: 1659 Total; 1603 Censored
Parameters Estimated: 3
Threshold Parameter: 0

> fitExp <- censorReg(formula=censor(YrsComp,DemiseInd)~OrgCode,
+       data=DissSurAnal4801SDFr1, na.action = na.exclude,
+       distribution = "exponential", threshold = 0, control = list(e.scale = 0.0001))
> fitLogExp <- censorReg(formula=censor(YrsComp,DemiseInd)~OrgCode,
+       data=DissSurAnal4801SDFr1, na.action = na.exclude,
```

```
+       distribution = "logexponential", threshold = 0, control = list(e.scale = 0.0001))
> fitLog <- censorReg(formula=censor(YrsComp,DemiseInd)~OrgCode,
+       data=DissSurAnal4801SDFr1, na.action = na.exclude,
+       distribution = "logistic", threshold = 0, control = list(e.scale = 0.0001))
> fitLogLog <- censorReg(formula=censor(YrsComp,DemiseInd)~OrgCode,
+       data=DissSurAnal4801SDFr1, na.action = na.exclude,
+       distribution = "loglogistic", threshold = 0, control = list(e.scale = 0.0001))
> fitNor <- censorReg(formula=censor(YrsComp,DemiseInd)~OrgCode,
+       data=DissSurAnal4801SDFr1, na.action = na.exclude,
+       distribution = "normal", threshold = 0, control = list(e.scale = 0.0001))
> fitLogNor <- censorReg(formula=censor(YrsComp,DemiseInd)~OrgCode,
+       data=DissSurAnal4801SDFr1, na.action = na.exclude,
+       distribution = "lognormal", threshold = 0, control = list(e.scale = 0.0001))
> fitRay <- censorReg(formula=censor(YrsComp,DemiseInd)~OrgCode,
+       data=DissSurAnal4801SDFr1, na.action = na.exclude,
+       distribution = "rayleigh", threshold = 0, control = list(e.scale = 0.0001))
> fitLogRay <- censorReg(formula=censor(YrsComp,DemiseInd)~OrgCode,
+       data=DissSurAnal4801SDFr1, na.action = na.exclude,
+       distribution = "lograyleigh", threshold = 0, control = list(e.scale = 0.0001))
> fitWbl <- censorReg(formula=censor(YrsComp,DemiseInd)~OrgCode,
+       data=DissSurAnal4801SDFr1, na.action = na.exclude,
+       distribution = "weibull", threshold = 0, control = list(e.scale = 0.0001))
> fitExt <- censorReg(formula=censor(YrsComp,DemiseInd)~OrgCode,
+       data=DissSurAnal4801SDFr1, na.action = na.exclude,
+       distribution = "extreme", threshold = 0, control = list(e.scale = 0.0001))

> anova(fitRay,fitExp,fitLogExp,fitLogRay,fitExt,fitNor,fitLog,fitLogLog,fitLogNor,
fitWbl)
Likelihood Ratio Test(s)

Response: censor(YrsComp, DemiseInd)
```

	Model	Terms	N.Params	LogLik	-2*LogLik	AIC
1	Rayleigh	OrgCode	3	-1019.584	2039.168	2043.168
2	Exponential	OrgCode	3	-327.0986	654.1972	658.197
3	Logexponential	OrgCode	3	-313.5187	627.0374	631.037
4	LogRayleigh	OrgCode	3	-237.8268	475.6535	479.654
5	Extreme	OrgCode	3	-185.7033	371.4065	377.406
6	Normal	OrgCode	3	-172.5992	345.1984	351.198
7	Logistic	OrgCode	3	-169.6192	339.2383	345.238
8	Loglogistic	OrgCode	3	-153.5195	307.0389	313.039
9	LogNormal	OrgCode	3	-152.0353	304.0706	310.070
10	Weibull	OrgCode	3	-150.8128	301.6255	307.626

```
> fitWblBase <- censorReg(formula=censor(YrsComp,DemiseInd)~1,
+       data = DissSurAnal4801SDFr1, na.action = na.exclude,
```

```
+       distribution = "weibull", threshold = 0, control = list(e.scale = 0.0001))
> summary(fitWblBase)
Call:
censorReg(formula = censor(YrsComp, DemiseInd) ~ 1, data =
        DissSurAnal4801SDFr1, na.action = na.exclude, distribution = "weibull",
        threshold = 0, control = list(e.scale = 0.0001))

Distribution:  Weibull

Standardized Residuals:
          Min   Max
Uncensored 0.001 1.015
  Censored 0.000 1.625

Coefficients:
              Est.      Std.Err.   95% LCL   95% UCL   z-value   p-value
(Intercept)   3.73      0.0727     3.59      3.87      51.3      0

Extreme value distribution: Dispersion (scale) = 0.3700828
Observations: 1659 Total; 1603 Censored
-2*Log-Likelihood: 628

> summary(fitWbl)
Call:
censorReg(formula = censor(YrsComp, DemiseInd) ~ OrgCode, data =
        DissSurAnal4801SDFr1, na.action = na.exclude, distribution = "weibull",
        threshold = 0, control = list(e.scale = 0.0001))

Distribution:  Weibull

Standardized Residuals:
             Min     Max
Uncensored   0.004   3.202
Censored     0.000   1.937

Coefficients:
              Est.      Std.Err.   95% LCL   95% UCL   z-value   p-value
(Intercept)   2.954     0.01985    2.9151    2.9929    148.8     0.00e+000
OrgCode       0.027     0.00114    0.0248    0.0293    23.7      4.48e-124

Extreme value distribution: Dispersion (scale) = 0.137182
Observations: 1659 Total; 1603 Censored
-2*Log-Likelihood: 302

Correlation of Coefficients:
              (Intercept)
```

OrgCode 0.383

```
> fitWblFull <- censorReg(formula=censor(YrsComp,DemiseInd)~OrgCode + YrID +
+       OrgType + OrgStruct + CohortGrp + Region + Density + EntryDensity +
+       CohtDensity + EntryCohtDen + RegionDensity + EntryRgnDen + Den2 +
+       CohtDen2 + RgnDen2, data = DissSurAnal4801SDFr1, na.action = na.exclude,
+       distribution = "weibull", threshold = 0, control = list(e.scale = 0.0001))

> summary(fitWblFull)
Call:censorReg(formula = censor(YrsComp, DemiseInd) ~ OrgCode + YrID +
        OrgType + OrgStruct + CohortGrp + Region + Density + EntryDensity +
        CohtDensity + EntryCohtDen + RegionDensity + EntryRgnDen + Den2 +
        CohtDen2 + RgnDen2, data = DissSurAnal4801SDFr1, na.action = na.exclude,
        distribution = "weibull", threshold = 0, control = list(e.scale = 0.0001))
```

Distribution: Weibull

Standardized Residuals:

	Min	Max
Uncensored	0.007	2.867
Censored	0.000	0.678

Coefficients:

	Est.	Std.Err.	95% LCL	95% UCL	z-value	p-value
(Intercept)	3.4592134	0.400077	2.675076	4.243351	8.646	5.32e-018
OrgCode	0.0256208	0.004150	0.017488	0.033754	6.174	6.64e-010
YrID	0.0198685	0.009700	0.000856	0.038881	2.048	4.05e-002
OrgType	-0.1007664	0.039669	-0.178515	-0.023017	-2.540	1.11e-002
OrgStruct	-0.0333122	0.022425	-0.077265	0.010640	-1.485	1.37e-001
CohortGrp	-0.6827757	0.148636	-0.974097	-0.391454	-4.594	4.36e-006
Region	0.1377238	0.086912	-0.032621	0.308068	1.585	1.13e-001
Density	-0.0267998	0.018141	-0.062355	0.008755	-1.477	1.40e-001
EntryDensity	0.0205739	0.008222	0.004458	0.036690	2.502	1.23e-002
CohtDensity	0.0730027	0.025386	0.023248	0.122758	2.876	4.03e-003
EntryCohtDen	-0.0374484	0.007753	-0.052645	-0.022252	-4.830	1.37e-006
RegionDensity	-0.0213560	0.011406	-0.043711	0.000999	-1.872	6.12e-002
EntryRgnDen	0.0069881	0.004679	-0.002182	0.016158	1.494	1.35e-001
Den2	0.0000306	0.000202	-0.000364	0.000426	0.152	8.79e-001
CohtDen2	-0.0010065	0.000589	-0.002161	0.000148	-1.708	8.76e-002
RgnDen2	0.0007350	0.000268	0.000209	0.001261	2.738	6.17e-003

Extreme value distribution: Dispersion (scale) = 0.1096004
Observations: 1659 Total; 1603 Censored
-2*Log-Likelihood: 244

Correlation of Coefficients:

	(Intercept)	OrgCode	YrID	OrgType	OrgStruct	CohortGrp	Region
OrgCode	0.575						
YrID	-0.358	-0.869					
OrgType	-0.245	-0.157	-0.050				
OrgStruct	-0.493	-0.082	-0.111	0.429			
CohortGrp	-0.337	0.039	-0.272	0.107	0.300		
Region	-0.238	0.032	-0.165	0.131	-0.063	-0.020	
Density	-0.568	-0.010	-0.321	0.178	0.386	0.254	0.214
EntryDensity	0.649	0.616	-0.378	-0.151	-0.214	-0.697	-0.124
CohtDensity	0.132	-0.133	0.449	-0.196	-0.360	-0.440	-0.099
EntryCohtDen	-0.364	-0.075	-0.198	0.122	0.290	0.935	-0.016
RegionDensity	-0.075	-0.029	0.068	0.059	0.034	-0.098	-0.032
EntryRgnDen	-0.284	-0.063	-0.122	0.044	0.048	0.091	0.645
Den2	0.548	-0.016	0.302	-0.147	-0.344	-0.155	-0.284
CohtDen2	0.002	0.225	-0.459	0.137	0.276	0.255	0.078
RgnDen2	0.049	0.077	-0.102	-0.035	-0.034	0.081	0.200

	Density	EntryDensity	CohtDensity	EntryCohtDen	RegionDensityy
OrgCode					
OrgType					
OrgStruct					
YrID					
CohortGrp					
Region					
Density					
EntryDensity	-0.215				
CohtDensity	-0.621	0.152			
EntryCohtDen	0.252	-0.731	-0.419		
RegionDensity	-0.172	0.230	-0.148	-0.093	
EntryRgnDen	0.429	-0.350	-0.128	0.065	-0.528
Den2	-0.981	0.148	0.534	-0.146	0.207
CohtDen2	0.557	0.045	-0.961	0.214	0.212
RgnDen2	0.142	-0.192	0.200	0.071	-0.956

	EntryRgnDen	Den2	CohtDen2
OrgCode			
OrgType			
OrgStruct			
YrID			
CohortGrp			
Region			
Density			
EntryDensity			
CohtDensity			
EntryCohtDen			
RegionDensity			

```
EntryRgnDen
Den2          -0.454
CohtDen2      0.073         -0.498
RgnDen2       0.527         -0.208  -0.273
> fitWblSig1 <- censorReg(formula=censor(YrsComp,DemiseInd)~OrgCode + YrID +
+       OrgType + CohortGrp + EntryDensity +
+       CohtDensity + EntryCohtDen + RegionDensity +
+       CohtDen2 + RgnDen2, data = DissSurAnal4801SDFr1, na.action = na.exclude,
+       distribution = "weibull", threshold = 0, control = list(e.scale = 0.0001))
> summary(fitWblSig1)
Call:
censorReg(formula = censor(YrsComp, DemiseInd) ~ OrgCode + YrID + OrgType +
        CohortGrp + EntryDensity + CohtDensity + EntryCohtDen + RegionDensity +
        CohtDen2 + RgnDen2, data = DissSurAnal4801SDFr1, na.action =
        na.exclude, distribution = "weibull", threshold = 0, control = list(
        e.scale = 0.0001))

Distribution:  Weibull

Standardized Residuals:
             Min    Max
Uncensored   0.003  3.805
Censored     0.000  1.438

Coefficients:
               Est.       Std.Err.  95% LCL    95% UCL     z-value  p-value
(Intercept)    3.312419   0.311237  2.702406   3.9224313   10.643   1.88e-026
OrgCode        0.025651   0.004258  0.017305   0.0339971   6.024    1.70e-009
YrID           0.006146   0.009233  -0.011949  0.0242416   0.666    5.06e-001
OrgType        -0.075266  0.040549  -0.154741  0.0042085   -1.856   6.34e-002
CohortGrp      -0.344682  0.150162  -0.638994  -0.0503693  -2.295   2.17e-002
EntryDensity   0.015892   0.007592  0.001012   0.0307714   2.093    3.63e-002
CohtDensity    -0.036831  0.019314  -0.074686  0.0010243   -1.907   5.65e-002
EntryCohtDen   -0.019931  0.007785  -0.035190  -0.0046716  -2.560   1.05e-002
RegionDensity  0.014668   0.008709  -0.002401  0.0317369   1.684    9.21e-002
CohtDen2       0.001218   0.000512  0.000214   0.0022211   2.378    1.74e-002
RgnDen2        -0.000414  0.000223  -0.000850  0.0000223   -1.860   6.29e-002

Extreme value distribution: Dispersion (scale) = 0.1289921
Observations: 1659 Total; 1603 Censored
-2*Log-Likelihood: 281

Correlation of Coefficients:
              (Intercept)  OrgCode  YrID   OrgType  CohortGrp  EntryDensity
OrgCode       0.743
YrID          -0.783       -0.927
```

```
OrgType         -0.057    -0.234    0.136
CohortGrp       -0.108    0.132     -0.312   -0.064
EntryDensity    0.631     0.564     -0.412   -0.111    -0.716
CohtDensity     -0.632    -0.313    0.388    0.073     -0.231     -0.071
EntryCohtDen    -0.140    0.041     -0.230   -0.051    0.924      -0.746
RegionDensity   -0.162    -0.053    0.156    -0.139    -0.262     0.187
CohtDen2        0.670     0.376     -0.384   -0.103    0.030      0.268
RgnDen2         0.119     0.040     -0.163   0.139     0.332      -0.240

                CohtDensity  EntryCohtDen  RegionDensity   CohtDen2
OrgCode
YrID
OrgType
CohortGrp
EntryDensity
CohtDensity
EntryCohtDen    -0.204
RegionDensity   -0.136       -0.315
CohtDen2        -0.950       -0.012        0.263
RgnDen2         0.124        0.379         -0.964          -0.302
> fitWblSig2 <- censorReg(formula=censor(YrsComp,DemiseInd)~OrgCode +
+       OrgType + CohortGrp + EntryDensity +
+       CohtDensity + EntryCohtDen +
+       CohtDen2 + RgnDen2, data = DissSurAnal4801SDFr1, na.action = na.exclude,
+       distribution = "weibull", threshold = 0, control = list(e.scale = 0.0001))
> summary(fitWblSig2)
Call:
censorReg(formula = censor(YrsComp, DemiseInd) ~ OrgCode + OrgType +
      CohortGrp + EntryDensity + CohtDensity + EntryCohtDen + CohtDen2 +
      RgnDen2, data = DissSurAnal4801SDFr1, na.action = na.exclude,
      distribution = "weibull", threshold = 0, control = list(e.scale = 0.0001))

Distribution:  Weibull

Standardized Residuals:
             Min    Max
Uncensored   0.004  4.070
Censored     0.000  1.391

Coefficients:
                Est.        Std.Err.  95% LCL    95% UCL    z-value   p-value
(Intercept)     3.5036032   0.1928220 3.125679   3.8815274  18.170    8.90e-074
OrgCode         0.0278720   0.0015933 0.024749   0.0309948  17.493    1.63e-068
OrgType         -0.0716783  0.0403986 -0.150858  0.0075016  -1.774    7.60e-002
CohortGrp       -0.2689274  0.1375137 -0.538449  0.0005944  -1.956    5.05e-002
EntryDensity    0.0153764   0.0066046 0.002432   0.0283212  2.328     1.99e-002
```

```
CohtDensity     -0.0354895  0.0175987 -0.069982   -0.0009968  -2.017    4.37e-002
EntryCohtDen    -0.0156452  0.0073039 -0.029961   -0.0013299  -2.142    3.22e-002
CohtDen2         0.0010716  0.0004488  0.000192    0.0019513   2.388    1.70e-002
RgnDen2         -0.0000486  0.0000681 -0.000182    0.0000848  -0.714    4.75e-001

Extreme value distribution: Dispersion (scale) = 0.1318503
Observations: 1659 Total; 1603 Censored
-2*Log-Likelihood: 284

Correlation of Coefficients:
                (Intercept)  OrgCode  OrgType CohortGrp EntryDensity  CohtDensity
OrgCode          0.036
OrgType          0.117      -0.272
CohortGrp       -0.620      -0.393   -0.096
EntryDensity     0.573       0.486    0.018   -0.974
CohtDensity     -0.608       0.245   -0.040   -0.188     0.183
EntryCohtDen    -0.563      -0.407   -0.103    0.921    -0.945        -0.211
CohtDen2         0.708      -0.082    0.033   -0.016     0.028        -0.942
RgnDen2         -0.230      -0.193    0.003    0.260    -0.249        -0.014

                EntryCohtDen  CohtDen2
OrgCode
OrgType
CohortGrp
EntryDensity
CohtDensity
EntryCohtDen
CohtDen2        -0.002
RgnDen2          0.265        -0.250
> fitWblSig3 <- censorReg(formula=censor(YrsComp,DemiseInd)~OrgCode +
+       CohortGrp + EntryDensity +
+       CohtDensity + EntryCohtDen +
+       CohtDen2, data = DissSurAnal4801SDFr1, na.action = na.exclude,
+       distribution = "weibull", threshold = 0, control = list(e.scale = 0.0001))
> summary(fitWblSig3)
Call:
censorReg(formula = censor(YrsComp, DemiseInd) ~ OrgCode + CohortGrp +
        EntryDensity + CohtDensity + EntryCohtDen + CohtDen2, data =
        DissSurAnal4801SDFr1, na.action = na.exclude, distribution = "weibull",
        threshold = 0, control = list(e.scale = 0.0001))

Distribution:  Weibull

Standardized Residuals:
              Min    Max
Uncensored   0.004  4.233
```

Censored 0.000 1.427

Coefficients:

	Est.	Std.Err.	95% LCL	95% UCL	z-value	p-value
(Intercept)	3.51557	0.187853	3.147382	3.88375	18.71	3.77e-078
OrgCode	0.02717	0.001542	0.024149	0.03019	17.62	1.71e-069
CohortGrp	-0.26926	0.130575	-0.525186	-0.01334	-2.06	3.92e-002
EntryDensity	0.01472	0.006310	0.002351	0.02708	2.33	1.97e-002
CohtDensity	-0.03708	0.017505	-0.071389	-0.00277	-2.12	3.42e-002
EntryCohtDen	-0.01580	0.006980	-0.029483	-0.00212	-2.26	2.36e-002
CohtDen2	0.00103	0.000434	0.000177	0.00188	2.37	1.78e-002

Extreme value distribution: Dispersion (scale) = 0.1342571
Observations: 1659 Total; 1603 Censored
-2*Log-Likelihood: 288

Correlation of Coefficients:

	(Intercept)	OrgCode	CohortGrp	EntryDensity	CohtDensity
OrgCode	0.018				
CohortGrp	-0.599	-0.399			
EntryDensity	0.557	0.478	-0.974		
CohtDensity	-0.635	0.249	-0.175	0.161	
EntryCohtDen	-0.543	-0.418	0.913	-0.943	-0.192
CohtDen2	0.698	-0.134	0.032	-0.009	-0.975

	EntryCohtDen
OrgCode	
CohortGrp	
EntryDensity	
CohtDensity	
EntryCohtDen	
CohtDen2	0.042

> anova(fitWbl,fitWblSig5,test = "Chisq")
Likelihood Ratio Test(s)
Response: censor(YrsComp, DemiseInd)

	Terms	N.Params	-2*LogLik	Test Df	LRT	Pr(Chi)
1	OrgCode	3	301.6255			
2	OrgCode + CohortGrp + EntryDensity + CohtDensity + EntryCohtDen + CohtDen2	8	287.7343	5	13.891	0.016315

APPENDIX E

S Codes for Missing Data Effectiveness Analysis for the Period 1976 to 2001

S Codes for Missing Data Effectiveness Analysis for the Period 1976 to 2001

```
S-PLUS : Copyright (c) 1988, 2002 Insightful Corp.
S : Copyright Lucent Technologies, Inc.
Professional Edition Version 6.1.3 Release 3 for Micros
oft Windows : 2002
Working data will be in C:\Program Files\Insightful\spl
us61\users\Cotter
> censorReg(formula=censor(YrsEff,EffInd)~SOrgCode,
+       data = DissEffAnal7601MDA, na.action = na.exclude,
+       distribution = "exponential",threshold = 0, control = list(e.scale = 0.0001))
Call:
censorReg(formula = censor(YrsEff, EffInd) ~ SOrgCode, data =
        DissEffAnal7601MDA, na.action = na.exclude, distribution =
        "exponential", threshold = 0, control = list(e.scale = 0.0001))

Distribution: Exponential

Coefficients:
 (Intercept)   SOrgCode
   11.31132 0.04602931

Dispersion (scale) fixed at 1
Log-likelihood: -5208.501

Observations: 1144 Total; 785 Censored
Parameters Estimated: 2
Threshold Parameter: 0
> censorReg(formula=censor(YrsEff,EffInd)~SOrgCode,
+       data = DissEffAnal7601MDA, na.action = na.exclude,
+       distribution = "logexponential",threshold = 0, control = list(e.scale = 0.0001))
Call:
censorReg(formula = censor(YrsEff, EffInd) ~ SOrgCode, data =
        DissEffAnal7601MDA, na.action = na.exclude, distribution =
        "logexponential", threshold = 0, control = list(e.scale = 0.0001))

Distribution: Logexponential

Coefficients:
 (Intercept)   SOrgCode
   2.471825 0.004606262

Dispersion (scale) fixed at 1
Log-likelihood: -1255.759
```

```
Observations: 1144 Total; 785 Censored
Parameters Estimated: 2
Threshold Parameter: 0
> censorReg(formula=censor(YrsEff,EffInd)~SOrgCode,
+       data = DissEffAnal7601MDA, na.action = na.exclude,
+       distribution = "logistic",threshold = 0, control = list(e.scale = 0.0001))
Call:
censorReg(formula = censor(YrsEff, EffInd) ~ SOrgCode, data =
        DissEffAnal7601MDA, na.action = na.exclude, distribution = "logistic",
        threshold = 0, control = list(e.scale = 0.0001))

Distribution: Logistic

Coefficients:
 (Intercept)  SOrgCode
   8.735152 0.0263617

Dispersion (scale) est = 3.91082
Log-likelihood: -1516.232

Observations: 1144 Total; 785 Censored
Parameters Estimated: 3
Threshold Parameter: 0
> censorReg(formula=censor(YrsEff,EffInd)~SOrgCode,
+       data = DissEffAnal7601MDA, na.action = na.exclude,
+       distribution = "loglogistic",threshold = 0, control = list(e.scale = 0.0001))
Call:
censorReg(formula = censor(YrsEff, EffInd) ~ SOrgCode, data =
        DissEffAnal7601MDA, na.action = na.exclude, distribution =
        "loglogistic", threshold = 0, control = list(e.scale = 0.0001))

Distribution: Loglogistic

Coefficients:
 (Intercept) SOrgCode
   2.179627 0.006659

Dispersion (scale) est = 1.037086
Log-likelihood: -1248.121

Observations: 1144 Total; 785 Censored
Parameters Estimated: 3
Threshold Parameter: 0
> censorReg(formula=censor(YrsEff,EffInd)~SOrgCode,
+       data = DissEffAnal7601MDA, na.action = na.exclude,
```

```
+       distribution = "normal",threshold = 0, control = list(e.scale = 0.0001))
Call:
censorReg(formula = censor(YrsEff, EffInd) ~ SOrgCode, data =
        DissEffAnal7601MDA, na.action = na.exclude, distribution = "normal",
        threshold = 0, control = list(e.scale = 0.0001))

Distribution: Normal

Coefficients:
 (Intercept)   SOrgCode
   9.48969 0.02359979

Dispersion (scale) = 6.908893
Log-likelihood: -1497.429

Observations: 1144 Total; 785 Censored
Parameters Estimated: 3
Threshold Parameter: 0
> censorReg(formula=censor(YrsEff,EffInd)~SOrgCode,
+       data = DissEffAnal7601MDA, na.action = na.exclude,
+       distribution = "lognormal",threshold = 0, control = list(e.scale = 0.0001))
Call:
censorReg(formula = censor(YrsEff, EffInd) ~ SOrgCode, data =
        DissEffAnal7601MDA, na.action = na.exclude, distribution = "lognormal",
        threshold = 0, control = list(e.scale = 0.0001))

Distribution: Lognormal

Coefficients:
 (Intercept)    SOrgCode
  2.192898 0.006204842

Dispersion (scale) = 1.794062
Log-likelihood: -1234.035

Observations: 1144 Total; 785 Censored
Parameters Estimated: 3
Threshold Parameter: 0
> censorReg(formula=censor(YrsEff,EffInd)~SOrgCode,
+       data = DissEffAnal7601MDA, na.action = na.exclude,
+       distribution = "rayleigh",threshold = 0, control = list(e.scale = 0.0001))
Call:
censorReg(formula = censor(YrsEff, EffInd) ~ SOrgCode, data =
        DissEffAnal7601MDA, na.action = na.exclude, distribution = "rayleigh",
        threshold = 0, control = list(e.scale = 0.0001))
```

```
Distribution: Rayleigh

Coefficients:
 (Intercept)    SOrgCode
   16.99588 -0.02504915

Dispersion (scale) fixed at 0.5
Log-likelihood: -6807.072

Observations: 1144 Total; 785 Censored
Parameters Estimated: 2
Threshold Parameter: 0
> censorReg(formula=censor(YrsEff,EffInd)~SOrgCode,
+         data = DissEffAnal7601MDA, na.action = na.exclude,
+         distribution = "lograyleigh",threshold = 0, control = list(e.scale = 0.0001))
Call:
censorReg(formula = censor(YrsEff, EffInd) ~ SOrgCode, data =
        DissEffAnal7601MDA, na.action = na.exclude, distribution =
        "lograyleigh", threshold = 0, control = list(e.scale = 0.0001))

Distribution: Lograyleigh

Coefficients:
 (Intercept)    SOrgCode
   2.317936 0.002555746

Dispersion (scale) fixed at 0.5
Log-likelihood: -1610.274

Observations: 1144 Total; 785 Censored
Parameters Estimated: 2
Threshold Parameter: 0
> censorReg(formula=censor(YrsEff,EffInd)~SOrgCode,
+         data = DissEffAnal7601MDA, na.action = na.exclude,
+         distribution = "weibull",threshold = 0, control = list(e.scale = 0.0001))
Call:
censorReg(formula = censor(YrsEff, EffInd) ~ SOrgCode, data =
        DissEffAnal7601MDA, na.action = na.exclude, distribution = "weibull",
        threshold = 0, control = list(e.scale = 0.0001))

Distribution: Weibull

Coefficients:
 (Intercept)    SOrgCode
   2.610528 0.005306049
```

```
Dispersion (scale) = 1.189321
Log-likelihood: -1246.107

Observations: 1144 Total; 785 Censored
Parameters Estimated: 3
Threshold Parameter: 0
> censorReg(formula=censor(YrsEff,EffInd)~SOrgCode,
+       data = DissEffAnal7601MDA, na.action = na.exclude,
+       distribution = "extreme",threshold = 0, control = list(e.scale = 0.0001))
Call:
censorReg(formula = censor(YrsEff, EffInd) ~ SOrgCode, data =
        DissEffAnal7601MDA, na.action = na.exclude, distribution = "extreme",
        threshold = 0, control = list(e.scale = 0.0001))

Distribution: Extreme

Coefficients:
 (Intercept)   SOrgCode
   14.54639 0.03200257

Dispersion (scale) = 7.190624
Log-likelihood: -1605.884

Observations: 1144 Total; 785 Censored
Parameters Estimated: 3
Threshold Parameter: 0
> fitExp <- censorReg(formula=censor(YrsEff,EffInd)~SOrgCode,
+       data = DissEffAnal7601MDA, na.action = na.exclude,
+       distribution = "exponential",threshold = 0, control = list(e.scale = 0.0001))
> fitLogExp <- censorReg(formula=censor(YrsEff,EffInd)~SOrgCode,
+       data = DissEffAnal7601MDA, na.action = na.exclude,
+       distribution = "logexponential",threshold = 0, control = list(e.scale = 0.0001))
> fitLogExp <- censorReg(formula=censor(YrsEff,EffInd)~SOrgCode,
+       data = DissEffAnal7601MDA, na.action = na.exclude,
+       distribution = "logexponential",threshold = 0, control = list(e.scale = 0.0001))
> fitLog <- censorReg(formula=censor(YrsEff,EffInd)~SOrgCode,
+       data = DissEffAnal7601MDA, na.action = na.exclude,
+       distribution = "logistic",threshold = 0, control = list(e.scale = 0.0001))
> fitLogLog <- censorReg(formula=censor(YrsEff,EffInd)~SOrgCode,
+       data = DissEffAnal7601MDA, na.action = na.exclude,
+       distribution = "loglogistic",threshold = 0, control = list(e.scale = 0.0001))
> fitNor <- censorReg(formula=censor(YrsEff,EffInd)~SOrgCode,
+       data = DissEffAnal7601MDA, na.action = na.exclude,
+       distribution = "normal",threshold = 0, control = list(e.scale = 0.0001))
> fitLogNor <- censorReg(formula=censor(YrsEff,EffInd)~SOrgCode,
+       data = DissEffAnal7601MDA, na.action = na.exclude,
```

```
+       distribution = "lognormal",threshold = 0, control = list(e.scale = 0.0001))
> fitRay <- censorReg(formula=censor(YrsEff,EffInd)~SOrgCode,
+       data = DissEffAnal7601MDA, na.action = na.exclude,
+       distribution = "rayleigh",threshold = 0, control = list(e.scale = 0.0001))
> fitLogRay <- censorReg(formula=censor(YrsEff,EffInd)~SOrgCode,
+       data = DissEffAnal7601MDA, na.action = na.exclude,
+       distribution = "lograyleigh",threshold = 0, control = list(e.scale = 0.0001))
> fitWbl <- censorReg(formula=censor(YrsEff,EffInd)~SOrgCode,
+       data = DissEffAnal7601MDA, na.action = na.exclude,
+       distribution = "weibull",threshold = 0, control = list(e.scale = 0.0001))
> fitExt <- censorReg(formula=censor(YrsEff,EffInd)~SOrgCode,
+       data = DissEffAnal7601MDA, na.action = na.exclude,
+       distribution = "extreme",threshold = 0, control = list(e.scale = 0.0001))
>
anova(fitRay,fitExp,fitLogRay,fitExt,fitLog,fitNor,fitLogExp,fitLogLog,fitWbl,fitLogNo
r)
Likelihood Ratio Test(s)

Response: censor(YrsEff, EffInd)

   Model           Terms    N.Params LogLik     -2*LogLik  AIC
1  Rayleigh        OrgCode  3        -6807.072  13614.144  13618.144
2  Exponential     OrgCode  3        -5208.501  10417.002  10421.002
3  LogRayleigh     OrgCode  3        -1610.274   3220.548   3224.548
4  Extreme         OrgCode  3        -1605.884   3211.769   3217.769
5  Logistic        OrgCode  3        -1516.232   3032.465   3038.465
6  Normal          OrgCode  3        -1497.429   2994.858   3000.858
7  LogExponential  OrgCode  3        -1255.759   2511.518   2515.518
8  LogLogistic     OrgCode  3        -1248.121   2496.241   2502.241
9  Weibull         OrgCode  3        -1246.107   2492.214   2498.214
10 LogNormal       OrgCode  3        -1234.035   2468.070   2474.070

> fitLogNorBase <- censorReg(formula=censor(YrsEff,EffInd)~1,
+   data = DissEffAnal7601MDA, na.action = na.exclude,
+   distribution = "lognormal", threshold = 0, control = list(e.scale = 0.0001))
> summary(fitLogNorBase)
Call:
censorReg(formula = censor(YrsEff, EffInd) ~ 1, data = DissEffAnal7601MDA,
   na.action = na.exclude, distribution = "lognormal", threshold = 0,
   control = list(e.scale = 0.0001))

Distribution:  Lognormal

Standardized Residuals:
          Min   Max
Uncensored 0.196 1.964
```

Censored 0.287 1.449

Coefficients:

	Est.	Std.Err.	95% LCL	95% UCL	z-value	p-value
(Intercept)	2.27	0.0877	2.1	2.44	25.9	9.44e-148

Gaussian distribution: Dispersion (scale) = 1.817803
Observations: 1144 Total; 785 Censored
-2*Log-Likelihood: 2485

```
> summary(fitLogNor)
Call:
censorReg(formula = censor(YrsEff, EffInd) ~ SOrgCode, data =
    DissEffAnal7601MDA, na.action = na.exclude, distribution = "lognormal",
    threshold = 0, control = list(e.scale = 0.0001))
```

Distribution: Lognormal

Standardized Residuals:

	Min	Max
Uncensored	0.154	2.635
Censored	0.227	1.791

Coefficients:

	Est.	Std.Err.	95% LCL	95% UCL	z-value	p-value
(Intercept)	2.1929	0.0868	2.02287	2.36293	25.28	5.61e-141
SOrgCode	0.0062	0.0015	0.00326	0.00915	4.14	3.54e-005

Gaussian distribution: Dispersion (scale) = 1.794062
Observations: 1144 Total; 785 Censored
-2*Log-Likelihood: 2468

Correlation of Coefficients:
(Intercept)
SOrgCode -0.094

```
> fitLogNorFull <- censorReg(formula=censor(YrsEff,EffInd)~SOrgCode + YrID +
+     OrgType + OrgStruct + CohortGrp + Region + ITPat + OtherPat +
+     NPMF + NPMini + NPPC + NPWS + NSTEffcy + SMktPar + SMktIT +
TtlMktIT +
+     SGNPHMkt + SGNPWMkt + PwPrd + Density + EntryDensity + CohtDensity +
+     EntryCohtDen + RegionDensity + EntryRgnDen, data = DissEffAnal7601MDA,
+     na.action = na.exclude, distribution = "lognormal", threshold = 0,
+     control = list(e.scale = 0.0001))
> summary(fitLogNorFull)
Call:
```

```
censorReg(formula = censor(YrsEff, EffInd) ~ SOrgCode + YrID + OrgType +
        OrgStruct + CohortGrp + Region + ITPat + OtherPat + NPMF + NPMini +
        NPPC + NPWS + NSTEffcy + SMktPar + SMktIT + TtlMktIT + SGNPHMkt +
        SGNPWMkt + PwPrd + Density + EntryDensity + CohtDensity + EntryCohtDen
+
        RegionDensity + EntryRgnDen, data = DissEffAnal7601MDA, na.action =
        na.exclude, distribution = "lognormal", threshold = 0, control = list(
        e.scale = 0.0001))
```

Distribution: Lognormal

Standardized Residuals:

	Min	Max
Uncensored	0.044	5.080
Censored	0.017	4.378

Coefficients:

	Est.	Std.Err.	95% LCL	95% UCL	z-value	p-value
(Intercept)	6.9297374	2.18e+000	2.66e+000	1.12e+001	3.1804	1.47e-003
SOrgCode	0.0102960	1.89e-003	6.60e-003	1.40e-002	5.4536	4.94e-008
YrID	-0.1986868	6.21e-002	-3.20e-001	-7.70e-002	-3.1999	1.37e-003
OrgType	0.5888147	1.67e-001	2.61e-001	9.16e-001	3.5252	4.23e-004
OrgStruct	-0.2023900	1.03e-001	-4.04e-001	-7.55e-004	-1.9673	4.91e-002
CohortGrp	0.0029330	1.75e-001	-3.41e-001	3.47e-001	0.0167	9.87e-001
Region	1.1293621	1.73e-001	7.90e-001	1.47e+000	6.5136	7.34e-011
ITPat	-0.0007203	4.20e-004	-1.54e-003	1.03e-004	-1.7151	8.63e-002
OtherPat	0.0009870	6.16e-004	-2.20e-004	2.19e-003	1.6027	1.09e-001
NPMF	-0.0682502	6.13e-002	-1.88e-001	5.20e-002	-1.1125	2.66e-001
NPMini	0.0514714	3.36e-002	-1.44e-002	1.17e-001	1.5307	1.26e-001
NPPC	-0.0040336	2.23e-002	-4.78e-002	3.97e-002	-0.1808	8.57e-001
NPWS	0.0417344	7.29e-002	-1.01e-001	1.85e-001	0.5724	5.67e-001
NSTEffcy	0.0000015	8.57e-007	-1.79e-007	3.18e-006	1.7510	7.99e-002
SMktPar	-0.9794282	6.37e-001	-2.23e+000	2.69e-001	-1.5378	1.24e-001
SMktIT	3.7281088	1.12e+000	1.52e+000	5.93e+000	3.3164	9.12e-004
TtlMktIT	0.4963571	3.12e-001	-1.15e-001	1.11e+000	1.5906	1.12e-001
SGNPHMkt	-0.0002927	6.28e-004	-1.52e-003	9.37e-004	-0.4664	6.41e-001
SGNPWMkt	-0.0003604	5.19e-004	-1.38e-003	6.57e-004	-0.6944	4.87e-001
PwPrd	-0.4201073	2.11e-001	-8.35e-001	-5.67e-003	-1.9868	4.69e-002
Density	-0.0166003	1.21e-002	-4.04e-002	7.20e-003	-1.3672	1.72e-001
EntryDensity	-0.0136725	9.14e-003	-3.16e-002	4.24e-003	-1.4957	1.35e-001
CohtDensity	0.0259247	1.97e-002	-1.26e-002	6.45e-002	1.3187	1.87e-001
EntryCohtDen	-0.0260	0.0118	-0.04914	-0.00292	-2.21	2.73e-002
RegionDensity	0.0164	0.0095	-0.00227	0.03498	1.72	8.52e-002
EntryRgnDen	0.0759	0.0138	0.04878	0.10292	5.49	3.97e-008

Gaussian distribution: Dispersion (scale) = 1.419212

Observations: 1144 Total; 785 Censored
-2*Log-Likelihood: 2131

Correlation of Coefficients:

	(Intercept)	SOrgCode	YrID	OrgType	OrgStruct	CohortGrp	Region
SOrgCode	0.079						
YrID	-0.938	-0.050					
OrgType	-0.105	0.008	-0.029				
OrgStruct	-0.227	-0.160	0.004	0.504			
CohortGrp	-0.059	0.057	-0.023	-0.063	-0.053		
Region	-0.026	-0.141	-0.071	0.008	-0.156	0.039	
ITPat	0.144	0.168	-0.127	0.052	-0.039	-0.097	-0.136
OtherPat	0.074	-0.065	-0.085	0.023	-0.019	0.016	-0.018
NPMF	-0.023	-0.086	0.012	-0.161	0.013	0.072	-0.078
NPMini	-0.080	-0.153	0.052	-0.104	-0.049	0.043	0.213
NPPC	0.066	-0.129	-0.041	-0.041	-0.099	-0.052	-0.008
NPWS	-0.028	-0.094	0.034	0.031	0.040	-0.006	0.011
NSTEffcy	-0.162	-0.105	0.105	-0.017	0.083	0.062	0.141
SMktPar	-0.067	-0.088	0.116	0.054	-0.078	-0.048	-0.099
SMktIT	-0.011	-0.167	-0.049	0.024	0.091	0.104	0.182
TtlMktIT	0.803	0.053	-0.903	-0.012	0.008	-0.056	0.019
SGNPHMkt	0.057	0.031	-0.070	0.034	0.051	0.018	0.143
SGNPWMkt	-0.091	-0.068	0.143	-0.033	-0.045	-0.028	-0.105
PwPrd	0.538	-0.009	-0.511	0.018	0.017	-0.033	0.034
Density	-0.688	-0.017	0.626	0.073	0.024	0.347	-0.107
EntryDensity	0.063	0.141	0.033	0.063	0.047	-0.536	-0.471
CohtDensity	0.059	0.056	0.025	-0.127	-0.044	-0.790	-0.099
EntryCohtDen	-0.080	0.015	0.053	0.021	-0.164	0.442	0.160

	ITPat	OtherPat	NPMF	NPMini	NPPC	NPWS	NSTEffcy	SmktPar
SOrgCode								
YrID								
OrgType								
OrgStruct								
CohortGrp								
Region								
ITPat								
OtherPat	-0.390							
NPMF	0.055	-0.053						
NPMini	-0.202	0.080	0.047					
NPPC	0.064	-0.096	0.023	0.053				
NPWS	0.086	-0.053	-0.077	-0.254	0.106			
NSTEffcy	-0.057	0.087	-0.075	0.076	-0.306	0.062		
SMktPar	0.194	-0.770	-0.021	-0.028	0.100	0.060	-0.045	

SMktIT	-0.668	0.631	-0.087	-0.043	-0.120	-0.131	0.003	-0.654
TtlMktIT	0.106	0.066	0.002	-0.068	0.078	-0.036	-0.176	-0.107
SGNPHMkt	-0.046	0.078	-0.036	0.052	0.021	-0.017	-0.023	-0.058
SGNPWMkt	0.028	-0.101	0.055	-0.022	-0.017	0.000	0.060	0.085
PwPrd	0.077	0.066	0.070	0.000	-0.021	-0.073	-0.024	-0.090
Density	0.020	0.010	-0.077	0.017	-0.077	0.008	0.096	0.044
EntryDensity	0.107	-0.057	0.087	0.010	0.015	-0.046	-0.243	0.085
CohtDensity	0.029	0.027	0.083	-0.076	0.029	-0.065	-0.065	-0.035
EntryCohtDen	-0.015	-0.082	-0.144	-0.004	0.201	0.173	0.214	0.035

	SMktIT	TtlMktIT	SGNPHMkt	SGNPWMkt	PwPrd	Density	EntryDensity
SOrgCode							
YrID							
OrgType							
OrgStruct							
CohortGrp							
Region							
ITPat							
OtherPat							
NPMF							
NPMini							
NPPC							
NPWS							
NSTEffcy							
SMktPar							
SMktIT							
TtlMktIT	0.033						
SGNPHMkt	0.080	0.063					
SGNPWMkt	-0.093	-0.263	-0.740				
PwPrd	0.025	0.192	0.090	0.074			
Density	-0.013	-0.608	-0.075	0.053	-0.262		
EntryDensity	-0.136	-0.006	-0.049	0.091	0.017	-0.230	
CohtDensity	-0.016	0.085	0.002	-0.004	0.051	-0.433	0.396
EntryCohtDen	-0.005	-0.112	-0.023	0.045	-0.064	0.191	-0.388

	CohtDensity	EntryCohtDen	RegionDensity
SOrgCode			
YrID			
OrgType			
OrgStruct			

```
CohortGrp
Region
ITPat
OtherPat
NPMF
NPMini
NPPC
NPWS
NSTEffcy
SMktPar
SMktIT
TtlMktIT
SGNPHMkt
SGNPWMkt
PwPrd
Density
EntryDensity
CohtDensity
EntryCohtDen   -0.498

               (Intercept) SOrgCode YrID   OrgType  OrgStruct  CohortGrp  Region
RegionDensity  -0.085      0.052    0.000  0.099    0.047      -0.005     0.416
EntryRgnDen    -0.015      -0.126   -0.078 -0.029   0.086      -0.007     0.557

               ITPat  OtherPat  NPMF    NPMini  NPPC    NPWS    NSTEffcy
               SMktPar
RegionDensity  -0.084 -0.068    -0.047  0.071   0.006   0.052   0.184
               0.024
EntryRgnDen    -0.069 0.068     0.030   0.082   -0.138  -0.092  0.019     -
0.106

               SMktIT   TtlMktIT  SGNPHMkt SGNPWMkt  PwPrd Density
EntryDensity
RegionDensity  -0.015   0.009     -0.005   -0.001    -0.019 -0.277   0.084
EntryRgnDen    0.164    0.052     0.011    -0.046    0.032  0.076    -
0.610

               CohtDensity  EntryCohtDen  RegionDensity
RegionDensity  -0.101       0.164
EntryRgnDen    0.005        -0.227        -0.215

> fitLogNorSig1 <- censorReg(formula=censor(YrsEff,EffInd)~SOrgCode + YrID +
+      OrgType + OrgStruct + Region + ITPat + NSTEffcy + SMktIT + PwPrd +
+      EntryCohtDen + RegionDensity + EntryRgnDen, data = DissEffAnal7601MDA,
+      na.action = na.exclude, distribution = "lognormal", threshold = 0,
+      control = list(e.scale = 0.0001))
```

```
> summary(fitLogNorSig1)
Call:
censorReg(formula = censor(YrsEff, EffInd) ~ SOrgCode + YrID + OrgType +
        OrgStruct + Region + ITPat + NSTEffcy + SMktIT + PwPrd + EntryCohtDen +
        RegionDensity + EntryRgnDen, data = DissEffAnal7601MDA, na.action =
        na.exclude, distribution = "lognormal", threshold = 0, control = list(
        e.scale = 0.0001))
```

Distribution: Lognormal

Standardized Residuals:

	Min	Max
Uncensored	0.044	5.111
Censored	0.016	4.398

Coefficients:

	Est.	Std.Err.	95% LCL	95% UCL	z-value	p-value
(Intercept)	4.83e+000	1.09e+000	2.68e+000	6.97e+000	4.408	1.04e-005
SOrgCode	1.06e-002	1.71e-003	7.30e-003	1.40e-002	6.240	4.38e-010
YrID	-1.26e-001	2.26e-002	-1.70e-001	-8.13e-002	-5.550	2.86e-008
OrgType	7.25e-001	1.58e-001	4.15e-001	1.03e+000	4.582	4.60e-006
OrgStruct	-1.60e-001	1.01e-001	-3.58e-001	3.72e-002	-1.591	1.12e-001
Region	9.73e-001	1.30e-001	7.19e-001	1.23e+000	7.511	5.87e-014
ITPat	-3.14e-004	3.66e-004	-1.03e-003	4.02e-004	-0.859	3.90e-001
NSTEffcy	1.03e-006	7.72e-007	-4.84e-007	2.54e-006	1.333	1.83e-001
SMktIT	2.56e+000	8.02e-001	9.83e-001	4.13e+000	3.186	1.44e-003
PwPrd	-4.27e-001	1.98e-001	-8.15e-001	-3.90e-002	-2.157	3.10e-002
EntryCohtDen	-2.44e-002	9.44e-003	-4.29e-002	-5.91e-003	-2.587	9.69e-003
RegionDensity	1.78e-002	8.29e-003	1.56e-003	3.40e-002	2.148	3.17e-002
EntryRgnDen	6.15e-002	8.90e-003	4.41e-002	7.89e-002	6.912	4.77e-012

Gaussian distribution: Dispersion (scale) = 1.440996
Observations: 1144 Total; 785 Censored
-2*Log-Likelihood: 2151

Correlation of Coefficients:

	(Intercept)	SOrgCode	YrID	OrgType	OrgStruct	Region	ITPat
SOrgCode	0.127						
YrID	-0.824	-0.068					
OrgType	-0.249	0.031	-0.069				
OrgStruct	-0.469	-0.218	0.045	0.513			
Region	-0.146	-0.008	-0.048	0.047	-0.260		
ITPat	0.261	0.122	-0.216	0.042	-0.125	-0.123	
NSTEffcy	-0.064	-0.049	-0.083	-0.016	0.083	-0.050	0.070
SMktIT	-0.156	-0.355	0.036	0.051	0.114	0.248	-0.741
PwPrd	0.668	-0.003	-0.839	0.039	0.011	-0.021	0.119

EntryCohtDen	-0.031	0.117	0.039	0.002	-0.196	-0.018	0.001
RegionDensity	-0.484	0.096	0.242	0.088	0.034	0.490	-0.064
EntryRgnDen	0.064	0.055	-0.191	-0.001	0.114	0.320	-0.042

	NSTEffcy	SMktIT	PwPrd	EntryCohtDen	RegionDensity
SOrgCode					
YrID					
OrgType					
OrgStruct					
Region					
ITPat					
NSTEffcy					
SMktIT	-0.109				
PwPrd	-0.015	-0.052			
EntryCohtDen	0.255	-0.003	-0.032		
RegionDensity	0.222	0.005	-0.081	0.123	
EntryRgnDen	-0.358	0.181	0.025	-0.607	-0.218

```
> fitLogNorSig2 <- censorReg(formula=censor(YrsEff,EffInd)~SOrgCode + YrID +
+       OrgType + Region + SMktIT + PwPrd + EntryCohtDen + RegionDensity +
+       EntryRgnDen, data = DissEffAnal7601MDA, na.action = na.exclude,
+       distribution = "lognormal", threshold = 0, control = list(e.scale = 0.0001))
> summary(fitLogNorSig2)
Call:
censorReg(formula = censor(YrsEff, EffInd) ~ SOrgCode + YrID + OrgType +
        Region + SMktIT + PwPrd + EntryCohtDen + RegionDensity + EntryRgnDen,
        data = DissEffAnal7601MDA, na.action = na.exclude, distribution =
        "lognormal", threshold = 0, control = list(e.scale = 0.0001))
```

Distribution: Lognormal

Standardized Residuals:

	Min	Max
Uncensored	0.045	4.149
Censored	0.022	4.243

Coefficients:

	Est.	Std.Err.	95% LCL	95% UCL	z-value	p-value
(Intercept)	4.3582	0.94364	2.50873	6.20772	4.62	3.86e-006
SOrgCode	0.0104	0.00166	0.00711	0.01361	6.25	4.14e-010
YrID	-0.1277	0.02214	-0.17106	-0.08427	-5.77	8.14e-009
OrgType	0.8916	0.13479	0.62741	1.15579	6.61	3.73e-011
Region	0.9053	0.12368	0.66288	1.14770	7.32	2.49e-013
SMktIT	2.1666	0.53612	1.11586	3.21741	4.04	5.31e-005
PwPrd	-0.3894	0.19707	-0.77569	-0.00318	-1.98	4.81e-002

EntryCohtDen	-0.0318	0.00892	-0.04927	-0.01433	-3.57	3.61e-004
RegionDensity	0.0147	0.00808	-0.00111	0.03055	1.82	6.84e-002
EntryRgnDen	0.0684	0.00823	0.05226	0.08453	8.31	9.84e-017

Gaussian distribution: Dispersion (scale) = 1.447182
Observations: 1144 Total; 785 Censored
-2*Log-Likelihood: 2157

Correlation of Coefficients:

	(Intercept)	SOrgCode	YrID	OrgType	Region	SMktIT	PwPrd
SOrgCode	0.006						
YrID	-0.913	-0.043					
OrgType	-0.043	0.155	-0.090				
Region	-0.288	-0.054	-0.076	0.240			
SMktIT	0.079	-0.408	-0.196	0.117	0.251		
PwPrd	0.759	-0.013	-0.844	0.024	0.001	0.051	
EntryCohtDen	-0.131	0.097	0.068	0.153	-0.080	0.028	-0.021
RegionDensity	-0.536	0.123	0.259	0.109	0.533	-0.048	-0.069
EntryRgnDen	0.136	0.074	-0.254	-0.107	0.388	0.203	0.018

	EntryCohtDen	RegionDensity
SOrgCode		
YrID		
OrgType		
Region		
SMktIT		
PwPrd		
EntryCohtDen		
RegionDensity	0.070	
EntryRgnDen	-0.559	-0.156

```
> fitLogNorSig3 <- censorReg(formula=censor(YrsEff,EffInd)~SOrgCode + YrID +
+       OrgType + Region + SMktIT + PwPrd + EntryCohtDen + EntryRgnDen,
+       data = DissEffAnal7601MDA, na.action = na.exclude,
+       distribution = "lognormal", threshold = 0, control = list(e.scale = 0.0001))
> summary(fitLogNorSig3)
Call:
censorReg(formula = censor(YrsEff, EffInd) ~ SOrgCode + YrID + OrgType +
        Region + SMktIT + PwPrd + EntryCohtDen + EntryRgnDen, data =
        DissEffAnal7601MDA, na.action = na.exclude, distribution = "lognormal",
        threshold = 0, control = list(e.scale = 0.0001))
```

Distribution: Lognormal

Standardized Residuals:

Min Max

Uncensored	0.04	3.99
Censored	0.02	3.86

Coefficients:

	Est.	Std.Err.	95% LCL	95% UCL	z-value	p-value
(Intercept)	5.298	0.79722	3.73526	6.8603	6.65	3.03e-011
SOrgCode	0.010	0.00165	0.00679	0.0133	6.08	1.19e-009
YrID	-0.139	0.02142	-0.18055	-0.0966	-6.47	9.74e-011
OrgType	0.867	0.13417	0.60439	1.1303	6.46	1.02e-010
Region	0.788	0.10472	0.58254	0.9930	7.52	5.36e-014
SMktIT	2.221	0.53634	1.16938	3.2718	4.14	3.47e-005
PwPrd	-0.365	0.19694	-0.75100	0.0210	-1.85	6.38e-002
EntryCohtDen	-0.033	0.00889	-0.05045	-0.0156	-3.71	2.06e-004
EntryRgnDen	0.071	0.00814	0.05499	0.0869	8.71	2.98e-018

Gaussian distribution: Dispersion (scale) = 1.449939
Observations: 1144 Total; 785 Censored
-2*Log-Likelihood: 2160

Correlation of Coefficients:

	(Intercept)	SOrgCode	YrID	OrgType	Region	SMktIT	PwPrd
SOrgCode	0.084						
YrID	-0.950	-0.077					
OrgType	0.018	0.144	-0.123				
Region	0.000	-0.140	-0.264	0.218			
SMktIT	0.062	-0.405	-0.189	0.123	0.326		
PwPrd	0.856	-0.005	-0.856	0.031	0.044	0.046	
EntryCohtDen	-0.110	0.090	0.052	0.145	-0.141	0.030	-0.015
EntryRgnDen	0.063	0.095	-0.223	-0.091	0.564	0.200	0.007

Correlation of Coefficients:

	EntryCohtDen
SOrgCode	
YrID	
OrgType	
Region	
SMktIT	
PwPrd	
EntryCohtDen	
EntryRgnDen	-0.558

```
> fitLogNorSig4 <- censorReg(formula=censor(YrsEff,EffInd)~SOrgCode + YrID +
+       OrgType + Region + SMktIT + EntryCohtDen + EntryRgnDen,
+       data = DissEffAnal7601MDA, na.action = na.exclude,
+       distribution = "lognormal", threshold = 0, control = list(e.scale = 0.0001))
```

```
> summary(fitLogNorSig4)
Call:
censorReg(formula = censor(YrsEff, EffInd) ~ SOrgCode + YrID + OrgType +
        Region + SMktIT + EntryCohtDen + EntryRgnDen, data =
        DissEffAnal7601MDA, na.action = na.exclude, distribution = "lognormal",
        threshold = 0, control = list(e.scale = 0.0001))

Distribution:  Lognormal

Standardized Residuals:
             Min    Max
Uncensored   0.045  4.173
Censored     0.021  3.938

Coefficients:
              Est.     Std.Err.  95% LCL   95% UCL   z-value  p-value
(Intercept)   6.5819   0.41329   5.77188   7.3919    15.93    4.20e-057
SOrgCode      0.0100   0.00166   0.00679   0.0133    6.06     1.36e-009
YrID          -0.1731  0.01112   -0.19487  -0.1513   -15.56   1.27e-054
OrgType       0.8775   0.13488   0.61314   1.1419    6.51     7.74e-011
Region        0.7992   0.10528   0.59289   1.0056    7.59     3.16e-014
SMktIT        2.2726   0.53858   1.21697   3.3282    4.22     2.45e-005
EntryCohtDen  -0.0334  0.00895   -0.05091  -0.0158   -3.73    1.93e-004
EntryRgnDen   0.0713   0.00819   0.05527   0.0874    8.71     3.15e-018

Gaussian distribution: Dispersion (scale) = 1.458197
Observations: 1144 Total; 785 Censored
-2*Log-Likelihood: 2164

Correlation of Coefficients:
              (Intercept)  SOrgCode YrID   OrgType  Region  SMktIT
              EntryCohtDen
SOrgCode      0.169
YrID          -0.811       -0.156
OrgType       -0.017       0.145    -0.186
Region        -0.074       -0.140   -0.438 0.216
SMktIT        0.044        -0.405   -0.290 0.121    0.324
EntryCohtDen  -0.188       0.089    0.076  0.145    -0.141  0.031
EntryRgnDen   0.110        0.096    -0.420 -0.091   0.564   0.198    -0.558

> anova(fitLogNor,fitLogNorSig4,test = "Chisq")
Likelihood Ratio Test(s)

Response: censor(YrsEff, EffInd)

   Terms                          N.Params  -2*LogLik   Test Df   LRT        Pr(Chi)
```

1	SOrgCode	3	2468.070		
2	SOrgCode + YrID + 0.0000000 OrgType + Region + SMktIT + EntryCohtDen + EntryRgnDen	9	2163.827	6	304.2429

APPENDIX F

S Codes for Complete Data Effectiveness Analysis for the Period 1976 to 2001

S Codes for Complete Data Effectiveness Analysis for the Period 1976 to 2001

```
S-PLUS : Copyright (c) 1988, 2002 Insightful Corp.
S : Copyright Lucent Technologies, Inc.
Professional Edition Version 6.1.3 Release 3 for Micros
oft Windows : 2002
Working data will be in C:\Program Files\Insightful\spl
us61\users\Cotter
> censorReg(formula=censor(YrsEff,EffInd)~SOrgCode,
+       data = DissEffAnal7601CmpA, na.action = na.exclude,
+       distribution = "exponential", threshold = 0, control = list(e.scale = 0.0001))
Call:
censorReg(formula = censor(YrsEff, EffInd) ~ SOrgCode, data =
        DissEffAnal7601CmpA, na.action = na.exclude, distribution =
        "exponential", threshold = 0, control = list(e.scale = 0.0001))

Distribution: Exponential

Coefficients:
Coefficients:
 (Intercept)   SOrgCode
   15.12325 -0.01948452

Dispersion (scale) fixed at 1
Log-likelihood: -3471.615

Observations: 873 Total; 633 Censored
Parameters Estimated: 2
Threshold Parameter: 0
> censorReg(formula=censor(YrsEff,EffInd)~SOrgCode,
+       data = DissEffAnal7601CmpA, na.action = na.exclude,
+       distribution = "logexponential", threshold = 0, control = list(e.scale = 0.0001))
Call:
censorReg(formula = censor(YrsEff, EffInd) ~ SOrgCode, data =
        DissEffAnal7601CmpA, na.action = na.exclude, distribution =
        "logexponential", threshold = 0, control = list(e.scale = 0.0001))

Distribution: Logexponential

Coefficients:
 (Intercept)   SOrgCode
   2.631251 0.004643677
```

```
Dispersion (scale) fixed at 1
Log-likelihood: -880.4253

Observations: 873 Total; 633 Censored
Parameters Estimated: 2
Threshold Parameter: 0
> censorReg(formula=censor(YrsEff,EffInd)~SOrgCode,
+       data = DissEffAnal7601CmpA, na.action = na.exclude,
+       distribution = "logistic", threshold = 0, control = list(e.scale = 0.0001))
Call:
censorReg(formula = censor(YrsEff, EffInd) ~ SOrgCode, data =
        DissEffAnal7601CmpA, na.action = na.exclude, distribution = "logistic",
        threshold = 0, control = list(e.scale = 0.0001))

Distribution: Logistic

Coefficients:
 (Intercept)   SOrgCode
    9.81096 0.02577699

Dispersion (scale) est = 4.092867
Log-likelihood: -1047.705

Observations: 873 Total; 633 Censored
Parameters Estimated: 3
Threshold Parameter: 0
> censorReg(formula=censor(YrsEff,EffInd)~SOrgCode,
+       data = DissEffAnal7601CmpA, na.action = na.exclude,
+       distribution = "loglogistic", threshold = 0, control = list(e.scale = 0.0001))
Call:
censorReg(formula = censor(YrsEff, EffInd) ~ SOrgCode, data =
        DissEffAnal7601CmpA, na.action = na.exclude, distribution =
        "loglogistic", threshold = 0, control = list(e.scale = 0.0001))

Distribution: Loglogistic

Coefficients:
 (Intercept)    SOrgCode
   2.408101 0.005739898

Dispersion (scale) est = 1.037163
Log-likelihood: -880.0303

Observations: 873 Total; 633 Censored
Parameters Estimated: 3
Threshold Parameter: 0
```

```
> censorReg(formula=censor(YrsEff,EffInd)~SOrgCode,
+       data = DissEffAnal7601CmpA, na.action = na.exclude,
+       distribution = "normal", threshold = 0, control = list(e.scale = 0.0001))
Call:
censorReg(formula = censor(YrsEff, EffInd) ~ SOrgCode, data =
        DissEffAnal7601CmpA, na.action = na.exclude, distribution = "normal",
        threshold = 0, control = list(e.scale = 0.0001))

Distribution: Normal

Coefficients:
 (Intercept)  SOrgCode
   10.42751 0.02385895

Dispersion (scale) = 7.153145
Log-likelihood: -1031.62

Observations: 873 Total; 633 Censored
Parameters Estimated: 3
Threshold Parameter: 0
> censorReg(formula=censor(YrsEff,EffInd)~SOrgCode,
+       data = DissEffAnal7601CmpA, na.action = na.exclude,
+       distribution = "lognormal", threshold = 0, control = list(e.scale = 0.0001))
Call:
censorReg(formula = censor(YrsEff, EffInd) ~ SOrgCode, data =
        DissEffAnal7601CmpA, na.action = na.exclude, distribution =
        "lognormal", threshold = 0, control = list(e.scale = 0.0001))

Distribution: Lognormal

Coefficients:
 (Intercept)  SOrgCode
    2.44592 0.005481084

Dispersion (scale) = 1.840745
Log-likelihood: -872.4615

Observations: 873 Total; 633 Censored
Parameters Estimated: 3
Threshold Parameter: 0
> censorReg(formula=censor(YrsEff,EffInd)~SOrgCode,
+       data = DissEffAnal7601CmpA, na.action = na.exclude,
+       distribution = "rayleigh", threshold = 0, control = list(e.scale = 0.0001))
Call:
censorReg(formula = censor(YrsEff, EffInd) ~ SOrgCode, data =
        DissEffAnal7601CmpA, na.action = na.exclude, distribution = "rayleigh",
```

```
        threshold = 0, control = list(e.scale = 0.0001))

Distribution: Rayleigh

Coefficients:
 (Intercept)    SOrgCode
   17.03634 -0.02499002

Dispersion (scale) fixed at 0.5
Log-likelihood: -4581.471

Observations: 873 Total; 633 Censored
Parameters Estimated: 2
Threshold Parameter: 0
> censorReg(formula=censor(YrsEff,EffInd)~SOrgCode,
+       data = DissEffAnal7601CmpA, na.action = na.exclude,
+       distribution = "lograyleigh", threshold = 0, control = list(e.scale = 0.0001))
Call:
censorReg(formula = censor(YrsEff, EffInd) ~ SOrgCode, data =
        DissEffAnal7601CmpA, na.action = na.exclude, distribution =
        "lograyleigh", threshold = 0, control = list(e.scale = 0.0001))

Distribution: Lograyleigh

Coefficients:
 (Intercept)    SOrgCode
     2.3771 0.003480407

Dispersion (scale) fixed at 0.5
Log-likelihood: -1095.003

Observations: 873 Total; 633 Censored
Parameters Estimated: 2
Threshold Parameter: 0
> censorReg(formula=censor(YrsEff,EffInd)~SOrgCode,
+       data = DissEffAnal7601CmpA, na.action = na.exclude,
+       distribution = "weibull", threshold = 0, control = list(e.scale = 0.0001))
Call:
censorReg(formula = censor(YrsEff, EffInd) ~ SOrgCode, data =
        DissEffAnal7601CmpA, na.action = na.exclude, distribution = "weibull",
        threshold = 0, control = list(e.scale = 0.0001))

Distribution: Weibull

Coefficients:
 (Intercept)    SOrgCode
```

```
  2.767788 0.005028456

Dispersion (scale) = 1.153831
Log-likelihood: -876.1603

Observations: 873 Total; 633 Censored
Parameters Estimated: 3
Threshold Parameter: 0
> censorReg(formula=censor(YrsEff,EffInd)~SOrgCode,
+       data = DissEffAnal7601CmpA, na.action = na.exclude,
+       distribution = "extreme", threshold = 0, control = list(e.scale = 0.0001))
Call:
censorReg(formula = censor(YrsEff, EffInd) ~ SOrgCode, data =
        DissEffAnal7601CmpA, na.action = na.exclude, distribution = "extreme",
        threshold = 0, control = list(e.scale = 0.0001))

Distribution: Extreme

Coefficients:
 (Intercept)   SOrgCode
  15.06366 0.04524017

Dispersion (scale) = 6.857493
Log-likelihood: -1094.679

Observations: 873 Total; 633 Censored
Parameters Estimated: 3
Threshold Parameter: 0
> fitExp <- censorReg(formula=censor(YrsEff,EffInd)~SOrgCode,
+       data = DissEffAnal7601CmpA, na.action = na.exclude,
+       distribution = "exponential", threshold = 0, control = list(e.scale = 0.0001))
> fitLogExp <- censorReg(formula=censor(YrsEff,EffInd)~SOrgCode,
+       data = DissEffAnal7601CmpA, na.action = na.exclude,
+       distribution = "logexponential", threshold = 0, control = list(e.scale = 0.0001))
> fitLog <- censorReg(formula=censor(YrsEff,EffInd)~SOrgCode,
+       data = DissEffAnal7601CmpA, na.action = na.exclude,
+       distribution = "logistic", threshold = 0, control = list(e.scale = 0.0001))
> fitLogLog <- censorReg(formula=censor(YrsEff,EffInd)~SOrgCode,
+       data = DissEffAnal7601CmpA, na.action = na.exclude,
+       distribution = "loglogistic", threshold = 0, control = list(e.scale = 0.0001))
> fitNor <- censorReg(formula=censor(YrsEff,EffInd)~SOrgCode,
+       data = DissEffAnal7601CmpA, na.action = na.exclude,
+       distribution = "normal", threshold = 0, control = list(e.scale = 0.0001))
> fitLogNor <- censorReg(formula=censor(YrsEff,EffInd)~SOrgCode,
+       data = DissEffAnal7601CmpA, na.action = na.exclude,
+       distribution = "lognormal", threshold = 0, control = list(e.scale = 0.0001))
```

```
> fitRay <- censorReg(formula=censor(YrsEff,EffInd)~SOrgCode,
+       data = DissEffAnal7601CmpA, na.action = na.exclude,
+       distribution = "rayleigh", threshold = 0, control = list(e.scale = 0.0001))
> fitLogRay <- censorReg(formula=censor(YrsEff,EffInd)~SOrgCode,
+       data = DissEffAnal7601CmpA, na.action = na.exclude,
+       distribution = "lograyleigh", threshold = 0, control = list(e.scale = 0.0001))
> fitWbl <- censorReg(formula=censor(YrsEff,EffInd)~SOrgCode,
+       data = DissEffAnal7601CmpA, na.action = na.exclude,
+       distribution = "weibull", threshold = 0, control = list(e.scale = 0.0001))
> fitExt <- censorReg(formula=censor(YrsEff,EffInd)~SOrgCode,
+       data = DissEffAnal7601CmpA, na.action = na.exclude,
+       distribution = "extreme", threshold = 0, control = list(e.scale = 0.0001))
> anova(fitLogRay,fitExt,fitLog,fitNor,fitLogExp,fitLogLog,fitWbl,fitLogNor)
Likelihood Ratio Test(s)

Response: censor(YrsEff, EffInd)
```

	Model	Terms	N.Params	LogLik	-2*LogLik	AIC
1	Rayleigh	OrgCode	3	-4581.471	9162.942	9166.942
2	Exponential	OrgCode	3	-3471.615	6943.230	6947.230
3	Extreme	OrgCode	3	-1094.679	2189.358	2195.358
4	LogRayleigh	OrgCode	3	-1095.003	2190.006	2194.006
5	Logistic	OrgCode	3	-1047.705	2095.410	2101.410
6	Normal	OrgCode	3	-1031.620	2063.240	2069.240
7	LogLogistic	OrgCode	3	-880.030	1760.060	1766.060
8	LogExponential	OrgCode	3	-880.425	1760.850	1764.850
9	Weibull	OrgCode	3	-876.160	1752.320	1758.320
10	LogNormal	OrgCode	3	-872.462	1744.924	1750.924

```
> summary(fitLogNor)
Call:
censorReg(formula = censor(YrsEff, EffInd) ~ SOrgCode, data =
    DissEffAnal7601CmpA, na.action = na.exclude, distribution =
    "lognormal", threshold = 0, control = list(e.scale = 0.0001))

Distribution:  Lognormal

Standardized Residuals:
```

	Min	Max
Uncensored	0.145	1.692
Censored	0.212	1.508

Coefficients:

	Est.	Std.Err.	95% LCL	95% UCL	z-value	p-value
(Intercept)	2.44592	0.11165	2.22710	2.66474	21.91	2.20e-106
SOrgCode	0.00548	0.00178	0.00199	0.00898	3.07	2.11e-003

```
Gaussian distribution: Dispersion (scale) = 1.840745
Observations: 873 Total; 633 Censored
-2*Log-Likelihood: 1745

Correlation of Coefficients:
         (Intercept)
SOrgCode -0.116

> fitLogNorFull <- censorReg(formula=censor(YrsEff,EffInd)~SOrgCode + YrID +
+       OrgType + OrgStruct + CohortGrp + Region + ITPat + OtherPat +
+       NPMF + NPMini + NPPC + NPWS + NSTEffcy + SMktPar + SMktIT +
TtlMktIT +
+       SGNPHMkt + SGNPWMkt + PwPrd + Density + EntryDensity + CohtDensity +
+       EntryCohtDen + RegionDensity + EntryRgnDen, data = DissEffAnal7601CmpA,
+       na.action = na.exclude, distribution = "lognormal", threshold = 0,
+       control = list(e.scale = 0.0001))
> summary(fitLogNorFull)
Call:
censorReg(formula = censor(YrsEff, EffInd) ~ SOrgCode + YrID + OrgType +
        OrgStruct + CohortGrp + Region + ITPat + OtherPat + NPMF + NPMini +
        NPPC + NPWS + NSTEffcy + SMktPar + SMktIT + TtlMktIT + SGNPHMkt +
        SGNPWMkt + PwPrd + Density + EntryDensity + CohtDensity + EntryCohtDen
+
        RegionDensity + EntryRgnDen, data = DissEffAnal7601CmpA, na.action =
        na.exclude, distribution = "lognormal", threshold = 0, control = list(
        e.scale = 0.0001))

Distribution:  Lognormal

Standardized Residuals:
             Min    Max
Uncensored   0.029  4.935
Censored     0.014  3.403

Coefficients:
```

	Est.	Std.Err.	95% LCL	95% UCL	z-value	p-value
(Intercept)	9.16e+000	2.79e+000	3.69e+000	1.46e+001	3.2837	1.02e-003
SOrgCode	1.31e-002	2.36e-003	8.48e-003	1.77e-002	5.5536	2.80e-008
YrID	-2.07e-001	7.83e-002	-3.60e-001	-5.36e-002	-2.6447	8.18e-003
OrgType	6.38e-001	2.15e-001	2.17e-001	1.06e+000	2.9687	2.99e-003
OrgStruct	-2.33e-001	1.34e-001	-4.95e-001	2.87e-002	-1.7454	8.09e-002
CohortGrp	-2.69e-002	3.48e-001	-7.08e-001	6.54e-001	-0.0774	9.38e-001
Region	2.77e-001	8.35e-002	1.14e-001	4.41e-001	3.3247	8.85e-004
ITPat	-6.45e-004	4.54e-004	-1.53e-003	2.45e-004	-1.4207	1.55e-001
OtherPat	1.43e-003	8.03e-004	-1.48e-004	3.00e-003	1.7763	7.57e-002

NPMF	-6.07e-002	7.05e-002	-1.99e-001	7.74e-002	-0.8616	3.89e-001
NPMini	3.23e-002	3.73e-002	-4.08e-002	1.05e-001	0.8669	3.86e-001
NPPC	-1.76e-002	2.31e-002	-6.29e-002	2.78e-002	-0.7605	4.47e-001
NPWS	2.24e-002	7.67e-002	-1.28e-001	1.73e-001	0.2922	7.70e-001
NSTEffcy	1.06e-006	1.14e-006	-1.16e-006	3.29e-006	0.9373	3.49e-001
SMktPar	-8.21e-001	7.83e-001	-2.36e+000	7.14e-001	-1.0485	2.94e-001
SMktIT	3.52e+000	1.24e+000	1.09e+000	5.95e+000	2.8430	4.47e-003
TtlMktIT	3.95e-001	3.82e-001	-3.55e-001	1.14e+000	1.0330	3.02e-001
SGNPHMkt	1.32e-004	7.26e-004	-1.29e-003	1.55e-003	0.1826	8.55e-001
SGNPWMkt	-9.49e-004	6.20e-004	-2.16e-003	2.65e-004	-1.5317	1.26e-001
PwPrd	-5.05e-001	2.58e-001	-1.01e+000	1.27e-003	-1.9550	5.06e-002
Density	2.92e-003	1.44e-002	-2.53e-002	3.12e-002	0.2023	8.40e-001
EntryDensity	-1.74e-002	1.89e-002	-5.45e-002	1.97e-002	-0.9210	3.57e-001
CohtDensity	4.34e-002	1.79e-002	8.34e-003	7.84e-002	2.4263	1.53e-002
EntryCohtDen	-0.0261	0.0217	-0.0687	0.0165	-1.20	2.29e-001
RegionDensity	-0.0405	0.0113	-0.0627	-0.0184	-3.59	3.35e-004
EntryRgnDen	0.0892	0.0187	0.0525	0.1258	4.77	1.86e-006

Gaussian distribution: Dispersion (scale) = 1.414303
Observations: 873 Total; 633 Censored
-2*Log-Likelihood: 1476

Correlation of Coefficients:

	(Intercept)	SOrgCode	YrID	OrgType	OrgStruct	CohortGrp	Region
SOrgCode	0.115						
YrID	-0.941	-0.095					
OrgType	-0.123	-0.050	-0.004				
OrgStruct	-0.259	-0.110	0.038	0.558			
CohortGrp	-0.044	-0.060	-0.053	-0.128	-0.189		
Region	-0.037	-0.131	-0.020	-0.006	-0.081	0.205	
ITPat	0.180	0.183	-0.172	0.035	-0.052	-0.120	-0.118
OtherPat	0.097	-0.079	-0.110	0.029	-0.028	0.060	-0.174
NPMF	-0.031	-0.129	0.031	-0.156	0.027	-0.009	-0.083
NPMini	-0.089	-0.190	0.077	-0.085	-0.013	0.030	0.263
NPPC	0.020	-0.139	0.008	-0.043	-0.075	-0.076	0.033
NPWS	-0.048	-0.106	0.047	-0.009	-0.013	0.120	0.035
NSTEffcy	-0.122	-0.122	0.085	-0.025	0.112	-0.027	0.074
SMktPar	-0.096	-0.116	0.158	0.026	-0.124	-0.044	-0.116
SMktIT	0.018	-0.098	-0.080	0.048	0.104	0.133	0.131
TtlMktIT	0.809	0.087	-0.909	-0.021	-0.010	0.013	-0.030
SGNPHMkt	0.106	0.065	-0.097	-0.013	-0.014	0.049	0.061
SGNPWMkt	-0.138	-0.096	0.170	-0.011	0.011	-0.050	-0.027
PwPrd	0.525	0.021	-0.500	-0.060	-0.063	0.016	-0.012
Density	-0.709	-0.103	0.636	0.110	0.034	0.148	0.057
EntryDensity	0.068	0.186	0.025	0.103	0.139	-0.789	-0.372
CohtDensity	0.078	0.265	0.010	-0.226	-0.058	-0.516	-0.283

EntryCohtDen	-0.079	-0.082	0.007	-0.091	-0.224	0.814	0.317

	ITPat	OtherPat	NPMF	NPMini	NPPC	NPWS	NSTEffcy	SmktPar
SOrgCode								
YrID								
OrgType								
OrgStruct								
CohortGrp								
Region								
ITPat								
OtherPat	-0.360							
NPMF	0.041	-0.001						
NPMini	-0.222	0.052	0.084					
NPPC	0.055	-0.102	0.056	0.097				
NPWS	0.092	-0.051	-0.072	-0.246	0.106			
NSTEffcy	-0.038	0.086	-0.046	0.063	-0.339	0.066		
SMktPar	0.164	-0.698	-0.031	-0.048	0.073	0.065	-0.011	
SMktIT	-0.634	0.627	-0.094	-0.035	-0.114	-0.137	-0.055	-0.686
TtlMktIT	0.135	0.084	-0.035	-0.103	0.030	-0.052	-0.150	-0.135
SGNPHMkt	-0.048	0.103	-0.027	0.039	-0.023	-0.024	0.040	-0.056
SGNPWMkt	0.030	-0.127	0.069	0.004	0.042	0.001	-0.026	0.073
PwPrd	0.127	0.074	0.111	-0.018	-0.035	-0.077	-0.015	-0.125
Density	0.006	0.042	-0.087	0.037	-0.062	0.059	0.121	0.053
EntryDensity	0.137	-0.102	0.073	0.015	0.095	-0.145	-0.188	-0.008
CohtDensity	0.000	0.039	0.137	-0.132	-0.016	-0.156	-0.037	-0.043
EntryCohtDen	-0.075	-0.033	-0.100	0.038	0.083	0.223	0.125	-0.004

	SMktIT	TtlMktIT	SGNPHMkt	SGNPWMkt	PwPrd	Density	EntryDensity
SOrgCode							
YrID							
OrgType							
OrgStruct							
CohortGrp							
Region							
ITPat							
OtherPat							
NPMF							

NPMini							
NPPC							
NPWS							
NSTEffcy							
SMktPar							
SMktIT							
TtlMktIT	0.072						
SGNPHMkt	0.079	0.086					
SGNPWMkt	-0.097	-0.275	-0.766				
PwPrd	0.028	0.199	0.099	0.064			
Density	-0.011	-0.617	-0.056	0.042	-0.217		
EntryDensity	-0.107	-0.002	-0.058	0.087	0.032	-0.242	
CohtDensity	0.034	0.060	0.043	-0.048	0.043	-0.312	0.384
EntryCohtDen	0.054	-0.059	0.020	-0.010	-0.019	0.175	-0.707

	CohtDensity	EntryCohtDen	RegionDensity
SOrgCode			
YrID			
OrgType			
OrgStruct			
CohortGrp			
Region			
ITPat			
OtherPat			
NPMF			
NPMini			
NPPC			
NPWS			
NSTEffcy			
SMktPar			
SMktIT			
TtlMktIT			
SGNPHMkt			
SGNPWMkt			
PwPrd			
Density			
EntryDensity			
CohtDensity			
EntryCohtDen	-0.587		

	(Intercept)	SOrgCode	YrID	OrgType	OrgStruct	CohortGrp	Region
RegionDensity	-0.141	-0.029	0.112	0.086	0.102	-0.085	0.132
EntryRgnDen	-0.010	-0.074	-0.057	-0.002	0.100	0.079	0.374

```
                ITPat  OtherPat  NPMF    NPMini  NPPC    NPWS    NSTEffcy
                SMktPar
RegionDensity   -0.014 -0.184    -0.007  0.058   0.089   0.039   0.050
                0.066
 EntryRgnDen    -0.081 0.118     0.006   0.018   -0.179  -0.056  0.114      -
0.024

                SMktIT    TtlMktIT   SGNPHMkt SGNPWMkt   PwPrd Density
EntryDensity
RegionDensity   -0.137    -0.054     -0.152   0.145      -0.060 -0.244   0.275
 EntryRgnDen    0.125     0.033      0.003    -0.044     -0.036 0.221    -
0.550

                CohtDensity  EntryCohtDen  RegionDensity
RegionDensity   -0.182       0.030
 EntryRgnDen    0.020        -0.045        -0.509
```

```
> fitLogNorSig1 <- censorReg(formula=censor(YrsEff,EffInd)~SOrgCode + YrID +
+       OrgType + OrgStruct + Region + OtherPat + SMktIT + PwPrd + CohtDensity +
+       RegionDensity + EntryRgnDen, data = DissEffAnal7601CmpA,
+       na.action = na.exclude, distribution = "lognormal", threshold = 0,
+       control = list(e.scale = 0.0001))
> summary(fitLogNorSig1)
Call:
censorReg(formula = censor(YrsEff, EffInd) ~ SOrgCode + YrID + OrgType +
        OrgStruct + Region + OtherPat + SMktIT + PwPrd + CohtDensity +
        RegionDensity + EntryRgnDen, data = DissEffAnal7601CmpA, na.action =
        na.exclude, distribution = "lognormal", threshold = 0, control = list(
        e.scale = 0.0001))
```

Distribution: Lognormal

Standardized Residuals:

	Min	Max
Uncensored	0.029	4.261
Censored	0.017	5.097

Coefficients:

	Est.	Std.Err.	95% LCL	95% UCL	z-value	p-value
(Intercept)	8.6959659	1.404902	5.942408	11.4495	6.190	6.03e-010
SOrgCode	0.0146915	0.002112	0.010552	0.0188	6.956	3.51e-012
YrID	-0.1648663	0.028813	-0.221338	-0.1084	-5.722	1.05e-008
OrgType	0.6446115	0.209669	0.233669	1.0556	3.074	2.11e-003
OrgStruct	-0.3269049	0.129043	-0.579824	-0.0740	-2.533	1.13e-002
Region	0.2593731	0.070020	0.122136	0.3966	3.704	2.12e-004
OtherPat	0.0000908	0.000514	-0.000917	0.0011	0.177	8.60e-001

SMktIT	1.9274634	0.541867	0.865424	2.9895	3.557	3.75e-004
PwPrd	-0.3705298	0.238119	-0.837234	0.0962	-1.556	1.20e-001
CohtDensity	0.0341103	0.013083	0.008468	0.0598	2.607	9.13e-003
RegionDensity	-0.0305163	0.009571	-0.049274	-0.0118	-3.189	1.43e-003
EntryRgnDen	0.0544534	0.008466	0.037861	0.0710	6.432	1.26e-010

Gaussian distribution: Dispersion (scale) = 1.437352
Observations: 873 Total; 633 Censored
-2*Log-Likelihood: 1494

Correlation of Coefficients:

	(Intercept)	SOrgCode	YrID	OrgType	OrgStruct	Region	OtherPat
SOrgCode	0.032						
YrID	-0.865	-0.023					
OrgType	-0.172	-0.134	-0.123				
OrgStruct	-0.500	-0.138	0.065	0.582			
Region	-0.043	-0.026	-0.072	0.051	-0.029		
OtherPat	0.279	-0.137	-0.154	0.078	-0.253	-0.526	
SMktIT	0.116	-0.334	-0.207	0.118	0.025	0.110	0.019
PwPrd	0.644	-0.031	-0.778	-0.025	-0.075	-0.012	0.059
CohtDensity	-0.132	0.324	0.192	-0.338	-0.258	-0.214	-0.009
RegionDensity	-0.417	-0.103	0.291	0.141	0.162	0.314	-0.099
EntryRgnDen	0.142	0.252	-0.303	0.004	0.128	0.314	-0.157

	SMktIT	PwPrd	CohtDensity	RegionDensity
SOrgCode				
YrID				
OrgType				
OrgStruct				
Region				
OtherPat				
SMktIT				
PwPrd	0.056			
CohtDensity	0.050	0.012		
RegionDensity	-0.154	-0.074	-0.328	
EntryRgnDen	0.226	-0.009	-0.107	-0.300

```
> fitLogNorSig2 <- censorReg(formula=censor(YrsEff,EffInd)~SOrgCode + YrID +
+       OrgType + OrgStruct + Region + SMktIT + CohtDensity +
+       RegionDensity + EntryRgnDen, data = DissEffAnal7601CmpA,
+       na.action = na.exclude, distribution = "lognormal", threshold = 0,
+       control = list(e.scale = 0.0001))
> summary(fitLogNorSig2)
Call:
censorReg(formula = censor(YrsEff, EffInd) ~ SOrgCode + YrID + OrgType +
```

OrgStruct + Region + SMktIT + CohtDensity + RegionDensity + EntryRgnDen, data = DissEffAnal7601CmpA, na.action = na.exclude, distribution = "lognormal", threshold = 0, control = list(e.scale = 0.0001))

Distribution: Lognormal

Standardized Residuals:

	Min	Max
Uncensored	0.033	4.239
Censored	0.018	5.165

Coefficients:

	Est.	Std.Err.	95% LCL	95% UCL	z-value	p-value
(Intercept)	10.0466	1.02159	8.04428	12.0488	9.83	8.02e-023
SOrgCode	0.0147	0.00210	0.01060	0.0188	7.00	2.47e-012
YrID	-0.1997	0.01783	-0.23462	-0.1647	-11.20	4.07e-029
OrgType	0.6345	0.20987	0.22315	1.0458	3.02	2.50e-003
OrgStruct	-0.3338	0.12516	-0.57912	-0.0885	-2.67	7.65e-003
Region	0.2693	0.05994	0.15180	0.3868	4.49	7.04e-006
SMktIT	1.9787	0.54302	0.91437	3.0430	3.64	2.69e-004
CohtDensity	0.0344	0.01314	0.00864	0.0601	2.62	8.86e-003
RegionDensity	-0.0314	0.00953	-0.05012	-0.0128	-3.30	9.65e-004
EntryRgnDen	0.0550	0.00840	0.03850	0.0714	6.54	5.98e-011

Gaussian distribution: Dispersion (scale) = 1.444568
Observations: 873 Total; 633 Censored
-2*Log-Likelihood: 1496

Correlation of Coefficients:

	(Intercept)	SOrgCode	YrID	OrgType	OrgStruct	Region	SMktIT
SOrgCode	0.118						
YrID	-0.750	-0.102					
OrgType	-0.244	-0.124	-0.215				
OrgStruct	-0.562	-0.181	-0.032	0.624			
Region	0.150	-0.114	-0.265	0.107	-0.196		
SMktIT	0.104	-0.334	-0.262	0.118	0.033	0.140	
CohtDensity	-0.187	0.325	0.322	-0.338	-0.268	-0.257	0.050
RegionDensity	-0.480	-0.120	0.361	0.149	0.140	0.311	-0.148
EntryRgnDen	0.258	0.237	-0.535	0.016	0.093	0.276	0.231

	CohtDensity	RegionDensity
SOrgCode		
YrID		
OrgType		
OrgStruct		

Region
SMktIT
CohtDensity
RegionDensity -0.332
EntryRgnDen -0.110 -0.320

> anova(fitLogNor,fitLogNorSig2,test = "Chisq")
Likelihood Ratio Test(s)

Response: censor(YrsEff, EffInd)

	Terms	N.Params	-2*LogLik	Test Df	LRT	Pr(Chi)
1	SOrgCode	3	1744.923			
2	SOrgCode + YrID + 0.0000000 OrgType + OrgStruct + Region + SMktIT + CohtDensity + RegionDensity + EntryRgnDen	11	1496.154	8	248.7694	

APPENDIX G

S Codes for Subpopulation Top 4 Effectiveness Analysis for the Period 1976 to 2001

S Codes for Subpopulation Top 4 Effectiveness Analysis for the Period 1976 to 2001

```
S-PLUS : Copyright (c) 1988, 2002 Insightful Corp.
S : Copyright Lucent Technologies, Inc.
Professional Edition Version 6.1.3 Release 3 for Micros
oft Windows : 2002
Working data will be in C:\Program Files\Insightful\spl
us61\users\Cotter
> censorReg(formula=censor(YrsEff,EffInd)~SOrgCode,
+       data = DissEffAnal7601Top4A, na.action = na.exclude,
+       distribution = "exponential", threshold = 0, control = list(e.scale = 0.0001)
Call:
censorReg(formula = censor(YrsEff, EffInd) ~ SOrgCode, data =
        DissEffAnal7601Top4A, na.action = na.exclude, distribution =
        "exponential", threshold = 0, control = list(e.scale = 0.0001))

Distribution: Exponential

Coefficients:
 (Intercept)  SOrgCode
  -5.767692 0.2633974

Dispersion (scale) fixed at 1
Log-likelihood: -174.1834

Observations: 88 Total; 74 Censored
Parameters Estimated: 2
Threshold Parameter: 0
> censorReg(formula=censor(YrsEff,EffInd)~SOrgCode,
+       data = DissEffAnal7601Top4A, na.action = na.exclude,
+       distribution = "logexponential", threshold = 0, control = list(e.scale = 0.0001))
Call:
censorReg(formula = censor(YrsEff, EffInd) ~ SOrgCode, data =
        DissEffAnal7601Top4A, na.action = na.exclude, distribution =
        "logexponential", threshold = 0, control = list(e.scale = 0.0001))

Distribution: Logexponential

Coefficients:
 (Intercept)   SOrgCode
   17.53144 -0.1972229

Dispersion (scale) fixed at 1
```

```
Log-likelihood: -56.3006

Observations: 88 Total; 74 Censored
Parameters Estimated: 2
Threshold Parameter: 0
> censorReg(formula=censor(YrsEff,EffInd)~SOrgCode,
+       data = DissEffAnal7601Top4A, na.action = na.exclude,
+       distribution = "logistic", threshold = 0, control = list(e.scale = 0.0001))
Call:
censorReg(formula = censor(YrsEff, EffInd) ~ SOrgCode, data =
        DissEffAnal7601Top4A, na.action = na.exclude, distribution =
        "logistic", threshold = 0, control = list(e.scale = 0.0001))

Distribution: Logistic

Coefficients:
 (Intercept)  SOrgCode
   67.10634 -0.7606538

Dispersion (scale) est = 3.567887
Log-likelihood: -59.75219

Observations: 88 Total; 74 Censored
Parameters Estimated: 3
Threshold Parameter: 0
> censorReg(formula=censor(YrsEff,EffInd)~SOrgCode,
+       data = DissEffAnal7601Top4A, na.action = na.exclude,
+       distribution = "loglogistic", threshold = 0, control = list(e.scale = 0.0001))
Call:
censorReg(formula = censor(YrsEff, EffInd) ~ SOrgCode, data =
        DissEffAnal7601Top4A, na.action = na.exclude, distribution =
        "loglogistic", threshold = 0, control = list(e.scale = 0.0001))

Distribution: Loglogistic

Coefficients:
 (Intercept)  SOrgCode
   15.78508 -0.1807223

Dispersion (scale) est = 0.6980171
Log-likelihood: -55.91412

Observations: 88 Total; 74 Censored
Parameters Estimated: 3
Threshold Parameter: 0
> censorReg(formula=censor(YrsEff,EffInd)~SOrgCode,
```

```
+       data = DissEffAnal7601Top4A, na.action = na.exclude,
+       distribution = "normal", threshold = 0, control = list(e.scale = 0.0001))
Call:
censorReg(formula = censor(YrsEff, EffInd) ~ SOrgCode, data =
        DissEffAnal7601Top4A, na.action = na.exclude, distribution = "normal",
        threshold = 0, control = list(e.scale = 0.0001))

Distribution: Normal

Coefficients:
 (Intercept)  SOrgCode
   69.43929 -0.7755491

Dispersion (scale) = 6.794839
Log-likelihood: -58.90394

Observations: 88 Total; 74 Censored
Parameters Estimated: 3
Threshold Parameter: 0

> censorReg(formula=censor(YrsEff,EffInd)~SOrgCode,
+       data = DissEffAnal7601Top4A, na.action = na.exclude,
+       distribution = "lognormal", threshold = 0, control = list(e.scale = 0.0001))
Call:
censorReg(formula = censor(YrsEff, EffInd) ~ SOrgCode, data =
        DissEffAnal7601Top4A, na.action = na.exclude, distribution =
        "lognormal", threshold = 0, control = list(e.scale = 0.0001))

Distribution: Lognormal

Coefficients:
 (Intercept)  SOrgCode
   21.25273 -0.2540451

Dispersion (scale) = 1.354256
Log-likelihood: -55.9824

Observations: 88 Total; 74 Censored
Parameters Estimated: 3
Threshold Parameter: 0
> censorReg(formula=censor(YrsEff,EffInd)~SOrgCode,
+       data = DissEffAnal7601Top4A, na.action = na.exclude,
+       distribution = "rayleigh", threshold = 0, control = list(e.scale = 0.0001))
Call:
censorReg(formula = censor(YrsEff, EffInd) ~ SOrgCode, data =
        DissEffAnal7601Top4A, na.action = na.exclude, distribution =
```

```
        "rayleigh", threshold = 0, control = list(e.scale = 0.0001))

Distribution: Rayleigh

Coefficients:
 (Intercept)  SOrgCode
    -9.8854 0.3332611

Dispersion (scale) fixed at 0.5
Log-likelihood: -244.8968

Observations: 88 Total; 74 Censored
Parameters Estimated: 2
Threshold Parameter: 0
> censorReg(formula=censor(YrsEff,EffInd)~SOrgCode,
+       data = DissEffAnal7601Top4A, na.action = na.exclude,
+       distribution = "lograyleigh", threshold = 0, control = list(e.scale = 0.0001))
Call:
censorReg(formula = censor(YrsEff, EffInd) ~ SOrgCode, data =
        DissEffAnal7601Top4A, na.action = na.exclude, distribution =
        "lograyleigh", threshold = 0, control = list(e.scale = 0.0001))

Distribution: Lograyleigh

Coefficients:
 (Intercept)    SOrgCode
   6.632532 -0.05435405

Dispersion (scale) fixed at 0.5
Log-likelihood: -60.34283

Observations: 88 Total; 74 Censored
Parameters Estimated: 2
Threshold Parameter: 0
> censorReg(formula=censor(YrsEff,EffInd)~SOrgCode,
+       data = DissEffAnal7601Top4A, na.action = na.exclude,
+       distribution = "weibull", threshold = 0, control = list(e.scale = 0.0001))
Call:
censorReg(formula = censor(YrsEff, EffInd) ~ SOrgCode, data =
        DissEffAnal7601Top4A, na.action = na.exclude, distribution = "weibull",
        threshold = 0, control = list(e.scale = 0.0001))

Distribution: Weibull

Coefficients:
 (Intercept)   SOrgCode
```

```
  13.44614 -0.1443247

Dispersion (scale) = 0.8124529
Log-likelihood: -55.73843

Observations: 88 Total; 74 Censored
Parameters Estimated: 3
Threshold Parameter: 0

> censorReg(formula=censor(YrsEff,EffInd)~SOrgCode,
+       data = DissEffAnal7601Top4A, na.action = na.exclude,
+       distribution = "extreme", threshold = 0, control = list(e.scale = 0.0001))
Call:
censorReg(formula = censor(YrsEff, EffInd) ~ SOrgCode, data =
        DissEffAnal7601Top4A, na.action = na.exclude, distribution = "extreme",
        threshold = 0, control = list(e.scale = 0.0001))

Distribution: Extreme

Coefficients:
 (Intercept) SOrgCode
   78.22998 -0.81166

Dispersion (scale) = 6.79774
Log-likelihood: -64.54748

Observations: 88 Total; 74 Censored
Parameters Estimated: 3
Threshold Parameter: 0
> fitExp <- censorReg(formula=censor(YrsEff,EffInd)~SOrgCode,
+       data = DissEffAnal7601Top4A, na.action = na.exclude,
+       distribution = "exponential", threshold = 0, control = list(e.scale = 0.0001))
> fitLogExp <- censorReg(formula=censor(YrsEff,EffInd)~SOrgCode,
+       data = DissEffAnal7601Top4A, na.action = na.exclude,
+       distribution = "logexponential", threshold = 0, control = list(e.scale = 0.0001))
> fitLog <- censorReg(formula=censor(YrsEff,EffInd)~SOrgCode,
+       data = DissEffAnal7601Top4A, na.action = na.exclude,
+       distribution = "logistic", threshold = 0, control = list(e.scale = 0.0001))
> fitLogLog <- censorReg(formula=censor(YrsEff,EffInd)~SOrgCode,
+       data = DissEffAnal7601Top4A, na.action = na.exclude,
+       distribution = "loglogistic", threshold = 0, control = list(e.scale = 0.0001))
> fitNor <- censorReg(formula=censor(YrsEff,EffInd)~SOrgCode,
+       data = DissEffAnal7601Top4A, na.action = na.exclude,
+       distribution = "normal", threshold = 0, control = list(e.scale = 0.0001))
> fitLogNor <- censorReg(formula=censor(YrsEff,EffInd)~SOrgCode,
+       data = DissEffAnal7601Top4A, na.action = na.exclude,
```

```
+       distribution = "lognormal", threshold = 0, control = list(e.scale = 0.0001))
> fitRay <- censorReg(formula=censor(YrsEff,EffInd)~SOrgCode,
+       data = DissEffAnal7601Top4A, na.action = na.exclude,
+       distribution = "rayleigh", threshold = 0, control = list(e.scale = 0.0001))
> fitLogRay <- censorReg(formula=censor(YrsEff,EffInd)~SOrgCode,
+       data = DissEffAnal7601Top4A, na.action = na.exclude,
+       distribution = "lograyleigh", threshold = 0, control = list(e.scale = 0.0001))
> fitWbl <- censorReg(formula=censor(YrsEff,EffInd)~SOrgCode,
+       data = DissEffAnal7601Top4A, na.action = na.exclude,
+       distribution = "weibull", threshold = 0, control = list(e.scale = 0.0001))
> fitExt <- censorReg(formula=censor(YrsEff,EffInd)~SOrgCode,
+       data = DissEffAnal7601Top4A, na.action = na.exclude,
+       distribution = "extreme", threshold = 0, control = list(e.scale = 0.0001))
> anova(fitExt,fitLogRay,fitNor,fitLogExp,fitLogNor,fitLogLog,fitLog,fitWbl)
Likelihood Ratio Test(s)

Response: censor(YrsEff, EffInd)
```

	Model	Terms	N.Params	LogLik	-2*LogLik	AIC
1	Rayleigh	OrgCode	3	-244.8968	489.7936	493.794
2	Exponential	OrgCode	3	-174.1834	348.3668	352.367
3	Extreme	OrgCode	3	-64.5475	129.0950	135.095
4	Logistic	OrgCode	3	-59.7522	119.5044	125.504
5	LogRayleigh	OrgCode	3	-60.3428	120.6856	124.686
6	Normal	OrgCode	3	-58.9039	117.8078	123.808
7	LogNormal	OrgCode	3	-55.9648	111.9648	117.965
8	LogLogistic	OrgCode	3	-55.9141	111.8282	117.828
9	Weibull	OrgCode	3	-55.7384	111.4768	117.477
10	LogExponential	OrgCode	3	-56.3006	112.6012	116.601

```
> summary(fitWbl)
Call:
censorReg(formula = censor(YrsEff, EffInd) ~ SOrgCode, data =
    DissEffAnal7601Top4A, na.action = na.exclude, distribution = "weibull",
    threshold = 0, control = list(e.scale = 0.0001))

Distribution:  Weibull

Standardized Residuals:
```

	Min	Max
Uncensored	0.017	2.397
Censored	0.001	1.021

Coefficients:

	Est.	Std.Err.	95% LCL	95% UCL	z-value	p-value
(Intercept)	13.446	7.0520	-0.376	27.2679	1.91	0.0566

SOrgCode	-0.144	0.0949	-0.330	0.0418	-1.52	0.1285

Extreme value distribution: Dispersion (scale) = 0.8124529
Observations: 88 Total; 74 Censored
-2*Log-Likelihood: 111

Correlation of Coefficients:
(Intercept)
SOrgCode -0.999

```
> fitWblFull <- censorReg(formula=censor(YrsEff,EffInd)~SOrgCode + YrID +
+       OrgType + ITPat + OtherPat + NSTEffcy + SMktPar + SMktIT + TtlMktIT +
+       NPMF + NPMini + NPPC + NPWS + SGNPHMkt + SGNPWMkt + PwPrd +
Density +
+       CohtDensity + RegionDensity, data = DissEffAnal7601Top4A,
+       na.action = na.exclude, distributon = "weibull", threshold = 0,
+       control = list(e.scale = 0.0001))
> summary(fitWblFull)
Call:
censorReg(formula = censor(YrsEff, EffInd) ~ SOrgCode + YrID + OrgType + ITPat +
       OtherPat + NSTEffcy + SMktPar + SMktIT + TtlMktIT + NPMF + NPMini +
       NPPC + NPWS + SGNPHMkt + SGNPWMkt + PwPrd + Density + CohtDensity
+
       RegionDensity, data = DissEffAnal7601Top4A, na.action = na.exclude,
       threshold = 0, control = list(e.scale = 0.0001), distributon =
       "weibull")
```

Distribution: Weibull
Standardized Residuals:

	Min	Max
Uncensored	0.00	1.38
Censored	0.00	1.76

Coefficients:

	Est.	Std.Err.	95% LCL	95% UCL	z-value	p-value
(Intercept)	3.22e+001	9.61e+000	1.33e+001	5.10e+001	3.349	8.11e-004
SOrgCode	-1.07e-001	1.23e-001	-3.48e-001	1.35e-001	-0.864	3.88e-001
YrID	-9.01e-001	1.02e-00	-1.10e+000	-7.02e-001	-8.866	7.61e-019
OrgType	7.45e+000	1.37e+000	4.75e+000	1.01e+001	5.418	6.01e-008
ITPat	1.53e-004	2.00e-004	-2.39e-004	5.45e-004	0.765	4.44e-001
OtherPat	1.14e-002	2.95e-003	5.61e-003	1.72e-002	3.864	1.11e-004
NSTEffcy	-2.17e-006	1.77e-006	-5.65e-006	1.30e-006	-1.226	2.20e-001
SMktPar	1.53e+001	3.32e+000	8.76e+000	2.18e+001	4.600	4.22e-006
SMktIT	-7.07e+000	3.21e+000	-1.34e+001	-7.79e-001	-2.203	2.76e-002
TtlMktIT	3.77e+000	3.01e-001	3.18e+000	4.36e+000	12.500	7.47e-036
NPMF	3.24e-001	4.34e-002	2.39e-001	4.09e-001	7.461	8.61e-014

NPMini	-1.82e-001	3.75e-002	-2.56e-001	-1.09e-001	-4.865	1.14e-006
NPPC	-9.31e-002	5.10e-002	-1.93e-001	6.88e-003	-1.825	6.80e-002
NPWS	1.04e-001	5.65e-002	-6.77e-003	2.15e-001	1.840	6.58e-002
SGNPHMkt	2.37e-002	1.54e-002	-6.42e-003	5.38e-002	1.542	1.23e-001
SGNPWMkt	-4.17e-003	8.09e-004	-5.75e-003	-2.58e-003	-5.150	2.61e-007
PwPrd	3.98e-001	2.93e-001	-1.76e-001	9.72e-001	1.359	1.74e-001
Density	2.73e-002	2.94e-002	-3.03e-002	8.48e-002	0.928	3.53e-001
CohtDensity	8.07e-002	5.91e-002	-3.51e-002	1.97e-001	1.366	1.72e-001
RegionDensity	-2.69e-001	5.02e-002	-3.67e-001	-1.70e-001	-5.354	8.62e-008

Extreme value distribution: Dispersion (scale) = 0.1400455
Observations: 88 Total; 74 Censored
-2*Log-Likelihood: 43.9

Correlation of Coefficients:

	(Intercept)	SOrgCode	YrID	OrgType	ITPat	OtherPat	NSTEffcy
SOrgCode	-0.960						
YrID	-0.254	0.021					
OrgType	-0.185	0.385	-0.707				
ITPat	0.222	-0.121	-0.228	0.396			
OtherPat	0.087	0.037	-0.811	0.521	-0.084		
NSTEffcy	-0.185	0.151	-0.129	-0.061	-0.124	0.187	
SMktPar	-0.013	0.010	0.065	0.344	0.402	-0.324	0.084
SMktIT	0.149	-0.063	-0.494	0.034	-0.271	0.685	0.023
TtlMktIT	0.088	0.091	-0.602	0.411	0.172	0.190	0.062
NPMF	0.014	0.025	0.045	-0.069	0.081	-0.243	0.074
NPMini	-0.062	-0.082	0.767	-0.463	-0.289	-0.756	-0.308
NPPC	-0.014	0.028	0.121	-0.135	-0.050	-0.049	-0.288
NPWS	0.144	-0.070	-0.583	0.493	-0.095	0.734	0.025
SGNPHMkt	-0.006	0.001	-0.355	-0.080	-0.439	0.758	0.168
SGNPWMkt	0.078	-0.084	0.113	-0.031	0.142	0.016	-0.339
PwPrd	0.146	-0.006	-0.503	0.513	0.379	0.272	0.176
Density	-0.039	0.085	-0.611	0.501	-0.064	0.906	0.241
CohtDensity	-0.041	-0.006	-0.207	0.045	-0.137	0.268	0.612
RegionDensity	-0.040	-0.097	0.852	-0.652	-0.013	-0.926	-0.330

	SMktPar	SMktIT	TtlMktIT	NPMF	NPMini	NPPC	NPWS	SGNPHMkt
SOrgCode								
YrID								
OrgType								
ITPat								
OtherPat								
NSTEffcy								
SMktPar								
SMktIT	-0.876							

```
TtlMktIT      0.041    0.167
NPMF          0.009   -0.092   0.171
NPMini        0.274   -0.604  -0.379   0.020
NPPC         -0.199    0.070  -0.320  -0.236   0.161
NPWS          0.050    0.263   0.061  -0.136  -0.361  -0.192
SGNPHMkt     -0.670    0.752  -0.129  -0.236  -0.519   0.141  0.446
SGNPWMkt     -0.199    0.125  -0.410  -0.262   0.051   0.488 -0.153   0.045
PwPrd         0.476   -0.197   0.065   0.279  -0.306  -0.160  0.375  -0.132
Density      -0.171    0.507   0.014  -0.329  -0.656  -0.157  0.716   0.697
CohtDensity   0.274   -0.061   0.129  -0.094  -0.287  -0.530  0.339   0.140
RegionDensity 0.058   -0.494  -0.299   0.207   0.782   0.197 -0.724  -0.562

              SGNPWMkt  PwPrd   Density  CohtDensity
SOrgCode
YrID
OrgType
ITPat
OtherPat
NSTEffcy
SMktPar
SMktIT
TtlMktIT
NPMF
NPMini
NPPC
NPWS
SGNPHMkt
SGNPWMkt
PwPrd        -0.116
Density      -0.043     0.180
CohtDensity  -0.424     0.329   0.325
RegionDensity 0.164    -0.427  -0.885   -0.460

> fitWblSig1 <- censorReg(formula=censor(YrsEff,EffInd)~SOrgCode + YrID +
+       OrgType + OtherPat + SMktPar + SMktIT + TtlMktIT +
+       NPMF + NPMini + NPPC + NPWS + SGNPWMkt +
+       RegionDensity, data = DissEffAnal7601Top4A,
+       na.action = na.exclude, distributon = "weibull", threshold = 0,
+       control = list(e.scale = 0.0001))
> summary(fitWblSig1)
Call:
censorReg(formula = censor(YrsEff, EffInd) ~ SOrgCode + YrID + OrgType +
        OtherPat + SMktPar + SMktIT + TtlMktIT + NPMF + NPMini + NPPC + NPWS
+
        SGNPWMkt + RegionDensity, data = DissEffAnal7601Top4A, na.action =
        na.exclude, threshold = 0, control = list(e.scale = 0.0001),
```

distributon = "weibull")

Distribution: Weibull

Standardized Residuals:

	Min	Max
Uncensored	0.001	1.426
Censored	0.000	1.802

Coefficients:

	Est.	Std.Err.	95% LCL	95% UCL	z-value	p-value
(Intercept)	26.06085	7.627959	11.11032	4.10e+001	3.416	6.34e-004
SOrgCode	-0.07489	0.098997	-0.26892	1.19e-001	-0.756	4.49e-001
YrID	-0.70343	0.088700	-0.87728	-5.30e-001	-7.930	2.18e-015
OrgType	6.41048	0.951688	4.54521	8.28e+000	6.736	1.63e-011
OtherPat	0.00693	0.001343	0.00430	9.56e-003	5.160	2.48e-007
SMktPar	14.39354	2.474316	9.54397	1.92e+001	5.817	5.98e-009
SMktIT	-8.11482	2.586794	-13.18484	-3.04e+000	-3.137	1.71e-003
TtlMktIT	3.21801	0.359244	2.51390	3.92e+000	8.958	3.31e-019
NPMF	0.28897	0.066024	0.15957	4.18e-001	4.377	1.20e-005
NPMini	-0.11378	0.027083	-0.16687	-6.07e-002	-4.201	2.65e-005
NPPC	-0.06961	0.064699	-0.19641	5.72e-002	-1.076	2.82e-001
NPWS	-0.02461	0.049772	-0.12216	7.29e-002	-0.494	6.21e-001
SGNPWMkt	-0.00137	0.000705	-0.00275	1.31e-005	-1.941	5.22e-002
RegionDensity	-0.18304	0.027716	-0.23736	-1.29e-001	-6.604	4.00e-011

Extreme value distribution: Dispersion (scale) = 0.2159685
Observations: 88 Total; 74 Censored
-2*Log-Likelihood: 56.2

Correlation of Coefficients:

	(Intercept)	SOrgCode	YrID	OrgType	OtherPat	SMktPar	SMktIT
SOrgCode	-0.935						
YrID	-0.285	-0.067					
OrgType	-0.186	0.489	-0.814				
OtherPat	0.258	0.057	-0.875	0.773			
SMktPar	-0.074	0.033	0.016	0.135	-0.173		
SMktIT	0.238	-0.065	-0.402	0.202	0.509	-0.899	
TtlMktIT	0.117	0.177	-0.888	0.721	0.669	0.057	0.246
NPMF	-0.090	-0.004	0.243	-0.160	-0.166	-0.315	0.149
NPMini	0.060	-0.231	0.461	-0.515	-0.385	0.243	-0.480
NPPC	-0.081	0.153	-0.176	0.189	0.135	0.291	-0.130
NPWS	0.172	-0.099	-0.190	0.211	0.352	0.044	-0.016
SGNPWMkt	-0.015	-0.079	0.254	-0.232	-0.103	-0.092	0.026
RegionDensity	-0.165	-0.168	0.891	-0.849	-0.779	-0.010	-0.380

	TtlMktIT	NPMF	NPMini	NPPC	NPWS	SGNPWMkt
SOrgCode						
YrID						
OrgType						
OtherPat						
SMktPar						
SMktIT						
TtlMktIT						
NPMF	-0.040					
NPMini	-0.467	-0.183				
NPPC	0.004	-0.466	0.053			
NPWS	0.075	0.144	0.148	-0.088		
SGNPWMkt	-0.374	0.004	-0.048	0.017	-0.170	
RegionDensity	-0.712	0.171	0.587	-0.317	-0.178	0.176

```
> fitWblSig2 <- censorReg(formula=censor(YrsEff,EffInd)~ YrID +
+       OrgType + OtherPat + SMktPar + SMktIT + TtlMktIT +
+       NPMF + NPMini + SGNPWMkt +
+       RegionDensity, data = DissEffAnal7601Top4A,
+       na.action = na.exclude, distributon = "weibull", threshold = 0,
+       control = list(e.scale = 0.0001))
> summary(fitWblSig2)
Call:
censorReg(formula = censor(YrsEff, EffInd) ~ YrID + OrgType + OtherPat +
        SMktPar + SMktIT + TtlMktIT + NPMF + NPMini + SGNPWMkt +
RegionDensity,
        data = DissEffAnal7601Top4A, na.action = na.exclude, threshold = 0,
        control = list(e.scale = 0.0001), distributon = "weibull")
```

Distribution: Weibull

Standardized Residuals:

	Min	Max
Uncensored	0.001	1.618
Censored	0.000	1.379

Coefficients:

	Est.	Std.Err.	95% LCL	95% UCL	z-value	p-value
(Intercept)	21.23285	2.505700	16.32177	26.143932	8.47	2.37e-017
YrID	-0.71878	0.082925	-0.88131	-0.556253	-8.67	4.40e-018
OrgType	6.91109	0.797846	5.34734	8.474840	8.66	4.63e-018
OtherPat	0.00722	0.001226	0.00481	0.009618	5.88	4.00e-009
SMktPar	14.72452	2.407567	10.00578	19.443267	6.12	9.60e-010
SMktIT	-8.35974	2.461081	-13.18337	-3.536110	-3.40	6.82e-004
TtlMktIT	3.22075	0.346755	2.54112	3.900381	9.29	1.57e-020

NPMF	0.27027	0.063513	0.14579	0.394757	4.26	2.09e-005
NPMini	-0.11005	0.026119	-0.16125	-0.058862	-4.21	2.51e-005
SGNPWMkt	-0.00158	0.000672	-0.00290	-0.000266	-2.36	1.85e-002
RegionDensity	-0.19375	0.024836	-0.24243	-0.145072	-7.80	6.14e-015

Extreme value distribution: Dispersion (scale) = 0.2217949
Observations: 88 Total; 74 Censored
-2*Log-Likelihood: 59.3

Correlation of Coefficients:

	(Intercept)	YrID	OrgType	OtherPat	SMktPar	SMktIT	TtlMktIT
YrID	-0.969						
OrgType	0.857	-0.895					
OtherPat	0.843	-0.856	0.832				
SMktPar	-0.114	-0.025	0.197	-0.160			
SMktIT	0.476	-0.357	0.214	0.501	-0.906		
TtlMktIT	0.793	-0.903	0.747	0.673	0.145	0.178	
NPMF	-0.281	0.262	-0.247	-0.209	-0.306	0.188	-0.098
NPMini	-0.438	0.455	-0.501	-0.425	0.169	-0.443	-0.415
SGNPWMkt	-0.232	0.241	-0.181	-0.060	-0.092	0.035	-0.366
RegionDensity	-0.902	0.862	-0.860	-0.736	0.047	-0.425	-0.677

	NPMF	NPMini	SGNPWMkt
YrID			
OrgType			
OtherPat			
SMktPar			
SMktIT			
TtlMktIT			
NPMF			
NPMini	-0.269		
SGNPWMkt	0.083	-0.121	
RegionDensity	0.076	0.645	0.103

> anova(fitWbl,fitWblSig2,test="Chisq")
Likelihood Ratio Test(s)

Response: censor(YrsEff, EffInd)

	Terms	N.Params	-2*LogLik	Test Df	LRT	Pr(Chi)
1	SOrgCode	3	111.4769			
2	YrID + OrgType + 4.18619e-008 OtherPat + SmktPar + SMktIT + TtlMktIT +	11	59.3005	8	52.1764	

NPMF + NPMini +
SGNPWMkt +
RegionDensity

APPENDIX H

S Codes for Subpopulation Next 7 Effectiveness Analysis for the Period 1976 to 2001

S Codes for Subpopulation Next 7 Effectiveness Analysis for the Period 1976 to 2001

```
S-PLUS : Copyright (c) 1988, 2002 Insightful Corp.
S : Copyright Lucent Technologies, Inc.
Professional Edition Version 6.1.3 Release 3 for Micros
oft Windows : 2002
Working data will be in C:\Program Files\Insightful\spl
us61\users\Cotter
> censorReg(formula=censor(YrsEff,EffInd)~SOrgCode,
+       data = DissEffAnal7601Nxt7A, na.action = na.exclude,
+       distribution = "exponential", threshold = 0, control = list(e.scale = 0.0001))
Call:
censorReg(formula = censor(YrsEff, EffInd) ~ SOrgCode, data =
        DissEffAnal7601Nxt7A, na.action = na.exclude, distribution =
        "exponential", threshold = 0, control = list(e.scale = 0.0001))

Distribution: Exponential

Coefficients:
 (Intercept)  SOrgCode
   -47.83933 0.9654333

Dispersion (scale) fixed at 1
Log-likelihood: -460.0177

Observations: 149 Total; 110 Censored
Parameters Estimated: 2
Threshold Parameter: 0
> censorReg(formula=censor(YrsEff,EffInd)~SOrgCode,
+       data = DissEffAnal7601Nxt7A, na.action = na.exclude,
+       distribution = "logexponential", threshold = 0, control = list(e.scale = 0.0001))
Call:
censorReg(formula = censor(YrsEff, EffInd) ~ SOrgCode, data =
        DissEffAnal7601Nxt7A, na.action = na.exclude, distribution =
        "logexponential", threshold = 0, control = list(e.scale = 0.0001))

Distribution: Logexponential

Coefficients:
 (Intercept) SOrgCode
   -7.233791 0.158513

Dispersion (scale) fixed at 1
Log-likelihood: -142.5444
```

```
Observations: 149 Total; 110 Censored
Parameters Estimated: 2
Threshold Parameter: 0
> censorReg(formula=censor(YrsEff,EffInd)~SOrgCode,
+       data = DissEffAnal7601Nxt7A, na.action = na.exclude,
+       distribution = "logistic", threshold = 0, control = list(e.scale = 0.0001))
Call:
censorReg(formula = censor(YrsEff, EffInd) ~ SOrgCode, data =
        DissEffAnal7601Nxt7A, na.action = na.exclude, distribution =
        "logistic", threshold = 0, control = list(e.scale = 0.0001))

Distribution: Logistic

Coefficients:
 (Intercept)  SOrgCode
  -45.52865 0.9006156

Dispersion (scale) est = 4.181962
Log-likelihood: -170.0143

Observations: 149 Total; 110 Censored
Parameters Estimated: 3
Threshold Parameter: 0
> censorReg(formula=censor(YrsEff,EffInd)~SOrgCode,
+       data = DissEffAnal7601Nxt7A, na.action = na.exclude,
+       distribution = "loglogistic", threshold = 0, control = list(e.scale = 0.0001))
Call:
censorReg(formula = censor(YrsEff, EffInd) ~ SOrgCode, data =
        DissEffAnal7601Nxt7A, na.action = na.exclude, distribution =
        "loglogistic", threshold = 0, control = list(e.scale = 0.0001))

Distribution: Loglogistic

Coefficients:
 (Intercept)  SOrgCode
  -8.330081 0.1723743

Dispersion (scale) est = 0.9976912
Log-likelihood: -143.527

Observations: 149 Total; 110 Censored
Parameters Estimated: 3
Threshold Parameter: 0
> censorReg(formula=censor(YrsEff,EffInd)~SOrgCode,
+       data = DissEffAnal7601Nxt7A, na.action = na.exclude,
```

```
+       distribution = "normal", threshold = 0, control = list(e.scale = 0.0001))
Call:
censorReg(formula = censor(YrsEff, EffInd) ~ SOrgCode, data =
        DissEffAnal7601Nxt7A, na.action = na.exclude, distribution = "normal",
        threshold = 0, control = list(e.scale = 0.0001))

Distribution: Normal

Coefficients:
 (Intercept)  SOrgCode
   -41.67922 0.8466956

Dispersion (scale) = 7.402445
Log-likelihood: -167.9107

Observations: 149 Total; 110 Censored
Parameters Estimated: 3
Threshold Parameter: 0
> censorReg(formula=censor(YrsEff,EffInd)~SOrgCode,
+       data = DissEffAnal7601Nxt7A, na.action = na.exclude,
+       distribution = "lognormal", threshold = 0, control = list(e.scale = 0.0001))
Call:
censorReg(formula = censor(YrsEff, EffInd) ~ SOrgCode, data =
        DissEffAnal7601Nxt7A, na.action = na.exclude, distribution =
        "lognormal", threshold = 0, control = list(e.scale = 0.0001))

Distribution: Lognormal

Coefficients:
 (Intercept)  SOrgCode
   -8.630793 0.1777238

Dispersion (scale) = 1.79741
Log-likelihood: -142.627

Observations: 149 Total; 110 Censored
Parameters Estimated: 3
Threshold Parameter: 0
> censorReg(formula=censor(YrsEff,EffInd)~SOrgCode,
+       data = DissEffAnal7601Nxt7A, na.action = na.exclude,
+       distribution = "rayleigh", threshold = 0, control = list(e.scale = 0.0001))
Call:
censorReg(formula = censor(YrsEff, EffInd) ~ SOrgCode, data =
        DissEffAnal7601Nxt7A, na.action = na.exclude, distribution =
        "rayleigh", threshold = 0, control = list(e.scale = 0.0001))
```

```
Distribution: Rayleigh

Coefficients:
 (Intercept) SOrgCode
  -52.98783 1.063498

Dispersion (scale) fixed at 0.5
Log-likelihood: -664.9789

Observations: 149 Total; 110 Censored
Parameters Estimated: 2
Threshold Parameter: 0
> censorReg(formula=censor(YrsEff,EffInd)~SOrgCode,
+       data = DissEffAnal7601Nxt7A, na.action = na.exclude,
+       distribution = "lograyleigh", threshold = 0, control = list(e.scale = 0.0001))
Call:
censorReg(formula = censor(YrsEff, EffInd) ~ SOrgCode, data =
       DissEffAnal7601Nxt7A, na.action = na.exclude, distribution =
       "lograyleigh", threshold = 0, control = list(e.scale = 0.0001))

Distribution: Lograyleigh

Coefficients:
 (Intercept)  SOrgCode
  -5.137724 0.1205129

Dispersion (scale) fixed at 0.5
Log-likelihood: -173.6599

Observations: 149 Total; 110 Censored
Parameters Estimated: 2
Threshold Parameter: 0
> censorReg(formula=censor(YrsEff,EffInd)~SOrgCode,
+       data = DissEffAnal7601Nxt7A, na.action = na.exclude,
+       distribution = "weibull", threshold = 0, control = list(e.scale = 0.0001))
Call:
censorReg(formula = censor(YrsEff, EffInd) ~ SOrgCode, data =
       DissEffAnal7601Nxt7A, na.action = na.exclude, distribution = "weibull",
       threshold = 0, control = list(e.scale = 0.0001))

Distribution: Weibull

Coefficients:
 (Intercept)  SOrgCode
  -7.575572 0.1654131
```

```
Dispersion (scale) = 1.097579
Log-likelihood: -142.253

Observations: 149 Total; 110 Censored
Parameters Estimated: 3
Threshold Parameter: 0
> censorReg(formula=censor(YrsEff,EffInd)~SOrgCode,
+       data = DissEffAnal7601Nxt7A, na.action = na.exclude,
+       distribution = "extreme", threshold = 0, control = list(e.scale = 0.0001))
Call:
censorReg(formula = censor(YrsEff, EffInd) ~ SOrgCode, data =
        DissEffAnal7601Nxt7A, na.action = na.exclude, distribution = "extreme",
        threshold = 0, control = list(e.scale = 0.0001))

Distribution: Extreme

Coefficients:
 (Intercept) SOrgCode
  -56.35564 1.153341

Dispersion (scale) = 6.716371
Log-likelihood: -176.1401

Observations: 149 Total; 110 Censored
Parameters Estimated: 3
Threshold Parameter: 0
> fitExp <- censorReg(formula=censor(YrsEff,EffInd)~SOrgCode,
+       data = DissEffAnal7601Nxt7A, na.action = na.exclude,
+       distribution = "exponential", threshold = 0, control = list(e.scale = 0.0001))
> fitLogExp <- censorReg(formula=censor(YrsEff,EffInd)~SOrgCode,
+       data = DissEffAnal7601Nxt7A, na.action = na.exclude,
+       distribution = "logexponential", threshold = 0, control = list(e.scale = 0.0001))
> fitLog <- censorReg(formula=censor(YrsEff,EffInd)~SOrgCode,
+       data = DissEffAnal7601Nxt7A, na.action = na.exclude,
+       distribution = "logistic", threshold = 0, control = list(e.scale = 0.0001))
> fitLogLog <- censorReg(formula=censor(YrsEff,EffInd)~SOrgCode,
+       data = DissEffAnal7601Nxt7A, na.action = na.exclude,
+       distribution = "loglogistic", threshold = 0, control = list(e.scale = 0.0001))
> fitNor <- censorReg(formula=censor(YrsEff,EffInd)~SOrgCode,
+       data = DissEffAnal7601Nxt7A, na.action = na.exclude,
+       distribution = "normal", threshold = 0, control = list(e.scale = 0.0001))
> fitLogNor <- censorReg(formula=censor(YrsEff,EffInd)~SOrgCode,
+       data = DissEffAnal7601Nxt7A, na.action = na.exclude,
+       distribution = "lognormal", threshold = 0, control = list(e.scale = 0.0001))
> fitRay <- censorReg(formula=censor(YrsEff,EffInd)~SOrgCode,
+       data = DissEffAnal7601Nxt7A, na.action = na.exclude,
```

```
+       distribution = "rayleigh", threshold = 0, control = list(e.scale = 0.0001))
> fitLogRay <- censorReg(formula=censor(YrsEff,EffInd)~SOrgCode,
+       data = DissEffAnal7601Nxt7A, na.action = na.exclude,
+       distribution = "lograyleigh", threshold = 0, control = list(e.scale = 0.0001))
> fitWbl <- censorReg(formula=censor(YrsEff,EffInd)~SOrgCode,
+       data = DissEffAnal7601Nxt7A, na.action = na.exclude,
+       distribution = "weibull", threshold = 0, control = list(e.scale = 0.0001))
> fitExt <- censorReg(formula=censor(YrsEff,EffInd)~SOrgCode,
+       data = DissEffAnal7601Nxt7A, na.action = na.exclude,
+       distribution = "extreme", threshold = 0, control = list(e.scale = 0.0001))
> anova(fitExt,fitLogRay,fitLog,fitNor,fitLogLog,fitLogNor,fitLogExp,fitWbl)
Likelihood Ratio Test(s)

Response: censor(YrsEff, EffInd)
```

	Model	Terms	N.Params	LogLik	-2*LogLik	AIC
1	Rayleigh	OrgCode	3	-664.9789	1329.9578	1333.958
2	Exponential	OrgCode	3	-460.0177	920.0354	924.035
3	Extreme	OrgCode	3	-176.1401	352.2802	358.280
4	LogRayleigh	OrgCode	3	-173.6599	347.3198	351.320
5	Logistic	OrgCode	3	-170.0143	340.0286	346.029
6	Normal	OrgCode	3	-167.9107	335.8214	341.821
7	LogLogisitc	OrgCode	3	-143.5270	287.0540	293.054
8	LogNormal	OrgCode	3	-142.6270	285.2540	291.254
9	Weibull	OrgCode	3	-142.2530	284.5060	290.506
10	LogExponential	OrgCode	3	-142.5444	285.0888	289.089

```
> summary(fitWbl)
Call:
censorReg(formula = censor(YrsEff, EffInd) ~ SOrgCode, data =
    DissEffAnal7601Nxt7A, na.action = na.exclude, distribution = "weibull",
    threshold = 0, control = list(e.scale = 0.0001))

Distribution:  Weibull

Standardized Residuals:
```

	Min	Max
Uncensored	0.022	1.900
Censored	0.022	1.010

Coefficients:

	Est.	Std.Err.	95% LCL	95% UCL	z-value	p-value
(Intercept)	-7.576	2.6318	-12.7337	-2.417	-2.88	0.0040
SOrgCode	0.165	0.0425	0.0821	0.249	3.89	0.0001

Extreme value distribution: Dispersion (scale) = 1.097579

```
Observations: 149 Total; 110 Censored
-2*Log-Likelihood: 285

Correlation of Coefficients:
        (Intercept)
SOrgCode -0.997

> fitWblFull <- censorReg(formula=censor(YrsEff,EffInd)~SOrgCode + YrID +
+       OrgType + ITPat + OtherPat + NSTEffcy + SMktPar + SMktIT + TtlMktIT +
+       NPMF + NPMini + NPPC + NPWS + SGNPHMkt + SGNPWMkt + PwPrd +
Density +
+       CohtDensity + RegionDensity, data = DissEffAnal7601Nxt7A,
+       na.action = na.exclude, distribution = "weibull", threshold = 0,
+       control = list(e.scale = 0.0001))
> summary(fitWblFull)
Call:
censorReg(formula = censor(YrsEff, EffInd) ~ SOrgCode + YrID + OrgType + ITPat +
        OtherPat + NSTEffcy + SMktPar + SMktIT + TtlMktIT + NPMF + NPMini +
        NPPC + NPWS + SGNPHMkt + SGNPWMkt + PwPrd + Density + CohtDensity
+
        RegionDensity, data = DissEffAnal7601Nxt7A, na.action = na.exclude,
        distribution = "weibull", threshold = 0, control = list(e.scale =
        0.0001))

Distribution:  Weibull
Standardized Residuals:
             Min    Max
Uncensored   0.005  2.687
Censored     0.000  0.698

Coefficients:
```

	Est.	Std.Err.	95% LCL	95% UCL	z-value	p-value
(Intercept)	-3.14e+000	4.41e+000	-1.18e+001	5.5006232	-0.7129	4.76e-001
SOrgCode	-5.52e-003	4.16e-002	-8.70e-002	0.0759913	-0.1327	8.94e-001
YrID	1.57e-001	1.06e-001	-4.96e-002	0.3642966	1.4901	1.36e-001
OrgType	-1.08e+000	4.65e-001	-1.99e+000	-0.1696268	-2.3244	2.01e-002
ITPat	-2.66e-003	8.38e-004	-4.31e-003	-0.0010204	-3.1769	1.49e-003
OtherPat	-8.27e-004	1.29e-003	-3.35e-003	0.0016945	-0.6429	5.20e-001
NSTEffcy	5.55e-006	4.35e-006	-2.98e-006	0.0000141	1.2758	2.02e-001
SMktPar	2.64e+000	1.18e+000	3.29e-001	4.9576152	2.2383	2.52e-002
SMktIT	3.33e+000	2.13e+000	-8.50e-001	7.5001883	1.5611	1.18e-001
TtlMktIT	-7.33e-001	5.74e-001	-1.86e+000	0.3917223	-1.2774	2.01e-001
NPMF	5.02e-004	9.31e-002	-1.82e-001	0.1829347	0.0054	9.96e-001
NPMini	-5.99e-004	5.90e-002	-1.16e-001	0.1150227	-0.0102	9.92e-001
NPPC	-9.38e-002	1.44e-001	-3.75e-001	0.1877882	-0.6530	5.14e-001
NPWS	8.54e-002	1.20e-001	-1.50e-001	0.3205726	0.7122	4.76e-001

SGNPHMkt	-1.61e-003	1.43e-003	-4.42e-003	0.0011954	-1.1257	2.60e-001
SGNPWMkt	5.99e-004	1.10e-003	-1.56e-003	0.0027620	0.5427	5.87e-001
PwPrd	-1.76e+000	4.89e-001	-2.72e+000	-0.8047003	-3.6059	3.11e-004
Density	-5.00e-002	2.38e-002	-9.66e-002	-0.0033514	-2.1008	3.57e-002
CohtDensity	1.68e-001	2.92e-002	1.11e-001	0.2257154	5.7686	7.99e-009
RegionDensity	3.24e-002	2.01e-002	-6.92e-003	0.0717974	1.6154	1.06e-001

Extreme value distribution: Dispersion (scale) = 0.5866728
Observations: 149 Total; 110 Censored
-2*Log-Likelihood: 189

Correlation of Coefficients:

	(Intercept)	SOrgCode	YrID	OrgType	ITPat	OtherPat	NSTEffcy
SOrgCode	-0.428						
YrID	-0.779	-0.161					
OrgType	0.132	-0.039	-0.123				
ITPat	0.207	0.030	-0.335	0.195			
OtherPat	0.084	-0.085	-0.002	0.026	-0.700		
NSTEffcy	0.023	-0.448	0.283	-0.183	-0.453	0.212	
SMktPar	-0.258	0.169	0.162	-0.049	0.227	-0.737	-0.060
SMktIT	0.218	-0.038	-0.171	0.105	-0.344	0.612	0.002
TtlMktIT	0.418	0.258	-0.795	0.087	0.359	-0.059	-0.433
NPMF	0.183	0.039	-0.122	-0.344	-0.207	0.113	0.120
NPMini	0.186	-0.488	0.095	0.132	0.078	0.103	0.073
NPPC	-0.025	0.378	-0.265	-0.017	0.223	-0.117	-0.671
NPWS	-0.019	0.037	-0.012	-0.227	-0.020	-0.084	0.129
SGNPHMkt	0.061	-0.170	-0.010	0.114	0.068	0.194	-0.003
SGNPWMkt	-0.018	0.095	0.055	-0.088	-0.053	-0.204	0.031
PwPrd	0.482	-0.149	-0.360	0.095	0.184	0.020	-0.070
Density	-0.679	0.016	0.617	0.083	0.241	-0.249	0.033
CohtDensity	0.001	-0.522	0.314	-0.296	-0.130	0.047	0.297
RegionDensity	-0.059	-0.024	0.076	-0.157	-0.420	0.200	0.136

	SMktPar	SMktIT	TtlMktIT	NPMF	NPMini	NPPC	NPWS	SGNPHMkt
SOrgCode								
YrID								
OrgType								
ITPat								
OtherPat								
NSTEffcy								
SMktPar								
SMktIT	-0.653							
TtlMktIT	-0.064	0.000						
NPMF	-0.129	0.081	-0.159					
NPMini	-0.166	-0.140	-0.032	-0.162				

NPPC	0.106	-0.163	0.443	0.048	-0.091			
NPWS	0.130	-0.066	0.080	-0.145	-0.264	0.016		
SGNPHMkt	-0.162	0.045	0.113	-0.359	0.291	0.008	-0.225	
SGNPWMkt	0.173	-0.039	-0.343	0.444	-0.305	-0.078	-0.204	-0.616
PwPrd	-0.238	0.184	-0.113	0.439	-0.011	-0.077	-0.194	-0.146
Density	0.059	-0.168	-0.357	-0.333	-0.029	-0.083	-0.004	0.068
CohtDensity	-0.082	-0.097	-0.218	-0.057	0.357	-0.346	-0.122	0.135
RegionDensity	0.292	-0.050	-0.111	0.096	-0.283	0.010	0.129	-0.145

	SGNPWMkt	PwPrd	Density	CohtDensity
SOrgCode				
YrID				
OrgType				
ITPat				
OtherPat				
NSTEffcy				
SMktPar				
SMktIT				
TtlMktIT				
NPMF				
NPMini				
NPPC				
NPWS				
SGNPHMkt				
SGNPWMkt				
PwPrd	0.391			
Density	-0.076	-0.167		
CohtDensity	-0.145	-0.168	-0.015	
RegionDensity	0.176	0.018	-0.272	-0.153

```
> fitWblSig1 <- censorReg(formula=censor(YrsEff,EffInd)~SOrgCode + YrID +
+       OrgType + ITPat + SMktPar +
+       PwPrd + Density +
+       CohtDensity + RegionDensity, data = DissEffAnal7601Nxt7A,
+       na.action = na.exclude, distribution = "weibull", threshold = 0,
+       control = list(e.scale = 0.0001))
> summary(fitWblSig1)
Call:
censorReg(formula = censor(YrsEff, EffInd) ~ SOrgCode + YrID + OrgType + ITPat +
        SMktPar + PwPrd + Density + CohtDensity + RegionDensity, data =
        DissEffAnal7601Nxt7A, na.action = na.exclude, distribution = "weibull",
        threshold = 0, control = list(e.scale = 0.0001))

Distribution:  Weibull

Standardized Residuals:
```

	Min	Max
Uncensored	0.005	2.954
Censored	0.000	0.850

Coefficients:

	Est.	Std.Err.	95% LCL	95% UCL	z-value	p-value
(Intercept)	-5.33123	3.424208	-12.04255	1.380095	-1.56	1.19e-001
SOrgCode	0.07830	0.026446	0.02647	0.130133	2.96	3.07e-003
YrID	0.07132	0.059265	-0.04483	0.187482	1.20	2.29e-001
OrgType	-1.01802	0.469069	-1.93738	-0.098659	-2.17	3.00e-002
ITPat	-0.00214	0.000681	-0.00348	-0.000805	-3.14	1.68e-003
SMktPar	2.66210	0.867611	0.96161	4.362584	3.07	2.15e-003
PwPrd	-1.96684	0.441198	-2.83157	-1.102106	-4.46	8.27e-006
Density	-0.06797	0.021806	-0.11071	-0.025233	-3.12	1.83e-003
CohtDensity	0.15440	0.026673	0.10212	0.206678	5.79	7.10e-009
RegionDensity	0.04061	0.019119	0.00314	0.078084	2.12	3.36e-002

Extreme value distribution: Dispersion (scale) = 0.6618375
Observations: 149 Total; 110 Censored
-2*Log-Likelihood: 205

Correlation of Coefficients:

	(Intercept)	SOrgCode	YrID	OrgType	ITPat	SMktPar	PwPrd
SOrgCode	-0.460						
YrID	-0.859	0.011					
OrgType	0.304	-0.184	-0.273				
ITPat	0.303	-0.204	-0.386	0.317			
SMktPar	-0.099	0.136	0.080	-0.029	-0.626		
PwPrd	0.508	-0.108	-0.684	0.196	0.459	-0.294	
Density	-0.536	0.035	0.413	0.058	0.443	-0.490	0.095
CohtDensity	-0.179	-0.139	0.320	-0.486	-0.329	0.049	-0.298
RegionDensity	-0.016	-0.134	0.068	-0.167	-0.372	0.672	-0.056

	Density	CohtDensity
SOrgCode		
YrID		
OrgType		
ITPat		
SMktPar		
PwPrd		
Density		
CohtDensity	-0.222	
RegionDensity	-0.400	0.028

```
> fitWblSig2 <- censorReg(formula=censor(YrsEff,EffInd)~SOrgCode +
+       OrgType + ITPat + SMktPar +
```

+ PwPrd + Density +
+ CohtDensity + RegionDensity, data = DissEffAnal7601Nxt7A,
+ na.action = na.exclude, distribution = "weibull", threshold = 0,
+ control = list(e.scale = 0.0001))
> summary(fitWblSig2)
Call:
censorReg(formula = censor(YrsEff, EffInd) ~ SOrgCode + OrgType + ITPat + SMktPar + PwPrd + Density + CohtDensity + RegionDensity, data = DissEffAnal7601Nxt7A, na.action = na.exclude, distribution = "weibull", threshold = 0, control = list(e.scale = 0.0001))

Distribution: Weibull

Standardized Residuals:

	Min	Max
Uncensored	0.007	2.929
Censored	0.000	0.720

Coefficients:

	Est.	Std.Err.	95% LCL	95% UCL	z-value	p-value
(Intercept)	-1.69552	1.847016	-5.315602	1.924570	-0.918	3.59e-001
SOrgCode	0.07801	0.027527	0.024062	0.131967	2.834	4.60e-003
OrgType	-0.87698	0.475213	-1.808377	0.054422	-1.845	6.50e-002
ITPat	-0.00187	0.000668	-0.003180	-0.000564	-2.804	5.04e-003
SMktPar	2.60057	0.901316	0.834021	4.367113	2.885	3.91e-003
PwPrd	-1.64940	0.384443	-2.402894	-0.895904	-4.290	1.78e-005
Density	-0.08057	0.022056	-0.123800	-0.037342	-3.653	2.59e-004
CohtDensity	0.14602	0.026612	0.093862	0.198179	5.487	4.09e-008
RegionDensity	0.03920	0.019712	0.000566	0.077836	1.989	4.67e-002

Extreme value distribution: Dispersion (scale) = 0.6878724
Observations: 149 Total; 110 Censored
-2*Log-Likelihood: 207

Correlation of Coefficients:

	(Intercept)	SOrgCode	OrgType	ITPat	SMktPar	PwPrd	Density
SOrgCode	-0.862						
OrgType	0.118	-0.191					
ITPat	-0.080	-0.221	0.251				
SMktPar	-0.019	0.135	-0.038	-0.676			
PwPrd	-0.282	-0.131	0.090	0.340	-0.347		
Density	-0.419	0.022	0.230	0.713	-0.592	0.657	
CohtDensity	0.211	-0.143	-0.457	-0.247	0.036	-0.154	-0.423
RegionDensity	0.117	-0.140	-0.176	-0.392	0.669	-0.071	-0.485

CohtDensity

```
SOrgCode
OrgType
ITPat
SMktPar
PwPrd
Density
CohtDensity
RegionDensity   0.022

> fitWblSig3 <- censorReg(formula=censor(YrsEff,EffInd)~SOrgCode +
+       ITPat + SMktPar + PwPrd + Density + CohtDensity + RegionDensity,
+       data = DissEffAnal7601Nxt7A, na.action = na.exclude,
+       distribution = "weibull", threshold = 0, control = list(e.scale = 0.0001))
> summary(fitWblSig3)
Call:
censorReg(formula = censor(YrsEff, EffInd) ~ SOrgCode + ITPat + SMktPar +
        PwPrd + Density + CohtDensity + RegionDensity, data =
        DissEffAnal7601Nxt7A, na.action = na.exclude, distribution = "weibull",
        threshold = 0, control = list(e.scale = 0.0001))

Distribution:  Weibull

Standardized Residuals:
             Min     Max
Uncensored   0.008   2.800
Censored     0.000   0.780

Coefficients:
                 Est.       Std.Err.   95% LCL    95% UCL     z-value   p-value
(Intercept)      -1.44304   1.80586    -4.98246   2.096372    -0.799    4.24e-001
SOrgCode         0.07159    0.02715    0.01838    0.124806    2.637     8.37e-003
ITPat            -0.00167   0.00066    -0.00296   -0.000371   -2.522    1.17e-002
SMktPar          2.55489    0.89114    0.80828    4.301500    2.867     4.14e-003
PwPrd            -1.59749   0.36844    -2.31962   -0.875355   -4.336    1.45e-005
Density          -0.07340   0.02136    -0.11527   -0.031540   -3.437    5.89e-004
CohtDensity      0.13058    0.02425    0.08305    0.178111    5.384     7.27e-008
RegionDensity    0.03392    0.01905    -0.00341   0.071255    1.781     7.49e-002

Extreme value distribution: Dispersion (scale) = 0.701388
Observations: 149 Total; 110 Censored
-2*Log-Likelihood: 210

Correlation of Coefficients:
                 (Intercept)  SOrgCode   ITPat    SMktPar   PwPrd   Density
                 CohtDensity
SOrgCode         -0.872
```

```
ITPat          -0.105     -0.177
SMktPar        0.000      0.115      -0.687
PwPrd          -0.243     -0.141     0.315    -0.368
Density        -0.454     0.081      0.678    -0.601    0.632
CohtDensity    0.321      -0.273     -0.192   0.069     -0.171   -0.432
RegionDensity  0.183      -0.209     -0.360   0.655     -0.079   -0.508   0.052

> fitWblSig4 <- censorReg(formula=censor(YrsEff,EffInd)~SOrgCode +
+       ITPat + SMktPar + PwPrd + Density + CohtDensity,
+       data = DissEffAnal7601Nxt7A, na.action = na.exclude,
+       distribution = "weibull", threshold = 0, control = list(e.scale = 0.0001))
> summary(fitWblSig4)
Call:
censorReg(formula = censor(YrsEff, EffInd) ~ SOrgCode + ITPat + SMktPar +
        PwPrd + Density + CohtDensity, data = DissEffAnal7601Nxt7A, na.action
         = na.exclude, distribution = "weibull", threshold = 0, control = list(
        e.scale = 0.0001))

Distribution: Weibull

Standardized Residuals:
             Min    Max
Uncensored   0.006  2.652
Censored     0.000  1.099

Coefficients:
               Est.      Std.Err.  95% LCL   95% UCL     z-value  p-value
(Intercept)    -1.97888  1.837536  -5.58038  1.6226255   -1.08    2.82e-001
SOrgCode       0.08165   0.027590  0.02757   0.1357268   2.96     3.08e-003
ITPat          -0.00129  0.000643  -0.00255  -0.0000262  -2.00    4.54e-002
SMktPar        1.59293   0.659059  0.30119   2.8846576   2.42     1.57e-002
PwPrd          -1.59926  0.364110  -2.31291  -0.8856218  -4.39    1.12e-005
Density        -0.05479  0.018375  -0.09081  -0.0187780  -2.98    2.86e-003
CohtDensity    0.13130   0.025585  0.08116   0.1814450   5.13     2.87e-007

Extreme value distribution: Dispersion (scale) = 0.7218177
Observations: 149 Total; 110 Censored
-2*Log-Likelihood: 213

Correlation of Coefficients:
             (Intercept)  SOrgCode  ITPat   SMktPar  PwPrd  Density
SOrgCode     -0.871
ITPat        -0.097       -0.218
SMktPar      -0.184       0.337     -0.603
PwPrd        -0.202       -0.168    0.291   -0.420
Density      -0.441       -0.006    0.604   -0.316   0.655
```

CohtDensity	0.365	-0.331	-0.145	-0.048	-0.139	-0.460

```
> anova(fitWbl,fitWblSig4,test="Chisq")
Likelihood Ratio Test(s)

Response: censor(YrsEff, EffInd)
```

	Terms	N.Params	-2*LogLik	Test Df	LRT	Pr(Chi)
1	SOrgCode	3	284.5060			
2	SOrgCode + ITPat + 4.38538e-014 SmktPar + PwPrd + Density + CohtDensity +	8	212.7377	5	71.76833	

CURRICULUM VITA

for

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Master of Science in Engineering Management
Concentration: Quality Systems Management and Engineering
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May 1994

Master of Business Administration
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Electronics Technology
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PROFESSIONAL CHRONOLOGY:

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PROFESSIONAL SOCIETIES:

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Certified Reliability Engineer – ASQ