GENERAL ORGANIZATIONAL CLASSIFICATION: AN EMPIRICAL TEST USING THE UNITED STATES AND JAPANESE ELECTRONICS INDUSTRIES*

DAVE ULRICH AND BILL MCKELVEY

Graduate School of Business Administration, The University of Michigan, Ann Arbor, Michigan 48109
Graduate School of Management, University of California, Los Angeles, California 90024

This study empirically tests the existence of populations. It reports a general organizational classification for both the United States and Japanese electronics industries. It tests for and identifies populations within a family of electronics industries and demonstrates the relevance of a general organizational classification for explaining how different natural selection processes affect different populations. Data include 669 US and 144 Japanese electronics firms. The results suggest that classification should play a more central role in development of organizational science.

(ORGANIZATION CLASSIFICATION; INTRA-INDUSTRY POPULATIONS; NATURAL SELECTION)

The definition and classification of organizations into populations remains a significant challenge for organizational science (Dess and Beard 1984; Astley 1985). Virtually all successful sciences include a general classification of their phenomena as an essential prerequisite to scientific development (McKelvey 1982). Lacking a useful classification, a satisfactory understanding of organizations could remain unfulfilled.

The scientific reasons for constructing a general classification of organizations have been discussed elsewhere (Carper and Snizek 1980; McKelvey 1982). A general classification organizes a diverse set of facts into a form from which laws, propositions, and theories may be derived. It underlies development of organizational science and attempts to explain why some organizations are unique. These explanations allow for nomological nets to develop specific propositions about a particular type of organization. It provides a framework for the retrieval of scientific information about organizations. In addition, it defines a set of homogeneous populations, the use of which should dramatically increase levels of explained variance.

A construct that improves both the quality of organizational research findings and the use of them by both scientists and practitioners makes a contribution of considerable importance to the field. The timely development of a general organizational classification gains further importance due to the use of populations as a central element in modern organization theory (Hannan and Freeman 1977; Aldrich 1979; McKelvey 1982) and strategic groups as a central element of industry substructures (McGee and Thomas 1986). The emergence of the population perspective as an overarching framework for better understanding organizations (Ulrich and Barney 1984) also points to a need for general classification.

To date researchers have only superficially examined how common organizational forms may cluster into populations. To derive and test populations, assessment must go beyond common sense typologies of populations that currently exist in the literature (Carroll 1981; Carroll and Delacroix 1982).

*Accepted by Special Senior Editor Graham Astley; received September 30, 1987. This paper has been with the authors 3 months for 2 revisions.
While general classification of organizations appears promising, a pivotal assumption remains untested: Do identifiable homogeneous populations exist and can analytical techniques be used to define nonartifactual populations? Our research tests for the existence and identification of populations in the United States and Japanese electronics industries by combining statistical analysis with agglomerative clustering methods. Ninety-eight percent of the 680 U.S. and all of the 144 Japanese publicly held electronics firms were studied. Our results show that populations do exist in the electronics industry.

Background

Most organizational scholars rely on theoretical definitions and common sense typologies stressing one or two organizational or industrial attributes to form populations (see reviews by Carper and Snizek 1980; Scott 1981). Taxonomists label such approaches special classifications (Jeffrey 1968) that consist of monothetic groups in which all group members must possess all of the attributes used to define the group (McKelvey 1982, p. 38). Once biologists comprehended the complexities of biological organisms, they abandoned special classifications for general classifications. The latter consist of polythetic groups in which most members share most, but not all, attributes. The polythetic group concept allows for the general classification of complex organisms. General classification enables scientists to identify the set of variables that define a population and subsequently to carry out studies describing, predicting, and explaining the behavior of members of a given population (McKelvey 1982, Chapter 2).

Organizational scientists have treated organizations as complex for two decades (Hage and Aiken 1969; Perrow 1972; Hall 1977; Miller and Friesen 1984), but special classifications still predominate. The monothetic groups defined by special classifications (e.g. Etzioni 1961; Blau and Scott 1962; Thompson 1967) point to some important features of organizations but they do not incorporate many other attributes found in most complex organizations. Monothetic classes also have not been central to guiding theory or research about organizations (Carper and Snizek 1980). Considering organizations at least as complex as biological organisms, McKelvey and Aldrich (1983) call for a shift from the use of special classifications and monothetic groups to general classifications and polythetic groupings.

A number of important advantages accrue to organizational scientists from the development of a general classification of organizations into populations. Descriptions of organizations would focus on distinctive characteristics of organizations and populations that might lead to better predictions about how and why organizations differ (Albert and Whetten 1984). Generalizations would be bound to the set of organizations within the population. Predictors and levels of explained variance would improve for organizations within a population, and systematic retrieval of information on organizational practices within a population would be possible. For example, a general classification, if it existed, would greatly facilitate the call for an organizational data base by Freeman (1986). Such a classification would help determine which organizational attributes to add to the data base (e.g., those characteristics which make an organization or population unique), what intra-population sample frame to use to collect the data, and which populations should be included, if not all.

General Classification

Shifting the basis of empirical organizational science from a special to general classification approach raises substantial issues and difficulties. To begin with: Do homogeneous groups or populations of organizations actually exist and can they be identified? McKelvey's (1982, pp. 137–141) review of the literature suggests a number of theoretical and empirical bases for believing that populations exist. Furthermore,
evidence of populations comes from recent empirical population ecology studies that
typically draw on special classifications for grouping organizations into common sense
industry families such as unions, semiconductor firms, newspapers, restaurants, or
voluntary organizations (Brittain and Freeman 1980; Freeman and Hannan 1983;
Carroll and Delacroix 1982; Carroll 1984a; Singh, Tucker, and House 1986).

However, an industry may include several kinds of populations or organizational
forms. Whether populations exist within common sense industry groupings and whether
it makes sense to study populations within industries versus studying industries as
populations remains unclear. We distinguish between “populations” which are at the
species level of botanical categories and represent groupings of organizations with
similar internal structure and processes and “families” which represent an industry
level of analysis.

As such, many populations may exist within an industry. We should also acknowl-
edge that organizations, populations, and industries evolve and change over time. As
environmental resources and opportunities become available, organizations emerge to
attract those resources. Over time, organizational forms or populations emerge within
an industry because they develop competencies in acquiring resources through meeting
environmental opportunities. An early study of voluntary organizations by Dodder
(1969) suggested that populations exist within one industry family, but he did not carry
out any tests indicating whether the populations of volunteer organizations were
statistically significant. As indicated by McKelvey and Aldrich (1983) the prevalence of
the “all alike” and “all unique” models of organizations steers investigators away from
direct tests of whether significantly different populations exist within industries.

The problem of how to discover and define populations also remains unsolved
(Warriner 1979). Until recent work by McKelvey (1982), basic theory explaining how
populations emerge, attain internal homogeneity, and remain separate from other
populations had not been developed (Astley 1985). A theory of population evolution
necessarily assumes that populations exist and can be identified. The community
ecology approach taken by Astley (1985) proposes a theory for population evolution,
but fails to deal with how to statistically define populations. We feel that before
exploring population evolution, growth, and decline much further, organizational
scientists need a rigorous process to empirically discover and define populations and
identify their members. The challenge remains: though industry families such as those
produced by the Standard Industrial Classification are used by researchers in industrial
economics and organizational strategy, studies of the validity of industry structure
remain at a very primitive stage (Porter 1980, 1985; McGee and Thomas 1986).

This study tests for the existence of populations within a family grouping of United
States and Japanese electronics firms. We think that testing for populations within a
common sense grouping such as the electronics industry offers a stiffer test of whether
populations exist than testing across common sense groups (Haas, Hall, and Johnson
1966) because the differences are more subtle. We presume differences among intra-
industry populations are much less obvious than, say, differences among industries
such as machine tools, construction, automobiles, and ship building. As we show the
existence of populations within industry families, we need to identify populations that
are neither random nor trivial. Although early attempts at classification of organiza-
tions (Haas et al. 1966; Pugh et al. 1968, 1969; Dodder 1969; Goronzy 1969) were
instructive, three problems remain unresolved.

First, a theory of organizational differences is needed to select taxonomic characters.
Biologists have relied on a well-developed theory of evolution to identify significant
characters that distinguish one species from another. Lacking a well-developed theory
of organizational evolution, (Aldrich and Mueller 1982) organizational scientists must
begin any classification with an effort to establish an explicit theory of organizational
differences. Such a theory identifies the characteristics that distinguish one organization from another, reduces the potential sample of characters from unlimited lists to key identifiers, and clarifies why an organization might fall in one grouping rather than another.

Second, organizational researchers need a parsimonious method of identifying organizational differences. Numerical taxonomic methods have found favor in biological systematics because they allow the use of many attributes and their advocates claim they are more objective than the traditional evolutionary methods of classification (Sneath and Sokal 1973). In fact, numerical solutions require several subjective decisions at various points (McKelvey 1982, Chapter 12). Some methodological difficulties with numerical taxonomic methods are alleviated in biology because biological systematists may draw on the existing well accepted evolutionary classification scheme for the definition of samples, the identification of characters, and the external validation of the resultant clusters. Organizational systematists cannot resolve sampling, character definition, and population validation problems by referring to a well accepted external validation criterion.

Third, we need an approach to bring the benefits of statistical rigor to the evaluation of the results of numerical taxonomic solutions. Over ten years ago Hartigan (1975) lamented the lack of a statistical basis for the clustering methods then in use in biology. Typically biological numerical taxonomic studies did not produce cluster sizes large enough for reasonable statistical analysis. More recent studies in social science (Mezzich and Solomon 1980; Rolmesburg 1984; Aldenderfer and Blashfield 1984), organizational science (Lewis and Alexander 1986) or competitive strategy (Hawes and Crittenden 1984; Dess and Davis 1984; Harrigan 1985; McGee and Thomas 1986) show little progress. Since all clustering algorithms produce clusters, whether artificial or not, statistical applications are essential.

After considering the foregoing issues involved in choosing from among several different theories of classification, McKelvey (1982) recommended a combined numerical taxonomic/evolutionary approach. The evolutionary approach offers the best possibility of selecting taxonomic characters that measure evolutionarily significant organization attributes, that is, attributes that achieve importance in enhancing an organization’s probability of selection and survival in its niche and environment. A researcher likely would find this approach difficult since it also requires knowing enough about the environment to know which characters have adaptive significance. Unfortunately, for most kinds of organizations or populations, researchers do not know which organizational and environmental attributes have evolutionary adaptive significance.

The numerical taxonomic approach avoids the problem of specifying the significant attributes by simply selecting all available characters. But, researchers may not know of all organizational attributes or have adequate measures. Besides many available characters may have trivial effects. The combined approach appears superior because each theory compensates for the weaknesses of the other. But the time and cost realities of conducting both kinds of studies are severe.

Our ability to pursue a combined evolutionary/numerical taxonomic approach to deal with the two foregoing sets of issues was limited by the nature of the data. We chose to study many firms using secondary, and thus limited, data rather than few firms with primary, and thus more extensive, data. The large number of organizations meant we could apply a variety of statistical methods to test for the nonchance basis of the resultant populations and test for existence of populations within an industry family. The 813 organizations and 78 taxonomic characters we ultimately used provided an excellent opportunity to grapple with a number of the numerical taxonomic issues and to test for populations within the electronics industry.
The nature of the data precluded us from drawing on a robust theory of organizational differences to guide us in selecting taxonomic characters. Consequently, we accepted a rather elementary theory. Following the stream of research on organizations operating within open systems (Katz and Kahn 1978), we worked on the premise that organizational survival depends on offering goods or services to a niche on a competitive basis in return for resources. The market, or customers, of firms in the electronics industry comprises a large component of their niche. Hence, we identified a typology of markets (components, electric power, industrial, instruments, communications, retail/consumer, computer, government, and transportation) served by firms in the electronics industry. We assessed whether a firm did or did not operate in each of these markets. This typology of markets served evolved from existing typologies used by electronics analysts and industry associations and interviews and a delphi process with a panel of industry experts.\footnote{This panel consisted of ten industry experts from the Electronics Industry Association and Semiconductor Industry Association. These experts were asked to identify the "markets served" in the electronics industry. After three iterations, the ten agreed to the presented typology of markets served.} In addition to "markets served" as a key element of our elementary theory of organizational speciation, we proposed that organizational identity is also a composite of work place and organizational competencies that produce a competitive product or service. Given this rationale, we measured the business competencies each firm drew upon to serve each market (research & development/ engineering, manufacturing/assembly, marketing, distribution, leasing). The matrix of markets served by business competencies has been used by others (Nathanson and Cassano 1982; Hambrick and Lei 1985) to analyze key characteristics of firm identity.

The final component of our elementary theory of organizational differences included firm characteristics such as firm size, a concept extensively studied in the organizational literature (Starbuck 1965; Blau and Schoenherr 1971; Kimberly 1976), macro productivity measures, e.g., sales per employee; and organizational diversification as measured by Rumelt's (1974) specialization ratio. Our elementary theory of organizational speciation encompasses core technology and marketing as suggested by Hannan and Freeman (1984) and includes internal firm characteristics which may affect the authority structure and goals of the firm. We recognize that this elementary theory of specialization fails to account for many significant elements of organizational identity, such as financial capability, technological capability, or organizational capability (Ulrich 1987a, b). However, given the choice of collecting selected data on many firms or extensive data on few firms, we opted for the selected data to fully test classification within an existing family of organizations.

Using this elementary theory of organizational differences and numerical taxonomy, this study identifies and tests for statistically significant differences among populations. We accomplish this by working with a very large sample of organizations and a reasonably large number of characters. Our taxonomic characters reflect an elementary theory of organizational differences based on the survival and competence emphases of Ulrich (1982) and McKeelvey (1982). We experiment with several techniques for evaluating the best cluster structure and use several ways of testing whether the resulting groups are statistically significant. This logic leads to a hypothesis, that:

\[ H_1: \text{Discrete populations distinguished by nonrandom differences can be identified in the electronics industry.} \]

Testing for the existence and identification of populations within an industry family strengthens the foundation for a general classification by showing such an approach feasible. These tests also reveal that another level of analysis may be used for organizational science, that of populations.
Method

Cases

Our sector (the initial aggregate or statistical population from which cases were taken; in what follows we will refer to it as a family in the taxonomic hierarchy of categories) consisted of all publicly held firms in the United States and Japanese electronics industries. Since our study attempts to form a general classification of populations within a family rather than a classification of families, we accepted the following commonsense definitions of our families. In the United States, Fairchild Publications publishes an annual directory of information on all public electronics firms called the Electronic News Financial Fact Book and Directory (hereafter called the Fact Book). The 1980 Fact Book listed 684 publicly held firms. For Japanese firms, we used the Japan Company Handbook (hereafter called Handbook). This book is published semiannually and reports summary information on publicly held Japanese firms. From the Handbook we identified a total of 144 firms operating in the electronics industry.

We chose to work with a sample as close to the total family in size as possible. Unlike some previous numerical taxonomic studies (Haas et al. 1966), we did not want to undermine the strengths of the numerical taxonomic approach by preceding it with arbitrary decisions reducing the sample. We felt that a strictly random sample might leave out key organizations. To use a stratified sample, we would have to make preliminary arbitrary decisions about what strata, that is populations, to use. This did not make sense as we wanted the classification study to define the populations. Our final sample in the U.S. totaled 669 firms (98%); 15 firms were removed from the sample because they were Canadian, not U.S. firms, they refused to discuss any information in our telephone interviews, or their phones were disconnected. All data in the Handbook were confirmed by phone calls so our sample of Japanese firms totaled 144, the same as the population. Because of the isomorphism between sample and statistical population, we will use the term, family, to refer to the U.S. and Japanese data, rather than calling them samples.\footnote{Private firms were not included in the study because (1) access to comparative data was particularly difficult, (2) private firms may comprise uniqueness because they are private, e.g., ownership may lead to different organizational form.}

Taxonomic Characters

Our elementary theory of organizational differences suggested that we examine markets served, business competencies, and internal firm characteristics. The Fact Book summarizes each firm's public information derived from annual reports, 10-K's and Security Exchange Commission (SEC) statements. It presents information on each firm's business competencies, markets served, size, internal processing capabilities, balance sheet, and performance. To ensure accuracy, we called each firm\footnote{In the analyses for this research, we kept the United States and Japanese families separate. This provided two independent data sets to test our hypothesis about discrete populations. It is also consistent with research that argues that the U.S. and Japanese industries differ significantly (Vogel 1979; Baranson 1981; Sasaki 1981). Future analyses could empirically assess the extent to which the total sample of U.S. and Japanese firms represent one or two families.} to verify the information in the Fact Book or Handbook about the firm's business competencies, markets served, number of divisions, year of incorporation, and specialization ratio. In

\footnote{These phone calls were made to an officer of the firm, generally public relations, corporate affairs, or corporate secretary. After introducing ourselves as researchers, we reviewed with the officer the data we had collected from the secondary sources. These individuals confirmed or modified the information collected. The calls were conducted in English for U.S. firms and Japanese for Japanese firms and lasted an average of 20 minutes.}
addition, we collected information on all beneficiary stock owners. A beneficiary stock owner holds at least 5% of the firm's stock. For U.S. firms, stock information came from Form 13-G, filed with the SEC; we examined Form 13-G for each firm in the family. For Japanese firms, stock information was listed in the Handbook.

We acknowledge the elementary nature of our theory of organizational speciation based on markets served, business competencies, and internal firm characteristics (size, productivity, and diversification). Using secondary data, however, we were constrained in data available on which to base our theory. Based on our elementary theory of organizational speciation, we collected data for 78 taxonomic characters representing distinctive attributes of a firm. (See Appendix for a list of measures.)

The Resemblance Matrix

Once researchers select cases and characters, the next step in numerical taxonomic analysis requires the development of a numerical coefficient representing an average level of similarity or dissimilarity between each possible pairing of organizations across all characters. In this research, two data matrices represented the data, a 669 (rows) by 78 (columns) data matrix for the U.S. family and a 144 by 78 matrix for the Japanese family.

In forming the data matrices for U.S. and Japanese firms, we worried primarily about avoiding the inadvertent introduction of weighting and bias among the characters via coding, a possibility despite the presumed objectivity of numerical taxonomic methods (McKelvey 1982). We standardized all binary and continuous characters to the same range and variance. Standardizing data equalizes both the range and variance of all variables. Many standardization procedures have been demonstrated. The formula used by Sokal (1961) and recommended by Sneath and Sokal (1973) standardizes multistate characters by mirroring z-scores:

\[ X' = \frac{X - \bar{X}}{\text{standard deviation}}. \]

This formula makes the mean equal to zero and variances equal to one for each variable. Thus, we avoided any undue weighting of any single character with unusual range and variance.

Nearly as many resemblance coefficients exist as researchers. No consensus prevails that one resemblance coefficient is better than another (Sneath and Sokal 1973). In fact, those creating coefficients run the risk of inappropriately engineering their solutions to better fit some external validity criterion variable, if one exists. The orthodox evolutionary classification acts as such a criterion variable in biological numerical taxonomy, giving rise to some engineering of numerical classifications to better fit the orthodox one. The absence of an accepted pre-existing classification scheme in organizational science precludes this possibility. Alternatively, some risk avails in blindly accepting a particular coefficient, since it may be decidedly inferior. We chose to use two frequently used coefficients, product-moment correlation and Euclidean distance. Consequently we begin our structural analysis with four resemblance matrices: a U.S. and Japanese matrix for each coefficient. Each matrix consists of a resemblance coefficient representing the similarity or dissimilarity between all possible pairings of cases.

Structural Analysis

A host of options prevail for analyzing the substructure of a statistical population (Bailey 1975; Mezzich and Solomon 1980; McKelvey 1982). The basic choice between
joining and sorting methods (Hartigan 1975) subsumes most of them, except for choice of linkage method (McKelvey 1982).

(a) *Joining vs. sorting techniques.* Joining methods (cluster programs) agglomerate individual organizations into small groups on the basis of highest resemblance; then they join the small groups into larger groups, repeating the sequence until all are joined in one large group. A hierarchy of ranks results, consisting of groups that do not overlap. Sorting techniques (factor analysis, multidimensional scaling) start with one large group and divide it into a number of smaller groups; they are not hierarchically arranged or related. Usually, overlapping groups are produced. Both techniques produce polythetic groups. Biological taxonomists use joining much more than sorting methods.\(^5\)

We used joining methods for two reasons. First, we did not have enough characters (78) to factor analyze (Q type) 669 cases. Second, joining methods are used more frequently (Blashfield and Aldenderfer 1978), and produce more discrimination among the minor branches and smaller groups.

(b) *Linkage technique.* Joining methods offer a large variety of algorithms for clustering, but most researchers use one of three more popular techniques: single linkage (nearest neighbor), complete linkage (farthest neighbor), or group average method. These algorithms are described by Sneath and Sokal (1973), Clifford and Stephenson (1975), and McKelvey (1982). McKelvey (1982) concludes in favor of the group average method, based on a review of the literature. Nevertheless, we carried out analyses using all three methods since in particular circumstances each one may outperform the others.

**Results**

*Existence of Significantly Different Populations*

Our study tests whether populations within an industry have statistically significant different characteristics (H1). In this instance the entire publicly held electronics industry family forms the statistical population. Since uncertainties exist about which resemblance coefficients and cluster algorithms work best, six combinations are used for families in the U.S. and Japan industries, resulting in 12 resemblance matrices and 12 cluster solutions or phenograms:

<table>
<thead>
<tr>
<th>Resemblance Matrix</th>
<th>Joining Technique</th>
<th>United States (669 × 669)</th>
<th>Japan (144 × 144)</th>
</tr>
</thead>
<tbody>
<tr>
<td>correlation</td>
<td>+ single linkage</td>
<td>•</td>
<td>•</td>
</tr>
<tr>
<td>correlation</td>
<td>+ complete linkage</td>
<td>•</td>
<td>•</td>
</tr>
<tr>
<td>correlation</td>
<td>+ group average</td>
<td>•</td>
<td>•</td>
</tr>
<tr>
<td>distance</td>
<td>+ single linkage</td>
<td>•</td>
<td>•</td>
</tr>
<tr>
<td>distance</td>
<td>+ complete linkage</td>
<td>•</td>
<td>•</td>
</tr>
<tr>
<td>distance</td>
<td>+ group average</td>
<td>•</td>
<td>•</td>
</tr>
</tbody>
</table>

Three alternatives exist for determining the best phenogram. First, biologists often use the orthodox evolutionary classification as an external validity criterion and compare numerical solutions with it. No such orthodox classification exists for organizational scientists and consequently no external validity criterion exists.

\(^5\)Some biologists now use both because joining methods seem to work best in finetuning the lower ranks of a hierarchical classification whereas sorting methods seem most useful in clarifying the main branches or groups (McKelvey 1982). But their ratio of cases to characters usually falls short of Nunnally's standards, or they use very few cases.
Second, researchers may synthesize results from different clustering techniques to form one set of populations. Barney (1982) used this approach in synthesizing the results of different clustering methods into one output through joint homomorphic reduction. With our data, this method did not work as all 669 U.S. and all 144 Japanese firms merged into one large population, which may be explained by all firms being part of the same family of firms.

Third, investigators may base evaluations of different cluster phenograms on the internal validity of the solutions. We take this approach, using four internal criteria. Our goal was to identify the best cluster phenogram for each family.

(A) We began with the Sokal and Rohlf (1962) cophenetic correlation. The cophenetic correlation tests how well the similarity among organizations implied by the output phenogram compares with the similarity implied by the input resemblance matrix. This technique is comparable to reconstructing the original correlation matrix from factor scores and then correlating the original and reconstructed correlation matrices to test the internal validity of factor analysis.

For both U.S. and Japanese families, the distance resemblance matrix with single linkage and group average joining methods produces significantly higher cophenetic correlations than the other four methods (see Table 1). In Table 1, the cophenetic correlations are between the output cophenetic matrices based on the single linkage and group average joining methods and the distance input resemblance matrix. For both the U.S. and Japan, these results (using an r-to-z transformation for each cophenetic output) indicate that the distance resemblance matrix with single \((r = 0.954\) for U.S. and 0.945 for Japan) and group average \((r = 0.972\) for U.S. and 0.966 for Japan) joining methods produces significantly better results than all other methods. However, the cophenetic correlations between the distance resemblance matrix and single and group average joining methods are not significantly different. Thus, we eliminate four and still have two clustering phenograms in each family which may offer the best representation of populations within the U.S. and Japanese electronics industries. In addition, the distance resemblance coefficient clearly outperforms the correlation resemblance coefficient.

Based on these findings, we examined the phenograms for each family with the single linkage and group average joining techniques. For the U.S. family, we identify 12 clusters with the single linkage and 13 clusters with the group average joining method. For the Japanese family, we identify eight clusters with the single linkage and nine with the group average joining method. We define these clusters by examining the fusion, or joining, level of each organization to other organizations. When there is a major jump in fusion levels, we group organizations into clusters. As Hartigan (1975) and Sneath and Sokal (1973) suggest, these groupings are somewhat subjective. Because of this subjectiveness, we define two sets of outcomes—the results of the single linkage and group average linkage—then we attempt to statistically define the best of the two outcomes.

(B) Multiple discriminant analysis across populations using the 78 characters provides three results which helped us choose between the single linkage and group average methods. First, the sum of the eigenvalues in the discriminant analysis measures the total between-group variance existing in the discriminating characters. For the U.S. family, the sum of the eigenvalues is 5.66 for single linkage and 8.43 for group average (Table 2). Second, discriminant analysis identifies the number of significant functions (based on Wilks' lambda). For the U.S. family, the single linkage method identifies four significant functions whereas the group average method identi-

---

6While defining clusters is subjective (Sneath and Sokal 1973, pp. 290–297), our results provide the best indication that our definition of populations is nontrivial.
TABLE 1
Criteria to Evaluate Clustering Solution: Correlation of Cophenetic Output and Resemblance Input Matrix

<table>
<thead>
<tr>
<th>Resemblance Measure</th>
<th>Joining Technique</th>
<th>United States</th>
<th>Japan</th>
</tr>
</thead>
<tbody>
<tr>
<td>distance</td>
<td>+ single linkage</td>
<td>0.954*</td>
<td>0.945*</td>
</tr>
<tr>
<td>distance</td>
<td>+ complete</td>
<td>0.873</td>
<td>0.877</td>
</tr>
<tr>
<td>distance</td>
<td>+ group average</td>
<td>0.972*</td>
<td>0.966*</td>
</tr>
<tr>
<td>correlation</td>
<td>+ single linkage</td>
<td>0.181</td>
<td>0.127</td>
</tr>
<tr>
<td>correlation</td>
<td>+ complete</td>
<td>0.512</td>
<td>0.529</td>
</tr>
<tr>
<td>correlation</td>
<td>+ group average</td>
<td>0.609</td>
<td>0.594</td>
</tr>
</tbody>
</table>

1 Each number in the table represents the correlation between the distance or correlation input resemblance matrix and the cophenetic output matrix based on the joining clustering algorithm (single linkage, complete, or group average). It is based on the correlations between each entry in the input (669 × 669 for U.S. and 144 × 144 for Japan) matrix and the output matrix. In total this correlation is based on 223,111 entries for the U.S. family (669 × 669/2 – 669) and 10,224 entries for the Japanese family (144 × 144/2 – 144).

2 The statistical significance is calculated by translating each entry into a z score using the r-to-z transformation (McCall 1975). Then, within each family, the statistically significant difference between each score is calculated. For both the U.S. and Japanese families, the distance + single linkage and group average scores are significantly higher than the other four scores, but not significantly different from each other.

* p < 0.05.

TABLE 2
Criteria to Evaluate Clustering Solutions: Discriminant Analysis, T-tests, F-test

<table>
<thead>
<tr>
<th>Disciminant Analysis</th>
<th>United States</th>
<th>Japan</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Single Linkage</td>
<td>Group Average</td>
</tr>
<tr>
<td><strong>Total eigenvalue in</strong></td>
<td>5.66</td>
<td>8.43</td>
</tr>
<tr>
<td><strong>Number of significant functions (p &lt; 0.05)</strong></td>
<td>4</td>
<td>10</td>
</tr>
<tr>
<td><strong>% of cases accurately grouped</strong></td>
<td>60%*</td>
<td>69%*</td>
</tr>
</tbody>
</table>

T-Tests

<table>
<thead>
<tr>
<th>% of significant differences of each characteristic with all populations</th>
<th>United States</th>
<th>Japan</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>45.2%</td>
<td>62.9%</td>
</tr>
</tbody>
</table>

F-Test

<table>
<thead>
<tr>
<th>-between group variance (average for each characteristic with all populations)</th>
<th>United States</th>
<th>Japan</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>4.6</td>
<td>8.6</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>-within group variance</th>
<th>United States</th>
<th>Japan</th>
</tr>
</thead>
<tbody>
<tr>
<td>55.2</td>
<td>52.5</td>
<td>14.0</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>-F-test</th>
<th>United States</th>
<th>Japan</th>
</tr>
</thead>
<tbody>
<tr>
<td>4.9*</td>
<td>8.0*</td>
<td>3.4*</td>
</tr>
</tbody>
</table>

* = significant at p < 0.05.
Japanese family, the single linkage and group average figures are, respectively, 93% and 97% (versus 12.5% and 11.1% that would be correctly classified by chance). The level of accuracy jumps up considerably above random distribution, but both methods perform about the same. Each of these three results from the discriminant analysis supports group average clustering as more appropriate than single linkage clustering (see Table 2).

(C) Next we calculated t-tests to determine significant differences among firms in each population versus firms in all other populations, using each of the 78 taxonomic characters. It is a two-group comparison: firms in a population comprise one group and all other firms comprise the other group. The question we ask of the data is: Is the score for each character significantly different in a population group compared to the mean for all other organizations? For the U.S. family, 45% of the t-tests show significant difference for single linkage clustering whereas 63% of the t-tests show significant differences for group average clustering. For the Japanese data the numbers are 37.1% and 37.7%, respectively. These results suggest group average clustering is superior to single linkage clustering in the U.S. data but not in the Japanese family. More importantly they also show that each population is significantly different from firms outside that population across a majority of characters. We would not expect all characters to show significant differences since some could be trivial, have low variance, or be the same for two or more populations.

(D) Finally we performed a test to determine the best cluster solution by assessing between- and within-group variance for each of the 78 characters, using analysis of variance. We average the between-group and within-group variance for each of the 78 characters across all populations defined by each cluster solution to determine an overall between-group and within-group variance for each cluster method. For the U.S. family, between-group variance averages 4.6 while within-group variance averages 55.2 for single linkage clustering. The variances average 8.6 and 52.5, respectively, for group average clustering. With these results, we calculated F-tests to determine the overall differences between cluster methods. For single linkage clustering, the F-test is 4.9 (12,656 df); for group average clustering, it is 8.0 (13,655 df). While both F-tests significantly differ from zero (p < 0.05) the results are stronger for group average than for single linkage clustering (Table 2).

In summary, the four internal criteria point toward the distance resemblance matrix with group average clustering as the phenogram which produces the statistically best result in both the U.S. and Japanese samples. These results demonstrate that null of hypothesis H1 is rejected: homogeneous populations can be shown to be statistically significant using the foregoing methods. For our data, at least, the distance coefficient coupled with the group average algorithm produces populations that are not artifacts based on chance.

Characteristics of Populations

United States Electronics Industry Family

Characteristics of each of the 13 populations within the U.S. electronics family, based on distance resemblance matrix and average linkage algorithm are described below.

Population 1 (transportation focus) includes 14 firms. These firms are involved in manufacturing, selling, or research and development activities in the transportation market. They are smaller firms (fewer divisions, plants and facilities, and employees) and specialize in electronics, with a majority of their products used in the electronics industry. They are less involved in components, power, industrial, communications, consumer-business, and computer markets. They are somewhat more involved in
instruments and government markets, although not as prevalent as the transportation market. Some firms in this population include Aerosonic Corporation, Gates Learjet Corporation, and United Aircraft Corporation.

Population 2 (industrial focus) has 46 firms. Firms in this population work in the industrial market. They, like firms in population 1, are small and highly specialized in electronics. Firms in this population work less in instruments, consumer-business, computer, government, transportation, or nonelectronics markets. They are somewhat involved in components and communications markets. They are also characterized by a high income to sales ratio. Representative firms in this population include Art's-Way Manufacturing, Electric Regulator, Gleason Works, and Oak Industries.

Population 3 (components focus) has 69 firms. These firms are involved in the components market and less likely to work in any other markets. They are much smaller firms on all characteristics of size, with the majority of their business in the electronics industry. They are likely to have somewhat lower sales per employee ratios which may indicate a somewhat less than efficient use of employees. Firms representative of this population are General Semiconductor, Transducer Systems, Inc., and United States Components, Inc.

Population 4 (instruments and components market) has 56 firms. These firms operate in manufacturing and research and design in the instruments market and are somewhat involved in the components market, but are unlikely to work in any other markets. These firms specialize in electronics with a large portion of sales in the electronics market. Unlike firms in populations 1, 2, or 3, firms in this population operate in more product lines than firms in the first three populations. Firms in this population also have a lower debt per total assets ratio, which indicates their lack of dependence on debt. Analog Devices, Inc., Datatron, Inc., and Scientific Industries are some of the firms in this population.

Population 5 (manufacture and market in consumer-business and computer market) has 43 firms. These firms manufacture and market in the consumer-business market; and manufacture, market, and research and develop in the computer market. They function less in any other market. These firms are smaller, more specialized overall, and more specialized in electronics. They also have a lower sales per total assets ratio which may indicate that firms in this population are not selling what they might expect given the total assets of the firm. Some of these firms include Base Ten Systems Inc., Data General Corporation, and Tektronix, Inc.

Population 6 (research and development and distribution in consumer-business and computer market) has 50 firms. These firms are involved with distribution and research and development activities in the consumer-business market, and market and distribution activities in the computer market. Firms in this population foil firms in population 5—they are in the same markets, but involved in different activities within those markets. These firms may also be somewhat involved in other activities in consumer-business, computer, and government markets. These firms, while not the largest of firms in any population, are larger than firms in populations 1 through 5. They have a high proportion of their business in electronics, although they are not as specialized overall as firms in other populations. Firms in this population include Advent Corporation, Four-Phase Systems, and Koss Corporation.

Population 7 (diversified markets, high internal efficiency) has 61 firms. These firms perform some activities in three markets. In the components market, they distribute; in the instruments market, they manufacture, market, distribute, and research and develop; in the nonelectronics market, they manufacture and market. They also operate in the power and industrial markets. They are unlikely to work in communications, consumer business, computer, government, or transportation markets. These firms are small, but not specialized overall or in electronics. Of all the 13 populations, firms in
this population have higher income per employee, sales per employee, and sales per total assets. Firms in this population include Eli Lilly and Company, Intel Corporation, and John Fluke Mfg. Co.

Population 8 (nonelectronics markets) has 42 firms. These firms manufacture and research and design for government markets and manufacture for nonelectronics markets. Firms in this population operate in components, power, instruments, and communications markets. The firms in this population are not as small as firms in populations 1 through 7. The firms in this population are less specialized and more involved in markets beyond electronics. Firms in this population also have a somewhat lower sales per employee ratio than firms in other populations. Representative firms in this population include Dynamics Corporation, Martin Marietta Corporation, and Snap-On Tools.

Population 9 (communication market) has 31 firms. These firms function in the communications market, involved in manufacturing, marketing, and research and design activities. They are somewhat involved in components, instruments, power, consumer-business, and transportation markets. In each of these markets, they engage in manufacturing activities. These firms are generally smaller and more highly specialized in electronics. Some firms in this population include Scientific Radio Systems, Comtech Telecommunications, and E. F. Johnson Company.

Population 10 (distribution focus) has 66 firms. These firms function in marketing and distribution for the industrial market and distribution for the consumer-business market. Firms in this population are also somewhat involved in components, power, instruments, computer, and nonelectronics markets. These firms are smaller, not specialized in electronics and not specialized overall. These firms also have a higher debt per total assets ratio which may indicate their tendency to finance their products through debt. Firms in this population include Advance Ross Corporation, Bell & Howell Company, and Grumman Corporation.

Population 11 (dispersed markets, average performance) has 52 firms. These firms operate in many markets. They manufacture, market, and research and design for the power market; manufacture in the industrial market; distribute and research and develop in the instruments market; lease in the computer market; research and develop in the transportation market; and manufacture, market, and research and develop in the nonelectronics market. These firms are not significantly larger or smaller than other firms, nor are they more or less likely to be specialized in the electronics market. In brief, these firms are not specialized, but are in dispersed markets, with average size and internal process ratios. Some firms in this population include Bunker Ramo Corporation, Keltron Corporation, and The Singer Company.

Population 12 (diversified markets, moderate performance) contains 88 firms. These firms perform nearly all activities in all markets. The only two markets in which they do not work are components and computers. These firms are large with more employees, total assets, and common shares than firms in other populations. These firms are less specialized overall and less specialized in the electronics industry. Firms in this population have a higher ratio of sales per employee, although the sales per total assets is somewhat lower. Some of the firms in this population are E. I. DuPont, Esmark, Inc., Lockheed Aircraft, and Wells Benrus.

Population 13 (diversified markets, above average performance) has 51 firms. This population, like population 12, represents firms in many markets. Firms in this population work in all markets except instruments. They are large firms with lower specialization ratios overall and in electronics. These firms also have higher total assets per employee and income per total assets ratios, indicating the profitability and large assets of firms in this population. This population is much like population 12, except that it includes the markets not included in population 12 and it has firms with higher
ratios of total assets per employee and income per total assets. Firms in this population include Allegheny Ludlum Industries, Control Data Corporation, Honeywell, Inc., and Rockwell International.

**Japanese Electronics Industry Family**

Characteristics of each of the 9 populations within the Japanese electronics family, based on distance resemblance matrix and average linkage algorithm are described below.

Population 1 (power market) has 12 firms. These firms work in the power market. They are smaller firms (fewer divisions, plants and facilities, and employees) and specialized in electronics, with a majority of their products being used in the electronics industry. They are unlikely to operate in components, consumer-business, communications, or computer markets. They are somewhat involved in instruments markets. The firms in this market also have a higher debt to sale ratio, which indicates their dependence on debt financing. Some firms indicative of this population include Fuji Electric, Osaka Transformer, Aichi Electric Mfg., and Japan Storage Battery.

Population 2 (industrial market) has 19 firms. This population is characterized by firms which work in the industrial market and are not involved in any other markets. These firms are also smaller (fewer employees, number of divisions, plants and facilities). These firms are not significantly different from firms in other populations on overall and electronics specialization. Firms representative of this population include Nippon Signal, Okuma Machinery Works, and Kimmon Manufacturing.

Population 3 (components market) has 13 firms. These firms only function in the components market. They are smaller firms (on all characteristics of size), and not highly specialized in electronics. They have lower income to sales and income per total assets ratios than firms in other clusters. Firms in this population are Mitsumi Electric, Hosiden Electronics, and Shindengen Electric.

Population 4 (consumer-business market) has 20 firms. These firms are involved in the consumer-business market and unlikely to be in any other markets. These firms specialize in electronics. Firms in this population operate in more product lines than firms in population 1. Firms in this population also have a lower debt per sales ratio and debt per total assets ratio, and higher income per employee, sales per employee, sales per total assets, and income per total assets ratios. These higher performance ratios indicate that firms in this population are attaining comparatively high profits. Firms in this population include Sharp Corporation, Pioneer Electronics, and Sansui Electric.

Population 5 (transportation market) has 30 firms. These firms are involved in only the transportation market. These firms are of average size with average internal operating ratios. Some firms in this population include Nippon Electric, Isuzu Motors, and Daihatsu Motor.

Population 6 (moderately diverse market, electronics specialists) has 13 firms. These firms work in communications and consumer-business markets. These firms are somewhat involved in other activities for the industrial and instruments markets. These firms are about average size, but specialize in the electronics industry. Firms in this population include Omron Tateisi Electric, Japan Radio, and Toyo Communication Electronics.

Population 7 (nonelectronics focus) has 7 firms. These firms are not involved in components, power, communications, consumer-business, or computer markets, and only somewhat involved in industrial, instruments, and transportation markets. They are average-size firms, not specialized in electronics (unlike firms in population 6). Firms in this population include Nitto Electric Industry, Copal, and Kawai Musical Instruments.
Population 8 (distribution market) has 14 firms. These firms specialize in distribution activities within the components and consumer-business markets. They do not operate in any other markets or any other activities. These firms are slightly smaller, but in general they are not substantially different from other firms. Firms in this population include Sanken Electric, Toko Electric, and Dai-ichi Katei Denki.

Population 9 (diverse markets, vertically integrated) has 16 firms. These firms work in the communications and computer markets. They are also involved in components, power, industrial, instruments, consumer-business and transportation markets. These are large, vertically integrated firms. Their larger size is indicated by the larger number of plants and facilities, number of employees, number common shares, and other size measures. These firms are not specialized overall or in electronics. Examples of these larger, more integrated firms include Hitachi, Toshiba, Mitsubishi Electric, and Fujitsu.

Conclusion

The results support the objective of our study. Our analyses corroborate the hypothesis of intra-industry populations in separate analyses for the U.S. and Japanese electronics families and further show the populations statistically different. Several resemblance coefficients and clustering methods were compared and the significance of the difference among methods and among populations was tested in a variety of ways. The distance coefficient of resemblance proved superior to the product-moment correlation coefficient for all three cluster algorithms. The group average clustering method consistently outperformed the other clustering methods, though, for our data, single linkage clustering worked quite well, also.

Strictly speaking, statistics do not make a lot of sense in our analysis since our sample and statistical population (initial aggregate or family) nearly coincide; therefore sample and population means also must nearly coincide and there is no small sample induced instability in our regression equations. Our statistical populations at both family and population levels are also finite (see Table 3). Since the representativeness of our samples of the populations is not at issue we use statistics to demonstrate that our findings are not due to the chance alignment of a large number of small, random, or unorganized causes (Stinchcombe 1965, 1968). The group average method accurately classified 97% of the Japanese firms. Since the sample and population almost totally overlap, we conclude that we accomplished about as much as possible, given our taxonomic characters. For U.S. firms we did not achieve as much success. The niche focus of the Japanese clusters seems more crisply focused than that of the U.S. clusters and the best method, group average, classified only 69% accurately. Clearly, room for improvement remains. Some possible reasons for the lower accuracy include the greater diversity of U.S. firms versus Japanese firms, the fewer number of populations for the U.S. family relative to the total number of firms or the limited taxonomic characters used to define the populations. Perhaps the larger number of U.S. firms reflects the need for more diversity in characters to classify those firms into populations. We realize that this preliminary investigation can be embellished by more elaborate theories of speciation that lead to expanded data collection and analysis.

TABLE 3
Multiple Regression of Selection Processes on Prosperity: Total Family vs. Each Population

<table>
<thead>
<tr>
<th></th>
<th>UNITED STATES</th>
<th></th>
<th></th>
<th></th>
<th></th>
<th>JAPAN</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>COLUMN 1</td>
<td>2</td>
<td>3 MULTIPLE</td>
<td>4 ADJUSTED</td>
<td>5 MULTIPLE</td>
<td>6</td>
</tr>
<tr>
<td></td>
<td>POPULATION</td>
<td>df</td>
<td>R</td>
<td>df</td>
<td>R</td>
<td>POPULATION</td>
</tr>
<tr>
<td>Total Sample</td>
<td>669</td>
<td>0.08</td>
<td>0.005</td>
<td>Total Sample</td>
<td>144</td>
<td>0.37</td>
</tr>
<tr>
<td>1</td>
<td>14</td>
<td>0.74*</td>
<td>0</td>
<td>1</td>
<td>12</td>
<td>0.84*</td>
</tr>
<tr>
<td>2</td>
<td>46</td>
<td>0.31*</td>
<td>0</td>
<td>2</td>
<td>19</td>
<td>0.44*</td>
</tr>
<tr>
<td>3</td>
<td>69</td>
<td>0.28*</td>
<td>0.19**</td>
<td>3</td>
<td>13</td>
<td>0.85*</td>
</tr>
<tr>
<td>4</td>
<td>56</td>
<td>0.40*</td>
<td>0</td>
<td>4</td>
<td>20</td>
<td>0.64*</td>
</tr>
<tr>
<td>5</td>
<td>43</td>
<td>0.18</td>
<td>0</td>
<td>5</td>
<td>30</td>
<td>0.64*</td>
</tr>
<tr>
<td>6</td>
<td>50</td>
<td>0.49*</td>
<td>0.32**</td>
<td>6</td>
<td>13</td>
<td>0.91*</td>
</tr>
<tr>
<td>7</td>
<td>61</td>
<td>0.79*</td>
<td>0.76**</td>
<td>7##</td>
<td>7</td>
<td></td>
</tr>
<tr>
<td>8</td>
<td>42</td>
<td>0.49*</td>
<td>0.24**</td>
<td>8</td>
<td>14</td>
<td>0.87*</td>
</tr>
<tr>
<td>9</td>
<td>31</td>
<td>0.66*</td>
<td>0.48**</td>
<td>9</td>
<td>16</td>
<td>0.81*</td>
</tr>
<tr>
<td>10</td>
<td>66</td>
<td>0.57*</td>
<td>0.49**</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>11</td>
<td>52</td>
<td>0.29*</td>
<td>0</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>12</td>
<td>88</td>
<td>0.31*</td>
<td>0.04</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>13</td>
<td>51</td>
<td>0.46*</td>
<td>0.25**</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mean of 13 populations</td>
<td>0.46</td>
<td></td>
<td></td>
<td>Mean of 9 Populations</td>
<td>0.78</td>
<td></td>
</tr>
</tbody>
</table>

Significant differences between the score for each population and the score for the overall family for both the Multiple $R$ and Adjusted Multiple $R$. Probability: * < 0.05. ** < 0.01.

Column 1: Population number, U.S. firms
Column 2: Number of firms in each U.S. population
Column 3: Multiple $R$ of selection process on prosperity for U.S. firms
Column 4: Z-Score of population correlation with total sample correlation for U.S. firms
Column 5: Population number, Japanese firms
Column 6: Number of firms in each Japanese population
Column 7: Multiple $R$ of selection processes on prosperity for Japanese firms
Column 8: Z-Score of population correlation with total sample correlation for Japanese

## Deleted from consideration because of inadequate degrees of freedom.

Carroll (1981, 1984a, b). Two root concepts of the organizational world predominate in this theory: relatively homogeneous populations of organizations exist, and the structure and process, or form, of populations materializes through the protracted effects of environmental resources alterations and access constraints, known as selection processes.

The results reported here are the first corroboration of the first foundation concept. Nonrandom, nontrivial populations exist in at least one industry or family in two countries. Whether industry groups formally classify as families, genera, or species, remains unknown. It is possible that some industries include many populations. Others may consist only of one. The review by McGee and Thomas (1986) suggests that many industries have a substructure. There appears to be considerable need for further investigation of methods leading to definitions of these structures.

One source of important further investigation will assess which organizational characteristics should be used to differentiate and classify organizations. This research relied on publicly visible, replicable, and objective data that focused extensively on a firm’s product and strategies. We would speculate that analyses which assess the less public, more idiosyncratic, and more subjective characteristics of organizations may lead to more exact classifications of organizations. In particular, future research may assess a hierarchy of organizational characteristics which may be used to classify firms,
ranging from the more externally visible and replicable to more internally focused and unique.

We feel that this paper marks the beginning of an empirical effort to corroborate the theories of the population perspective. A considerable research agenda remains, however. More elegant theory about what attributes best help us identify populations of organizations is needed, thus lending to selection of taxonomic characters. We could not use evolutionary analysis at all to directly identify evolutionarily significant environmental and organizational attributes and have only begun to use cluster algorithms. Better operationalization remains an important objective. The main outlines of population and natural selection theory offer a host of deductive propositions—we barely scratched the surface in our study.7

Acknowledgements

This research has been sponsored by grants from Office of Naval Research, Hewlett Packard, International Business Machines, Alcoa Foundation, and the General Electric Foundation; Bill Ouchi, Principal Investigator; Jay Barney, Investigator. The help and comments by Mitchell Koza, and Danny Miller are gratefully appreciated. We owe a special debt of gratitude to Barbara Lawrence for her tireless effort on our behalf and to Graham Astley as a Special Editor. The flaws that remain are our responsibility.

Appendix

For each firm in the United States and Japanese electronics industry, the following data were collected from secondary data and from interviews with representatives of each firm.

A. Market/business competency matrix.

Each firm responded “yes” or “no” to each cell in the matrix depending on the firms participation in a market with a particular set of competencies.

<table>
<thead>
<tr>
<th>BUSINESS COMPETENCY</th>
<th>MARKETS</th>
<th>COMPONENTS</th>
<th>POWER</th>
<th>INDUSTRIAL</th>
<th>INSTRUMENTS</th>
<th>COMMUNICATIONS</th>
<th>CONSUMER-BUSINESS</th>
<th>COMPUTERS</th>
<th>GOVERNMENT</th>
<th>TRANSPORTATION</th>
<th>NONELECTRONICS</th>
</tr>
</thead>
<tbody>
<tr>
<td>R &amp; D/ DESIGNS/ TESTS</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>PRODUCES/ MANUFACTURES/ FABRICATES</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>SELLS/ MARKETS</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>DISTRIBUTES/ SERVICES/ INSTALLS</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>LEASES/ RENTS</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>OTHER</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
B. Firm characteristics used in the analyses

1. Firm Size:
   - Total number of operating divisions
   - Number of plants and facilities
   - Number of employees
   - Revenues or sales
   - Current assets
   - Total assets
   - Current liabilities
   - Shareholder's equity
   - Net income

2. Macro productivity measures:
   - Income/sales
   - Total assets/employee
   - Income/employee
   - Sales/employee
   - Sales/total assets
   - Income/total assets

3. Organizational diversification:
   - Specialization ratio: percent of sales in leading line of business (measured following Rumelt 1974)
   - Electronics related ratio: percent of sales in electronics related businesses
   - Electronics specialization ratio: percent of sales in leading line of electronics business

References


